International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

# An Adaptive Boosting Approach for Plant Classification through Deep CNN

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A B S T R A C T

Convolutional neural network is collected of various handling layers to acquire the representations of data with various sstages. But, this model hasmany parametersand layers. The layers are hard to train, and also several days are taken to tune the parameters. In this paper, we address the usage of a trained deep convolutional neural network model to extract the features of the leaf images, and then, used the Adaptive Boosting method to collect the softmax classifiers into detectableleaf images. This method resulted in 4% increase growth of accuracy of the trained CNN model and reduced the retraining time cost.

Keywords: Deep Learning, Deep Convolutional Neural Network, Ensemble Learning, Boosting

## 1. Introduction

Plants show a role in environmental protection. There are almost four million types of plants on earth. Only few plants are known. Many of the plants are still unidentified. It is difficult to identify all the plants manually. There is anessential to improve an automated Plant identification system to identify the plants. The procedure of plant identification can be achieved using the plants leaves. The leaves of the plants fetch a lot of information about the plants. This information can be used to build plant identification model.Data extraction needs to done from leaf through Deep Learning. Deep learning is a specialized form of machine learning. Deep learning methods are able to extract more detailed information as compared to the machine learning methods. The machine learning methods are used to identify and plants with manually extracted features (shape, texture, colour and vein) from leaf images. With the development of Information Technology, We can extract necessary features (shape, texture, colour and vein) from leaf image automatically using Deep learning methods. So, Automatic feature data extraction needs to done from leaf images through techniques as deep learning, rather than manually entering the feature data as done in case of Machine learning.

## 2. Related Work

Research Studies have completed on the classification of plants. Various Research Studies were classification the plants by the mining of features from the leaf image. Some Research papers were published on classification of plant leafs in Journals and conferences. Several researchers have worked on ANN and Machine Learning methods for classification of plants.

The Convolutional Neural Network has become the effective deep learning model in the computer vision. Itis a neural network used absolutely to process data with a frame structure.

**Ensemble Learning**: Ensemble learning concludes learning jobs throughmaking and cooperating with some learnerswhere a collection of individual

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learners are trained.Individual learners can be if the same type or of different types; if they are similar type, then integration ishomogeneous and the individual learners in homogeneous integration are base learners. For instance, a neural network is network recognized by the integration of neurons. If the individual learners are different, then the integration is called heterogeneous, and the individual learners of heterogeneous integration are generated by different learning algorithms. Ensemble learning is a ''bottom-to-top'' construction: the first step is to obtain learners; then, attention is paid to how to organize them to form integrity. Conversely, the neural network is a ''top-to-bottom'' construction: the first step is to integrate the learners; then, all the learners in the learning structure are adjusted. Ensemble learning combines several learners, and often shows better generalization than individual learners, especially for weak learners. Hence, many theoretical studies of ensemble learning have been conducted for weak learners. Sometimes, base learners are directly called weak learners. In addition, ensemble learning may bring three strengths, which are described, as follows, and shown in Figure 14. First, ensemble learning can statistically offset the probability of the wrong selection of the hypothesis space of individual learners. As the hypothesis space of learning tasks is usually large, and several hypotheses may share the same performance in the training set, wrong individual learners may result in poor generalization. Therefore, the integration of several learners will reduce such risk. Second, in terms of computation, ensemble learning can reduce the risk of overfitting. As an individual learning algorithm tends to be trapped by a partial optimum, the generalization of some partial optimums may be poor, thus, integration based on several operations can reduce the risk of poor partial optimums. Third, regarding expression, ensemble learning can expand the hypothesis space of individual learners, and thus, facilitate the learning of an approximating function. The true hypothesis of some learning tasks may not be in the hypothesis space considered by the current learning algorithm; in this case, individual learners will be invalid; however, if several learners are combined, it is possible to acquire a better approximating function, as the corresponding hypothesis space has been expanded.

**Boosting method**: This method combines weak classifiers by certain approaches to form a strong classifier with high classification performance. The work flow of the Boosting method is as follows: the first step is to train the first learner in the initial training data; then, the sharing of the training data is adjusted according to the earlier learner, and a higher sampling probability is given to data that are difficult to identify. With a focus on these data in the next round of learning; the above steps are repeated until the number of learners reaches the preset number; finally, the weights of all the trained learners are aggregated. The process of Boosting classification is, as follows: 1) Train the first weak classifier (h1) in the initialized training dataset; 2) Combine the poorly-trained data of the weak classifier (h1) with new data to form the training data for a new round, and train the second weak classifier (h2); 3) Combine the poorly-trained data of weak classifier (h1) and weak classifier (h2) with new data to form the training data for a new round, and train the third weak classifier (h3); 4) Repeat Steps 2-3 until an adequate number of weak classifiers have been attained. 5) Form a strong classifier through the weighted voting of all weak classifiers. While the Boosting algorithm can enhance the generalization of algorithms, it has two weaknesses: first, it is necessary to know the lower limit of the learning performance of weak learners, which is difficult to do in reality; second, this method may lead to the problem of learners focusing so much attention on some data that are extremely difficult to train (maybe noise data), in follow-up learning, the algorithm performance becomes unstable. Worse still, there are two difficult problems in the application of the Boosting algorithm, as follows: 1) How to adjust the training dataset, in order that weak learners are able to acquire the feature information that has not been acquired in future training. 2) How to combine all weak classifiers obtained from training to form a strong classifier

**Adaptive Boosting method:** Itis one of the most representative Boosting methods. As its name suggests, according to the trained classifiers, Adaptive Boosting can self-adjust weak classifiers after learning and is sensitive to noise data and outliers. In some tasks, it can efficiently resist overfitting. Even if an individual learner is weak, Adaptive Boost can converge into a strong classifier in the final integration, provided that the trained weak classifiers are better than the random classifiers. Compared with the original Boosting algorithm, Adaptive Boost replaces random sampling with weighted sampling to train data. In this way, focus is placed on training data that are difficult to process, which renders training more targeted. Regarding the combination of classifiers, it replaces the average voting mechanism with a weighted voting mechanism when combining weak classifiers. By equipping the weak classifiers that are effective in classification with a higher weight, and equipping those that are ineffective in classification with a lower weight, it guarantees that the integrated weak classifiers will be effective in classification. To use AdaBoost, it is not necessary to know the learning performance of the weak algorithm in advance, and the classification accuracy of the integrated strong classifier depends on the classification accuracy of all weak classifiers.

In this paper, we combine the convolution neural network with the Adaptive Boost method to form the Boost-CNN model. In a traditional integrated neural network, the neural network is usually taken as a base learner for ensemble learning; however, as it takes a long time to train an individual neural network, it has high total training cost, even though the integration of several neural networks can enhance the performance of individual neural networks.

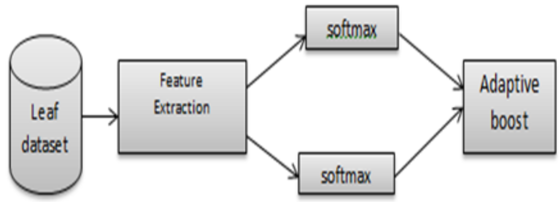


Fig 1. Adaptive Boosting method

Therefore, Boost-CNN is different from the traditional integrated neural network in the following aspects. a) Use a convolution neural network for optimization training, in order to develop the optimal convolution neural network; b) Remove the output layer of the trained convolution neural network and fix all the layers; extract the features and take them as the data for new training; c) Use the extracted new training data and the Softmax classifier on the last layer of Step 1 as the base learners of AdaBoost for ensemble learning.

Training Steps of CNN

Step 1: Data are randomly selected

Step 2: Calculate the gradient of the current sample data

Step 3: Update the current velocity

Step 4: Update the current learning efficiency

Step 5:Update the frequency of training

Step 6: Update parameter

Training steps of Adaptive Boost

Step-1: Remove the output layer of the convolution network and extract the features from the original training data.

Step-2: Take the trained Softmax classifier of the output layer of the convolution network as the first base learner of Adaptive Boost; store the training accuracy; adjust the data sampling weights of the feature extraction data.

Step-3: Use the new data sampling weights for the iterative training of the next base learner and store the training accuracy.

Step-4: Conduct the iterative training of several Softmax classifiers.

Step-5: Fix all Softmax classifiers and use their training accuracies as the final voting weights; conduct the integrated output of Adaptive Boost.

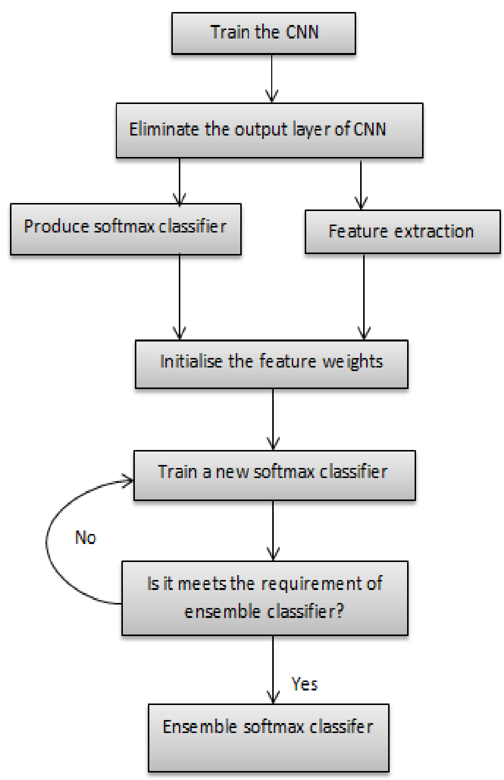


Fig. 2 Training Steps of CNN

To analyse the performance of the Boost-CNN model, we use the four-layered convolution network and Softmax classifier as the feature learning architecture, and adopt the Adaptive Boost algorithm to generate several Softmax classifiers as the output.

As shown in below table, the leaf dataset is adopted to test the performance of Softmax, AdaBoost + Softmax, CNN + Softmax, and CNN + AdaBoost.

Table 1 Classifer and Accuracy

| **Classifer** | **Accuracy** |
|---|---|
| softmax | 40.5% |
| Adaboost + softmax | 59.4% |
| CNN + Softmax | 87.8% |
| CNN + AdaBoost | 91.1% |

According to above, when the leaf images are learned without feature extraction, the testing accuracy of the Softmax classifier is only 40.5%; after Adaptive Boost ensemble learning, while accuracy increases to 59.4%, the overall performance remains low. After the deep convolution network is adopted for feature extraction, the accuracy of testing significantly increases to 87.8%. The CNN + AdaBoost architecture, as adopted in this paper, can increase the accuracy of the original CNN by 4%, and its classification accuracy can reach 91.1%.According to the experimental results, BoostCNN can enhance CNN performance by 3%.

## 3. Conclusion

In this paper, we combine a convolution neural network with Adaptive Boost method to enhance the leaf image identification performance. After the convolution neural network is trained into the deep feature extraction model, and the original images are converted to acquire the deep features. Adaptive Boost method is used for ensemble learning. The conclusions of this paper are, as follows: 1) After the feature extraction of the deep convolution neural network, the original image data are fully abstracted, thus, the traditional learning algorithms can also effectively learn highly complicated image data. 2) Through the comparative experiments of the leaf image dataset, Adaptive Boost method can generally enhance the performance of base learners by 3%. The model of this study does have some limitations. 1) The identification performance of the model is largely dependent on the first stage, meaning the image feature extraction of the convolution neural network. It is relatively passive in learning abstract features. 2) While the model can effectively improve accuracy, it still has high time costs. The convolution neural network is one of the most successful machine learning models to emerge from the deep learning industry in recent years. As the hardware of computers and available datasets advance, the convolution neural network has become increasingly larger, and its performance has become better. At the same time, the requirements of the infrastructure for the training of deep learning models have become stricter, and training has become increasingly difficult. Even if a high-performance computing device is available, it may still take days and even weeks to train a deep learning model. Therefore, how to reduce the time and resource costs for the training of a deep learning model is an important research issue. This paper separates the feature extraction layer and the output layer classifiers of the deep convolution network from each other, and replaces the output layer with the AdaBoost algorithm in an attempt to combine deep learning with traditional algorithms. Likewise,a trained deep convolution network can be integrated with Bagging or SVM to enhance the performance of algorithms, while saving training cost.

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