An experimental set up for utilizing convolutional neural network in automated weed detection

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Abstract: Weeds present in the crops are one of the factors that lead to decrease in crop production. The weeds take up nutrients, water which leads to weight reduction in plant and decreases the grains per ear and grain yield.so a method needs to be developed which would detect these weeds in the field and then herbicide is sprayed on them to completely destroy through the use of new drone technology and deep learning in field of convolutional neural networks. Using the dataset from the fields of Indian Agriculture Research Institute (IARI), THE AUTHORS have applied transfer learning technique to identify three weeds Phalaris minor, Dactyloctenium aegyptium, Digera arvensis, Echinochloa colona which achieved achieve accuracy of 95%,65%,61%,54% respectively for the datasets which were not involved in training of model.

Keywords: Deep Learning, Convolutional Neural Network, Weed Detection

1. INTRODUCTION

Accounting for almost 23% of GDP, and employment of 59% of the country's total workers in 2016 in Agriculture [3], India is the second-largest country producing rice, wheat, sugarcane, cotton and groundnuts [3]. The production of Indian agricultural has to supply l7.5% of the world's population with just 2.4% of land and 4% of the accessible water resources at its disposal. [3].

From the beginning of Green Revolution, Rice and wheat systems of India have been playing an important role in the worldwide food economy. The food, mainly rice that is produced by India feed the local population of 1.25 billion and many countries through export [4]. The agriculture sector is one of the most volatile sectors as it depends on the rain since rice is a kharif crops which require a lot of water [4]. This stresses the requirement for consistent endeavours to increase crop productivity and production to meet the demands of expanding populace by creating innovation which would
reduce weeds which adjust well to develop in any situations and cause yield and quality loss, while rivalling crops for resources.

To meet the requests of an expanding populace and avoid importing of food, crop productivity needs real upgrades in India, which can be accomplished by recognizing the hurdles that prevent farmers in achieving high yields [5]. Weeds are one of the main factors that restrict productivity of crops in India. They compete with crops for natural and applied resources. They are accountable for:

a) weight reductions: Reduction of weight in crops due to weed i.e. CGR (Crop Growth Rate), dry weight (weight of crop after water is removed from it)[5].
b) nutrient uptake: The process by which plant take nutrients from environment i.e. carbon, oxygen, etc. so unwanted plant takes up the nutrients and thus crop starves of nutrients [5].
c) number of ear-bearing tillers: They are tip portion of the crop which bears the food which is grown which gets reduced due to presence of weed [5]
d) grains per ear and grain yield: The grain which are present in the crops is known as grains per ear and grain yield so presence of weed decrease it [5].

Estimation of losses due to weeds have been done in various countries producing rice. In India, losses were evaluated at 10% of the crop and also losses due to herbicide expenses and machine-driven practices, and hand weeding to restrain even greater losses, these losses result in 5% As a result total loss due to weeds results to 15% annually [7]. In plantation crops, fruits, vegetables, grasslands, forestry and aquatic environments losses of this extent because of weeds may happen. The aggregate monetary losses will be significantly higher, if indirect effects of weeds on wellbeing, losses of biodiversity, nutrient reduction, grain quality, etc. are considered [7]. Figure 1 shows the various interdisciplinary research areas where "weed" has been used in research papers published in web of science. To generate this analysis, the authors have used the query *TI=("weed detection")*in web of science advanced search category. All the papers from 1989 to 2018 were listed in the search whose title contained the word *weed detection*. Now the further analysis revealed that these papers are used and cited in other papers as well which belong to various interdisciplinary research area.

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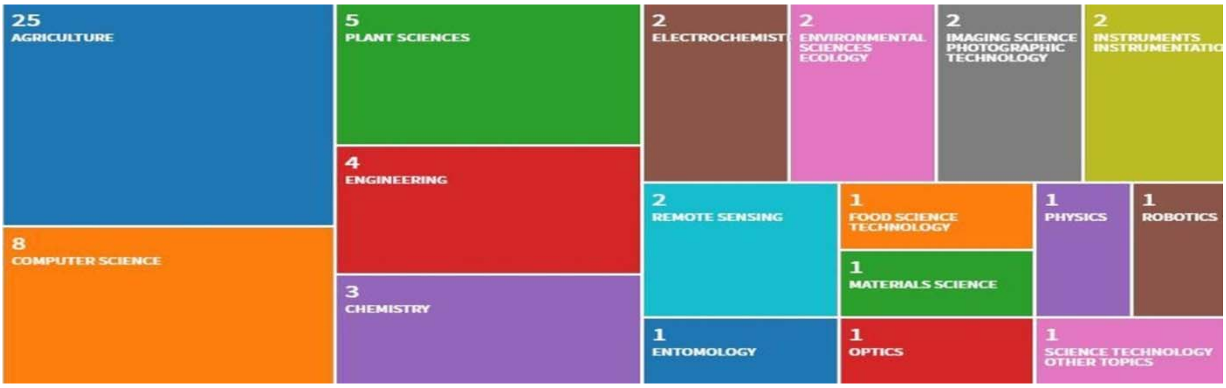

Figure 1: Description of various interdisciplinary research areas where "weed" has been used in research papers published in web of science

Table 1 examines the related research work that has been done in the field of weed detection. We have identified the various salient features and scope for improvement in these papers and tried to improve upon these in our research work.

Table 1: Background study

Paper Discussed	Salient features described	Scope for improvement
[15]	• This paper uses Hough transform method and BP method to analyse the center line of rows of crops. • Achieves a high accuracy of 92.5%. • Uses YCrCb colour model.	Improvement in accuracy by using modern techniques such as Deep learning and Convolutional Neural Net
[16]	• Spectral and fluorescence sensors used in this system often require less computationa l power than imaging systems, that leads to the less data produced • Distinguished weed species with multi- spectral classification approach with accuracy of 90.3%	The detection system is bulky. Space needed for this autonomous spraying application and the safety provision for unmanned vehicles, results in high cost
[17]	• This paper has shown the use of different types of camera in classifying weed from crop. • The use of UAV for taking images from the ground	The accuracy can be further be improved with use of Neural networks.
[18]	• The authors have used supervised learning for hyperspectral in differentiating weed and crop. • The authors of the paper have used ground vehicle with different image capturing devices.	The performance and accuracy can be further be improved with the help of neural networks.
[19]	• The authors have used Neural network and aerial vehicle to identify weed in rice crop • The datasets of 250 images is stitched together.	• The time complexity can be decreased further • The current system deploys an approach that is on the higher side of time complexity.

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The authors have examined that Echinochloa Colona [12], Dactyloctenium aegyptium [13], Phalaris minor [2] and Digera arvensis [6] are one the most common weed present mainly in the Pigeon pea (Arhar) [11], rice, maize, vegetables crop. It has the power to invade natural areas and outgrow the native vegetation present over there [8]. Hence the aim of this paper is to detect Echinochloa Colona, Dactyloctenium aegyptium [10], Phalaris minor [2], Digera arvensis [6]. Traditional weed identification approaches rely on manually spraying of post-emergence herbicides for destroying of weeds such as bisparybacbispyribac, “fenoxaprop + safener”, etc. and manual and mechanical weeding [9]. Which increases the overall cost of the crop which is sown in the field. The method developed would help in areas where internet is slow or there is no internet, smartphone and unmanned aerial vehicle (UAV) technologies offer new mechanisms for in-field weed detection based on automated image weed detection. This paper provides an overview of weed detection through the use of Transfer learning in ConvNet also known Convolution Neural Network (CNN) as a future view on evolution of technology in India [8].

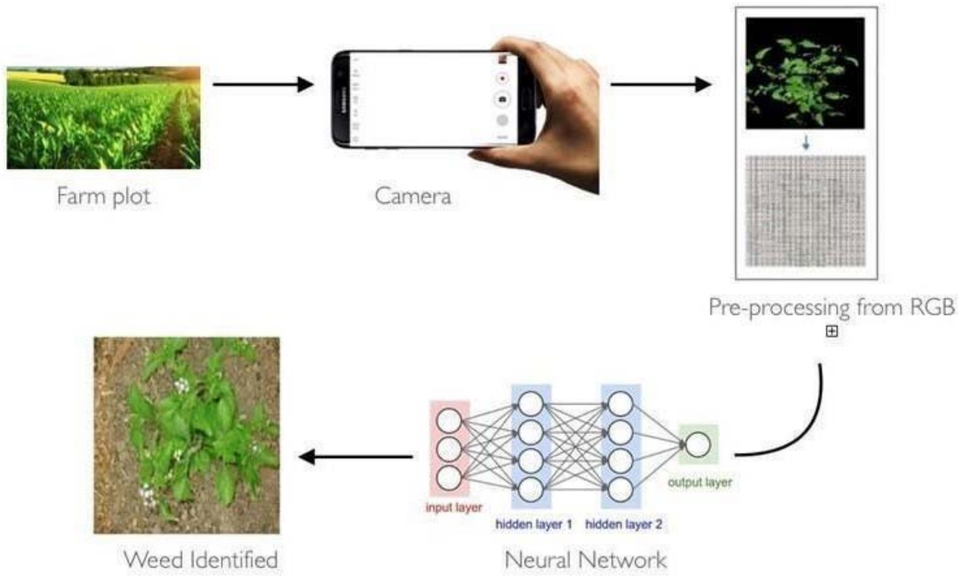

Figure 2. Approach Diagram for weed Detection

Figure 2: Approach Diagram for weed detection

Figure 2 shows the approach adopted in this paper for weed detection which mainly deploys transfer learning. In order to get better equipped with this technique, figure 3 has been shown. In this technique of deep learning, the model which is trained for large set of datasets in this case Microsoft Common Objects in Context (COCO) which takes input of everyday of common object of over 2,500,000 image datasets these are trained over different and then some of the layers were freezed that were present in t pretrained model and put our own layers. The model uses the pretrained/weights of the previous model instead of random initialization to solve our problem. Since the pretrained models are trained on large datasets took a lot of time and computational power to train to learn different parameters/weights with optimized hyperparameters this can save us lot of time in building a custom object detection.Some of the benefits of deploying transfer learning are stated as follows:

- **i.** Helps boost performance of the Neural Networks
- **ii.** Saves lot of time in training large Datasets
- **iii.** Commercially more viable

It includes

- a) Methodology and approaches used to detect weeds in the crop, alongside with the cost of losses caused by weed: Discussed in section 2
- b) Performance how does the neural networks perform in different conditions with accuracy
- c) Result
- **d)** Future scope of the technology**.**

2. APPROACH AND IMPLEMENTATION

This paper uses Python 3 and TensorFlow to write the program for implementing the proposed approach. TensorFlow is an open source framework created by Google for performing deep learning. [1]. Using the version(V2) of the Inception model (based on GoogLeNet), the authors have executed the image recognition code with ssd_inception_V2_coco [5] in TensorFlow. The authors have trained the computer to recognize images and classify them into one category i.e. weed. Classes of images and

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that trained model of those images is used to detect images of that type. In this paper instead of developing a neural network from the scratch the method uses those learned parameters present in the pretrained model into our neural network from our custom (weed datasets). The model developed is feed with images which were obtained from fields into the neural netwo

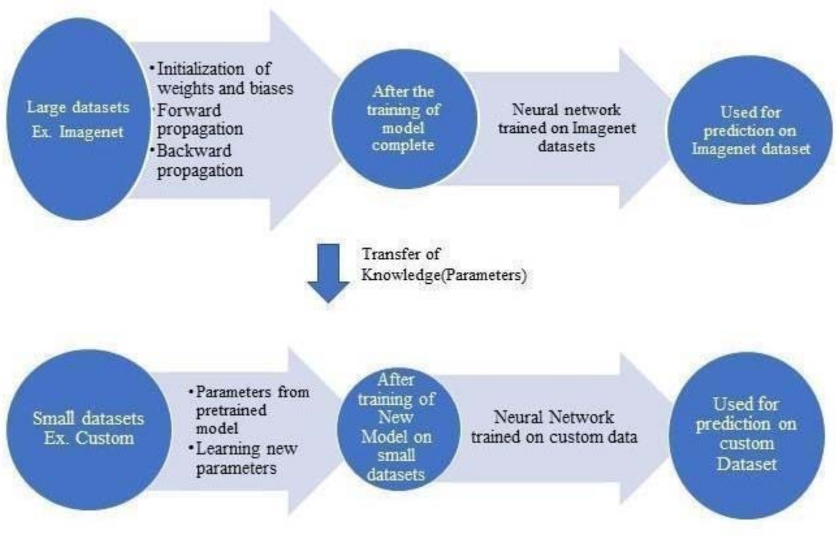

Figure 3.Transfer Learning Approach

Figure 3: Transfer learning approach

The further process adopted in this paper is listed as in table 2.

Table 2: Stepwise execution in this paper

S.No.	Step	Explanation
1	Pre-processing	First, little bit of variance is need to be added to the data since the images from the dataset are very organized and contain little to no noise. (by resizing the image)
2	Splitting our dataset	It takes a long time to calculate the gradient of the model using the larger dataset. So, a smaller batch of images was used.
3	Building a Convolutional Neural Network	The algorithm is going with 500 iterations and learning rate of 0.004.

The weed images used for training and testing were taken with the mobile camera (16 Mega Pixel) and DSLR (24 Mega Pixel). The total number of images taken were 555 images with different exposure, brightness and saturation. The images are small, clearly labelled and have no noise which makes the dataset ideal for this task with considerably much less pre-processing. These were then cropped to 800 X 450 and 800 X 534 pixels. All the images were labelled for weed and plant characteristics. The more weed images the computer

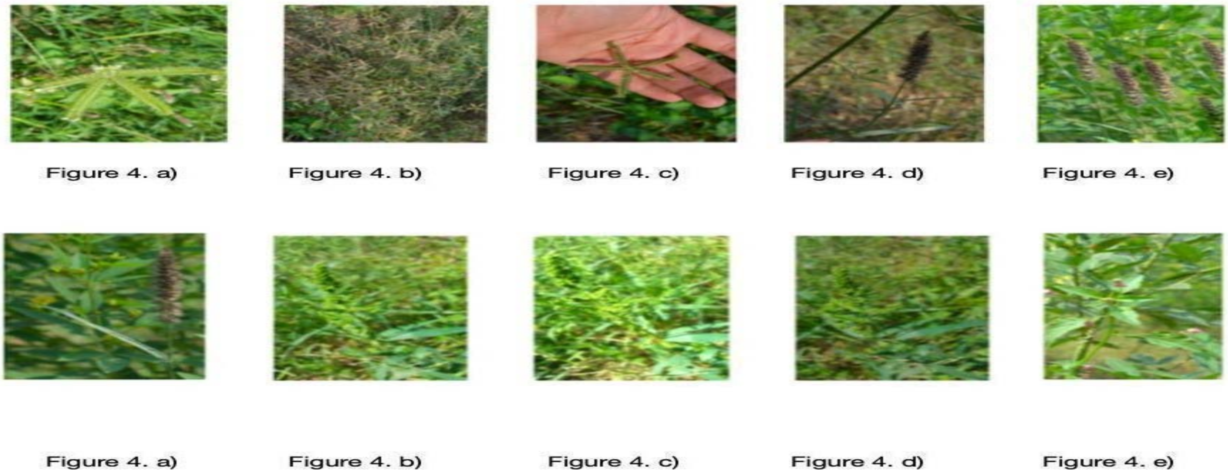

Figure4: Test data under varied conditions

sees, the better it gets in recognizing weed. The task labeling the images was carried out Labeling software (graphical image annotation tool), the computer will start recognizing patterns present in weed pictures that are absent from other ones and will start building its own cognition. Due to unavailability of enough computational power, fortraining, called the 'Train Dataset', 50 images were used. The other dataset, called the 'Test Dataset', comprised 10 images. The key presumption in transfer learning was that the cropped weed images would improve model predictability to correctly identify a weed in the dataset. Figure 4 depicts the test data under varied conditions like under the influence of various hues. Table 3 shows the description of data as highlighted in figure 4.

Table 3: Description of data in figure 4

Figure Number	Description
4a, 4b, 4c	Dactyloctenium aegyptium
4d,4e, 4f	Phalaris minor
4g, 4h, 4i	Echinochloa colona

3. RESULTS:

The experiment was carried out on a well-conditioned dataset for validation and test for any immanent bias in the datasets. Experiments were conducted for a range of training-testing data splits. When the model is setup for training, 30% of the dataset was reserved to authenticate training steps, Therefore the dataset was divided into varying training and test dataset groupings. The training and test were divided in the ratio of 10:80 where 10% of dataset for testing and 80% for training and furthermore 10% dataset is reserved for cross-validation of the weeds to be detected. After training, testing was done 10 unknown images were taken to detect weed in them which were not in the datasets in training. The transfer learning approach was able to detect weed with accuracy of 98%. The imprecise predictions look pretty close to what the computer thought it is. Figure 5 shows the overall accuracies for the model. The performance of transfer learning model was excellent as it was able to detect weeds, even with different backgrounds in the images such as hand, soil and also with varied environment conditions such as morning time, noon time and evening time. Figure 5 is showing a snapshot of the various results obtained for weed detection for the concerned test data.

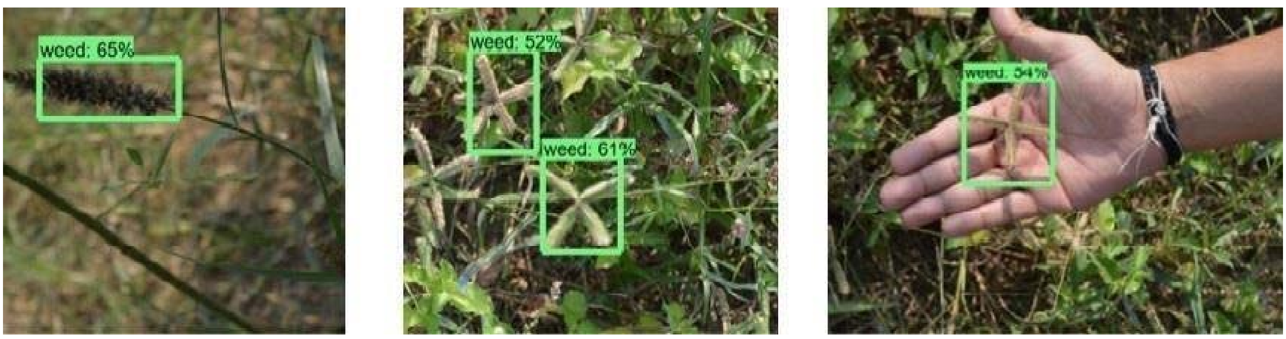

Figure 5: Results for test data

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4. CONCLUSION

The Inception model (V2) used in transfer learning helps us reduce time and effective in detecting of weeds in crops. This technique helps us eliminates the difficult part and time-consuming of feature extraction from images in order to train models. Transfer learning uses pretrained models which does not require a lot of data to train and also boost the performance of neural networks. The future provision can be added as the model which is trained for detecting weeds can also be trained for detecting Diseases, Nutrients and water requirement deficiency in plants through the use of deep learning (transfer learning) neural networks. We also want to add a robotic arm in the Drone which can be used to destroy weeds and disease through the use of different chemical use to destroy or kill other organisms.

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