School of

Computer Science and Engineering

Machine Learning Project Report on

Plant Seedlings Classification

Kaggle challenge:v2-plant-seedlings-dataset

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CERTIFICATE

This is to certify that project entitled **"Kaggle challenge: v2-plant-seedlings-dataset-image-classification"** is a bonafide work carried out by the student team of **"Anusha Raikar SRN:01FE18BCS043, Apoorva Jinde SRN:01FE18BCS044, Archana Badagi SRN:01FE18BCS045, Rachana Patil SRN:01FE18BCS060 "** . The project report has been approved as it satisfies the requirements with respect to the Machine Learning Project work prescribed by the university curriculum for BE (V Semester) in School of Computer Science & Engineering of KLE Technological University for the academic year 2020-2021.

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ABSTRACT

For several years, many people have tried to solve the problem of identifying plant seedlings and weeds. They used wide range of approaches with the common goal of identifying weeds from normal plants but no system that has made a commercial breakthrough has been developed. There are various reasons for these systems to be not able to solve the problem like one of them is dataset. A research paper on similar problem identifying plant species by the shape of leaf is published by Ji-Xiang Du, Xiao Feng Wang & Guo-Jun Zhang, Department of Automation, University of Science and Technology of China.

It is strongly believed that this problem can be solved using deep learning because the technology(hardware) is capable of doing image identification tasks easily and now is the right time for such breakthrough systems because of the latest techniques in deep learning. Until very recently, the main problem was acquisition of the image data to be used to build robust systems. But, in November of 2017, to support and encourage the development of species recognition techniques for the agricultural industry, the Computer Vision and Biosystems Signal Processing Group, Department of Engineering, Aarhus University has collected the data and made it available to the public for free.The Aarhus University Signal Processing group, in collaboration with University of Southern Denmark, has recently released a dataset containing images of approximately 960 unique plants belonging to 12 species at several growth stages. Our goal is to build a classifier that classifies the seedling's class based on the image input, using state of the art deep learning techniques.

Contents

Chapter 1

Introduction

1.1 Overview

Agriculture is vital for human survival and remains a major driver of several economies around the world more so in underdeveloped and developing economies.

With increasing demand for food and cash crops, due to a growing global population and the challenges posed by climate change, there is a pressing need to increase farm outputs while incurring minimal costs

One major reason for reduction in crop yield is weed invasion on farmlands. Weeds generally have no useful value in terms of food, nutrition or medicine yet they have accelerated growth and parasitically compete with actual crops for nutrients and space

Inefficient processes such as hand weeding has led to significant losses and increasing costs due to manual labour

The robots and the vision machines need to be able to precisely and reliably detect a weed from the useful plants. Machine vision technologies developed for selective weeding have faced the challenge of reliable and accurate weed detection.

1.2 Motivation

Differentiating a weed from a crop seedling by the image can pave a significant way to intelligent weed control systems and thus eliminating the unwanted plants in its initial stages only. The ability to do so effectively can mean better crop yields and better stewardship of the environment. The goal is to build a classifier that classifies the seedling's class based on the image input, using state of the art deep learning techniques.

1.3 Objective

Weed control is considered a major obstacle for the growers in organic farming. Lower plant productivity in organic farming is mainly related to poor weed control. It is widely known, in most cases, that losses caused by weeds exceeded the losses from any category of agricultural pests. Under water-stress condition, weeds can reduce crop yields more than 50% through moisture competition alone.

In this model, we are provided with a dataset of 12 plant species, including weed. The idea is to have an effective weed control and in order to do so, the first critical requirement is a correct weed identification.

We will try to solve this weed identification problem with Machine Learning. The aim is to build a model a classifier that recognizes plant species images and differentiates between crop seedlings and weed.

1.4 Literature survey

Seedling Classification Techniques:

1] Computer vision with seedlings:Here they have tried to only segment out the plant seedling from the pebble background.The dataset has an unconscious target leakage. It leads to a model that learns from the size of the stones in the background to predict the plant species. But by using Computer vision segmentation techniques they have bypassed this behaviour by extracting plant information only and thereby removing the pebble stones background.

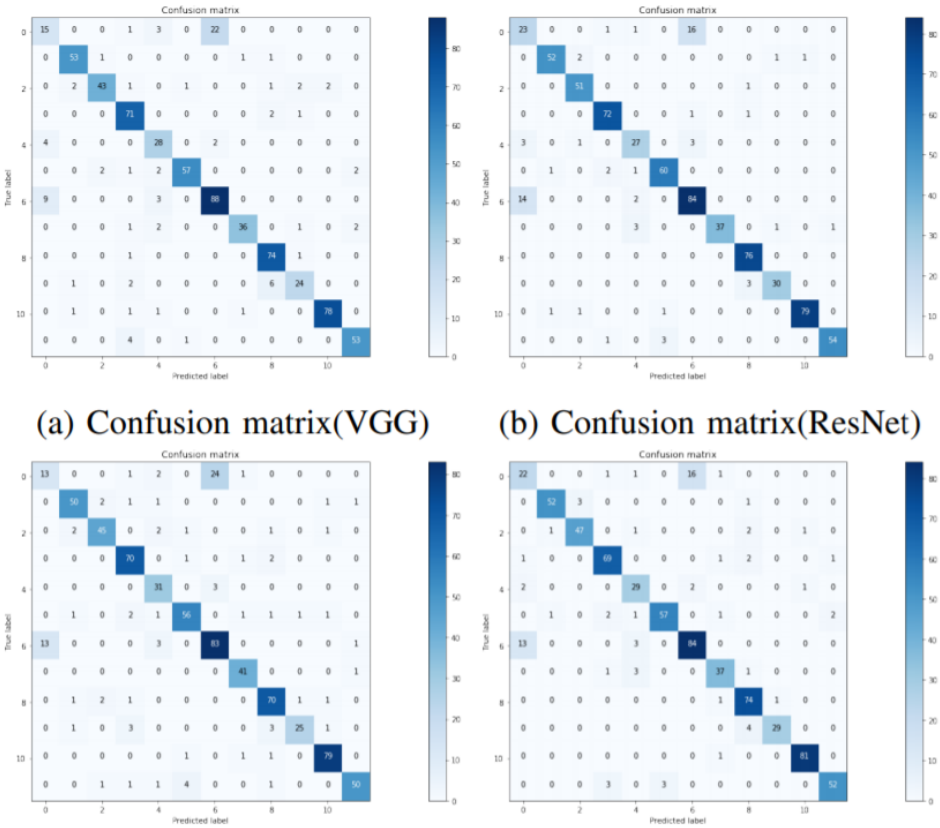
2] CNN Based Model for Seed Classification: The Convolutional Neural Network developed can have the following architecture: LeNet, Alexnet, VGG, Inception, Custom Model, the primary result of the original paper was that the depth of the model was absolutely required for its high performance. This was quite expensive computationally but was made feasible due to GPUs or Graphical Processing Units, during training.

The Convolutional Neural Network models are designed to map image data to an output variable. The benefit of using CNNs is their ability to develop an internal representation of a two-dimensional image. This allows the model to learn position and scale in variant structures in the data, which is important when working with images.

They have proven so effective that they are the go-to method for any type of classification problem involving image data as an input.

The CNN model we have built has the following characteristics :-

Conv2D layers, MaxPool layers, Dense layers



(a) Confusion matrix(VGG) (b) Confusion matrix(ResNet)

(c) Confusion matrix(DenseNet) (d) Confusion matrix(MobileNet)

Figure 1.1: Comparisions between different CNN architecture's Confusion matrix

1.5 Problem statement

To identify different weed seedlings and the crop of 12 different plant species.

Chapter 2

Proposed System

2.1 Description of Proposed System

Figure 2.1: Block Diagram

2.2 Description of Target Users

The fields are vulnerable to weeds, which threaten to destabilize food yield. These weeds consume water and nutrients which actually are provided for the crops for their growth. Hence, classifying the weeds from crop seedlings at the early stage would be helpful for the farmers.

2.3 Advantages of Proposed System

1. The application provides quick accurate results.
2. The application can be handled easily by the users.
3. Avoids farmers to manually classify the weeds from the crops and predict the type of the weed and crop seedling.

Chapter 3

Implementation

3.1 Data Pre-Processing:

Data Preprocessing has to be done on the dataset some of the data preprocessing techniques used are:

1] Transforming Images (Resize:The images are in different sizes. We will resize all images to 96x96 and use only 250 images from each class.)

2] Splitting data for training and Validation .

We have to choose an appropriate model to train on the dataset. Then the task is to classify the plant seedling.

3.2 Model Description

We implemented a CNN model to classify plant seedlings into its respective labels. We built the model with convolutional layers(Conv2D, MaxPooling). We have used adam optimizer with learning rate of 0.0001 and categorical crossentropy loss . Accuracy we obtained is 0.82622 and loss is 0.81999

Model structure (optimizer: Adam):

1]Input

2](Conv2D*3 – MaxPool2D – Dropout) X3 – (filters = 16, 32, 64)

3]Flatten

4]Dense (256)

5]Dropout

6]Output

We have shown the model summary here

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 94, 94, 32)        896
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 92, 92, 32)        9248
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 90, 90, 32)        9248
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 45, 45, 32)        0
_________________________________________________________________
dropout (Dropout)            (None, 45, 45, 32)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 43, 43, 64)        18496
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 41, 41, 64)        36928
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 39, 39, 64)        36928
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 19, 19, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 19, 19, 64)        0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 17, 17, 128)       73856
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 15, 15, 128)       147584
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 13, 13, 128)       147584
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 6, 6, 128)         0
_________________________________________________________________
dropout_2 (Dropout)          (None, 6, 6, 128)         0
_________________________________________________________________
flatten (Flatten)            (None, 4608)              0
_________________________________________________________________
dense (Dense)                (None, 256)               1179904
_________________________________________________________________
dropout_3 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 12)                3084
=================================================================
Total params: 1,663,756
Trainable params: 1,663,756
Non-trainable params: 0
```

Figure 3.1: Model Summary

3.3 Implementation Description

The model is trained on 90% of the given dataset. Then provided with the rest 10% of the dataset to predict the plat seedling.Adam Optimizer with 0.0001 learning rate. Loss function used is categorical_crossentropy. Hypertuning of the parameters is done to reduce the error.

Chapter 4

Results and discussions

These are results obtained.

For training dataset - accuracy is 0.9468 ,for validation dataset - accuracy is 0.8100

For training dataset - loss is 0.1320 ,for validation dataset - loss is 1.0334

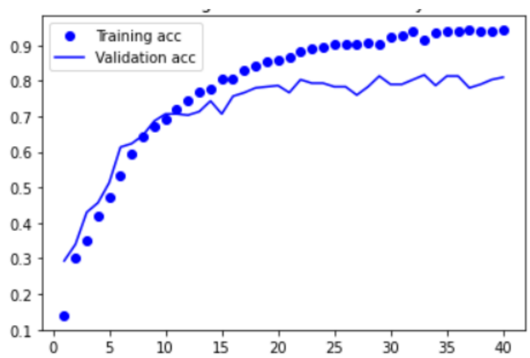


Figure 4.1: Accuracy for training and validation dataset

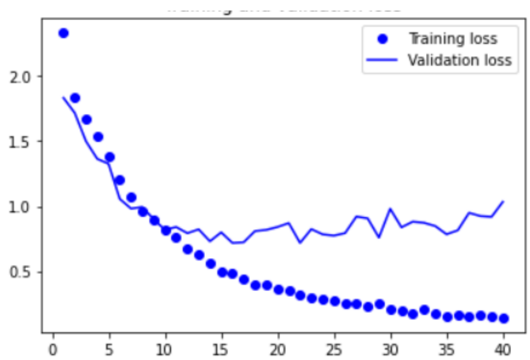


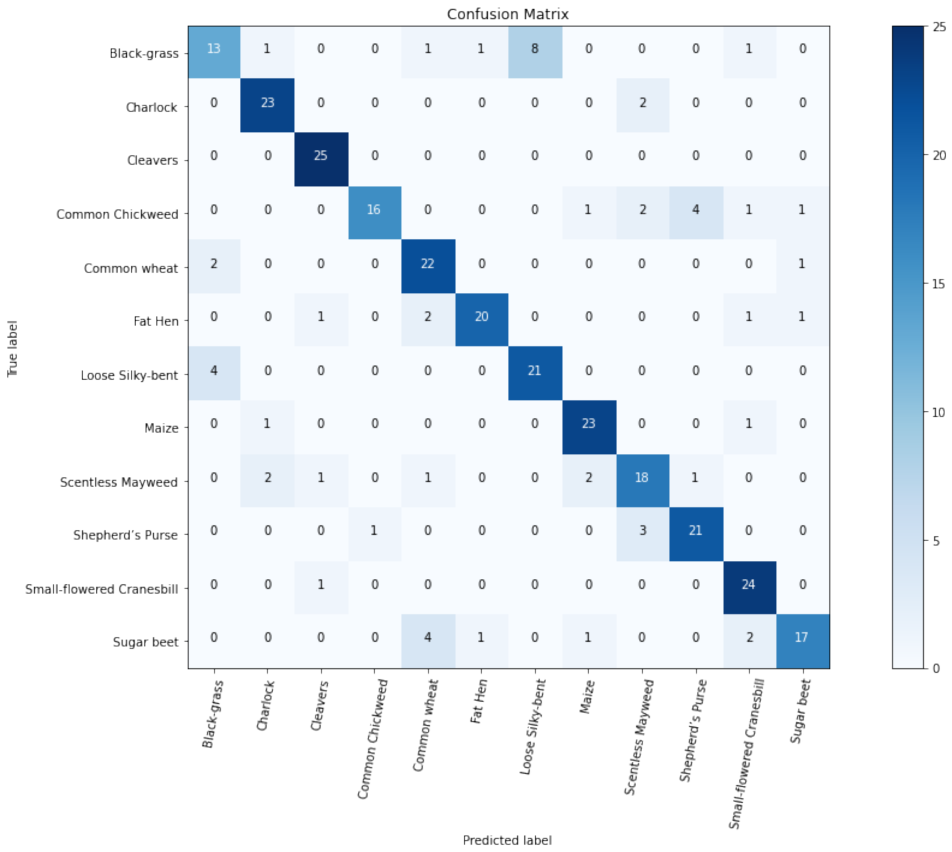
Figure 4.2: Loss for training and validation dataset

Chapter 5

Conclusions and future scope

5.1 Conclusion

The model we built was with the aim of identifying weed plants in initial stages. Let us see the confusion matrix and analyze the performance.



1] Model did find hard time in identifying Black-Grass from Loose Silky Bent.

2] Model did very good job in detecting Cleavers with very accuracy with f1-score of 0.94.

5.2 Future scope

As the further improvement to our model, we can build a model by over or undersampling the data because of the irregular count in images and build a more generalized model. We can also improve the accuracy by doing some other preprocessing techniques. Finally, the model we built can be used for real-time identification of weed plants by the farmers using a mobile application built on this model.

The limitation of the current working of the app is that the images are required to be processed before feeding it to the CNN TensorFlow Lite model. To overcome this situation, we can upload the image to a web app which can do the required pre-processing and return the resultant image back to the device.

Moreover, the model can be hosted on Firebase MLKit which can improve the developers' effort as bundling the model to the app seems a daunting task every time the .tflite model is updated. MLKit can help to update the model without requiring the users to update the app itself.

Bibliography

[1] Ashqar, Belal AM, Bassem S. Abu-Nasser, and Samy S. Abu-Naser. "Plant seedlings classification using deep learning." (2019).

[2] Alimboyong, Catherine R., Alexander A. Hernandez, and Ruji P. Medina. "Classification of plant seedling images using deep learning." TENCON 2018-2018 IEEE Region 10 Conference. IEEE, 2018.

[3] Alimboyong, Catherine R., and Alexander A. Hernandez. "An improved deep neural network for classification of plant seedling images." 2019 IEEE 15th International Colloquium on Signal Processing Its Applications (CSPA). IEEE, 2019.

[4] Dyrmann, Mads, Henrik Karstoft, and Henrik Skov Midtiby. "Plant species classification using deep convolutional neural network." Biosystems Engineering 151 (2016): 72-80.

[5] Silva, L. O. L. A., et al. "Comparative assessment of feature selection and classification techniques for visual inspection of pot plant seedlings." Computers and electronics in agriculture 97 (2013): 47-55.