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Development of Enhanced Weed Detection System with Adaptive Thresholding, K-Means and Support Vector Machine

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DEVELOPMENT OF ENHANCED WEED DETECTION SYSTEM WITH ADAPTIVE THRESHOLDING, K-MEANS AND SUPPORT VECTOR MACHINE

BY

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This dissertation is approved as a creditable and independent investigation by a candidate for the Master of Computer Science in Computer Science degree and is acceptable for meeting the dissertation requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidates are necessarily the conclusions of the major department.

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I would like to dedicate this work to my parents (Nanda Dulal Saha and Snehalata Saha) and to my spouse (Swarna Banerjee) for their unconditional support.

"We don't stop going to school when we graduate."

Carol Burnett

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CONTENTS

ABBREVIATIONS

FN	False Negative
FP	False Positive
GPS	Global Positioning Systems
MO	Morphological Operations
NDVI	Normalized Differential Vegetation Index
PA	Precision Agriculture
PCC	Percentage Correct Classification
RFC	Random Forest Classifier
RGB	Red, Green, Blue
SE	Structuring Elements
SSM	Site-Specific Management
TN	True Negative
TP	True Positive
VCI	Vegetation Color Index

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ABSTRACT

DEVELOPMENT OF ENHANCED WEED DETECTION SYSTEM WITH ADAPTIVE THRESHOLDING, K-MEANS AND SUPPORT VECTOR MACHINE

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This paper proposes a sophisticated classification process to segment the leaves of carrots from weeds (mostly *Chamomile*). In the early stages, of the plants' development, both weeds and carrot leaves are intermixed with each other and have similar color texture. This makes it difficult to identify without the help of the domain experts. Therefore, it is essential to remove the weed regions so that the carrot plants can grow without any interruptions. The process of identifying the weeds become more challenging when both plant and weed regions overlap (inter-leaves). The proposed system addresses this problem by creating a sophisticated means for weed identification. The major components of this system are composed of three processes: Image Segmentation, Feature Extraction, and Decision-Making.

In the Image Segmentation process, the input images are processed into lower units where the relevant features are extracted. In the second proposed method, K-Means clustering is applied to extract the images that will be used for the identification process. The images are then normalized into a binary image using Otsu's Thresholding.

Next, in the Feature Extraction stage, relevant information of the weed and leaves are extracted from the lower unit images. Furthermore, to extract the information from the Region of Interest (ROI), Histogram of Oriented Gradient (HoG) is used to locate and label all the weed and carrot leaves regions.

In the Decision-Making process, the system makes use of Support Vector Machine (SVM), which is a supervised learning algorithm, is used to analyze and segregate the weeds from the plants. Afterward, the findings are used to dictate which plants receive herbicides and which do not. The main priority for the Image Segmentation process is on

overlapping images where weeds need to be isolated from plants; otherwise, in the later stages, those plants cannot be used for cultivation purposes. These methods of weed detection are effective as it automates the identification process and fewer herbicides will be used, which in turn is beneficial to the environment.

The evaluation of the approach was done using an open dataset of images consisting of carrot plants. The system was able to achieve 88.99% accuracy for weed classification using this dataset. Further improvement of the proposed method successfully classifies the plant regions at a success rate of 92%. These methodologies will help reduce the use of herbicides while improving the performance and costs of Precision Agriculture.

CHAPTER 1 INTRODUCTION

Precision Agriculture (PA) is a modern farming method that makes use of the updated technologies for the purpose of agricultural commodities. This use of technology makes the crop production more efficiently but other things that are not part of cultivation need to be taken care of so that the production of the crops are not interrupted. The PA is better referred to as Site-Specific Management (SSM) where the farmers give more emphasize on portions of the crop fields. This way of farming methodology focuses on the infected regions and makes sure that other parts of the farming productions are not affected.

To have a better understanding of the infected regions additional information is required like weather conditions, temperature, soil conditions, humidity, yield, and so on. Moreover, farmers need to be aware of the impact of the use of pesticides, as using a huge amount of the harmful chemicals in the fields may reduce the yield factor and will have an impact on the environment too.

Other technologies also play a key role in identifying the infected regions like Global Positioning Systems (GPS) , drones, cameras attached to moving tractors. Some farmers install GPS in their tractors, which helps them to navigate in the agricultural fields. The use of GPS enables them to have an overview understanding of the fields from the satellite images. However, this satellite imagery works well when considering a large portion of the fields is analyzed. But, the drawback of such an approach is that examination of the areas are only possible when a huge chunk of crop fields is already damaged. This analysis of the data can only be helpful to take precautions for the next cultivation season.

The use of drones for this purpose is very useful because the field images are taken much closer. However, taking images using drones is not cost-effective, as it is expensive in operating drones over large agricultural fields. Moreover, the battery lifetime of the drones are limited and can be operated for a small amount of time. Furthermore, operating the device is bit unstable and the altitude of each image may not be constant. But drones provide flexibility in taking close-up images of the fields and then those images can be used to map the weed regions.

A much better option that can be considered is taking the field image by installing a camera in front of the moving tractor, where the images can be generated automatically. Moreover, this mechanism is helpful as close-on field images are taken and those images can be used for weed identification. This way of identifying the weed regions is extremely helpful during the early phase of the crop cultivation because early detection of the weeds can help farmers accurately apply pesticides to the affected areas. Moreover, those weeds can be extracted so that other cops or plants can grow without any interruption. In this way, the cultivating will increase crop yield and the environment will be less polluted. It is important to place the camera at an appropriate height, so that dirt generated by a moving tractor does not block the vision of the lens. Due to these reasons, recent research studies have focused on specific-site based weed control using Image Processing. Furthermore, Image Processing methodologies can be used to extract relevant information from the agricultural fields like plant health, density, shape, size, etc. The information that is extracted from the field images needs further analysis with Machine Learning algorithms for continuous advancements in the field of PA. The primary task of the Machine Learning algorithms is to identify and classify the weed regions and using such an approach is effective as less manpower will be utilized.

Spot control of weeds has the potential to reduce the number of chemicals applied by as much as 80% for improved farm profitability and water quality [1]. This leads to a reduction in the usage of the herbicides in the agricultural fields and will have a great, positive impact on environmental pollution. This improvement will increase productivity and leave the environment less polluted. Moreover, the weed portions in agricultural fields are manually identified by farmers, which is tedious and time-consuming work.

Therefore, an automated system needs to be developed where weed control can be performed round the clock and will increase crop production.

In a practical environment, the weed plants normally grow close-to-crop or intra-row, which needs to be regulated to avoid substantial yield loss [2]. The weeds that are situated between the inter-rows are easily identified and extracting those weeds will not be a challenging task. This is because those weeds are not intermixed with the plant leaves and can be easily extracted without adding any pesticides. But the weed regions identification becomes challenging when both are inter-mixed. This is because additional analysis needs to be carried out to identify the overlapping regions and careful examination is required to identify the regions. Therefore, sophisticated detection mechanisms and classification methods are required to evaluate the overlap regions and minimize crop loss [3].

The goal of this research is to identify the weed regions in the overlapping areas where further steps are needed to extract those weeds. If this task can be performed in the early stage of the detection then the plants can grow without much interruption. The focus of our method is to develop an automated system which identifies the weed regions with minimal help from the domain experts. To achieve that goal, the following contributions are made in two different approaches:

1. In the first approach, the below following are considered:

    - In the segmentation stage, the color bands are separated and are normalized. Then automatic thresholding is performed to extract the greenness portion of the image.
    - Features are extracted from the overlapping regions using Morphological Operations.
    - Linear Support Vector Machine (SVM) is used to classify the weed regions from the plants.

2. In the second approach, some additional steps are considered to those of the previous approach:

    - The K-Means Clustering algorithm is applied to the initial input image to extract the plant and weed portion of the image.
    - The Histogram of Oriented Gradient (HoG) is used a feature extractor, which helps to locate and label the weed and plant regions.
    - Features are extracted from the overlap regions using Morphological Operations.
    - The Linear Support Vector Machine (SVM) is being considered as the number of features is increased and location of those overlapping regions are also considered.

The remainder of the sections are organized as follows: Chapter 2 gives an overall Literature Review. Chapter 3 will discuss about the existing method and the issues that are located from the current method. Chapter 4 and 5 describes the Proposed Method, Feature Extraction for the images, and an overview of the Support Vector Machine (SVM) employed. The Experimental Results are discussed in Chapter 6 and Conclusions are drawn in Chapter 7.

CHAPTER 2 LITERATURE REVIEW

Many different approaches are employed for weed control in Precision Agriculture (PA). Most of the identification of the weed regions use the concepts of Computer Vision, Pattern Recognition, and Machine Learning. In other cases, the use of Feature Extraction like that of shape, aspect ratio, and length ratio is used to determine the presence of weeds in fields [4]–[8]. Color, for instance, has been used for separating diseased and damaged plants in fields. Researchers have even made use of different classification algorithms for discerning weeds from plants [9], [10]. Gerhards et al. used the Fuzzy Logic algorithm for planning Site-Specific herbicide applications [11]. Clustering algorithms also be used in Remote Sensing environments; like in paper [12], where region-based clustering is performed to locate the agricultural fields. Schirrmann et al. [13] used three different clustering algorithms (K-Means, Partition Around Methods (PAM), and Fuzzy C-Means) to detect the spatial changes of biomass in wheat fields.

Another common Machine Learning algorithm that is used in recent research papers is the Support Vector Machine (SVM) for identifying regions of weeds or infected regions in an agricultural field. In Tellaeche and Shi's studies [14] [15], input images of the crop fields are subdivided into different cells than Support Vector Machine (SVM) is used to identify those regions that consist only of crop plants. The method stated in that paper is that images are split into grid cells where each cell is analyzed to determine whether to spray pesticides or not. This cell-based analysis is not suitable when the high precision treatment is required as it is computationally inefficient. Other papers used classifiers like Fuzzy Clustering [16], Artificial Neural Networks [17] (ANN), and Bayesian Classifier [18] as classifiers for weed area identification in farmlands. Furthermore, Hamuda et al. [19] paper discussed numerous approaches that are used for weed identification.

In any agricultural fields evaluating individual leave is not commercially suitable and will not have any significant impact in cultivation. Therefore, priority should be given to performing Remote Sensing in agricultural fields where weed density is high [20]. On the other hand, in the PA classification of plants from weeds need to be performed at ground level [21]. That means images generated from the fields consist of inter-mixed of plant and weed leaves. Haug et al. [3] performed weed and plants regions identification without segmenting any of the regions. Neto et al. [22] performed leaf segmentation that is convex in shape and that methodology cannot be applied to any other form of leaves. Thus, this methodology is ineffective for commercial usage.

Although improvements have been made in identifying weed regions, the above techniques are not suitable for detecting weeds when overlapped with crop plants. Weed growth is stochastic in nature and thus overlap is a very real occurrence. It is thus valuable to focus on those regions and remove the unwanted foliage around the intended plants. In this way, more plants can be considered for cultivation. Therefore, efficient techniques are required to identify overlapping crop regions so that more plants can be identified from the infected regions. This problem becomes more challenging when both plants and weeds have the same green color and texture. In that instance, only an experienced farmer can manually identify the plants from the agricultural fields. However, this manual process for weed identification is time-consuming and the accuracy of detection is subject to human error.

The proposed system has taken these issues into account and performs selective spraying on plants. Selective spraying minimizes the wastage of products required for the effective control of weeds, diseases, and pests to ensuring that plants receive adequate nutrients [23]. The method uses SVM for decision-making, which has two main advantages. First, the model is robust that is numerous features can be included in the system which helps to maximize the width of the SVM margin. This maximization directly improves the classification performance by reducing the chances of misclassification. Secondly, the employed SVM makes use of the Support Kernels which can model non-linear relationships. Non-linear relationships arise when multiple features are present within the system. The proposed approach considers three major features to maximize weed region identification: region area, perimeter, and convex area. These features are extracted from the input image and then used for analysis and classification by the SVM. Further improvement is been made on the proposed method with the addition of the K-Means clustering algorithm. This clustering approach by-passes the conventional methods of green region extractions. Then, the Feature Extractor Histogram of Oriented Gradients (HoG) is used to label the overlapping and non-overlapping regions. Finally, the SVM classifier detects the weed regions from the leaves both from the overlapping and non-overlapping regions within a field.

CHAPTER 3 EXISTING METHOD

Ostermann et al. [24] discussed an approach to discriminate crops from weeds. Their proposed method able to receive a success rate of 85.9%. However, there are some issues in their approach which are examined in detail. Firstly, the Vegetation Mask is manually made from the image and the value of the Normalized Differential Vegetation Index (NDVI) is calculated. Then a human expert manually annotates each image to determine the locations of weeds and plants. This is an issue with their approach, where consistent evaluation is marred by human subjectivity.

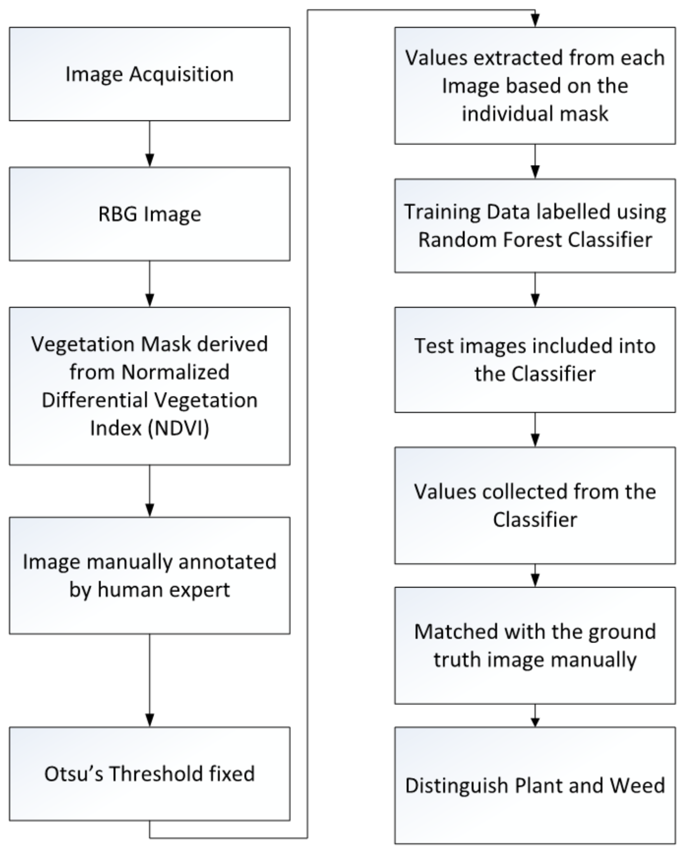


Figure 1. The flowchart of the weed and plants detection system using Random Forest Classifier.

Secondly, Otsu's Thresholding [25] is also applied manually to extract the greenness part of the images. The thresholding is performed manually by examing the greenness of all the images individually and then, the thresholding value is determined.

This approach of manual thresholding quickly becomes prohibitively expensive on larger datasets. In the proposed method, this issue is taken care of by using automated thresholding which is based on the greenness of the input images.

Ostermann also overlooked overlapping regions between weeds and plants. This is a major issue, as skipping such scenarios enable the weeds plants to grow uninterruptedly and may infect other portions of the plant. If the weeds in these regions are not removed then fewer plants will be available for cultivation and therefore also reduces the overall cultivated yield. The proposed method considers the overlapped images, providing more accurate weed detection.

For the classification of weed from plants, Ostermann's research made use of the Random Forest Classifier (RFC) [26]. The outcome of the classifier's values is again manually compared to the manual predictions made by human experts. Thus, the addition of multiple manual steps incurs a tremendous amount of computational cost to the researcher's approach. In contrast, the method proposed eliminates the need for manual steps by employing an SVM classifier which determines the weed and plant regions.

CHAPTER 4 PROPOSED METHOD - 1

This section describes the proposed method's structure and implementation. The following Figure 2 depicts the general functional flow of the system.

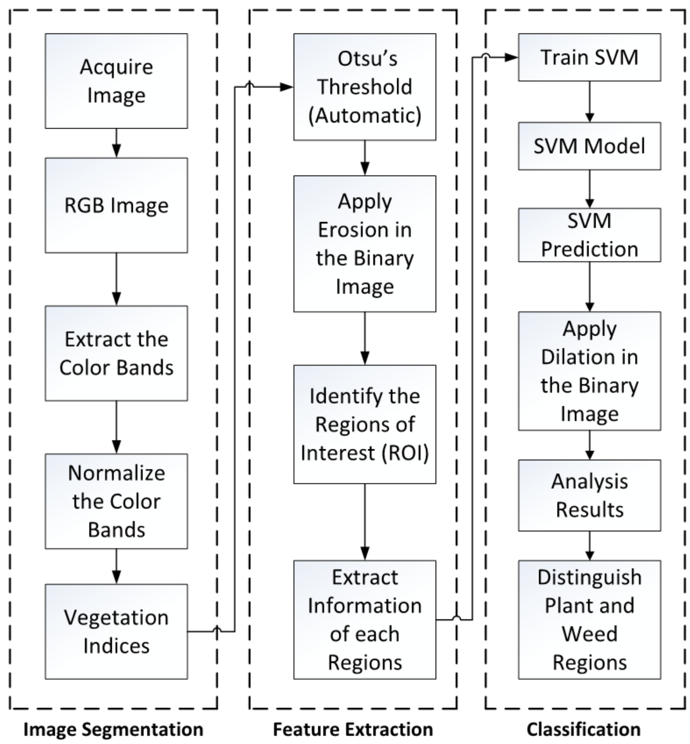


Figure 2. The flowchart of the proposed method for classifying and decision-making process.

The system can be subdivided into three principal components: Image Segmentation, Feature Extraction, and Classification. These components are critical for region classification and discerning plants from weeds. The tasks carried out in each component is described in the following subsections.

4.1 Image Segmentation

Initially, an image database of color in-field images are used to produce viable training data. The set is created by highlighting greenness regions of plants and weeds. This is done by extracting each band of color from an RGB image and then normalizing each color components. This is done using the modified equations from Shi et al. [15].

$$NormalizedRed = \frac{red}{red^2 + blue^2 + green^2} \tag{1}$$

$$NormalizedGreen = \frac{green}{red^2 + blue^2 + green^2} \tag{2}$$

$$NormalizedBlue = \frac{blue}{red^2 + blue^2 + green^2} \tag{3}$$

Equations 1 through 3 are used to find the value of each color band from an RGB image. Then, by using the set of equations below [15], the normalized component values of the image are calculated. These normalized values are then used as a means of highlighting the “greenness” regions.

$$r = \frac{NormalizedRed}{NormalizedRed + NormalizedBlue + NormalizedGreen} \tag{4}$$

$$g = \frac{NormalizedGreen}{NormalizedRed + NormalizedBlue + NormalizedGreen} \tag{5}$$

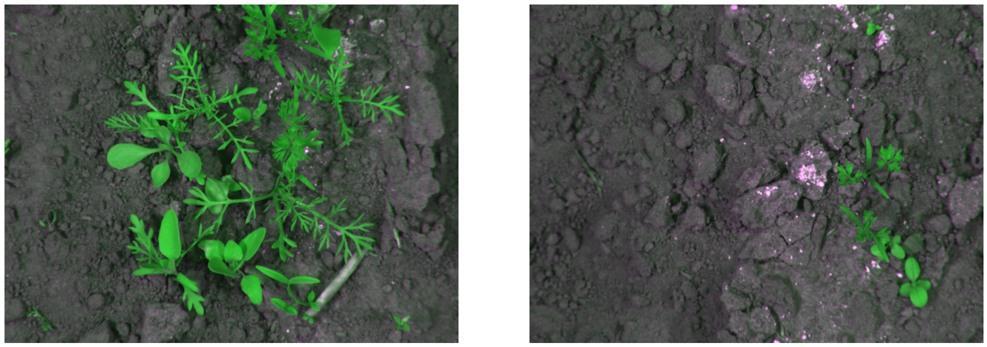
$$b = \frac{NormalizedGreen}{NormalizedRed + NormalizedBlue + NormalizedGreen} \tag{6}$$

The “greenness” part of the image relies on the common Vegetation Color Index (VCI) [27] in Equation 7 to further emphasize the greenness part of the plant. This equation applies more weight to greener regions of the plant and removes other color bands from the image.

$$ExcessGreen = 2 * (g) - (r) - (b) \tag{7}$$

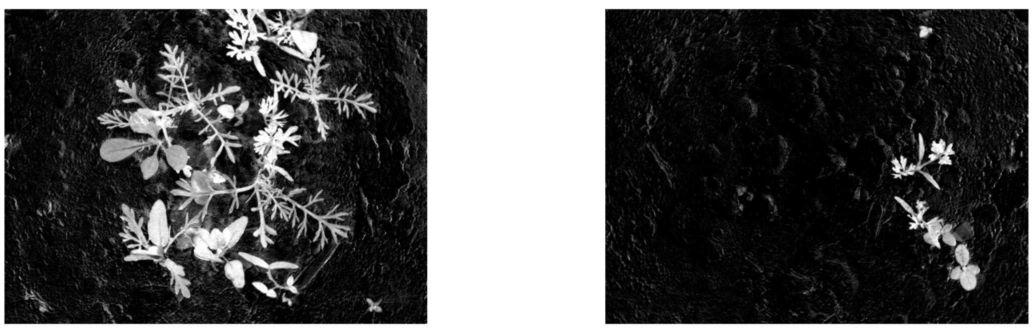
Figures 3(a) to 7(b) display images as they go through the segmentation process. The image in Figure 3(a) and 3(b) displays the original RGB image prior to any enhancement. These images clearly show that the plants and weeds are intermixed with one another. Moreover, all the leaves color are green which make it difficult for the naked eye to determine which regions are weeds and which ones are plants.

Next, the images color bands are normalized by using Equation 7 and the value of the “greenness” part of the images are displayed in Figure 4(a) and 4(b). These images show that the highlighted greenness part of the image and other parts are darkened out.



(a) (b)

Figure 3. (a) and (b) Type of Input Images



(a) (b)

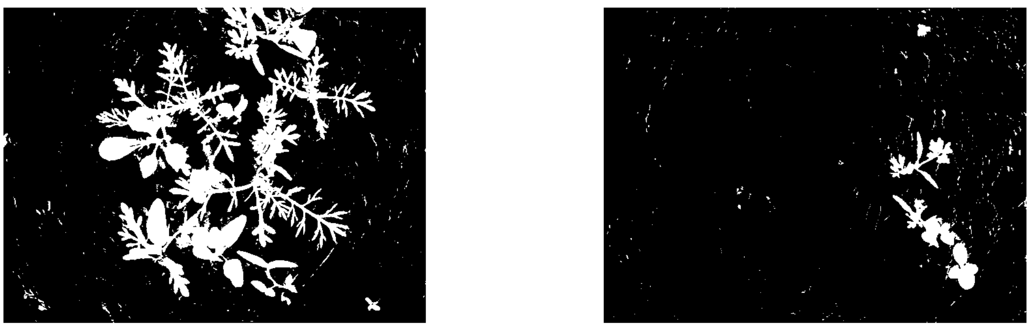
Figure 4. (a) and (b) Show the Excessive Greenness in the Input Images

4.1.1 Automatic Thresholding

Automatic thresholding is then applied to get the “greenness” of the plant region. This is done by using Otsu’s Thresholding [25] which is helpful in separating the plant’s pixels from the background’s pixels. The outcome of the Otsu’s Thresholding is represented in Figure 5(a) and 5(b) where the thresholding is performed only on the green pixels of the image. To have a better understanding of the extracted images, we can see that there are some white pixels which are small in size. Those are actually picked up from the soil, which may consist of algae or fungus. The Otsu’s Threshold basically *minimizes the weight with-in the class variance* and *maximize the weight between-class* *variance*. The Otsu's Thresholding is based on some assumptions which are taken from the paper [25].

The stated assumptions to perfrom Otsu's Thresholding are:

- Histogram and the image are *bimodal*.
- No use of *spatial coherence*, nor any other notion of an object structure.
- Assumes stationary statistics but can be modified to be locally adaptive.
- Assumes uniform illumination (implicitly), so the bimodal brightness behavior arises from object appearance differences only.



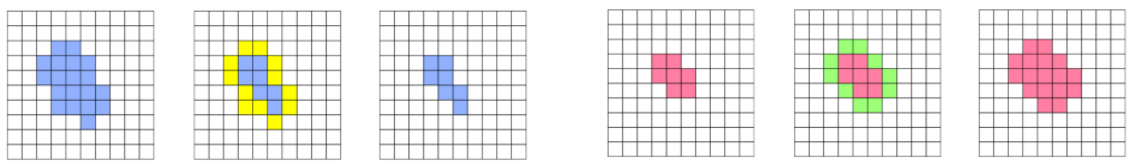
(a) (b)

Figure 5. (a) and (b) After applying Otsu's Thresholding

4.1.2 Morphological Operations

After successfully applying the Automatic Thresholding. The next step is to identify the overlapping regions. As we can see in Figure 5(a) and 5(b) all white pixels are merged together consisting of both plants and weeds. These white pixels compromise of the weed and plant regions. The Morphological Operations (MO) are used to separate the weeds from the plants [28].

The MO are represented in the binary image where the values of the pixels are integer values Set **Z**. The points in the image foreground are members of Set **X**, where **X** $\subseteq$ **Z** [29]. The values that are represented in the foreground are the member of the Set **X** and the point that is represented in the background is the complement values of **X** which is termed as $\mathbf{X}^c$. The two main operational techniques that are used for our purpose are *Erosion* and *Dilation*. Both these operations are used to analyze the shape and form of an image. Theses operations make use of the set of known shapes called Structuring Elements (SE) .



(a) (b)

Figure 6. (a) Example of Erode and (b) Example of Dilation

The task of *Erosion* operation is basically removal of pixels in the border region. The *Erosion* operation is represented in Equation 8 which is interpreted as; when the *InputImage* matches with the operation assigned in the *SE* then, the pixel values around the border regions will be reduced. The resulting image from the operation is defined as the *ErodeImage*. In other words, the *Erosion* operation can be stated as the place where the SE hits the input image. The *Erosion* operation on the input images is shown in Figure 6(a) and 6(b), where the leaves of the plants are separated from the weeds. After multiple *Erosion* operations, each of the components are separated and now it is possible to collect data of the plants and weeds based on the selected features.

$$InputImage \ominus SE = \{PixelValue \in BinaryImage | ErodeImage \subseteq BinaryImage\} \quad (8)$$

The *Dilation* operation is the reverse of the *Erosion* operation. This operation is carried out based on Equation 9, where the *InputImage* performs a plus operation along with SE. That is, the surrounding pixels are added up and the pixels around the border regions will be inflated. This sort of operation means that the output image consists of the places where the shape considered in SE fits with the *InputImage*. *Dilation* is applied on the final image when weed regions are detected by SVM. In the *Dilation* process, all of

(a) (b)

Figure 7. (a) and (b) After applying Morphological Operation: Erosion

the white pixels are remerged back into a new black and white images as shown in Figure 7(a) and 7(b).

$$InputImage \oplus SE = \{PixelValue \in BinaryImage | DilateImage \subseteq BinaryImage\} \qquad (9)$$

(a) (b)

Figure 8. (a) and (b) After applying Morphological Operation: Dilation

4.2 Feature Extraction

The Feature Extraction is performed after the *Erosion* stage, shown in Figure 7(a) and 7(b). A set of shape and contour features, commonly employed in similar approaches [30], [31], are applied. The list of features that are used for examination are *Area*, *Perimeter* and *Convex Area*. The *Area* calculates the regions where the value of a pixel is 1. The feature *Perimeter* defines the number of border pixels with a value of 1. Lastly, the *Convex Area* represents the area of the convex hall of a region. Table 1 delineates the aforementioned feature types and their descriptions. The set of values of these features are taken from the eroded binary image where all the pixels representing the plants are separated from that of the weeds. As shown in Figure 5(a) and 5(b), the plant leaves are rounder than of the weed's leaves, which are much thinner and straighter. Therefore, the shapes '*disk*' and '*line*' are selected as the primary structures for SE. The features within the interrogated images corresponding to these selected shapes are extracted and the values are stored for further evaluation.

Feature Number	**Feature**	**Description**
$feature_1$	Area	Area of the pixels covered by leaves and weeds
$feature_2$	Perimeter	Length of the pixels covered by leaves and weeds
$feature_3$	Convex Area	Area of the Convex Hall for leaves and weeds

Table 1. List of Features considered for the experiment

4.3 Classification

The Support Vector Machine (SVM) is a quintessential mechanism for classification. In general, a classifier is constructed in the N-dimensional hyper-plane that optimally separates the two classes [32]. The SVM consists of two phases: *Training* and *Testing* phases. In the *Training* phase, the SVM makes use of the two-class classification linear model to label the points in the form:

$$y(x) = w^T \phi(x) + b \tag{10}$$

where $\phi(x)$ denotes a fixed feature-space transformation and b is the bias parameter. The *Training* dataset comprises of N input vectors $x_1, x_2, ..., x_N$ with the corresponding target values $t_1, t_2, ..., t_N$ where $t_n \in \{-1, +1\}$ and the labelings are carried for points $y(x_n) > 0$ then $t_n = +1$ and $y(x_n) < 0$ for points having $t_n = -1$, so that $t_n y(x_n) > 0$ for all the training data points [32].

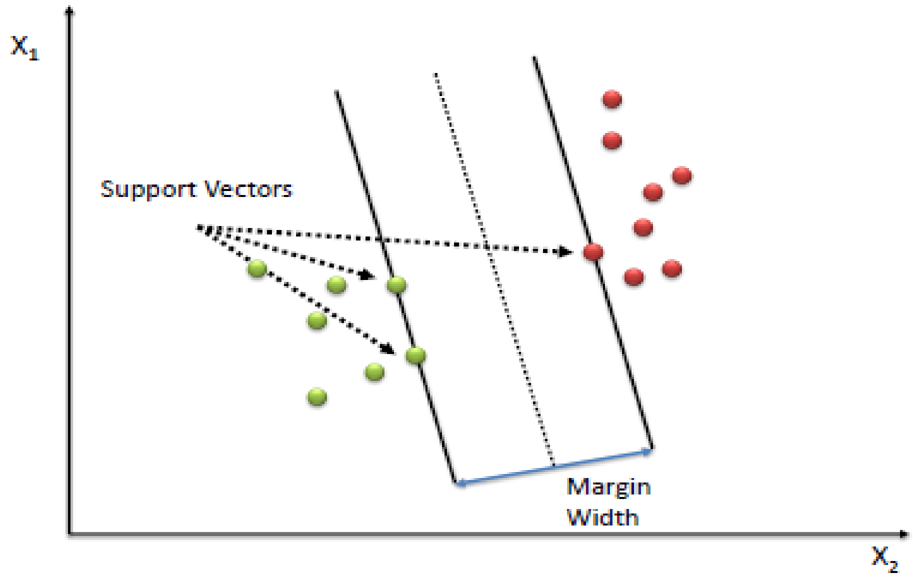


Figure 9. An Overview of the Support Vector Machine

Figure 9 shows an overview of the SVM where the main task is to maximize the decision boundary and that will create the optimal *hyperplane*. Equation 11 is used to generate the optimal *hyperplane*. The main advantage of using SVM for classification due to reason, it is computational less intensive than other supervised classifiers. By that, it means that SVM does not make use of all the points for the classification purpose. It only makes use of the *Support Vectors* which are located close to the optimal *hyperplane*. Only those *Support Vector* are only considered for the classification purpose and the other points that are situated within the clusters are labeled accordingly.

$$\underset{w,b}{argmax}\left\{\frac{1}{||w||}\underset{n}{min}[t_n(w^T\phi(x_n)+b)]\right\} \tag{11}$$

In our case, the extracted dataset of the three focal features compose the training data while $t_n \in \{-1,+1\}$ comprise the labels -1 and +1, indicating the identified class. The label -1 is produced by the SVM if the input data falls within the weed class. Whereas the label +1 is generated by the SVM if the input data is of the plant class. The SVM becomes significantly more accurate in classification as the margin along the separating *hyperplane* increases [33]. Therefore, it is important that the training dataset produces a maximal *hyperplane* margin. The equation of the plane that maximizes the margin is given in Equation 11 where w is the weight vector and b is the bias. The value of $x\dot{}n$ is defined as the input dataset from the extracted features.

The use of SVM for weed detection purpose is carried out in numerous research papers [34]–[36]. However, the performance of the SVM can be distinguished by the use of the SVM Kernel functions which are used for the SVM training purpose. As mentioned in paper [34] the authors used multiple Kernel functions as shown in Equations 11 to 15 for classification purpose. The author also used *Cross-Validation* to avoid misclassification among the SVM Kernel functions. In the case of the paper, [37] the authors used the Linear Kernel in Equation for the classification purpose and stated that linear classifier performance is cost-effective than other kernel functions. Thus, these kernel functions evaluations suggested us to move ahead with Linear Kernel.

$$\text{Gaussian Kernel} : k(x,y) = \exp\left(-\frac{||x-y||^2}{2\sigma^2}\right) \tag{12}$$

$$\text{Polynomial Kernel} : k(x,y) = (x \cdot y)^2 \tag{13}$$

$$\text{Sigmoid Kernel} : k(x,y) = \tanh(\alpha x^T y + c) \tag{14}$$

$$\text{Linear Kernel} : k(x,y) = x^T y \tag{15}$$

The Linear Kernel function in Equation 15 is actually a dot product of the input dataset and the weight vector. Based on the paper [38], the Linear Kernel is used in the proposed method to improve the optimization of the training dataset.

CHAPTER 5 PROPOSED METHOD - 2

This section describes the proposed method's structure, which is actually a further improvement than the previous method. The following Figure 10 depicts the general functional flow of the system.

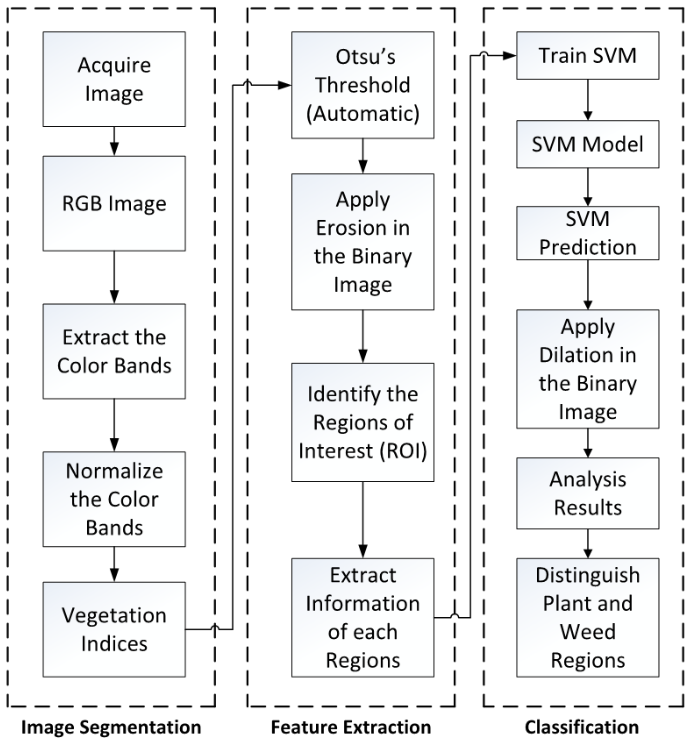


Figure 10. The flowchart of the improved method for classifying and decision-making process.

Similar to that of the previous chapter this system is subdivided into three principal components: Image Segmentation, Feature Extraction, and Classification. These components are important for discriminating the weed and plant regions. In the below sub-divided sections, the required components that are used will be discussed in detail.

5.1 Image Segmentation

Initially, in the Image Segmentation stage, the images are loaded into the system from the database. The main task of this section is to pick up the image that consists of plants and weed where other unnecessary items are eliminated like soil, pesticides, algae, etc. To achieve this task, we did not make use of the traditional approach mentioned in Shi et al. [15], where individual bands of colors are examined to identify the greenness of the regions.

Instead, we used the K-Means clustering algorithm [39] where each of the cluster regions is analyzed and then the desired image is stored in the new dataset. In this algorithm, the number of observations *n* is broken down into *k* different clusters. The clusters develop around the mean value which changes until all the pixel values are considered.

One thing needs to be considered is that the clustering positions of the K-Means algorithm are random. Therefore, randomness needs to be eliminated so that the images which consist of only plants and weeds are always selected. This step can be accomplished with the help of the algorithm stated in Figure 11.

```
if(Total_Red_1 < Total_Red_2 && Total_Red_1 < Total_Red_3)
    if(Total_Blue_1 < Total_Blue_2 && Total_Blue_1 < Total_Blue_3)
        if(Total_Green_1 < Total_Green_2 && Total_Green_1 < Total_Green_3)
          input_image = segmented_image{1};
        end
    end
elseif(Total_Red_2 < Total_Red_1 && Total_Red_2 < Total_Red_3)
    if(Total_Blue_2 < Total_Blue_1 && Total_Blue_2 < Total_Blue_3)
        if(Total_Green_2 < Total_Green_1 && Total_Green_2 < Total_Green_3)
          input_image = segmented_image{2};
        end
    end
elseif(Total_Red_3 < Total_Red_1 && Total_Red_3 < Total_Red_2)
    if(Total_Blue_3 < Total_Blue_1 && Total_Blue_3 < Total_Blue_2)
        if(Total_Green_3 < Total_Green_1 && Total_Green_3 < Total_Green_2)
            input_image = segmented_image{3};
        end
    end
end
```

Figure 11. The algorithm that is used to eliminate the KMeans clustering randomness.

The algorithm stated in Figure 11 evaluates the band of colors in each cluster. That means individual color bands of Red, Green, and Blue are extracted from different clusters generated from the K-Means algorithm. It has been pre-analyzed that the desired cluster consists of the least number of pixel values in each RGB image, which is measured between the values of 0 and 255. Then, using a loop each of the clusters is evaluated using the *if-statement* and then the desired *segmented˙image* is stored in the new dataset. The advantage of doing this one is that the selected image eliminates the unwanted elements in the image like soil particles, any dead leaves, etc. and the analysis can now only be performed on the image which only consists of green plants and weeds.

Figure 12 shows three different clusters that are generated from the K-Means algorithm. These clusters are named as *Segmentation-1*, *Segmentation-2* and *Segmentation-3*. The figure clearly shows that the image generated from *Segmentation-1* contains only leaves and weed. Where else both the images from *Segmentation-2 and Segmentation-3* show all the unwanted components of the input image. Then using the logic mentioned in Figure 11, the image with leaves and weed is selected.

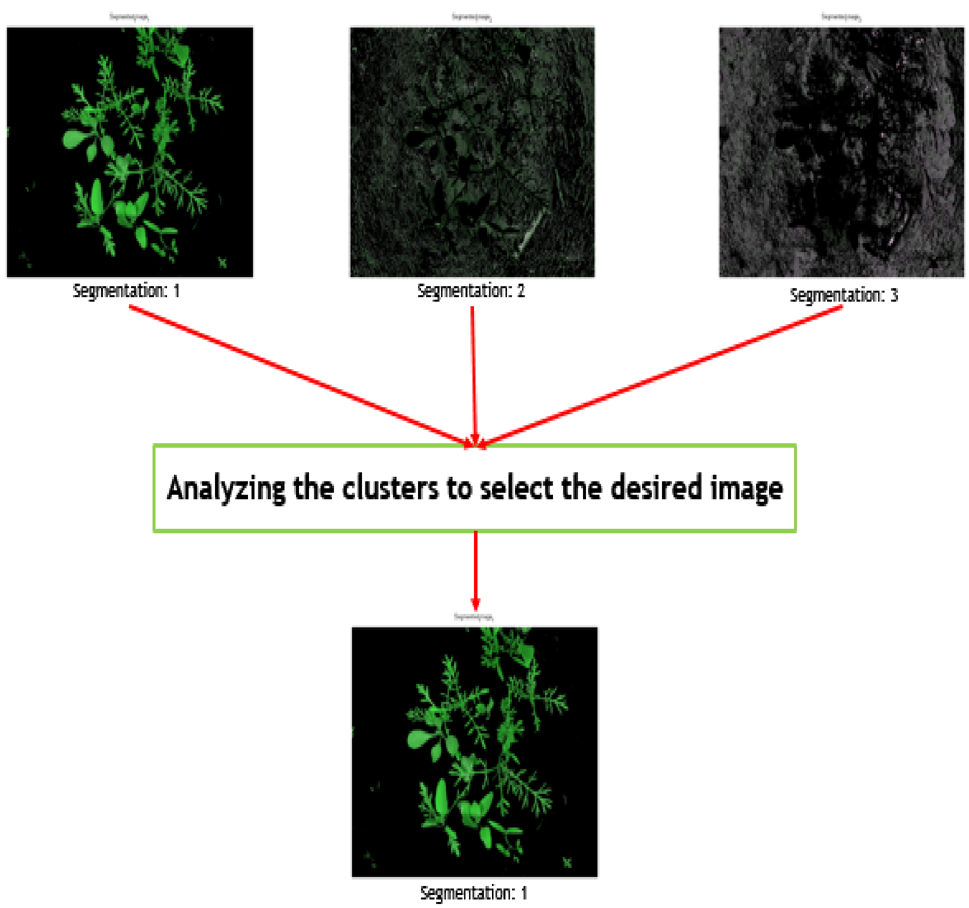


Figure 12. The algorithm mentioned in Figure 9 is used to select the desired image

The final image is stored in the database and is considered as an input image for the weed identification process. Subsequently, *ExcessGreen* in Equation 7 is executed where more weight is assigned to the green pixel and other color bands are eliminated.

Afterward, Otsu's Thresholding [25] which is automatic thresholding is applied to convert the RGB image into a binary image.

The next step is to identify the overlapping regions from the binary image. As stated in our previous approach [40] the Morphological Operations are used to separate the weed from the plants. The Morphological Operations are a class of techniques that analyze the shape information in monochrome images [29]. The features of both weed and leaves regions are extracted using *Bounded Erosion*, where the *Erosion* operation is carried out in a loop process. This continues until all the regions are separated and are possible to label the regions of both plants and weed as shown in Figure 7(a) and 7(b). The *Dilation* operation is the reverse operation of the *Erosion*. *Bounded Dilation* is carried out until all the regions remerged to that of the initial binary image as shown in Figure 8(a) and 8(b). The labeling of the regions is carried out with the help of Histogram of Oriented Gradient (HoG) , which will be discussed in the following subsection.

5.1.1 K-Means Algorithm

The K-Means algorithm [39] is based on the Equation 16 which states that given a set of observations (i.e pixel values) $(x_1, x_2, ..., x_n)$, where each of the observation is in the *d-dimensional* vector space. The K-Means clustering aims to partition the n observations into k different sets $S = S_1, S_2, ..., S_k$ so that it can minimize the with-in cluster *Sum-of-Squares*. The objective function of this clustering algorithm is:

$$\underset{S}{argmin} \sum_{i=1}^{k} \sum_{x \in S_i} ||x - \mu_i||^2 = \underset{S}{argmin} \sum_{i=1}^{k} |S_i| \, VarS_i \tag{16}$$

where μ_i is the mean of the points in S_i. This is equivalent to minimizing the pairwise squared deviations of points in the same cluster:

$$\underset{S}{argmin} \sum_{i=1}^{k} \frac{1}{2|S_i|} \sum_{x,y \in S_i} ||x - y||^2 \tag{17}$$

Thus, based on the above set of equations it is seen that K-Means clustering only take those observations into account that are closest to the mean value of the clusters.

Figure 13 represents the outcome of the K-Means clustering based on the image in Figure 12. From the outcome, it is seen that there are three different groups labeled as *Cluster-1, Cluster-2*, and *Cluster-3*, where the centroids of each of the clusters are marked with “X”. Thus, just by looking at the outcome of the clusters it is challenging to determine, the segmented image that consists of the plant and weed regions. However, using the logic mentioned in Figure 11, this situation is overcome.

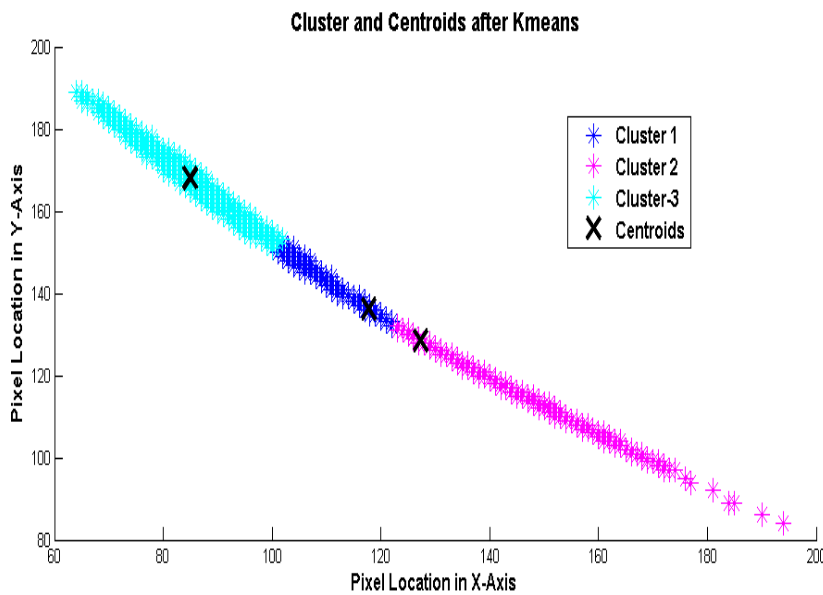


Figure 13. The outcome of K-Means Clustering

5.2 Feature Extraction

The set of features that are used for the classification purpose are similar to that of Section 1.2. The features are extracted after the *Bounded Erosion* operation as shown in Figure 6(a) and 6(b). Table 1 from Section 1.2 shows the list of features that are considered and they are *Area*, *Perimeter*, and *Convex Area*. Both the *Erosion* and *Dilation* operations use the SE which define the neighboring structure of an object. As previously stated, plant leaves are bit rounder and convex shaped where else weed leaves are much thinner and straighter. Therefore, the SE of *disk* and *line* are selected as the primary structure of the regions in the image. Features within interrogated images corresponding to these selected shapes are extracted and the values are stored. When all the feature values are extracted the *Bounded Dilation*, the operation is carried out to restore the image back to the initial image.

5.2.1 Histogram of Oriented Gradient

The Histogram of Oriented Gradient (HoG) [41] is a feature descriptor, which is used to identify and label objects of an image. The objects are identified based on the values of intensity gradient or edge direction. Figure 14 explains the use of HoG descriptor. The approach outlines the local intensity of small spatial regions called *cells*. The value in each cell represents a 1-D histogram of gradient directions or edge orientations. The paper [41] also stated that the invariant regions like overlapping of objects, shadowing, etc. are considered as a larger spatial region called *blocks*. The results generated in each block are normalized into cell regions. After that, all these extracted regions are combined histogram entries of HoG descriptor.

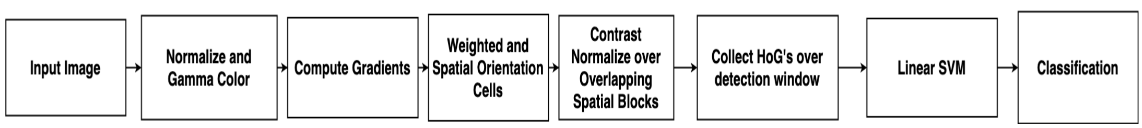


Figure 14. Overview of feature extraction and object detection [41]

For our purpose, the HoG feature descriptor is used to allocate the shape information of the regions and label the regions of weeds and plants. The HoG descriptor makes use of the connected regions called *cells* which map the direction of each of the gradient vector [42]. The cell size set for our experiment is a 4x4 window. This is because if we increase the cell size than a lot of detail of the image will not be considered and if the smaller cell size is considered then the computational costs will increase. Figure 15 shows the outcome of the HoG descriptor, where the gradient direction of both weed and plants are mapped and are considered as a set of features along with the other extracted features for the SVM.

Figure 15. The outcome of Histogram of Oriented Gradient

5.3 Classification

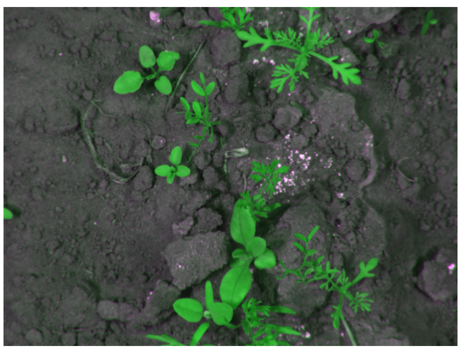
In the revised proposed method the same SVM is used as stated in Section 4.3. Even the same Linear Kernel is been used so that the classification methodology for the process remains the same.

CHAPTER 6 RESULTS AND ANALYSIS

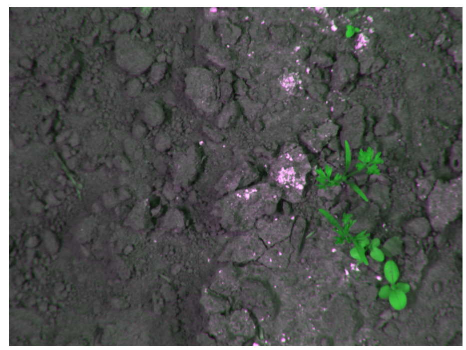
The following sections will give an overview of the results that are generated and will be evaluated to have a better understanding of the outcome.

6.1 Type of Images

This section discusses the type of input images that are used for the experimental purpose. As seen from the Figure 16(a) and 16(b), the input images are a mixture of weed and leaves, wherein some images the weed density is much heavier than of the leaves.



(a)



(b)

Figure 16. (a) Dense Weeds and Leaves and (b) Less Dense Weeds and Leaves

The complete dataset consisted of 60 images from organic carrot fields provided by Haug and Ostermann [24]. The specification of each of the images is given in Table 2.

Parameter	**Value**
Camera model	JAI AD-130GE
Image resolution	1296 x 966 pixels
Lens	Fujinon TF15-DA-8
Focal Length	150 mm
F-number	4
Mean distance to ground (d)	450 mm
Ground resolution	8.95 pixels/mm

Parameter	Value
Field of view x (at distance d)	145 mm
Field of view y (at distance d)	108 mm

Table 2. Description of the Camera Setup and Acquisition Parameters

6.2 Implementation and Tools

The following table provides an overview of the tools and the softwares that are used for the implementation purpose.

Components	Configuration
Operating System	Windows 10
Programming Language	Matlab 2014
Machine's Processor	Intel Core i7
Memory	16 GB RAM
Processor Base Frequency	2.93 GHz
Bus Speed	2.5 GT/s DMI

Table 3. Overview of the System

6.3 Evaluation of the Results

The carrot plants dataset is broken into 40 training and 20 test images. The training images are selected to maximize the interclass variability in order to improve the *hyperplane* margin of the SVM. Selected images included a wide variety of weed to plant ratios, some with a large number of weeds, others with a large number of plants and are selected randomly from the actual dataset. These setup of the images helps to determine if the SVM Model is working properly or not and the outcome is represented in Figure 16(a) and 16(b).

The remaining 20 images which are not selected for the training purpose are considered as test images. These 20 images are subdivided into four test cases and each is evaluated separately and the outcome is displayed in Figure 18. The results are compared to those of the human experts and with the values generated from the proposed model. The analysis of the results leveraged using the equation *Percentage Correct Classification* [43].

To understand the performance of the algorithm, these four different parameters that are considered in Equation 18:

- *True Positive (TP)* : The number of locations that are correctly identified as leaves.
- *True Negative (TN)* : The number of locations that are correctly identified as weed
- *False Positive (FP)* : The number of locations that are not correctly identified as leaf, and instead, incorrectly as weed.
- *False Negative (FN)* : The number of locations that are not correctly identified as weed, and instead, incorrectly as plant.

$$Percentage\ Correct\ Classification\ (PCC) = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{18}$$

Before evaluating the test data set, let's analysis the list of features that are considered for the experimental purpose. Figure 17 gives an overview of the outcome of the SVM Model, by considering the features individually and combining all the features for the same set of test images. Figure 17 clearly shows that among all the individual features *Area* has provided the most accurate predictions among all the individual features and having a *PCC* about 99%. Where else the feature *Convex Area* give the least *PCC* value about 86.51%. Thus, it can be seen that by considering an individual feature for SVM Model will not be an appropriate idea as the results are not stable. Therefore, to make a better accuracy of the weeds detection it is logical to consider a cluster of features for the SVM Model.

Another important point that can be taken into consideration is the computational time of the algorithm. It is seen that if an individual feature is considered then the average computational time is about 142.47 seconds. Where else if multiple features are considered then the average computational time is about 143.80 seconds. This gives a clear impression that including multiple features into the SVM Model does not increase the overall computational time.

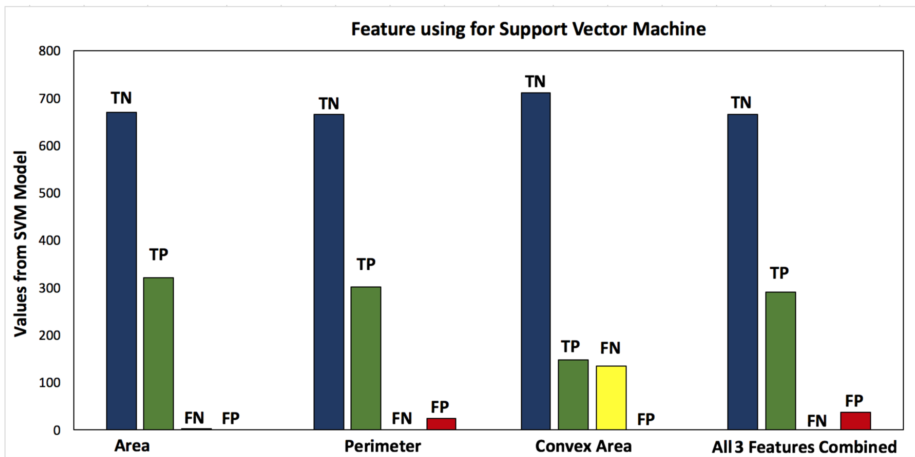


Figure 17. Analysis of the features

Figure 18 represented below, displays the outcome of the four test cases. Based on the results, it can be seen that, in Test Case-4, weed classification is much higher than the plants. Conversely, in the other test cases, the detected plant regions are not substantially higher. The test cases are separated to have a better idea about the type of input images that are considered for the evaluation purpose.

In total, 1780 regions are located from the 20 test images. Among them, 666 regions are classified as *True Negative* and 291 regions are identified as *True Positive*. These results indicate that the input images for the test cases mostly consists of the weeds. Moreover, as overlapping regions are considered, the quantity of weeds in the images has increased. The number of misclassifications of plant leaves and weeds is 36. Therefore,

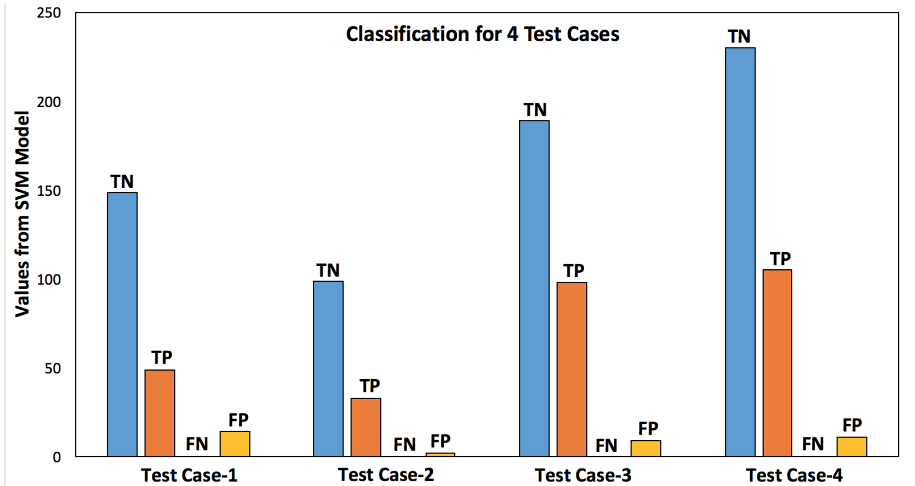


Figure 18. Analysis of the test cases

the *PCC* value of 96.37% means that the classifier is a viable weed and plant region classifier.

In the second proposed method the Equation 19 *Plant Leaves Identification* is used to determine the detection accuracy of the plant leaves and the follow information are generated.

$$Plant\ Leaves\ Identification = \frac{TP}{TP+FP} * 100\% \tag{19}$$

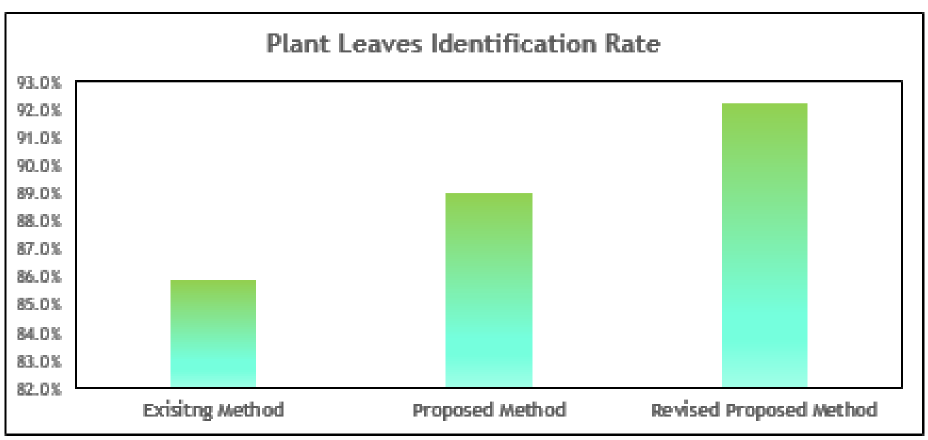


Figure 19. Plant Leaves Identification Rate

The overall success rate of the plant leaves is about 92.01%. As stated in Figure 19 the proposed system showed improvement when compared with previous weed detection methods in the papers [3], [40], where the average accuracy mentioned are around 85% and 90%. Higher accuracy of the carrot leaves is achieved as the feature descriptor, HoG descriptor locates and labels the regions in both the overlapping and non-overlapping portions. This inclusion of the labeled features along with other features increased the accuracy of the object identification and minimized any false identification.

CHAPTER 7 CONCLUSIONS

An improved weed and plant detection algorithm are proposed and the overall discussion is carried out in detail. The proposed approach is separated into two parts where the required information is gathered from the images and then used to train the SVM Model to classify the weed from the plants. In order to evaluate the system, four different test cases are carried out where the weed to plant ratio is much higher in all of the test cases. The system is able to identify plant and weed regions with a success rate of 96.37% and the accuracy for the weed detection is 88.99%. The initially proposed system showed vast improvement when compared with weed detection in the paper [24], where the average accuracy mentioned is about 85.9%. This difference in result is due to the fact that the proposed system considered the evaluation of the overlapping images which are omitted from consideration in the paper [24]. Although, the number of steps for weed detection is a bit higher but eliminating the use of manual thresholding and the knowledge of the human experts for weed identification overcame those overheads and improved the level of computation.

The second improved weed detection mechanism consists of two additional approaches to that of the previous approach stated in the paper [40]. Initially, in the pre-processing step, the K-Means clustering algorithm selects the image that consists of plant and weed regions only and avoided unnecessary tasks like handling noises from the images. This new dataset is considered for further evaluation purpose, where Morphological Operations are carried out to separate the plant leaves from weeds. Furthermore, Histogram of Oriented Gradients is used to locate and label the regions of weeds and plants even in the overlapping regions. Then, the extracted features from the images are used to train the SVM Model to classify the weeds from the plants. The system can identify plant regions with a success rate of 92.01%. This detection method is significant as weeds normally grow close-to-crop or between intra-row which need to be regulated to avoid substantial yield loss [2].

In future research, the larger dataset will be evaluated to bolster the credibility of the proposed methods. Additionally, extensive weeds and plants segmentation research will be carried out to improve the detection accuracies.

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