Project Document: Weed Detection using Deep Learning
Team : Encoders

Puranjit Singh
Shiva Paudel
Shubham Bery
Kantilata Thapa

Contents

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. At first, we presented how deep learning can be used to detect weeds in crop and second we explored the techniques that are being implemented to detect and classify fruits based on their rottenness. Then we selected the former idea as our final project that is use of deep learning to detect weeds in soybean crop. Two different deep learning based models were proposed for this problem. We identified a data set to train the model. As the data set was not big enough to train the model from scratch, both the models make use of transfer learning with fine tuning of base layers. For our first approach, we tried to implement residual layers based pre-trained model on ImageNet data set called as ResNet50. Till now, we are able to get 95% weighted accuracy. But, this performance was not consistent as loss values changed drastically because the model showed some signs of overfitting. We implemented a variation of ResNet50 architecture that makes use of Inception blocks to make the network wider and overcome the overfitting problem. Till now, we managed to achieve a validation accuracy of more than 98 % with not so varying loss against epochs graph.

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 [9]. 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 [5]. 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.

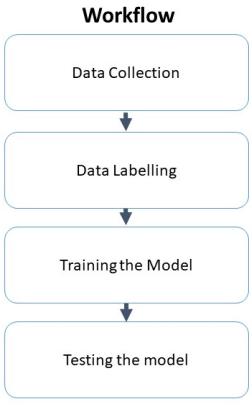


Figure 1.1: Proposed workflow

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. [8]. 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 [10]. 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 [7]. 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.

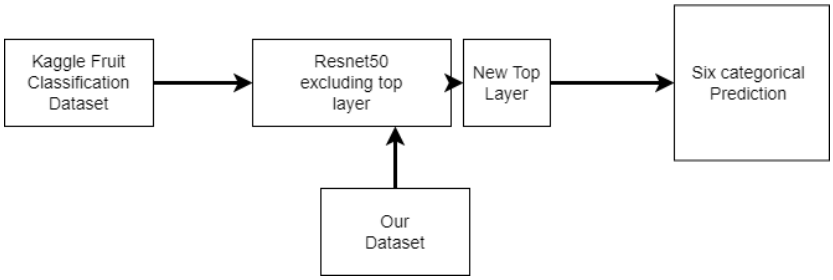


Figure 1.2: Basic Model Scamatic

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 [6]. 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 [12]. 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.

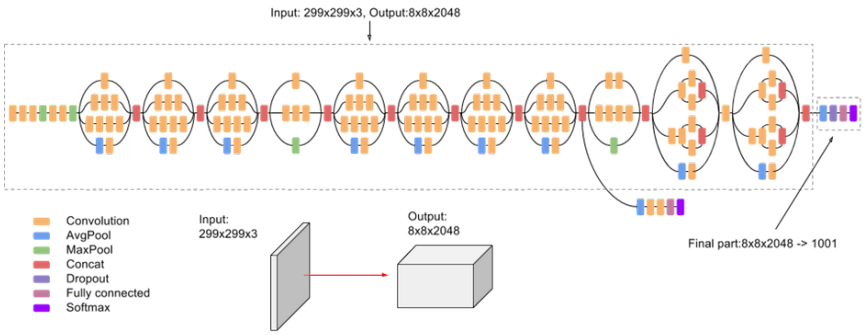


Figure 2.2: Inception V3 Model [12]

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.

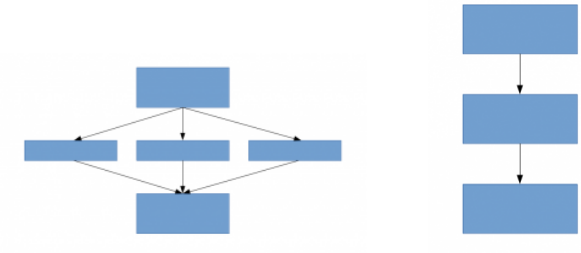


Figure 2.3: Sparsely connected model vs Densely connected model

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.

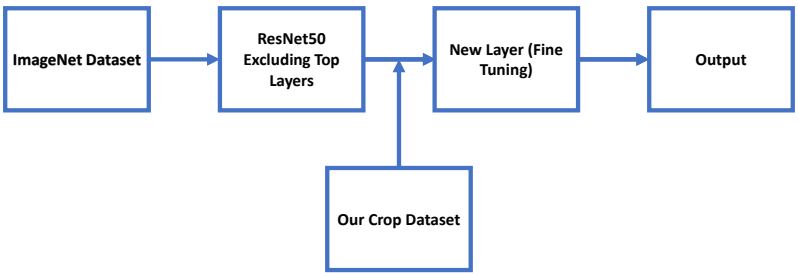


Figure 2.4: Flowchart

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.

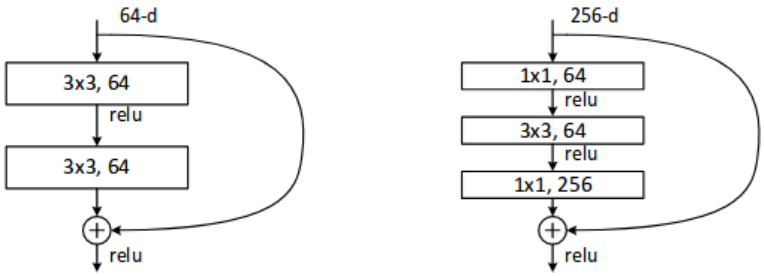


Figure 2.5: Residual block

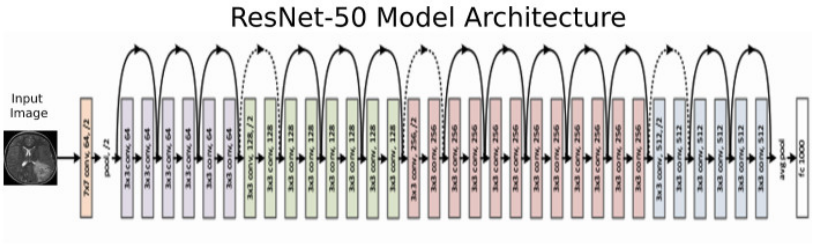


Figure 2.6: ResNet50 Architecture

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

Chapter 3

Milestone 3: Progress Report 1

3.1 Introduction

As proposed in the last milestone, we are working on our weed detection model using deep learning techniques. Our aim is to develop a convolutional neural network (CNN) using transfer learning technique that can detect weeds in an input image of field. For this milestone, we tried implementing one of the proposed approaches that makes use of residual networks to construct the deep learning model. The reason behind using this architecture is the presence of (1 $\times$ 1) convolutional layers in it which help the model to detect even the slightest significant features in an image. This enables the model to see the minute differences between the main crop and similar looking unwanted growth. Residual layers are helpful in developing neural networks, involving deeper layers as it skips connections between layers to address the problem of overfitting and vanishing gradient during the training phase. As the dataset used for training was comparatively smaller, we had to use data augmentation techniques that generated different versions of the existing dataset artificially to increase its size. To speed up the training process, we are making use of transfer learning techniques. We used a model that is based on ResNet50 architecture pretrained on the ImageNet dataset. To best fit the model to the dataset at hand, we also fine-tuned the weights of existing layers in the base architecture. Furthermore, we implemented early stopping not to overfit the model by training it for a longer duration. With this architecture, we noticed some large fluctuation in loss value indicating a poor fit. We tried fine tuning the model which made the significant improvement in performance. We plan to implement Inception-ResNetV2 architecture along with hyper-parameter optimization in our future runs.

3.2 Experimental Setup

To complete this project, labeled image dataset with 15336 labeled images were downloaded from Kaggle [2]. Further information on how and where the images were collected is not disclosed by the authors. To increase the size of the training dataset we used the data augmentation technique. We used the techniques such as rotating, shifting, and flipping of the images using existing techniques available in keras for data augmentation. We used the updated dataset including images from data augmentation to train a convolution neural network for a classification task. We decided to implement the ResNet50 model with an additional dense layer with 4 neurons with softmax activation function for categorical classification. To compile the model, we used 'adam' as the optimizer, 'categorical cross entropy' loss function as an accuracy metric. The model was trained with the augmented images as input and corresponding label as target. We used Crane, a powerful computing machine at our disposal during the course to train the model.

3.2.1 Datasets

The 'Weed Detection in Soybean Crop' dataset contains a total of 15336 segmented images, being 3249 of soil, 7376 of soybean, 3520 grass and 1191 of broadleaf category of weeds. Each image in the dataset has a pixel size of around 200x180. We split the dataset into 8:2 training and testing images. We use augmentation techniques to increase variability as well as the number of images. For data augmentation we used already available method in Keras namely ImageDataGenerator with a batch size of 32 and randomly shifted, flipped, and scaled the images to increase our existing dataset.

3.2.2 Architecture

The model architecture we used for the weed detection problem in a soyabean crops is ResNet50. We used this architecture because it allows us to train ultra-deep neural network with hundreds or thousands of layers and still can achieve higher accuracy. Also, ResNet50 architecture can 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. We used transfer learning techniques and used a pre-trained model already trained on ImageNet datasets. This dataset was split into training and testing set. The training was performed on training dataset and the model performance was observed on testing dataset. ResNet50 model already has pre-trained weights which were uploaded and used in our code from TensorFlow Keras API. This pre-trained network extract the features and train the network to detect four categories of objects inserted into a model. Our approach is to fit the model firstly freezing the existing weights and then fine tuning the exisitng weights which were automatically done based on the demand for our dataset. We have added one dense layer with 4 neurons for four categorical classification of the

intended identification. The figure 3.1 summarizes our approach on training the model.

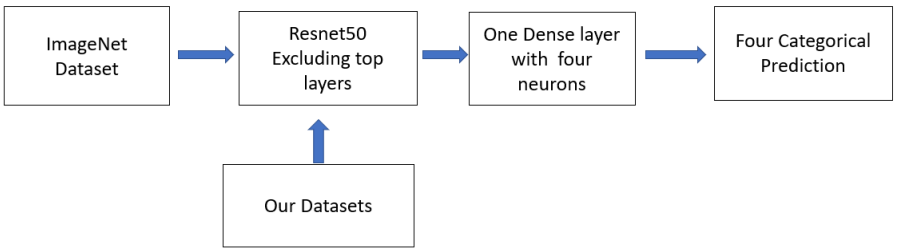


Figure 3.1: Flowchart

3.2.3 Performance Measures

The four categories labels were converted to one hot vector and probabilistic categorical cross entropy is used as our performance metric. The categorical cross entropy loss computes the loss between true and predicted labels. We implemented early stopping to limit training of our model at an appropriate time by monitoring the improvement in the validation loss metric.

3.2.4 Hyper-parameter

As we have decided to fine tune ResNet50 architecture. The predefined model architecture has limited our ability to try different sets of hyper-parameters. For the first progress report we have decided to run our model with early stopping callbacks of 5 epochs patience for 10 epochs. Even though we were bound to limited sets of hyper-parameters for tuning we still have power over the number of neurons on additional layers and the dropout percentage in subsequent layers. In our future runs we plan to add a few more fully connected dense layers with a dropout layer in between. Along with additional layers, we will also be seeking other logical ways of hyper-parameter optimization.

3.3 Experimental Results

We fitted our model as described in the previous section. We froze all the layers except the initial input layer, we added one dense layer with 4 neurons to categorically classify the four distinct categories. With the weight frozen we achieve a training loss as low as 0.6 and validation loss as low as 0.62. The following figure 4.1 shows the learning curve of the fitted model. The validation curve clearly shows the sign of a poorly fitted model as it is fluctuating over large loss value. With this performance, we hypothesize that unfreezing all the layers of ResNet50 and fine tuning the weights with our dataset might lead to a better performance.

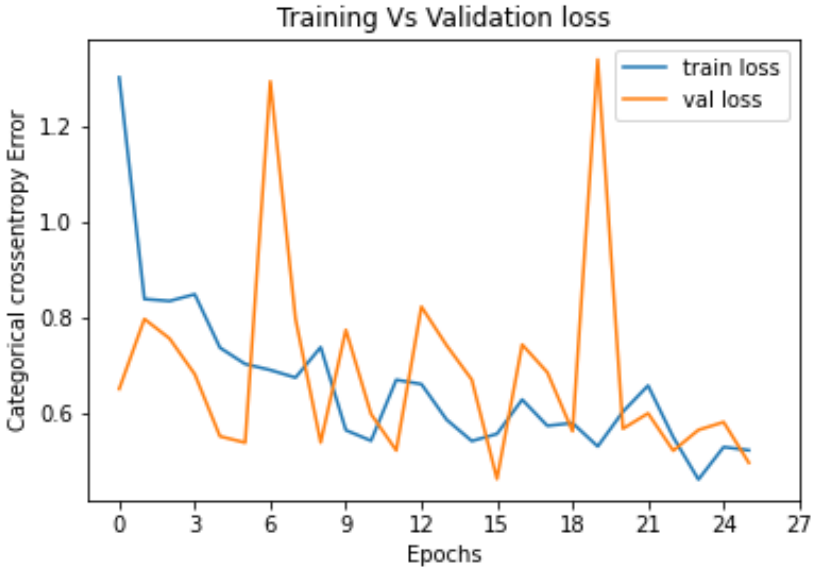


Figure 3.2: Learning Curve for ResNet50 with weight frozen

The figure 3.3 shows the learning curve for the fine-tuned fitting approach. With fine tuning we achieve a final loss of below 0.4 for both training and validation dataset with little fluctuation in validation loss. In our next progress report, initially we will seek a way to optimize the hyper-parameters. The results from optimized model will be compared with the performance of the current model. The ResNet50 architecture had approximately 23 million trainable parameters. As we have discussed in milestone 2 there are other architecture which might perform better than using ResNet50. We are reviewing some literature to identify a better approach to obtain much better result. We also plan to implement InceptionResNetV2 model for transfer learning. However, the trainable parameters in both ResNet50 and InceptionResNetV2 are equal, the wider approach of InceptionResNetV2 model might lead to better classification.

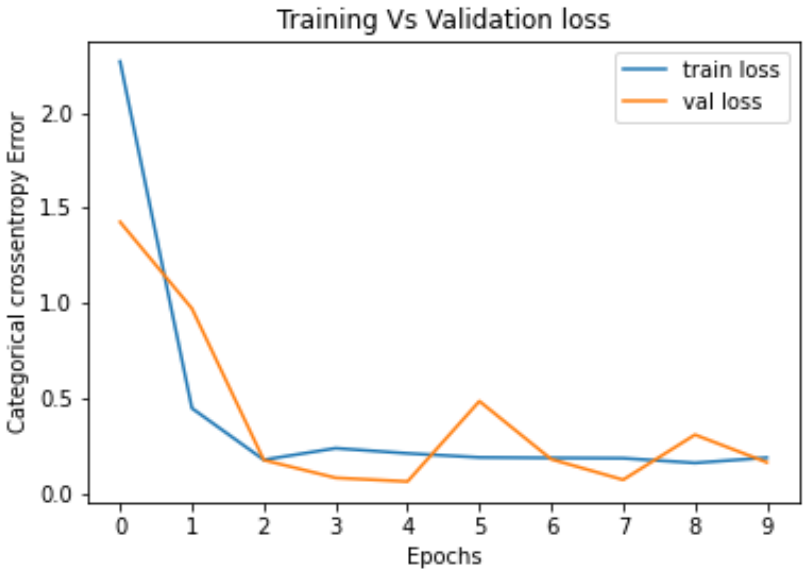


Figure 3.3: Learning Curve for ResNet50 fine-tuned

Table 3.1 :Metrics				
Serial Number	Precision	Recall	F1-Score	Support
0 - Grass	0.93	0.89	0.91	350
1 - Soil	0.98	1.00	0.99	324
2 - Soybean	0.97	0.99	0.98	733
3 - Weeds	0.78	0.76	0.77	120
Accuracy			0.95	1527
Macro Average	0.92	0.91	0.91	1527
Weighted Average	0.95	0.95	0.95	1527

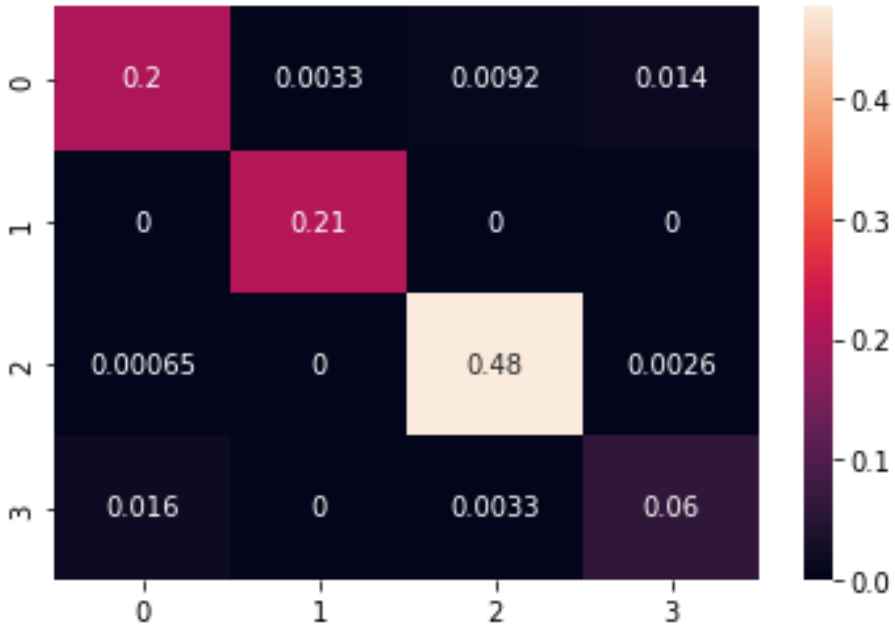


Figure 3.4: Confusion Matrix True vs Predicted

3.4 Discussion

Reviewing the literature, use of residual networks was a step taken in the right direction. However, the results we got were not aligned to what we thought [13]. We initially froze the base network weights and quickly found that it was a dead-end with no gradual improvement in the model performance as both the training and validation losses were significantly higher. After this, we fine-tuned the model along with unfreezing the weights of base layers, we witnessed an improvement over the first trial. Still, we believe that the hyper-parameters can further be tuned to get a better performance out of this architecture. However, fine-tuning comes at a significant computation cost and a higher risk for overfitting to the training data. So, sufficient measures will be needed to mitigate this overfitting problem such as the use of dropout layers. In our future work we will work towards reducing the overfitting of this model along with implementation of our second proposed architecture, InceptionResNetV2 . The main intuition behind using transfer learning techniques using weights already trained on InceptionResNetV2 architecture is because these are wider networks as compared to ResNet architectures and could help us to learn and perform better on training the model and therefore getting good results for further classification tasks.

3.5 Conclusion

Till now, we observed that transfer training is one of the right approaches that we could use to train a deep learning model with a smaller dataset. We used a pretrained ResNet50 model already trained on ImageNet dataset for our project. All the results, such as the learning curves, showed some benefit of fine-tuning but the results were not promising as expected. We could not perform ample hyper-parameter tuning in the work so far but expect that our findings will get better with the right set of hyper-parameters. For the next milestone, we also plan to implement a different architecture InceptionResnetV2 and will try to compare the results with further fine-tuned ResNet50.

Table 3.1: Contributions by team member for Milestone 1.

Team Member	**Contribution**
Shubham Bery	Writing the report
Shiva Paudel	Writing the report and helping on final model development
Puranjit Singh	Writing the code and running the entire model
Kantilata Thapa	Writing and finalizing the report

Chapter 4

Milestone 4: Progress Report 2

4.1 Introduction

Our project aims to develop a model that can detect weeds in soyabean crops using deep learning techniques. The method involves developing a supervised learning model based on convolutional neural network (CNN) making use of transfer learning that can classify weeds in an input image. In the last milestone, we tried implementing one of the proposed approaches that made use of ResNet50 pretrained model to build a deep learning model. But the model did not work as expected and showed inconsistent performance. After fine-tuning the model and unfreezing the weights, loss curve showed some consistency and improvement over the previous trials. We wanted to try out a different architecture so that the performance can be improved. After reviewing the literature, we found that using residual connections along with inception blocks can lead to an even better performance [11]. InceptionResNetV2 is a convolutional neural network that is trained on more than a million images from the ImageNet database. The network is 164 layers deep and can classify images into 1000 object categories. So, we went ahead and used a pretrained instance of InceptionResNetV2. As the dataset used for training was comparatively smaller, we had to use data augmentation techniques that generated different versions of the existing dataset artificially to increase its size. We witnessed a significant improvement in model's performance with validation accuracy of more than 98%.

4.2 Experimental Setup

For this project, labeled image dataset with 15336 labeled images were downloaded from Kaggle [2]. To increase the size of the training dataset we used the

data augmentation technique. We used techniques such as rotating, shifting, and flipping of the images using existing techniques available in keras for data augmentation. Further information on how and where the images were collected is not disclosed by the authors. We used the updated dataset including images from data augmentation to train a convolution neural network for a classification task. For this time, we decided to implement InceptionResnetV2 Model with dense layer and SoftMax activation function for categorical classification. To compile the model, we used 'Adam' as the optimizer, 'categorical cross entropy' loss function as an accuracy metric. The model was trained with augmented images as input and corresponding label as target. We used Crane, a powerful computing machine at our disposal during the course to train the model. The following figure summaries, the architecture of our implemented model. Our model takes the image of size $256 \times 256 \times 3$ as an input to the base model i.e., InceptionResnetV2 model and outputs the 4 labels categories at end.

4.2.1 Architecture

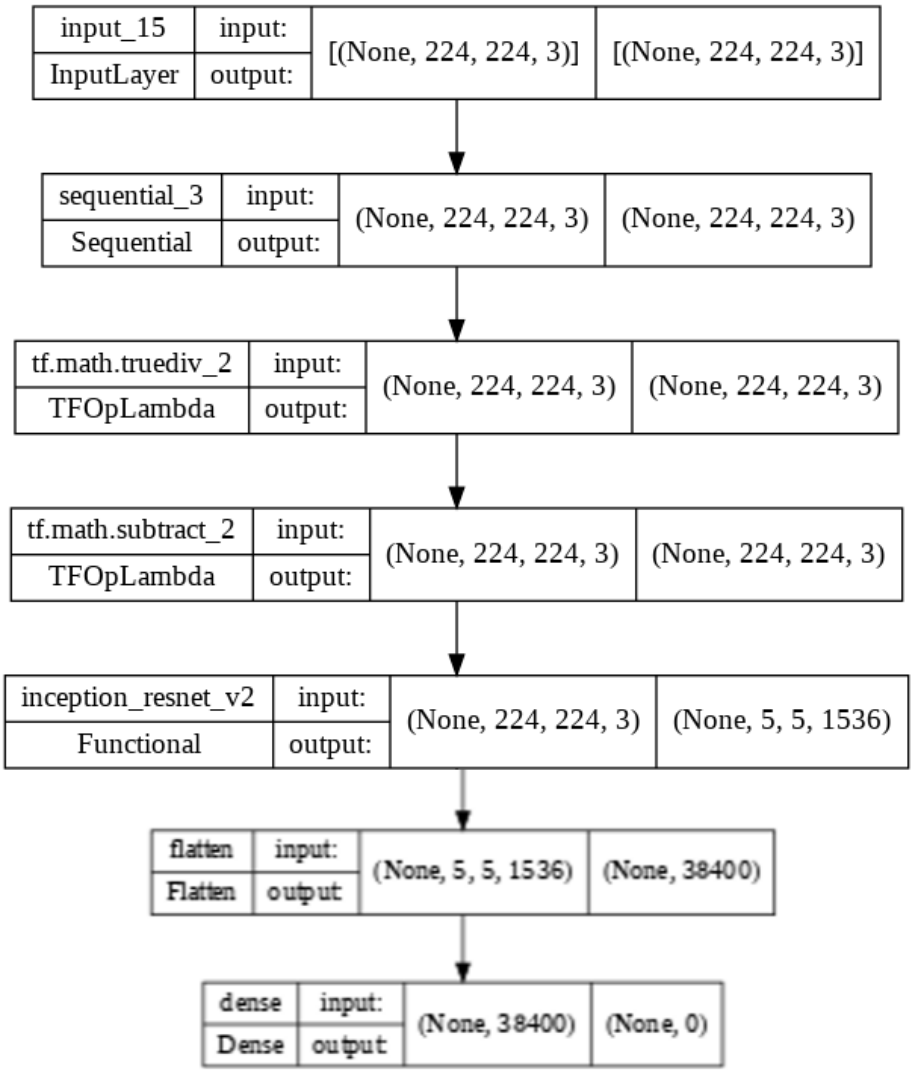


Figure 4.1: Architecture For Inception Resnet V2 model

4.2.2 Datasets

The Weed Detection datasets in Soybean Crop consists of a total of 15336 segmented images, with 3249 of soil, 7376 of soybean, 3520 grass and 1191 of broadleaf category of weeds. Each image in the dataset has a pixel size of around 200x180. We split the dataset into 8:2 training and testing images. We use augmentation techniques to increase variability as well as the number of

images.

4.2.3 Data Augmentation

For data augmentation we used already available method in Keras API namely ImageDataGenerator with a batch size of 32 and randomly shifted, flipped, and scaled the images to increase our existing dataset. The ImageDataGenerator provides a quick and easy way to perform the task of data augmentation. The main benefit of keras ImageDataGenerator is that it augments images on the fly when the model is being trained. The ImageDataGenerator doesnot add new images to the training dataset but it augments all the dataset after each epoch. In our case we have 12268 images in our training dataset, all these images were augmented after each epoch, therefore in our training process for 10 epoch we trained our model on 12268 original images and 12268×10 augmented images.

4.2.4 Performance Measures

The four categories' labels were converted to one hot vector and probabilistic categorical cross entropy is used as our performance metric. The categorical cross entropy loss computes the loss between true and predicted labels. We implemented early stopping to limit training of our model at an appropriate time by monitoring the improvement in the validation loss metric.

4.3 Experimental Results

We fitted our model as described in the previous section. We froze all the layers except the initial input layer, we added one dense layer with 4 neurons to categorically classify the four distinct categories. After freezing the weight, we obtained training accuracy of around 0.97 and validation accuracy of 0.97. Similarly, we achieve a training loss as low as 0.38 and validation loss as low as 0.32. Figures 4.2 and 4.3 are the learning curves with weight freezing. The validation curve clearly shows that the model is poorly fitted. With this performance, again we hypothesize that unfreezing all the layers of InceptionResNetV2 model and fine-tuning the weights with our dataset might lead to a better performance.

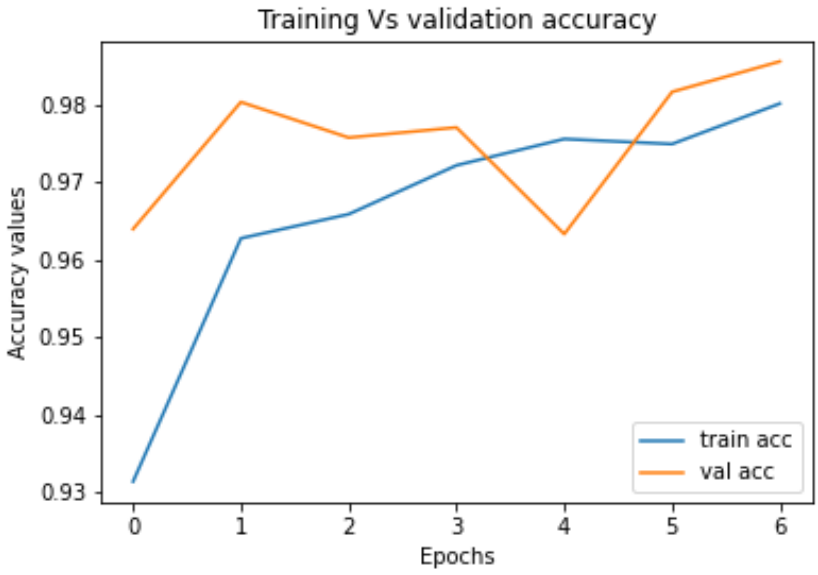


Figure 4.2: Accuracy curve for InceptionResNetV2 model with weights frozen

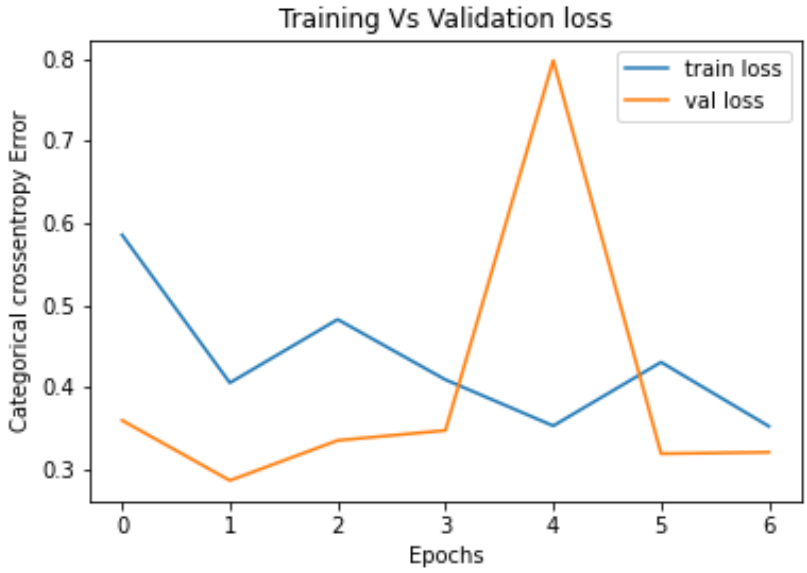


Figure 4.3: Loss curve for InceptionResNetV2 model with weight frozen

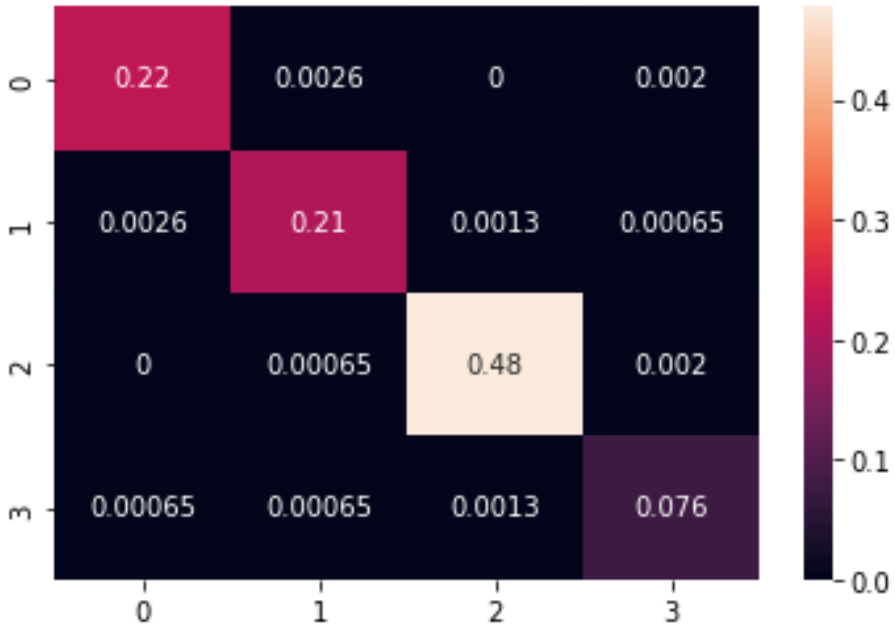


Figure 4.4: Confusion matrix with freezing of weights

Table 3.1 :Metrics for Freezing weights during training				
Serial Number	Precision	Recall	F1-Score	Support
0 - Grass	0.99	0.98	0.98	350
1 - Soil	0.98	0.98	0.98	324
2 - Soybean	0.99	0.99	0.99	733
3 - Weeds	0.94	0.97	0.95	120
Accuracy			0.99	1527
Macro Average	0.98	0.98	0.98	1527
Weighted Average	0.99	0.99	0.95	1527

The figures 4.5 and 4.6 show the learning curves for the fine-tuned fitting approach. With fine tuning we achieve a training accuracy as high as 0.98 and validation accuracy as high as 0.99. Similarly, we obtained training loss to zero and for validation loss even though it shows drastic fluctuation in loss values, finally it reaches to zero.

Furthermore, the confusion matrix in figure 4.4 shows the true level and predicted levels. Also, table 3.1 shows various metrics of performance. We can see that the model very rarely being confused between four categories.

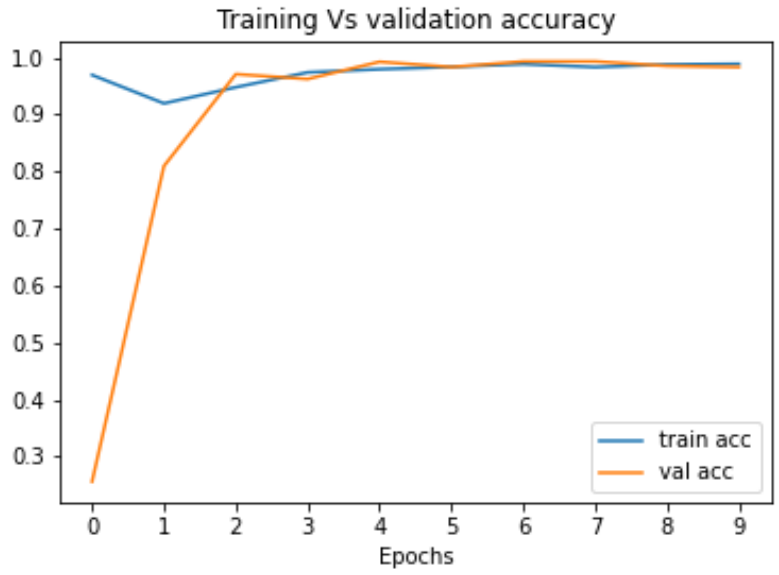


Figure 4.5: Accuracy curve for InceptionResNetV2 model with fine-tuning

Figure 4.6: Loss curve for InceptionResNetV2 model with fine-tuning

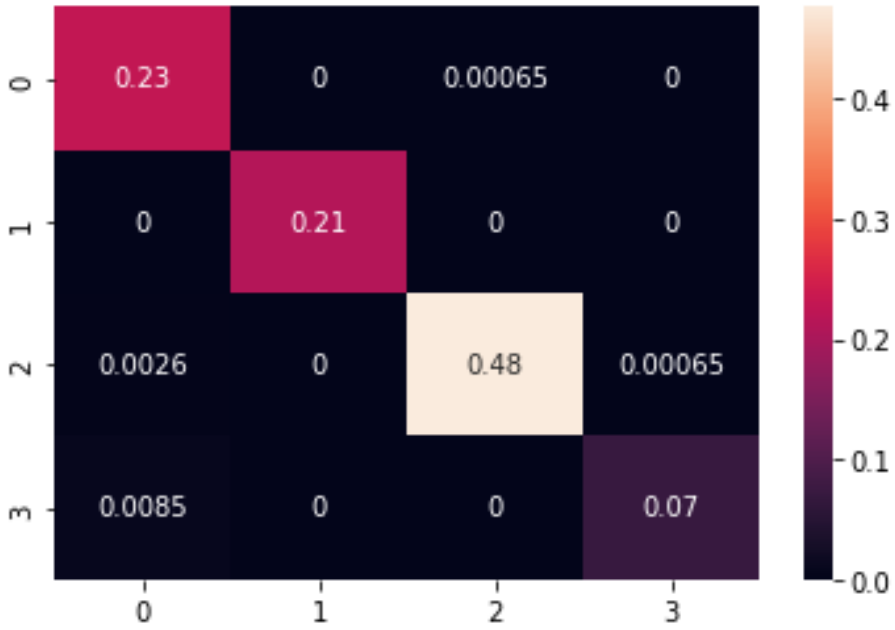


Figure 4.7: Confusion Matrix with fine-tuning

Table 3.1 :Metrics for Fine Tuning weights during training				
Serial Number	Precision	Recall	F1-Score	Support
0 - Grass	0.95	1.00	0.97	350
1 - Soil	1.00	1.00	1.00	324
2 - Soybean	1.00	0.99	1.00	733
3 - Weeds	0.99	0.89	0.94	120
Accuracy			0.99	1527
Macro Average	0.99	0.97	0.98	1527
Weighted Average	0.99	0.99	0.99	1527

4.4 Discussion

Reviewing the literature, use of residual networks was a step taken in the right direction. However, the results we got were not aligned to what we thought. We initially froze the base network weights and quickly found that it was a dead-end with no gradual improvement in the model performance. For this milestone, we implemented a convolutional neural architecture that builds on the inception family of architectures but incorporates residual connections, InceptionResNetV2. Since Inception networks tend to be very deep, it is natural to replace the filter concatenation stage of the Inception architecture with residual connections. This would allow Inception to reap all the benefits of the residual

approach while retaining its computational efficiency [11] and it leads to getting good results for further classification tasks. We got a better performing model with training efficiency of more than 98% with patience parameter of 5.

4.5 Conclusion

Till now, we observed that transfer training is one of the right approaches that we could use to train a deep learning model with a smaller dataset. We used a pretrained ResNet50 model already trained on ImageNet dataset for our project. All the results, such as the learning curves, showed some benefit of fine-tuning but the results were not promising as expected. So, we worked on Inception-ResNetV2 implementation that makes improvement to ResNet50 architecture with introduction of inception block that leads to a wider network and also being computationally efficient. This approach was significantly better and led to good results. For future work, we will try to run this architecture with more data augmentation and analyse how the performance will vary.

Table 4.1: Contributions by team member for Milestone 4.

Team Member	**Contribution**
Shubham Bery	Model deployment and report writing
Shiva Paudel	Model deployment and report writing
Puranjit Singh	Model development and deployment
Kantilata Thapa	Model deployment and report writing

Chapter 5

Milestone 5: Final Report

5.1 Introduction

Agriculture is the life-sustaining element for many people around the globe. Agriculture today faces numerous challenges in terms of biological, ecological, and developmental aspects. On the other hand, agricultural consumption is growing rapidly. 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. 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. In this project, we have tried to address a burning issue of today's agricultural society, automating weed control using machine learning and deep learning. As mentioned, to address the problem we have applied two different deep learning methods to identify weed in soyabean.

Our aim was to develop a convolutional neural network (CNN) using transfer learning technique that can detect weeds in an input image of field. In original work by Rerriera et.al they have achieved overall accureacy of 98% in classification with the data that we are planning to use, therefor we aim to get accuracy of our model atleast as good as their [4]. We tried implementing one of the proposed approaches that makes use of residual networks to construct the deep learning model. The reason behind using this architecture is the presence of (1×1) convolutional layers in it which help the model to detect even the slightest significant features in an image.

This enables the model to see the minute differences between the main crop and similar looking unwanted growth. Residual layers are helpful in developing neural networks, involving deeper layers as it skips connections between layers to address the problem of overfitting and vanishing gradient during the training

phase [11]. As the dataset used for training was comparatively smaller, we had to use data augmentation techniques that generated different versions of the existing dataset artificially to increase its size. We used a model that is based on ResNet50 architecture pretrained on the ImageNet dataset. To best fit the model to the dataset at hand, we also fine-tuned the weights of existing layers in the base architecture. Furthermore, we implemented early stopping not to overfit the model by training it for a longer duration. With this architecture, we noticed some large fluctuation in loss value indicating a poor fit. But the model did not work as expected and showed inconsistent performance. After fine-tuning the model and unfreezing the weights, loss curve showed some consistency and improvement over the previous trials. We wanted to try out a different architecture so that the performance can be improved.

After reviewing the literature, we found that using residual connections along with inception blocks can lead to an even better performance . InceptionResNetV2 is a convolutional neural network that is trained on more than a million images from the ImageNet database. The network is 164 layers deep and can classify images into 1000 object categories. So, we went ahead and used a pretrained instance of InceptionResNetV2. As the dataset used for training was comparatively smaller, we had to use data augmentation techniques that generated different versions of the existing dataset artificially to increase its size. We witnessed a significant improvement in the model's performance with validation accuracy of more than 98

5.2 Experimental Setup

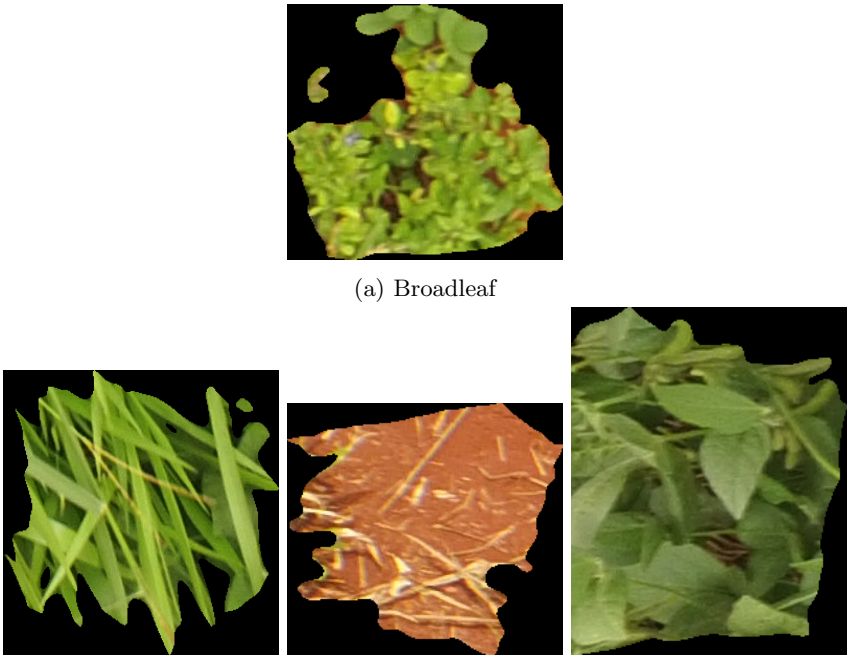
5.2.1 Motivation and Application

The strongest motivation behind 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. Recent advancements and interesting applications of convolutional neural networks in object detection field have motivated us to learn their application in agriculture and farming too. Another factor motivating us to choose is 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 an incredibly 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 [6]. 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.

5.2.2 Datasets

For this project we used a dataset openly available on the Kaggle website called Weed Detection in Soybean Crop [2]. The 'Weed Detection in Soybean Crop' dataset contains a total of 15336 segmented images, being 3249 of soil, 7376 of soybean, 3520 grass and 1191 of broadleaf category of weeds. Each image in the dataset has a pixel size of around 200×180. We split the dataset into $8:2$ training and testing images. We use augmentation techniques to increase variability as well as the number of images. For data augmentation we used already available method in Keras namely ImageDataGenerator with a batch size of 32 and randomly shifted, flipped, and scaled the images to increase our existing dataset.



(a) Broadleaf

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

Figure 5.1: Four different categories of images in datasets

5.2.3 Data Augmentation

For data augmentation we used already available method in Keras API namely ImageDataGenerator with a batch size of 32 and randomly shifted, flipped, and scaled the images to increase our existing dataset. The ImageDataGenerator provides a quick and effortless way to perform the task of data augmentation. The main benefit of keras ImageDataGenerator is that it augments images on the fly when the model is being trained. The ImageDataGenerator doesnot add new images to the training dataset but it augments all the dataset after each epoch. In our case we have 12268 images in our training dataset, all these images were augmented after each epoch, therefore in our training process for 10 epochs, we trained our model on 12268 original images and 12268×10 augmented images.

5.2.4 Performance Measure

The four categories labels were converted to one hot vector and probabilistic categorical cross entropy is used as our performance metric. The categorical cross entropy loss computes the loss between true and predicted labels. We implemented early stopping to limit training of our model at an appropriate time by monitoring the improvement in the validation loss metric.

5.2.5 Hyperparameter

As we have decided to fine tune ResNet50 and ResNetInceptionV2 architecture. The predefined model architectures have limited our ability to try different sets of hyper-parameters. We chose 'Adam' as optimizer with 0.001 learning rate for both the architecture. For both the architectures we have decided to run our model with early stopping callbacks of 5 epochs patience for 10 epochs.

5.2.6 Architecture

In this project we were successful in implementing two different models of architecture. Initially we chose resnet50, but with resnet50 the results were not as expected therefore we also trained another architecture with a wider approach to improve the model's performance. Resnet50 is a residual model with skip connection to overcome the vanishing gradient problem. Resnet50 contains a total of 50 convolution layers; initial layer with kernel size of 7×7 convolution, 9 layers of $1 \times 1, 64$ kernel following this a $3 \times 3, 64$ kernel and at last a $1 \times 1, 256$ kernel repeating three times, 12 layers of kernel $1 \times 1, 128$ after that a kernel of $3 \times 3, 128$ and at last a kernel of $1 \times 1, 512$ repeating 4 times, 18 layers of $1 \times 1, 256$ and two more kernels with $3 \times 3, 256$ and $1 \times 1, 1024$ repeating 6 times and, 9 more layers with $1 \times 1, 512$ kernel, $3 \times 3, 512$ and $1 \times 1, 2048$ repeating 3 times and a dense layer with 1000 nodes at last. The reason behind selecting resnet50 model was it allows us to train ultra-deep neural network with tens of layers and can achieve higher accuracy. We used transfer learning techniques and used a pre-trained model already trained on ImageNet datasets. This dataset was

split into a training and testing set. The training was performed on training dataset and the model performance was observed on testing dataset. ResNet50 model already has pre-trained weights which were uploaded and used in our code from TensorFlow Keras API. This pre-trained network extract the features and train the network to detect four categories of objects inserted into a model. Our approach is to fit the model firstly freezing the existing weights and then fine tuning the existing weights which were automatically done based on the demand for our dataset. We have added one dense layer with 4 neurons for four categorical classifications of the intended identification.

The second architecture we used for the problem was InceptionResnetV2. It is a convolutional neural architecture that builds on the inception family of architectures but incorporates residual connections (replacing the filter concatenation stage of the inception architecture). We chose this architecture because it reduces the complexity and dimension of neural network, and it has wider approach than Resnet50. Inception-ResNet-V2 model is trained on more than million images from the ImageNet database. The network is 164 layers deep and can classify images into various object categories.

5.3 Experimental Results

We fitted our model as described in the previous section. We froze all the layers except the initial input layer, we added one dense layer with 4 neurons to classify the four distinct categories. With the weight frozen we achieved a training loss as low as 0.6 and validation loss as low as 0.62. The validation curve clearly shows the sign of a poorly fitted model as it is fluctuating over large loss value. With this performance, we hypothesize that unfreezing all the layers of ResNet50 and fine tuning the weights with our dataset might lead to a better performance.

The figure shows 5.2 the learning curve for the fine-tuned fitting approach for resnet50 architecture. With fine tuning we achieve a final loss of below 0.4 for both training and validation dataset with little fluctuation in validation loss. The ResNet50 architecture had approximately 23 million trainable parameters but is a deep architecture with only 50 layers. As mentioned in previous section, we also implemented InceptionResNetV2 model as it is combination of inception as well as inception approach of classification and is much deeper than the ResNet50. However, the trainable parameters in both ResNet50 and Inception-ResNetV2 are equal, the wider approach of InceptionResNetV2 model might lead to much more efficient performance.

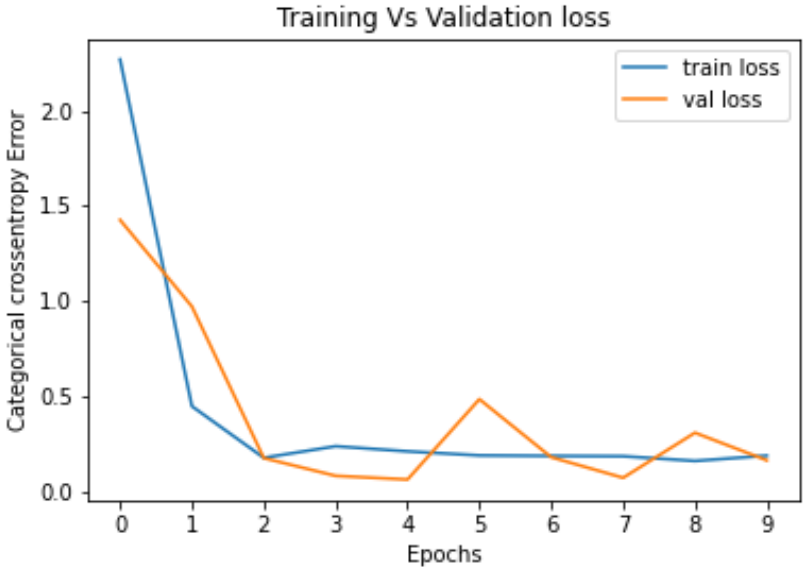


Figure 5.2: Learning Curve for ResNet50 fine-tuned

Table 3.1 :Metrics				
Serial Number	Precision	Recall	F1-Score	Support
0 - Grass	0.93	0.89	0.91	350
1 - Soil	0.98	1.00	0.99	324
2 - Soybean	0.97	0.99	0.98	733
3 - Weeds	0.78	0.76	0.77	120
Accuracy			0.95	1527
Macro Average	0.92	0.91	0.91	1527
Weighted Average	0.95	0.95	0.95	1527

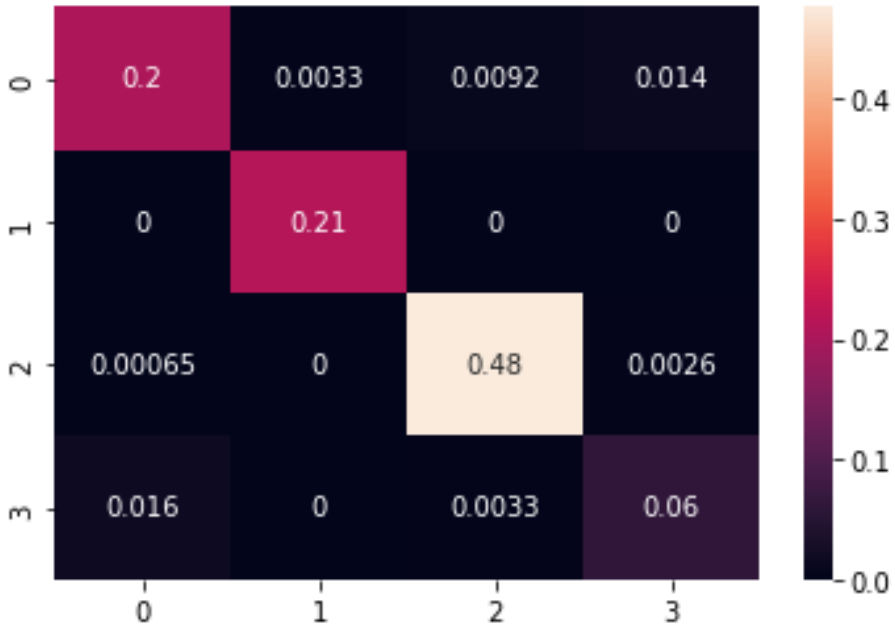


Figure 5.3: Confusion Matrix True vs Predicted

Similarly, as in ResNet50 we froze all the layers of InceptionResNetV2 architecture except the initial input layer, we added one dense layer with 4 neurons to categorically classify the four distinct categories. With weight frozen, we obtained training accuracy of around 0.97 and validation accuracy of 0.97. The validation curve shown in milestone 4 clearly shows that the model is poorly fitted. Even though we achieved accuracy of 97% which is much more accurate than ResNet50, there was still room for improvement by fine tuning the weights.

The figure 5.4 shows the learning curves for the fine-tuned fitting approach. With fine tuning we achieve a training accuracy as high as 0.98 and validation accuracy as high as 0.99. Similarly, we obtained training loss to zero and for validation loss even though it shows slight fluctuation in loss values, finally it reaches zero. Furthermore, the confusion matrix in figure 5.5 shows the true level and predicted levels. Also, table 3.1 shows various metrics of performance. We can see that the model very rarely being confused between the four categories.

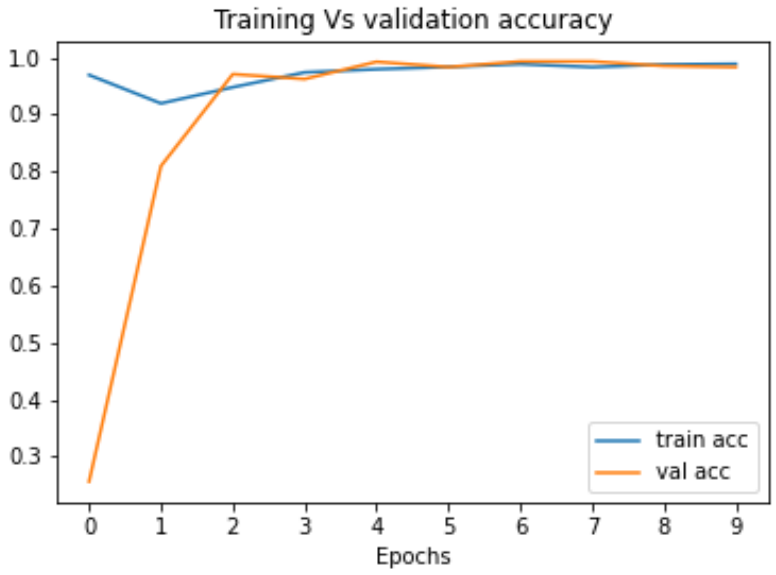


Figure 5.4: Accuracy curve for InceptionResNetV2 model with fine-tuning

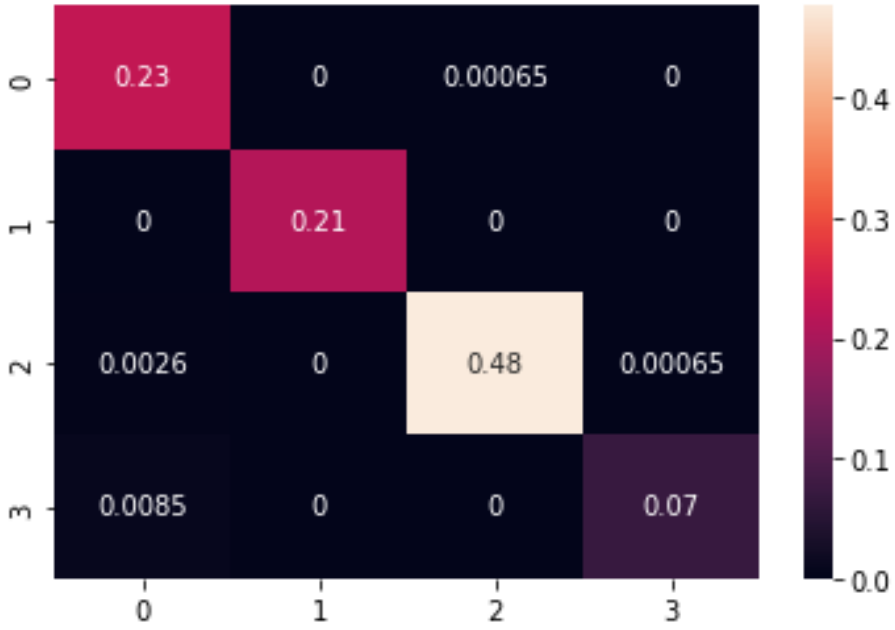


Figure 5.5: Confusion Matrix with fine-tuning

Table 3.1 :Metrics for Fine Tuning weights during training				
Serial Number	Precision	Recall	F1-Score	Support
0 - Grass	0.95	1.00	0.97	350
1 - Soil	1.00	1.00	1.00	324
2 - Soybean	1.00	0.99	1.00	733
3 - Weeds	0.99	0.89	0.94	120
Accuracy			0.99	1527
Macro Average	0.99	0.97	0.98	1527
Weighted Average	0.99	0.99	0.99	1527

5.4 Discussion

Use of residual networks was a step taken in the right direction. However, the results we got were not aligned to what we thought. We initially froze the base network weights and quickly found that it was a dead-end with no gradual improvement in the model performance. Fine tuning the model did improve the accuracy of classification but was not good enough to satisfy our expectation. With an ardent desire to seek the utmost accuracy in classification, we implemented a convolutional neural architecture that builds on the inception family of architectures but incorporates residual connections, InceptionResNetV2. Since Inception networks tend to be very deep, it is natural to replace the filter concatenation stage of the Inception architecture with residual connections. This would allow Inception to reap all the benefits of the residual approach while retaining its computational efficiency [11] and it leads to getting superior results for further classification tasks. Finally, with InceptionResNetV2 we achieve 99% accurate classification of weed, soyabean, soil and grass.

5.5 Conclusion

We came to the conclusion that transfer learning is one of the right approaches that we could use to train a deep learning model with a smaller dataset. We used a pretrained ResNet50 model already trained on ImageNet dataset for our project. All the results, such as the learning curves, showed some benefit of fine-tuning but the results were not promising as expected. So, we worked on InceptionResNetV2 implementation that makes improvement to ResNet50 architecture with introduction of inception block that leads to a wider network and being computationally efficient. This approach was significantly better and led to exceptional results. Finally, in classification task, we observed that the residual architecture performs well but the combination of residual and inception architecture is far superior.

Table 5.1: Contributions by team member for Milestone 5.

Team Member	**Contribution**
Puranjit Singh	Coding, pre-processing, model training and visualizations
Shiva Paudel	Modeling suggestions and report writing
Shubham Bery	Report writing, proofreading and editing
Kantilata Thapa	Report proofreading and editing

Appendix A

First Appendix

Results that are obtained after preparing the report are presented here.

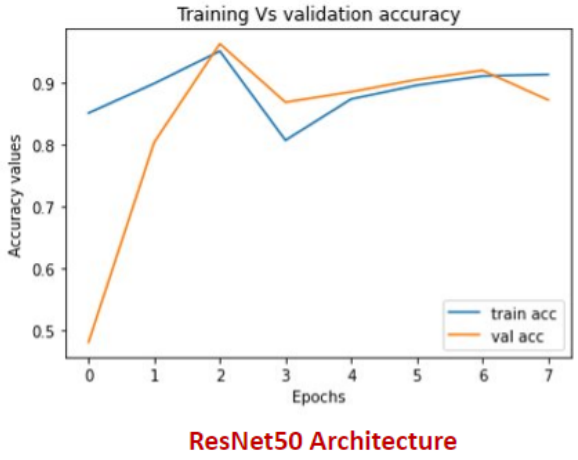


Figure A.1

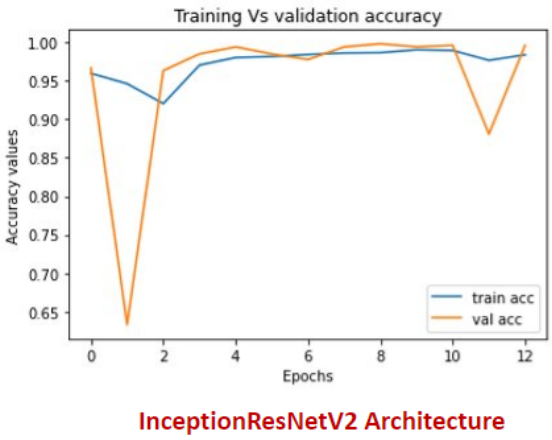


Figure A.2

Figure A.3

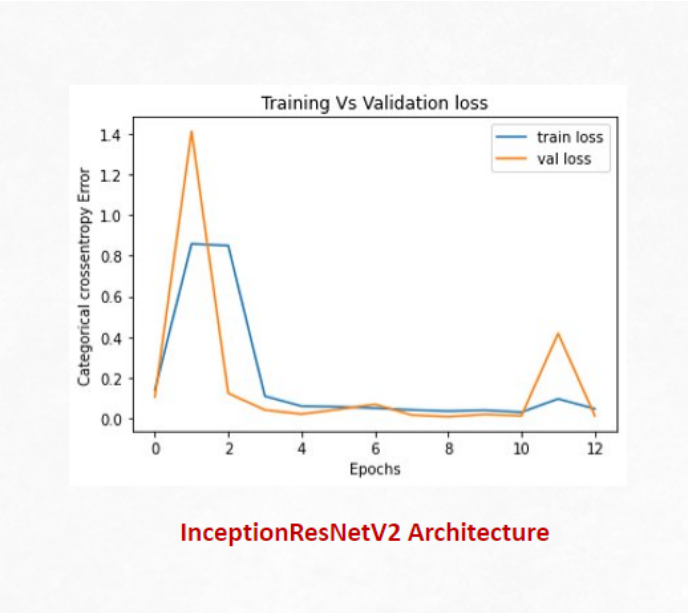

Training Vs Validation loss
train loss
val loss
Categorical crossentropy Error
Epochs
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
0
2
4
6
8
10
12
InceptionResNetV2 Architecture

Figure A.4

Bibliography

[1] Deep Residual Networks - ResNet50. `https://viso.ai/deep-learning/resnet-residual-neural-network/`. Accessed: 2022-01-14.

[2] Weed Detection in Soybean Crops. `https://www.kaggle.com/fpeccia/weed-detection-in-soybean-crops/activity`. Accessed: 2012-11-12.

[3] Bhagirath Singh Chauhan. Grand challenges in weed management. *Frontiers in Agronomy*, 1:3, 2020.

[4] Alessandro dos Santos Ferreira, Daniel Matte Freitas, Gercina Gonçalves da Silva, Hemerson Pistori, and Marcelo Theophilo Folhes. Weed detection in soybean crops using convnets. *Computers and Electronics in Agriculture*, 143:314–324, 2017.

[5] CM Ghersa and JS Holt. Using phenology prediction in weed management: a review. *Weed research*, 35(6):461–470, 1995.

[6] ASM Mahmudul Hasan, Ferdous Sohel, Dean Diepeveen, Hamid Laga, and Michael GK Jones. A survey of deep learning techniques for weed detection from images. *Computers and Electronics in Agriculture*, 184:106067, 2021.

[7] M Shamim Hossain, Muneer Al-Hammadi, and Ghulam Muhammad. Automatic fruit classification using deep learning for industrial applications. *IEEE Transactions on Industrial Informatics*, 15(2):1027–1034, 2018.

[8] Karina Perez-Daniel, A Fierro-Radilla, and JP Peñaloza-Cobos. Rotten fruit detection using a one stage object detector. In *Mexican International Conference on Artificial Intelligence*, pages 325–336. Springer, 2020.

[9] David Pimentel, Rodolfo Zuniga, and Doug Morrison. Update on the environmental and economic costs associated with alien-invasive species in the united states. *Ecological economics*, 52(3):273–288, 2005.

[10] Colin Rennie, Rahul Shome, Kostas E Bekris, and Alberto F De Souza. A dataset for improved rgbd-based object detection and pose estimation for warehouse pick-and-place. *IEEE Robotics and Automation Letters*, 1(2):1179–1185, 2016.

[11] Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke, and Alexander A Alemi. Inception-v4, inception-resnet and the impact of residual connections on learning. In *Thirty-first AAAI conference on artificial intelligence*, 2017.

[12] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2818–2826, 2016.

[13] Dhananjay Theckedath and RR Sedamkar. Detecting affect states using vgg16, resnet50 and se-resnet50 networks. *SN Computer Science*, 1(2):1–7, 2020.