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Classification of Leaf Images with CNN and RF

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Abstract – Agricultural production in a country highly decreases by infecting pests to the agricultural plants. Today, in general, an agricultural engineer or a farmer tries to detect plant diseases by checking the plant leaves, but this process is very hard and time-consuming because of harsh environmental conditions. Instead of this, leaf images of plants can be controlled by drones automatically, and diseased plants can be detected. In this work, leaf images have been categorized as diseased and healthy leaves using Convolutional Neural Networks and Random Forests. The leaf data set which consists of healthy and diseased RGB leaf images has been divided into a train data set and a test data set. The systems with Convolutional Neural Networks and Random Forest classifiers have been trained in the train set. Convolutional Neural Networks include feature maps and classification operations, but in feature maps, convolution, batch normalization, ReLU, and max pooling operations are performed. For the Random Forest classifier, the training features are obtained and trained from the feature map of the Convolutional Neural Network. After the training stage, the trained models detect the diseased and healthy leaf images in the leaf image test set. For the evaluation of the systems, the accuracy and F1-score metric values of the models have been computed, and they have been compared with each other.

Keywords – Leaf Categorization, Deep Learning, Machine Learning, CNN, RF, Artificial Neural Networks

I. INTRODUCTION

Nowadays, classifying healthy and diseased leaves or plants is vital for the production of more food. The number of hungry people is increasing every day in the world, however, food production does not rise at the same rate. In addition, because of plant diseases, the great amount of crop production has decreased [1]-[2].

Leaf disease detection operation is based on manual detection today, however, the success rate of manual leaf disease detection will be low since harsh environmental conditions and lack of knowledge of leaf diseases can prevent correct detection[3]-[4].

With the developing drone technology, the use of a drone has become widespread. Drones have begun to be used in agriculture and botany [5]-[7]. They are beneficial to detect the number of crops in that year or to predict the amount of damage to the crops due to any disaster. Thus, we can take precautions to prevent the decrease in the crops. Using drones, agricultural plants can be sprayed with pesticides, fertilizers, and plant protection products. This provides to spray only the area of a diseased plant. In this way, both healthy plants are not sprayed and the use of excessive pesticides, fertilizer, and protection product use is constrained.

Many studies of Artificial Neural Networks (ANN) have been applied to image classification areas until now. Leaf image classification is a sub-field of image categorization, and in recent years, the works of leaf image classification using ANN have been increasing fast [8]-[15]. Mainly Convolutional Neural Networks (CNN) [9]-[15] which is a type of ANN have been preferred because of their greater success rate than the other classification methods.

Random Forest (RF) classifier [16]-[18] which is an ensemble method using many decision tree classifiers is also one of the most effective classification methods. This method is highly successful in overcoming the overfitting problem by reducing the variance on the training set.

In this study, with a leaf disease data set the systems have been designed and implemented using CNN and RF classifiers. The data set is divided into train and test sets. After the training of the CNN network, in the testing operation, the accuracy and F1-score values are computed. The input samples of the RF classifier have been obtained from the feature map of the CNN network. After the RF models are generated using this train set, all the systems are compared to each other.

The remainder of this work is structured as follows. In the next section, Convolutional Neural Networks and Random Forests have been described briefly. In the following section, the results of the classification systems are utilized and compared. This work is summarized in the conclusion section.

II. MATERIALS AND METHOD

In this study, the leaf classification has been designed and implemented by Convolutional Neural Networks and Random Forest classifier. These methods are explained briefly in the following subsections.

A. *Convolutional Neural Network*

CNN is a type of artificial neural network which is preferred for image classification and image segmentation in general. In a supervised manner, CNN is trained by updating the filter weights.

CNN includes one input layer, some hidden layers, and one output layer. The hidden layers of CNN consist of layers that apply and perform convolution operations. The convolution operation is a Frobenius inner product of convolution filters and input matrices. The convolution filter is moved on the input matrix step by step, and at the end, filter maps are constituted. After the convolution operations, the output of the convolution is used as an input of the activation function, mostly used ReLU activation function. Then, pooling operations are performed, mostly max pooling operations. Until now, these operations are in the convolution part of CNN. The next part of CNN is classification. The classification part includes a fully connected layer and normalization layers.

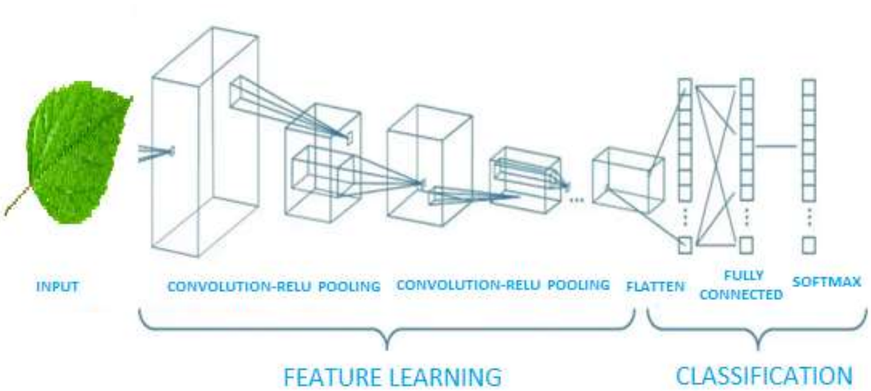

Fig. 1 Structure of CNN

B. *Convolutional layer*

The convolutional layer is the main part of CNN. CNN performs a convolution kernel or filter to an input. In general, this input is a matrix obtained by an image. This filter is applied by sliding on the inputs. This operation leads to constructing the feature map and determining the particular features on the images.

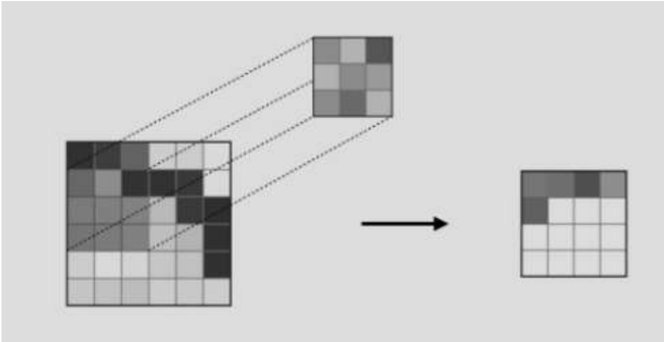

Fig. 2 Convolution operation

C. *ReLU activation function*

The Rectified Linear Unit (ReLU) function is a zero-threshold function. Namely, the ReLU activation function calculates with the max function and then applies zero threshold value as shown in Equation 1.

$$\mathrm{ReLU}(x) = \max(0, x) \tag{1}$$

Where x is a real number value.

ReLu activation function is more advantageous than other activation functions such as tanh, sigmoid, or softmax since ReLU is a faster convergent function. In CNN, the most used activation is the relu function.

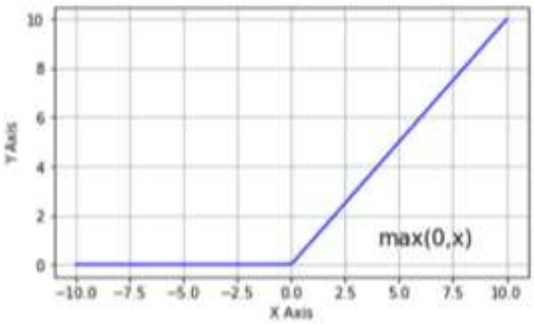

Fig. 3 ReLU activation function

D. *Pooling layer*

Pooling reduces the size of input weights and the number of computations. The pooling layer summarizes the input matrix by shrinking some neighborhood locations of the input. The commonly used pooling function is max pooling. Max pooling is performed by detecting the max value in the neighborhood. However, average pooling with calculating average values of the square neighborhood, weighted average pooling, and min pooling are some pooling functions that are used preferably.

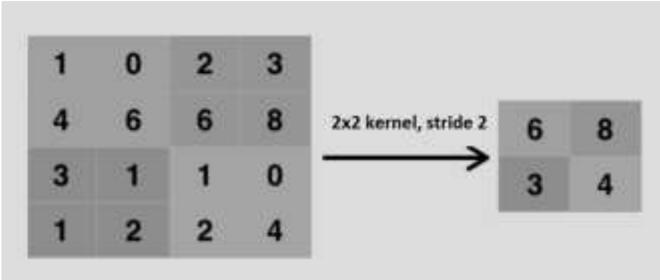

Fig. 4 An example of a Max pooling operation

E. *Fully Connected Layer*

These layers of neurons are fully connected to the next layers of neurons as Multi-Layer Perceptron. Computations of this layer are matrix multiplication of weights matrices. For the categorization of images, the flattened matrices continue with fully connected layers. The fully-connected layer is useful for mapping the relationships between the output and the input layer.

F. *Random Forest*

Random Forest (RF) [1,2] is an ensemble technique that is used for regression or classification. RF is one of the most used and successful methods in machine learning. The strategy of RF is based on creating multiple times decision trees. Namely, a lot of decision trees are constituted, and the output classes of these decision trees are computed. In the classification task, the output of the RF method is the class that is the most predicted by the decision trees. RF was first developed by Ho [1,2] in 1995. Ho constructed forests dividing the oblique hyperplanes to increase the accuracy of the classification and reduced the feature set or dimensions. This process eliminates the problem of overfitting. The extended variant of RF was proposed by Breiman [3, 4], and Cutler in 2006. They designed a forest with CART, bagging, and randomized node optimization.

Decision trees encounter mostly the overfitting problem while learning from the trainset. However, RF using many decision trees tries to prevent this overfitting problem by decreasing the high variance. For this, in general, RF gains a high accuracy rate. RF performs a collective task of many decision trees. Hence, it improves the success of a single decision tree. RF is also thought of as a bagging or bootstrap of some decision trees.

G. *Random Forest training algorithm*

Let $X = \{x_1, x_2, \ldots, x_k\}$ be an input training set and $T = \{t_1, t_2, \ldots, t_k\}$ be an output set for the input set. The bagging operation is performed by m times randomly choosing samples from the training set. Each selected training set is trained with a decision tree.

Step 1: For i=1 to m
Step 2: Select training samples from X and T.
Step 3: Train these samples for classification and regression problems.
Step 4: end

III. Results and Discussion

For the regression problem, the mean of the predictions of regression trees is the output of the regression Random Forest. But, For the classification problem, the majority voting of the predictions of classification trees is classification Random Forest’s output. Because of reducing the variance, this bootstrap process causes to obtain more success in accuracy.

In this work, the systems based on the Convolutional Neural Networks and Random Forest classifier are implemented and the results are compared with each other. The successes of the systems are evaluated by benchmark metrics such as accuracy and F1-score. These metric values are calculated as shown in Equations 14, 15, 16, 17 and 18.

Accuracy and F1-score have been used to evaluate the leaf image classification systems. The F1-score for different classes has been generalized by the Macro averages of the F1-score. The accuracy values of the systems are measured as shown in Equation 17 [21-22].

$$\text{Precision} = TP / (TP+FP) \tag{15}$$

$$\text{Recall} = TP / (TP+FN) \tag{16}$$

$$\text{Accuracy} = (TP+TN) / (TP+FP+FN+TN) \tag{17}$$

$$\text{F1-score} = 2*(\text{Recall}*\text{Precision}) / (\text{Recall} + \text{Precision}) \tag{18}$$

TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative

The systems have been implemented with Matlab and the computer with the features as Intel Core i7 2.40 GHz CPU, 16 GB RAM, and 64-bit Windows 10 Operating System.

Leaf dataset [19]-[20] consists of diseased and healthy leaf images. The data set which includes 4502 leaf images is categorized into 22 classes. The resolutions of the leaf images are high, and all of them are jpg images. The required space in a hard drive is 6.81 GB. The data type of these RGB images is an unsigned integer between 1 and 255.

Fig. 6 Healthy leaf images

Fig. 7 Diseased leaf images

For developing systems, the data set is divided into train and test sets with selecting the samples five times randomly. The train set includes 70 percent of the leaf data set. The other 30 percent is used for the test set to evaluate the systems. The accuracy and F1-score values are calculated as their average of them. The systems are performed by the CNN and RF classifiers. The designed CNN network is designed and constituted of 20 layers. These include image input, convolution, ReLU, batch normalization, max pooling, fully connected, softmax, and classification output layers. As shown in Fig. 8, convolution layers have 64, 32, 32, 32, and 8 filters respectively. In the training process, the systems have been trained with or without augmentation, and according to the learning rate=10^{-2}, 10^{-3}, and 10^{-4}.

RF classifier has taken the input values as the weights of relu5 after training the CNN network. The classifier has been constructed when the number of variables to sample is fifty, and the number of learning cycles is one hundred.

In Tables 1, 2, 3, 4, and 5, the accuracy and F1-score results of the systems have been displayed for CNN and RF.

When evaluating the success of training the methods, the best average accuracy and micro average F1-score are obtained by the RF classifier with 99% and % 98 respectively. However, CNN has 94% training accuracy and F1-score values. In the same way, the RF classifiers are more successful than CNN according to the test data set.

It can be said that the effect of augmentation is not much since the training data set has many images. Without augmentation, the best results have been reached with the learning rate $= 10^{-3}$.

Table 1. The success rates of the leaf data set without augmentation, $lr = 10^{-2}$.

	Methods	Accuracy	F1-score
Training	CNN	0.85±0.011	0.84±0.020
	RF	0.93±0.015	0.93±0.010
Testing	CNN	0.81±0.004	0.79±0.006
	RF	0.80±0.038	0.79±0.032

Table 2. The success rates of the leaf data set without augmentation, $lr = 10^{-3}$.

	Methods	Accuracy	F1-score
Training	CNN	0.94±0.009	0.94±0.012
	RF	0.98±0.005	0.97±0.009
Testing	CNN	0.87±0.014	0.87±0.018
	RF	0.90±0.008	0.90±0.009

Fig. 8 The structure of CNN

Table 3. The success rates of the leaf data set without augmentation, $lr = 10^{-4}$.

	Methods	Accuracy	F1-score
Training	CNN	0.84±0.016	0.83±0.012
	RF	0.98±0.12	0.98±0.014
Testing	CNN	0.82±0.008	0.81±0.012
	RF	0.86±0.004	0.86±0.012

Table 4. The success rates of the leaf data set with augmentation (RandXTranslation: [-20,20], RandYTranslation: [-20,20]), $lr = 10^{-3}$.

	Methods	Accuracy	F1-score
Training	CNN	0.86±0.012	0.86±0.016
	RF	0.99±0.009	0.98±0.012
Testing	CNN	0.87±0.012	0.86±0.009
	RF	0.87±0.004	0.87±0.008

Table 5. The success rates of the leaf data set with augmentation (RandRotation: [-20,20]), $lr = 10^{-3}$.

	Methods	Accuracy	F1-score
Training	CNN	0.90±0.013	0.79±0.014
	RF	0.98±0.004	0.98±0.009
Testing	CNN	0.88±0.009	0.88±0.009
	RF	0.88±0.008	0.88±0.005

IV. CONCLUSION

In this study, leaf images in the leaf data set are classified as diseased and healthy leaves. The systems are developed by methods such as CNN and RF. The leaf images have been divided into train data and test data sets. The systems have been trained in the train set. Convolutional Neural Network includes two main parts as a feature map, however, the feature map consists of convolution, batch normalization ReLU, and max pooling operations. Random Forest classifier has been trained with the features from the feature map of CNN. After the training stage, the trained models detect the diseased and healthy leaf images in the leaf image test set. After testing the systems, according to the accuracy and F1-score metrics, it can be said that RF outperforms the CNN classifier.

For future work, it is planned to implement other deep learning and transfer learning algorithms. A hybrid system of these methods will be developed for leaf classification.

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