

# Weeds Detection in Agricultural Fields using Convolutional Neural Network



Hea Choon Ngo, Umami Raba'ah Hashim, Yong Wee Sek, Yogan Jaya Kumar, Wan Sing Ke

**Abstract:** Weeds are very annoying for farmers and also not very good for the crops. Its existence might damage the growth of the crops. Therefore, weed control is very important for farmers. Farmers need to ensure their agricultural fields are free from weeds for at least once a week, whether they need to spray weeds herbicides to their plantation or remove it using tools or manually. The aim of this research is to build an automated weed control robot using the Lego Mindstorm EV3 which connected to a computer. The robot consists of motors, servo motors and a camera which we use to capture the image of the crops and weeds. An automated image classification system has been designed to differentiate between weeds and crops. The robot will spray the weed herbicides directly to the area that have been detected weeds near or at it. For the image classification method, we employ the convolutional neural network algorithm to process the image of the object. Therefore, by the use of technology especially in artificial intelligence, farmers can reduce the amount of workload and workforce they need to monitor their plantation. In addition, this technology also can improve the quality of the crops.

**Keywords:** automated weed control robot, image classification, convolutional neural network, artificial intelligence.

## I. INTRODUCTION

Weeds are an all too common occurrence in lawns and gardens. While some may be deemed useful or attractive, most types of weeds are considered a nuisance. Learning more about weed control and detection can make it easier for gardeners to decide whether these weeds should be welcomed or if they must go. Let's take a look at some common weed plants and when or what weed control methods may be necessary. By definition, a weed is known as "a plant in the wrong place." For the most part, these plants are known more for their undesirable qualities rather than for their good ones, should there be any [1]. Weeds are competitive, fighting your garden plants or lawn grass for water, light, nutrients and space. Most are quick growers and will take over many of the areas in which you find them.

Manuscript published on 30 September 2019.

\*Correspondence Author(s)

**Hea Choon Ngo**, faculty member of the Faculty of Information and Communication Technology of the Universiti Teknikal Malaysia Melaka (UTeM).

**Umami Raba'ah Hashim**, Faculty of Information and Communication Technology of the Universiti Teknikal Malaysia Melaka (UTeM).

**Yong Wee Sek**, Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka (UTeM)

**Yogan Jaya Kumar**, Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka (UTeM).

**Wan Sing Ke**, Faculty of Information and Communication Technology, and she will be graduating with a bachelor degree of Computer Science (Artificial Intelligence) in 2020

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an [open access](https://creativecommons.org/licenses/by-nc-nd/4.0/) article under the CC-BY-NC-ND license <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

While most types of weeds thrive in favorable conditions, native types may be found growing nearly anywhere the ground has been disturbed. In fact, they may even offer clues to your current soil conditions [2]. This is a very big problem to the farmer because the weed plant consumes a large amount of nutrition and water so that the other plant cannot grow in a good shape [3]. Weed plant can be seen more in a plantation because in the plantation have all nutrition and water for the weed to grow. Weed is a major component in mustard plant production system [4]. The composition of weeds is a mixture of grasses, sedges and broadleaves which often change according to the crop growth stages which provide specific climatic and environmental condition suitable for specific weed growth [5]. The shade provided by the mustard canopy influence the nature of weeds composition, and grass species tend to dominate as the mustard plant get bigger is difficult [6] because of their long economic life but they affect the growth of crops or cause yield losses [7]. Weeds in plantation are managed using several methods such as cultural, mechanical, integrated production system using livestock to control the weeds, or chemical (herbicides). Weed management with the use of chemical herbicides is the most common practice in mustard plant plantations at some stages of crop development [8]. The robot that has been designed and developed is weeds control robot. This robot system can effectively improve the efficiency in controlling the weeds without using a lot of workforce in finding the weeds manually and spray the herbicides. The ability of weeds control robot is it will able to detect the weeds within the crop and then perform a spray of chemical (herbicides) [9][10]. For the weed detection algorithm, the convolutional neural network is suitable for this project because CNN are most commonly applied to analyzing visual image. CNN use variation of multilayer perceptron's designed to use minimal preprocessing [11]. Convolutional network work like human brain that connectivity pattern between neurons resemble the organization of animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field.

## II. METHODOLOGY

### A. Method of Data Collection

In this project, we attempt to build a classifier that can identify the weed based on the module we built. The data collection is the primary data which we take data manually by our self.



# Weeds Detection in Agricultural Fields using Convolutional Neural Network

The data collected has been checked one by one before taking it as input data. There are 2 classes named as crop and crop weed which will be classified and each of the class contains 123 images. From the 80% of images used for training and 20% of images used for validation and testing.

Hence there are 99 images for training and 24 images for testing. All of the images are RGB and in jpg format. Figure 1-4 show the images that we used for both training and testing purposes.

## Crop:



Fig. 1: Three random input images (crop images)

## Crop Weed:



Fig. 2: Three random input images (crop and weed images)

## Test Data:



Fig. 3: Three random input images for testing purpose

## Noisy Data:

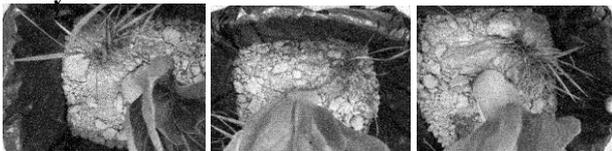


Fig. 4: Noisy data that used for prediction purpose

## B. Image pre-processing using data augmentation

Data augmentation is a method by which you can virtually increase the number of samples in your dataset using data you already have [12]. For image augmentation, it can be achieved by performing geometric transformations, changes to color, brightness, contrast or by adding some noise. In order to let our model adapt to a different situation that might occur noisy data such as when raining season. We decide to have data augmentation such as Figure 5 shows below as our image pre-processing method. We used the noisy data in Figure 4 that have been generated during this process for training and testing purpose.

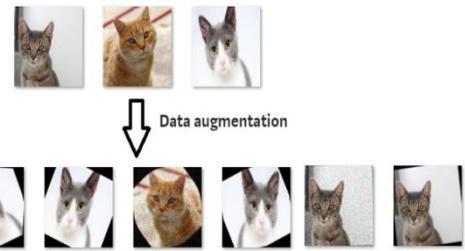


Fig. 5: The example dataset been produced after data augmentation process [12]

## C. Convolutional Neural Network

Convolutional neural networks have a different architecture than regular neural networks. Regular neural networks transform an input by putting it through a series of hidden layers. Every layer is made up of a set of neurons, where each layer is fully connected to all neurons in the layer before. Finally, there is a last fully-connected layer, the output layer that represent the predictions.

Convolutional neural networks are a bit different. Layers are organized into 3 dimensions: width, height and depth. Furthermore, the neurons in one layer do not connect to all the neurons in the next layer but only to a small region of it. Lastly, the final output will be reduced to a single vector of probability scores, organized along the depth dimension.

Figure 6 shows the parameter number that has been used for each layer in the CNN model. There is the total number of 16, 390, 691 of the parameters that we used for our CNN model.

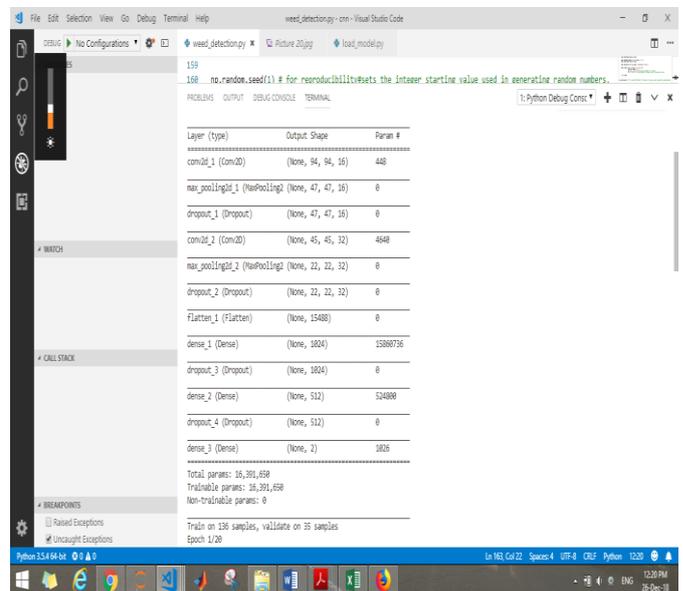


Fig. 6: Specific information about parameters of CNN

## D. Network Architecture

The model architecture consists of one image input layer, two 2-D convolutional layers, four rectified linear unit (ReLU) layers, two 2-D max pooling layers, four dropout layers, one flatten layer, three fully connected layers, one softmax layer, one final output layer.

The sequence of layers of the model architecture is shown in Figure 7. The input for image input layer is the input images with size 100dm \* 100dm RGB. The first and second convolutional 2D layers (2<sup>nd</sup> layer and 6<sup>th</sup> layers respectively) take in the inputs of filter sizes as [3 3] and the number of filters for both the layers are 32. The third, seventh, twelfth and fifteenth layer is the ReLU layer which is used to improve the network by speeding up the training process. Maxpooling 2D layer is the fourth and eighth layer in the network architecture which perform down-sampling with a pooling size of 3\*3.

The input for this layer is nothing but the output produced by the second ReLU layer. Dropout layer is the fifth layer which dropout random set of activation [13] in a particular layer and setting them to 0. The input hyperparameters remain the same for all max pooling 2d layers in the network. The flatten layer is to convert the 3D image to 1D images so that inputs can be used in the fully connected layer. The first fully connected layers with 256 neurons and on another final fully connected layer with 2 neurons were used in the final layers to flatten the incoming data and for classifying the input images into 2 classes.

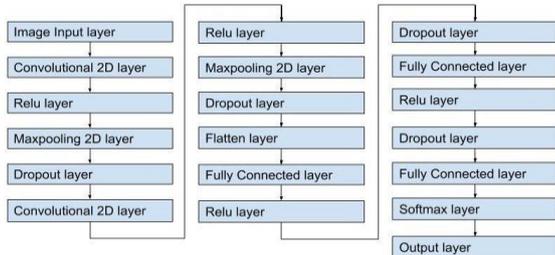


Fig. 7: Sequence of different layers in Convolutional Neural Network that was used for predictions [10]

E. Convolutional neural network algorithm in robot

Table 1: The comparison result among different image classification method in term of run time and accuracy

Image Classifier	First running time(sec)	Following running time(sec)	Accuracy (%)
K-nearest neighbours	2	2	64.29
Backpropagation Neural Network	2	2	64.29
Support Vector Machine (Max iteration=100)	3	3	42.86
CNN (original image)(Epoch=20)	101	5	95.45
CNN (with data augmentation)(Epoch=20)	117	5	90.01

In Table 1, in term of accuracy only the convolutional neural network CNN model being accepted since the other algorithm have significantly lower accuracy that is not suitable for apply in weed detection. In term of running time for both CNN model gets the quite similar run time for the first run and the subsequent run but in term of accuracy rate there is 5% more accuracy for original CNN algorithm compared to CNN algorithm with data augmentation. Further analysis in testing phase need to be considered in order to choose which is the best model for weed detection and control.

F. Structure Chart of Proposed Robotic Application

Figure 8 shows the structure chart of the current proposed application.

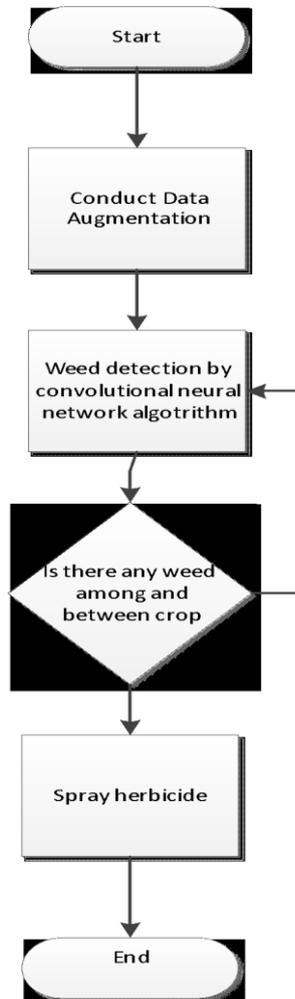


Fig. 8: Structure chart of the current proposed application

CNN model simply simulates how the human brain works. The proposed weed control robot has better image classification result, since they can adapt and learn a variety of weed and crop. The noisy data can be solved in implementing data augmentation for a model to learn the noisy data in the first place.

III. RESULT

A. Result in convolutional neural network algorithm

After nearly 2-minute training for each model, the final two models were generated. One model was trained directly based on original images, while the other one was created using image data produced by data augmentation. Model history was used to record the training process. From Figure 9 and Figure 10, which displays the accuracy on the training set and testing set, it is described that the accuracy for the training set is having differences with 5% by with and without data augmentation.

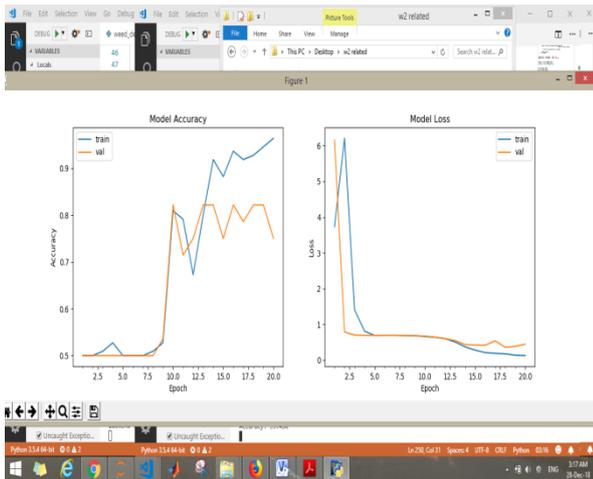


# Weeds Detection in Agricultural Fields using Convolutional Neural Network

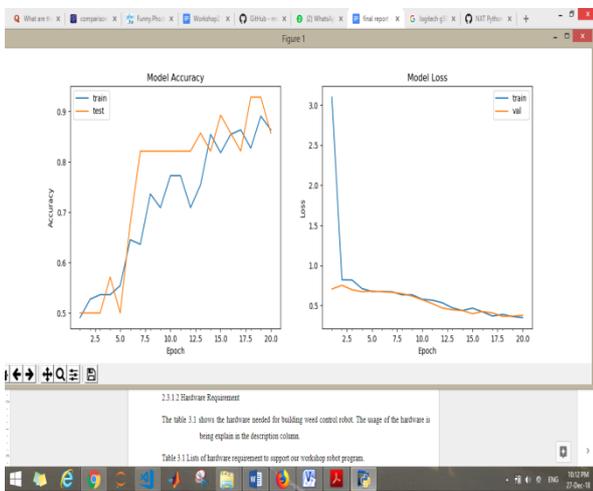
Besides, the performance of the model without data augmentation having lower accuracy on the validation set, while the model with data augmentation has a higher result in the testing set.

**Table 2: The final score for training set and test set**

Image Classifier	Train Accuracy (%)	Test Accuracy (%)
Convolutional Neural Network(original image)(Epoch=20)	90.01	85.5
Convolutional Neural Network(with data augmentation)(Epoch=20)	95.45	70.5



**Fig. 9: CNN model without data augmentation**



**Fig. 10: CNN (with data augmentation) model accuracy result**

## IV. DISCUSSION

### A. Robot advantages and commercial value

This robot provides a lot of advantage hence make it suitable to be used in the agricultural industrial field. Firstly, the robot having weed detect function in order to eliminate weed efficiently. Second, the autonomous function of the robot in weed control can also reduce the need for the workforce. The weed control robot can be beneficial to agriculture since it helps save cost, time and manpower which help the agriculture in industrial fully operate in optimal condition and in more sustainable ways.

### B. Robot weakness

Every advantage has its disadvantage. This is several advantages that the robot consists of. The instability of the dc motor rotation causing it cannot stop at a certain time constant. Since position to stop is wrong when it detects the plant which caused by not capturing pictures in the plantation area, the wrong position of plantation image has been taken and causing the bad image classification result. The limitation of the dc motor also causing the robot cannot turn 180 degrees perfectly causing it cannot have the right direction to crossing the plantation and hence we decide to have forward direction only. Limit of battery power which let the robot cannot run in a long time. Limit of the capacity of herbicide also cannot eliminate the weed in long run. The unspecific direction of spraying herbicide causing the harmful effect in the crop. Lastly, the process takes a long time from making image capturing, weed detection and automation spray will take 4 minutes for each plantation.

### C. Suggestions for robot improvement

The robot improvement can be having the more quality of the dc motor to ensure the constant movement. The direction of spray herbicide can be more specific in order not to have a harmful effect on another crop and using less amount of herbicide. The larger dataset can be obtained to increase the accuracy of the convolutional neural network algorithm, but the larger dataset of the image needs a more powerful processor to conduct hence the central processing unit can be considered to update to the graphics processing unit in order to have faster weed detection process. The simultaneous localization and mapping can be used to let the robot navigate autonomously in the agricultural area. The battery-powered robot can consider a change to the solar-powered robot in order to make it run for a much longer hour. The robot needs to have a larger capacity of herbicide in order to cover all area that needs herbicide.

## V. CONCLUSION

The robot that has been developed provides a lot of benefit to the user according to the place where it was needed and required. It has a high commercial potential. But the robot still needs to be improvised so it can fulfill the requirement in industries. The main factor that can affect the efficiency of the robot is the quality of software and hardware.

## ACKNOWLEDGEMENT

This research work supported by Universiti Teknikal Malaysia Melaka (UTeM) under UTeM Short Term Research Grant (PJP/2018/FTMK(3B)/S01630).

## REFERENCES

1. P.Sakthi, P.Yuvarani(2018),Detection and Removal of Weed between Crops in Agricultural Field using Image Processing, 5(1), pp. 1-13.
2. P.Sakthi, P.Yuvarani (2018). Detection and Removal of Weed between Crops in Agricultural Field using Image Processing.Electronics and Instrumentation Engineering, 118(8), 201-206.
3. Tobal, A. and Mokhtar, S. (2014). Weeds identification using evolutionary artificial Intelligence algorithm. Journal of Computer Science,10(8),pp.1355-1361.



4. Tilley, N. (2019). What Is A Weed: Weed Info And Control Methods In The Garden. Available at: <https://www.gardeningknowhow.com/plant-problems/weeds/what-is-a-weed.htm>. [Accessed on 26 July 2019].
5. Guerrero, J., Guijarro, M., Montalvo, M., Romeo, J., Emmi, L., Ribeiro, A., & Pajares, G. (2013). Automatic expert system based on images for accuracy crop row detection in maize fields. *Expert Systems With Applications*, 40(2), 656-664.
6. M.Dian. Bah , Adel Hafiane , Raphaël Canals. (2018). Deep Learning with unsupervised data labeling for weeds detection on UAV images. *Conference Paper, IEEE Computing Conference 2018*.
7. Blasco, J., Aleixos, N., Roger, J., Rabatel, G., & Moltó, E. (2002). AE—Automation and Emerging Technologies. *Biosystems Engineering*, 83(2), 149-157.
8. Burgos-Artizzu, X., Ribeiro, A., Guijarro, M., & Pajares, G. (2011). Real-time image processing for crop/weed discrimination in maize fields. *Computers And Electronics In Agriculture*, 75(2), 337-346.
9. Petre Lameski. (2017). *Plant Species Recognition Based on Machine Learning and Image Processing*. Thesis.
10. Junfeng, G., David, N., Peter, L., Yong, H. (2018). Recognizing weeds in a maize crop using random forest machine-learning algorithm and near-infrared snapshot mosaic hyperspectral imagery, 12(2), pp. 23-26.
11. K.Kantipudi , C.Lai , C.Hong. Min , Ron C. Chiang (2018). Weed Detection among Crops by Convolutional Neural Networks with Sliding Windows. *Conference Paper*.
12. Thomas Himblot (2018). Data Augmentation: boost your image data with few lines of Python. Available at: <https://medium.com/@thimblot/data-augmentation-boost-your-image-dataset-with-few-lines-of-python-155c2dc1baec>. [Accessed on 26 July 2019]
13. Ana I. de Castro, Jorge Torres-Sanchez, Jose M. Pena, Francisco M. Jimenez-Benes, Ovidu Csillik and Francisca Lopez-Granados (2018). An Automatic Random Forest-OBIA Algorithm for Early Weed Mapping between and within Crop Rows Using UAV Imagery, 21(17), pp. 25-29.

research, information systems, web based and multimedia learning and mathematics. He is currently a member of the Computational Intelligence and Technologies Lab under the Centre for Advanced Computing Technology, UTeM.



**Yogan Jaya Kumar** is a senior lecturer at the Department of Intelligent Computing and Analytics, Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka (UTeM). He earned both his Bachelor degree and Master degree from Universiti Sains Malaysia (USM), in the field of Mathematical Science in year 2003 and 2005. He joined the Centre for Affiliate & Diploma Programme, MMU as assistant lecturer in 2006. He was then offered a lecturer position at UTeM in 2008. He went on to complete his PhD studies at Universiti Teknologi Malaysia (UTM), in 2014 in the field of Computer Science under the supervision of Professor Dr. Naomie Salim. Currently, his research involves in the field of text Mining, information extraction and AI applications.



**Wan Sing Ke** was born in Terengganu, Malaysia in 1996. She is a third year student from the Universiti Teknikal Malaysia Melaka (UTeM) and member of the Faculty of Information and Communication Technology, and she will be graduating with a bachelor degree of Computer Science (Artificial Intelligence) in 2020. She has been graduated from the High School (science stream) at SMK Chung Hwa Wei Sin, Terengganu. She is actively involved in competition-based projects at the university level and been awarded second place in the data science competition. Her research interests include AI applications, intelligent agents, image processing and machine learning.

## AUTHORS PROFILE



**Hea Choon Ngo** received his Bachelor's degree in Computer Science (Software Development) from the Universiti Teknikal Malaysia Melaka (UTeM) in 2004, a Master's degree in Information Technology from University of New South Wales (UNSW, Sydney) in 2007 and a PhD in Computer Science from Universiti Sains Malaysia (USM) in 2016. His research interests involve computational

intelligence, data science and analytics, planning and scheduling, optimization, health informatics and intelligent systems. He is currently a faculty member of the Faculty of Information and Communication Technology of the Universiti Teknikal Malaysia Melaka (UTeM). He is also a member of the Computational Intelligence and Technologies Lab under the Centre for Advanced Computing Technology, UTeM.



**Umami Raba'ah Hashim** received her Bachelor's degree in Computer Science from the Universiti Teknologi Malaysia (UTM) in 2000, a Master's degree in Multimedia (E-Learning Technologies) from Multimedia University, Malaysia in 2008 and a PhD in Computer Science from UTM in 2015. Her PhD work focused on detection of defect on timber images using pattern recognition technique.

Her current research interests include pattern recognition, machine vision, machine learning and deep learning. She is currently a faculty member of the Faculty of Information and Communication Technology of the Universiti Teknikal Malaysia Melaka (UTeM). She is also a member of the Computational Intelligence and Technologies Lab under the Centre for Advanced Computing Technology, UTeM.



**Yong Wee Sek** is a senior lecturer at the Department of Intelligent Computing and Analytics, Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka (UTeM). He completed his PhD in Business Information System in 2017 from RMIT University Melbourne, Australia. He received his Bachelor degree of Statistics at the Universiti Kebangsaan

Malaysia (UKM) and Master degree in Information Technology at the Universiti Putra Malaysia (UPM). His research interests involve operation