Analysis on Weed Identification using Deep Learning and Image Processing in Vegetable Plantation

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ABSTRACT
This analysis should determine which weeds are present in the field and the density of those weeds so that herbicides targeting those weeds may be selected. 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.

Keywords
Weed identification, deep learning, image processing, genetic algorithms, color index.

1. INTRODUCTION
Due to their abundance in vitamins, minerals, and antioxidants, vegetables are among the foods that are considered to be the most nutrient-dense in the entire globe. Green vegetables become more prevalent in our diets as living standards rise, adding to their importance to our daily lives and significant economic value. Vegetables are more vulnerable to infestation by insects and diseases when weeds compete with them for water, sunlight, and nutrients. When weeds and vegetables competed, the vegetable output dropped by 45% to 95%. Overuse of chemical herbicides leads to over application in areas with little to no weed infestation and has negative effects on the ecosystem, such as soil and ground water pollution. Furthermore, weed management without chemicals is necessary for organic food production. As a result, hand weeding is still the main weed management method used in vegetable plantations today. [5]. Development of a visual method of differentiating between vegetables and weeds is a crucial and essential step towards ecologically viable weed management given the significantly higher labour cost.

Various machine vision techniques for weed detection have been the subject of extensive investigation. In a collection of 224 photos, Ahmed used Support Vector Machines (SVMs) to identify six weed species with 97.3% accuracy using the best extractors. Herrera built a weed-crop classifier utilising shape descriptors and fuzzy decision-making, and in a collection of 66 photos, he achieved a classification accuracy of 92.9%. The crop typically outgrows weeds at the beginning stages of growth. Chen developed a crop and weed discrimination method employing a binocular stereo system using this height feature. Using a depth dimension analysis-based height-based segmentation technique, it was possible to distinguish between crops and weeds. Plant spacing information was used to separate the weeds from the crops for the relative higher weeds.

Deep learning has recently shown astounding performance when automatically extracting complicated information from photos. It is widely used as a promising technique for object recognition and image categorization. For image detection, deep learning uses two groups of techniques. Object classification comes initially, followed by the drawing of bounding boxes around photos to classify the object. The second category is semantic segmentation, commonly referred to as classifying object pixels. Olsen classified photos of sixteen different varieties of weed using benchmark deep learning models, with an average classification accuracy of 95.1% and 95.7%, respectively. Dos Santos Ferreira used convolutional neural networks to identify weeds in soybean crop photos and to categories them as either grass or broadleaf (CNNs). On high-resolution colour photos of canola fields, Asad and Bais compared the performance of deep learning meta-architectures like SegNet and UNET and encoder blocks like VGG16 and ResNet-50. Khurana and Bawa employed morphological scanning and textural feature analysis to sugar beetroot plants, and then a KNN classifier was utilised to distinguish weed plants from field crops. For the purpose of weed detection in soybean fields using UAV imagery, Veeranampalayam Sivakumar examined and contrasted two object detection models, namely the Faster RCNN and the Single Shot Detector (SSD). Inference speed and mean Intersection over Union (IoU) were used to determine which model performed the best in weed detection. Osorio presented three techniques for weed detection in lettuce crops using deep learning and image processing. Support vector machines (SVM) were the foundation for one method, YOLOV3 (you only look once V3) for the second, and Mask R-CNN for the third. When the performances were compared to a group of weed specialists' estimates, it was discovered that these techniques increased weed coverage estimation accuracy and reduced.

In the growing of vegetables, there is no clear row spacing and plant spacing. Weed identification in vegetable plantations is more difficult than in crop plantations because vegetables and weeds grow irregularly. Additionally, during robotic harvesting, weeds in vegetables will also be mixed in with vegetables and must be manually sorted. Sales prices have increased as a result of various labour expenditures. Vegetable plantation weed identification has received very little attention thus far, and earlier crop weed identification methods primarily concentrated on detecting weeds directly. Vegetable weed species, however, vary widely. The remaining green objects in the segmented image were then classified as weeds. As a result, we proposed ways to first identify and segment the vegetable using deep learning, in particular the architecture of Convolutional Neural Networks. This approach can significantly reduce the amount of the training image dataset and the difficulty of weed detection, improving the performance and accuracy of weed identification.

2. MULTI-CLASS SUPPORT VECTOR MACHINE (MCSVM)
SVM classification is built on decision hyper planes, which

offer decision boundaries in input space or high-dimensional feature space. builds SVM models using a set of labelled training datasets and linear functions (hyperplanes either in input space or in feature space). This hyperplane will be used to differentiate the positive samples from the negative samples. It is common practise to construct the linear separator so that the nearest positive and negative samples are located as far away from the hyperplane as practicable. Intuitively, this leads to correctly classified training data that is close to, but not exactly, the testing data.

SVM employs a data matrix as input during the training phase to categorise each sample as either favourably or unfavourably belonging to a certain class (negative). The dimensionality of the space is determined by the number of characteristics, and SVM treats each sample in the matrix as a row in an input space or a high-dimensional feature space. The SVM learning algorithm selects the best hyperplane that divides each positive and negative training sample. The trained SVM can be utilised to predict test samples (new) in the class.

Since there must be M mutually exclusive classes and there may be many classes of outputs, multi-class classification issues are more challenging to solve. The multi-class classification problems for SVM can be handled by One-Against-One (OAO), One-Against-All (OAA), Binary Tree (BT), and Directed Acyclic Graph (DAG) classifiers, to name a few.

The Multi-class SVM (MCSVM) problem is to construct a decision function given N samples typically with noise: (x_1, y_1), …, (x_N, y_N), where x_i : i = 1, …, N is a vector of length n and $y_i \in \{1, …, M\}$ represents the class of the sample. The classical approach to solving MCSVM classification problems is to consider the problem as a collection of binary classification problems. In the OAA method one constructs M classifiers, one for each class. The m^{th} classifier constructs a hyperplane between class m and the M – 1 remaining classes. A new test sample is allocated to the class that the distance from the margin, in the positive direction, is maximal. We can generalize optimization problem (12) to the following by minimizing:

$$\Phi(w,\xi) = \frac{1}{2}\sum_{m=1}^{M}(w_m T w_m) + C\sum_{i=1}^{N}\sum_{m=y_i}\xi_i^m$$

s.t. $\left(w_{yi}^T X_i\right) + b_{yi} \geq \left(w_{mi}^T X_i\right) + b_m + 2 - \xi_i^m$

$\xi_i^m \geq 0,$ for i=1,…………………..N: m$m \in \{1, \dots\dots M\}\{y_i\}$

The decision boundary can be written as follows:

$f(x) = argmax_m[(w_m^T x) + b_m]$ for m=1,…….M

By finding saddle point of the Lagrangian, optimization problem will be solved. The final classifier is of the form:

$$f(x) = \sum a_i x_i^T x + b_m$$

In above equation there are only N coefficients (independent of the number of classes, M), and the regularization directly attempts to reduce the number of nonzero α.

3. PROPOSED METHOD

In this section, the basic steps for plant disease detection and classification using image processing are shown (Fig.1).

3.1 Image Acquisition

Through the camera, pictures of the plant leaf are recorded. In RGB (Red, Green, and Blue) format, this image. A device-independent colour space transformation is then done to the colour transformation structure after creating a colour transformation structure for the RGB leaf image. [6].

3.2 Image Pre-processing

To lessen noise from photos or other objects, various pre-processing techniques are taken into account. The technique of choosing the prefered section of a leaf image is known as image clipping or cropping. Image smoothing is accomplished with the smoothing filter. Enhancement of images is done to increase contrast. using an equation to convert colours from RGB photos to grey images (1).

f(x)=0.2989*R + 0.5870*G + 0.114.*B - - - - - - - - - - - - - (1)

Then, histogram equalisation, which distributes picture intensities, is used to the image to improve the photographs of plant illnesses. The cumulative distribution function is used to disperse intensity values.

3.3 Image Segmentation

A picture is segmented into separate components with the same characteristics or a degree of resemblance. For segmentation, a variety of methods can be utilised, such as the otsu method, k-means clustering, and converting the RGB image into the HIS model. 1] By converting the RGB image to the HIS model, segmentation is carried out on the RGB image using the boundary and spot detection technique. Boundary detection and spot detection help locate the afflicted area of the leaf, as indicated in [9]. The boundary detection procedure is applied while accounting for the pixels' eight connections. [9].

K-means clustering, second: Using a set of features, this technique divides objects into a K-number of classes. Objects are categorised by decreasing the sum of the squares of the distance between the object and the matched cluster.

The K-means algorithm Clustering:

1. Choose the K cluster's centre, either at random or via a heuristic.

2. Pick the cluster in which the separation between each pixel and the cluster centre is the smallest.

3. Once more determine the cluster centres by averaging every pixel within the cluster. Steps 2 and 3 should be repeated until convergence is reached.

3] Otsu Threshold Algorithm: Thresholding transforms greyscale images into binary images by putting all pixels below a specific threshold to zero and all pixels above that threshold to one. According to [5], the Otsu algorithm is as follows:

I Separate the pixels into two clusters in accordance with the threshold.

ii) Next, determine each cluster's mean.

iii) Squaring the mean difference.

iv) Multiply the quantity of pixels in one cluster by the quantity in the opposite cluster.

The diseased leaf's colour changes to reflect the disease's symptoms. As a result, it is possible to recognise the sick portion of a leaf by its colour. The R, G, and B parts of the image are removed. The threshold is established using the Otsu's approach. Green pixels are then mask and removed if their intensities fall below the calculated threshold.

3.4 Feature Extraction

Feature extraction plays a significant role in the identification of an object. In image processing, feature extraction is frequently used. The use of colour, texture, morphology, edges, and other features can be used to identify plant diseases. For the purpose of identifying illnesses, Monica Jhuria et al. consider morphology, colour, and texture in paper [3]. They found that morphological outcomes perform better than other features. The word "texture" describes the hardness, roughness, and coloration of an image. It can also be used to locate areas with ill plants.

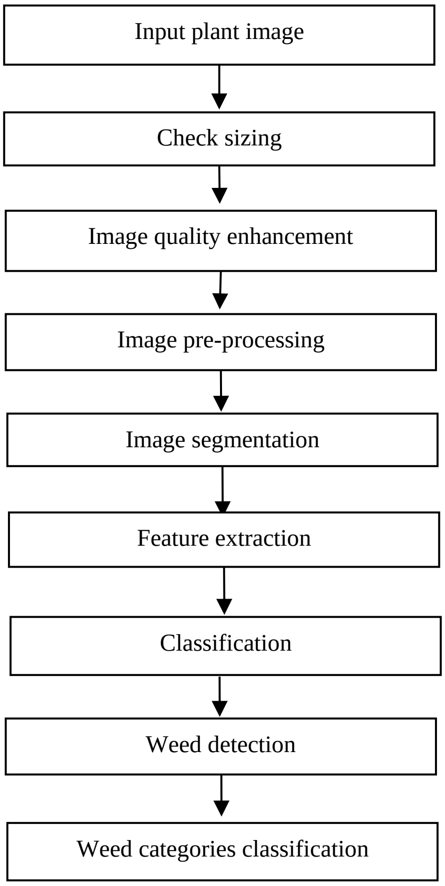


Figure 1 Basic Steps for Plant Disease Detection and Classification

4. RESULT

In this section we are detect weed. Here we take input from the agriculture land by any camera and process it in local system. Here we are classify image in RGB Then HSV to extract colour Region. Classify object with their property. Detect weed from the image.

Fig.2: Input Image

Figure 2 is show input image. This image is capture by normal camera and processes it on our proposed system. After the input image we are process it for color reorganization. We are separate select R, G and B color then convert it to HSV.

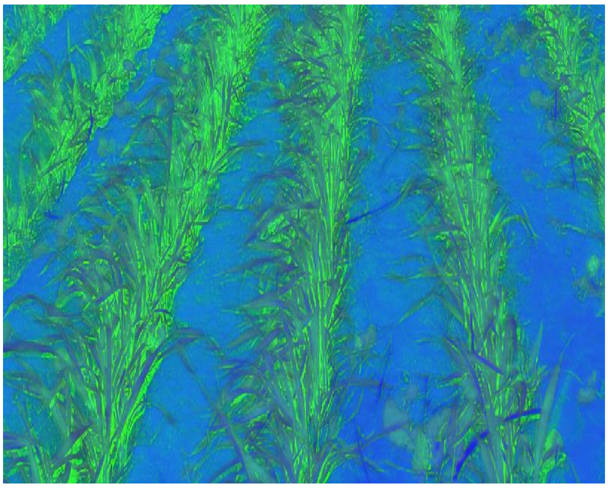


Fig.3: HSV Image

Figure 3 is show HSV image. This image is conversion of RGB to HSV and select separate color of H,S and V from the image. Change the image's colour space to HSV. Process the HSV image using HSV = rgb2hsv(RGB). By scaling up the S channel in this example, the saturation of the image is increased.

Fig.4: Separate image of H,S and V

Figure 4 is show image with separate color region . This is separate image of each color. H, S, and V components of color images: H component, S component, and V component.

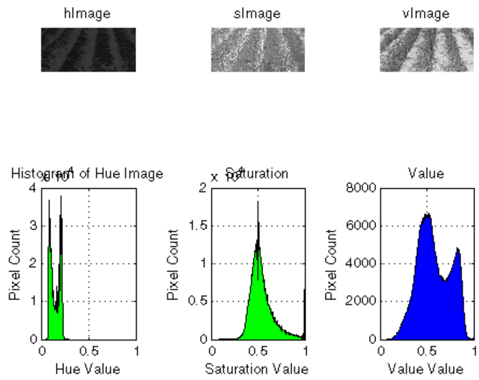
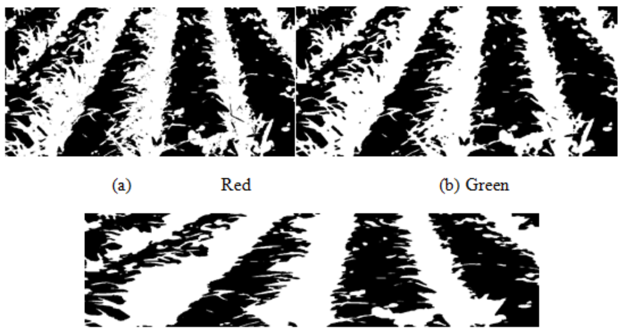


Fig. 5 Histogram of Image

Figure 5 is show histogram value of separate image along with their histogram value. In this figure there are three histogram of three separate images. In this histogram x axis shows the hue value, saturation value and value. It also y axis shows the pixel count.

Fig. 6 After Masking of every color

Figure 6 this image show masking output of image. A smaller "image fragment" is defined and used to alter a bigger image using the image processing technique known as masking. Many methods of image processing, such as edge detection, motion detection, and noise reduction, all start with the masking process.



(a) Red (b) Green

(c) Blue

Fig.7 Extract Information of each region

Figure 7 shows the Extract Information of each region. In this figure different thre color region red, green and blue and extract the information from these color regions.

Fig.8 Output

Figure 8 show output of project. This is a final output of proposed work is weed detection. we have implemented image processing using MATLAB to detect the weed areas in an image we took from the fields.

5. CONCLUSION

In this study, we used MATLAB to construct image processing in order to identify weeds in a field image. Through picture segmentation, feature extraction, and object classification, the suggested method produces the best classification results. We can identify any image taken by any camera using the suggested method, and we can even find marijuana. The proposed method employs the Kmeans clustring algorithm to identify green colour and classify objects from images. Moreover, weed was chosen from the image using SVM. Using support vector machines, artificial neural networks, and image processing, we suggested a method to identify weeds in vegetable plantations in this study.

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