B.Sc Project Proposal

PlantOpt: A Framework for Maximizing Crop Yield Using Deep Learning

Submitted by:

Mahmudul Hassan Nashim (AE-092-010)
Mohammad Abul Hasnat(AE-092-022)
Department of Robotics & Mechatronics Engineering
University of Dhaka

Supervised by:

Md. Shifat-E-Arman Bhuiyan
Lecturer, Department of Robotics & Mechatronics Engineering
University of Dhaka
Email: shifatearman@du.ac.bd

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Introduction

The world food production needs to be increased by 70% by 2050 compared to 2010 level to feed the growing population of the world which will become roughly 9.2 billion [1] [2]. But the food production will face many challenges in the coming decades like scarcity of water [3], climate change [4] etc. Food production has to be increased without negatively impacting the environment. For example, carbon emission can not be increased, soil quality cannot be reduced, water supply cannot be depleted and the use of pesticide has to be limited.

In the conventional approach of farming - fertilizer, pesticide, water and nutrients are equally in all parts of the field. This is wasteful and expensive as all parts of the field do not require these in equal proportion. In this challenging era of climate change precision agriculture can be a good solution. Keeping in mind about green revolution, precision agriculture can play a major role in modern agriculture. precision agriculture is a major component of the third wave of modern agricultural revolutions.

Plant population density is the number of plant stands per unit area. In agriculture plant density is a very important part which directly affects the potential deep crop yield. Plant density is deeply related to seedlings. Without healthy and vigorous seedlings proper plant density and potential crop yield cannot be achieved. Plant density should be at a rate where maximum crop yield can be achieved. It should not be so high that a plant cannot reach its potential production and also should not be so low that causes the imperfect use of agricultural land. So plant density should be at a optimal rate where overall maximum crop yield can be achieved.

Counting of seedling is one way of estimating plant population density. By seedling counting, estimation of plant density will be easier because it will be counted in very early life of plants. Seedling detection is the basis of seedling counting. Proper distribution of seedling also can be done in this process.

Weeds are another major challenge for achieving maximum crop yield. Weeds are dangerous yield reducer which is a harmful factor both agriculturally and economically. Early detection of weeds can help the whole sector of agriculture from this notorious problem.

The objectives of this project are

- Maximize yield of crop using deep learning.
- Proper use of agricultural land by plant density optimization based on seedling count.
- Minimization of the adverse effect of weeds on plant by identifying weeds at early stage.
- Reducing the cost of agricultural production and maximizing the profit.

The proper incarnation of these operations of plant density optimization and early detection of weeds will create a positive notion in modern and precision agriculture.

Related Work

Seedling has been used for classification purposes for farming automation in order to improve productivity. A publication has introduced a two-class classifier that takes input as plant seedling images with 12 different species and predicts the type of images of plant seedlings by a model using Deep Convolutional Neural Network (DCNN) [5] [6]. For object detection, Faster RCNN (Regional Convolutional Neural Network) [7] has been used to identify objects, which is an extension of RCNN (Regions with CNN). RCNN suggests areas in an image that may contain objects. Therefore, it applies CNN to classify the object and marks the object with a bounding box. RPN (Region Proposal Network) cannot detect objects. It is a part of Faster RCNN. The RPN and CNN work together in the Faster R-CNN algorithm to achieve faster and more accurate object detection. That's why it is one of the most successful object detection algorithm.

Previously, manually calculating the density of the plant was very laborious and inaccurate, although it is a very important factor for the optimal use of croplands. Three researchers worked on it [8] and found better results. They have bought quite better F1 score (0.727 at IOU_{all} and 0.969 at $IOU_{0.5}$) and R^2 (0.98) results.

For the purpose of weed management and robotic weed control, a classification model was developed with the title "DeepWeeds: A Multiclass Weed Species Image Dataset for Deep Learning' [9] where researchers collected image datasets consist of 17509 images in Australian rangelands. In that place, we have a chance to improve the accuracy for the reason of average classification performance (accuracy of Inception-v3 and ResNet-50 CNN models are 95.1% and 95.7% respectively) there.

No framework has been designed so far that combines the two different types of work. So, we will continue to upgrade by focusing on that in our project. Just as it is important to keep the plant density equal throughout the land for the maximum use of the cropland, it is necessary to apply fertilizers and pesticides by detecting the weeds at the early stage to ensure the growth of the plant and proper nutrition. If accuracy can be confirmed, in that case, an overlapping framework will provide overall better performance.

Methodology

Object detection is the primary consideration in both Deepseedling as well as Deepweeds. CNN, DCNN, RCNN, and Faster RCNN algorithms were used in the papers mentioned above to identify any object in any image. There are several other algorithms, for instance, YOLO (You Only Look Once) [10], SSD (Single Shot MultiBox Detector) [11]. YOLO is much faster than Faster RCNN due to being a single neural network and its real-time object detection algorithm and dividing an image into a grid of cells where each cell predicts a number of bounding boxes and class probabilities. But there is a trade off between YOLO and Faster RCNN in the case of speed and accuracy. Until Yolo v3, it produced less accurate results than Faster RCNN.

SSD (Single Shot MultiBox Detector) is also a real-time object detection algorithm, single neural network and is faster than RCNN. Similar to YOLO, it can classify objects in an image and predict their bounding boxes. But the key difference is that, while YOLO uses a single feature map and divides it into a grid of cells, SSD uses multiple feature maps at different scales. SSD uses anchor boxes, predefined bounding boxes, so as to match the aspect ratio and size of the objects in the image.

At the beginning of the project, our purpose will be to collect as much data as possible. The more data a model trains with, the better accurate results are expected from that model. As data, we can capture videos or images. If possible, it will be easier to train the model if we can capture the images using a high-resolution camera.

Then we will divide our dataset into three sections. As we know, in the case of machine learning, datasets are divided into training, testing, and validation datasets. Although there are many algorithms for image analysis, we have to see which model will perform the best for our image set. CNN (Convolutional Neural Network), RCNN, DCNN, Faster RCNN, YOLO, and SSD all have to be learned well to find the suitable algorithm. To train a model, we always need a well-configured PC with a powerful GPU. If not possible, Google Colab's TPU will be used to train the model.

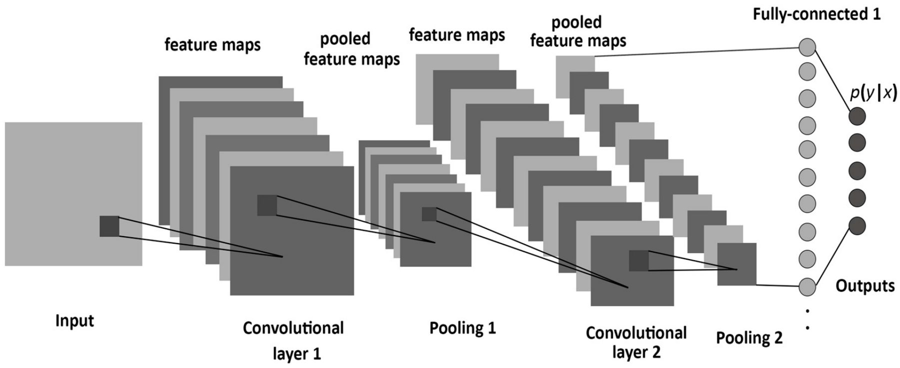

Figure 1: Deep Convolutional Neural Network
[12]

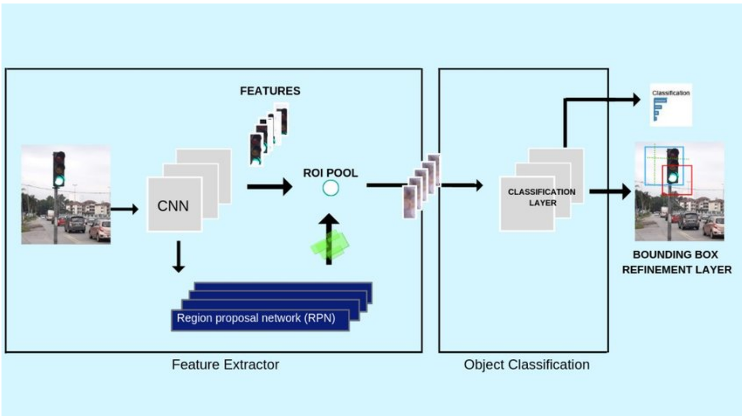

Figure 2: Faster Regional Convolutional Neural Network
[13]

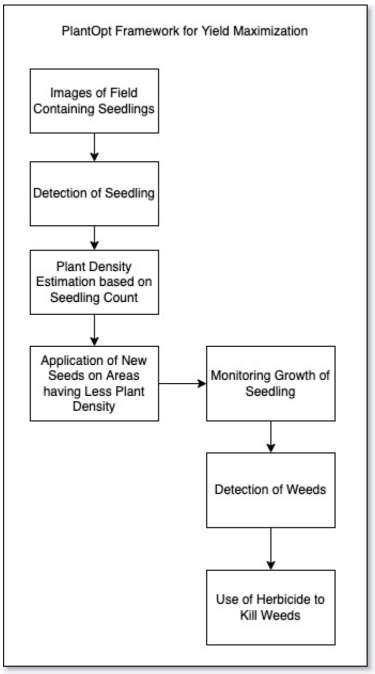

Figure 3: PlantOpt Framework for Yield Maximization

During the training, to observe how the model performs on unseen data, the predictions of the model are first verified on the validation data. Hyperperameters are adjusted slightly based on those predictions. If the training and validation datasets are leveled, it is important to confirm that the test datasets are not. Once the model is learned, it is necessary to test it with test datasets that will actually assess the model.

When our machine learning model is complete, our job will be to work at the field level, determining where the seedlings are taking place. Seedling information will help us to determine the density of the plant in the whole land. Where the seedlings could not grow, the seeds should be sprinkled again. Later, we will have to check if the growth of new seedlings have been completed in those regions. The next task is to ensure proper nutrition. To achieve that, we must reduce the growth of weeds. Hence, we need another model created in the same architecture following the above method that will identify the weeds. The next task will be using pesticides.

Finally, in this project, we would like to develop a framework named PlantOpt that will assist in maximizing crop yield by optimizing density of plant and by detecting weeds early using deep learning.

Conclusion

This project will contribute the whole agriculture sector with advanced technological development. We have a very opmistic view towards this project where our goal is to maximize crop yield by optimizing plant density and indentify the weeds at a very early stage. And we are confidient that through a proper number of sequential operations and processes early discussed in methodology part we will be successful to achieve all objectives and reach our goal.

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