Real-Time Machine-Learning Based Crop/Weed Detection and Classification for Variable-Rate Spraying in Precision Agriculture

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***Abstract*—Traditional agrochemical spraying techniques often result in over or under-dosing. Over-dosing of spray chemicals is costly and pose a serious threat to the environment, whereas, under-dosing results in inefficient crop protection and thereby 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. This paper presents a real-time computer vision-based crop/weed detection system for variable-rate agrochemical spraying. Weed/crop detection and classification were performed through the Random Forest classifier. The classification model was first trained offline with our own created dataset and then deployed in the field for testing. Agrochemical spraying was done through application equipment consisting of a PWM-based fluid flow control system capable of spraying the desired amounts of agrochemical directed by the vision-based feedback system. The results obtained from several field tests demonstrate the effectiveness of the proposed vision-based agrochemical spraying framework in real-time.**

Keywords-Random forest classifier; variable-rate spraying; weed control

I. Introduction

Agriculture contributes approximately 26 percent to Pakistan's Gross Domestic Product (GDP) and employs half of the country's labor force, thereby making it an important sector of the country's economy. However, due to the lack of availability of advanced agricultural equipment, imprecise input application methods, and the shrinking arable land due to fast urbanization, the gap between food production and consumption is increasing at a fast rate.

In order to deal with the rising risk of food insecurity, there is a dire 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 sporadically. Weeds are unwanted plants that regrow vigorously and are the strongest yield-reducers resulting in 10 to 20% of yield losses [1]. 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 pivotal 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, except for countries like Pakistan where conventional methods are still in practice. 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 menace. Most of the farmers in Pakistan face health issues because of exposure to the agrochemicals while they are applied to crops/weeds. The government of Pakistan has provided a list of registered herbicides with detailed information about safety and health guidelines, but unfortunately, none of them are followed due to the illiteracy of the farmers.

In this backdrop, we propose the use of intelligent agricultural sprayers that can detect and classify plants and weeds in real-time and can adjust the required amount agrochemicals accordingly. This will: (1) result in reduced cost and improved spraying quality by guaranteeing the optimum application of spraying material, (2) reduce farmers' exposure to toxic agrochemicals, and (3) reduce the environmental footprint. The proposed technology will also help ease the prevailing non-tariff barriers (NTBs) currently faced by Pakistan's agricultural exports due to concerns on their safety and quality standards under the WTO's Sanitary and Phytosanitary (SPS) agreement.

Variable flow-rates in sprayers can be achieved by implementing automatic control systems on individual boom sections or nozzles. Different methods, each having pros and cons have been adopted over different times for variable rate flow control, but Pulse Width Modulation based variable rate flow control stands out amongst the others because of the numerous advantages that it offers as compared to the other methods such as pressure-based variable rate flow control, or direct injection system. The only challenge associated with PWM-based spraying is the basic requirement to detect and classify plant/weeds, and their sizes and location in the field.

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The principal goal of this research is aimed at finding a solution to the aforementioned problem by splitting it into three sub-problems. The initial step involved in the overall process is to spot a particular plant in an image in the presence of other plants and weeds. Then, the next step involved in the process is to address the challenges of segmenting a particular type of plant from the crop field image. Lastly, it proposes the most suitable machine learning algorithm for precision spraying that is best both in terms of accuracy and real-time performance. The outcome of this research work is a machine learning-based vision system having the capability to be detected weeds and can, therefore, be used for precise weed control. The proposed work can be extended to several farming jobs such as irrigation, harvesting, and crop health monitoring after slight modifications.

II. Review of Previous Work

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 citrus diseases. The proposed technique applied color difference algorithm to separate the disease affected area. Furthermore, the classification of diseases was done via color histogram and textural features. The authors claim to have obtained an accuracy of about 99.9% with 0.99 area under the curve. Moreover, color 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 by 50%. The experiments demonstrated the ability of the system to target objects with sub-centimeter 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 color indexes. The use of the R/B index, B/G ratio, and the MLC method helped in achieving fine results. Herbicide savings ranging from 71.7 to 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 compared 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 medianBlur and gaussianblur 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%.

III. Methodology

The first step involved in the precise application of agrochemicals to crops is detection and classification of crops and weeds, and the second step is the application of exact desired amounts of agrochemicals through application equipment incorporated with a fluid control system. Our proposed framework for agrochemical spraying comprises two sub-systems namely: (a) vision system (b) fluid flow control or spray actuation/application system, as shown in Fig. 1. This research work mainly focuses on the vision system for providing feedback to the fluid flow control system.

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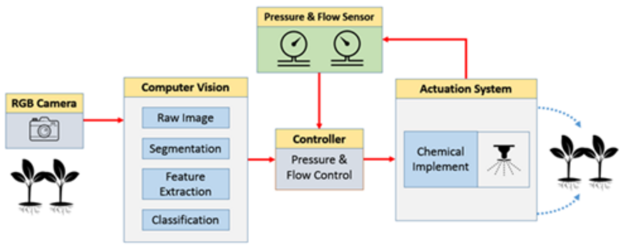

Figure 1. Block Diagram of the Proposed Framework

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 main task of the vision system is to recognize crops and weeds which is a challenging task in real-time. The image classification step involves the identification of an image into its separate classes with the support of features from hundreds of images. Mostly, crop and weeds have intra-class variations, which makes the image segmentation very complex. 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 labeled by the classifier as shown in Fig. 2.

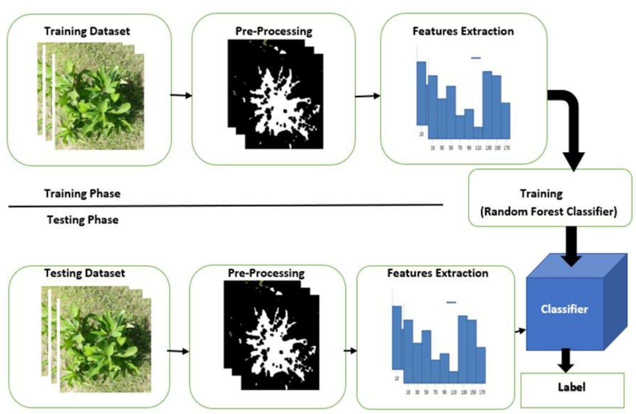

Figure 2. Block Diagram of the Vision System

The steps involved in both training and testing phases for image classification are the acquisition of datasets, pre-processing, and feature extraction. A brief explanation of these steps is given as follows:

a) Image / Data acquisition

In machine learning applications the most time-consuming, costly, onerous, while an important task is acquiring a relevant dataset. The availability of dedicated fields and the timing factor makes this task even more challenging in the agricultural domain. High-resolution RGB cameras are usually used for capturing images of crops and weeds at different timings and lightning conditions. In order to increase the accuracy of the classifier, images of crops and weeds with different canopy sizes are captured at different angles. The camera is mounted at some height from the field. The images captured with the high-resolution camera are usually resized to decrease computation times.

For this research study, a dataset was created by capturing images of crop plants and weeds over a course of several days at different timings and lightning conditions. The dataset included three types of images (1) crop plants (2) weeds (3) irrelevant images. Each class comprised of 97 images, therefore, a total of 291 images were used to train the machine learning-based classification model for crop and weed recognition.

b) Pre-Processing

In image pre-processing, the image data recorded by a camera mostly consists of errors related to geometry and brightness values of the pixels which are corrected by using appropriate mathematical techniques. The undesired and noisy regions are removed from and morphological features are applied to remove illumination and motion blurring effects from the images. Image enhancement techniques are used for improving the visual appearance of images or for converting them to a form, which is better suited for human or machine interpretation. In image enhancement, the pixel brightness values are modified in order to improve its quality.

c) Image segmentation

For image segmentation, the background content of an image needs to be removed. Segmenting is a difficult task due to noise, blurring, and illumination. Different techniques are used for segmentation such as color-based segmentation, watershed segmentation and edge-based segmentation. In this research study, we have used a thresholding-based segmentation technique, as shown in Fig. 3. Once this phase is done the next phase is the extraction of features (descriptors) for classification.

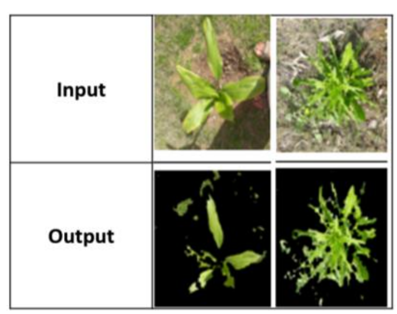

Figure 3. Image Segmentation

d) Features

The next step in crop and weed recognition is feature extraction, in which features from the image i.e. local and global features e.g. shape, textures, and color are extracted. Feature selection plays a very important role in image classification. Several features such as color, texture and shape can be selected for performing crop and weed classification. But since these aforementioned features alone

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are not adequate to characterize an image, therefore in this research study we used a set of global features for obtaining better results, such as Color Histograms, Hu Moments, Haralick Textures, and Histogram of Oriented Gradients (HOG).

e) Features extraction

By observing images of both weeds and crops it can be noticed that they have slight differences in color, edges, textures, and shapes. Therefore, all these characteristics are used for the classification of weeds and crops. The extraction of features is described in the following subsections.

i. Shape matching using Hu moments

Weeds and crops both have different shaped and sized leaves, as shown in Fig. 4. Therefore, Hu moments are used for shape analysis and their feature vectors are shown in Table I. The image moments are a weighted average of image pixels intensities. Moment is calculated by using the following formula:

$$M = \sum_x \sum_y I(x,y) \tag{1}$$

I is the image and (x, y) shows the pixel values.

(a) (b)

Figure 4. (a) crop (b) weed

TABLE I. HU MOMENT VALUES FOR PLANTS

Images	H_0	H_1	H_2	H_3	H_4	H_5	H_6
	$1.1462288e^{-03}$	$1.6934800e^{-10}$	$4.2147795e^{-12}$	$8.6361182e^{-13}$	$-4.4740000e^{-25}$	$-9.8434416e^{-18}$	$-1.5857767e^{-24}$
	$1.1117829e^{-03}$	$3.2734436e^{-10}$	$7.5721110e^{-13}$	$1.2735506e^{-13}$	$2.8466634e^{-26}$	$-1.8784482e^{-18}$	$2.7451195e^{-26}$

ii. Edge orientation feature

By observing the weeds and crops from a top view i.e. spatially, 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 filters 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. After determining the edge orientation feature their histogram was calculated. In Figure 6 it can be seen that weeds have more edges at different orientations than the crops. In Fig. 5, it can be clearly seen that the crops show lower variation in the edge due to their leaves' shapes.

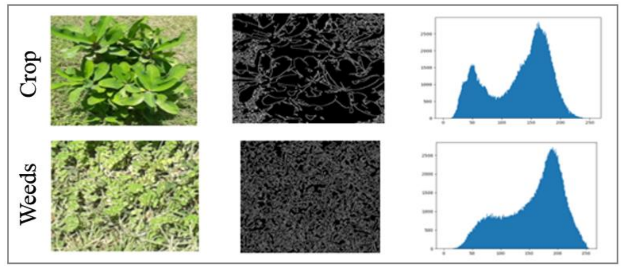


Figure 5. EOH of Crop & Weeds

iii. Haralick texture feature

Crops and weeds both have different textures. To classify an object in an image on the basis of textures, the surface of the object should be analyzed. Therefore, to classify weeds and crops in an image, texture characteristics are availed. Haralick textures were brought into service for texture-based classification. For computing the Haralick feature, Gray Level Co-occurrence Matrix (GLCM) was calculated. It uses the adjutancy concept in images and tries to find the pairs of adjusting pixels in different directions. Based upon the directions it has four types Fig. 6 shows left-right adjutancy calculations.

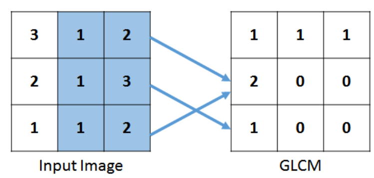
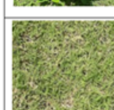


Figure 6. Gray Level Co-occurrence Matrix

From the four GLCM matrices, the Haralick features vector is calculated having 14 values. Only 13 out of the 14 values were taken in order to avoid the risk of increasing the computation time. Table II shows the 13 values feature vector for both weeds and crops.

TABLE II. HARALICK FEATURE VECTOR FOR WEEDS AND CROPS

Image	Haralick Feature Vector
	[2.28956955e-04 2.39704275e+02 9.55611617e-01 2.70003705e+03 1.71628124e-01 2.56406649e+02 1.05604439e+04 8.43482749e+00 1.29587584e+01 2.16880117e-04 4.74143807e+00 -2.61750102e-01 9.88824945e-01]
	[6.73336724e-05 1.19350916e+03 6.66863506e-01 1.79138053e+03 4.40507406e-02 3.34926976e+02 5.97201298e+03 8.26874652e+00 1.42522083e+01 5.34979576e-05 6.13358276e+00 -7.06091495e-02 7.91475299e-01]

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iv. Color histogram

From the spatial view of weeds and crops, it is observed that both have different colors. So, color histogram features can 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. It can be noticed in Fig. 7 that there is a difference between color histograms of weeds and crops.

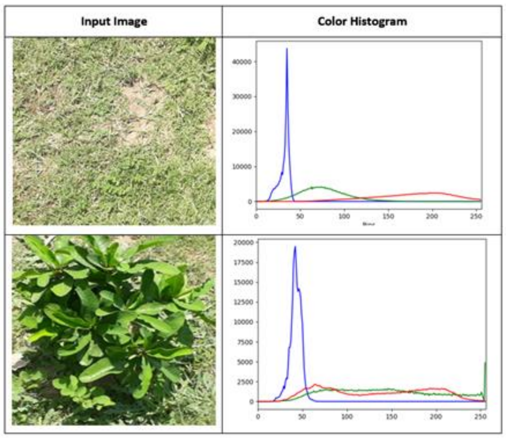

Figure 7. Images Conversion to Color Histogram

f) Training

After features extraction and labeling of the training dataset, the next step is to train the machine learning-based classification model. The training process is a supervised learning approach in which labeled data is fed to the model, and the system figures out how to segregate each image (by learning the pattern behind each image). The main goal of training is to the model robust so that it could classify crops and weeds in the presence of noise, illumination (sun-light) variation, and image blurring due to motion. We used several learning models from Scikit-learn i.e. Random Forest, Logistic Regression, K-Nearest Neighbours, Gaussian Naive Bayes and Support Vector Machine in this research study. For training purposes, we used 97 images of each class i.e. crop plants, weeds, and irrelevant.

g) Random forest classifier

Random Forest algorithm, a supervised machine learning algorithm, is used both for classification and regression problems. A forest is formed by creating multiple decision trees on randomly selected samples. Each decision tree that serves 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. Generally, the greater the number of trees in the forest, the more accurate the results are as shown in Fig. 8. The prediction that gets the most number of votes is picked as the final result by the model.

Assume we have n plants (samples) and feature vectors with outcomes Yi:

$$\{X_i\} = i^n = 1 \tag{2}$$

$$D = \{(x_1, y_1, \ldots, (X_n,\ Y_n)\} \tag{3}$$

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

$$x_k = (x_{k1}, \ldots, y_{kd}) \tag{4}$$

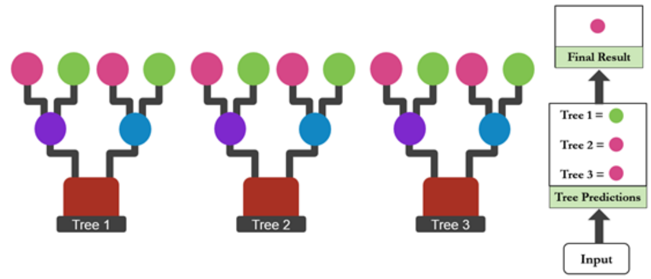

Figure 8. Representation of Random Forest Algorithm

IV. EXPERIMENTAL SETUP

The complete spraying system comprised of a 4-wheeler trolley as application equipment, which was designed to be pushed manually for movement. The boom consisted of four nozzles with digital solenoid valves for spraying. Two 16MP cameras were placed 4 feet apart from each other at a height of 3 feet from the ground for acquiring field images in real-time as shown in Fig. 9.

Figure 9. Prototype of Spraying System

An ATmega2560 microcontroller was connected serially with the laptop for controlling the pump and solenoid valves mounted on each of the four nozzles. A fixed displacement pump driven by an electric DC motor was used to deliver the agrochemical at 6 liters/min and at the desired pressure of 60 psi to the nozzles (TeeJet HSS8002E, 40 PSI, 0.2 gal/min). Application rate i.e. flow rate, through nozzles mounted on the boom, 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. A 100% duty cycle i.e. a fully on signal resulted in maximum flow rate whereas lower duty cycles resulted in reduced flow rates accordingly. The system worked at approximately 10 pulses per second i.e. 10Hz. Each nozzle

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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.

V. RESULTS AND DISCUSSIONS

The images captured were processed in a Core i5 PC having 2.4 GHz processor and 4 GB DDR3 RAM with visual studio IDE using Python and OpenCV library.

A. *Dataset*

The dataset collected for crops and weeds comprised of a total of 396 images. The plants' dataset consisted of 99 training images and 33 testing images. The dataset for weeds also consisted of 99 training images and 33 testing images. A third dataset that contained irrelevant objects that were neither plants nor weeds was also used. This dataset also consisted of 99 training images and 33 testing images. In order to increase the classifier's accuracy, all the images were taken at distinct times of the day and conditions.

B. *Segmentation Phase*

Segmentation is a very challenging task since it easily gets affected by illumination and blurring due to motion. In image segmentation, background and brown colored weeds were eliminated from the input image. Feature extraction and classification depend upon this segmentation process which makes it the key phase of the complete image processing task. Details of the segmentation process are given in the following subsections:

C. *Illumination Effect on Segmentation*

Illumination affects the segmentation process which consequently affects the feature extraction, and the result thereupon ultimately leads to misclassification. For reducing the effects of illumination, several images were captured in different lighting conditions, and various experiments were conducted to set the best threshold value for segmentation. The segmentation results of the proposed model under different environmental conditions are shown in Fig. 10 and Fig. 11.

Figure 10. Crop Images and their Segmented Results

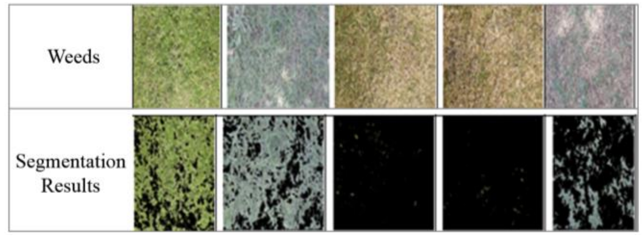

Figure 11. Weeds Images and their Segmented Results

D. *Motion Blur Effect on Segmentation*

The blurriness present in the images, due to motion while capturing images, affects the segmentation process which as a result affects the classification process. Therefore, it is necessary to find the effect of blurring on the segmentation process. Different experiments were conducted to find the effect of blurring by inducing blurring in images due to camera movement. Fig. 12 and Fig. 13 shows the results of blurring on segmentation.

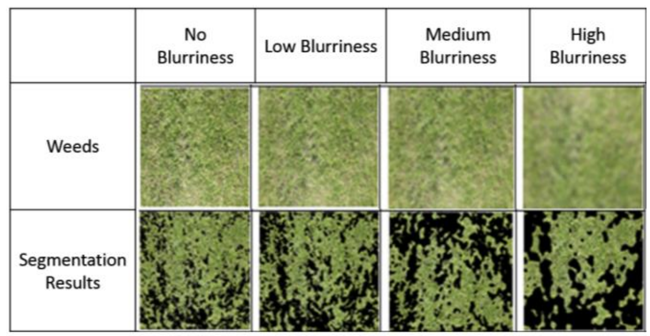

Figure 12. Weed Images with different Blurring Effects

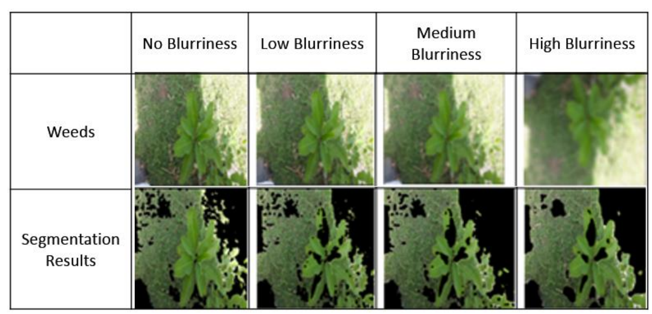

Figure 13. Weed Images with different Blurring Effects

E. *Effect of Noise on Segmentation*

Low illuminations, different field conditions, and low-quality vision sensors can induce noise in the images which affects the segmentation process. In this study, Gaussian noise is introduced with different intensities to evaluate the performance of the proposed segmentation process. Different levels of noises are introduced in the images and different experiments are conducted to see the performance of segmentation as shown in Fig. 14.

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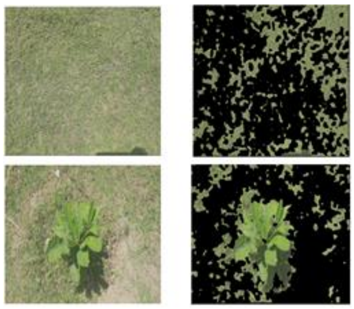

Figure 14. Different Levels of Noises in Crops and Weeds

F. Contouring

The final step is the contouring of that area which includes plants of our desire and on which we want to spray a specific amount. For that purpose, we used the contouring method to detect the plant area and isolate that area for spraying. The results of the contouring are shown in Fig. 15 and Fig. 16.

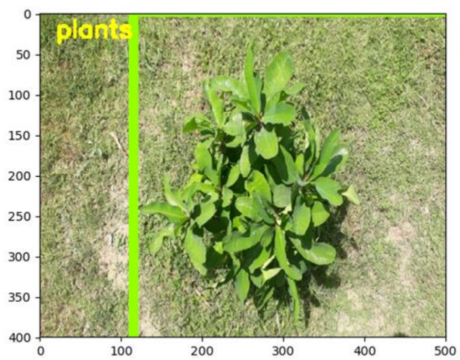

Figure 15. Contouring of Crop Detected Area

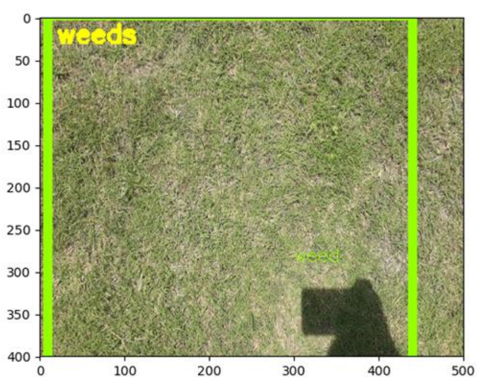

Figure 16. Contouring of Weed Detected Area

G. Classification Performance

In many computer vision applications, supervised machine learning has shown promising results. Random forest classifier is an efficient algorithm, which is used for solving classification and regression problems. The accuracy of the Random Forest classifier by using different features for classification is shown in Fig. 17. The classifier gives an accuracy of 95% when all the features are selected for classification. The accuracy decreases when the few features are selected for classification.

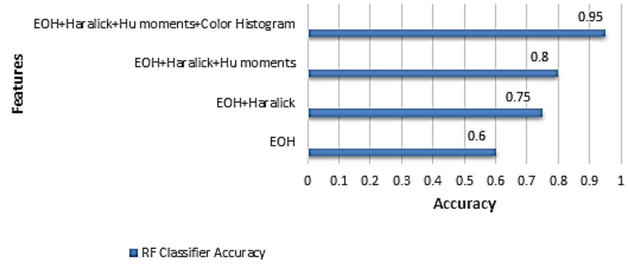

Figure 17. Classification Accuracy on the Basis of Different Features

H. Computation Time Analysis

The execution time indicates the feasibility of a real-time computer vision algorithm in terms of the computational cost. From Table III it can be concluded that the proposed algorithm performs well in real-time. Haralick feature is computationally expensive as it took 38.9ms. The EOH module ran faster than Haralick features and took5.9ms. The shape analysis module took 0.9ms and the color histogram takes 1.9ms. The classification took 7.9ms and the segmentation process was done under 3.9ms. Overall the whole algorithm required 57.4ms and did processing at 17.4 frames per second.

TABLE III. EXECUTION TIME OF DIFFERENT FEATURES

Processing Module	Execution Time (per Image)
Segmentation	3.9ms
EOH	5.9ms
Hu Moments	0.9ms
Haralick Textures	36.9ms
Color Histogram	1.9ms
Classification	7.9ms
Total Time	**57.4ms (@17.4 FPS)**

VI. CONCLUSION

This research study presents a vision-based agricultural sprayer. The system comprised of a real-time computer vision-based crop and weed detection module, and application hardware for spraying. The vision system was first trained with an offline dataset comprising several images of the crop, weeds, and other objects. The system was then deployed for testing in real environments with a 16MP camera mounted on top of the application equipment for capturing images. The captured data was processed in a standard PC laptop. Different features (such as Color Histogram, Hu Moments, Haralick Texture, and Histogram of Oriented Gradients) were in order to classify the input data as either weed or crop. Then, the Random Forest classifier was used to predict whether the plant in the input image was a weed or crop. After the detection of plants/crops, the pixel area was calculated for determining the plant canopy size, and then the results were sent to a microcontroller connected serially to the PC laptop for spraying agrochemicals according to the density of the plant

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leaves. Pulse Width Modulation technique was used to control the flow rate of the agrochemical. After conducting several experiments, it was concluded that the system works well in real-time in varying environmental conditions.

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