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Detection of weeds in agricultural crops using deep neural networks

Radhika Venkateshrao Kulkarni
rvkulkarni1998@gmail.com
R. V. College of Engineering, Bengaluru, Karnataka

ABSTRACT

Weeds creates dangerous situation for growing crops in the agricultural field. They directly affect the growth of the crops and hinder the yield byreducing the quality and quantity of crops. In order to find solution for the problems created by weeds, so many researches havebeen carried out in the different domainsso that crop yield can be increased and the pollution of the soil and environment can be reduced which is caused by the excess use of fertilizers on the agricultural field toremove the weeds. Deep Neural Network algorithms have been used in the proposed system to classify the weeds and crops using different algorithms and discover which the optimal solution is. By considering the results obtained from the algorithms of the Deep Neural Network, The comparison has been made by considering the parameter like accuracy and finally by applying which algorithm the highest accuracy has been obtained is noted.

Keywords: *Image Processing, Deep Neural Network, DNN, YOLOV4, ResNet50, InceptionV3*

1. INTRODUCTION

Agriculture plays an important role in the production of food for living organisms. There are so many factors which influence poor yield of the crops like flood, drought, soil quality interns of PH and moisture content, minerals available for the growth of plants, salinity of water, excess acid content in the soil, animal intrusion, weedsetc. Weed is the common but very hazardous problem which should be detected in the early stage of the crop life cycle otherwise it leads to massive growth of the weeds in the agricultural field and weeds take all the nutrients which are essential for the growth of the crops and hinders the growth.

In the proposed system, the weeds and crops has been classified and the modelaccuracy is compared for 3 different models. They are ResNet50, InceptionV3 and DNN. YOLO algorithm is used to detect the objects in the images of the dataset in the form of bounding boxes.

2. PROBLEM STATEMENT

It is very essential to detect the weeds in the early stage of the crop cycle. Negligence of the weeds leads to majorissues related to yield and pollution of environment and soil. So many techniques have been already introduced to detect weeds but they are not efficient because of some issues related to consideration of parameters to classify the weeds and crops and the background noise detected when images have been captured from aerial vehicles and cameras of the electronic gadgets. There is a need to detect weeds and classify the weeds and crops so that necessary actions can be taken to improve yield and protect the environment from thepollution.

3. RELATED WORK

Andreas Kamilaris [1] Described about how some technologies, such as automation and machine learning, are becoming more and more important in agriculture to boost productivity. Modern artificial intelligence (AI) and deeplearning (DL) approaches have replaced traditional image processing and machine learning techniques as the preferred approach. The main difficulties in this field include variations in lighting, poorlearning transfer, and object occlusion. Due to its advantages in object detection, classification, and feature extraction, DLhas recently attracted a lot of interest.

Maria Guijarro [2] described a computer vision system that can distinguish in real time between crop rows and weed patches in environments with unpredictablelighting. The system consists of two independent subsystems: Fast Image Processing (FIP), which produces results instantly; and Robust Crop Row Detection (RCRD), which is used to rectify the errorsmade by the first subsystem. Thiscombination results in a system that performs effectively in a wide range of circumstances. The system successfully recognises an average of 95% of weedsand 80% of crops under various lighting, soil humidity, and weed/crop development circumstances, according to tests conducted on many maize movies shot in different fields and during different years.
Guofeng Zhang [3] provides a summary ofhow smart weeding

systems that carry out plant-specific activities can support environmental and agricultural sustainability. Although autonomousrobotic technology has made enormous advances in recent years for precise weed management, under-canopy weeding infields has yet to be achieved. Such systemsmust be able to accurately identify and classify weeds in order to prevent unintentional spraying that could harm the nearby plants. Real-time multi-class weed identification makes it possible to treat weeds according to their species, thereby reducing the need for herbicides.

Kamal Alameh [4] demonstrates the effectiveness of deep learning for object detection, which has received extensive research and recently shown encouraging results. In site-specific weed management in precision agricultural applications, weed detection is essential. Only a small number of crop and weed datasets with complicated field situations, such as illumination, weather, various growthphases, high occlusion and overlap, and weeds with similar features, are availablein public resources. The identification of wild radish (Raphanus raphanistrum) and capeweed (Arctotheca calendula) in barley fields (Hordeum vulgare) is explored based on their negative impacts on crop output.

ZHANG, XIAOGUang [5] describes the Crop Recognition process, which is essential for robotic weeding in precision agriculture but is still a work in progress because of the unstructured nature of the field environment and the diversity of plant species. It becomes more difficult when weeds are noticeable and encroach on crop plants. This study proposes a novel technique for identifying crop plants in photographs of fields with high weed content. Using a convolutional neural network, this technique separates agricultural plants from overlapping weedsbased on the human visual system's visual attention mechanism. Resnet-10 serves as the network's backbone, and side outputs and short connections are added for multi- scale feature fusion.

Om Tiwari, Vidit Goyal, Pramod Kumar, and Sonakshi Vij [6] employed innovative drone technology and Deep Learning in the field of convolutional neural network in order to totally eradicate the weeds by spraying herbicide on them. The dataset was created using information obtained from the Indian Agricultural ResearchInstitute. Apart from the training dataset, they successfully identified 3 particular weeds using the applied transfer learning technique.

Mulham Fawakherji, Ali Youssef, Domenico D. Bloisi, Alberto Pretto, and Daniele Nardi [7] concentrated on developing tools and technology to enhance precision agriculture by using cutting-edge machinery, including robotic systems. Selective spraying or the mechanical approach for weed detectionand removal are used to solve the weed problem. The authors used a batch of RGBimage data to categorise using two convolutional neural networks in succession. The first network is built on a sequence design for encode-decodeapproach. Each plant will be categorised inthe second neural network in accordance with the relevant class.

E. Granger, M. Kiran, and L.-A. Blais- Morin [8] examined Real-world videosurveillance applications and discovered that it was challenging to identify facesand heads in the video due to some variance variables. In this study, the performance of single pass and region- based neural network architectures is compared. They were compared taking into account factors like time, memory, etc. Although they outperformed other conventional detectors in terms of accuracy, they nevertheless had asignificant computational cost.

T.-Y. Lin et al. [9] considered deformable components model and also gave baseline performance study for the results of bounding box and segmentation detection for common objects in their natural context. The statistical evaluations of PASCAL, Image Net, and SUN were contrasted by the author. 2.5 million tagged instances of 91 item kinds were included in 328k photos.

V. N. T. Le, S. Ahderom, B. Apopei and Alameh [12] focused on precisionagriculture. Authors discussed about reducing the cost for weed management. They had particularly considered wildradish plant for study. They have studied about LBP method and Support Vector Machines. They applied these methods to the weeds along with fuzzy logic. It helpedthem to easily detect the weed and apply less amount of weedicide by particularly detecting the exact weed in the group of plants.

4. OBJECTIVES

1. To detect weed plants in the particular area of agricultural field.
2. To build a model using Deepneural network algorithms to detectweed plants.
3. To compare the performance of thealgorithms and to find out which is optimal.
4. To help the farmers in reducing the investment on the agriculture procedures.

5. METHODOLOGY

The aim of the proposing system is executing a Weed Detection System. It could be reached with the aid of using and creating an application equipped to differentiate actual crops and weeds using image dataset dealing with image processing methods and deep learningalgorithms. The system is fed with RGB and HSV images. The steps are as follows:

1. Grey-scale transformation and pixel subtraction: The preliminary step for the weed detection is the grey-scale transformation with "RGB to Grey" and inexperienced pixel subtraction from the changed-over image, to discover inexperienced green plants within side the images.

2. Labelling and Classification: Next step is labelling and classification, in which related elements are marked with "bwlabel" and the extras are taken out considering the fact that they're regarded as weeds.

3. Threshold based Classification and Comparison: Finally, a threshold basedon classification values for a yield or aweed is taken for further comparisons.

The final output will be in the form oflabels Weed/ Crop. The analysis is done by comparing the performance of three algorithms i.e., ResNet50, InceptionV3, DNN. The individual graph will be obtained for model accuracy, model loss and RoC for each algorithm.

The comparison graph represents the performance of above mentioned algorithms. The performance with accuracy and confusion matrix is obtained for the analysis. The final conclusion isderived from this comparison graph with accuracy.

5. RESEARCH ANALYSIS

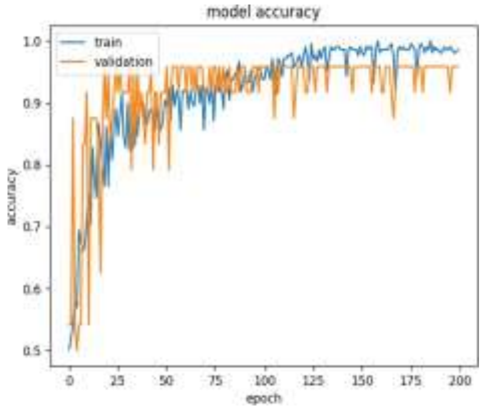

Fig 1: Model Accuracy graph forResNet50

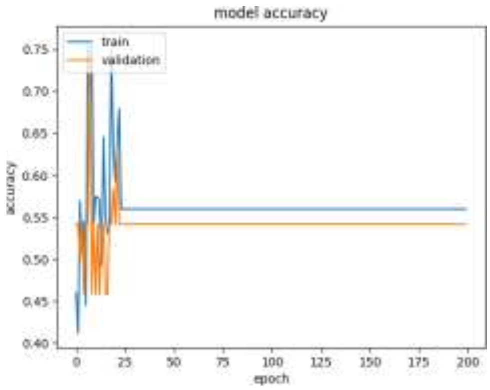

Fig 2: Model Accuracy graph forInceptionV3

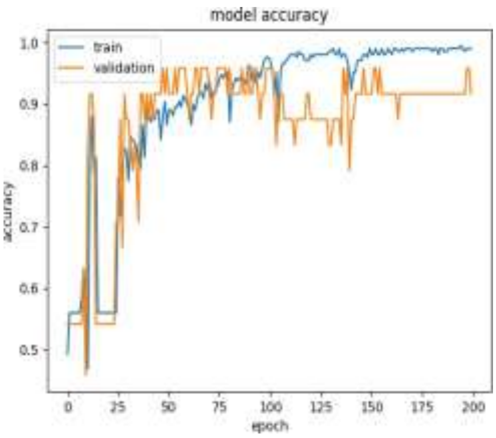

Fig 3: Model Accuracy graph for DNN

Figure 1, 2 and 3 describes about 3 accuracy models. The ResNet50 Model gives an accuracy of 55.79. The InceptionV3 Model gives an accuracy of 98.28. The DNN Model gives an accuracy of 98.71.

6. RESULTS

Fig 4: Detected Weed

Fig 5: Detected Crop

The Figure 4 and 5 describes about thedetected weed and crop from image dataset.

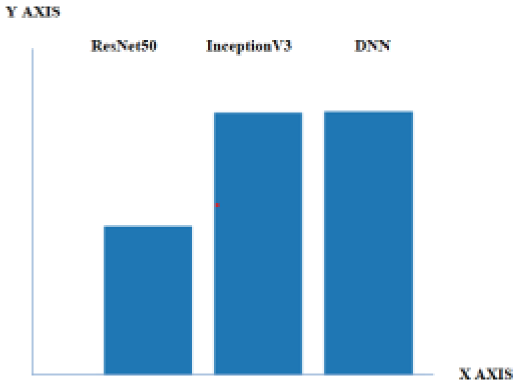

Fig 6: Comparison graph of ResNet50, InceptionV3 and DNN Models

Figure 6 gives accuracy comparison of above 3 mentioned models

7. CONCLUSION

The system used 4 algorithms to detectweeds in the agricultural fields namely ResNet50, InceptionV3, Deep Neural Network belongs to Deep Neural Network algorithms list and YOLO which belong toimage processing.

The comparison of the Deep Neural Network algorithms gives the optimal solution for the detection of weeds. DNN model provides an accuracy of 98.71% and InceptionV3 model provides an accuracy of 98.28% and ResNet50 provides an accuracy of 55.79%. By comparing the performance of the 3 algorithms interns of accuracy the DNN provides highly optimal solution.

The better dataset with larger size can also be utilised to increase the accuracy of the results. The proposed system helps the farmers to detect the weeds in the agricultural field and it leads to early removal of weeds from the crops field.

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