MobileNet을 사용한 학습되지 않은 옥수수 질병 예측

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Using MobileNet to Predict Unseen Corn Diseases

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Abstract

Agriculture and the plants and crops that are the results of it are essential to our everyday lives. Without agriculture our current society can not function and as such it is extremely important to make sure that we can assure that farms and farmers can continuously and steadily harvest enough produce. One big challenge that keep hindering the farming process are plant diseases that account for a large number of dead crops. They spread fast and can be troublesome to detect, especially manually. Datasets are also sparce and often lacking. To ease the detection process and speed it up, in an effort to aid farmers, we propose a pretrained MobileNet CNN deep learning AI model that can automatically detect maize/corn diseases from images. However, since data is rather sparce, not all diseases can be accounted for. This is why we have trained the model with one set of diseases (leaf spot and leaf blight) and healthy plant leaves, but tested it with a set of images of maize leaves that are infected with a disease the model has never seen before (leaf rust). The model has managed to not only learn and master the test set, but also managed to generalize to the before unseen rust infected leaf images. This promises to help future models learn robust and effective models that can generalize to diseases that can even classify diseases new to the model, which can be important in a field with limited data.

1. Introduction

Plant Disease recognition is a field that is essential to humanity. Without it a sufficient supply of food can not be guaranteed. This is why good, fast and reliable detection of diseases is necessary. Traditional methods, like manually walking through the fields and looking for infected plants, are tedious, slow, expensive and require trained personal. The sooner one can detect a diseased planned, the sooner the disease can be prevented from spreading to other plants, limiting the loss of harvest [1].

Deep Learning is a powerful tool that can be used in numerous fields to utilize AI to automate certain processes. DL, as a whole, however, relies heavily on large datasets to train competent models that can generalize to new data. Creating sufficient datasets is no easy task, and as such there are not always publicly available for all fields. For plant leaf disease detection there are a number of sets like FieldPlant [2] or PlantVillage [3]. In this work a subset of the PlantVillage dataset was used. PlantVillage is not without it's downsides either. While it does boast a rather wide array of plants and diseases, there are still many that are missing from the dataset. Additionally, the dataset was taken under lab conditions, which also limits its applicability to images taken in the field. These lab images are of high quality though and a large number is available in the dataset males PlantVillage one of the best datasets available. PlantVillage being an image dataset makes CNN models the obvious choice. CNN models excel in the field of image-based DL. There exist many different CNN architectures. MobileNet [4] is a model that is small and lightweight and can run on less powerful end-devices [8], which is beneficial for the use in field.

2. Methodology

The experiments carried out in this paper were carried out to see whether or not a CNN model can be trained to detect a disease that never before seen by the model during training or validation. During training the model was trained with healthy corn leaf images as well as images of corn leaves that are infected with leaf spot or leaf blight. The training dataset, however, contained leaf rust images exclusively. If the model can successfully adapt to the new data during training and therefore adapt to a new disease without additional training data, large datasets might not be required for all diseases, which could be very beneficial in a field where data is not as readily available as one might hope.

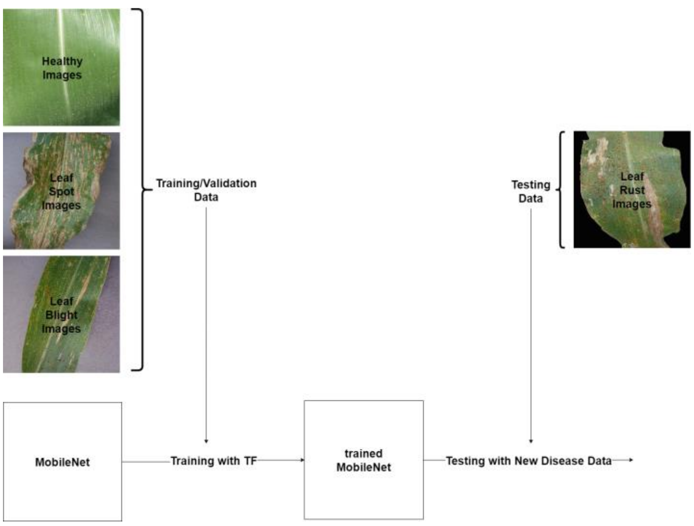

Figure 1: Image depicting the process of training and testing with the new data

1. Data

	Healthy	Bacterial Spots
Train	930	1199
Validation	232	299
Test	0	1192

Table 1: Make up pf the initial dataset

The PlantVillage dataset, might be the most well-known dataset in the field of plant leaf disease classification and also the most often used dataset. (e.g. [6], [7]). The dataset encompasses a sizable number of different plants and diseases. In this work only maize (corn) images were used. In the train and validation sets a combined number of 2660 images were used (see Table 1). The infected images in the train and validation set were comprised of a combined 513 leaf spot images and 985 leaf blight images that were together grouped into the infected dataset. The other class was, as mentioned above, the 1162 healthy images. The test set contained none of the above, but was rather made up of 1192 rust infected images (see Figure 1). With this setup it is possible to see if the model can be used on diseases that were not used for training.

All the training and validation images were first augmented (see Table 2) which resulted in a final number of 17415 healthy images and 22455 infected images.

Figure 2: Example of healthy leaves (Top Left: Rust, Bottom Left: Healthy, Top Right: Blight, Bottom Right: Spot)

Augmentation	Values
Contrast	-0.25, 0.25
Brightness	-0.75, 0.75
Zoom	0.25
Flip	Horizonal, Vertical
Rotate	-90, 90
Hue Shift	-20, 20
Channel Shift	75
Noise	0, 1
Histogram Equalization	-

Table 2: Data Agumentation

2. Model

The used in this work was the MobileNet architecture, the MobileNet v3 [5] to be exact. Additionally, the minimized version of the model was used, which is even smaller. Small models like MobileNet are desirable

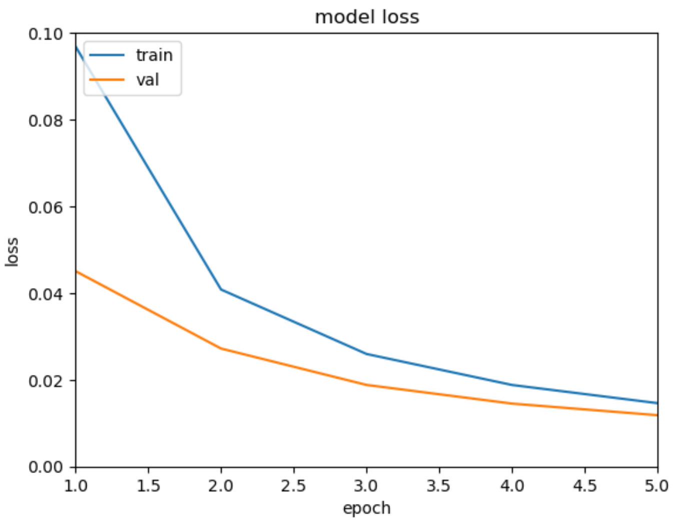

Figure 3: Training accuracy over time

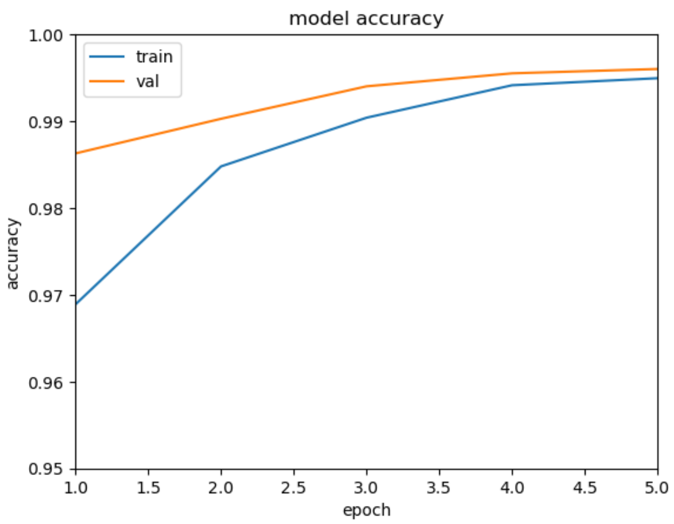

Figure 4: Training loss over time

because they allow the trained model to be used on an end device that is not as powerful, which would make them much more applicable to the actual in field usage. To speed up the training process, transfer learning technology was used. The pretrained weights were obtained from a minimalized MobileNet v3 that was trained on the imageNet dataset.

3. Results

Due to the nature of TF models not requiring much training, we only trained the model for 5 epochs. Even after such a small amount of training, the model managed to reach over 99% on both the training and validation dataset. But even on the before unseen images dataset containing rust infected leaf images the model managed to reach over 98% accuracy (see Figures 2 and 3 and Table 3). This does not only show that the model is capable of detecting diseases that are outside of the scope of diseases, but that the model can excel in them. One limitation that needs to be disclosed is the fact that the lab images are easier to learn than field images would be. This means that a field dataset might not perform as well.

Dataset	Acc.	Loss
Training	99.48%	0.0197
Validation	99.57%	0.0166
Testing	98.66%	0.0278

Table 3: Results

4. Future Work

In future experiments it would be preferable if the dataset would be made up of images taken in the field as opposed to images in the lab. Additionally, it would be preferable if the images would taken in similar conditions across the different classes in the training set. Another possibility would be to also include more tahtn one plant.

5. Conclusion

In this paper we have used the minimized MobileNet v3 architecture CNN to asses the performance of a model, trained with TF, on a plant leaf disease that it was not shown during training. The results are very promising and show that the model does indeed manage to not only perform well on the training and validation data, but also excels on the testing dataset.

Acknowledgements

This work was supported by Korea Institute of Planning and Evaluation for Technology in Food, Agriculture and Forestry(IPET) through the Agriculture and Food Convergence Technologies Program for Research Manpower development, funded by Ministry of Agriculture, Food and Rural Affairs(MAFRA)(project no. RS-2024-00397026). This work was supported by Institute of Information & communications Technology Planning & Evaluation (IITP) under the Artificial Intelligence Convergence Innovation Human Resources Development (IITP-2023-RS-2023-00256629) grant funded by the Korea government(MSIT)

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