The Thirty-First International Florida
Artificial Intelligence Research Society Conference (FLAIRS-31)

Soybean Plant Disease Identification Using Convolutional Neural Network

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Abstract

Plants have become an important source of energy, and are a fundamental piece in the puzzle to solve the problem of global warming. However, plant diseases are threatening the livelihood of this important source. Convolutional neural networks (CNN) have demonstrated great performance (beating that of humans) in object recognition and image classification problems. This paper describes the feasibility of CNN for plant disease classification for leaf images taken under the natural environment. The model is designed based on the LeNet architecture to perform the soybean plant disease classification. 12,673 samples containing leaf images of four classes, including the healthy leaf images, were obtained from the PlantVillage database. The images were taken under uncontrolled environment. The implemented model achieves 99.32% classification accuracy which show clearly that CNN can extract important features and classify plant diseases from images taken in the natural environment.

Introduction

Agriculture has become much more than simply a means to feed ever growing populations. However, plant diseases are threatening the livelihood of this important source. Plant diseases cause major production and economic losses in agriculture and forestry. For example, soybean rust (a fungal disease in soybeans) has caused a significant economic loss and just by removing 20% of the infection, the farmers may benefit with an approximately 11 million-dollar profit (Sankaran et al. 2010). Therefore, early detection and identification of plant diseases plays the utmost important role to take timely measures.

There are several ways to detect plant pathologies. Some diseases do not have any visible symptoms associated, or those appear only when it is too late to act. In these cases, it is necessary to perform sophisticated analysis, usually by means of powerful microscopes. In some cases, the signs can only be detected in parts of the electromagnetic spectrum that are not visible to humans (Barbedo 2013).

Most diseases, however, generate some kind of manifestation in the visible spectrum. The diseases may exhibit symptoms on different parts of the plant, i.e. leaves, stem, fruits/seeds etc. This research focuses on detection and classification of soybean plant diseases based on the symptoms of the diseases that show signs on the leaves of the plant. In most cases, the diagnosis, or at least a first guess about the disease, is performed visually by humans (Barbedo 2013). Trained experts may be efficient in recognizing the disease. Unfortunately, most of the time there are no experts in the area to give a data based analysis and advise to the farmers. Therefore; looking for a fast, automatic, less expensive and accurate method to detect plant diseases is of great importance. Since the late 1970s, computer-based image processing technology applied in the agricultural engineering research has become a common practice (Al Bashish, Braik, and Bani-Ahmad 2011).

Machine learning methods, such as artificial neural networks (ANNs), Decision Trees, K-means, k nearest neighbors, and Support Vector Machines (SVMs) have been applied in agricultural research (Rumpf et al. 2010). The traditional approach for image classification tasks has been based on hand-engineered features such as SIFT (Lowe 2004), HoG (Dalal and Triggs 2005), SURF (Bay et al. 2008), etc., and then to use some form of learning algorithm in these feature spaces. This led to the performance of all these approaches depending heavily on the underlying predefined features (Atabay 2016b). However, a recent trend in machine learning has demonstrated that learned representations are more effective and efficient. The main advantage of representation learning is that algorithms automatically analyze large collections of images and identify features that can categorize images with minimum error (Reyes, Caicedo, and Camargo 2015).

Recently convolutional neural networks(CNN) have been used for object recognition and image classification(Atabay 2016b; Reyes, Caicedo, and Camargo 2015; Hanson, Joy, and Francis 2017; Mohanty, Hughes, and Salathé 2016). A convolutional neural network is a type of deep neural network (DNN) inspired by the human visual system, used for processing images. Various CNN architectures were proposed to be used for object recognition. Among them LeNet (LeCun et al. 1998) and AlexNet (Krizhevsky, Sutskever, and Hinton 2012) have been considered as a baseline for various tasks (Atabay 2016a).

In this paper, the feasibility of CNN to classify plant diseases from leaf images taken under uncontrolled environment has been studied. The models are designed based on the LeNet architecture. The dataset for training is downloaded from PlantVillage (Hughes, Salathé, and others 2015) database. Since CNN requires large amount of data, data augmentation is used to increase the training data.

The paper is organized as follows; part II deals with the previous works conducted in the similar area. Part III describes the steps and the materials used to perform the experiment. The results obtain is presented in part IV and it concludes by recommending methods for future improvement.

Literature Review

In this section the recent trends in using CNN and deep learning architectures in agricultural application are discussed. Prior to the advent of deep learning, image processing and machine learning techniques have been used to classify different plant diseases (Barbedo 2013; Pydipati, Burks, and Lee 2005; Camargo and Smith 2009b; 2009a). Generally, most of these systems follow the following steps:

First digital images are acquired using digital camera. Then image processing techniques, such as image enhancement, segmentation, color space conversion and filtering, are applied to make the images suitable for the next steps. Then important features are extracted from the image and used as an input for the classifier (Al-Hiary et al. 2011).

The overall classification accuracy is therefore dependent on the type of image processing and feature extraction techniques used. However, latest studies have shown that state of the art performance can be achieved with networks trained using generic data.

CNNs are multi-layer supervised networks which can learn features automatically from datasets. For the last few years, CNNs have achieved state-of-the-art performance in almost all important classification tasks. It can perform both feature extraction and classification under the same architecture (Atabay 2016b).

A CNN is a special kind of neural networks that has been widely applied to a variety of pattern recognition problems, such as computer vision, speech recognition, etc. The CNN is based on the human visual system; first inspired by (Hubel and Wiesel 1962) and continually implemented by many researchers. CNNs combine three architectural ideas to ensure some degree of shift, scale, and distortion invariance: local receptive fields, shared weights and spatial or temporal subsampling (LeCun et al. 1998). Various CNN architectures were proposed to be used for object recognition eg. LeNet, AlexNet, GoogLeNet etc.

The LeNet architecture is the first CNN introduced by LeCun et al. to recognize hand written digits (LeCun et al. 1998). It consists of two convolutional layers and two subsampling layers followed by a fully connected MLP.

Few researchers proposed the use of CNN for leaf recognition and plant disease classification. Atabay (Atabay 2016b) designed a convolutional neural network architecture to identify plants based on leaf images. The proposed architecture consists five layers. After each convolutional layer a Rectified Linear Unit (ReLU) or Exponential Linear Unit (ELU) activation function is used and for each pooling layer, MaxPooling approach is applied. The proposed system is applied on Flavia (Wu et al. 2007) and Swedish (Söderkvist 2001) leaf datasets containing 32 plant species with 1907 samples and 15 species with 1125 samples respectively. The images in the dataset are pictures of a single leaf taken at uniform background. All the input images are 160x160 pixel grayscale images. The model achieved a classification accuracy of 97.24% and 99.11% accuracy for each dataset. The results showed that the proposed architecture for CNN-based leaf classification is closely competing with the latest extensive approaches on devising leaf features and classifiers.

Angie K. Reyes et al. (Reyes, Caicedo, and Camargo 2015), used a deep learning approach in which the complete system was learned without hand-engineered components. The designed system has 5 Conv layers followed by 2 fully connected layers. The CNN is trained using 1.8 million images from ILSVRC 2012 dataset [1] and used a fine-tuning strategy to transfer learned recognition capabilities from general domains to the specific challenge of Plant Identification task. The dataset is combination of images of a plant or part of a plant taken both under a controlled environment as well as in the natural environment. They obtained an average precision of 0.486.

Sharada P. Mohanty et al. (Mohanty, Hughes, and Salathé 2016), used the existing deep CNN architectures, i.e AlexNet (Krizhevsky, Sutskever, and Hinton 2012) and GoogLeNet (Szegedy et al. 2015) to classify plant diseases. Using a public dataset of 54,306 images of diseased and healthy plant leaves collected under controlled conditions, the CNN was trained to identify 14 crop species and 26 diseases (or absence thereof). The models achieved 99.35% accuracy. When tested on a set of images taken at a different environment than the images used for the training, however, the model's accuracy dropped to 31.4%. Overall the result demonstrates the feasibility of deep CNN for plant disease classification.

Materials and Methods

To classify soybean plant diseases a large collection of the plant's leaf images is required. The images are downloaded from the PlantVillage database [2]. In this section the methodology followed is discussed in detail.

Dataset

Proper and large dataset is required for all classification research during the training and the testing phase. The dataset for the experiment is downloaded from the PlantVillage database which contains different plant leaf images and their labels. It contains a collection of images taken at different environment. A dataset containing 12,673 leaf images of four classes including healthy leaves is downloaded. The samples per class of the dataset is summarized in Table 1.

[1] http://www.image-net.org/challenges/LSVRC/2012/

[2] https://plantvillage.org

No.	Type of Disease	Number
1	Healthy Leaf	6234
2	Septorial leaf blight	3565
3	Frogeye leaf spot	2023
4	Downy Mildew	851
Total		12673

Table 1: Dataset used for the classification

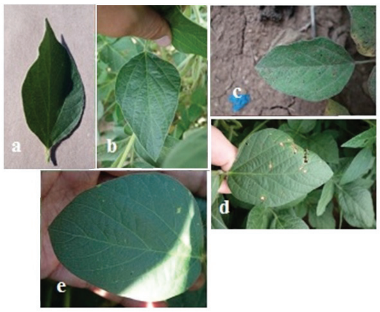

Figure 1: Sample images from the database a) healthy leaf image taken under a constant background b) healthy leaf image taken under uncontrolled environment [c-e] leaf images from a plant affected by: c) septorial leaf blight d) frogeye leaf spot e) downy mildew

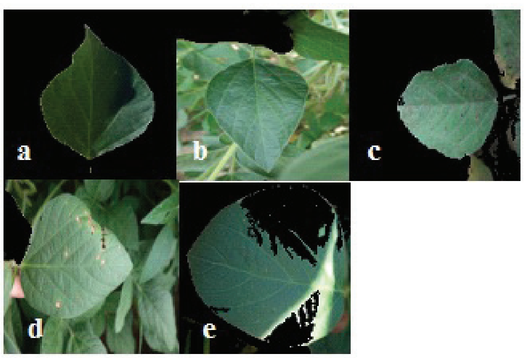

Figure 2: Sample segmented images resized to 64x64 pixels a) healthy leaf image taken under a constant background b) healthy leaf image taken in uncontrolled environment [c-e] leaf images from a plant affected by: c) septorial leaf blight d) frogeye leaf spot e) downy mildew

Few samples from the database are shown in figure 1. To prepare the dataset for the training, the images originally at different resolution are re-sized to 128x128 pixels.

Since the images were taken in the uncontrolled environment the different lighting condition and background in the training images may bias the neural network. To test this, the experiment was also performed using the grayscale and the segmented version of the database. Sample images of the gray and segmented leaf images are shown in figure 2 and figure 3 respectively.

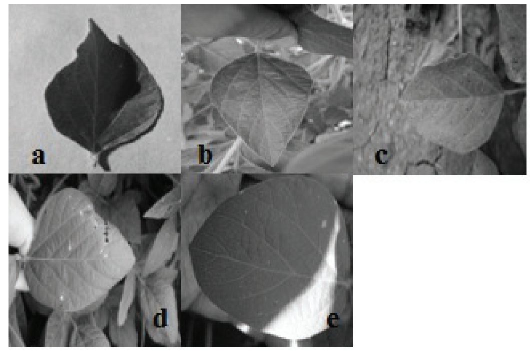

Figure 3: Sample grayscale images size 128x128 pixels a) healthy leaf image taken under a constant background b) healthy leaf image taken in uncontrolled environment [c-e] leaf images from a plant affected by: c) septorial leaf blight d) frogeye leaf spot e) downy mildew

Layer	Type	Filter Size	Stride	Output size
L1	Conv	3x3	1	128x128x32
	Pool	2x2	2	64x64x32
L2	Conv	4x4	1	61x61x64
	Pool	2x2	2	64x64x32
L3	Conv	1x1	1	30x30x128
	Pool	2x2	2	15x15x128

Table 2: Architecture of the proposed model

The proposed CNN model

CNN architectures vary with the type of the problem at hand. The proposed model consists of three convolutional layers each followed by a maxpooling layer. The final layer is fully connected MLP. ReLu activation function is applied to the output of every convolutional layer and fully connected layer.

The first convolutional layer filters the input image with 32 kernels of size 3x3. After maxpooling is applied, the output is given as an input for the second convolutional layer with 64 kernels of size 4x4. The last convolutional layer has 128 kernels of size 1x1 followed by a fully connected layer of 512 neurons. The output of this layer is given to softmax function which produces a probability distribution of the four output classes. The architecture of the proposed model is shown in Table 2.

The model is trained using adaptive moment estimation (Adam) with batch size of 100 for 1000 epochs.

Experimental Results

The dataset is divided 70% for the training, 10% for validation and 20% for testing. Different models with different architectures and learning rate are tested. The parameters of the network like the kernel size, filter size, learning parameter were selected by trial and error. ReLu activation function is used since researches have shown that ReLU result in faster training (Krizhevsky, Sutskever, and Hinton 2012). The result obtained is shown in Table 3 below.

	Architecture	Validation accuracy	Test accuracy
Grayscale	**[3X3, 4X4]**	**77.60%**	**78.74%**
	[5X5,5X5]	70.20%	70.07%
	[3X3, 4X4]	77.20%	78.67%
	[3X3, 2X2]	77.60%	77.87%
Color	**[3X3,4X4, 1X1]**	**89.30%**	**88.20%**
	[3X3,2X2,2X2]	89.50%	86.90%
	[3X3,4X4,3X3]	89.90%	88.00%
	[3X3,4X4]	88.00%	85.50%
	[3X3,2X2]	87.30%	85.30%
Segmented	**[5X5, 3X3]**	**87.40%**	**86.00%**
	[3X3,4X4]	87.60%	85.90%
	[3X3,2X2]	87.00%	85.50%

Table 3: Classification result from different models

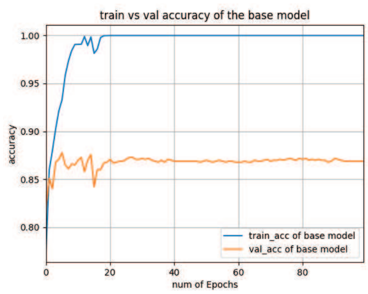

Figure 4: Training vs validation accuracy of the base model

As we can see from the result, the classification accuracy from the color images is better than the gray scale and the segmented images. This shows the color feature is important to extract important features for classification. The model that provides good classification accuracy contains three convolutional layers each followed by max pooling layer. ReLu activation function is used for each layer. We used this model as a base model for further improvements.

The graphs of the training accuracy versus validation accuracy of the model is shown in figure 4. It can be seen from the graphs that the model is overfitting. Overfitting happens when the model fits too well to the training set. It then becomes difficult for the model to generalize to new examples that were not in the training set.

Several techniques have been developed to overcome overfitting, such as data augmentation, introducing weight penalties of various kinds such as L1 and L2 regularization and dropout (Srivastava et al. 2014).

Experiments were conducted to see the effect of each technique on the performance of the model. Since the dataset is too small when compared to the total number of trainable parameters of the model, the first experiment we did is to increase the training data by rotating, flipping, re-scaling of the images. The data augmentation is performed only on the training data. The result obtained when using data augmentation is shown in figure 5.

The result shows that data augmentation alone solves overfitting significantly. It also increases the validation accuracy to 98.82%. This explains the original dataset was so small compared to the total number of trainable parameters of the model. Dropout and L2 regularization is also performed and the result is summarized in Table 4 below. Both models showed a slight improvement over the performance of the model.

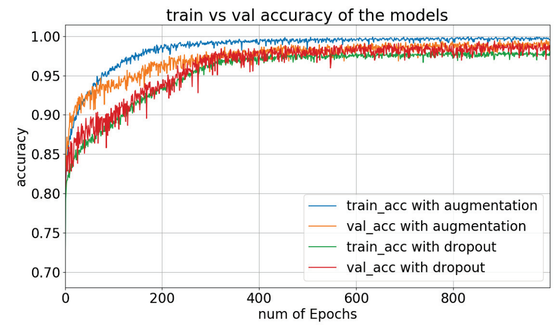

Figure 5: Training vs validation accuracy of the models.

Model	Validation accuracy	Test accuracy
Base model with aug. and dropout	**99.21%**	99.32%
Base model with aug. and L2 regularization	98.62%	98.73%

Table 4: Effect of dropout and regularization

	Precision	Recall	f1-score	Support
Healthy	1.0	1.0	1.0	1228
Septorial	0.99	1.0	1.0	718
Frogeye	0.99	0.97	0.98	407
Downy Mildw	0.98	1.0	0.99	182
Avg/total	0.99	0.99	0.99	2535

Table 5: Performance metrics of the best model

Therefore, adding a dropout layer after the MLP with a probability of 0.5 results in a good classification accuracy. The classification metrics of the proposed model is summarized in Table 5.

Figure 6b shows the visualization of the filters in the first activation layer in response to the image in figure 6a during the forward pass. It can be seen from the figure that the network has detected the diseased symptoms on the leaf. The visualization of some of filters in first, second and third activation layers is shown in figure 7.

Conclusions

In this study convolutional neural network is used to detect and classify soybean plant diseases. The Network is trained using the images taken in the natural environment and achieved 99.32% classification ability. This shows the ability of CNN to extract important features in the natural environment which is required for plant disease classification. As far as our knowledge this is the first attempt which used the images taken in the wild environment and achieved

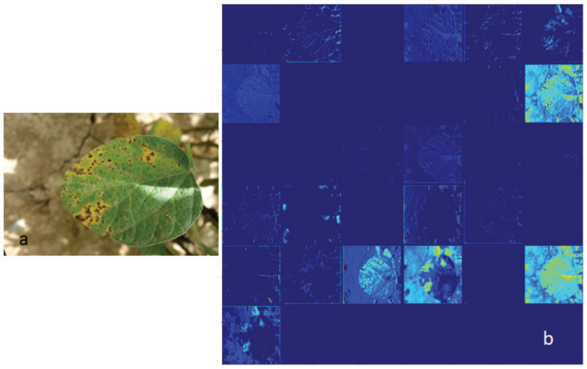

Figure 6: Visualization of feature maps in the first activation layer a) sample image b) feature maps of the first activation layer

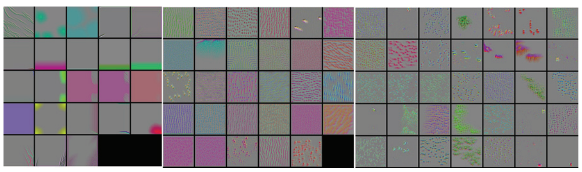

Figure 7: Visualization of activated filters in the three activation layers

remarkable performance. The experiments also show that applying data augmentation on the training set improves the performance of the network when the dataset is very small. The effect of dropout and regularization to overcome overfitting also validated.

The data sample used in this work is unbalanced, i.e 49.19% of the data is of class 1, 28.13% class 2, 15.96% class 3 and 6.72% class 4. For future work, deep learning methods to solve sample imbalance will be implemented (Huang et al. 2016). (Yin et al. 2017) suggested the use of batch normalization to speed up the training process and boost accuracy, therefore we will also investigate batch normalization in the future.

Acknowledgments

This research is funded by Embassy of French and the Ethiopian Ministry of Education (MoE) through the higher education capacity building program.

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