Ilkogretim Online - Elementary Education Online, 2020; Vol 19 (Issue 3): pp. 4626-4633
http://ilkogretim-online.org
doi: 10.17051/ilkonline.2020.03.735616

Plant Uses And Disease Identification Using Svm Technology

S.Hemavathi[1] ,V.K.Hemachandran[2] , D.Mothish[3] , M.Ramprakash[4]

[1,2,3]Department of Computer Science and Engineering, Sri Sairam Engineering College, Chennai, India

[5]Software Engineer, Photon Infotech Pvt Ltd, Chennai, India.

Abstract:

Now a day's plant diseases discovery has received increasing attention in looking at greatly sized field of the years produce. In this paper we need of simple plant Leaf's disease discovery system that would help moves-forward in farming. Early information on the years produce being healthy and disease discovery can help the control of diseases through right business manager's designs. This paper also makes a comparison the benefits and limiting conditions of these possible and unused quality ways of doing. It includes several steps viz. image acquisition, image pre- processing, features extraction and minimum distance classifiers. Plants become an important source of energy and only a primary source to the problem of global warming. The damage caused by emerging, re-emerging and endemic pathogens, is important in plant systems and leads to potential loss economically. In addition, crop diseases contribute directly and indirectly to the spread of human infectious diseases and environmental damage. As these diseases are spreading worldwide causing damage to the normal functioning of the plant and also damaging the financial condition by significantly reducing the quantity of crops grown. The crop production losses its quality dueto much type diseases and sometimes they occur but are even not visible with naked eyes.In this paper, we havedone survey on different digital image processing techniques to detect the plant diseases. To detect these plant diseases many fast techniques, need to be adopt. In this paper, we use SVM to detect these diseases. And provide the fertilizer necessary to cure them.

Keywords: Global Warming, Crop Diseases, Digital Image Processing, Support Vector Machine

I. INTRODUCTION

Plant diseases can affect the whole produce which makes early diagnosis and classification vital.This helps save resources, time, money and adopt timely preventive measures to avoid the affliction in the future. To detect affected areas on plant leaves, thereare two major approaches that can be followed. The first approach is Image Processing by applying various techniques: filtering, clustering, histogram analysis among many others, to find the region of interest. The region of interest can effectively constitute the damagedportion of the leaf and the shape and size analysis can detect the disease that is afflicting the plant. Image processing algorithms are easy to understand and theuse of Python libraries, such as OpenCV, make applications of these techniques simpler. However, in these algorithms, the average accuracy of disease detection is not very high.

II. SYSTEM ANALYSIS

An image defined in the "real world" is considered tobe a function of twovariables, for example, f(x,y) withf as the amplitude (e.g. brightness) of the image at the real coordinate position (x,y). The effect of digitization is shown in Figure 2.1. The 2D continuous image f(x,y) is divided into Nrows and Mcolumns. The intersectionof a row and a column iscalled as pixel.Image Pre-Processing can be accomplished by Scaling, Magnification, Reduction and Rotation. Some of the image Enhancement techniques are Contrast Stretching,Noise Filtering and Histogram modification.

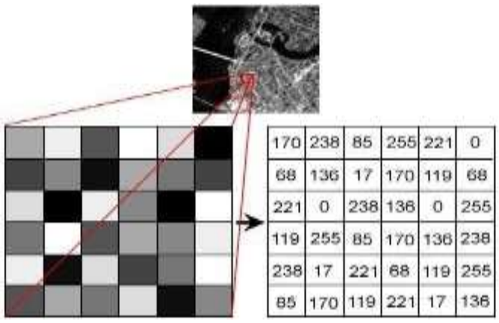

Fig.2.1 Image Representation

Image analysis is concerned with making quantitative measurements from an image to produce a description of it. In the simplest form, this task could be reading a label on a grocery item, sorting different parts on an assembly line, or measuring the size and orientation of blood cells in a medical image. More advanced image analysis systems measure quantitative information and use it to make a sophisticated decision, such as controlling the arm of a robot to move an object after identifying it or navigating an aircraft with the aid of images acquired along its trajectory. Image analysis techniques require extraction of certain features that aid in the identification of the object. Segmentation techniques are used to isolate the desired object from the scene so that measurements can be made on it subsequently. Quantitative measurements of object features allow classification and description of the image.

Image segmentation is the process that subdivides an image into its constituent parts or objects. The level to which this subdivision is carried out depends on the problem being solved, i.e., the segmentation should stop when the objects of interest in an application have been isolated e.g., in autonomous air-to ground target acquisition, suppose our interest lies in identifying vehicles on a road, the first step is to segment the road from the image and then to segment the contents of the road down to potential vehicles. Image thres holding techniques are used for image segmentation.

Classification is the labelling of a pixel or a group of pixels based on its grey value. Classification is one of the most often used methods of information extraction. In Classification, usually multiple features are used for a set of pixels i.e., many images of a particular object are needed. In Remote Sensing area, this procedure assumes that the imagery of a specific geographic area is collected in multiple regions of the electromagnetic spectrum and that the images are in good registration. Most of the information extraction techniques rely on analysis of the spectral reflectance properties of such imagery and employ special algorithms designed to perform various types of 'spectral analysis'. The process of multispectral classification can be performed using either of the two methods: Supervised or Unsupervised.

In Supervised classification, the identity and location of some of the land cover types such as urban, wetland, forest etc., are known as priori through a combination of field works and toposheets. The analyst attempts to locate specific sites in the remotely sensed data that represents homogeneous examples of these land cover types. These areas are commonly referred as TRAINING SITES because the spectral characteristics of these known areas are used to 'train' the classification algorithm for eventual land cover mapping of reminder of the image. Multivariate statistical parameters are calculated for each training site. Every pixel both within and outside these trainingsites is then evaluated and assigned to a class of which it has the highest likelihood of being a member.

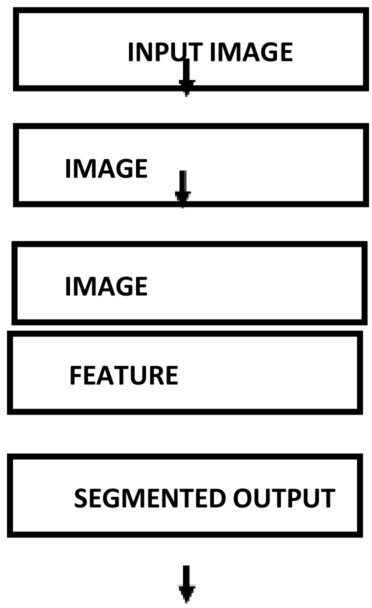

Fig 2.2. Block Diagram

III. SYSTEM DESIGN

The general framework to measure the accuracy of a SVM on a given database is composed ofPre-processing of the images in the database, Separation of the database in training and test sets, Choice of the representation of the input data and Choice of the way of training, which includes Method of multi-class training, Value of the penalty term C, Choice of the kernel, Training and Test and evaluation of the performance.

The choice of the representation of the input data and of the kernel are of the utmost important Support Vector Machines are designed for binary classification. When dealing with several classes, as in object recognition and image classification, one needs an appropriate method. Different possibilities are Modify the design of theSVM, as in [Weston and Watkins, 1998] in order to incorporate the multi-class learning directly in the quadratic solving, Combine several binary classifiers: “One against one” [Pontil and Verri, 1996], “One against the others” [Blanz et al., 1996].

According to a comparison study [Weston andWatkins, 1998], the accuracy of these methods is almost the same, so that we choose the one with the lowest complexity, which is “one against the others”. In the “one against the others” algorithm, n hyper planes are constructed, where n is the number of classes. Each hyper plane separates one class from the others classes. In this way, we get n decision functions (fk)1≤k≤n of the form (10). The class of a new point x is given by argmaxkfk(x), i.e. the class with the largestoutput of the decision function.

A SVM requires to fix C in the penalty term for misclassification. When training data which are notseparable, this constant has to be chosen carefully.However, when dealing with images, most of time, the dimension of the input space is large (≥ 1000) compared to the size of the training set, so that the dataare generally linearly separable. Consequently, the value of C do not matter and is fixed to an arbitrary large one.
In our different experiments, unless mentioned, we did not come across training errors. When trying to classify images, it is very difficult to have a representation which takes into account the intersect features of a class rather than the specific features ofits objects. In spite of the fact the colour histogram technique is a very simple and low-level method, it has shown good results in practice [Swain and Ballard,1991].

As colour is a discriminative component in image classification we keep this information, contrary to where the luminance component provides enough information to recognize objects. A colour is represented by a 3-dimensional vector corresponding to the position of the colour in the HSV space. The HSV space (Hue-Saturation-Value) is in bisection with the classic RGB space, but is more suitable since it is less sensitive to illumination changes.

As often in image processing, it might be interesting to consider not only the image itself, but also its derivatives. Thus, a first improvement is to compute the horizontal and vertical derivatives of the image and to construct for each one a similarhistogram as the one used for the pixel values. In this way, the input data for the SVM is not one histogram anymore, but three.

The problem generally encountered with histograms of derivatives is their lack of robustness, especially when images are noisy. To bypass this difficulty, images can be smoothed, with Gaussian filters, for example. We present here a new kind of histogram, called transition histogram to bypass this difficulty. As the histogram of derivative, it is meant to count the jumps in the signal.

Definition 1 The transition histogram of the discrete signal (x1, · · · ,xN) is an histogram H such that:

$$H_p = Card\{i \in [1..N-1],\ p \in [x_i, x_{i+1}[\}$$

The bin p in transition histogram counts the number of times the signal pass through the value p.

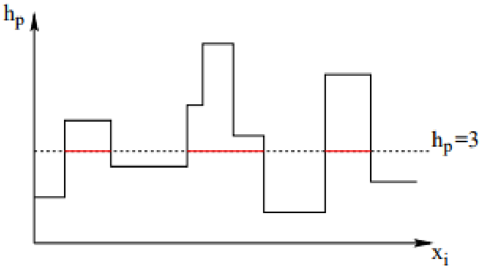

Fig. 3.1.Transition Histogram

It is quite straight forward to implement. Here is the core of the histogram computation:

Note that only the positive transitions contribute to the histogram (xi+1 > xi). It is also possible to take into consideration the negative transitions, but the histograms of positive and negative transitions are almost the same. Indeed, let H+ and H− be these histograms. Then it is obvious to see that:

∀p, |H+ p − H− p | <= 1. Thus, to avoid redundancy, only positive transitions are taken into account.
The characteristics of the transition histogram are the following,
Translation invariant: this characteristic is common to all the histograms, but is essential in image classification.
Scale invariant: consider the two signals of figure 5.On the left side the original signal and on the right sideafter subsampling and antialiasing. In both cases, the transition histograms are identical. Note that the derivative histogram is not scale invariant since the value of the derivative is proportional to the scale.

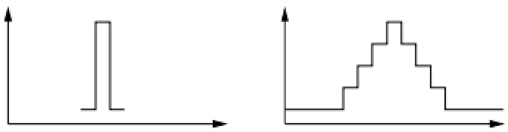

Fig. 3.2.Scale Invariant

The easiest way to cope with a n-dimensional signal, is to compute n transition histogram, one for each axe. For images, this leads to a horizontal transition histogram and a vertical one. To be rotation invariant, the two histograms are added. Strictly speaking, to have a real invariance to rotation, we should better compute the transition histogram of the norm of the gradient. The transition histogram takes only into account the local transitions in the image. Indeed, it considers only pixels which are side by side. It can be interesting to investigate into transitions between regions of an image. This can be achieved by subsampling the image at different scales and computing the transition histograms for each subsampled image.

PCA One of the main issue in image learning is the curse of dimensionality. Indeed, if the number oftraining examples is not big enough in front of the number of dimensions of the input data, the learning machine tends to learn by heart and has difficulty to generalize. For this reason, a dimension reduction if often needed. However, SVM are known to have very good performances even if the number of dimensionsis very high. For nonlinear SVM, the number of dimension of the hidden space can even be infinite. This good performance in high dimensional space comes from the margin maximization which keep under control the generalization capacity. We tried all the same to perform a dimensionality reduction. For this purpose, we used the easiest technic of dimensionality reduction, which is Principle Component Analysis (PCA). This “black box” has been implemented in a straight forward way on the various input data : bitmap images and color histograms.

IV. IMPLEMENTATION

This paper consist of the following Modules Input Module, Analysis Module, Detection Module and Output Module. Input Module for collect the pictures of the infected leaves and provide them as input to the system. Analysis Module for analyze the affected leaves. They are categorized based on their properties and futher their affected areas are identified with the help of the trained data using supervised machine learning. These data is passed on to then next module. Detection Module the data from the previous module is compared to that of the data set with identified diseases and then using SVM algorithm we find the type of disease the leaves are infected with. Output Module the plant disease is identified the system provides us with the type of disease the plant is affected with along with the fertilizers that are requiredto overcome the situation.

V. RESULTS

The Fig.5.1. shows the result of showing the affected areas in one of the leave input image.

Fig.5.1 Disease Affected Area in the input image

VI. CONCLUSION

In this paper we have discussed the need for a system to detect and classify plant disease supported by statistical parameters. We have also proposed a method so that we can identify and recommend the steps needed to take so that we can overcome these problems. The key issues and challenges are also presented. These points help to researchers and policy makers for taking right decisions. By using SVM we can provide better accuracy in more efficient way to detect these diseases.

REFERENCES

[1] Sumit S. Thote, Prof. Mrs. Snehal A. Bhosale, "Smart Irrigation System:Plant Diseases Recognition using IP", IJETSR, ISSN 2394 – 3386, Volume 3, Issue 2, February 2016.

[2] Sachin D. Khirade, A. B. Patil, "Plant Disease Detection Using Image Processing", IEEE, 2015.

[3] Amandeep Singh and Maninder Lal Singh," Automated Color Prediction of Paddy Crop Leaf Using Image Processing", 2015 IEEE International Conference on Technological Innovations in ICT for Agricultural and RuralDevelopment (TIAR).

[4] Sanjay B. Patil and Shrikant K. Bodhe," Leaf disease severity measurement using image processing", International Journal of Engineering and Technology, Vol.3(5), 2011, 297-301.

[5] Jobin Francis, Anto SahayaDhas D, Anoop B K, " Identification of Leaf Diseases in Pepper Plant Using Soft Computing Techniques", IEEE, 2016.

[6] Yuheng Song, Hao Yan, "Image Segmentation Techniques Overview", Proc. Of Asia Modelling Symposium (AMS), PP.103-107, 2017.

[7] R. C. Gonzalez and R. E. Woods, "Digital image processing", Pearson education, 2002

[8] Pragya Adhikari, Yeonyee Oh, Dilip R. Panthee" Current Status of Early Blight Resistance in Tomato: An Update," International Journal of Molecular Science",
September 2017

[9] Akansha Pandey, Sanjeev Dubey," Evaluations of brinjal germplasm for resistance to fusarium wilt disease," nternational Journal of Scientific and Research Publications,
Volume 7, Issue 7, July 2017

[10] Gittaly Dhingra, Vinay Kumar, Hem DuttJoshi ,"Study of digital image processing techniques for leaf disease detection and classification," Springer-Science, 29November 2017

[11] Shitala Prasad, Sateesh K. Peddoju, Debashis Ghosh ," Multi-resolution mobile vision system for plant leaf disease diagnosis," pp. 379–388, Springer-Verlag London 2015

[12] Shanwen Zhang, Zhuhong You, Xiaowei Wu," Plant disease leaf image segmentation based on superpixel clustering and EM algorithm," Springer, June 2017.

[13] Keyvan Asefpour Vakilian & JafarMassah," An artificial neural network approach to identify fungal diseases of cucumber (Cucumis sativus L.) Plants using digital image processing," Vol. 46, No. 13,1580–1588, Taylor &Francis, 2013

[14] Mohammed Brahimi, Kamel Boukhalfa & Abdelouahab Moussaoui," Deep Learning for Tomato Diseases: Classification and Symptoms Visualization," vol. 31, no.4, 299–315, Taylor & Francis, 2017

[15] H.Al-Hiary, S. Bani-Ahmad, M.Reyalat, M.Braik & Z.AlRahamneh, "Fast and Accurate Detection and Classification of Plant Diseases", International Journal of Computer Applications, Vol.17,No.1, pp.31-38.March 2011.

[16] Yuanyuan Shao, Guantao Xuan, Yangyan Zhu, Yanling Zhang, Hongxing Peng, Zhongzheng Liu &Jialin Hou," Research on automatic identification system of tobacco diseases", vol. 65, no. 4, 252–259, Taylor & Francis, 2017

[17] Vijai Singh, A.K. Misra," Detection of plant leaf diseases using image segmentation and soft computing Techniques, "Information Processing In Agriculture 4 (2017)41–49 , science direct, 2017

[18] Shanwen Zhang , XiaoweiWuc, Zhuhong You, Liqing Zhang," Leaf image based cucumber disease recognition using sparse representation classification," Computers and Electronics in Agriculture 135–141, science direct, 2017

[19] Amar Kumar Dey, Manisha Sharma, M.R. Meshram," Image Processing Based Leaf Rot Disease, Detection of Betel Vine (Piper BetleL.)," Procedia Computer Science 748 – 754, science direct, 2016

[20] Srdjan Sladojevic, Marko Arsenovic, Andras Anderla, Dubravko Culibrk and Darko Stefanovic," Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification," Hindawi Publishing CorporationComputational Intelligence and Neuroscience,Vol 2016, Article ID 3289801, 11 pages

[21] Manisha Bhange, H.A.Hingoliwala," Smart Farming: Pomegranate Disease Detection Using Image Processing," Procedia Computer Science 280 – 288, science direct, 2015

[22] Usama Mokhtar, Mona A. S. Ali, Aboul Ella Hassenian, Hesham Hefny," Tomato leaves diseases detection approach based on support vector machines,"IEEE,2015