Deep Convolutional Neural Networks For Cassava Leaf Disease Classification

Aakash Babubhai Gajera
MSc (Computer Science) Pr
Lakehead University
gajeraa@lakeheadu.ca

Govani Shruti
MSc (Computer Science) Pr
Lakehead University
sgovani@lakeheadu.ca

Shah Jay Samir
MSc (Computer Science) Pr
Lakehead University
jshah12@lakeheadu.ca

Abstract

Plant diseases are a common occurrence on many farms globally and these affect the normal growth and yield of various crops. One of the many crops affected by plant diseases is the cassava crop which is among the main sources of food especially in Sub-Saharan Africa. Cassava crop diseases such as the cassava mosaic, green mottle, brown streak and bacterial blight manifest themselves via the leaves of the crop whereas other diseases attack the shoots and stems. Early detection mechanisms for such cassava diseases are crucial for ensuring proper crop growth and yield without which the food security of communities that rely on this crop is at the mercy of the diseases. Previous research [1] has shown promising results in the classification of cassava leaf diseases using deep learning and also in the detection of diseases in other crop types [2]. We therefore propose a deep learning based approach for the classification and identification of cassava leaf diseases using deep convolutional neural networks.

1. Introduction

Cassava is the staple food for many very low income households mostly in Sub-Saharan Africa mainly because of its strong tolerance to harsh climate conditions such as drought and also because of its rich carbohydrates content. Many of the cassava growers are small holder farmers with usually low income and unable to acquire pesticides face risks of poor quality, low or no seasons' harvest once their crops are attacked by viruses. The end result is food insecurity and some farmers end up abandoning the cultivation of the crop for other alternatives. Because making routine checkups on crops on fairly large plantations is physically draining, unreliable and many times labour intensive, early disease detection methods especially automated ones are critical to the food security of these people. Deep Convolutional Neural Networks have shown good results in identifying certain types of cassava leaf diseases Ramcharan *et al*. [1] and it is upon these results that we aim to apply them to detect other kinds of diseases in the cassava leaves. We choose this [1] as our main reference paper because it studies cassava leaf diseases which is our focus in our own study albeit there are different cassava diseases under study. The authors in [1], use a deep learning technique known as transfer learning where an already trained model on another related dataset is applied as a base model to a similar task to learn new data features and predict the end result. This is achieved through extracting the feature embeddings learned by the trained model and then adding more neural network layers on top of these embeddings to learn new patterns in a new task dataset and finally return predictions. The authors apply the Inception v3 model for cassava leaf disease detection on a cassava leaf dataset of and evaluate the model based on the accuracy score metric which measures how close a given/predicted value is to the true value.

Our work aims to apply the lastest state of the art deep learning models such as the ResNet and EfficientNet models to solving this cassava leaf disease classification on a different leaf disease dataset. This is due to the improved performances of these latest models compared to the inception v3 that is quite obsolete.

2. Related Work

The authors in [1] do apply deep convolutional neural networks through transfer learning for cassva leaf disease detection and the report very good results on applying this training methodology. They do report accuracies of 0.95 and 0.98 for the two disease classes out of six on which this transfer learning methodology using the Inception v3 model performs well; it doesn't perform as this good however on other disease classes.

Researchers at the Makerere University AI lab [3] compiled images of 4 types of cassava leaf diseases and of healthy ones as well in the hope to out source models to accurately classify the 4 types of leaf diseases.

3. Our Model

Our final model architecture is composed of a pretrained EfficientNet (b3) Model as our backbone to the overall architecture joined to a set of dense, activation, dropout and batch-normalization layers by a pooling layer.
It is visualized below;

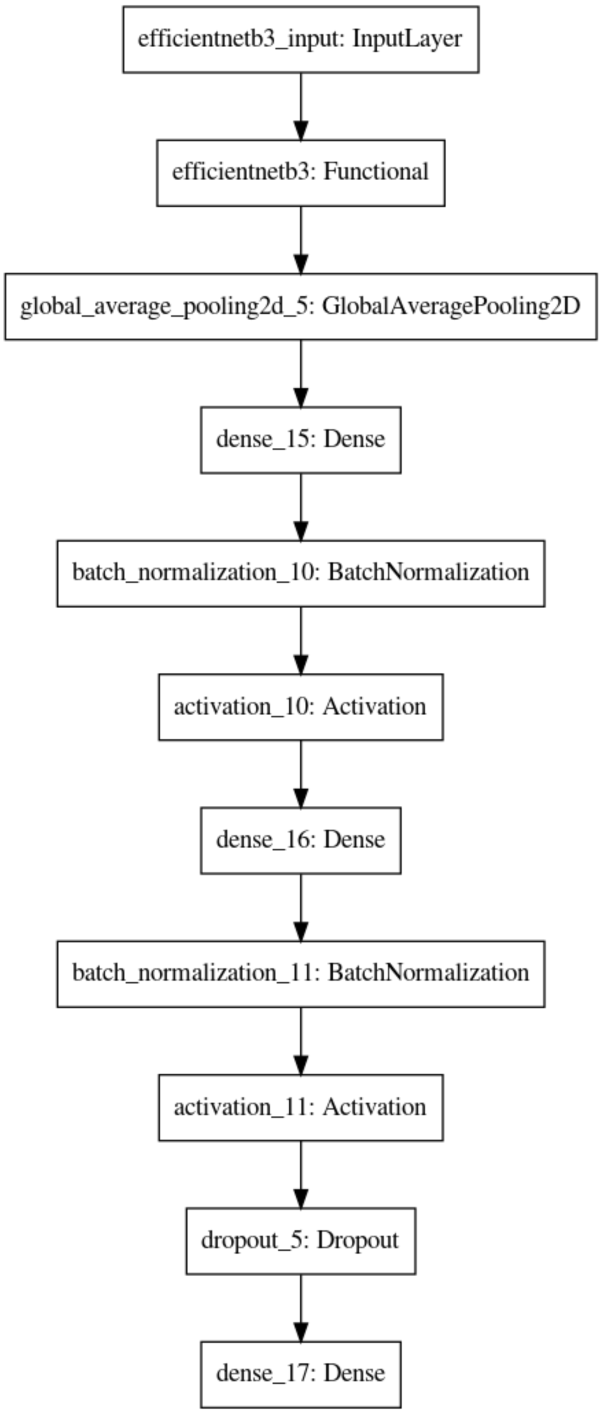

Figure 1. Model Architecture.

4. Data

The dataset [3] used for this task is composed of 21,397 cassava leaf images each falling under either of the 5 class labels; **Cassava Bacterial Blight (CBB): 0, Cassava Brown Streak Disease (CBSD): 1, Cassava Green Mottle (CGM): 2, Cassava Mosaic Disease (CMD): 3, or Healthy: 4**.

Figure 2. Sample leaf images per disease class.

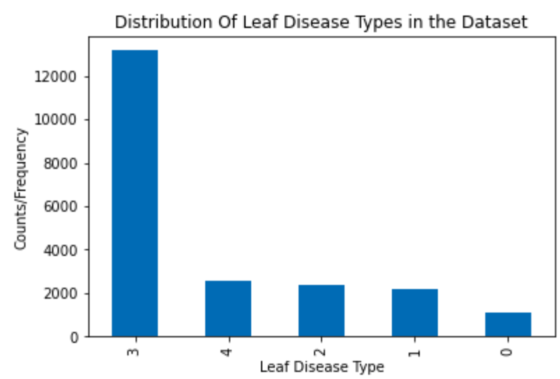

Figure 3. Dataset distribution.

Cassava Mosaic class has a significantly higher number of images throughout the dataset than all other classes and this therefore implies that the dataset is imbalanced. The dataset is also mostly preprocessed so there is very little more preprocessing required.

5. Results

We ran two experiments with two pretrained models; a ResNet50 and an EfficientNetB3 as our backbone models in our model architecture for either experiments and then trained them on the cassava leaf dataset [3] composed of 21,397 leaf images. The dataset was split into train and test sets using a ratio of 85:15 and then trained either models on the training data for 15 epochs each with a early stopping mechanisms to reduce over-fitting and learning rate decay. The ResNet50 model achieves an average test categorical accuracy of approximately 67.80% whereas the EfficientNetB3 model achieves an average test categorical accuracy of 81.46% . The models' training is done on the entire training dataset and the accuracy trend across all training epochs for either model is visualized as below:

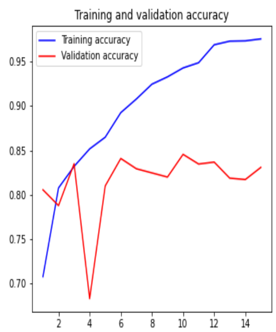

Figure 4. EfficientNet Training Accuracy plot.

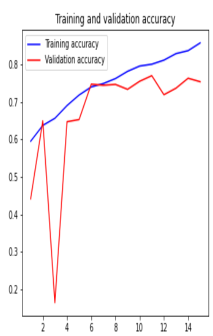

Figure 5. ResNet Training Accuracy plot.

It can be seen that there are fluctuations in the validation accuracy for both models which signals potential noise in the dataset. The model performance was further evaluated using other classification metrics such as the f1 score, recall and precision. Below the results of both models are compared.

It can be seen that both models predict class 3: Cassava Mosaic disease well but the EfficientNet model performs better on this class and all other classes.
The predictive performance of both models is however poor on class 0: Cassava Bacterial Blight.

	precision	recall	f1-score	support
0	0.54	0.21	0.30	147
1	0.60	0.64	0.62	330
2	0.50	0.57	0.53	356
3	0.90	0.90	0.90	1996
4	0.57	0.61	0.59	381
accuracy			0.77	3210
macro avg	0.62	0.59	0.59	3210
weighted avg	0.77	0.77	0.77	3210

Figure 6. ResNet50 Classification Report.

	precision	recall	f1-score	support
0	0.70	0.30	0.42	147
1	0.70	0.78	0.73	330
2	0.67	0.75	0.71	356
3	0.94	0.95	0.94	1996
4	0.66	0.63	0.64	381
accuracy			0.84	3210
macro avg	0.73	0.68	0.69	3210
weighted avg	0.84	0.84	0.84	3210

Figure 7. EfficientNetB3 Classification Report.

6. Challenges

Deep learning models require quite sizeable task datasets for training so as to achieve reasonable performance and near generalizable results on unseen data. Transfer learning did help solve this but the data available was imbalanced meaning that one leaf disease type had more images in the dataset than other leaf disease types. This does introduce subtle bias towards the leaf disease type with the most images in the resulting model. Shuffling was performed to allow for near equal representation of images from all leaf disease type classes but it doesn't completely eliminate the class bias rather it reduces it as was evident in the higher training accuracy but rather lower test accuracy. This class imbalance was a major hindrance to achieving higher test scores on the model. The dataset used is too noisy as can be inferred from the fluctuating validation loss and accuracy. This also hampers achieving higher test scores and more generalizable results on unseen data.

7. Limitations

Transfer learning is a great methodology to achieve a relatively high performing model on small datasets but it isn't a one size fits all methodology as the domains of the data both newer and that used for the pretraining; may vary greatly and this in turn means that certain key patterns in the new data domain may be overlooked during the training phase.

8. Discussion

The final model, an EfficientNetB3 model through the use of the transfer learning methodology does achieve good performance without the hustle of doing feature extraction from images. It also appears to perform well on this relatively imbalanced dataset with a macro average f1 score of 0.69 , weighted average f1 score of 0.84 and an average categorical accuracy of 81.46% across all 5 leaf disease categories. This is significantly lower that the 95% accuracy reported by the ramancharan *et al*. [1] but it should be noted that this is across two different datasets with different distributions and size.

9. Conclusion

Transfer learning is a great model training methodology that is has produced state of the art results on certain tasks but it isn't always appropriate to apply to some task domains because the variance in domains. It is therefore important to determine the appropriateness of this methodology especially for mission critical systems such as healthcare systems. This methodology however helped us to create a well performing cassava leaf disease classification model that can act as benchmark for future models solving a similar problem.

References

[1] Amanda Ramcharan, Kelsee Baranowski, Peter McCloskey, Babuali Ahmed, James Legg, and David Hughes (2017). Using Transfer Learning for Image-Based Cassava Disease Detection.

[2] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311-318

[3] https://www.kaggle.com/c/cassava-leaf-disease-classification/