CONVOLUTION NEURAL NETWORK BASED WEED DETECTION IN HORTICULTURE PLANTATION

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ABSTRACT

Weed classification plays a vital role in horticulture plantation to optimally use herbicides on the weeds and maintain the quality of crops. This paper discuses weed classification with the combination of Image Processing and Convolution Neural Network (CNN). The image with both crop and weed is segmented and CNN is used for classification of crop and weed. The experimental database comprises rgbweeddetection dataset from the github portal which consists of images of carrot plant along with weed. The complete approach is implemented using Python Programming along with keras and tensorflow Libraries of Python. The experimental results show 95% accuracy in classification using CNN with lower order of convolution and maxpooling layers supported by reduced rate of misclassification of weed and crop.

I. INTRODUCTION

Weeds are unwanted plants that grow along with the crops which compete with the crops resulting in lower crop yield. Usually weeds in rural sector are controlled by applying chemical herbicides manually which is a time consuming task. Also use of herbicides are not eco-friendly and expensive. The weeds are not uniformly distributed, spraying of herbicides for the whole field results in lower crop yield and its quality. Hence weed control plays a vital role in agricultural management for the higher productivity of crops.

In recent years different approaches are developed to control weeds through automation. One of the solutions addressing this problem is spraying on particular weed in mechanical manner. But this needs classified images of weeds and crops. There have been efforts for the classification of weeds using Neural Networks. In neural network where all the neurons are fully connected, large number of parameters is present and is very computationally expensive. Hence an efficient way to classify weeds and crops has been developed by using Convolution Neural Networks (CNN).

The main three key roles that paper aims at are:
1) Accurately performing the classification using CNN for overlapped crop and weed images 2) System must be flexible and robust for the real-time classification 3) To reduce the misclassification rate during the classification process.

The paper is organized as follows: Section I gives the brief introduction about the necessity of weed classification and goals of this paper. Section II presents different research work carried out for the weed classification by researchers. In section III the proposed approach is explained with the steps that carried out like Image Acquisition, Pre-processing of the images, Image Segmentation and Labeling and finally the training the images using CNN. Section IV provides the results obtained from this approach with the graph. Lastly section V gives the conclusion and future work that can be carried out further.

II. RELATED WORK

Weed and crop segmentation and classification using area thresholding by Su Hnin Hlaing, Aung Soe Khaing, introduces a method for weed and crop classification based on area and thresholding. It utilizes excess green gray transformation with area thresholding for efficient classification of weed and crop. However this method cannot classify as weed and crop when they are overlapped [2].

Real-time Semantic Segmentation of Crop and Weed for Precision Agriculture Robots Leveraging Background Knowledge in CNNs by Andres Milioto, Philipp Lottes, Cyrill Stachniss has been proposed a method for classification of weed and crop based on Convolution Neural Network (CNN). This work proposes a method to increase the dataset by means of using different vegetation indices as the input channels for classification task [3]. However the experimental set up needs GPU.

WeedNet: Dense Semantic Weed Classification Using Multispectral Images and MAV for Smart Farming, Inkyu Sa, Zetao Chen, Marija Popovi´c et.al,. has proposed a method based on the pixel-wise segmentation.

This proposed work uses 132, 243, 90 annotated multispectral images of crop, weed and weed-crop mixtures which consist of Near-Infrared (NIR), Red Channel and Normalized Difference Index (NDVI) in training and testing set [4]. However manually annotating the images is labor intensive task which took approximately 30 hours in this paper.

EddyNet: A Deep Neural Network For Pixel-Wise Classification of Oceanic Eddies, Redouane Lguensat, Miao Sun, Ronan Fablet, et.al, proposed a methodology to classify oceanic eddies based on the pixel-wise classification. The method EddyNet consists of encoder-decoder convolution layer with the pixel-wise classification layer [5]. However EddyNet training needs large memory with Nvidia K80 GPU card.

III. METHODOLOGY

The methodology of the proposed work is shown in Figure 1.

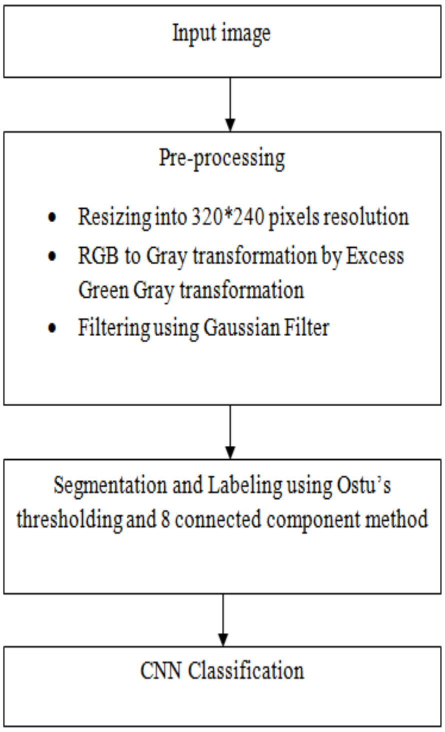

Figure 1: Flow chart for the proposed system

A) Image Acquisition:

Data Acquisition and data model are the very big challenges in obtaining the weed datasets. In this section Image data set that is used in this paper is described. The data set used in this approach is rgbweeddetection [1] from the github portal. The image dataset consists of 39 images of carrot plantation along with weed for various light conditions. One of the images from this dataset is shown in figure 2. The young carrot seedlings with weeds RGB images are captured in the month of February.

Figure 2: Carrot plants along with weed [1]

B) Pre-processing:

In this phase, all the images are resized into 320*240 pixels resolution. Image resizing is necessary to increase or decrease the range of pixels in an image which uses the interpolation factor. Excess green gray transformation [2] is used to convert RGB image into gray images by using the equations below.

Excess Green Image, ExG=2*g-r-b……………………(1)

where, r=R/(R+G+B)

b=B/(R+G+B)

g=G/(R+G+B)……………….…(2)

The gray images are then applied to Gaussian filter which removes the noise present in the images resulting in fast training.

Figure 3: Excess Green Gray Transformation

C) Image segmentation and Labeling:

The preprocessed image is segmented using the Ostu's thresholding for separating the background from the plants and weeds. The syntax used for segmentation is as follows: Thresh=cv2.threshold(blur,0,255,cv2.THRESH_BINARY_INV+cv2.THRESH_OTSU), Where blur is the filtered image from Gaussian filtering. Figure 4 shows the Ostu's threshold segmented image.

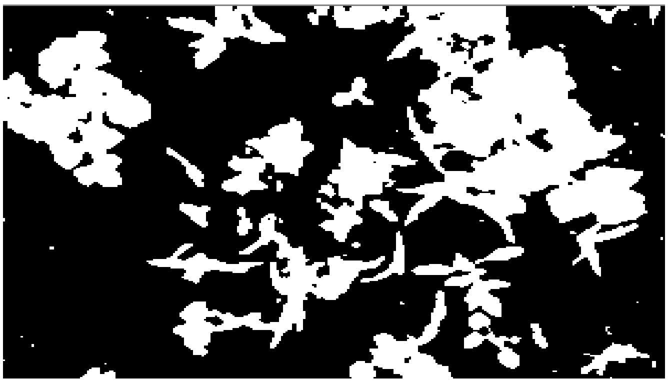

Figure 4: Segmented Image

In this proposed work labeling is done through 8 connected components method [2]. Connected component labeling can also be called as blob discovery, region extraction, region labeling etc. This method is used to detect the connected components in the binary image. Figure 5 shows the labeled output of this model.

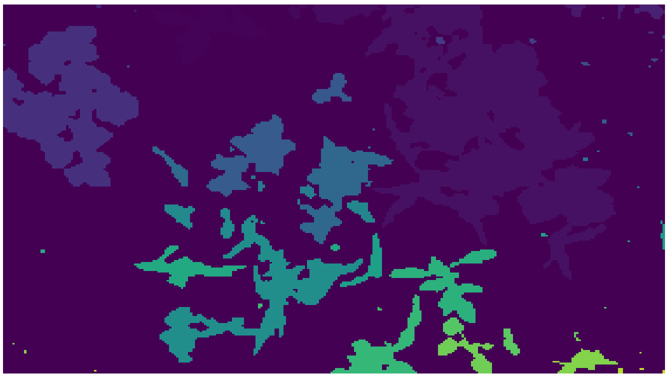

Figure 5: Labeled Image

D) Classification using Convolution Neural Network (CNN):

The final segmented and labeled images are classified based on the area threshold. Threshold value for this approach is taken as 3000 which means that if the area of labeled image is less than the threshold value it is classified as weed whereas if the area is greater than threshold it is said to be carrot. Convolution Neural Network is used to train the images. To obtain good accuracy in CNN one needs larger data set. To increase the data set the images are sent as the different input channels such as excess green channel, excess red channel, CIVE, NDI etc. In the proposed model, a sequential model which is known as the linear stack of layers is used. In any model, the first layer needs to receive the information regarding the shape of its input and automatic shape reference will be done by the following layers of the model.

The convolution layer is referred as core building block of the Convolution Neural Network in which convolution layer's parameters consist of set of learnable filters. During the forward pass in model, each learnable filter is convolved across the image to produce a 2D activation map of each filter. Then stacking the activation maps for each learnable filter forms the full output for the convolution layer. Normalization is done in the convolution layer by batch normalization process in which normalization of each activations are done by applying transformation of input with mean close to 0 and standard deviation close to 1. One of the important facts in batch normalization is that, it reduces the impacts of previous layers on the future layers. But one of the drawbacks in batch normalization is regularization which means that by using mini-batch size, noise also will be added to the model which increases the regularization effects.

Next step in the model is max pooling layer. Max-pooling layers can serve as the form of non-linear downsampling. Downsampling is the process of reducing the sampling rate of the image or the process. In this case, filters used are 2*2 pixels dimension which compute the maximum value of four pixels and make a stride of height and width at each depth. In this paper, two models of 6 convolution layers and 3 maxpooling layers, 4 convolution layers and 2 maxpooling layers are experimented. There is a flatten layer which is used to convert feature map into one dimensional (1-D) vector, by combining all the features from the previous layer. In the final layer softmax activation function is used which gives the output from the probability distribution from each class. Figure 6, figure 7 and figure 8 depict the test image with both weed and crop, classification of weed and crop. Figure 10 gives the misclassification of crop and weed for image in figure 9.

Figure 6: Original Image [1]

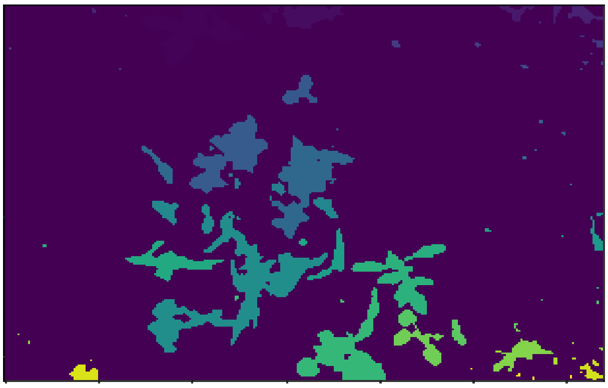

Figure 7: Classification as weed

Figure 9: Original Image for misclassification [1]

Figure 8: Classification as crop

Figure 10: Weed misclassified as crop

IV. RESULTS AND DISCUSSIONS

The experimental work uses rgbweeddetection database from github portal that comprises of 39 images of carrot plantation along with weed for the evaluation of CNN based weed classification. The images are segmented and fed to the CNN for weed classification. During the training process 60% of the images are considered and 40% for testing. Images are trained using two different models such as six convolution and three maxpooling layers, four convolution and two maxpooling layers. The performance of each model with varied epochs is tabulated in table 1. The experimental result shows that the Classification accuracy is notable of 95% for the model with four convolution, two maxpooling layers and 20 epochs. The whole approach is implemented using Open CV, keras and tensorflow libraries of Python. The use of area based threshold for labeling phase has reduced the human intervention in annotating the data, hence reducing the effort and time needed for training the model. The model is able to learn a decision boundary to precisely discriminate weeds from plants with minimal number of misclassifications when tested with crops in similar growth phase.

Table 1: Test Performance of Weed Classification for CNN models with different Convolution, Maxpooling Layers and Epochs

No. of Convolution layers=6 No. of Maxpooling layers=3		No. of Convolution layers=4 No. of Maxpooling layers=2	
Number of Epochs	Classification Accuracy (%)	Number of Epochs	Classification Accuracy (%)
10	70.83	10	85.83
15	75	15	91.66
20	87.5	20	95.83
30	91.66	30	95.83
35	95.82	35	95.83

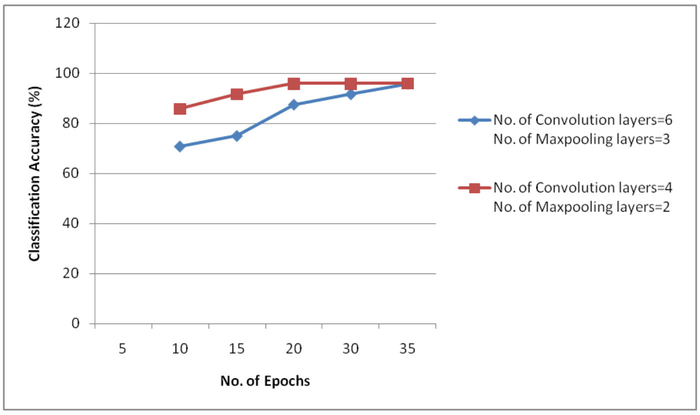

Figure 11: Plot of Classification Accuracy versus No. of Epochs for varied Convolution and Maxpooling layers

V. CONCLUSION AND FUTURE WORK

In the proposed work, Convolution Neural Network (CNN) has been explored along with Image Segmentation algorithm for Weed Classification in Horticulture Plants. Excess green gray method and Area thresholding algorithm is used for segmentation and CNN for weed classification. The system shows an effective and reliable classification of 95% with reduced misclassification rate for four convolution and two maxpooling layers.

Further work includes, investigating the use of deep neural networks for larger database comprising different types of weeds for a crop. This further helps in minimizing the use of herbicides and thus improving the productivity and quality of crops.

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