EVALUATING PERFORMANCE OF DIFFERENT NEURAL NETWORK MODELS ON CROP AND WEED DETECTION AND CLASSIFICATION

[1]SANDEEP MUSALE, [2]ASHOK KHEDKAR, [3]MADHURI SHRINIWAR, [4]TEJAL GADEKAR, [5]DIKSHA SWAMI

[1,2,3,4,5]Department of Electronics & Telecommunication, Cummins College of Engineering for Women, Pune, India

ABSTRACT: One of the most significant elements affecting agricultural yield is weeds. The waste and contamination of rural environments caused by full-coverage herbicide spraying is becoming more visible. With the continual improvement in agricultural production levels, it is critical to differentiate crops from weeds and to achieve accurate weed-only spraying. However, precise weed and crop identification and localization are required for spraying. In order to increase the crop yield and reduce the threats imposed by weeds in agriculture, a measure is taken to identify and classify the weeds and crops with the help of deep learning techniques. Convolutional neural networks render a good way to identify the weeds that harms the crop's growth. Aiming at achieving a greater accuracy, models such as CNN and MASKR-CNN were built. Comparatively, CNN resulted with 94.29% as training accuracy and 100% accuracy of validation in VGG16 architecture. Therefore, by the suggested method, there is a lot of possibility to reduce the manual work to identify crops and weeds. According to results, with the fine tuning of hyper parameters, accuracy can be increased.

KEYWORDS: Convolutional neural network, Mask RConvolutional neural network, weed and crop identification and Localization

I. INTRODUCTION

Agriculture is the backbone of India and the village people depend upon agriculture for their survival [1]. The profit of plants and vegetables will rely on the yield production. One way to get more benefit is the elimination of the weeds from the harvest. The conventional way of removing weeds from the harvest requires more time and more labour [2]; also the use of herbicides affects the plant and soil to a great extent. In this paper an automated method is proposed to eliminate the weeds in the yield [3].

In the automatic strategy, after capturing the image, Pre-processing operations like Image Resizing, Image Augmentation are performed on the image and the feature are extracted automatically by an algorithm. Based on the features the network is trained to classify weeds and crops [4-5].

II. LITERATURE SURVEY

Milioto, A., Lottes, P., & Stachniss, C..et.al [6]

UAVs are becoming an important tool for field monitoring and precision farming. A prerequisite for observing and analyzing fields is the ability to identify crops and weeds from image data. In this paper, we address the problem of detecting the sugar beet plants and weeds in the field based solely on image data. We propose a system that combines vegetation detection and deep learning to obtain a high-quality classification of the vegetation in the field into value crops and weeds. We implemented and thoroughly evaluated our system on image data collected from different sugar beet fields and illustrate that our approach allows for accurately identifying the weeds on the field.

Wendel, A., & Underwood, J. et.al [7]

A critical step in treating or eradicating weed infestations amongst vegetable crops is the ability to accurately and reliably discriminate weeds from crops. In recent times, high spatial resolution hyperspectral imaging data from ground based platforms have shown particular promise in this application. Using spectral vegetation signatures to discriminate between crop and weed species has been demonstrated on several occasions in the literature over the past 15 years. A number of authors demonstrated successful per-pixel classification with accuracies of over 80%. However, the vast majority of the related literature uses supervised methods, where training datasets have been manually compiled. In practice, static training data can be particularly susceptible to temporal variability due to physiological or environmental change. A self-supervised training method that leverages prior knowledge about seeding patterns in vegetable fields has recently been introduced in the context of RGB imaging, allowing the classifier to continually update weed appearance models as conditions change. This paper combines and extends these methods to provide a self-supervised framework for hyperspectral crop/weed discrimination with prior knowledge of seeding patterns using an autonomous mobile ground vehicle. Experimental results in corn crop rows demonstrate the system's performance and limitations.

Ashitosh K Shinde and Mrudang Y Shukla.et.al [8]

Weed management is one of the costliest input to the agriculture and it is one of the un-mechanised area. To bring mechanization in this area the most important step is the detection of weed in agricultural field. Weed can be detected by using machine vision techniques. Machine vision uses special image processing techniques. Weeds in agricultural field can be detected by its properties such as Size, Shape, Spectral Reflectance, Texture features. In this paper we are demonstrating weed detection by its Size features. After the image acquisition Excessive green algorithm is developed to remove soil and other unnecessary objects from the image. Image enhancement techniques are used to remove Noise from the images, By using Labelling algorithm each components in the Image were extracted, then size based features like Area, Perimeter, longest chord and longest perpendicular chord are calculated for each label and by selecting appropriate threshold value Weed and Crop segmentation is done . Result of all features is compared to get the best result.

Li, Pan, Dongjian He, Yongliang Qiao, and Chenghai Yang.et.al [9]

Soft set theory is originally proposed as a general mathematical tool for dealing with uncertainties present in most of our real life. This study applied soft sets to improve low accuracy of weed identification caused by similar features. Firstly, three types of plant leaf features including shape, texture and fractal dimension were extracted from the plant leaves after a series of image processing. Then the weed-classification matrix went through arithmetic operations on the relation-matrices constructed with eigenvalues and their weight factor coefficients, from which the label corresponding to its largest membership in every row was selected, finally the weed was distinguished according to the label. Also the soft set theory showed higher performance in terms of robustness and algorithm complexity comparing with the Bayesian classifier, support vector machine (SVM) and back-propagation (BP) neural network. The proposed method provides a useful tool for weed identification and selectively spraying herbicide.

Ahmed, Faisal, Hawlader Abdullah Al-Mamun, ASM Hossain Bari, Emam Hossain, and Paul Kwan.et.al [10]

In most agricultural systems, one of the major concerns is to reduce the growth of weeds. In most cases, removal of the weed population in agricultural fields involves the application of chemical herbicides, which has had successes in increasing both crop productivity and quality. However, concerns regarding the environmental and economic impacts of excessive herbicide applications have prompted increasing interests in seeking alternative weed control approaches. An automated machine vision system that can distinguish crops and weeds in digital images can be a potentially cost-effective alternative to reduce the excessive use of herbicides. In other words, instead of applying herbicides uniformly on the field, a real-time system can be used by identifying and spraying only the weeds.

This paper investigates the use of a machine-learning algorithm called support vector machine (SVM) for the effective classification of crops and weeds in digital images. Our objective is to evaluate if a satisfactory classification rate can be obtained when SVM is used as the classification model in an automated weed control system. In our experiments, a total of fourteen features that characterize crops and weeds in images were tested to find the optimal combination of features that provides the highest classification rate. Analysis of the results reveals that SVM achieves above 97% accuracy over a set of 224 test images. Importantly, there is no misclassification of crops as weeds and vice versa.

III. METHODOLOGY

A. Block Diagram:

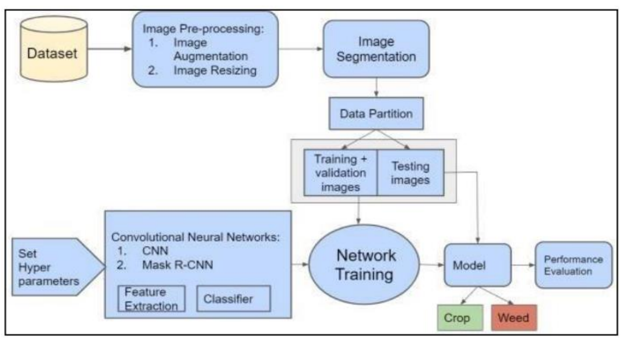

Fig. 1: BLOCK DIAGRAM OF PROJECT

B. Operational Steps:

- A dataset of 1300 RGB annotated images which contain combination of weeds and crops images from Kaggle are used.
- Our key objective in the pre-processing section is to perform image augmentation and resizing. Image augmentation is a technique to increase the size of a dataset by performing operations such as image flipping, zooming, shifting, and rotating. To make future processing, all images are resized to 224x224 in image resizing.
- The image dataset is then splitted into two sets: training (and validation) and testing. Deep learning models like CNN, Mask R-CNN are trained and evaluated.
- Training phase includes automatic feature extraction and image classification. CNN architecture is built by setting hyper parameters like epochs, filter, size, stride, filter count etc. During the testing phase, the resulting image is classified into weeds or crops.

• Performance of the different neural networks will be evaluated and compared in terms of MAP Score, F1-score, Precision and Recall.

IV. ALGORITHMS

In this paper, we are evaluating performance of two neural network models i.e. Convolutional neural network and Mask R-Convolutional neural network.

A. Convolutional Neural Network:

Convolutional neural network is a type of feedforward artificial neural network which is mostly used for classification tasks.

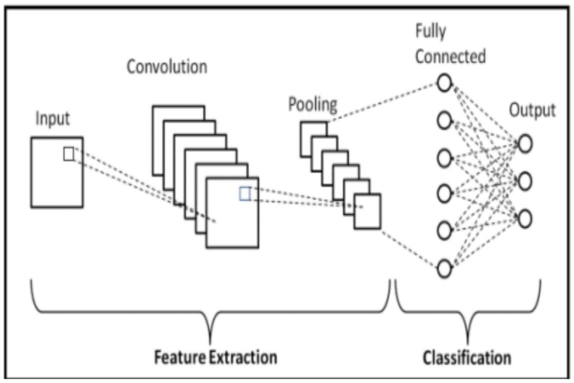

Fig. 2: ARCHITECTURE OF CNN

In CNN, The input image is convoluted with the application of filters, resulting in a Feature map. CNN is composed of multiple layers of artificial neurons. Artificial neurons calculate the weighted sum of multiple inputs and output as activation function. The first layer usually extracts the basic features which are passed onto the next layer. As it moves deeper into the network, it extracts more complex features. After passing an image through the convolutional layer, input images are converted into feature maps using feature detectors. Pooling layer is responsible for down sampling the convolved feature and hence reduces computation power required for processing data. From the feature map, max pooling chooses the most significant element. Finally, a fully connected layer classifies the images into categories.

B. Mask R-Convolutional Neural Network:

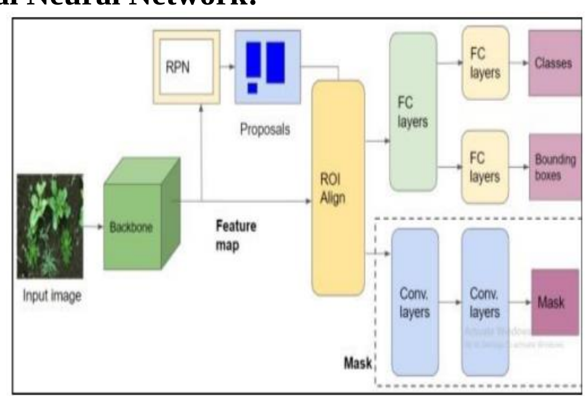

Fig. 3: ARCHITECTURE OF MASK R-CNN

Mask R-CNN is built on the top of faster R-CNN. Mask RCNN returns a class label, bounding box coordinates and object mask for given image. It uses Resnet architecture for feature extraction. Region proposal network scans the feature map and proposes regions that may contain objects (Region of Interest). The regions obtained from the RPN are of different shapes. ROI align extracts fixed-sized vectors from feature maps and generates fixed-sized ROI from region proposals. Finally fully connected layers map feature vectors into two classes and instance bounding box coordinates. Mask R-CNN also generates segmentation masks.

V. RESULTS

Table 1: COMPARISION OF RESULTS OF CNN AND MASK R-CNN

Sr. No	Performance Parameters		
	Parameters	**CNN**	**Mask R-CNN**
1.	Precision	0.9491	0.287
2.	Recall	0.875	0.401
3.	F1-Score	0.9105	0.33

The model gives training accuracy as 92.19%, validation accuracy as 95.70% and Testing accuracy as 91.50 % for Convolutional neural network and mean average precision score of 0.28 for mask R- CNN model.

VI. CONCLUSION

In this paper, Evaluation of Performance of different neural network models on Crop and weed detection and classification is done. The weeds and crops are classified with the help of Convolution neural network and Mask RConvolutional Neural Network. CNN architecture gives a validation accuracy of 95.70% and CNN has better performance in Evaluation parameters such as precision, recall and F1-Score as compared to Mask R-CNN model. Therefore, these generated deep learning models give a reasonable accuracy and further, fine-tuning of parameters can be done with more of weed datasets.

VII. REFERENCES

[1] Gao, Junfeng, David Nuyttens, Peter Lootens, Yong He, and Jan G. Pieters. "Recognising weeds in a maize crop using a random forest machine-learning algorithm and near-infrared snapshot mosaic hyperspectral imagery." Biosystems engineering 170 (2018): 39-50.

[2] Kunz, Christoph, Jonas F. Weber, Gerassimos G. Peteinatos, Markus Sökefeld, and Roland Gerhards. "Camera steered mechanical weed control in sugar beet, maize and soybean." Precision Agriculture 19, no. 4 (2018): 708-720.

[13] Zheng, Y., Zhu, Q., Huang, M., Guo, Y., & Qin, J. (2017). Maize and weed classification using color indices with support vector data description in outdoor fields. Computers and Electronics in Agriculture, 141, 215–222

[4] Tang, J., Wang, D., Zhang, Z., He, L., Xin, J., & Xu, Y. (2017). Weed identification based on kmeans feature learning combined with convolutional neural network. Computers and electronics in agriculture, 135, 63–70.

[5] Sa, I., Chen, Z., Popovi´c, M., Khanna, R., Liebisch, F., Nieto, J., & Siegwart, R. (2017). Weednet: Dense semantic weed classification using multispectral images and mav for smart farming. IEEE Robotics and Automation Letters, 3 (1), 588–595.
[6] Milioto, A., Lottes, P., & Stachniss, C. (2017). Real-time blob-wise sugar beets vs weeds classification for monitoring fields using convolutional neural networks. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 4, 41.
[7] Wendel, A., & Underwood, J. (2016). Self-supervised weed detection in vegetable crops using ground based hyperspectral imaging. 2016 IEEE international conference on robotics and automation (ICRA), 5128–5135.
[8] Ashitosh K Shinde and Mrudang Y Shukla, "Crop detection by machine vision for weed management", International Journal of Advances in Engineering & Technology, July, 2014.
[9] Li, Pan, Dongjian He, Yongliang Qiao, and Chenghai Yang. "An application of soft sets in weed identification." In 2013 Kansas City, Missouri, July 21-July 24, 2013, p. 1. American Society of Agricultural and Biological Engineers, 2013.
[10] Ahmed, Faisal, Hawlader Abdullah Al-Mamun, ASM Hossain Bari, Emam Hossain, and Paul Kwan. "Classification of crops and weeds from digital images: A support vector machine approach." Crop Protection 40 (2012): 98-104.