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Article Title: Efficient Supervised Classifier for Disease Predictions in Apple Leaf

Efficient Supervised Classifier for Disease Predictions in Apple Leaf

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ABSTRACT

Various non-separable and difficult computing issues are resolved using pattern classifiers (PCs). Another of the main issues is accurately predicting a particular disease in a normal fruit tree. A grower could be able to take necessary preventative steps ahead of time with the aid of a prompt and properly apple tree illness that was anticipated. The green leaves plague and apples disease infections are predicted in this essay using a method for diagnosing apple illnesses. The system's goal is to create a method for predicting apple disease. From different parts of Kashmir, several photographs of apple leaf disease have been gathered. In order to train the suggested human brain, these photos are used. An image can be used to extract a variety of features, including color, material, edge, and form characteristics. This study employs low grade and curve data to create an intelligent apple disease prediction system. The leaf ages are analyzed initially to obtain the key image information, including brightness, radiation, the IDM mean, standard deviation, perimeter, etc. Eleven apple leaf image characteristics and a multi-layer perceptron pattern classifier are used to train the suggested program's architecture. The autonomous robot that performs pattern categorization is built using the gradual descending rear technique. The proposed approach has a 99.1% diagnostic average accuracy after being tested on several random samples. The proposed prediction model has a sensitivity of 98.1% and a specificity of 99.9%.
Keywords: Inverse Difference Moment, Standard Deviation, Multi-Layer Perceptron, Pattern Classifiers.

1 Introduction

Kashmir is highly recognised for its distinctive apples throughout all of India. India provides 65% of the world's total apple harvest. The apples (Modifier pumila), a different kind of fruit, are susceptible to a number of illnesses, including apple disease and Alternaria leaf spot. These diseases may affect both fruit and leaves, which may lead to a loss in both number and quality (Kayalvizhi and Antony, 2011[4]. The fungus Venturia inaequalis is the culprit behind apple disease sickness. It affects fruit, leaflet, blast, blossom, and flowers. It is the most severe and widespread illness. The upper surface of the leaves develops a pale yellow, brown, or almond tint as a consequence of the illness. Older leaves have more distinct lesions that change from velvety grey to sooty black in colour and structure. The tumours might create a concave area if the bottom side has a comparable convex region. The foliage are becoming curled, deformed, and stunted and will usually fall off before their time if the illness is extreme. A machine learning model can be trained by comparing the texture or statistical characteristics of leaves from diseased and healthy trees. The method primarily leverages an initial cycle of apple leaf photos that were obtained in Kashmir, where 75% of all apples are grown in India. In 2013, Sanjeev S. Sannakki et al. suggested a system for the detection of illnesses affecting grape leaves. Using a straight forwarding structure as a classification, Sachin D. Khirade et al. (2015) [5] have suggested a forecasting model for leaf diagnosing. Furthermore, Meinanda et al. (2015) [7] offered a further framework for the detection of apple disease, with a program impact of 85%, which is a quite low price. Using low level characteristics of the leaves of the apple illness method. Using pattern classifiers like inter convolution layers may be the focus of future development on the apple disease prediction system.

2 Proposed Work Explanation

Figure 1 shows the structure of the apple illness forecasting system. The system's goal is to create a method for predicting apple disease. Below is a discussion of the numerous steps that make up the proposed methodology. From several parts of Kashmir, different photographs of apple leaf disease have been gathered.

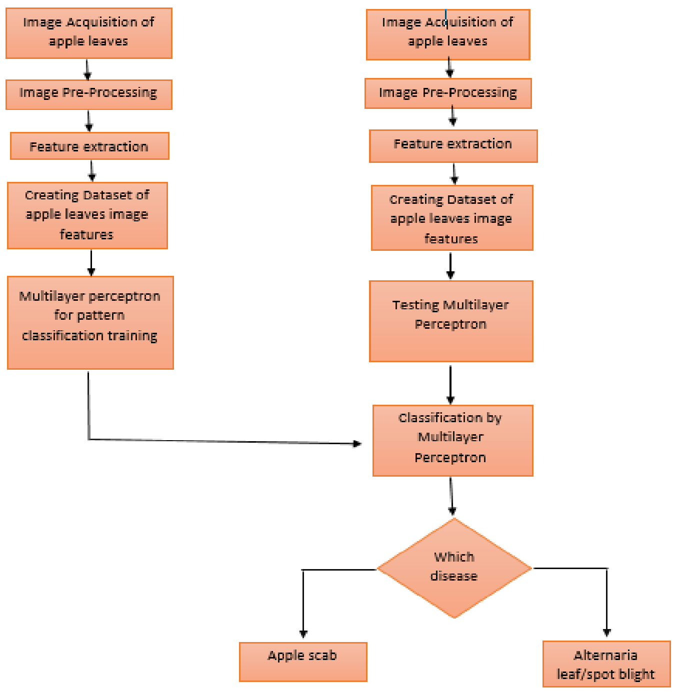

Figure 1: *The proposed apple disease prediction system's framework diagram*

This step's goal is to identify the aspects of an image. To identify apple diseases, these characteristics will be employed. A picture can be used to extract a host of options, including colour, roughness, boundary, and form features. Texture features can be extracted using a variety of techniques, including information that is quantitative, architectural, model-based, and transformation-based. In order to train the human brain, material and form characteristics are retrieved from a picture out of these image features. First order and second order statistical techniques are used for this. Mean, kurtosis, standard deviation, and skewness are examples of first order data analysis. Gray Level Co-occurrence Matrix features are examples of second order optimization methods.

3 Mathematical Expressions and Symbols

The most common approach for measuring variability or dispersion in statistics is the standard deviation. It gauges how widely the component frequencies of a picture deviate from the mean in terms of image analysis. A lower standard deviation value denotes that the data points are in close proximity to the mean, whereas a high standard deviation value denotes that the data sets are dispersed throughout a large variety of values. It is given in Equation 1 and indicated by the symbol.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Xi-\mu\right)^{2}} \quad (1)$$

Standard Deviation (σ)

Where μ is the mean, N is the no of pixels, xi represents value at the ith pixel

Skewness is a measurement of how symmetrical a collection or distributed is. Skewness in symmetric data should be close to zero. The skewness value in a symmetrical pattern is zero. Skewness and third order instants are connected. Data can be distorted either or adversely. Highly skewed indicates that the brighter and duller areas are examples of locations where the computation's result is less than zero, while positive bias implies that the computation's result is greater than zero (example: darker and glossier parts). Equation 2 contains it.

$$\text{Skewness} = E\left[\left(\frac{z-\mu}{\sigma}\right)^{3}\right] \quad (2)$$

Where σ is the standard deviation and μ is the mean.

A pixel's correlation to its neighbours throughout the entire image is measured by the term "correlation." It has a range of -1 to 1. If the image is constant, NaN is the value. Equation 3 following can also be used to determine the relationship.

$$\text{Correlation} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{\left(i-\mu\right)\left(j-\mu\right)T\left(i,j\right)}{\sigma_i\sigma_j} \quad (3)$$

Where σ is the standard deviation, T (i, j) represents relative frequency of that pixel, μ is the mean

Entropy: It can be used to describe the texture of the source images because it is a measure of uncertainty or unpredictability. The quantity of entropy will be at its highest when each of the components of the grey level co-occurrence matrix are identical. Equation 4 defines it as well.

$$\text{Entropy}= \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\left(T\left(i,j\right) * \log\left(T\left(i,j\right)\right)\right) \quad (4)$$

Where (i, j) represents position of the pixel of an image and T (i, j) represents relative frequency of that pixel.

Inverse Difference Moment: It is also employed to evaluate the image's texture. Entropy is another name for it. It gauges an article's consistency. When the majority of the instances in GLCM are concentrated close to the main diagonal, its value will be at its highest. The relationship between it and GLCM brightness is inverse. Equation 5 defines the inverted differentiation moment as follows:

$$\text{IDM}= \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{T\left(i,j\right)}{1+\left(i,j\right)^2} \quad (5)$$

Where (i, j) represents position of the pixel of an image and T (i, j) represents relative frequency of that pixel.

4 Preparation of Figures and Tables

Table 1 compares the outcomes of the suggested apple disease prediction system with those of other similar types of prediction systems. The proposed system exhibits an overall accuracy of 99.1%, which is significantly higher than earlier systems developed by Sharad Pawar et al. (2016) for cucumber disease with an accuracy of 80.4% and Meinda et al. (2015) for apple disease with an efficiency of 85%. The proposed method makes advantage of additional picture qualities, such as Mean, percentage point, volatility, association, and difference etc.

Table 1: *Comparative Analysis*

Disease Name	Network Used	Author	Year	Performance
Cucumber Disease	Feed Forward Back-Propagation Network	Pooja Pawar, Dr. Varsha Turkar, Prof. Pravin Patil	2016	80.4%
Apple Disease	K-Means algorithm, SURF algorithm	Bashir Sajo Mienda, Adibah Yahya, Ibrahim A. Galadima, Mohd Shahir Shamsir	2015	85%
Apple Disease	Gradient Descent with Back-propagation network	Mahvish Jan, Arvind Selwal	2018	99.1%

5 Conclusion

The study described in this paper was done to identify the illnesses affecting apples. The study concentrated on two prevalent disease types: apple disease and leaf/spot blight. To recover textural features, the GLCM and starting order statistical instants have been applied. The neural net has been trained using the leaf's circumferential and surface data. The suggested approach has 99.1% categorization accuracy. Upcoming hybrid classifiers may take into account additional apple leaf attributes to produce better outcomes. Convocational Neural Networks a type of deep neural network, may be utilised in the future to train models instead of features in order to build systems more effectively. The equivalent model for diagnosing apple illness may be constructed using supporting vector machines (SVM). Additionally, wearable networks might be installed in orchards to diagnose apple illnesses in real time.

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