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A Deep Learning Based Rover for Weed Destroying and Soil Fertility Testing

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ABSTRACT

Weed identification is more difficult in rice plantations due to uneven plant spacing. Traditional approaches to obtain a real-time solution, However, the majority of crops past research has required rapid and constant-time weed detection, which was mainly centred on the weed. Weed species, on the other hand, vary considerably. This project overtures a new method for combining the use of more advanced but time-consuming methods, such as CNN algorithm with image-processing technology approaches. To detect weeds in rice plantations Alex Net model in MATLAB was utilized. Then, the classification based on image processing is done. Furthermore, this method has the potential to substantially minimize the size of the dataset images used for training process to obtain the complexity of weed detection, resulting in improved identification of weeds performance and accuracy. Deep neural networks and image processing were utilized to differentiate the weeds from the background using grey scaling-based picture segmentation. The colour index that was used to determine. Image processing was used to classify weeds from the rice crop. Based on this the rover is designed which contains a pluckier to destroy the weeds and the fertility of the soil is also checked. This rover is controlled and monitored using IOT application. Thus this proposed rover is capable of destroying the weed without delays in detection occur in various topographical conditions and crop growth phases.

Index Terms: Weed detection, CNN, image processing.

I. INTRODUCTION

Weed control has been an ongoing problem for farmers for more than a century. Herbicide resistance, human health concerns, and environmental pollution are all caused by the continuous use of herbicides, which have proven to be effective in weed control. Because of the negative consequences, governments and farmers are attempting to reduce it.

The use of herbicides in agricultural production (Hillocks, 2012) can be overcome by precision farming, which uses weeding mechanisms to treat individual plants or small weed clusters (Weis et al., 2008). By doing so, the usage of chemicals in agriculture can be considerably reduced, if not completely eliminated. Human-oriented precision weeding technology, on the other hand, usually requires labour-intensive and human resources, diminishing the financial benefits of herbicide savings. Robots are controlled electro-mechanically to do tasks quickly and accurately. When various duties that people either don't want to undertake or are incapable of executing are replaced by robots. Rover is a contemporary autonomous robot that moves in accordance with the operator's wishes. A rover that is capable of performing agricultural duties is known as an Agri-rover. In the farm, several rovers can be utilized for tasks like spraying, collecting fruit, etc. Based on an analysis of the last 20 years' progress in vision technology for mobile robot navigation. This review has looked at a number of developments in a vision for rover outdoor navigation and how they relate to the potential automation of many elements of crop production. The process of destroying the weeds among crops is based more on the segmented and classified images captured and the pluckier is designed in such a way without harming and disturbing the crops. An application is developed prototyping system for monitoring mobile assistance rover. GPS is used for precision in localization and can be employed in tough conditions when the signal is greatly degraded due to dense vegetation. Currently, there is substantial development in the use of robotic weed management technology, which includes weed detection and destruction. This is because automated weed control helps in reducing the cost and boost the crop efficiency.

The rover's visual system is dependent on intelligent weeding equipment to recognize weeds. However, the efficiency of the machine vision system is influenced by environmental variables such as illumination and color variations in the soil as well as in leaves, limiting the precision of weed management. Since artificial intelligence is currently blooming, Deep-learning weed detection algorithms have made great progress. Crop/weed detection systems based on Convolutional Neural Networks (CNN) are being demonstrated to yield accurate results.

Weed control in agriculture is a time-consuming operation. It necessitates a considerable amount of manpower as well as, at times, machine power. Some of the issues with existing approaches are as follows:

• Using herbicides - Because chemicals like glycol are harmful, they pollute the land and degrade soil quality.

• Hand cutting - human labour is in short supply and has become an expensive investment. Furthermore, field labourers are threatened by toxic insects and reptiles.

• Mechanised cutting - Power tools run on petroleum fuels or batteries. Petroleum fuels have their own cost disadvantage. Manual labour is used to operate this equipment, and the labour cost for operating these machines is also rather high.

To overcome the limitations of current technologies, this deep learning-based rover will be a cost-effective weed-control option.

• A microprocessor-controlled rover will navigate the field.

• It will follow a course that spans the entire field.

• If it finds a weed in its path, it will halt and engage its cutters to cut it; if it detects a rice crop, it will navigate around it.

II.WORKING METHOD

The approach provided in this project for weed detection is divided into two parts. In this study, the first step comprises of the cutting-edge AlexNet algorithm [21] for weed detection. Weed images are gathered and utilised providing input dataset for the neural network that has been trained detects weeds and highlight it to identify class probabilities. The next stage is to perform colour segmentation on the weed in pixels within the boxes, resulting in a visual categorization of the detection of weeds among crops in the image. Figure 1 depicts the suggested method's procedural phases. The rest of this section goes over each stage in detail.

The AlexNet algorithm was used for testing and training in the MATLAB deep learning framework using a GPU(graphics processor unit).

A. IMAGE ACQUISITION

Weed images were captured with a Raspberry Pi camera. Images of rice plantations are being collected for training purposes. Weed pictures were captured under a variety of settings, including different lighting conditions (Fig. 2a), complicated backgrounds (Fig. 2b), and various growth stages.

Fig.2a Data collection of photos of rice plantations classified by crop size, colour, and spacing

Fig. 2b. Images of weed among plants based on several circumstances: low, medium, and high brightness, backdrop complexity

B. DETECTION OF WEEDS WITH DEEP LEARNING

IMAGE MODIFICATION

The training set contained 1000 photographs, which were later enlarged to 10000 images utilizing image augmentation techniques to boost the amount of information in the experimental dataset. As shown in Fig. 3, the gathered photographs were pre-processed under different conditions based on colour quality, brightness of the area, different angles and picture definition, and the dataset was expanded.

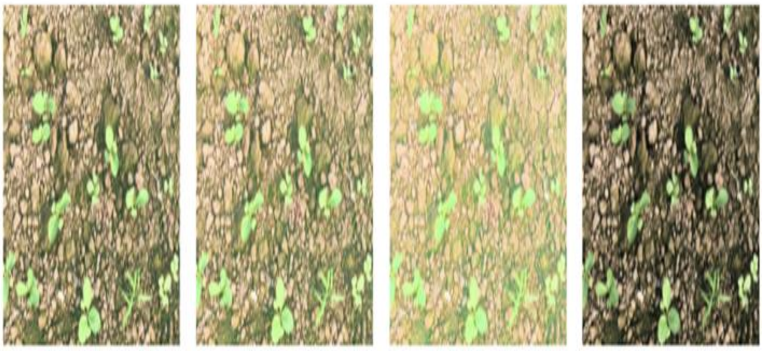


Fig.3: Images that have been pre-processed based on colour quality, brightness, angles, and picture definition

IMAGE ANNOTATION

Using MATLAB software LabelImg, boundary boxes were drawn onto the plants (in this case, rice) in the input photos for manual annotation. To train the AlexNet, appropriate XML format label files were created. Training and testing used 80% and 20% of the dataset, respectively.

TESTING AND LEARNING

The AlexNet algorithm is an advanced, completely unique object detector that uses significant estimations rather than anchors. In AlexNet, objects are illustrated as a single solid mark, and heat map visualizations are utilized to estimate their centres. The heatmap is constructed with an SDGN, and the predicted centres are determined by the peak values of the heatmap. Object attributes such as size and dimension are determined by the centre localization. Figure 4 depicts the AlexNet model created in MATLAB.

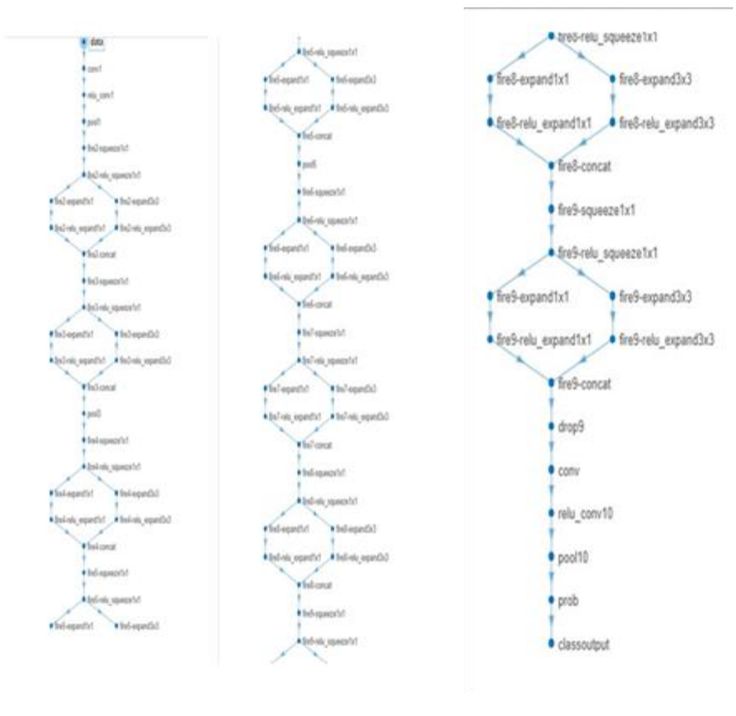


Figure 4: AlexNet MATLAB was used to create the model.

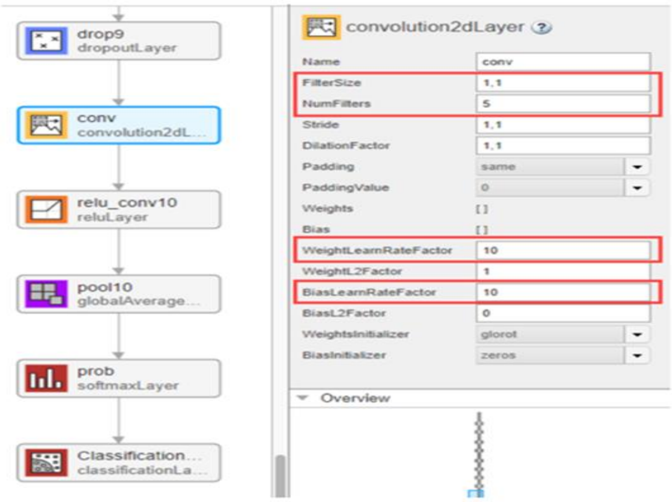


Fig.4.a. Convolutional 2d layer

When the vegetation was discovered, Rice crops were labelled as the other green particles that fell outside of the boundary boxes. Colour index segmentation for outdoor field conditions employing binary-coded defining weed in RGB colour space was researched and applied to differentiate weeds among other components in the image (i.e. dirt, soil and leftovers) was investigated and applied.

The resulting segmentation was then compared to the commonly used excess colour green index.

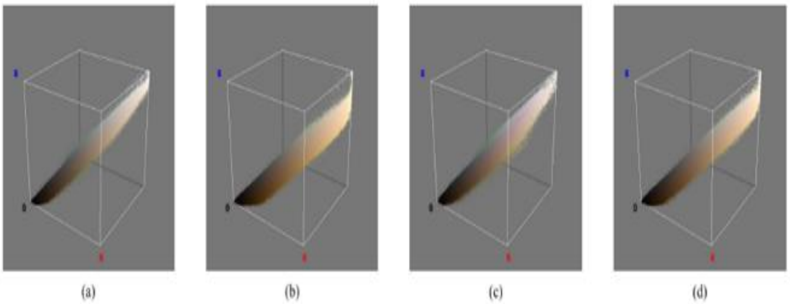
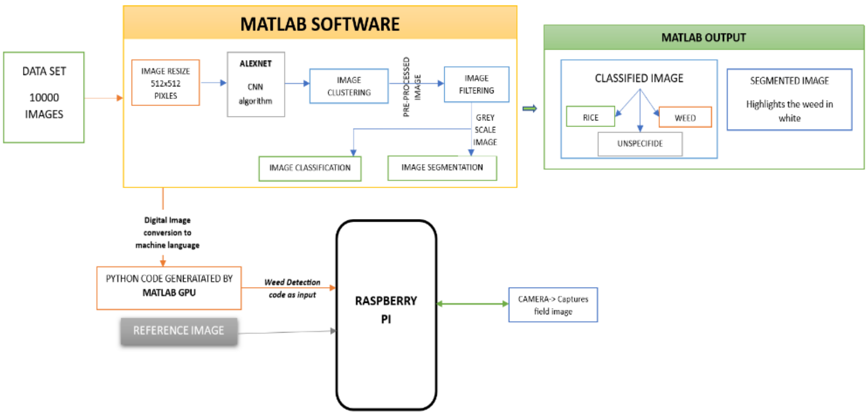


Fig 5 depicts the image pixel in grey scale.

The process of identifying an axis that intersects the RGB colour cube and thus classifying an image into rice and weed pixels is referred to as segmentation.

The equation aR + bG + cB = T (1) defines the plan. To distinguish plants the values of a, b, c, and T must be chosen in the context.



Block Diagram Of The Proposed System

III. RESULT AND DISCUSSION

WEED DETECTION PERFORMANCE

The input photos were shrunk to 512 512 pixels are needed to accommodate the Hourglass framework input. To further analyse training process, The highest possible value of epochs is fixed as 24 and the overall value of groups is fixed 2. Remaining elements (momentum, starting training rate, weight reduction regularization, and so on) referred to the AlexNet model's default values. By implementing the training procedure given in the original publication on AlexNet during the training stage, the algorithm is trained as per the specified parameters. To optimize training loss, the configuration 2d layer was modified the weights of networks according to training data. Table 3 displays the initialized values for the training parameters.

Figure 6 depicts the training and validation of datasets based on accuracy level.

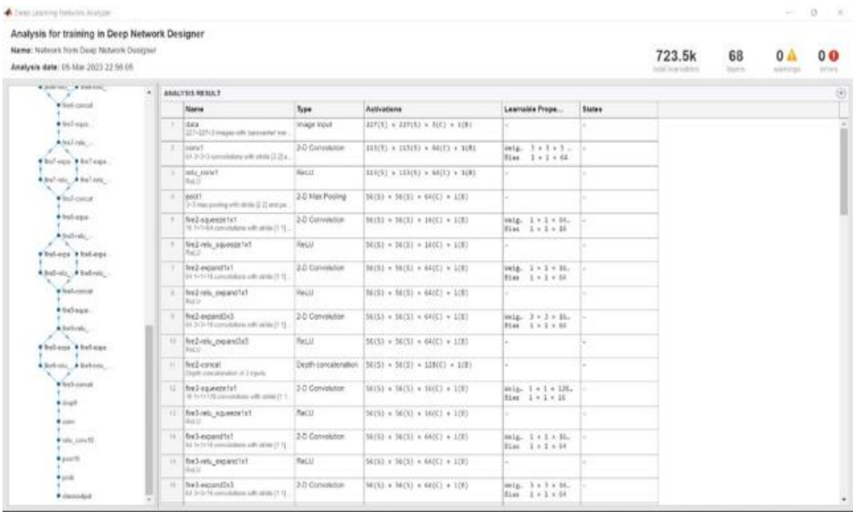


Figure 7. Deep Network Analysis Table

Identification of weeds among rice crop is shown in Fig 9. The outcome shows that the trained AlexNet model is also capable of distinguishing vegetation and weed. The fact that there are a significant variety in weed species is also important to note. Direct identification of weed is the conventional method. As a result, various weed datasets must be used to build deep learning models for categorization. The detection is probably to fail if there is some sort of weeds that haven't been observed during the training process. A suggested approach, in contrast, instructs the model to just recognize vegetation. This eliminates the need to manage different weed plants.

Whenever we come across unspecified weeds, misidentification is common. Occlusion may cause plant to be missed, according to observations of the detection instances (Fig. 10). Some crops were planted extremely close together and were entirely veiled in Fig. 10. If such cases were seen in the field, they would go unidentified. This scenario, however, can be overcome by including high obstructed data in the training set.

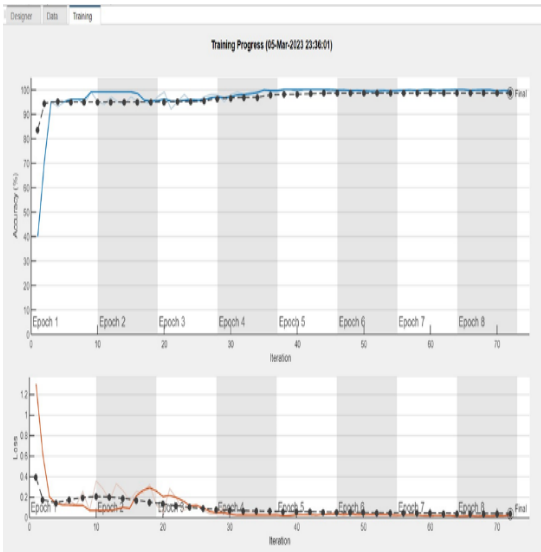


Figure 8. depicts the training procedure for determining accuracy and loss.

Results	
Validation accuracy:	98.54%
Training finished:	Max epochs completed
Training Time	
Start time:	05-Mar-2023 23:36:01
Elapsed time:	20 min 10 sec
Training Cycle	
Epoch:	8 of 8
Iteration:	72 of 72
Iterations per epoch:	9
Maximum iterations:	72
Validation	
Frequency:	2 iterations
Other Information	
Hardware resource:	Single CPU
Learning rate schedule:	Constant
Learning rate:	0.0001

Figure 9 shows the outcome of detecting the precision of the trained data.

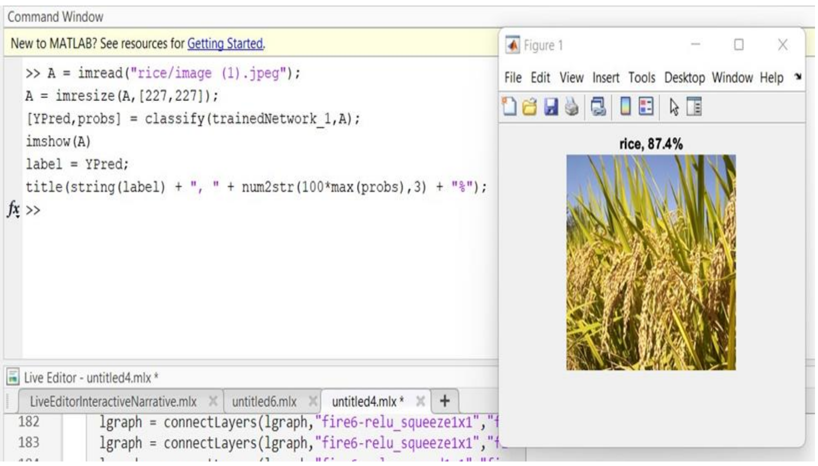


Fig.10: Image testing results with 87.4% accuracy.

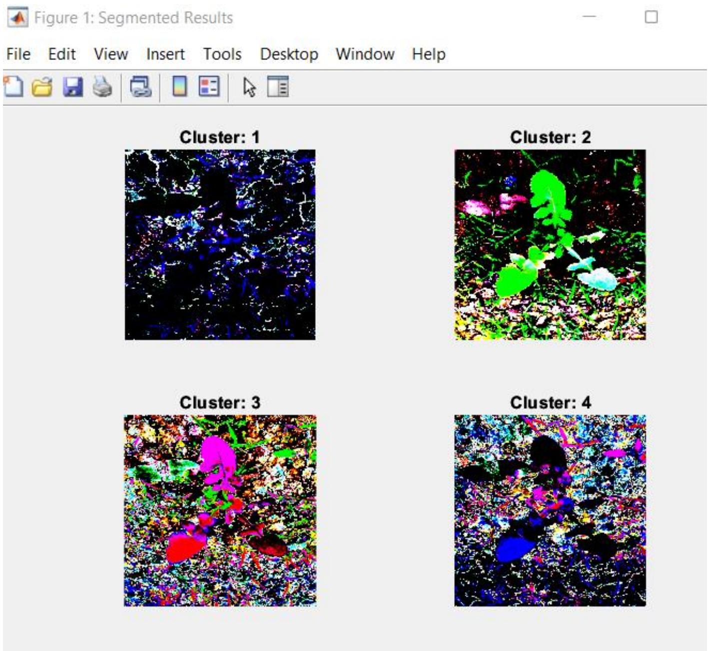


Figure 11: Image Clustering

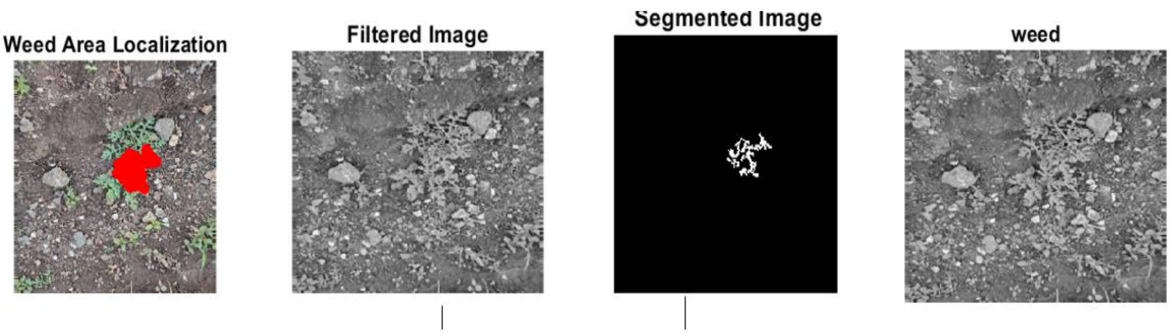


Fig.12 (a)) filter applied for locating the weed area to figure 11, (b) filter applied for locating the weed area to figure 11, (c) segmentation of the image from Figure 11.

PERFORMANCE OF WEED SEGMENTATION

The 11th figure shows the outcome of applying the suggested algorithm to the photos in Figure 2b, revealing that weeds were precisely segregated from the surrounding environment for images taken under natural conditions. This is known as clustering process. The image clustering result was compared in order to further validate the accuracy of the segmentation. The ExG indicators is frequently utilized and performs a good job of separating plants from the backdrop. The ExG index turned a colour picture to a grey scale picture, which was easily converted to a binary image using the algorithm. approach. A review of Fig. 11 revealed that the ExG + Otsu technique result was tainted by additional sounds. A few pixels in the backdrop were incorrectly categorized as dust or stones (noises) because to colour similarity between weeds and background. These noises were frequently dispersed throughout the image. To remove of the minute noise present in binary images, a filter using a thresholding method. Each related region's area was determined. Objects lesser than current threshold value (determined by test and errors) are classified as noise and it is filtered in (Figure. 12).

The segmentation results are displayed, with vegetation regions designated by a red mark. similarly just swapping reference photos and calculating the pixels that represent the distribution frequencies of the matching targets, this technique may be easily replicated.

IV. CONCLUTION

This research describes a method for detecting weeds among rice crop plantations utilizing deep learning technology with image processing and destroying it with a rover. The process is carried out in two stages. To classify vegetation, a AlexNet algorithm is used for training the model. The trained AlexNet achieved 98.6% precision. The segmented image, which highlights objects in white, is classified as weeds. As a result, this model focuses on detecting only weeds and avoids rice crop.

This research made the following contributions:

1) it investigated and presented a process for detecting weeds in vegetative plantations utilizing deep learning with image processing.

2) Created novel and indirect method for distinguishing between rice and weeds.

3) Under natural conditions, offer a colour index for extracting weeds from the background.

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