

Empirical Investigations to Plant Leaf Disease Detection Based on Convolutional Neural Network

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Abstract

Plant leaf diseases and destructive insects are major challenges that affect the agriculture production of the country. Accurate and fast prediction of leaf diseases in crops could help to build-up a suitable treatment technique while considerably reducing the economic and crop losses. In this paper, Convolutional Neural Network based model is proposed to detect leaf diseases of a plant in an efficient manner. Convolutional Neural Network (CNN) is the key technique in Deep learning mainly used for object identification. This model includes an image classifier which is built using machine learning concepts. Tensor Flow runs in the backend and Python programming is used in this model. Previous methods are based on various image processing techniques which are implemented in MATLAB. These methods lack the flexibility of providing good level of accuracy. The proposed system can effectively identify different types of diseases with its ability to deal with complex scenarios from a plant's area. Predictor model is used to precise the disease and showcase the accurate problem which helps in enhancing the noble employment of the farmers. Experimental results indicate that an accuracy of around 93% can be achieved using this model on a prepared Data Set.

Keywords

Image Classifier, Tensor Flow, Predictor model, Data Set, Leaf Diseases.

I. INTRODUCTION

One of the strongholds of the Indian economy is the Agriculture. Massive commercialisation of agriculture has created a negative effect on our environment. Due to heavy use of chemical pesticides in agriculture, enormous levels of chemical build up in our environment like soil, water and even in human bodies. Artificial fertilisers provide an instant result on productivity but a continuing harmful influence on the environment.

Plant disease detection with the naked eye observation based on the symptoms on leaves is sometimes difficult and increases the complexity. Due to Phyto pathological problems, even experienced agricultural experts and plant pathologists may fail to diagnose specific diseases and are consequently led to mistaken conclusions and concerned solutions. So an automated system is developed to efficiently identify leaf diseases by the plants appearance

This technique is very useful to agriculturalists because it alerts them at the right time before scattering the disease over large area and provide a boundless service in the farming process.

Deep learning is a contemporary method for image processing and data analysis that yields accurate outcomes with great potential. Deep learning is considered as a learning technique on neural networks. The main advantage of deep learning algorithm is that it can inevitably excerpt features from images [1]. The neural network extracts features from images while training. CNN is a popular deep learning model and it can be regarded as a multi-layer feed forward neural network. As deep learning algorithms have been successfully applied in various domains, recently it has arrived into the arena of agricultural science for automatic plant disease detection. So, deep learning is applied to create an algorithm for automated detection and classification of plant leaf infections. Nowadays, Convolutional Neural Networks based model is considered as the popular method for object detection.

Leaf pictures of plant are multifarious with its background and colour data received from a solo colour constituent is insufficient. Due to this, the feature extraction method yields a smaller amount of significant precision outcomes [2]. Information extracted by means of different colour components is promising as an alternative to single colour component. In this paper, the CNN model is suggested based on RGB constituents of the plant foliage imageries on Kaggle dataset. Image classifier is considered as an elementary model. This paper is structured as follows. Particulars of Convolutional Neural Network are described in section II. Image Classifier Model is described in section III. Section IV consists of the proposed technique for plant leaf virus detection and classification. Simulation outcomes are assessed in section V. Finally, concluding remarks are described in section VI.

II. CONVOLUTIONAL NEURAL NETWORK

Deep learning is a category of machine learning algorithms that uses several layers to gradually excerpt

higher level features from the raw input. Here each layer output is given as input to the next layer. Generally convolutional neural networks are analogous to regular neural networks. They are usually made up of neurons that have learnable weights and biases. Each nerve cell accepts the input and then performs a scalar product. The entire network articulates a single differentiable score function from the raw image pixels on one end to class scores at the other [3]. They usually have a loss function on the fully-connected layer and the procedures that are established for learning regular neural networks still applicable. The learning procedures can be supervised, semi supervised or unsupervised.

Convolution architectures make the clear supposition that the inputs are images, from which certain possessions are encrypted into the architecture. This makes to implement the forward function extra efficiently and enormously reduces the number of elements in the network.

Convolutional Neural Network is chosen as a deep learning technique because it is used to recognize and categorize entities with minimal pre-processing [4]. It is used to analyse visual representations successfully and can isolate the essential features easily with its multifaceted construction. Generally, it consists of four main layers. They are Convolutional layer, Pooling layer, Activation Function layer and Fully Connected layer. General architecture of CNN is shown in Fig. 1.

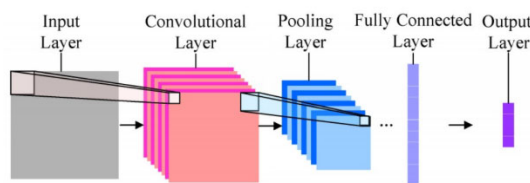


Fig.1: General Architecture of CNN

A. Convolutional Layer:

In this layer, series of mathematical operations are applied to excerpt the feature map of the input image. Convolution layer generally applies convolution operation on the input and then passes the outcome to the subsequent layer. Here, filter of required choice is used to reduce the input image to a smaller size. The filter is shifted step by step beginning from top left corner of the image. At each step, values stored in the image are multiplied by the values of the filter and are summed up to obtain the result. Then from the input image a different matrix with lesser size is generated. This procedure is described in Fig 2.

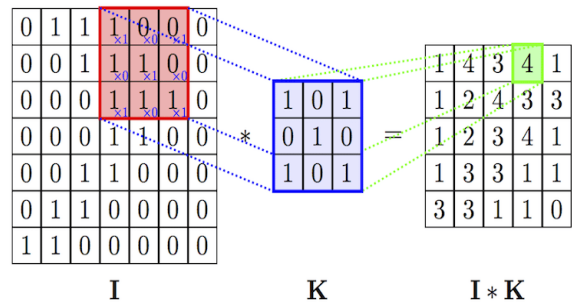


Fig.2: Convolution process using 7x7 input image and 3x3 filter

B. Pooling Layer:

The subsequent layer next to the convolution layer is the pooling layer. It is also considered as the down sampling layer. It consists of several layers but the most popular layer among them is the max pooling layer. This primarily takes a filter of dimension 2x2 and a pace of similar size. Then it is applied to the input volume and produces the highest range in each sub region that the filter convolves around.

Other alternatives of the pooling layer are average pooling and L2-norm pooling. The perceptive reason behind this layer is that once a precise feature is identified in the original input its precise location is not a vital as its relative position to the opposite choices. This layer significantly decreases the abstraction measurement such as length and consequently the breadth modification of the input volume. Max pooling is performed by choosing the biggest value in the sub windows and that value is transported to a new matrix. The max pooling process is exemplified in Fig.3.

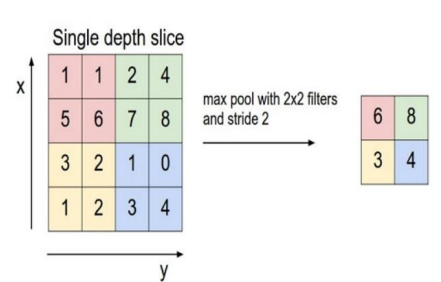


Fig.3: Max Pooling process using 2x2 matrix

C. Activation Layer:

The activation function in neural networks provides a curvilinear relationship between the input and output layers. Due to this, non-linear learning of the network occurs through activation function. This generally affects the performance of the system. Several activation functions like hyperbolic, linear, sigmoid and tangent exist but the nonlinear Rectified Linear Unit (ReLU) activation function is normally used in CNN. In this function values

larger than zero are unaffected whereas values smaller than zero are transformed to zero i.e.

$$f(x) = \begin{cases} 0, & \text{if } x < 0. \\ x, & \text{otherwise.} \end{cases}$$

D. Flattening Layer:

Flattening is the method of altering a two dimensional array into a single long unceasing linear vector. Generally flattening step is essential to make use of fully connected layers after convolutional layers. Convolutional layers have local limitation but fully connected layers do not have any local boundaries. That is all the indigenous features of the previous convolutional layers are combined at this step. Each feature map channel is a compressed two dimensional array generated by adding the results of multiple two dimensional kernels. Flattening process is described in Fig. 4.

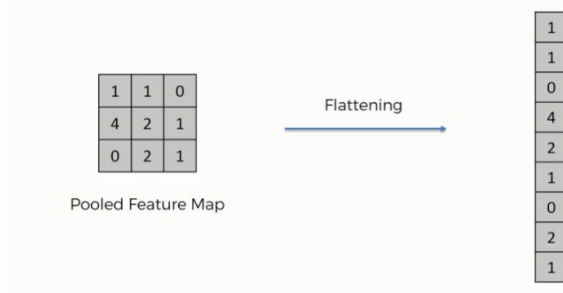


Fig.4: Flattening of max pooled matrix

E. Full Connection Layer:

After performing the convolution, pooling and activation operations, the last obtained matrix is given as input to the fully connected layer. The planate feature map is passed through a neural network after flattening operation. This step is created from the input layer, the fully connected layer and the output layer. In Artificial Neural Networks, the fully connected layer is like a hidden layer but in this method it is fully connected. The predicted classes are obtained from the output layer. The information that is obtained from the output layer is passed through the network and the error of prediction is calculated. To improve the prediction, the error is then back propagated through the system. Recognition and classification are also performed in this layer.

III. IMAGE CLASSIFIER MODEL

This method uses basic image classifier model to detect leaf diseases of a plant. An accurate and early identification is essential while tracking any diseases. Generally visual examination is the traditional technique of identifying plant diseases. This process is prone to human errors and plagued with inefficiencies. Diagnosing plant

disease is essentially pattern recognition for a trained computer. So a machine learning algorithm can efficiently spot disease type and severity after sorting through thousands of photos of morbid plants and in the future may even recommend management practices to limit loss from a disease [5]. Generally detection is carried out in two ways. They are:

- Binary Label Classification
- Multi Label Classification

A. Binary Label Classification

The term Binary refers to two. This type of classification mainly involves the two-level classification. It is used to classify the image based on the input that is given to it. This classification determines whether the input image given is healthy or unhealthy.

B. Multi Label Classification

Different Variants of the classification in machine learning are multi-label classification and multi-output classification. In multi-label classification, several labels may be allotted to each instance. Multi-label classification is a simplification of multiclass classification. In this, single label problem of classifying instances can be resolved into more than two classes. There is no restriction on the number of classes the instance can be allocated in the multi-label problem. Formally multi-label classification is the problem of identifying a model that maps inputs 'x' into binary vectors 'y'.

Detection of leaf infections of a tomato plant is primarily considered here. Major diseases of a tomato plant leaf like Bacterial spot, Late blight, Septoria leaf spot and yellow leaf curl are deliberated.

IV. PLANT LEAF DISEASE DETECTION AND CLASSIFICATION

In this technique around 4000 training and 1000 test images of tomato plant leaf from Kaggle dataset are used. The images are cropped to 512x512 sizes from the selected dataset. Different diseases to classify from the leaf images are bacterial spot, septoria leaf spot, late blight and yellow leaf curl [6]. Five dissimilar classes are considered, one of them is meant for healthy leaves and four of them are meant for leaf diseases.

Bacterial Spot: Indications of bacterial spot are dark, water soaked greasy appearing lesions or small, yellow-green scratches are seen on the leaves. This disease is very difficult to control and spreads rapidly. So it is considered as one of the most dangerous leaf diseases of a tomato plant. This disease causes substantial loss to the plant and its productivity also.

Late Blight: This disease is originally seen on old leaves as big brown spots with green grey edges. As the disease

develops, the spots become darker and finally it contaminates the whole plant and causes the plant to be extremely ruined.

Septoria Leaf Spot: It is primary seen on the lower leaves of a plant. The indications of this infection are round, yellow and water-soaked spots that arise beneath the leaves. Due to this small brown or black spots are formed on the leaves. The sizes of the spots may be varied between 1.5 mm and 6.5 mm.

Yellow Leaf Curl: This disease causes the plant to turn out to be short and dwarfed. The leaves are trundled upwards and inwards. It typically causes the leaves to turn downwards. Leaves have a rubbery skin texture and turn out to be rigid and denser than normal. Due to this new and contaminated leaves converted to slightly yellowish. Symptoms of several plant leaf diseases are described in Fig.5.

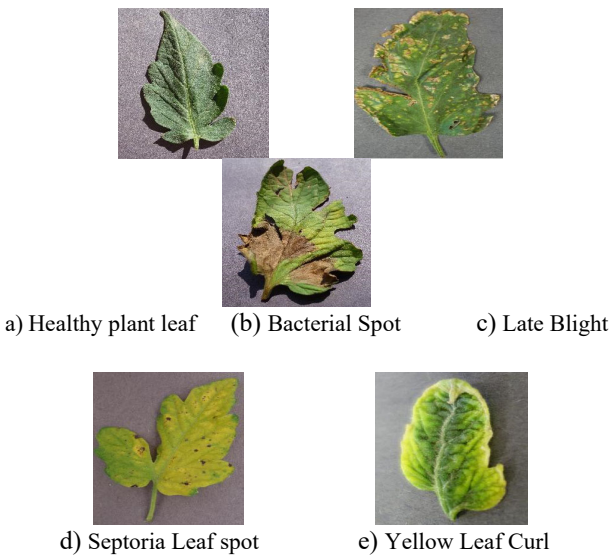


Fig.5: Symptoms of plant leaf diseases

In the proposed technique, the input image is convolved around 32 times with a 3x3 matrix and reLU activation function is applied once. Then the max pooling operation is applied to the output matrix twice using 2x2 matrix followed by the reLU activation function. The next layer is the Flattening Layer which translates the matrix into a linear vector. The final layer is the Full connection layer in which it interconnects 128 neuron units using reLU activation function and interconnection of one neuron unit using sigmoid activation function. The next step after the initialization is to train the model using a given path consisting of group of images (say 4000 images) of tomato plant leaves. Then epoch is chosen before training the model. The greater the number of epochs the better is the accuracy. The later step is to test the model by giving the whole testing dataset path to it which contains around 1000

images of tomato plant leaves. The last step is the prediction model in which various diseases are described and the output will be displayed on the console window.

In Multi Label, the path of the input image is given from which effected disease is obtained if affected or it displays the kind of disease. But the binary label only specifies whether the given input image is healthy or unhealthy.

V. EXPERIMENTAL RESULTS

Several tests were conducted on healthy and unhealthy tomato plant leaf images to validate the performance of the proposed method. One of the main challenges in plant leaf disease detection and classification is that leaves with diversified diseases are analogous to each other. Consequently this resemblance can cause some leaves to be folded into erroneous classes. Experimental results for the two classifier models are given below:

A. Binary Label:

Stage 1: Accuracy of 97% is achieved

```

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File Edit View Insert Cell Kernel Widgets Help
In [ ]: # Part 3 - Making new predictions

steps_per_epoch = 100,
epochs = 10,
validation_data = test_set,
validation_steps = 10)

Found 271 images belonging to 2 classes.
Found 263 images belonging to 2 classes.
Epoch 1/10
100/100 [-----] - 32s 322ms/step - loss: 0.2908 - acc: 0.8959 - val_loss: 0.8762 - val_acc: 0.9693
Epoch 2/10
100/100 [-----] - 28s 277ms/step - loss: 0.0865 - acc: 0.9688 - val_loss: 0.0633 - val_acc: 0.9727
Epoch 3/10
100/100 [-----] - 29s 290ms/step - loss: 0.0568 - acc: 0.9780 - val_loss: 0.0711 - val_acc: 0.9727
Epoch 4/10
100/100 [-----] - 26s 260ms/step - loss: 0.0226 - acc: 0.9959 - val_loss: 0.0633 - val_acc: 0.9795
Epoch 5/10
100/100 [-----] - 29s 292ms/step - loss: 0.0181 - acc: 0.9953 - val_loss: 0.0701 - val_acc: 0.9795
Epoch 6/10
100/100 [-----] - 28s 281ms/step - loss: 0.0143 - acc: 0.9971 - val_loss: 0.1170 - val_acc: 0.9727
Epoch 7/10
100/100 [-----] - 28s 281ms/step - loss: 0.0143 - acc: 0.9971 - val_loss: 0.1170 - val_acc: 0.9727
1/100 [-----] - ETA: 28s - loss: 0.0038 - acc: 1.0000
    
```

Fig.6: Results at the First Stage

Stage 2: Accuracy of 98% is achieved

```

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File Edit View Insert Cell Kernel Widgets Help
In [ ]: # Part 3 - Making new predictions

validation_data = test_set,
validation_steps = 10)

Found 271 images belonging to 2 classes.
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Epoch 1/10
100/100 [-----] - 32s 322ms/step - loss: 0.2908 - acc: 0.8959 - val_loss: 0.8762 - val_acc: 0.9693
Epoch 2/10
100/100 [-----] - 28s 277ms/step - loss: 0.0865 - acc: 0.9688 - val_loss: 0.0633 - val_acc: 0.9727
Epoch 3/10
100/100 [-----] - 29s 290ms/step - loss: 0.0568 - acc: 0.9780 - val_loss: 0.0711 - val_acc: 0.9727
Epoch 4/10
100/100 [-----] - 26s 260ms/step - loss: 0.0226 - acc: 0.9959 - val_loss: 0.0633 - val_acc: 0.9795
Epoch 5/10
100/100 [-----] - 29s 292ms/step - loss: 0.0181 - acc: 0.9953 - val_loss: 0.0701 - val_acc: 0.9795
Epoch 6/10
100/100 [-----] - 28s 281ms/step - loss: 0.0143 - acc: 0.9971 - val_loss: 0.1170 - val_acc: 0.9727
Epoch 7/10
100/100 [-----] - 26s 263ms/step - loss: 0.0053 - acc: 0.9994 - val_loss: 0.0974 - val_acc: 0.9795
Epoch 8/10
100/100 [-----] - 28s 277ms/step - loss: 0.0049 - acc: 0.9987 - val_loss: 0.0650 - val_acc: 0.9829
Epoch 9/10
100/100 [-----] - 27s 271ms/step - loss: 0.0050 - acc: 0.9984 - val_loss: 0.1503 - val_acc: 0.9795
Epoch 10/10
100/100 [-----] - 25s 252ms/step - loss: 0.5641e-04 - acc: 1.0000 - val_loss: 0.0644 - val_acc: 0.9795
Out[4]: keras.callbacks.History at 0x2182141f98b
    
```

Fig.7: Results at the Second Stage

Healthy plant Prediction

```
# Part 3 - Making new predictions
import numpy as np
from keras.preprocessing import image
test_image = image.load_img('data sheets/test44.jpg', target_size = (64, 64))
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image, axis = 0)
result = classifier.predict(test_image)
print(training_set.class_indices)

if result[0][0] == 1:
    prediction = 'healthy'
else:
    prediction = 'unhealthy'
print(prediction)

{'26': 0, '27': 1}
healthy
```

Fig.8: Healthy plant Prediction

Unhealthy plant Prediction

```
# Part 3 - Making new predictions
import numpy as np
from keras.preprocessing import image
test_image = image.load_img('data sheets/test33.jpg', target_size = (64, 64))
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image, axis = 0)
result = classifier.predict(test_image)
print(training_set.class_indices)

if result[0][0] == 1:
    prediction = 'healthy'
else:
    prediction = 'unhealthy'
print(prediction)

{'26': 0, '27': 1}
unhealthy
```

Fig.9: Unhealthy plant prediction

B. Multi Label:

Stage 1: Accuracy of 89% is achieved

Fig.10: Results at the First Stage

Stage 2: Accuracy of 93% is achieved

Fig.11: Results at the Second Stage

Unhealthy plant Prediction

Fig.12: Unhealthy plant Prediction

Healthy plant Prediction

Fig.13: Healthy plant Prediction

VI. CONCLUSION

In this paper, tomato plant leaf disease detection and classification methods are presented based on a simple image classifier model using the Convolutional Neural Network. The dataset consists of around four thousand training images and thousand test images of tomato leaves. For the given input image, processing is done in various layers and the output is generated based on the training dataset given to the model. Therefore related leaf diseases of tomato plant were taken into consideration for identification. Optimum results were obtained with less computational efforts. This shows that the efficiency of the proposed system for identification of plant leaf diseases is 98% for binary label and 93% for multi label. Another major benefit of this model is that, plant diseases can be recognized at the early stage or initial stage. To increase the recognition rate in the process of classification of Artificial Neural Network several optimization techniques like Byes classifier, SVM optimizer, LVQ algorithm, Fuzzy logic can be used.

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