Identification of Diseases in Corn Leaves using Convolutional Neural Networks and Boosting

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Abstract: Precision farming technologies are essential for a steady supply of healthy food for the increasing population around the globe. Pests and diseases remain a major threat and a large fraction of crops are lost each year due to them. Automated detection of crop health from images helps in taking timely actions to increase yield while helping reduce input cost. With an aim to detect crop diseases and pests with high confidence, we use convolutional neural networks (CNN) and boosting techniques on Corn leaf images in different health states. The queen of cereals, Corn, is a versatile crop that has adapted to various climatic conditions. It is one of the major food crops in India along with wheat and rice. Considering that different diseases might have different treatments, incorrect detection can lead to incorrect remedial measures. Although CNN based models have been used for classification tasks, we aim to classify similar looking disease manifestations with a higher accuracy compared to the one obtained by existing deep learning methods. We have evaluated ensembles of CNN based image features, with a classifier and boosting in order to achieve plant disease classification. Using an ensemble of Adaptive Boosting cascaded with a decision tree based classifier trained on features from CNN, we have achieved an accuracy of 98% in classifying the Corn leaf images into four different categories viz. Healthy, Common Rust, Late Blight and Leaf Spot. This is about 8% improvement in classification performance when compared to CNN only.

1 INTRODUCTION

Convolutional Neural networks (CNN) based deep learning methods are proving quite useful for image classification tasks as they can learn the high level features effectively. CNN's have made tremendous advances in computer vision tasks especially in object classification (He et al., 2016; Chollet, 2016; Szegedy et al., 2016; Simonyan and Zisserman, 2014). Considering Large Scale Visual Recognition Challenge (Russakovsky et al., 2015) based on ImageNet dataset (Deng et al., 2009), the benchmark for error rates, CNN models have achieved the lowest error rate of 3.57% (He et al., 2016) which is comparable to human error rate. It is also observed (Sharif Razavian et al., 2014) that extracting features of a new dataset from a deep network pre-trained on ImageNet database (Deng et al., 2009) and training Support Vector Machine (SVM) (Cortes and Vapnik, 1995) using these features performs better classification than other complex supervised classification approaches. This motivates us to leverage the high level features extracted from the trained convolutional neural networks which have been recently indicated to be very robust (Yosinski et al., 2014). Sharada Mohanty et. al in (Mohanty et al., 2016) have performed supervised leaf disease classification with 99.35% accuracy by fine tuning the top layer of CNN models with a dataset taken in near ideal conditions. Erika Fujita et. al in (Fujita et al., 2016) have proposed a CNN based classifier trained on cucumber viral diseases and achieved 82.3% average classification accuracy. We have explored the possibility of using deep CNN model pre-trained on the ImageNet database with 1000 classes of over 14 million images to extract the features of corn leaf images. Various methods are evaluated to develop a solution that gives the most accurate recognition results especially in similar looking disease manifestations.

We propose a system where the images are classified using features from a convolutional neural network pretrained on ImageNet data and then boosting is applied to accurately differentiate between similar looking classes in accordance with the confusion matrix. Classification performance of features from different CNN architectures viz. VGG-16, Inception-v2,

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ResNet-50 and MobileNet-v1 used with 3 different classifiers viz. Softmax, Random Forest and SVM have been presented in this paper. We achieved a reasonably good performance by using Adaptive boosting (AdaBoost) after getting class probabilities from a decision tree based classifier. Features extracted from a pre-trained Inception-v2 network used along with this ensemble gave the highest accuracy. The tensorflow (Abadi et al., 2015) implementation of CNN models has been used to extract the feature vector of the images. Scikit learn library (Pedregosa et al., 2011) has been used for application of Random forest and AdaBoost methods.

2 DATASET AND PREPROCESSING

We have utilized corn leaf images from PlantVillage dataset (Hughes and Salathé, 2015) for 4 health conditions, viz. Healthy, Common Rust, Late Blight and Leaf Spot. 500 images have been randomly taken from each class. Data augmentation with rotation, flipping and addition of salt and pepper noise have been done to avoid overfitting of the model and get better accuracy on the images taken in different conditions. This resulted in 2000 images of each class. Augmentation helped increase the data quality as well as quantity of images for training the classification models. Figure 1 shows the four classes of the images we have considered from the database. Images were resized according the the input size of the neural networks. We train and evaluate the models after performing normalization on the image data. Normalization of every image is performed for scaling the data to an acceptable range for the network. Image normalization results in contrast stretching, so it also enhances the poor contrast images in the dataset. Mean subtraction centers the data around zero mean for each channel and normalization binds the range of the image data values, thus helping the network to learn faster since gradients act uniformly for each channel as well as for all image data values. The images are resized according to the input size requirements of the CNN models. For VGG-16, MobileNet-v1 and ResNet-50, images are resized to 224x224x3, and for Inception-v2 they are resized to 299x299x3.

(a) (b) (c) (d)

Figure 1: Corn leaf Images from the PlantVillage database (a) Common Rust (b) Healthy (c) Late Blight (d) Leaf Spot.

3 CNN FEATURES OF IMAGE DATA

A CNN is made up of an arrangement of convolutional layers that can be seen as a linear transformation over the image, followed by activation layer to add non linearity in the network and then the pooling layer to reduce the propagation of the redundancy in the image in consecutive layers. A convolution layer in CNN extracts features of an input image while preserving spatial relation between pixels by using a small matrix that strides over the input image. This resulting image is called an *Activation map* or a *Feature map*. Rectified Linear Unit (ReLU), an element wise activation function *max(0,x)* replaces all negative pixel values in the feature map by zero. Activation functions introduce non-linearity in the CNN as most of real-world data that CNN would be used to learn is non-linear. Spatial Pooling, i.e. downsampling is applied on the feature map after ReLU to reduce the dimensionality. This reduces the number of parameters and computations in the network thereby reducing overfitting (Krizhevsky et al., 2012). It makes the feature invariant to scaling and small distortions in the input image. The last layer of a CNN is a Fully Connected (FC) neural network layer. Adding FC helps the network to learn the non-linear combination of features computed from convolutional layers. The FC layer is followed by an average or a max pooling layer for a classification task.

We evaluate performance of features from VGG-16 (Simonyan and Zisserman, 2014), Inception-v2 (Szegedy et al., 2016), ResNet-50 (He et al., 2016) and MobileNet-v1 (Howard et al., 2017) trained on ImageNet database for classification of corn leaf health state, as it has been seen that the models trained on this vast database generalize well on other datasets too after transfer learning (Zeiler and Fergus, 2014). VGG-16 is a sequential CNN with 8 convolutional layers having different number of filters with 3×3 receptive fields. Inception-v2 has blocks of multiple filters that are applied on the same tensor and then concatenated at the output of each block. It can be termed as a CNN made up of small convolutional

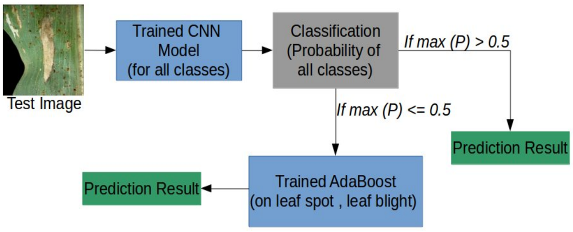


Figure 2: Proposed ensemble method of classification.

modules. ResNet-50 is 50 layered deep CNN with residual blocks which can be termed as shortcut connections between the layers. These residual connections help in combating the problem of vanishing gradient in case of networks with large number of layers, thus helping in better training of the network and increasing the accuracy. In MobileNet, the normal convolution is replaced by depthwise convolution followed by pointwise convolution. This is called depthwise separable convolution and significantly reduces the number of parameters compared to the normal convolutions for a network with the same depth.

4 METHOD

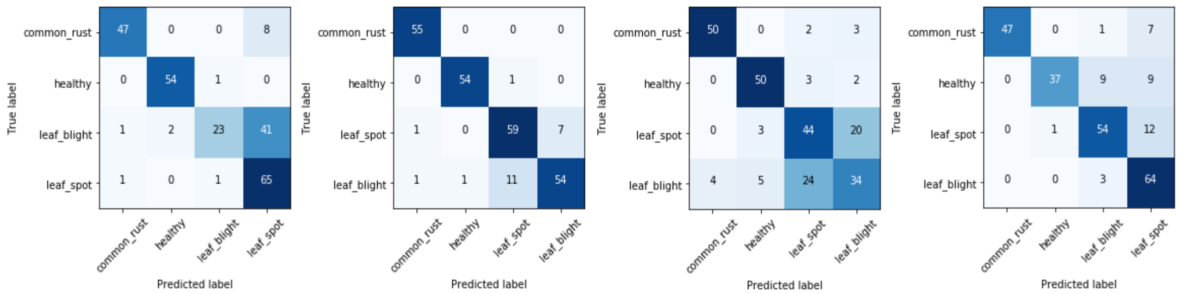
We perform feature extraction by forward passing an image through a trained convolutional neural network. These features are then fed to the classification module in order to accurately classify it into one of the four classes of corn health condition. In case the confidence level of the classification result i.e. the probability of predicted class is not satisfactorily high, the boosting method is utilized in the cascade to confidently predict the correct class. Figure 2 illustrates the classification approach that we have used in order to get maximum accuracy in predicting the correct health condition from the corn leaf image. If the class label is denoted as $\{c_i\}_{i=1}^{C}$ where C is the total number of classes, the classification output would be the C length array P of probabilities with which the image belongs to each class. It can be denoted as $P = \{p_i\}_{i=1}^{C}$ for $\{p_i = p(c_i/f_x, W)\}_{i=1}^{C}$ where f_x are the features of the image, p is probability of each class and W denotes the classifier parameters. As f_x are obtained using a neural network, considering all the network layers as a non-liner transformation of image pixels x, we can denote $f_x = W_n x + b_n$ where W_n and b_n represent CNN model parameters. Hence the probability or the confidence of classification depends on the CNN models for feature extraction as well as classification.

4.1 Feature Extraction

Robust feature extraction is one of the most important steps in order to achieve high classification accuracy in crop images because there can be a lot of variations within the images of single class. These variations can be due to different severity levels of diseases or pests, changes in light conditions, variations in size of the leaves and different growth stages of the crops. Hence, we evaluate different types of convolutional neural networks as feature extractors and different classifiers to classifiy health condition of corn leaves. Augmentation of image dataset is done in order to incorporate the variations in the images that would be captured in uncontrolled conditions. The top layers of deep CNNs - VGG-16, Inception-v2 and MobileNet-v1 pre-trained on ImageNet data have been re-trained with images from each class corresponding to Healthy, Common Rust, Late Blight, Leaf Spot conditions of corn leaves. As the considered CNN models have been trained on a large and varied database, they are seen to generalize well on other datasets too for classification using transfer learning (Zeiler and Fergus, 2014)). This helps us to utilize the optimal weights of deep architectures learned through large visual data. While training these CNN models, the softmax layer in each of these is replaced by a 4-neuron softmax layer. Then the weights of lower layers are fixed and the top layers of the network are fine-tuned by the corn leaf images. In case of VGG-16, for example, output of the pooling layer on top of the other networks is taken as the feature vector because higher levels of network learn generalized features. The topmost convolutional block before the max pooling and the three FC layers in VGG-16 were retrained, and output of topmost FC layer with 1000 neurons is taken as feature vector. For Inception-v2, ResNet-50 and MobileNet-v1, the last convolutional block and the FC layer are retrained and output of average pooling layer before the last FC layer is taken as the feature vector.

4.2 Classification

The standard classification method used with a CNN is using a dense layer of Fully Connected (FC) neurons and a softmax layer in order to get the probability that the given image belongs to a particular class. Adding FC layer helps the network to learn the non linear combination of features computed from convolutional layers followed by pooling for classification. The softmax layer at output of FC layer ensures that sum of output probabilities is 1. The softmax function takes arbitrary-sized real-valued vector and outputs



(a) (b) (c) (d)

Figure 3: Confusion matrices for CNN based classifiers without boosting: (a) VGG-16 (b) Inception-v2 (c) ResNet-50 (d) MobileNet-v1.

a probability vector of size [1x number of classes]. Number of neurons of softmax layer is equal to number of classes C. However, features from the trained CNN can also be fed into other classification algorithms like Support Vector Machine (SVM) (Hearst, 1998) or Random Forest (RF) (Breiman, 2001) in place of using a softmax classifier. We evaluated three methods for classification on the features extracted from the neural network: Softmax, Random Forest, and Support Vector Machine.

Random Forest classifier builds multiple decision trees and merges them to get a more accurate and stable prediction. While training, it sets a stopping criteria for node splits resulting in utilization of the entire feature space with a control in correlation between the trees. This helps in managing the trade-off between bias and variance. While RF is based on decision trees, SVM is a linear classifier, based on the idea of getting a best hyperplane to divide the data in two classes. The hyperplane with the greatest possible margin between itself and any point within the training set is considered to be best as it has a higher probability of new data being classified correctly. Different kernels like Radial Basis Function (RBF) can be used to map a higher dimensional data in a space where a linear separation is possible. The best performing classifer is then followed by boosting for increasing the overall accuracy when used as an ensemble.

4.3 Boosting

Boosting helps the base classifier to form a strong rule for separation between the classes. We have used Adaptive booosing (AdaBoost) (Freund and Schapire, 1997) on top of the base classification algorithm i.e. softmax, RF or SVM in this case to increase the accuracy between the two weakly classified classes. Adaboost is best used to boost the performance of decision trees as it is a sequential ensemble that aims to convert a set of weak classifiers or learners into a strong one. Each learner is added sequentially while training and trained using adaptively weighted training data. Every learner is assigned a weight and a more accurate one is given a higher weight. Iteratively, the learner(s) are added till the limit is reached or the accuracy stops increasing. Initially, equal weight is given to each image feature and if the prediction is incorrect in the first stage then a higher weight is given to such an image in the next iterations. So the idea is that the weights of classifers as well as the data points are set in such a way that the weightage of the classifiers is more on the points that are difficult to classifiy. If none of the output probability using the base classifier (CNN model with RF) exceeds the confidence level of 50%, i.e. if $max(p) < 0.5$, we use the next level of adaptive boosting to increase the confidence of classification and assign a probable health condition to the input image.

5 RESULTS AND EVALUATION

For our experiments, we retrain the models using transfer learning as mentioned in Sec. 3. The dataset has been split into 3 sets viz. training, cross validation and test. Using test images which the neural network has never seen, we get a more generalized measure of classification accuracy whereas cross validation data is used to tune the network parameters to prevent over-fitting or bias while training. The CNN models have been fine-tuned with the corn leaf images in a batch of 32 for every iteration using SGD optimizer with the learning rate of 0.001 with Nestrov momentum. We evaluated these re-trained CNN models for classification accuracy obtained on same test image set for all 4 classes with corn leaf health conditions. A total of 2000 images were taken from PlantVillage dataset where 1600 were used for training and the rest for validation. The 244 test images were taken randomly and not used for training and validation of the classification models. The test data

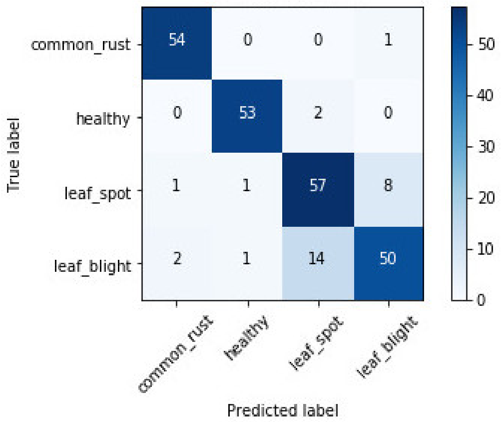


Figure 4: Confusion matrix: SVM on Inception-v2 features.

Table 1: Classification accuracy (%) for different methods.

Architecture	Softmax	Random Forest	SVM
VGG-16	85	87	85
Inception-v2	86	90	87
ResNet-50	73	72	80
MobileNet-v1	80	82	82

had 55 images of Healthy and Common Rust condition each, 67 images affected by Late Blight and Leaf Spot each. Equivalent scores for such test data also show that the models do not suffer from bias or overfitting.

Apart from Softmax, we evaluated RF and SVM that take features extracted from CNNs as input and classify them into 4 classes. Table 1 shows the average accuracy obtained on same test data when we used VGG-16, Inception-v2, MobileNet-v1 and ResNet-50 for classification using Softmax, RF and SVM classifiers. It is seen that for images taken in different conditions like size, resolution, angle and brightness the solution that uses Inception-v2 for feature extraction and Random Forest with 100 decision trees for classification gives the average classfication accuracy of 90% which is maximum of all. Once we observed that RF performs better than Softmax, we also experimented to classifiy CNN features with SVM classifier. We used RBF kernel SVM with parameters 'C = 1.0' and 'gamma = 0.1' values and obtained about 87% accuracy with Inception-v2 features, which is lower than that of RF. The confusion matrix for SVM classifer over Inception-v2 features for comparison is shown in Figure 4 while that for RF over same features is shown in Figure 3(b). Hence we selected a model based on features from Inception and RF to develop an ensemble for classification.

It was observed from confusion matrix for every classifier as seen in Figure 3 as well as Figure 4 that for all of the classification methods, there is most confusion in differentiating between Late Blight and Leaf Spot. We have evaluated accuracy over different CNN architectures as well as classification methods and then selected the one with highest accuracy to ensemble with AdaBoost. After adding Adaboost on the next level after Inception-v2 features classified by Random Forest, the accuracy increased to 98% because the classification accuracy between Leaf Spot and Late Blight increased through boosting as seen in Figure 5. We used adaptive boosting with 100 decision tree based estimators with learning rate of 1.0. Table 2 shows the precision, recall and F1-score of the proposed ensemble method.

Table 2: Classification scores for corn crop health using Adaboost.

Leaf state	Precision	Recall	f1-score
Healthy	1	1	1
Common Rust	0.98	0.98	0.98
Leaf Spot	0.96	0.95	0.94
Late Blight	0.97	0.98	0.96
Total	0.97	0.98	0.97

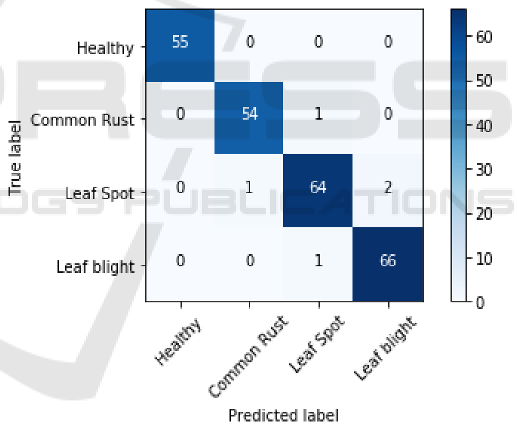


Figure 5: Confusion matrix: Classification with the proposed ensemble with CNN, RF and AdaBoost.

6 CONCLUSION AND FUTURE WORK

Through the proposed system utilizing transferability of CNN features along with boosting, we achieved a test accuracy of 98% with classification score of {precision, recall, f1-score} = {0.97, 0.98, 0.97} in automated crop state diagnosis of corn leaves. Data augmentation to increase the variety in the training image set also helped in extraction of robust features, thus resulting in better classification accuracy on different images. Hence, along with the basic classification techniques, using the features from CNN trained on augmented data, and ensembling with AdaBoost on similar looking classes seems to be a promising solution to automate the crop health diagnosis. This would help farmers and agriculture experts to take faster actions. Appropriate models can be selected based on the accuracy and computational efficiency.

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