Journal of Pharmacognosy and Phytochemistry

Available online at www.phytojournal.com

E-ISSN: 2278-4136
P-ISSN: 2349-8234
JPP 2019; SP1: 255-259

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(Special Issue- 1)
2nd International Conference
"Food Security, Nutrition and Sustainable Agriculture - Emerging Technologies"
(February 14-16, 2019)

Detection of apple leaf disease using deep belief networks

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Abstract
There are numbers of the diseases has been found in the fruits like apple, grapes etc. The presence of the disease is the major factor which is responsible for the degradation of the agricultural industry worldwide. In this paper, we have focused on the apple leaf disease and proposed a method to detect this disease. We have tried to improve the accuracy for the detection purpose so that proposed algorithm can work accurate to detect the disease in plant.

Keywords: CRF, plant disease, SDAE, K-Mean, DBN

Introduction

In the production of fruits India has a second rank. Sixty percent population is having employment by agriculture domain [3]. The established methodology for recognition of fruit product illnesses depends on the naked eye perception by the specialists. In some creating nations, counselling specialists are costly and tedious because of the inaccessible area of accessibility [2]. The other areas like twigs, leaves, and branches of the tree are also infected by these infections. Apple rot, apple blotch and apple rot are some most mutual diseases of apple fruits [1]. Apple fruit is having gray or brown corky spots then it is apple scab diseases [1]. If the surface of the apple fruit is slightly sunken, circular brown or black spots that may be covered by a red halo then it is referred as apple rot type diseases [1]. The surface of the apple fruit is having dark, irregular or lobed edges then it is apple blotch type diseases [1]. The diagnosis of apple cultures is most often conducted by visual inspection of leaves and fruits, typically on site by an expert. Laboratory analysis can be used in more complex or new cases. However, this approach bears a high cost, as it requires experts that demand specialized training. The need for experts not only limits scale but may also reduce effectiveness due to human errors since experts are often specialized in a few types of disorders.

There are mainly two types of images and these are Analog and Digital images. Processing of image means to convert an image into its digital form and then different kind of operations will be performed on it to get some kind of results with enhanced type of same image. These results will give us the useful information which can be extracted from it and can be very helpful. There are many type algorithms which can be implemented to perform a particular type of operations or task. Sometimes when some diseases are not visible to naked eye but actually they are present, then it is difficult to detect it with the naked eye. And when it is visible it will be too late to detect disease and can't help anymore. In earlier, this disease was detected with the microscopes but it was very difficult process to observe each and every plant and leaf. So now remote sensing techniques are developed and used in computer science. They can detect the disease from the multilevel and hyperspectral images of plants which can be digitally captured.

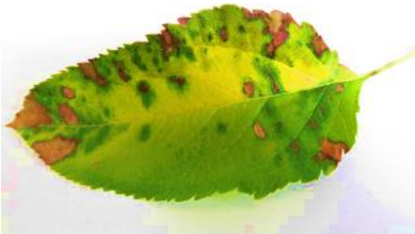


Fig 1: Apple Leaf disease

In this paper we report on results of training and applying machine learning models to automatically classify common disorders directly from images of apple tree leaves (*Malus domestica Borkh*). Our hypothesis is that the current state of-the-art models, in particular deep belief network and related training algorithms are able to attain Performance comparable to or better than human experts.

Related Work

There are a few commercial systems in use to help with the diagnosis of disorders in cultures, although not restricted or applicable to apple trees. In paper [1] apple scab, apple rot and apple blotch three diseases have been taken. Using K-means Clustering, image segmentation process has been done. In the next step features are extracted like color coherence vector (CCV), Global color Histogram (GCH), local binary pattern (LBP) and complete local binary pattern (CLBP). In paper [2] different methods like Local Binary Pattern, Color Invariant, Color histogram are used for the feature extraction from images and further classification is carried out with the help of neural network. In paper [3] Aimed to discriminate healthy from dangerous sugar beet leaves, to differentiate between three forms of diseases and to discover illnesses even earlier than unique signs and symptoms have become visible. The authors used Support Vector Machines and as enter they used 9 spectral plants indexes, as functions, resulting in classification accuracies up to 97% while differentiating healthful from dangerous, 86% while distinguishing between 3 illnesses and among 65% and 90% for pre-symptomatic detection of sicknesses. Notably, this technique requires specialized hardware to gain the spectral images and significant feature selection. In paper [4] five samples are considered. 3 samples of grapes leaves and 2 samples of apples leaves are picked up for detection. As a result 90% accuracy has been achieved using neural network algorithms. In paper [5] tried at categorizing six diseases from leaf images. The authors used from each of the six classes of leaves 32 leaves and for classification perform a Multilayer Perceptron. Features were manually extracted from the image and defined its 10 texture features and showing accuracies between 83% and 94%.

Deep Learning

Deep Learning is a new area of Machine Learning research, which has been introduced with the objective of moving Machine Learning closer to one of its original goal. Deep Learning is about learning multiple levels of representation and abstraction that help to make sense of data such as images, sound, and text.

- **Generative Architectures:** This class of deep networks is not required to be deterministic of the class patterns that the inputs belong, but is used to sample joint statistical distribution of data; moreover this class of networks relies on unsupervised learning. Some deep networks that implement this type architecture include Auto Encoders (AEs), Stacked Denoising Auto Encoders (SDAE), Deep Belief Networks (DBNs), Deep Boltzmann Machines (DBMs) etc. In general, they have been quite useful in various nondeterministic pre-training methods applied in deep learning and data compression systems. Main architectures for deep learning are as follow:
- **Discriminative Architectures:** Discriminative deep networks actually are required to be deterministic of the correlation of input data to the classes of patterns therein. Moreover, this category of networks relies on supervised learning. Examples of network that belong to this class include Conditional Random Fields (CRFs), Deep Convolutional Networks, Deep Convex Networks etc. In as much as these networks can be implemented as „stand-alone" modules in applications, they are also commonly used in the fine tuning of generatively trained networks under deep learning.
- **Hybrid Architectures:** Networks that belong to this class rely on the combination of generative and discriminative approach in their architectures. Generally, such networks are generatively pre-trained and then discriminately fine-tuned for deterministic purposes. e.g. pattern classification problems. This class of networks has sufficed in many applications with the state-of-art performances.

Models for Deep Learning: There are various models available for deep learning. These models are:

1. Stacked denoising auto encoder (SDAE): Stacked Auto Encoders (SDAEs) are basically multilayer feed forward networks with the little difference being the manner in which weights are initialized. Here, the weights initialization is achieved through a generative learning algorithm, as this provides good starting weight parameters for the network (and helps fight under-fitting during learning). An auto encoder (single layer network) is a feed forward network trained to replicate the corresponding inputs at the output. Auto encoders can be stacked on one another to achieve a more distributed and hierarchical representation of knowledge extraction from data; such architectures are referred to Stacked Auto Encoders (SAEs). Some undeveloped features are extracted in the first hidden layer, followed by more significant elementary features in the second, to more developed and meaningful features in the subsequent layers. The training approach that is used in achieving learning in generative network architectures is known as greedy layer-wise pre-training. The idea behind such an approach is that each hidden layer can be hand-picked for training as in the case of single hidden-layer networks; after which the whole network can be coupled back as whole, and fine-tuning done if required. Since the auto encoder is fundamentally a feed forward network, the training is described below. Encoder mode:

$$L_i(x) = p(c(x)) = \sum(b^{(L1)} + W_{Encoder}{}^{(L1)}\ X \qquad (1)$$

$$output = z(d(x)) = \sum(b^{y} + W_{decoder}^{(L1)}\ L1(x)) \qquad (2)$$

Where, c(x), d(x) is the pre-activation functions of the hidden layers L1 and y respectively. b (L1) and b(y) are biases of the hidden and output layers. By minimizing cost function, reconstruction is clearly achieved.

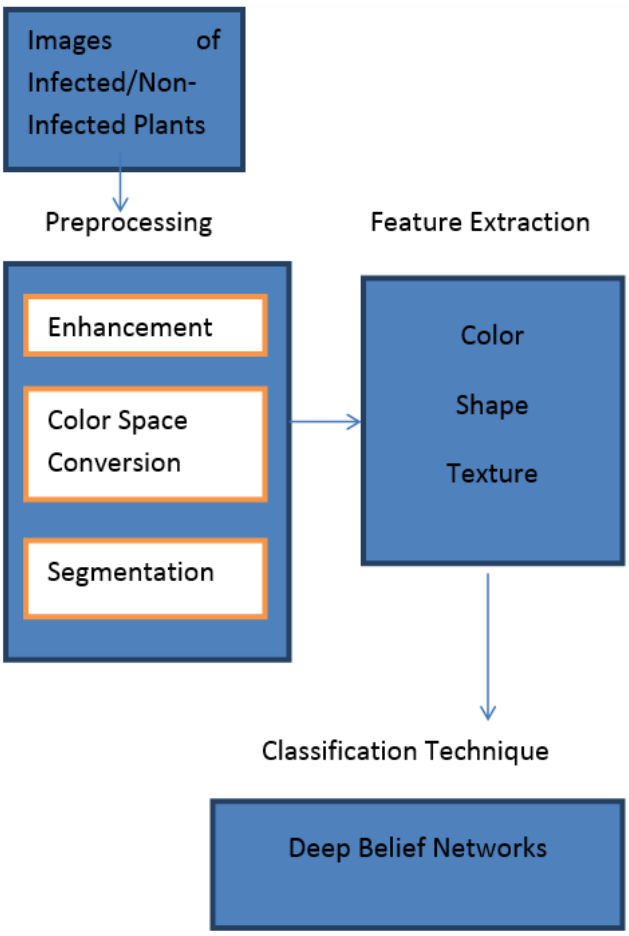
$$C(i,j) = \sum_1^r (i_r - j_r)^2 \quad (3)$$

$$C(i,j) = -\sum_1^k (i_r \log(j_r) + (1 - i_r)\log(1 - j_r)) \quad (4)$$

When the variety of values for the input are real, Equation 3 is used and at the output a linear activation is applied while equation 4 is applied when the inputs are binary or range lies between 0 to 1, and sigmoid functions are applied as activation functions. Moreover, Equation 4 is recognized as the sum of Bernoulli cross-entropies.
If input is removed, then L1 layer becomes input, L2 becomes hidden layer and output will be same. Finally, the original training data is supplied at the input layer and the corresponding target outputs or class labels are supplied at the output layer.

2. Deep Belief Network (DBN): A DBN is a deep network, which is graphical and probabilistic in nature; it is essentially a generative model too. A belief net is a directed acyclic graph composed of stochastic variables. These networks have many hidden layers which are directed, except the top two layers which are undirected. In section 4, we will discuss it in detail.

Methodology
In this paper we have proposed some color and texture features are extracted from the test images. After the feature extraction some color and texture features are fused together for better accuracy. Finally the apple fruit diseases are classified using random forest classifier and then if the fruit is infected by any of the diseases then the diseased part is segmented using k-means clustering technique.



Flowchart of Proposed Methodology

1. Input Image: Initially an image containing infected disease will be occupied and this image will be passed through a pre-processing stage for the removal of unwanted noise from the image.

2. Pre-processing and Segmentation: The pre-processing involved the procedures to prepare the images for subsequent analysis. The affected leaf images were converted from RGB color format to gray scale images. Segmentation refers to the process of clustering the pixels with certain properties into salient regions and these regions correspond to different faces, things or natural parts of the things. We proposed k-means segmentation technique to fragment goal areas. Target regions are those areas in the image that represented visual symptoms of a fungal disease.

2.1. Fuzzy Image Enhancement: It highlighted the suppressed background without introducing the artefacts. Fuzzy histogram, fuzzy statistics helps imprecision in gray levels well. It is calculated with the help of fuzzy membership function and provides smooth results. This helps in attaining its significant partitioning essential for brightness preserving equalization.

2.2. Highlighted the damaged Pixel: After fuzzy process, damaged pixels are highlighted in this process. For damaged pixel detection we used

Di [:,:,1]> Di[:,:,2]

&&

Di [:,:,1]> Di[:,:,3]

Therefore, pixel can be damaged. Here, 1, 2, 3 are the levels of RGB.

But this method is not works because it detects wooden section also. So to overcome this problem, K-mean clustering will be used.

2.3 K-Mean Clustering: K-means is a clustering algorithm discovered by Macqueen in 1967 [10]. K-means is generally carried to find the infected
Regions in an image.

The K-Means Algorithm Process

- The dataset is partitioned into K clusters and the data points are randomly assigned to the clusters resulting in clusters that have roughly the same number of data points.
- For each data point calculate the Euclidean distance from the data point to each cluster.
- If the data point is closest to its own cluster, leave it where it is. If the data point is not closest to its own cluster, move it into the closest cluster. Repeat the above step until a complete pass through all the data points results in no data point moving from one cluster to another. At this point the clusters are stable and the clustering process ends.
- The choice of initial partition can greatly affect the final clusters that result, in terms of inter-cluster and intra-cluster distances and cohesion [10].

3. Feature Extraction: Different features are chosen to describe different properties of the leaves. Some leaves are with very distinctive shape, some have very distinctive texture patterns, and some are characterized by a combination of these properties. Haralick textures features is a well-known method for quantifying textures, and gives information about the image region such as homogeneity, contrast, boundaries, and complexity. This approach has even enjoyed some success in biology. Calculating the Haralick features is handled via the haralick function, an m-file found on Matlab's File

3.1 Gray-Level Co-occurrence Matrix: This method was first proposed by Haralick in 1973 and still is one of the most popular means of texture analysis [8]. The key concept of this method is generating features based on gray level co-occurrence matrices (GLCM). The matrices are designed to measure the spatial relationships between pixels. The method is based on the belief that texture information is contained in such relationships. Co-occurrence features are obtained from a gray-level co-occurrence matrix. The GLCM from which these features are calculated is built by determining the distribution of co-occurring values at a given offset over an a×b image I, as:

$$C_{\Delta u\,\Delta v}(m,n)= \sum_{a=1}^{k}\sum_{b=1}^{l} \begin{cases} 1, \text{if } I(a,b) = m \text{ and } (a+\Delta u, \quad b+\Delta v = n \\ 0, \text{otherwise} \end{cases} \quad (4)$$

4. Deep Belief Network (DBN): A DBN is a deep network, which is graphical and probabilistic in nature; it is essentially a generative model too The lower hidden layers which are directed are referred to as a Sigmoid Belief Network (SBN), while the top two hidden layers which are undirected are referred to as a Restricted Boltzmann Machine (RBM). Since the last two layers of a deep belief network is an RBM, which is undirected, it can therefore be conceived that a deep belief network of only two layers is just an RBM. When more hidden layers are added to the network, the initially trained deep belief network with only 2 layers (also just an RBM) can be stacked with another RBM on top of it; and this process can be repeated with each new added layer trained greedily. The main aim of an RBM is to compute the joint distribution of v and h, p(v,h), given some model specific parameter, ϕ. This joint distribution can be described using an energy based probabilistic function as shown below.

$$E(i,j,\Phi)= -\sum_k \sum_m W_{km}\, i_k\, j_m - \sum_k b_k\, i_k - \sum_m b_m\, i_k \quad (5)$$

$$P(i,j,\Phi)= e^{(-E(i,j,\Phi))} / Z \quad (6)$$

$$Z=\sum_i \sum_j e^{(-E(i,j,\Phi))} \quad (7)$$

Here E(i,j,Φ) is the is the energy associated with the distribution of i given I and j are input and hidden layer units activations respectively, k is the number of units at the input layer, m is the number of units at the hidden layer. P(i,j;ϕ) is the joint distribution of variable i and j, while Z is a partition constant or normalization factor

For a RBM with binary stochastic variables at both visible and hidden layers, the conditional probabilities of a unit, given the vector of unit variables of the other layer can be written as:

$$p(j_m = |v;\Phi)=\sigma(W_{km}\, i_k + b_m) \quad (8)$$

$$p(i_m = |i;\Phi)=\sigma(W_{km} j_m + b_k) \quad (9)$$

Where σ is the sigmoid activation function.

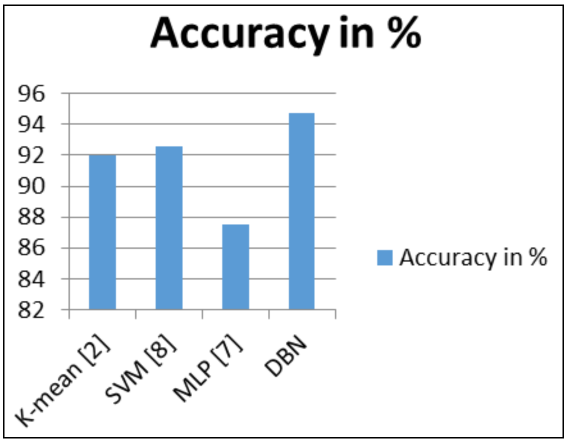


Fig 2: Accuracy of various algorithm

Fig. 2 depicts the accuracy of the various algorithms to detect the apple leaf disease. It shows that proposed algorithm DBN detect disease accurately with 94.7% accuracy which is better than the existing algorithm.

Algorithms	Accuracy in %
K-mean [2].	92
SVM [8].	92.6
MLP [7].	87.5
DBN	94.7

Conclusion

Most of the plant these days is suffering from the numbers of the diseases and apple plant is one of them. Apple rot, apple blotch and apple rot are some most mutual diseases of apple fruits [1]. Apple fruit is having gray or brown corky spots then it is apple scab diseases. These diseases are responsible for the degradation of the agricultural industry. Therefore, it is a need to develop an algorithm which can detect disease at the early stage. The proposed algorithm is based upon the deep belief network and data is trained using machine learning techniques so that it can detect the disease in the better and accurate rate. Experimental results show that the proposed algorithm detect disease 94.7% accurately as compared to the other existing methods.

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