Project Document: Deep learning
Team : Encoders

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Abstract

Deep learning is a rapidly growing field, expanding over variety of sectors. Vision-based machine learning techniques are being used in agriculture as well. In this work we are trying to explore two different deep learning methods which can be used in technical advancement of farming and fruit processing sector. First, we present how deep learning can be useful to detect weeds in crop and second we explore what techniques are being implemented to detect and classify fruit based on their rottenness, and how new methods can be implement to advance the techniques. Furthermore, we have presented two different methods on how weeds can be detected in soybean crops using computer vision techniques. Along with the methods, we have also identified and collected the dataset required for our project.

Chapter 1

Milestone 1: Project Ideas

1.1 Introduction

Agriculture is the life-sustaining element for many people around the globe. But agriculture itself faces numerous challenges in terms of biological, ecological and developmental aspects. People from both developing and developed countries are facing the challenges in their own terms regarding the production and consumption of agriculture commodities. On the other hand, production and consumption of agricultural products needs to be balanced side by side to feed the burgeoning population along with food safety measures. Among the numerous problems encountered so far, encroachment of major crop fields by weeds is the one, causing decline in yield and quality of crop products. Similarly, consumption of healthy and fresh fruits is must for the rapid advancement of human race and to boost immune system. Global agriculture demands more scientific study yet practical solutions to successfully combat the pressing challenges. Therefore, deep learning techniques come in frontier to deal with such challenges with promising results and large potentials with the use of large image datasets for image identification as well as classification approaches. This project deals with two different problems in agriculture world with different approaches of Convolution Neural Networks (CNNs).

1.2 Project Idea 1: Weed detection using Deep Learning

1.2.1 Problem

In the USA, weeds cost about approximately 33 billion USD in crop production annually [8]. Maize is the third most important staple cereal crop after Rice and wheat but yield loss in maize is estimated about 25 percent due to several types of weeds [4]. Additionally, weeds harbor various insects and pests that are very harmful to the main crop. Similarly, in many developing countries hand weeding is being replaced by herbicide use due to labor shortage and in developed countries there is already high dependency on herbicide for weed control. But over reliance on herbicide has resulted in many unique herbicide-resistant weeds which are even more difficult to control. Therefore, the application of deep learning and modeling approaches can be a solution to achieve site -specific and economical weed management for long term in maize crop. Weed management is one of the most important crop production practices. Global increase in herbicide use to control weeds has led to issues such as evolution of herbicide-resistant weeds, off-target herbicide movement, etc. Precision agriculture advocates site-specific herbicide application to achieve precise and right amount of herbicide spray and reduce off-target herbicide movement. Recent advancements in Deep Learning have opened possibilities for adaptive and accurate weed recognition for field based site-specific herbicide applications with traditional and emerging spraying equipment [3].

Due to identical spectral signature of weeds and host plants, spectral features are insufficient to distinguish between the two.

1.2.2 Application

With machine vision system we can leverage upon their easy to modify and implement advantage to develop site specific weed management strategies. A weed map of a specific site can be created. This method can be a huge steppingstone toward autonomous picking of weed and utilization of remote sensing techniques in farming. With the use of proper sensors, this method can further be advanced to in field weed density evaluation and precise positioning of weed. Currently, variety of unmanned aerial vehicles (UAVs) are being used in precision agriculture with limited applicability, with introduction of proper weed detection techniques UAVs scope can be stretch into weed management as well. Another big issue is that farmers are using immense number of herbicides to eradicate the unwanted weed, the herbicides affect the crop itself and might lead to health-related problem on consumer. This vision-based weed detection technique will also be very fruitful to lower the herbicide use.

1.2.3 Approaches

Initially our thoughts were to collect our own dataset, but with suggestion from Dr. Scott We have identified a dataset with 15000 labelled images from internet(). We will identify some object detection algorithm and use the dataset for fine tuning the model. Figure 1.1 shows the workflow of project.

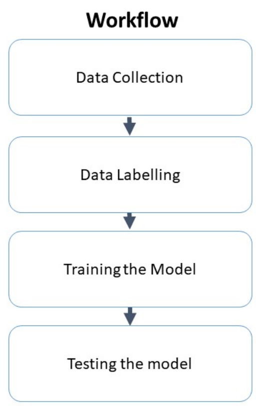


Figure 1.1: Proposed workflow

1.3 Project Idea 2: CNN-based rotten fruit identification

1.3.1 Problem

One of the most important challenge faced by today's fruit harvesters is properly identifying and isolating the rotten fruit from fresh fruit. Failing to remove rotten fruit in early stage of rottenness usually lead to large economic loss as the rottenness is highly infectious. Classifying rotten fruit is fundamental for higher productivity and long life of the fruit. Typically classification of fruit is done manually, and is a laboursome, expensive, and time-consuming task. Human efficiency in doing such types of repetitive tasks is usually very low. There is a need of automatic system which can classify the fruit based on rottenness.

In the past, several techniques have been tried to detect rottenness of the fruit such as X-ray classification, thermal imaging, impedance etc. [7]. These techniques are hazardous to fruit itself as well as to the human performing the test. With introduction of computer vision and deep learning several classification task are being done with trained automatic machine [9]. And use of machine vision to detect rottenness of a fruit could be a harmless and efficient way. In recent time people are starting to use several CNN based technique to classify the rotten fruit [6]. Here in this project we are trying to implement a deep learning model to classify the rotten fruits from the fresh ones.

1.3.2 Application

This deep learning based method of identifying fruit and classifying them into two group based on their rottenness will be very useful to separate the rotten fruit from those are good to use. detecting fruit might not be very useful for harvesters but classifying them into two group based on rottenness will cut off their most expensive and tiresome manual work. This method is useful itself, but we can confidently say that the most important application will be the further techniques in automation that this method brings into picture. Although, due to the resources and time constrain we are developing the method to classify only three types of fruit, this idea can be further expanded to classify other fruits with little effort.

1.3.3 Approaches

In this project we will train a model to classify three different fruits that are Tomato, Avocado, and Oranges into six categories:

- Fresh Apple
- Fresh Oranges
- Fresh Banana
- Rotten Apple
- Rotten Oranges
- Rotten Banana

We will use ResNet50 model as a base model for our transfer learning. To identify the fruit we will use kaggle fruit 360 datasets where they have 90438 images divided into 131 fruit and vegetable categories. Initially our thoughts were to collect our own dataset for rotten fruit identification, but with suggestion from Dr. Scott We now have identified labelled dataset available at Kaggle website for categorical classification of rotten and fresh fruits. Following Figure 1.2 shows a basic idea of the model.

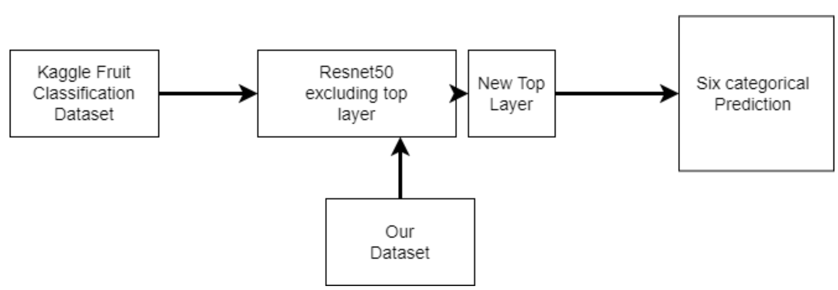


Figure 1.2: Basic Model Scamatic

1.4 Conclusions

Proper automation in agriculture using deep learning approaches can be used to increase substantial yield and decrease economic loss either by controlling weed or by identifying the rotten fruit. Similarly, image processing is a non-invasive and effective tool that can be applied to detect and identify the on the farm and storehouse and effectively remove them . Application of image processing algorithms helps to identify weeds by shape, color, texture, and size features. Since hand labor is getting expensive day by day using automatic detection and classifying technology might lead to a great economic growth.

Chapter 2

Milestone 2: Project Selection

2.1 Introduction

We will be going forward with our first project idea of using deep learning techniques to detect weeds in agricultural fields. There were two main reasons that inspired us to work on this project. First, this work is much related to our area of research in which all of us would be working on using advanced image processing techniques and deep learning methods later in our research work. Second, recent advancements and interesting applications of convolutional neural networks in object detection field have motivated us to learn their application too. We will make use of convolution neural networks and transfer learning approach to build deep learning model for our final project.

2.1.1 Problem Definition

The main goal of this project is to build a robust model that is able to detect weeds in agricultural fields. This model development has an array of use cases that would help in managing and increasing crop production to the farmers in multiple ways. The main advantages to develop a model like this would be to implement variable rate spraying of herbicides in the fields, that would prevent herbicide spray in unwanted areas and this could also help in increasing crop production. We have gathered an online dataset including images of soil, crops and weeds that we will use to build our model. The two different approaches that we would be using for developing our models involve use of inception and resnet networks in collaboration with transfer learning.

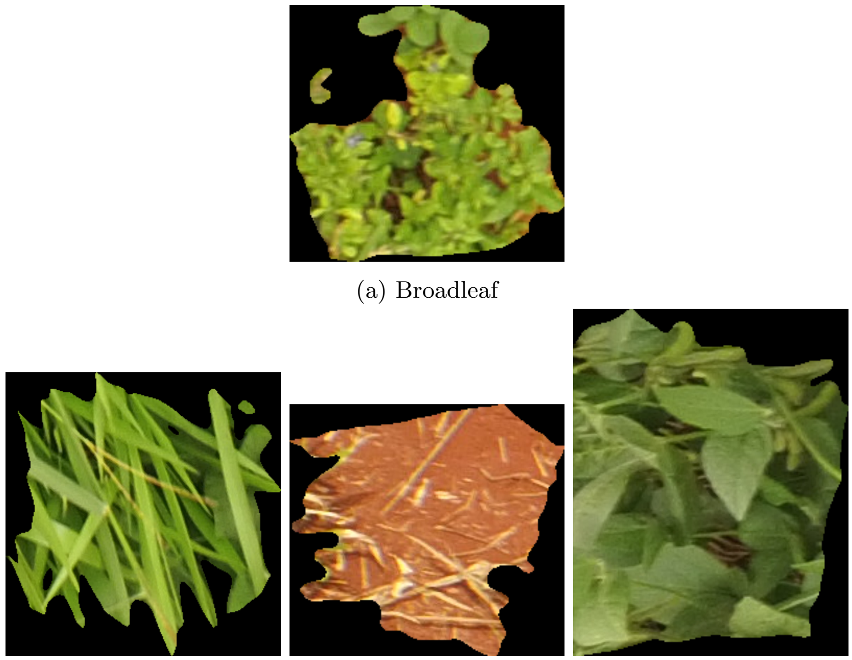
2.1.2 Motivation and Applications

The strong motivation behind this project first started with the growing application of computer vision techniques in agriculture that allows efficient and precise farming with less human labor. Weed detection in agricultural fields is a very challenging task. The main obstacles that one faces during training a deep learning model to detect weeds are color, texture and shape similarity of weeds with the crop. Some other problems associated with weed detection includes occlusion of crops and weeds, shadow effects in natural weed image, effects of illumination conditions, different species of weeds at different growth stages and motion blur and noise effects during capturing image [5]. Deep learning methods we will use during this project can be a base to successfully detect weeds considering human labor, time, and environmental impacts caused by the application of herbicides.

Also, they can be further modified to develop site-specific weed management strategies, weed density evaluation and the precise positioning of weeds in fields. Overall, these methods propose huge possibilities and solutions for reducing production cost, management cost, and protecting the environment by minimizing the traditional techniques of herbicide spraying over the whole field.

2.2 Dataset

Dataset being used has a set of UAV captured images, all those with occurrence of weeds were selected. These images were segmented and annotated with their respective class. The image dataset has a total of 15336 segments, being 3249 of soil, 7376 of soybean, 3520 grass and 1191 of broadleaf weeds [2].Each dataset has pixel size of around 200×180. We will use train to test ratio of 80:20. The loss function and the evaluation metric will be the mean squared error. Figure **??** shows the four different types of images in datasets.



(a) Broadleaf

(b) Grass (c) Soil (d) Soybean

Figure 2.1: Four different categories of images in datasets

2.3 Resources Required

In order to analyze the available datasets proposed for this project work, we plan to utilize the resources that are available on crane. We plan to use Keras API for training, testing, and evaluating.

2.4 Proposed Method 1: Weed detection using Inception models

Transfer learning means to take features learned on one problem, and leveraging them on a new problem. The first method uses a pre-trained model called Inception. This architecture includes inception modules, that combines pooling layers with filters of various sizes, allowing them to utilize the benefit of each filter size, for example, wide filters (5×5) are able to extract main information, whereas small filters (1×1) can extract local information [10]. This configuration can help the model to differentiate between plant leaves and weeds.

The following steps will be taken to implement our first approach:

1. Transform and split the images into training and testing set from dataset to feed into the model.

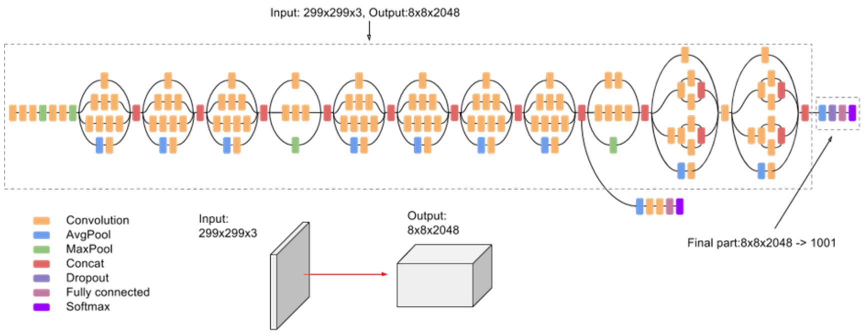


Figure 2.2: Inception V3 Model [10]

2. Download the pre-trained weights for the model.
3. Freeze weights to avoid deleting any of the information they contain during further training rounds.
4. Fine tune model to add new layers to the architecture to solve the potential problems of overfitting, low learning rates etc, so that it detects weeds better.

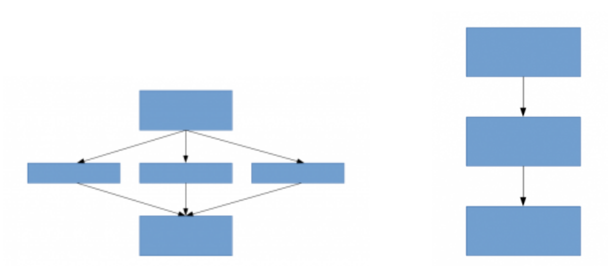


Figure 2.3: Sparsely connected model vs Densely connected model

Common problem faced while creating deeper models are overfitting the training set and increased computational resources. Inception tries to solve these with the use of sparsely connected network architectures that will replace fully connected network architectures, especially inside convolutional layers. Thus in the inception model instead of having deep layers, we have parallel layers making the model wider rather than making it deeper. We plan to fine tune and implement this method by the first week of March.

2.5 Proposed Method 2: Weed detection using Residual Architecture

In the second approach, we are basically interested to construct a deep learning model using Residual networks. During a literature review for the topic [1], we came to know that residual layers could be used to construct Neural networks, involving deeper layers and skip connections that help to overcome the problem of vanishing gradient descent during the training phase. Predicting weed locations in a soybean fields is a cumbersome task and would require extensive training of deep neural networks to detect weeds in the fields with high precision and recall outputs from the results. We would use transfer learning techniques and make use of a pre-trained model already trained on imagenet dataset with a ResNet50 architecture as a second approach towards our final goal of weed detection in agricultural fields which would help us to develop more robust models that could perform better as compared to former. The following steps will be taken to implement our first approach:

1. Splitting the original dataset into two separate categories : train and test. The training of our model would be performed on the training dataset and checking on how well our model is generalising is performed on the testing dataset.

2. Loading the pre-trained weights for ResNet50 model already trained on imagenet dataset from the Tensorflow Keras API

3. The pre-trained network is used to extract features and train the network to detect different categories of objects inserted into the model for training

4. Fine tune model to add new layers to the architecture to solve the potential problems of overfitting, low learning rates etc, so that it detects weeds better.

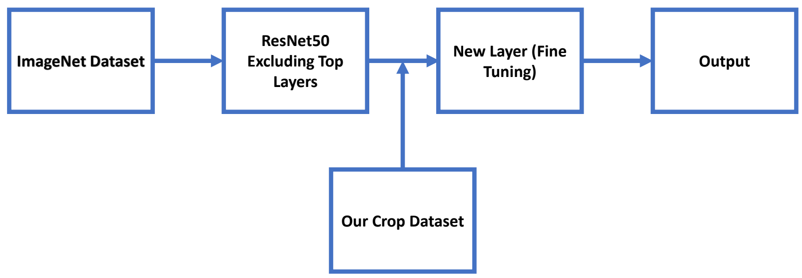


Figure 2.4: Flowchart

The main intuition behind using residual layers in training of our weed detection model is the presence of (1×1) convolutional layers in them. These (1×1) convolutional layers help the model in detecting even small features in an image. On comparison with other things like crops, grass that share quite resemblance with each other, it sometimes becomes difficult to detect difference between them from a naked eye. Using residual block with lower convolutional filters helps the model in detecting small feature sets of weeds and help in developing more robust models. The difference between a residual block and a set of normal convolutional filters in a neural network could be understood from Figure 2.5.

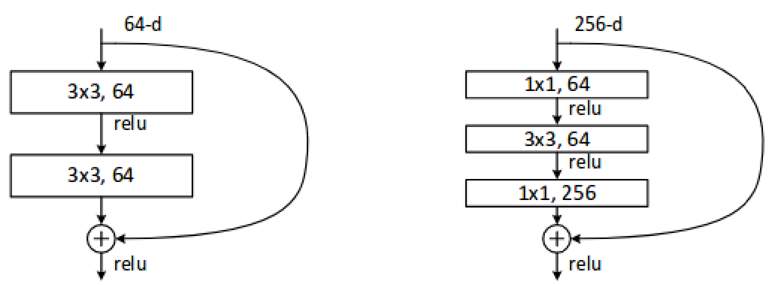


Figure 2.5: Residual block

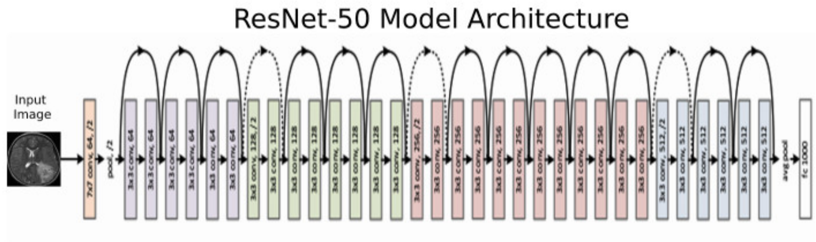


Figure 2.6: ResNet50 Architecture

We will use ResNet50 architecture in our second approach to work over our weed detection problem in our deep learning project. We will start working on this approach after we obtain the results for our first model i.e. right after our spring break.

2.6 Conclusions

We have decided to choose the weed detection project with little changes in the previously proposed objective. We have now figured out the datasets with labeled images for training and testing datasets. Here in milestone 2, we have proposed two methods for detecting weed in soybean crops. Firstly, we are proposing a method where we will build a transfer learning model based on the inception method. The inception method is supposed to be fast and can be useful for real-time weed detection. Secondly, we are proposing a similar model to detect weed but with ResNet50 which is slower but more efficient as compared to the former. If we get enough time and computational we also might want to train our dataset on both the models and compare them for execution time and efficiency trade-off.

Table 2.1: Contributions by team member for Milestone 1.

Team Member	**Contribution**
Shubham Bery	Method Description
Shiva Paudel	Documentation
Puranjit Singh	Concept and Idea Formulation
Kantilata Thapa	Documentation

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