ZKG INTERNATIONAL

ISSN: 2366-1313

Weed Identification in Vegetable Plantation Using Deep Learning & Image Processing

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Abstract: *Weed identification in vegetable plantations is more challenging than crop weed identification. So far, little work has been found on identifying weeds in vegetable plantations. Traditional methods of crop weed identification used to be mainly focused on identifying weed directly; however, there is a large variation in weed species. Here we propose a new method, which combines deep learning and image processing technology. Deep learning is the nucleus in machine learning discipline which uses knowledge representation of learning. Learning can be supervised or unsupervised. A Trained CenterNet model was used to detect vegetables and draw bounding boxes around them. The remaining green objects falling out of bounding boxes were considered as weeds. The image of the crop field is given as input training. By using the extracted feature, the images with weeds are detected and classified. A deep learning model is developed using convolution neural networks to detect weeds with a good accuracy so that the model could be used to detect the weeds in various crop fields within a shorter time.*

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

I. INTRODUCTION

Vegetables are considered one of the most nutrient-dense foods all around the world due to its sufficient vitamins, minerals and antioxidants. Raising living standards boosts the consumption of green vegetables, which makes them a substantial part of our lives and possess

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great commercial value. Weeds compete with vegetables for water, sunlight and nutrients, leaving them prone to insect and disease infestation. The yield of vegetables decreased by 45%-95% in the case of weed-vegetable competition. Excessive use of chemical herbicides results in overapplication in areas of low or no weed infestation and causes environmental impacts including soil and groundwater pollution. Moreover, organic production of vegetables requires nonchemical weed control. Thus, hand weeding is still the primary option for weed control in vegetable plantations at present. With the labor cost substantially increased, development of a visual method of discriminating between vegetable and weed is an important and necessary step towards ecologically sustain- able weed management. A considerable amount of research has been conducted on various machine vision techniques for weed detection. Support Vector Machines (SVMs) to identify six weed species in a database of 224 images; they achieved 97.3% precision with the best combination of extractors. Herrera et al. constructed a weed-crop classifier using shape descriptors and Fuzzy Decision-Making, and classification accuracy of 92.9% was obtained in a set of 66 images. Crop is usually much higher than weed at early growth stages. This height feature was used to establish a crop and weed dis- crimination method using a binocular stereo vision system. The discrimination between crop and weed was done by a height-based segmentation method using the depth dimension analysis. For the relatively higher weeds, plant spacing information was utilized to distinguish weed from the crops[1].

In recent years, deep learning has demonstrated remarkable performance in extracting complex features from images automatically. It has been widely employed as a promising method to image classification and object detection. There are two categories of methods found in deep learning for image detection. The first is classifying the object and then draw bounding boxes around images to make the object classified. Second category is classifying object pixels, also known as semantic segmentation.

We used the benchmark deep learning models to classify images of sixteen different types of weed, with an average classification accuracy of 95.1% and 95.7%, respectively. We performed weed detection in crop images and classified these weeds among grass and broadleaf by Convolutional Neural Networks (CNNs)[2].

The performances were compared with the estimations of a set from weed experts and they found that these methods improved accuracy on weed coverage estimation and minimized subjectivity in human-estimated data. There is no obvious row spacing and plant spacing in vegetable cultivation. Vegetables and weeds grow randomly, which makes weed identification in vegetable plantations more challenging than crop weed identification. Moreover, weeds in vegetables will also be mixed in vegetables during mechanized harvesting and need to be sorted manually. A variety of labor costs have pushed up sales prices. So far, little work has been found on identifying weeds in vegetable plantations, and previous crop weed identification used to be mainly focused on identifying weed directly, however, there is a large variation in weed species, but limited in vegetables. Therefore, we proposed methods to firstly identify and segment the vegetable using deep learning; in particular the architecture of Convolutional Neural Networks, then the remaining green objects in the segmented image were considered as weeds. This strategy can largely reduce the size of training image dataset as well as the complexity of weed detection, thereby enhancing the weed identification performance and accuracy. The main objective of this research is to develop a weed identification algorithm based on deep learning and image processing for robotic weed removal in the vegetable plantation. The specific objectives were to

1) Train a model using a deep learning approach that is capable of detecting the bounding boxes of vegetables.

2) Extract and segment vegetation falling out of bounding boxes, in this case, weeds by image processing utilizing color features.

BACKGROUND

Robotics and automation have become an emerging subject nowadays; substituting and aiding humans in manual tasks that can become not only tedious and repetitive, but also difficult due to different factors such as precision. In order to go in depth on this technology deep learning has been implemented with the purpose of giving these systems intelligence, making them capable of learning. Examples can be found everywhere, from industries to humankind ' s daily life. One of these examples is agriculture, where automation has found solution to some of the challenges faced by farmers on a daily basis such as crop diseases, infestations, pesticide control, weed management, lack of irrigation and drainage facilities and lack of storage management (Jha, et al., 2019). As a way to bring this new technology to urban orchards, FarmBot Inc. was created. It is a local startup that is working within advanced precision agriculture through automation and open-source technology (Brown, et al., 2017). FarmBot Inc. has developed a series of robots, called FarmBots, to take care of these orchards in an autonomous way while respecting the environment. Natur bruks för valtningen Sötåsen aims to teach its students how to combine agriculture and technology. To do so, they intend to introduce a FarmBot into their studies and go a step further, not only programming it to do the basic agricultural tasks, but also by including deep learning to make the system capable of differencing on its own whether there are weeds on the orchard or not [3].

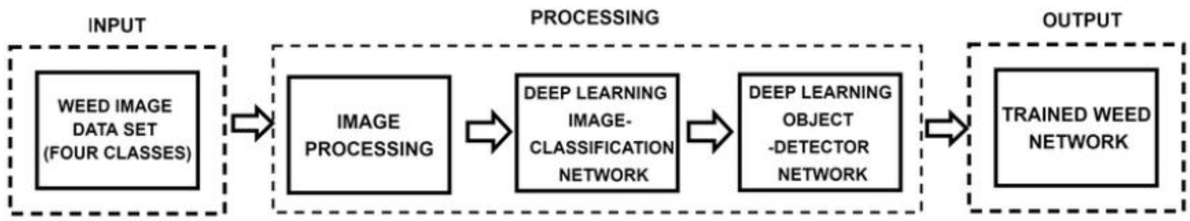

Fig.1 Basic Model

II. LITERATURE SURVEY

Evaluation of an algorithm for automatic detection of broad-leaved weeds in spring cereals:

T. W. Berge et al.[4] Lack of automatic weed detection tools has hampered the adoption of site-specific weed control in cereals. An initial object-oriented algorithm for the automatic detection of broad- leaved weeds in cereals developed by SINTEF ICT (Oslo, Norway) was evaluated. The algorithm (“WeedFinder”) estimates total density and cover of broad leaved weed seedlings in cereal fields from near-ground red–green–blue images. The ability of “WeedFinder” to predict ‘spray’/ ‘ no spray ’ decisions according to a previously suggested spray decision model for spring cereals was tested with images from two wheat fields sown with the normal row spacing of the region, 0.125m. Applying the decision model as a simple look-up table, “WeedFinder” gave correct spray decisions in 65 – 85% of the test images. With discriminant analysis, corresponding mean rates were 84 – 90%. Future versions of “WeedFinder” must be more accurate and accommodate weed species recognition.

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A survey of image processing techniques for plant extraction and segmentation in the field

E. Hamuda, et al.[5] In this review, we present a comprehensive and critical survey on image-based plant segmentation techniques. In this context, "segmentation" refers to the process of classifying an image into plant and non-plant pixels. Good performance in this process is crucial for further analysis of the plant such as plant classification (i.e.identifying the plant as either crop or weed), and effective action based on this analysis, e.g. precision application of herbicides in smart agriculture applications. The survey briefly discusses pre-processing of images, before focusing on segmentation. The segmentation stage involves the segmentation of plant against the background (identifying plant from a background of soil and other residues). Three primary plant extraction algorithms, namely

Based on its prevalence in the literature, this review focuses in particular on color index-based approaches. Therefore, a detailed discussion of the segmentation performance of color index based approaches is presented, based on studies from the literature conducted in the recent past, particularly from 2008 to 2015. Finally, we identify the challenges and some opportunities for future developments in this space.

Non-chemical weed management in vegetables by using cover crops

H. Mennan, K. Jabran, B. H. Zandstra, and F. Pala [6]Vegetables are a substantial part of our lives and possess great commercial and nutritional value. Weeds not only decrease vegetable yield but also reduce their quality. Nonchemical weed control is important both for the organic production of vegetables and achieving ecologically sustainable weed management. Estimates have shown that the yield of vegetables may be decreased by 45%-95% in the case of weed-vegetable competition. Non-chemical weed control in vegetables is desired for several reasons. For example, there are greater chances of contamination of vegetables by herbicide residue compared to cereals or pulse crops. Non-chemical weed control in vegetables is also needed due to environmental pollution, the evolution of herbicide resistance in weeds and a strong desire for organic vegetable cultivation. Although there are several ways to control weeds without the use of herbicides, cover crops are an attractive choice because these have a number of additional benefits (such as soil and water conservation) along with the provision of satisfactory and sustainable weed control. Several cover crops are available that may

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provide excellent weed control in vegetable production systems. Cover crops such as rye, vetch, or Brassicaceae plants can suppress weeds in rotations, including vegetables crops such as tomato, cabbage, or pumpkin. Growers should also consider the negative effects of using cover crops for weed control, such as the negative allelopathic effects of some cover crop residues on the main vegetable crop.

III. PROPOSED SYSTEM

In this paper, A convolutional neural network, or CNN, is a deep learning neural network is designed for processing structured arrays of data such as images. Convolutional neural networks are widely used in computer vision and have become the state of the art for many visual applications such as image classification, and have also found success in natural language processing for text classification.

Convolutional neural networks are very good at picking up on patterns in the input image, such as lines, gradients, circles, or even eyes and faces. It is this property that makes convolutional neural networks so powerful for computer vision. Unlike earlier computer vision algorithms, convolutional neural networks can operate directly on a raw image and do not need any pre-processing.

Convolution layers consist of a set of learnable filters (a patch in the above image). Every filter has small width and height and the same depth as that of input volume (3 if the input layer is image input).

For example, if we have to run convolution on an image with dimension 34x34x3. The possible size of filters can be axax3, where 'a' can be 3, 5, 7, etc but small as compared to image dimension.

During forward pass, we slide each filter across the whole input volume step by step where each step is called stride (which can have value 2 or 3 or even 4 for high dimensional images) and compute the dot product between the weights of filters and patch from input volume.

As we slide our filters, we'll get a 2-D output for each filter and we'll stack them together and as a result, we'll get output volume having a depth equal to the number of filters. The network will learn all the filters.

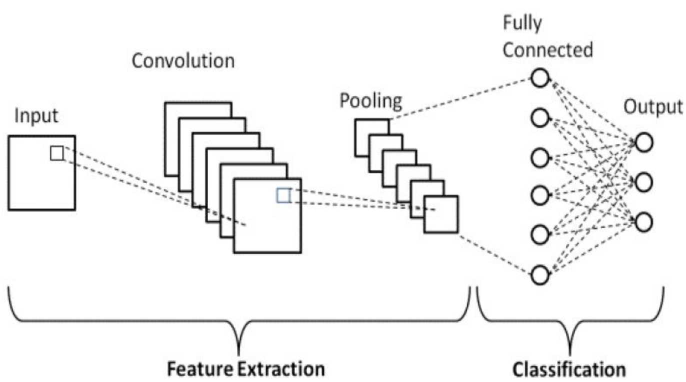

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Fig.2 CNN Architecture

A Convolutional Neural Network, also known as CNN or ConvNet, is a class of neural networks that specializes in processing data that has a grid-like topology, such as an image. A digital image is a binary representation of visual data. It contains a series of pixels arranged in a grid-like fashion that contains pixel values to denote how bright and what color each pixel should be. The human brain processes a huge amount of information the second we see an image. Each neuron works in its own receptive field and is connected to other neurons in a way that they cover the entire visual field. Just as each neuron responds to stimuli only in the restricted region of the visual field called the receptive field in the biological vision system, each neuron in a CNN processes data only in its receptive field as well. The layers are arranged in such a way so that they detect simpler patterns first (lines, curves, etc.) and more complex patterns (faces, objects, etc.) further along. By using a CNN, one can enable sight to computers.

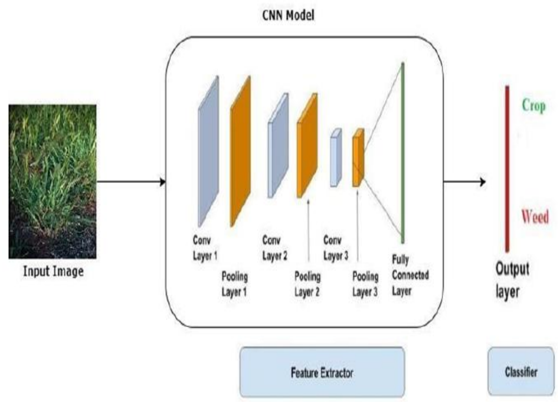

Fig.3 CNN Model

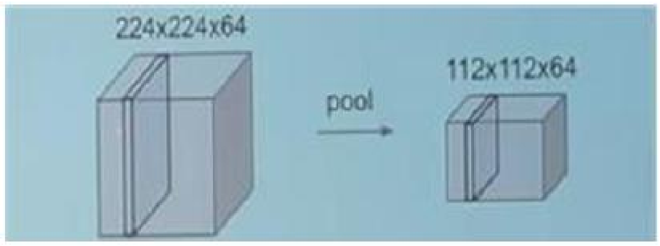

Fig.4 Represents Pooling Layer

IV. VEGETABLE DETECTION USING DEEP LEARNING

Image Augmentation:

The training dataset contained 1150 images; these images were then expanded to 11500 images using data augmentation methods for the purpose of enhancing the richness of the experimental dataset. The collected images were pre-processed in terms of color, brightness, rotation, and image definition, and the dataset was augmented as shown in Fig.5

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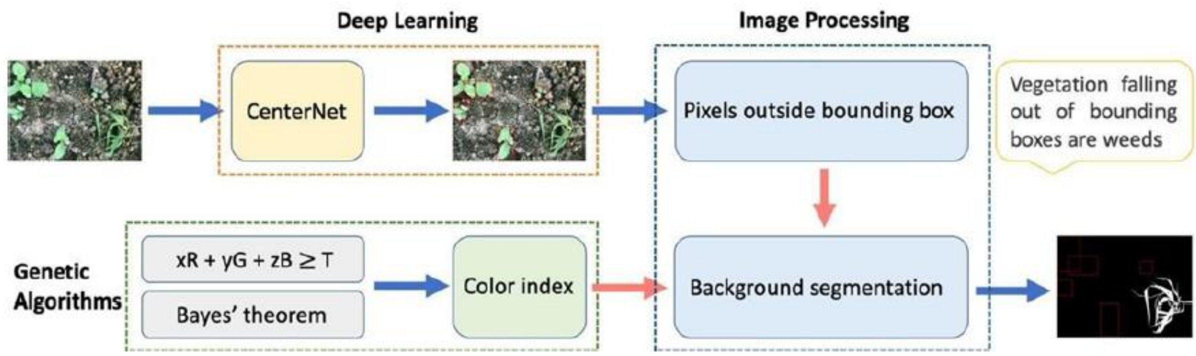

Fig.5 Flow diagram for proposed weed detection methodology

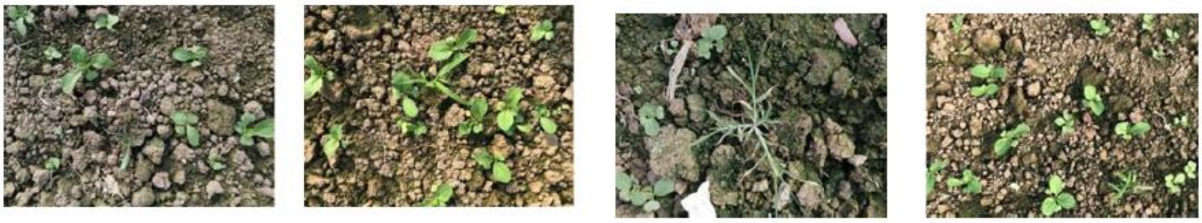

Fig.6 Bok choy images taken under various conditions:

(a) low brightness, (b) high brightness, (c) complex background, (d) various growth stages

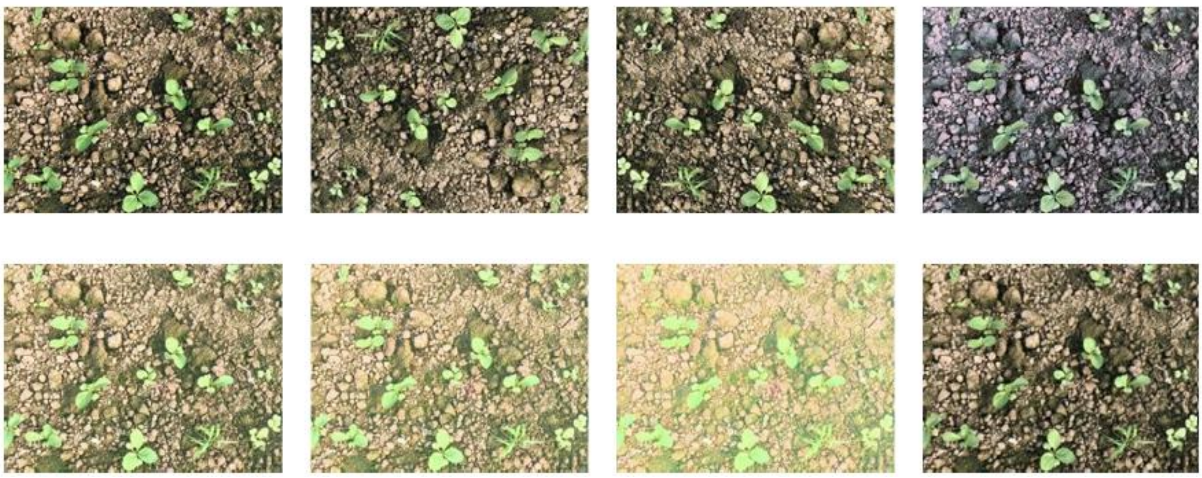

Figure 7 Image augmentation methods: (a) original image, (b) 180◦ clockwise rotation, (c) horizontal mirror, (d) color balance processing, (e-g) brightness transformation, and (h) blur processing.

Image Annotation

Manual annotation was applied by drawing bounding boxes on to the input images using a custom software Labeling. Corresponding XML format label files were generated to train the CenterNet. 80% and 20% of the dataset were used for training and testing, respectively.

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Training and Testing

The CenterNet model is a cutting edge and brand-new object detector, which is anchor-free and depends on the key points estimation. In CenterNet, objects are represented as asingle point, and heatmap is used to predict the centers of objects.
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Heatmap is created using a Gaussian kernel and an FCN, estimated centers are derived from the peak values in the heatmap. Based on the center localization, object properties such as size and dimension can be regressed directly without any prior anchor

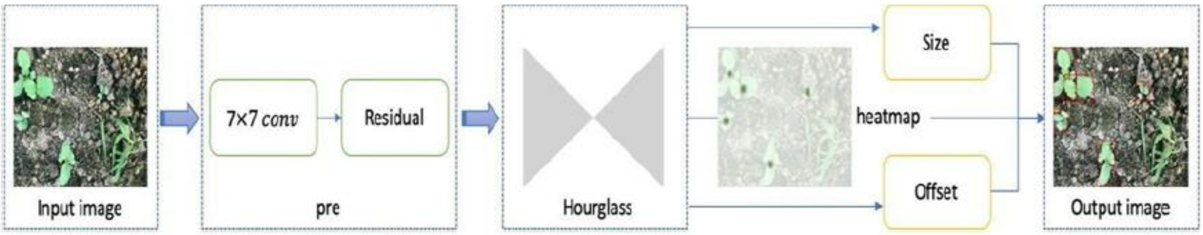

Fig.8 Detection model of CenterNet

CenterNet is a single-stage detection model, and it does not require the non-maximum suppression (NMS) as the post-processing step, thus it provides much faster detection. For the feature extraction, Hourglass was selected as backbone architecture in this study. To train the network, each ground truth key point is transformed to the lower size of key-point heatmap using a Gaussian kernel, with focal loss Lk. In addition, CenterNet also predicts the local offset to reduce the error caused by the size resample from input image to key-points heatmap. The offset is trained with a Loff loss. Finally, the object size is regressed from the center points with loss Lsize. Hence, the loss function (Ldet) is made up of three components: key-point loss (Lk), offset loss (Loff)and object size loss (Lsize):

Weed Identification Utilizing Image Processing: Once the vegetable was found, the remaining green objects falling out of the bounding boxes were marked as weeds. To extract weeds from other elements of the scene (i.e. soil, straws, stones, and other residues), color index-based segmentation using a binary-coded genetic algorithm (GAs) identifying weed in RGB color space for the outdoor field conditions was studied and implemented. Evaluation was then carried out by comparing the output of the segmentation result with the widely used excess green (Ex G) Index.

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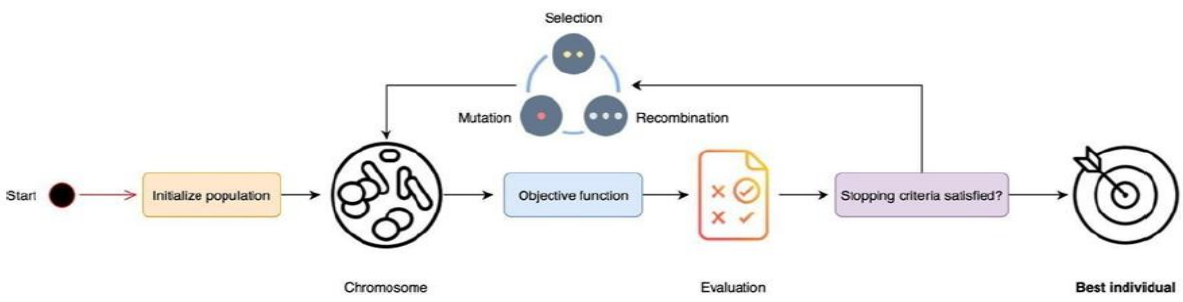

Fig.9 Represents the Genetic Algorithm

Color Index-Based Segmentation:

Image pixel distribution in RGB color space is shown in Fig. 5. Segmentation refers to the process of finding a plane that intersect the RGB color cube, thereby classifying image into vegetation and non-vegetation pixels. The plane is defined by the equation

$xR + yG + zB = T$

In order to separate vegetation from the background, the value of x, y, z and T need to be determined.

Genetic Algorithm:

Genetic Algorithms (GAs) are a family of adaptive search methods based on the mechanics of natural selection and natural genetic evolutionary system, which are particularly efficient in dealing with difficult combinatorial search problems without being trapped by local optima through their parallel exploration of the search space. The three parameters x, y , z are in the range (255,255). While T is limited to [0 to 1024]. This will lead to 510*510*510* 1024 possible combinations Thus, an efficient searching algorithm is necessary to solve this problem. GAs behaves well in exploiting accumulated information of an initially unknown domain in a highly efficient way. Therefore, GA was selected to design a search engine in this work. Procedures of a genetic algorithm are shown. To start the algorithm, an initial population was generated randomly.

Chromosome:

An 88-bit binary string, or a chromosome, was used to represent parameters encoded by the permutation method. The relative locations of the Bytes in chromosomes are crucial because of how GAs choose better combinations of parameters. Based on the length and range of parameters, the string was organized with the sign as the first byte in the chromosome, where 0 means negative, while 1 indicates positive. The next bytes were binary values of the parameters.

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The Population Size :

The basic element of a GA is called individual, which is characterized by a set of parameters (variables) known as Genes. Genes are then joined in a string to form a Chromosome. A set of individuals is referred to as a population. In this work, a population size of 200 was used to generate color index parameters.

SYSTEM ARCHITECTURE

The Identification Process using Convolutional Neural Networks technique in this project can be explained using this simple block diagram (Architecture). The graphical block representation of this system is shown in **figure 5**

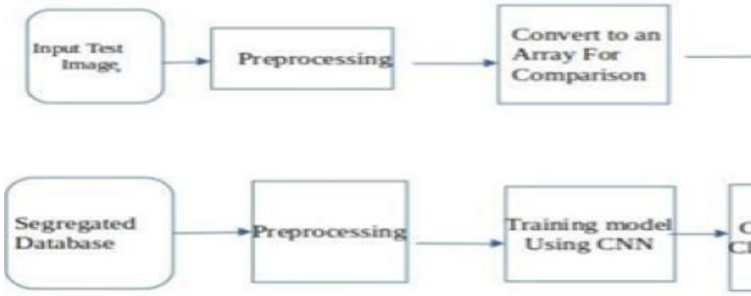

Fig.10 system architecture.

V. RESULTS

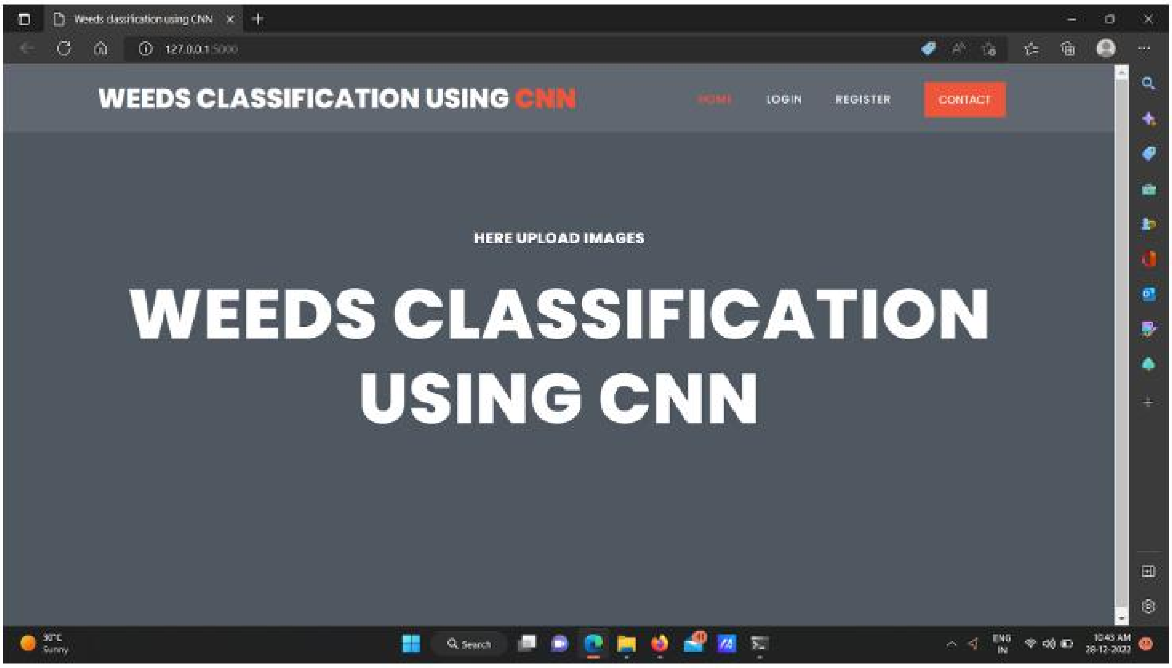

Fig.11 Homescreen

This is the first screen which shows up when the system is launched .

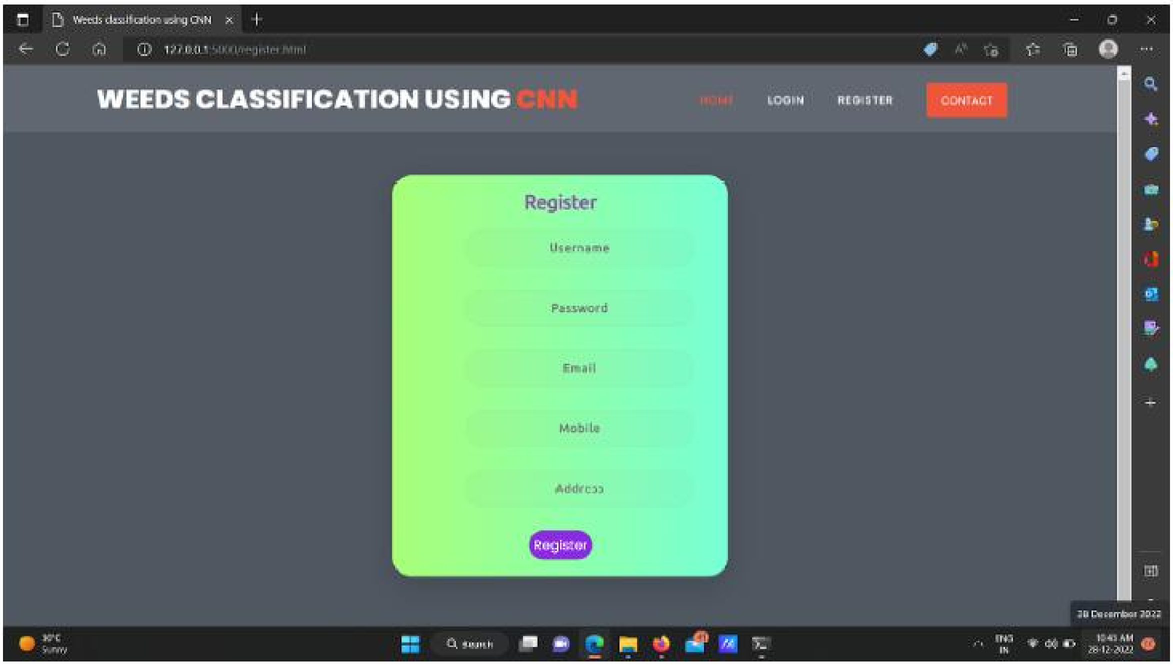

Fig.12 Registration page

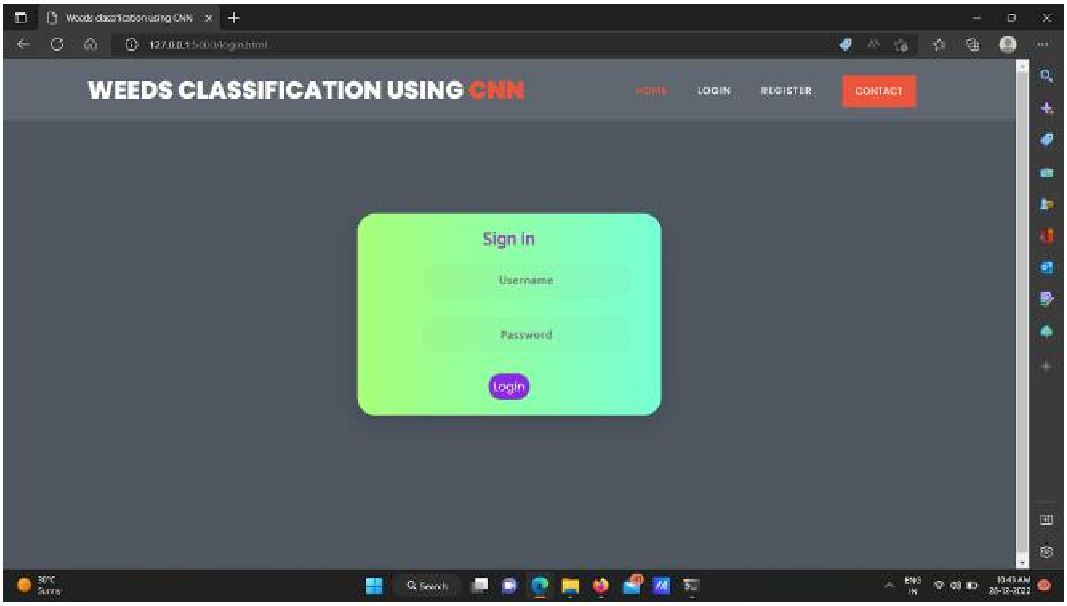

Fig.13.Login page

In this Page Registered users can login to their respective accounts by providing their appropriate username and password.

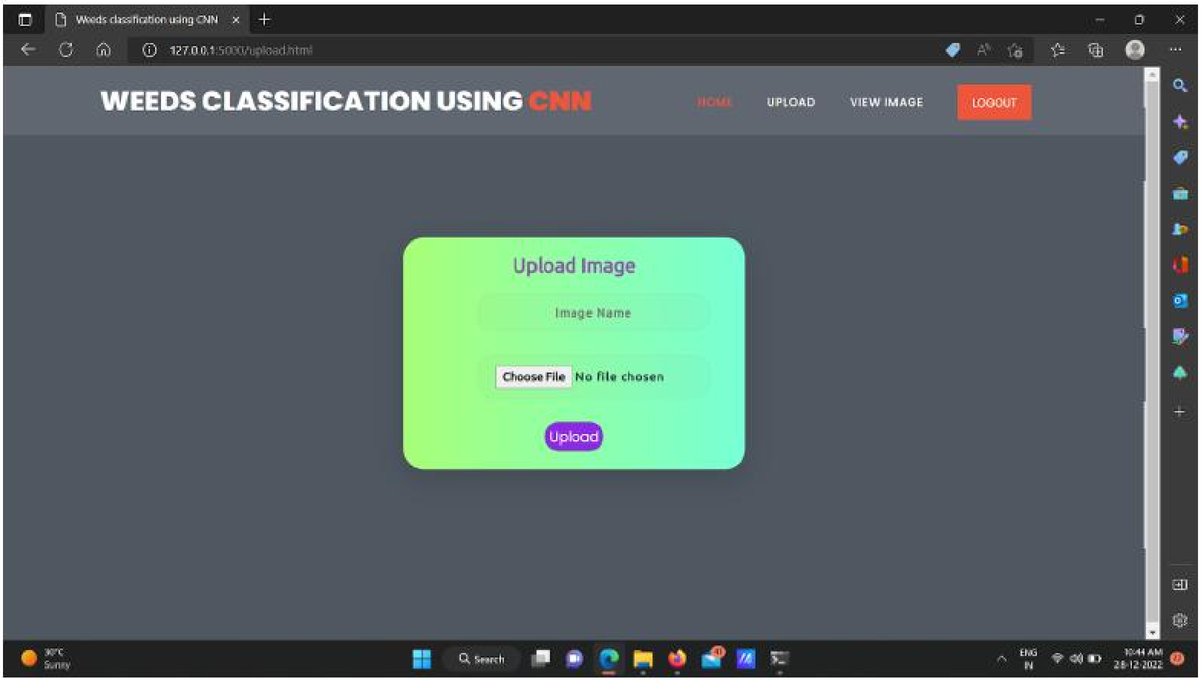

Fig.14 Image upload page

After a successful login, users will be prompted to the homepage of the website. In the webpage user will be able to upload the images of the plants that may or may not contains weed.

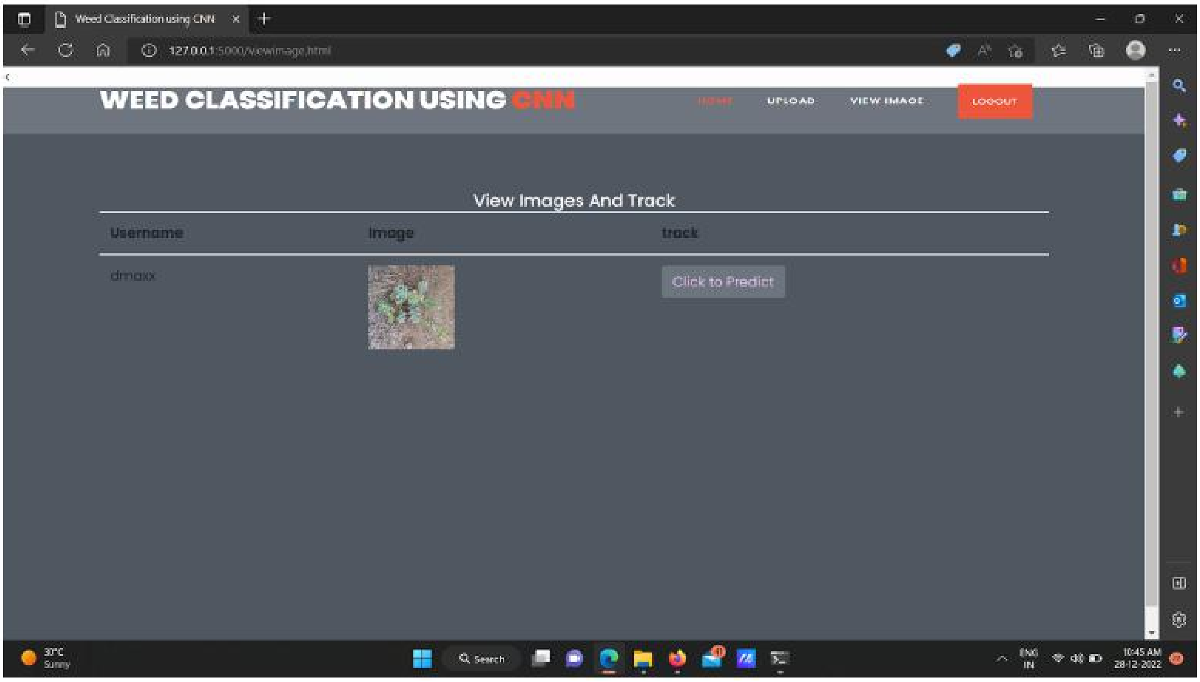

Fig.15 view image

The Results of the uploaded images will be displayed in the view image section

When a user clicks on the "Click to Predict" tab, then the output of the image is displayed

1. If the Image contains Weed then "This is Weed" will be displayed

2. If the Image does not contains Weed then "This is Plant" will be displayed

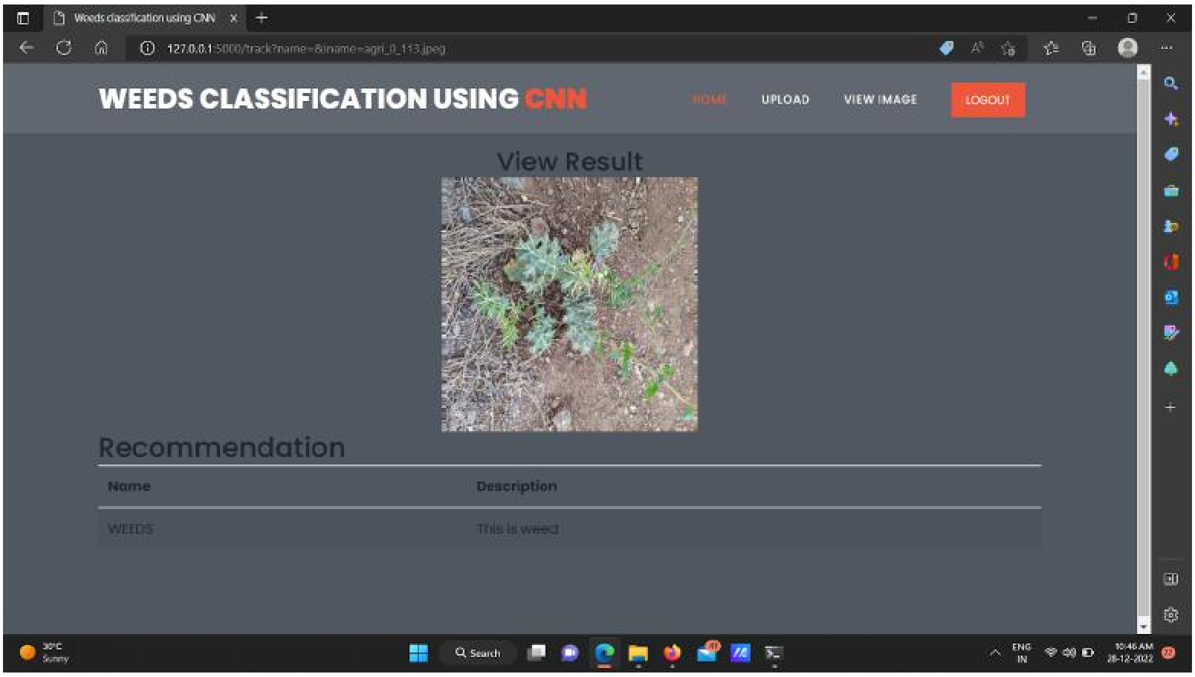

Fig.16 Result page

VI. CONCLUSION

In this study, we proposed an approach to identify weeds in vegetable plantation using deep learning and image processing. The algorithm was depicted in two steps. A CenterNet model was trained to detect vegetables. The trained CenterNet achieved a precision of 95.6%, a recall of 95.0% and a F1 score of 0.953. Then the remaining green objects in the color image were considered as weeds. To extract weeds from the background, a color index was determined and evaluated through Genetic algorithms (GAs) according to Bayesian classification error. In this way, the model focuses on identifying only the vegetables and thus avoid handling various weed species. Here we will study and present an approach to identify weeds in vegetable plantation using deep learning and image processing We develop a visual method of discriminating between vegetable and weed in a novel and indirect way and proposed a color index to extract weeds from the background under natural conditions.

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