CNN Based automated weed removal Bot using Raspberry Pi 3

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Abstract: **The paper presents a fully convolutional neural network model for semantic pixel-wise segmentation. In this paper, we propose a crop-weed classification system for potato which is row vegetation the model incorporates spatial information by considering image sequences. Exploiting the crop arrangement information that is observed from the image sequences enables our system to robustly estimate into crop and weed, i.e., a semantic segmentation. After classifying the contours in the captured image by the robot, the robotic cutter removes the weed. We provide a thorough experimental evaluation, which shows that our system generalizes well to previously unseen fields under varying environmental conditions such as variation in light and alignment a key capability to actually use such systems in precision farming. We provide a robust system that classifies best compared to the already existing systems which focus on image processing and supervised learning algorithms. The location of the weed is found through image processing and then weed cutter reaches the desired coordinate and defoliate the unwanted plant.**

Index Terms—Deep Learning, Fully convolutional neural network, Robots, semantic segmentation, contours, Coordinate Mapping, supervised learning algorithm.

I. INTRODUCTION

The main goal of sustainable agriculture is to minimize the use of herbicides and to increase the yield, weed removing can be automated by avoiding the use of herbicides and these days agriculture is lacking in manual labor as well to overcome these problem robots can be used, Robots that can perform targeted weed control offers the potential to contribute towards this issue, for example, through specialized weeding actions such as mechanical weed removal. With evolving technology in robotics and artificial intelligence, these problems can be overcome. A prerequisite of such robotic systems is a reliable and robust plant classification system that is able to distinguish crop and weed in the field. The key objective is to reduce the reliance on agrochemicals such as herbicides due to its side-effects on the environment, biodiversity, and partially human health. The removal of weed is traditionally done by manual labor and agrochemicals. These methods increase the crop production cost and not sustainable as well. The paper focuses on the reduction of human labor and various agrochemicals that are used for weed reduction which can lead to sustainable agrarian culture.

In this work, we are focusing on overcoming performance loss due to changes in input image due to environmental factors, to achieve this we are exploiting geometric patterns of the vegetation, Within a field of row crops (such as potato, tomato, sugar beet, carrot, turmeric, etc.), the plants share a similar distance along the row, whereas weeds appear more randomly. In contrast to the visual cues, the outcome is much less affected by changes in visual appearance. Thus, we propose an approach to exploit this information as an additional value by analyzing image sequences that cover a local area of the field surface in order to improve the classification performance. Key features of our approach, it generalizes well to data acquired from unknown fields and robustly classifies crops at different growth stages without the need for retraining the model, our approach also able to extract features about the spatial arrangement of the plantation from image sequences and can exploit this information to detect crops and weeds individually based on geometric patterns. These claims are experimentally validated on real-world datasets.

II. PROPOSED SYSTEM

The proposed system generates input images by capturing images through the Rpi-camera module. The input images are later processed using image processing for generating the region of interest images(plants and weeds) i.e. region of interest are cropped, which are iteratively fed to CNN model which is priorly trained for the differentiation and classification of the crops and weed. The model classifies the input in two classes namely plant and weed. The center point of all the classified weed is calculated with the reference original input image. Later the coordinates of the original image are mapped with the original coordinate in the field. The cutter then moves to the corresponding coordinate and defoliate the weed and process is iterated for the whole farm.

Fig 1. Creating a region of interest from the image.

III. HIGH-LEVEL DESIGN

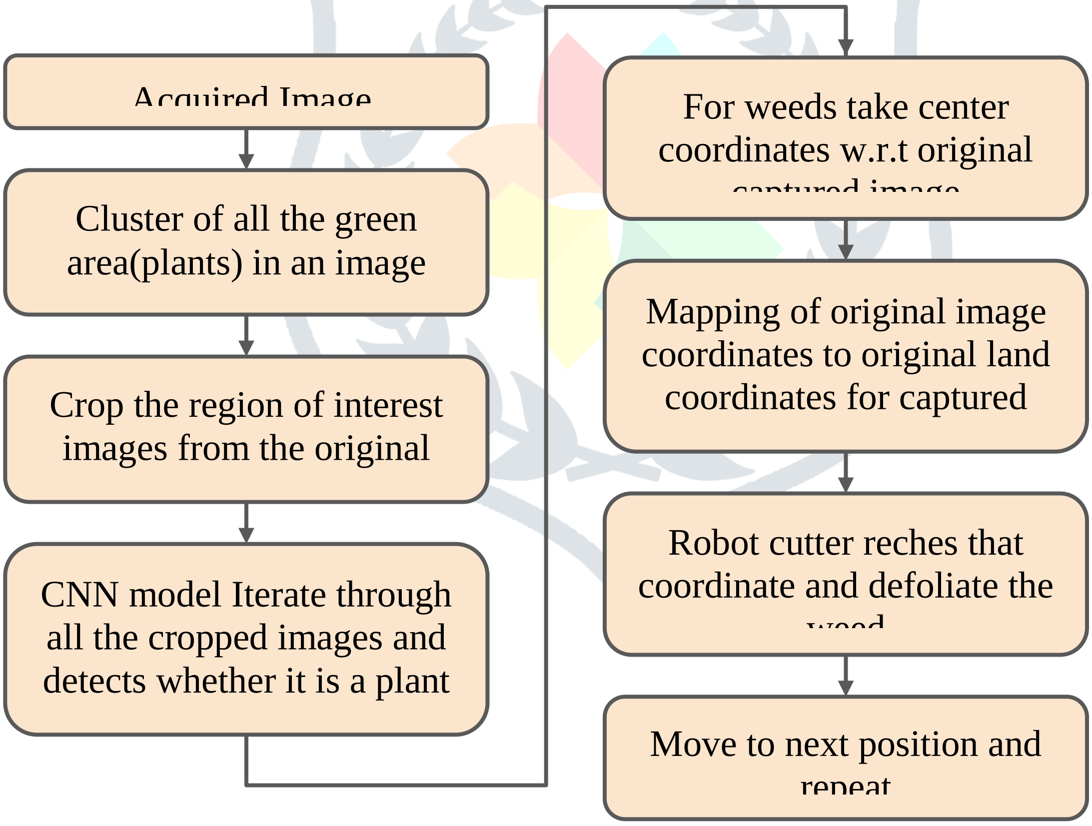

Fig 2. High-Level design for the proposed system

IV. THE ARCHITECTURE OF THE PROPOSED SYSTEM

The proposed bot has 8 wheels, 13 DC motors in which 8 are used for the locomotion, 3 motors for movement of the cutter in X-Y axis movement, 1motor for cutter movement in the Z-axis and 1 is installed as the cutter. Fig 3 shows the block diagram of the proposed system. The CNN is trained on the Raspberry-Pi3 which helps to distinguish the plant from a weed. For running the 13 DC motors two motor drivers L293D are used, one relay is used. Each driver has two I/O pins for running two motors. The Raspberry-Pi3 has 40 pins, GPIO 17 and 27 are connected to the first motor driver for X-axis forward and backward movement, GPIO 22 and 23 are connected to the first motor driver for Y-axis forward and backward movement, GPIO 5 and 6 are connected to the second motor driver for Z-axis up and down movement for the cutter. 1000 rpm motor is used for the X-axis movement, 500 rpm motor is used for the Y-axis movement, 100 rpm motor is used for the Z-axis movement, 500 rpm motor is used for the cutter. The proposed bot runs on the 12v dc power supply.

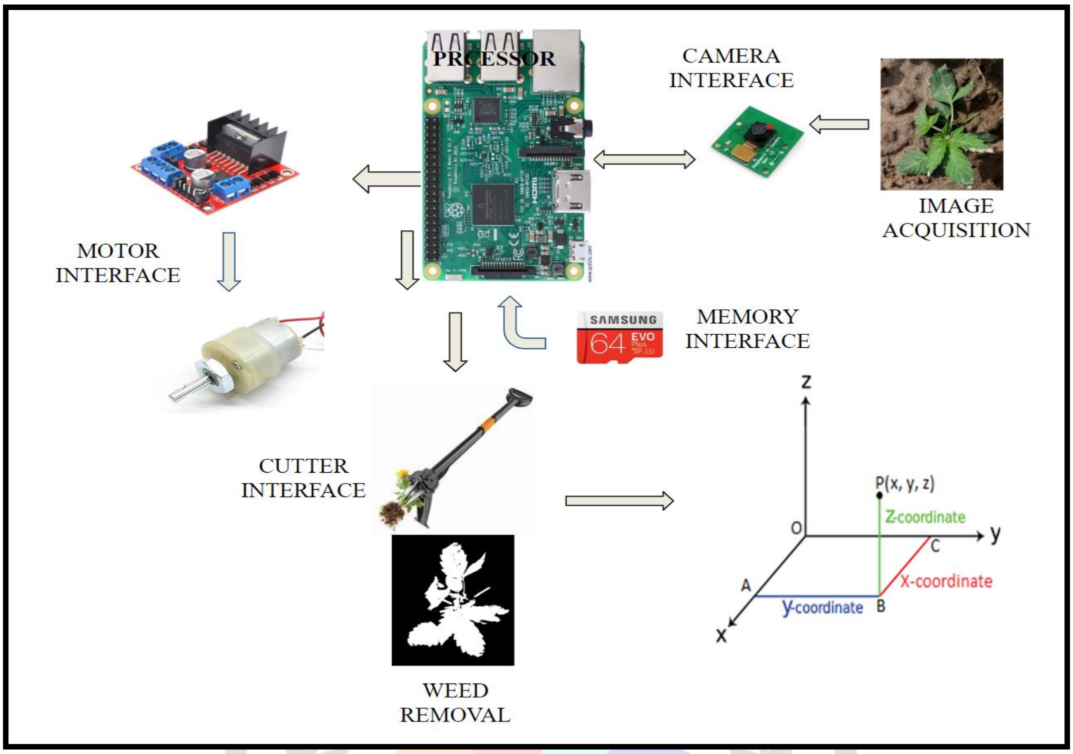

Fig 3. Block Diagram

Fig 4. shows the top view of the image which shows the processor module which controls the bot and, 5 side views of the bot respectively.

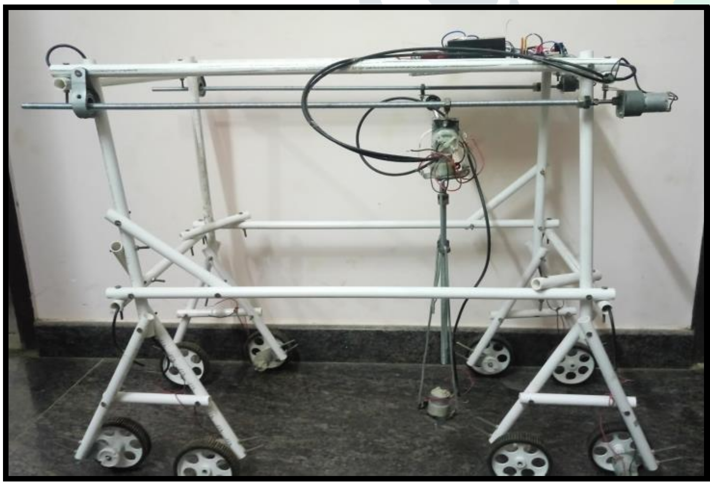

Fig 4. Side view of the robot

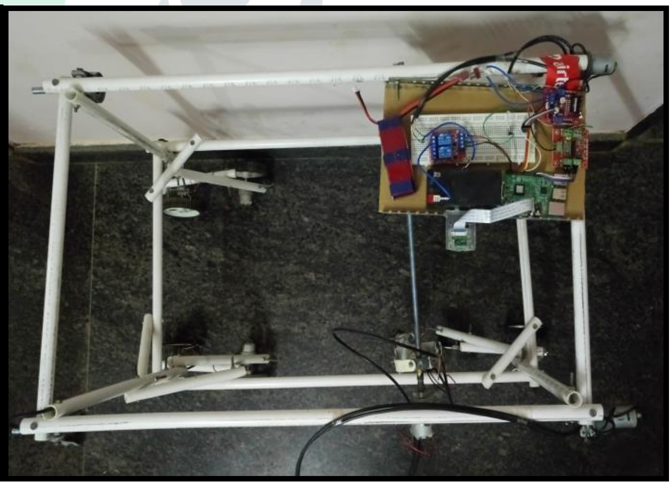

Fig 5. Top view of the robot

V. IMAGE PROCESSING

After the acquisition of image Fig 6. Shows the image acquired using Rpi-Camera. The image is subjected to preprocessing where we are creating the clusters of the vegetation present in image Fig 7. Shows the image having clusters of plants and weeds. Image processing technique like **dilation** is used to create the cluster, dilation is a morphological process. The dilation operator takes two pieces of data as inputs. The first is the image which is to be dilated. The second is a set of coordinate points known as a structuring element. It is this structuring element that determines the precise effect of the dilation on the input image. Fig 8. Shows the cluster contour images of each plant /weed present in an image and are highlighted by green color in. Fig

7. And the finding the contours also provides the spatial coordinates using which the image can be cropped for further classification in the neural network model fig. 9. Shows the cropped images of all plants and images present in the acquired image.

Fig 6. Acquired Image by Rpi-Camera

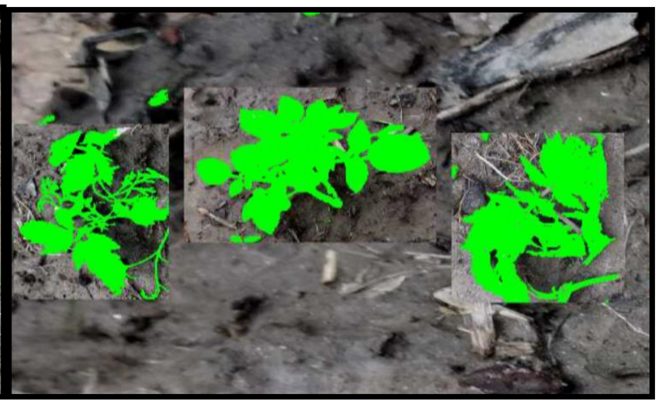

Fig 7. Clusters of Plants and weeds in image

Fig 8. Cluster Contoured images of plants and weeds

Fig 9. Cropped images from cluster contour

VI. CNN Model

The CNN model is trained on the images collected specifically for our model. Fig 10. Shows the flow diagram of CNN Model The CNN is trained on 5000 augmented images. The data is split into a 60 percent training set and a 40 percent test set. The CNN architecture has 8 convolution layer and 4 downsampling layer i.e. MaxPooling Layer and 2 Fully connected layer. The ReLU activation is used in the convolution Layer. The convolution layer extracts the feature map of the input images set of basic convolution and preserves the relationship between pixels by learning image features using filters with ReLU. The convolution calculates the dot product of the input images with filter. Each filter represents a specific feature.

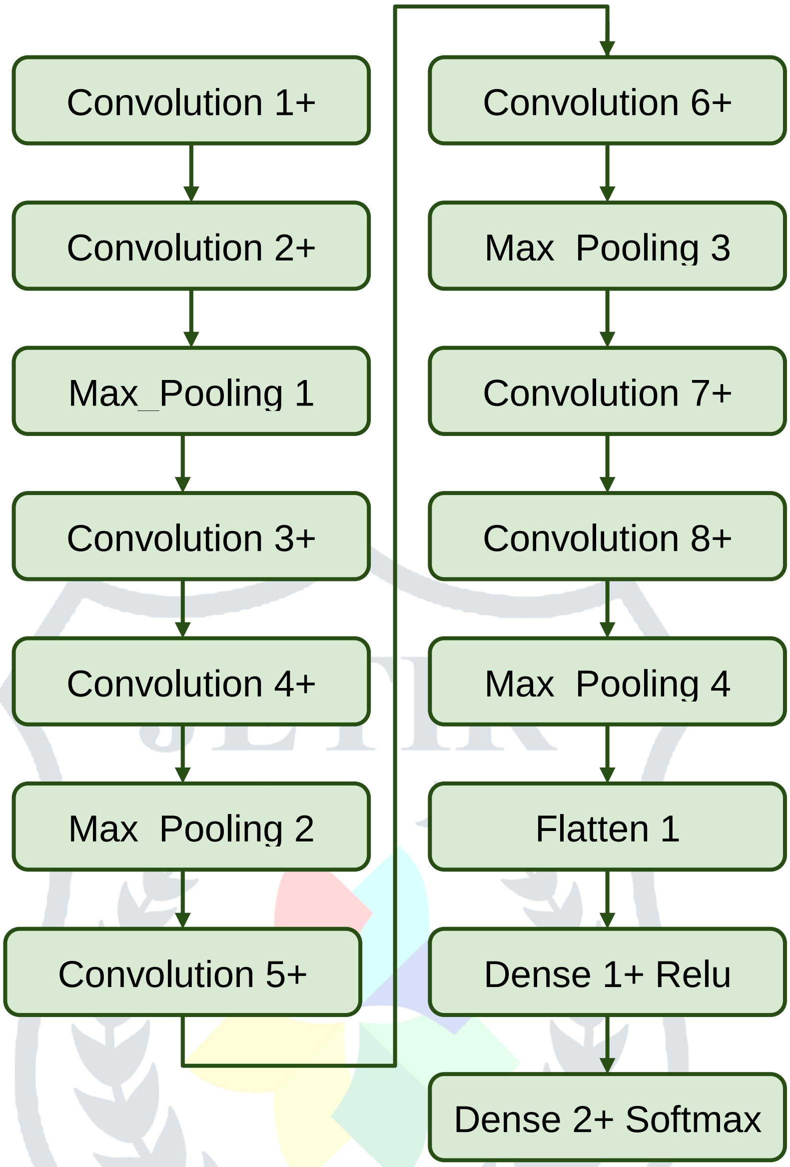

Fig 10. Flow Diagram of CNN Model

The proposed system takes convolved images. The kernel or filter size is 3 x 3. The convolution step takes a stride of 1. The batch the output by the previous layer by subtracting the previous layer means and dividing by batch standard deviation which increases the stability [6]. Then the output is passed on to the downsampling layer or Max Pooling layer. The purpose of Pooling Layers to reduce spatial invariance by reducing the resolution of the feature maps [7]. Relu activation function is used to introduce non-linearity in the network. The output of these layers are fed to the full connected layer is aggregated. Here we are making the network fully connected by using the Dense function it also performs classification on the features extracted byte convolutional layers.

The convolutional layer has multiple of 32,3*3 filters with ReLU activation function. And batch normalization. Max pooling layer with 2*2 pool size with strides 2 likewise in every next layer for, we have taken multiples of 32 as a number of filters and strides size remains constant and flatten layer flattens the feature map and feeds to the fully connected dense layer. Adam optimization is used to optimize the network.

VII. CONCLUSION

In this work, we have focused on reducing the herbicides and reduction in manual power in the field of agriculture by automizing the weed removing process, our robot removes weed automatically on the farm. As here we have worked on a potato farm specifically. The automized robot exploits the geometrical arrangement of the crop captures the image processes the raw image and uses the CNN model to classify between weed and crop on the processed images. Here we can increase the variety of datasets with a high-end processor.

VIII. ACKNOWLEDGMENT

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IX. REFERENCES

[1] Abhishek Patnaik, R.Narayanamoorthi "Weed Removal in Cultivated Field by Autonomous Robot using LABVIEW", IEEE Sponsored 2nd International Conference on Innovations in Information Embedded and Communication Systems ICIIECS'15, 2015.

[2] Philipp Lottes, Jens Behley, Andres Milioto, and Cyrill Stachniss "Fully Convolutional Networks with Sequential Information for Robust Crop and Weed Detection in Precision Farming" IEEE ROBOTICS AND AUTOMATION LETTERS, 2018.

[3] BIN LIU, Wencang ZHAO and Qiaoqiao SUN "Study Of Object Detection Based On Faster R-CNN" IEEE, 2017.

[4] T.Hague, J.A.Merchant, N.D. Tillet. "Ground-based sensing systems for autonomous agricultural vehicles", Computer and Electronics in Agriculture. 25 (2000), pp.II-28.

[5] Gehan MA, Fahlgren N, Abbasi A, Berry JC, Callen ST, Chavez L, Doust AN, Feldman MJ, Gilbert KB, Hodge JG, Hoyer JS, Lin A, Liu S, Lizárraga C, Lorence A, Miller M, Platon E, Tessman M, Sax T.2017. PlantCV v2.0: Image analysis software for high-throughput plant phenotyping, https://doi.org/10.7287/peerj.preprints.3225v1.

[6] Sergey Ioffe, Christian Szegedy Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift arXiv.org, 2015.

[7] Dominik Scherer, Andreas Muller, and Sven Behnke Evaluation of Pooling Operations in Convolutional Architectures for Object Recognition, University of Bonn, Institute of Computer Science VI.

[8] Adeel Arif, Khurram Mahmood Butt "Computer Vision based Navigation module for sustainable Broad -Acre Agriculture Robots" Sci. int(Lahore) 26(5), 20382088.2014 ISSN 1013-5316; CODEN: SINTE 8.

[9] D.C. Slaughter, D.K Giles, D. Downey, "Autonomous robotic weed control system: A Review", Computer and Electronics in Agriculture 6 1(2008), pp.63-78.