DETECTION OF WEEDS IN THE CROP FIELD USING MACHINE LEARNING

A project report submitted in partial fulfilment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS AND COMMUNICATIONS ENGINEERING

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CERTIFICATE

This is to certify that the project work entitled, "DETECTION OF WEEDS IN THE CROP FIELD USING MACHINE LEARNING" is a bonafide work of V. P L Padmaja (176K1A0454), I.S.S.Sameera (176K1A0420), S.HariPrasad M(176K1A0459), D.Rakesh (176K1A0414), D.Chithra Meghana (176K1A0411) submitted to the department of Electronics and Communications Engineering, in a partial fulfilment of the requirements for the award of the degree of BACHELOR OF TECHNOLOGY in ELECTRONICS AND COMMUNICATIONS ENGINEERING from IDEAL INSTITUTE OF TECHNOLOGY, Kakinada

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DECLARATION

We hereby declare that the project report entitled, **"DETECTION OF WEEDS IN THE CROP FIELD USING MACHINE LEARNING"** has been carried out and contents have been submitted in partial fulfilment of the requirements for the award of the degree of BACHELOR OF TECHNOLOGY in ELECTRONICS AND COMMUNICATION ENGINEERING, IDEAL INSTITUTE OF TECHNOLOGY, Affiliated to JNTUK, Kakinada, we assure that this project report has not been submitted to any other university or college.

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INDEX

ABSTRACT

Now a days the agrochemicals spraying techniques results either in over dosing or in under dosing. Both have their own disadvantages, over dosing of chemicals is not only costly but also affects the environment in a very serious manner and under dosing could result in inefficient crop protection and thus low crop yields. Therefore, in order to increase yields per acre and to protect crops from diseases, the exact amount of agrochemicals should be sprayed according to the field/crop requirements. So we design a real-time computer vision based crop/weed detection application. This application takes the images as input and it will generate an analysis report on how much percentage of weed and crop are present. Agrochemical spraying will be done by the farmer based on the report generated by the application.

List of Figures

List of Abbreviations

S.No	Short Name	Abbreviated Name
1	IDE	Integrated Development Environment
2	VCS	Version Control System
3	GUI	Graphical User Interface
4	OS	Operating System
5	GNU	GNU's Not Unix
6	UI	User Interface
7	HTML	Hypertext Markup Language
8	RF	Random Forest
9	RGB	Red Green and Green
10	HSV	Hue Saturation And Value
11	ROI	Region Of Interest
12	OPENCV	Open Source Computer Vision Library
13	UAV	Unmanned Aerial Vehicles
14	EPU	Electronic Proportional Control Valve
15	DUPS	Differential Global Positioning System
16	GIS	Geographical Information System
17	MIC	Maximum Likelihood Classification
18	SVM	Support Vector Machine
19	ANN	Artificial Neural Network
20	CNN	Convolution Neural Network

Chapter-1

INTRODUCTION

1. INTRODUCTION

1.1 Brief Information

The gap between food production and consumption is increasing at a fast rate, due to the lack of availability of advanced agricultural equipment, imprecise input application methods, and the shrinking arable land due to fast urbanization. In order to deal with the rising risk of food insecurity, there is an urgent need to adopt agricultural farming approaches that can help in not only enhancing crop yields but also in minimizing the input costs. Breakout of weeds, pest insects, and disease pathogens are usually considered to be the most harmful to crop productivity.

Growth of weeds is usually constant whereas pests and pathogens grow periodically. Weeds are the unwanted plants that regrow vigorously and are the strongest yield-reducers resulting in 10 to 20% of yield losses. Weeds occupy space, light, water, and nutrients which therefore makes them lethal for crop growth and productivity. Application of agro-chemicals i.e. herbicides and pesticides are commonly being used around the globe by farmers as they play a vital role in enhancing yields by controlling weeds in a cost-effective way. Due to the availability of a large variety of effective herbicides, the use of mechanical methods for weed control has been abandoned by farmers.

1.2 Problem Definition

The biggest drawback of agrochemicals for weed and pest control is that they are very harmful to the environment and population which thereby makes their over-utilization a threat. The existing spraying system is costly and sometimes may get overloaded. It may also give a false mixture of chemicals which results in menace.

1.3 Objectives

- The main objective of this project is to design a scalable application which reduces manpower in detecting weed and crop.
- To improve the accuracy better than the existing system, with less no. of techniques.

Chapter-2

LITERATURE REVIEW

2. LITERATURE REVIEW

2.1 Background

The rapid growth of global population compounded by climate change is putting enormous pressure on the agricultural sector to increase the quality and quantity of food production. It is predicted that the global population will reach nine billion by 2050,and therefore, agricultural production must double to meet the increasing demands .However, agriculture is facing immense challenges from the growing threats of plant diseases, pests and weed infestation. The weed infestations, pests and disease reduce the yield and quality of food, fibre and biofuel value of crops. Losses are sometimes cataclysmic or chronic, but on average account for about 42% of the production of a few important food crops.

Weeds are undesired plants which compete against productive crops for space, light, water and soil nutrients, and propagate themselves either through seeding or rhizomes. They are generally poisonous, produce thorns and burrs and hamper crop management by contaminating crop harvests. That is why farmers spend billions of dollars on weed management, often without adequate technical support, resulting in poor weed control and reduced crop yield. Hence, weed control is an important aspect of horticultural crop management, as failure to adequately control weeds leads to reduced yields and product quality. The use of chemical and cultural control strategies can lead to adverse environmental impacts when not managed carefully.

A low-cost tool for identification and mapping of weeds at early growth stages will contribute to more effective, sustainable weed management approaches. Along with preventing the loss of crop yield by up to 34%, early weed control is also useful in reducing the occurrence of diseases and pests in crops. Many approaches have been developed for managing weeds, and they normally consider current environmental factors. Among these approaches, image processing is promising.

In the image processing approach, unmanned aerial vehicles(UAVs) are used for monitoring crops and capturing the possible weeds in the fields. UAV are found to be beneficial for agriculture usage due to their ability to cover large areas in a very short amount of time, and at the same time, do not cause any soil compaction or damage in the fields. However, the interpretation of data collected from UAVs into meaningful information is still a painstaking task. This is because a standard data collection and classification require significant amounts of manual effort for segment size tuning, feature selection and rule-based classifier design.

As found in many studies in the literature, the quality and quantity of the crop yields were being hampered due to the water and nutrients consumed by weed. Therefore ,an effective solution for weed control in early stages of the crops is much needed. Hence, the objective of this project is to find an efficient and robust machine learning-based approach for detecting unwanted weed and parasites within crops.

A significant and fundamental phase involved in an image classification process is feature extraction. Therefore,for accurate identification of weeds, the most important features to focus on are morphology, texture, and spectral reflectance [2]. Irshad Ahmad et al. [2] presented a weed recognition system that was based on computer vision in real-time. They implemented grayscale segmentation for classifying weeds from the background view. Classification of weeds into broad, narrow, and small leaf classes was done by applying thresholding to the population and calculating sample variance for the complete image. As a continuation of [2], Jamil Ahmad et al. in [3] exploited boosted visual features, local shape, and texture, of images that consisted of weeds for improving the performance of their weed classifier.

The segmentation algorithm (i.e., AdaBoost with Naïve Bayes) had the ability to adapt to different illumination complications. The scientific community has paid significant attention to the development of weed control techniques for increasing crop yield and reducing costs as well as the negative repercussions of herbicides [4–6]. H. Ali et al. [7] presented a method for detecting and classifying the main citrusdiseases. The proposed technique applied colour difference algorithm to separate the disease affected area. Furthermore, the classification of diseases was done via colour histogram and textural features. The authors claim to have obtained an accuracy of about 99.9% with 0.99 area under the curve. Moreover, colour and texture features were combined for carrying out experiments.

The results acquired were similar as compared to the individual channels. Dimensionality reduction of the feature set was achieved by applying principal components analysis. Iqbal et al. [8] conducted a survey on various methods used for the detection and classification of diseases in the leaves of citrus plants. They reported that only 22% of herbicide is required for reducing unwanted plants when applied in a precise manner. The authors outlined the strengths and weaknesses of various image preprocessing, segmentation, feature extraction, feature selection, and classification methods. H. T. Sogaard et al. [9] presented an automated robotic system using a micro-dosage control system for weed detection and spraying precise amounts of herbicide. Weeds were detected using a computer vision approach from the data obtained through an autonomous vehicle which resulted in a reduction of herbicide usage by50%. The experiments demonstrated the ability of the system to target objects with sub-centimetre accuracy. A prototype model for a target-oriented weed control system was developed by M. Loghavi et al. in [10].

The patch sprayer comprised of a differential global positioning system (DGPS), Geographical Information System (GIS),and spray nozzles. The nozzles were activated by a solenoid in response to the signals received from a displacement sensor. The results showed that targeted spraying of herbicides in patches on weeds was able to bring 69.5%savings as compared to the conventional methods of application. De Castro et al. [11] used multi-spectral imagery of fields for distinguishing weeds in field patches using machine learning techniques and colour indexes. The use of the R/B index, B/G ratio, and the MLC method helped in achieving fine results.

Herbicide savings ranging from 71.7to 95.4% and from 4.3 to 12%, for no treatment areas and herbicide low dose areas, respectively, were achieved according to the obtained results. Midtiby et al. [12] evaluated a micro-spraying system for guiding sprayers using sensing technology and for distinguishing weeds from crops. Castaldi et al. [13] used a UAV for herbicide spraying which resulted in a substantial reduction in herbicide usage of about 15-39%. Dammer et al.[14] used real-time cameras for weed sensing and compare their proposed method with conventional broadcast spraying techniques. Berge et al. [15] applied a machine vision algorithm for selecting patches of cereal fields that required agrochemical spray.

A broad review of ground-based machine vision and image processing techniques for weed detection was given in [16] by Wang et al., 2019.C. Sullca et al. in [17] used Support Vector Machine(SVM), Artificial Neural Networks (ANN), Random Forest, and Convolutional Neural Network (CNN) for detecting disease or pest attacks on blueberry plants. Noise from the images were removed via median Blur and gaussian blur filers for the elimination of noise, and details were enhanced via the add Weighted filters. The results obtained via the Deep Learning-based model gave accuracy of up to 84%.

2.2 Existing System

The existing system framework for agrochemical spraying comprises two subsystems namely: (a) vision system (b) fluid flow control or spray actuation/application system.

This research work mainly focuses on the vision system for providing feedback to the fluid flow control system.

(a)Vision System:

The vision system is used for providing feedback to the fluid flow control system using image processing and machine learning algorithm. The complete approach is explained in the following subsections.

1) Crop / Weed detection

The detection and classification of crops and weeds in real-time is conducted in two phases. The first phase involves training the model on offline data. Once training is completed, the model becomes ready to classify crops from weeds in real-time. In the testing phase, features are extracted from the testing images and are labelled by the classifier.

The steps involved in both training and testing phases are:

a)Image / Data acquisition: This step involves acquiring the images of crops, weeds and combination of both at different timings and lightning conditions using high resolution RGB cameras.

b) Pre-Processing: In this step, undesired noisy regions, illumination and motion blurring effects are removed to improve the quality of the image.

c) Image segmentation: This step involves the extraction of features from the image for classification.

d) Features: In this step, several features like colour, texture, and shape are selected for performing crop and weed classification. The Digital Image Processing techniques used for feature extraction are

i. Shape matching using Hu moments

ii. Edge orientation feature

iii. Haralick texture feature

iv. Color histogram

e) Training: Here we train the machine learning-based classification model. It is a supervised learning approach in which labelled data is fed to the model, and the system finds out how to segregate each image by learning the pattern behind each image. The main goal of training the model is that it could classify crops and weeds in the presence of noise, illumination (sun-light) variation, and image blurring due to motion.

f) Random Forest algorithm: It is a Supervised Machine Learning algorithm. Here multiple decision trees created on randomly selected samples forms a forest. Each decision tree acts as the building block of the model predicts a classification for the input data. The input of each tree is sampled data from the original dataset.

b) Fluid flow control or spray actuation/application system:

The complete spraying system consisted of a 4-wheeler trolley as application equipment. ATmega2560 microcontroller was connected serially with the laptop for controlling the pump and solenoid valves mounted on each of the four nozzles. The flow rate was varied by changing duty cycles of the electric solenoid valves attached to each nozzle according to the feedback (reference) signal obtained from the vision system.

Each nozzle was controlled individually via ON/OFF solenoid valves which thereby allowed for more accurate application of agrochemicals. An electronic proportional control valve (EPV) mounted on the bypass line was used to maintain the desired pressure in the system. When the pressure in the system exceeded the set pressure due to closure of any outlet/nozzle, the EPV regulated the excess flow back to the tank.

2.2.1 Disadvantages

- The initial investment to purchase such system will be very high.
- Also maintenance cost would be high to keep the system in good condition.
- The spraying system may sometimes get overloaded.
- It may also give a false mixture of chemicals.

2.3 Proposed System

The proposed framework is actually a web application which is scalable. This application will take the images of crop, plants and both as input. Some Digital Image Processing Techniques will be applied to process those images and will generate a dataset from those processed images. Here we have two phases Training Phase and Testing

Phase. In Training Phase, the dataset generated is used to train the Supervised Machine Learning model. The model will be trained until good results are obtained. Once the model is trained completely it will be able to detect crop and weed in testing phase. Then the application will generate a report on how much percentage of crop and weed are present.

2.3.1 Advantages

- Since this is an application, there is no need of money, it is free of cost. All they need is a smartphone to click the photos of crop and weed.
- It will provide a better accuracy with less no. of techniques than the existing system.
- The application is scalable and can be able to run on any type of device.

Chapter-3
DESIGN

3. DESIGN

3.1 Block Diagram

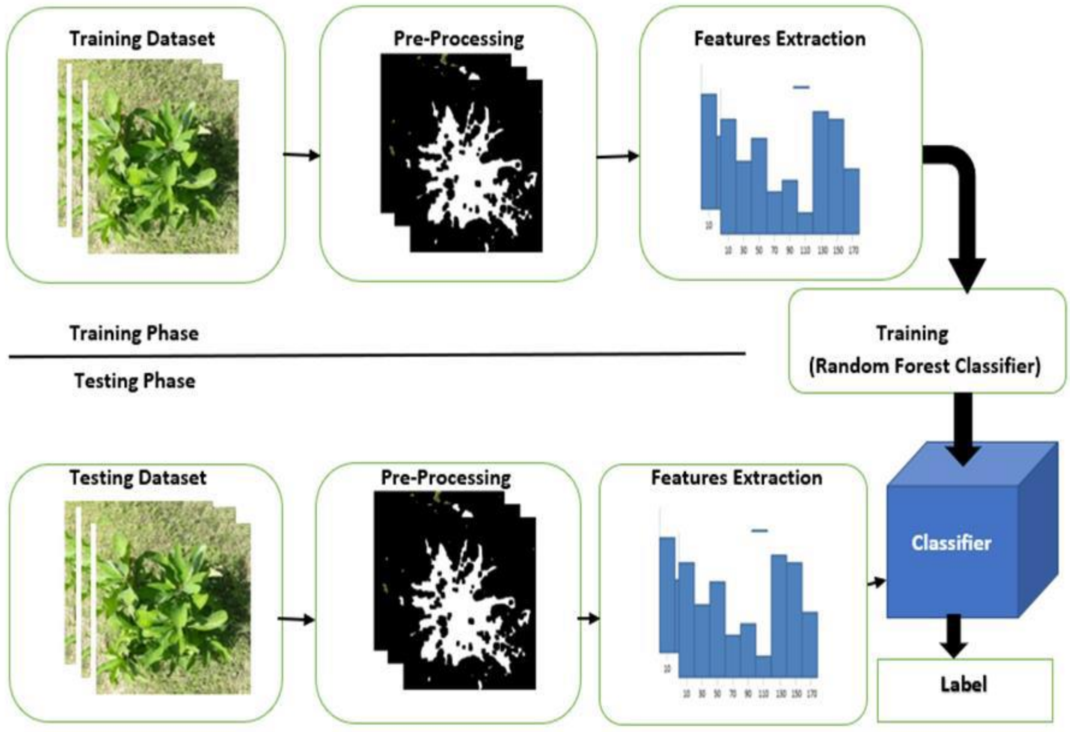


Figure 1-Block Diagram of Proposed System

3.2Hardware Requirements

1) A Smart Phone with camera of megapixels greater than 12MP.

3.3Software Requirements

1) Kivy library
2) OpenCV-Python library
3) IDLE Python 3.x-PyCharm
4) Supervised Machine Learning algorithm

1) Kivy library:

Kivy is an opensource multi-platform GUI development library for Python and can run on iOS, Android, Windows, OS X, and GNU/Linux. It helps develop applications that make use of innovative, multi-touch UI. The fundamental idea behind Kivy is to enable the developer to build an app once and use it across all devices, making the code reusable and deployable, allowing for quick and easy interaction design and rapid prototyping

Advantages

- Based on Python, which is the extremely powerful given it's library rich nature.
- Write code once and use it across all devices.
- Easy to use widgets built with multi-touch support.
- Performs better than HTML5 cross-platform alternatives.

Disadvantages

- Non-native looking User Interface.
- Bigger package size (because Python interpreter needs to be included).
- Lack of community support (Kivy Community isn't particularly large).
- Lack of good examples and documentation.
- Better and more community rich alternates available if only focusing on Mobile Cross-platform devices i.e React Native.

2) OpenCV-Python library:

OpenCV (Open Source Computer Vision Library) is an open source computer vision and machine learning software library. OpenCV was built to provide a common infrastructure for computer vision applications and to accelerate the use of machine perception in the commercial products.

The library has more than 2500 optimized algorithms, which includes a comprehensive set of both classic and state-of-the-art computer vision and machine learning algorithms. These algorithms can be used to detect and recognize faces, identify objects, classify human actions in videos, track camera movements, track moving objects, extract 3D models of objects, produce 3D point clouds from stereo cameras, stitch images together to produce a high resolution image of an entire scene, find similar images from an image database, remove red eyes from images taken using flash, follow eye movements, recognize scenery and establish markers to overlay it with augmented reality, etc.

3) IDLE Python 3.x-PyCharm:

PyCharm is an integrated development environment (IDE) used in computer programming, specifically for the Python language. It is developed by the Czech company JetBrains (formerly known as IntelliJ). It provides code analysis, a graphical debugger, an integrated unit tester, integration with version control systems (VCSes), and supports web development with Django as well as data science with Anaconda.

PyCharm is cross-platform, with Windows, macOS and Linux versions.

4) Supervised Machine Learning algorithm:

Supervised learning, also known as supervised machine learning, is a subcategory of machine learning and artificial intelligence. It is defined by its use of labeled datasets to train algorithms that to classify data or predict outcomes accurately. As input data is fed into the model, it adjusts its weights until the model has been fitted appropriately, which occurs as part of the cross validation process. Supervised learning helps organizations solve for a variety of real-world problems at scale, such as classifying spam in a separate folder from your inbox.

Supervised learning uses a training set to teach models to yield the desired output. This training dataset includes inputs and correct outputs, which allow the model to learn over time. The algorithm measures its accuracy through the loss function, adjusting until the error has been sufficiently minimized. It can be separated into two types of problems when data mining—classification and regression:

- **Classification** uses an algorithm to accurately assign test data into specific categories. It recognizes specific entities within the dataset and attempts to draw some conclusions on how those entities should be labeled or defined. Common classification algorithms are linear classifiers, support vector machines (SVM), decision trees, k-nearest neighbor, and random forest.
- **Regression** is used to understand the relationship between dependent and independent variables. It is commonly used to make projections, such as for sales revenue for a given business. Linear regression, logistical regression, and polynomial regression are popular regression algorithms.

Chapter-4
Methodology

4. Methodology

4.1Flow Chart

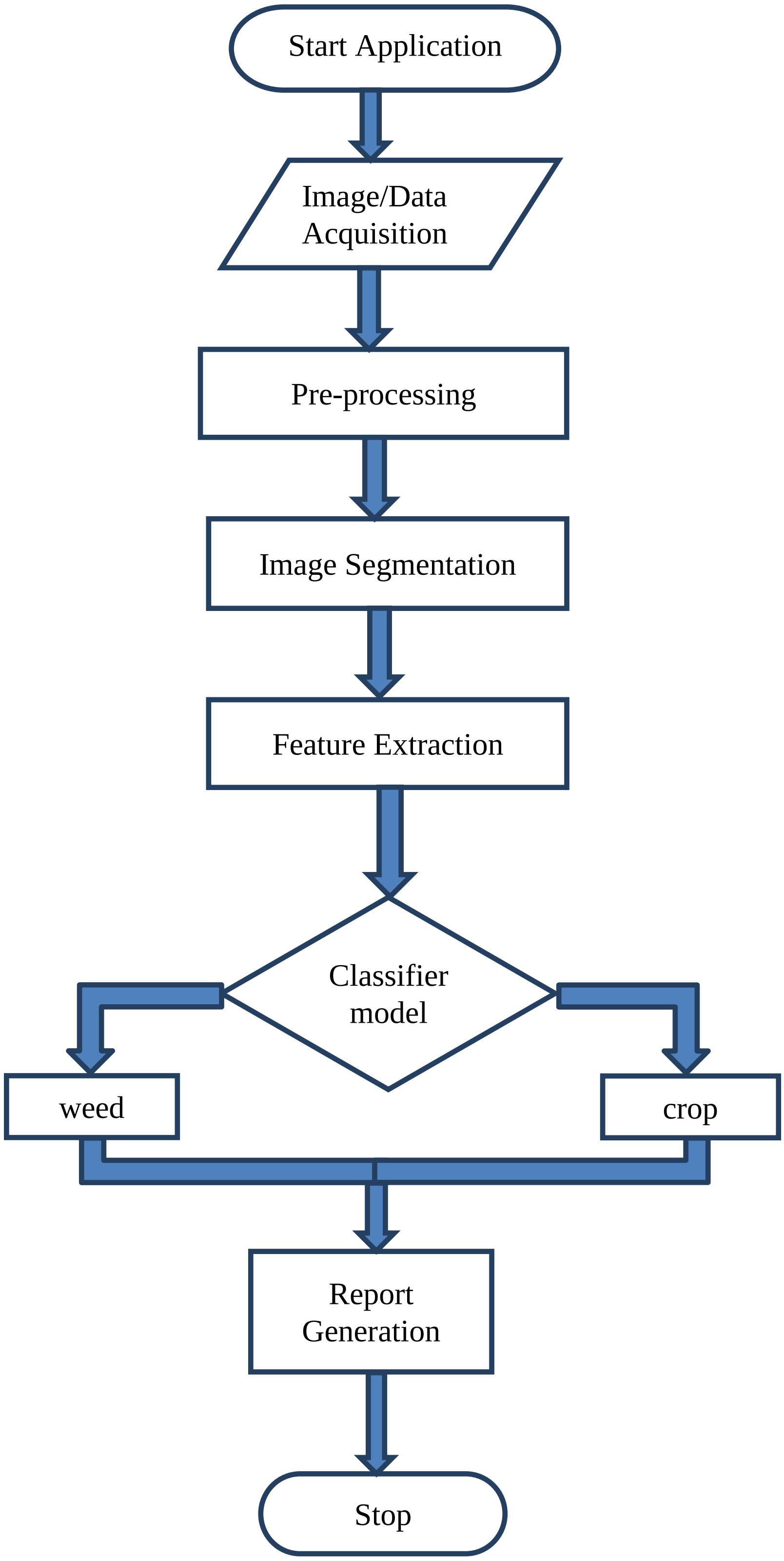


Figure 2-Flow Chart

As we said earlier, our project is application based one so first step here is to run that application. By using that application we have to click pictures of plants, weed and combination of both by doing so we acquire the images.

Now these images will be stored in the same folder where the application is present. These images first have to be preprocessed before performing any operations on those images, that is unnecessary noisy regions and motion blurring effects are to be removed to improve the quality of the image. After preprocessing, the ROI has to be separated from the background which is called image segmentation. Here the ROI is all the plants i.e., both weed and crop, and background is land or soil.

Then we do apply some digital image processing techniques for extracting certain features like size and shape of the plant, color and texture as well. They are:

Shape Matching with Hu Moments: Hu Moments (or rather Hu moment invariants) are a set of 7 numbers calculated using central moments that are invariant to image transformations. The first 6 moments have been proved to be invariant to translation, scale, rotation, and reflection. While the 7th moment's sign changes for image reflection.

Edge orientation feature: It was noticed that both have a different distribution of edges especially when they grow in shape. The shapes of leaves of weeds and crops can be utilized for computing the edge orientation features. The edge of the orientation histogram feature was extracted from the captured images. For detecting edges of different orientations, Canny filter were used. Before applying the Canny filter, the Gaussian filter was applied to convolve the image, which slightly smoothens the image and removes noise from the image and edge detector is applied.

Haralick texture feature: This technique is used classify an object basis of textures. So to classify weeds and crops in an image, texture characteristics are availed. For computing the Haralick feature, Gray Level Co-occurrence Matrix (GLCM)will be calculated. It uses adjacency concept in images and tries to find the pairs of adjacent pixels in different directions.

Color histogram: Color histogram feature scan be used for the classification of weeds and crops. For this, first, the image is converted to HSV(hue, saturation, value) scale. It is the alternative representation of an RGB (red, green, blue) image. When the image is converted to HSV than their color histogram is drawn. The main reason behind converting image from RGB color space to HSV color space is that unlike RGB, HSV separates luma, or the image intensity, from chroma or the color information. This is very useful in many applications. For example, if you want to do histogram equalization of a color image, you probably want to do that only on the intensity component, and leave the color components alone. Otherwise you will get very strange colors.

In computer vision you often want to separate color components from intensity for various reasons, such as robustness to lighting changes, or removing shadows.

After generating feature vectors dataset, those datasets have to be used to train the classifier. So for that purpose we use Random Forest (RF)Classifier .It belongs to Supervised Learning Technique. It is defined as “An ensemble of classification trees, where each decision tree employs a subset of training samples and variables selected by a bagging approach, while the remaining samples are used for internal cross-validation of the RF performance. The classifier chooses the membership classes having the most votes, for a given case.” RF has been proven to be highly suitable for high resolution image classification and for agricultural mapping.

Here multiple decision trees created on randomly selected samples forms a forest. Each decision tree acts as the building block of the model predicts a classification for the input data. The input of each tree is sampled data from the original dataset. Assume we have n plants (samples) and feature vectors with outcomes Yi:

$$\{X_i\} = i_n = 1$$

$$D = \{(x_1, y_1, \ldots, (X_n, Y_n)\}$$

Where D represents the data. Each feature vector can be represented by:

$$x_k = (x_{k1}, \ldots, y_{kd})$$

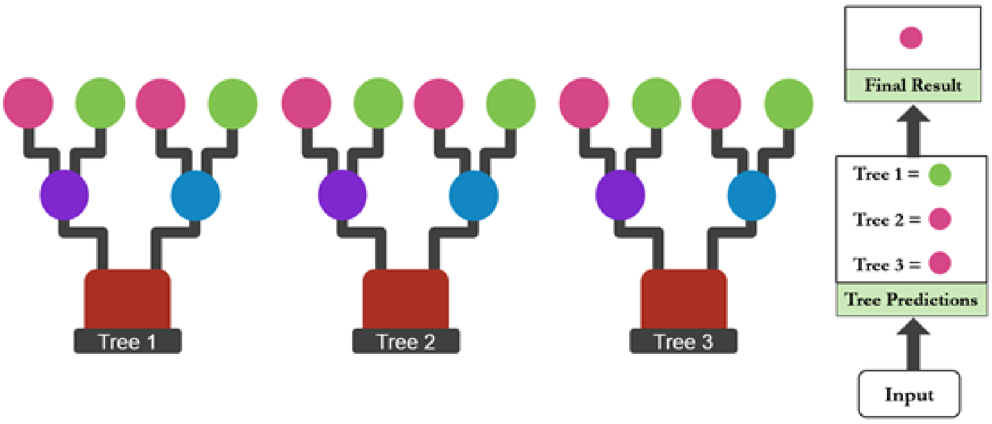


Figure 3 - Representation of Random Forest Algorithm

This classifier will classify weeds from crop and finally an analysis report will be generated on how much percentage of weed and crop are present. Based on that information a farmer will use a required amount of agrochemicals.

The outcome of this project work is a machine learning-based vision system having the capability to detect weeds and can, therefore, be used for precise weed control.

Chapter-5

IMPLEMENTATION OF THE PROJECT

5. IMPLEMENTATION OF THE PROJECT

Implementation of this project takes place in three phases:

5.1 App Development.

5.2 Machine Learning

5.1 App Development Phase

In this phase we developed a platform independent Application using Python and some libraries such as kivy, openCV-python. The code related to app development is given below:

Code:

```
fromkivy.appimportApp

fromkivy.langimportBuilder

fromkivy.uix.boxlayoutimportBoxLayout

importtime

Builder.load_string('''

<CameraC>:

    orientation: 'vertical'

    Camera:

        id: camera

        resolution: (640, 480)

        play: False

    ToggleButton:

text: 'Turn On/Off Camera'

        on_press: camera.play = not camera.play

        size_hint_y: None
```

```
        height: '48dp'

    Button:

        text: 'Capture'

        size_hint_y: None

        height: '48dp'

        on_press: root.capture()

''')

classCameraC(BoxLayout):

defcapture(self):

'''

        Function to capture the images and give them the names

        according to their captured time and date.

        '''

camera=self.ids['camera']

timestr=time.strftime("%Y%m%d_%H%M%S")

camera.export_to_png("IMG_{}.png".format(timestr))

print("Captured")

classApplication(App):

defbuild(self):

returnCameraC()

Application().run()
```

5.1.1 Operation/Working

The working of the application will be shown in steps below

Step1: Start to run the application by opening it. Then it will be appeared as follows

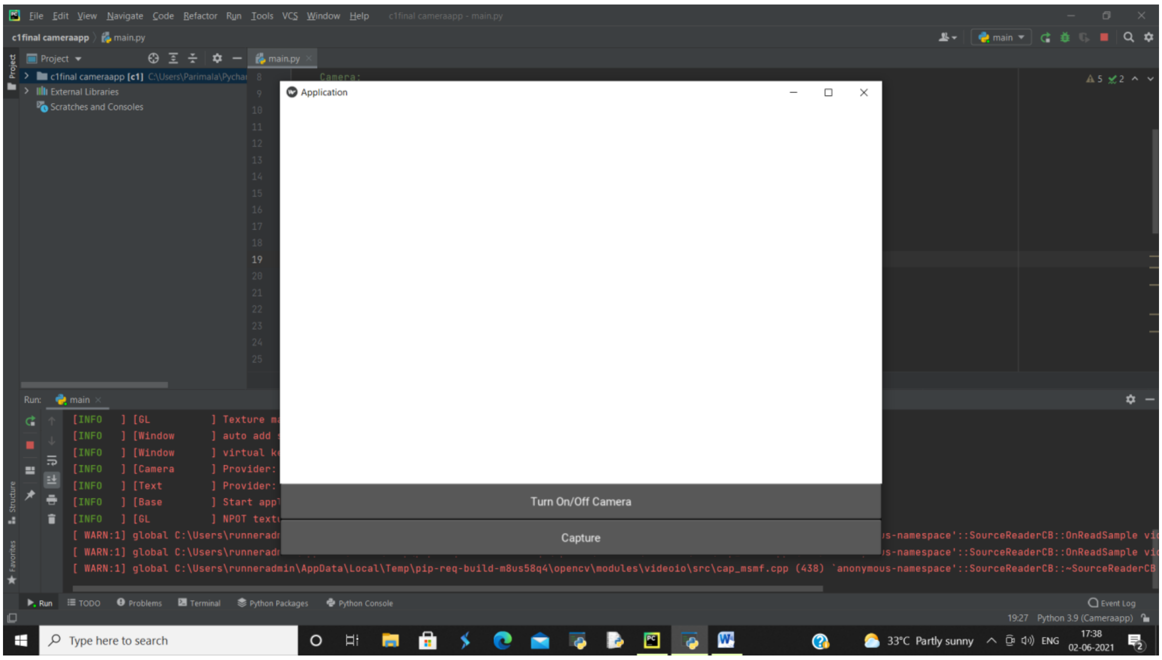


Figure 4-Running Application

Step2: Now click on the “Turn On/Off Camera” button to turn On the camera. After turning on the camera it will be as shown below

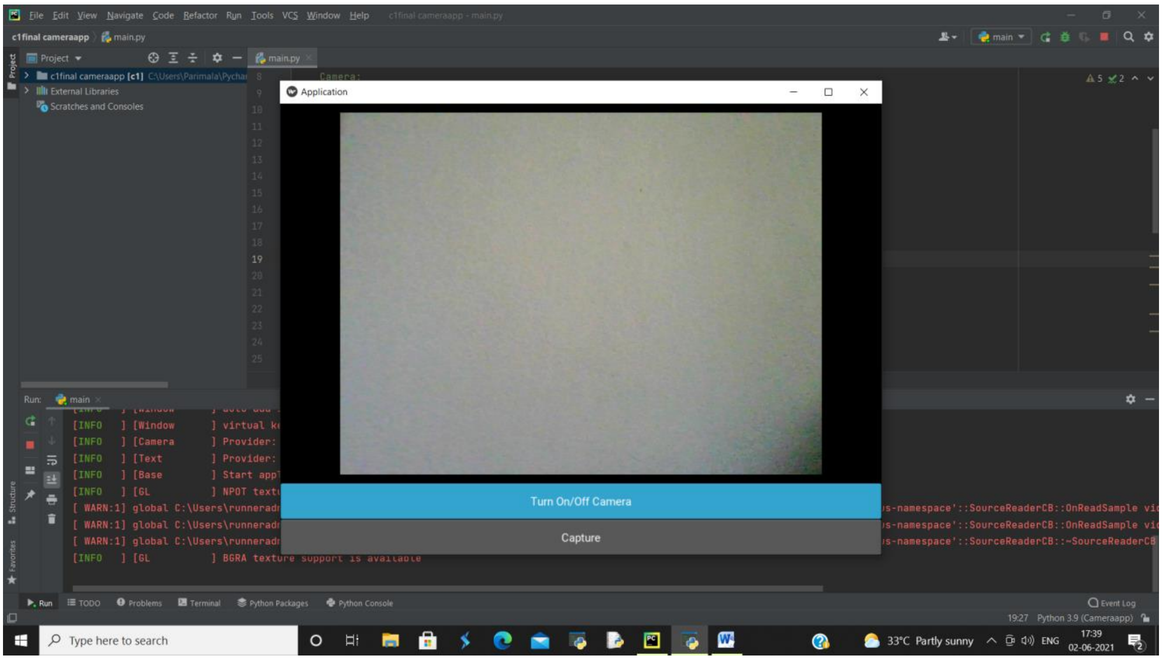


Figure 5-Accessing Camera

Step3: To click the picture click on the "Capture" button .The images captured will be stored in the same folder with date and stamps as shown below figure

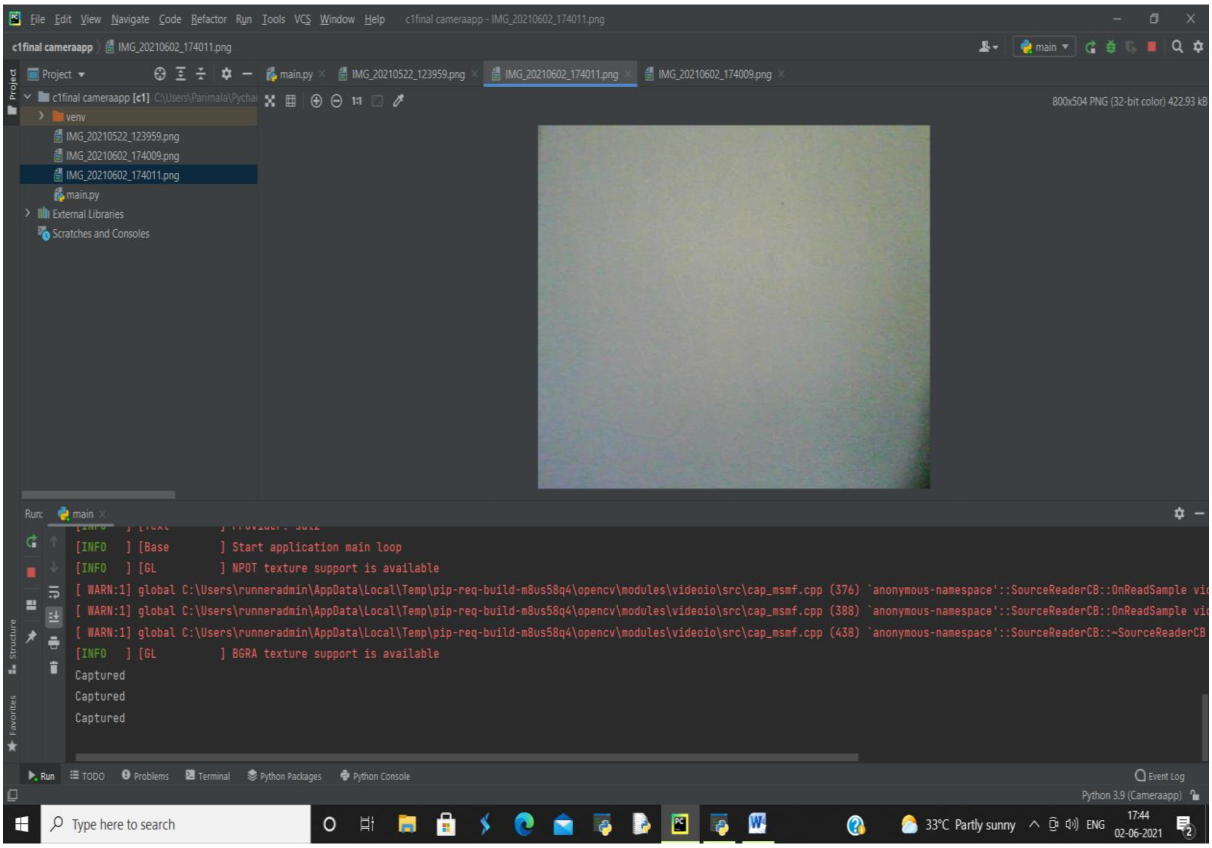


Figure 6- Displaying Captured Images

5.2 Machine Learning

After acquiring images, now these images have to be preprocessed and perform image segmentation on them. Then the necessary features have to be extracted to generate feature vectors for detection of weed. The code for performing the above mentioned operations is given below

Code:

Training model

```
import math
training_samples =9202
batch_size_training_generator=92
validation_samples =3067
batch_size_validation_generator=31

history = model.fit_generator(
```

```
      train_generator,
steps_per_epoch=math.ceil(training_samples/batch_size_training_generator
),
      epochs=15,
      validation_data=validation_generator,

validation_steps=math.ceil(validation_samples/batch_size_validation_gene
rator))
```

```
Epoch 1/15
101/101 [==============================] - 391s 4s/step - loss: 0.9288 - acc: 0.6439 - val_loss: 0.4971 - val_acc: 0.8076
Epoch 2/15
101/101 [==============================] - 269s 3s/step - loss: 0.5837 - acc: 0.7850 - val_loss: 0.8970 - val_acc: 0.6919
Epoch 3/15
101/101 [==============================] - 281s 3s/step - loss: 0.4434 - acc: 0.8246 - val_loss: 0.3871 - val_acc: 0.8758
Epoch 4/15
101/101 [==============================] - 291s 3s/step - loss: 0.4499 - acc: 0.8360 - val_loss: 0.3164 - val_acc: 0.8758
Epoch 5/15
101/101 [==============================] - 276s 3s/step - loss: 0.3417 - acc: 0.8711 - val_loss: 0.2253 - val_acc: 0.9123
Epoch 6/15
101/101 [==============================] - 243s 2s/step - loss: 0.3310 - acc: 0.8796 - val_loss: 0.3077 - val_acc: 0.8921
Epoch 7/15
101/101 [==============================] - 244s 2s/step - loss: 0.3021 - acc: 0.8890 - val_loss: 0.2249 - val_acc: 0.9306
Epoch 8/15
101/101 [==============================] - 243s 2s/step - loss: 0.2765 - acc: 0.8989 - val_loss: 0.1824 - val_acc: 0.9325
Epoch 9/15
101/101 [==============================] - 249s 2s/step - loss: 0.2476 - acc: 0.9127 - val_loss: 0.1899 - val_acc: 0.9250
Epoch 10/15
101/101 [==============================] - 253s 3s/step - loss: 0.2521 - acc: 0.9096 - val_loss: 0.2441 - val_acc: 0.9136
Epoch 11/15
101/101 [==============================] - 244s 2s/step - loss: 0.2331 - acc: 0.9174 - val_loss: 0.2838 - val_acc: 0.9038
Epoch 12/15
101/101 [==============================] - 245s 2s/step - loss: 0.2281 - acc: 0.9191 - val_loss: 0.7067 - val_acc: 0.7972
Epoch 13/15
101/101 [==============================] - 244s 2s/step - loss: 0.1983 - acc: 0.9303 - val_loss: 0.1388 - val_acc: 0.9465
Epoch 14/15
101/101 [==============================] - 246s 2s/step - loss: 0.2610 - acc: 0.9208 - val_loss: 0.1143 - val_acc: 0.9544
Epoch 15/15
101/101 [==============================] - 244s 2s/step - loss: 0.1868 - acc: 0.9340 - val_loss: 0.1428 - val_acc: 0.9455
```

Test & Prediction :-

```
test_samples =3067
batch_size_test=31

score= model.evaluate_generator(test_generator, steps =
math.ceil(test_samples/batch_size_test))
print("\nTest accuracy: %.1f%%" % (100.0 * score[1]))

Test accuracy: 94.7%
```

Prediction-

```
from PIL import Image
import numpy as np
from skimage import transform

def load(filename):
   np_image = Image.open(filename) #Open the image
   np_image = np.array(np_image).astype('float32')/255
np_image = transform.resize(np_image, (150, 150, 3))
np_image = np.expand_dims(np_image, axis=0)
return np_image
label_map = (test_generator.class_indices)
print (label_map)
```

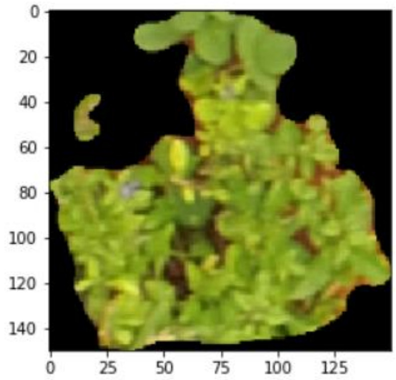
```
image_to_predict = load('D:/Project 2/dataset/broadleaf/1.tif')
result = model.predict(image_to_predict)
result= np.around(result,decimals=3)
result=result*100
print (result)
```

```
{'grass': 0, 'soil': 1, 'soybean': 2, 'weed': 3}
[[ 0.70000005  0.          0.2        99.1       ]]
```

In [20]:

```
#Transformar la imagen de (1, 150, 150, 3) a (150, 150, 3) y mostrarla
image_to_predict= np.squeeze(image_to_predict,axis=0)
image_to_predict.shape

from matplotlib import pyplot as plt
plt.imshow(image_to_predict, interpolation='nearest')
plt.show()
```



Chapter-6

RESULTS AND DISCUSSIONS

6. RESULTS AND DISCUSSIONS

6.1Results

- Successfully captured images of crop and weed and is as shown below:

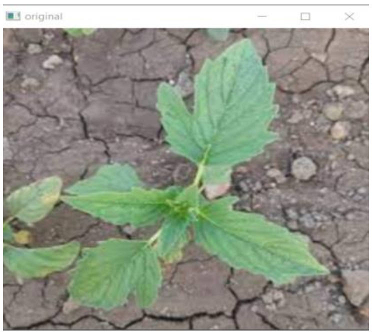


Figure 7- Captured Image

- Preprocessing results are as shown below:

Figure 8-Preprocessed image

- After segmentation the result is as follows:

Figure 9-Segmented Image

- Classifier model makes use of generated feature vectors and able classify weed and crop. Finally an analysis report has generated to specify the amount of weed present.

Chapter-7
CONCLUSIONS

7. CONCLUSIONS

7.1 Conclusions

Weed detection is crucial in agricultural productivity, as weeds act as a pest to crops. This project aimed to detect weeds in a crop field using image processing and machine learning techniques. The images collected from a crop field, and these images were pre-processed using image processing techniques. Then features are extracted from the images to distinguish properties of weeds and the crop. The RF Classifier is used to classify weed and crop. The experimental results demonstrate that RF performed better than the other classifiers in terms of accuracy and other performance metrics. RF offered 96% accuracy in weed detection from RGB images. In the future, we can explore multispectral and hyper spectral UAV images, and will apply deep learning algorithms to increase the accuracy of weed detection.

7.2 Future Scope

- In future, we can improve the system (application) to analyse the soil and can figure out whether that land is suitable for crop growth or not.
- The application can also be enhanced to suggest the correct amount of agrochemicals for utilization.
- It can be extended to detect pests and plant diseases after slight modifications.

Chapter-8
BIBLIOGRAPHY

8. BIBLIOGRAPHY

8.1 References

1) Savary S, Ficke A, Aubertot JN, Hollier C. Crop losses due to diseases and their implications for global food production losses and food security [Editorial]. Food Security, Springer 2012. DOI 10.1007/s12571-012-0200-5.

2) I. Ahmad, A. M. Naeem, M. Islam, and A. B. Abdullah, "Statistical based real-time selective herbicide weed classifier," in 2007 IEEE International Multitopic Conference, pp. 1–4, IEEE, 2007.

3) J. Ahmad, K. Muhammad, I. Ahmad, W. Ahmad, M. L. Smith, L. N. Smith, D. K. Jain, H. Wang, and I. Mehmood, "Visual features based boosted classification of weeds for real-time selective herbicidesprayer systems," Computers in Industry, vol. 98, pp. 23–33, 2018.

4) Slaughter, D.; Giles, D.K.; Downey, D. Autonomous robotic weed control systems: A review. Computers and electronics in agriculture 2008, 61, 63–78.

5) Jeon, H.Y.; Tian, L.F. Direct application end effector for a precise weed control robot. Biosystems engineering 2009, 104, 458–464.

6)Kaur, S.; Pandey, S.; Goel, S. Plants disease identification and classification through leaf images: A survey. Archives of Computational Methods in Engineering 2019, 26, 507–530.

7) Ali, H.; Lali, M.; Nawaz, M.Z.; Sharif, M.; Saleem, B. Symptom based automated detection of citrus diseases using color histogram and textural descriptors. Computers and Electronics in agriculture 2017, 138, 92–104.

8) Iqbal, Z.; Khan, M.A.; Sharif, M.; Shah, J.H.; ur Rehman, M.H.; Javed, K. An automated detection and classification of citrus plant diseases using image processing techniques: A review. Computers and electronics in agriculture 2018, 153, 12–32.

9) Søgaard, H.T.; Lund, I. Application accuracy of a machine vision controlled robotic micro-dosing system. Biosystems Engineering 2007, 96, 315–322.

10) Loghavi, M.; Mackvandi, B.B. Development of a target oriented weed control system. Computers and electronics in agriculture 2008, 63, 112–118.

11) de Castro, A.I.; Jurado-Expósito, M.; Peña-Barragán, J.M.; López- Granados, F. Airborne multispectral imagery for mapping cruciferous weeds in cereal and legume crops. Precision Agriculture 2012, 13, 302–321.

12) Midtiby, H.S.; Mathiassen, S.K.; Andersson, K.J.; Jørgensen, R.N. Performance evaluation of a crop/weed discriminating microsprayer. Computers and electronics in agriculture 2011, 77, 35–40.

13) Castaldi, F.; Pelosi, F.; Pascucci, S.; Casa, R. Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide patch spraying in maize. Precision Agriculture 2017, 18, 76–94.

14) Dammer, K.H. Real-time variable-rate herbicide application for weed control in carrots. Weed Research 2016, 56, 237–246.

15) Berge, T.; Goldberg, S.; Kaspersen, K.; Netland, J. Towards machine vision based site-specific weed management in cereals. Computers and electronics in agriculture 2012, 81, 79–86.

16) Wang, A.; Zhang, W.; Wei, X. A review on weed detection using ground-based machine vision and image processing techniques. Computers and electronics in agriculture 2019, 158, 226–240.

17) Sullca, C., Molina, C., Rodríguez, C. and Fernández, T., 2019. Diseases Detection in Blueberry Leaves using Computer Vision and Machine Learning Techniques. International Journal of Machine Learning and Computing, 9(5).