Volume: 13 Issue: 04 Pages: 5057-5062(2022) ISSN: 0975-0290

A Study of Emerging Image Processing and Machine Learning Methodologies for Classification of Plant Leaf Disease

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ABSTRACT

Agriculture and productivity are extremely important to a country's economy. Plants becoming infected with diseases are a natural occurrence, but it can result in significant losses in agricultural productivity if sufficient precautions are not taken to identify the disease and apply certain pesticides in a timely manner. As a result, it's critical to have certain automated ways for detecting plant leaf diseases that save time and effort. Many people presented a number of automated approaches to detect and classify plant leaf diseases with varying levels of accuracy due to developments in image processing and machine learning techniques. In this study, we examine a number of current strategies that have been developed in this field. As a result, we may draw conclusions about the performances and what further improvements can be made to design more efficient systems in the future.

Keywords – **Fuzzy logic, Gray Level Co-Inference Matrix**, **Image processing, Machine learning, Plant leaf disease.**

Date of Submission: Feb 02, 2022 Date of Acceptance: Feb 21, 2022

I. INTRODUCTION

Nowadays, the vast majority of farming land serves as more than just a food source. The Indian economy is heavily based on agricultural productivity. As a result, disease location in plants plays an important role in agribusiness. It is beneficial to use a disease identification approach to distinguish plant infection at an early stage. A little leaf infection, for example, is a dangerous disease prevalent in pine trees in the United States. The affected tree's development is hampered, and it dies after 6 years. Alabama, Georgia, and South America all had the same result. In certain situations, early detection could be beneficial. The current method for detecting plant disease is for professionals to use their unassisted eye perception to recognize and identify plant disease. To accomplish so, it takes a large team of experts and constant monitoring of the plant, which can be costly when dealing with large ranches. Simultaneously, in other countries, farmers lack access to the proper offices or the ability to consult specialists. It is time consuming and expensive to determine which consulting professionals are the most expensive. Under such circumstances, the proposed method for inspecting large fields of yields would be beneficial. Observing symptoms at the indications in plant leaves can make automatically distinguishing illness easier and less expensive. Machine vision is used to provide image-based computerized measurement control, inquiry, and robot guidance [2] [4] [5].

Visual approaches for distinguishing plant infection are more difficult and less precise, and must be performed in limited areas. Using an automated identification technique, on the other hand, requires less effort, is less time consuming, and is more accurate. Yellow and brown spots, early and late eating, and viral, fungal, and bacterial illness are among the most common diseases in plants. The influenced territory of the sickness is measured using image processing, and the colour difference in the influenced region is determined using image processing [1] [2] [6]. Crop production can be increased by the automatic detection of leaf disease in the early stages [4]. Assessment methods, such as spotting on the leaves and a change in leaf colour, can be used to identify the illness in its early stages. [5]. The colour of the leaf changes when it is infected. The healthy leaf and the damaged leaf will have unique colours. [6]. Plant diseases have a major impact on harvest quality and quantity [7]. Leaf diseases may be detected early on and crop creation increased [8] using various image processing algorithms including as segmentation and classification.

II. PLANT DISEASES AND TYPES

Plant disorders are caused by two types of elements: biotic elements and abiotic factors [9]. Organic agents such as parasites, bacteria, and viruses can cause illnesses caused by living beings. Abiotic issues include a lack of nourishment, a low soil pH, inadequate lighting, and extreme weather [10]. Parasite infections [9] - [14], bacterial infections [9] - [14], and viral infections [9] - [14] are the three types of plant infections.

2.1 Fungal disease

Shrinkage, fine build up, wool accumulation, anthracnose, alternia, leaf spot, dim growth, rodents, cankers, moulds are some common parasite infections [12], [15]. When a plant is infected by a parasitic organism, the entire plant becomes infected [16]. A variety of fungicides can be used to treat parasitic infestation [9]. The morphology of parasitic diseases is used to classify them [12].

2.2 Bacterial Disease

Bacterial infection, crown nerve, smooth spots, Wilts, and other bacterial infections are all common. [12], [15] are two examples. Light green dots on the leaves characterise these illnesses. Human-experience art appears to be dead art [17].

2.3 Viral Disease

Leaf twist, leaf fold, leaf roll, and other viral infection techniques are used in some cases [15]. Virus infections are caused by an infection that is difficult to detect. Virus-infected leaves have the ability to grow and expand [18].

A healthy and unhealthy leaf are depicted in Figure 1.

(a) **(b)**

Figure1:(a) Healthy leaf (b) Unhealthy leaf

III. LITERATURE REVIEW

The first paragraph under each heading or subheading should be flush left, and subsequent paragraphs should have a five-space indentation. A colon is inserted before an equation is presented, but there is no punctuation following the equation. All equations are numbered and referred to in the text solely by a number enclosed in a round bracket (i.e., (3) reads as "equation 3"). Ensure that any miscellaneous numbering system you use in your paper cannot be confused with a reference [4] or an equation (3) designation.The paper [1] describes an organization and discovery technique that may be used to determine the order of plant leaf disease. Before the element is split, it is pre-processed here. RGB photos are converted to white to distinguish a vein image from each leaf, and then to a dark level image. At that stage, the picture is given the necessary morphological capabilities. After that, the picture is converted to a binary image. If the parallel pixel esteem is 0, the comparative RGB image esteem will be used from that point on. Finally, disease discovers the Pearson connection and preponderance set, as well as the Naive Bayesian classifier.

The paper is divided into four sections [2]. The first is obtaining images from various parts of the country in order to prepare and test. The next step uses a Gaussian filter to remove all noise and thresholding to collect all of the green colour segments. K-means clustering is then used to segment the results. To eliminate the element, all RGB images are converted to HSV.

The study [3] describes an image-processing-based method for identifying jute plant infection. The picture is captured and then acknowledged in order to determine the size of the image that will be stored in the data set. The image is then enhanced in quality and the sounds are removed. With the use of an aredid thresholding equation, a colouring segment is applied to the image. The picture is then converted to HSV by RGB, which aids in the removal of the region of interest. The identification of stem-based disorders for the jute plant is based on this method.
The strategy for distinguishing cucumber infection is introduced in the paper [7]. The technique includes image acquisition, image pre-processing, and extraction with the Gray Level Co-Inference Matrix (GLCM) and is eventually arranged into two sorts: unaided grouping and solo order.

In the mainland, paddy is a prominent plant. The study [8] uses colour transformation to convert RGB photos to dark scale. Image quality is improved using various approaches such as histogram adjustment and differentiation coordination. SVM, ANN, and FUZZY order are some of the grouping features used here. Highlight Extract 6 employs a variety of highlight esteems, including the Structure include, Structure highlight, and Geo-metric element. It can differentiate paddy plant illness by using the ANN and FUZZY orders.

AI, image processing, and grouping-based algorithms were used to detect and assess agricultural product contamination in the article [9].

In the work [10], an image processing approach is used to differentiate citrus leaf illness. Image pre-processing, leaf analysis, highlight extraction, and infection organization using K-means clustering to determine ailing areas are all included in the system. The element is separated using the Gray-Level Co-Occurrence Matrix (GLCM), and the arrangement is completed using the Support Vector Machine (SVM).

Table 1: Comparison of different method and accuracy of detection.

Number	Methods	Accuracy Value
Paper 1	K-means clustering, basic morphological functions, Naïve Bayesian classifier, colour co-occurrence meth-od.	87%
Paper 2	K-means clustering algorithm with SVM, colour co-occurrence method.	88.89%
Paper 3	Colour co-occurrence method, Multi SVM classifier	86%

Paper 7	ANN, GLCM	80.45%
Paper 8	ANN, FUZZY classification, SVM, K-means algorithm, Colour co-occurrence method.	94.70%
Paper 9	K-means, GLCM, ANN, SURF, CCM, SVM	95%
Paper 10	GLCM, SVM, K-means	90%

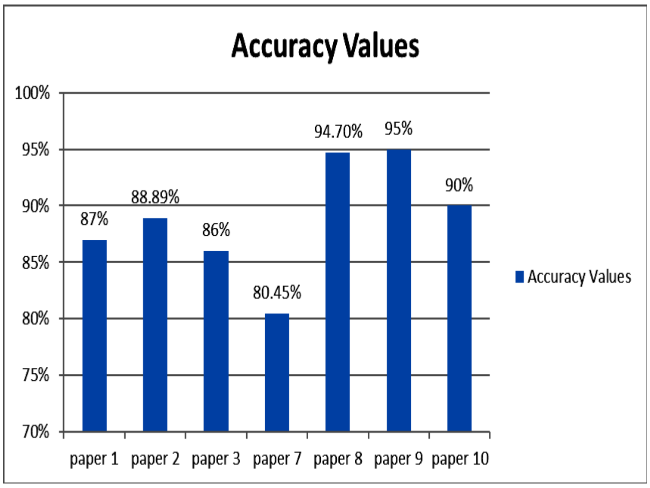

Figure 2: Accuracy of detection.

IV. IMPLEMENTATION MODEL

The main implementation model is depicted in Figure 3.

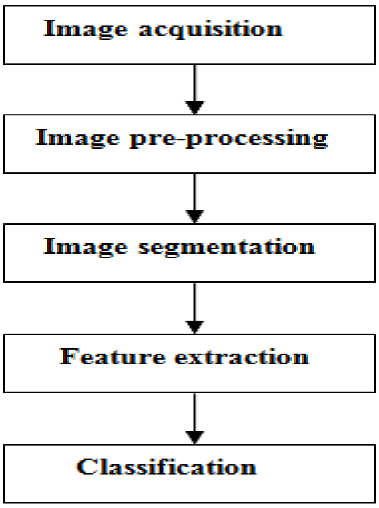

Figure 3: General Implementation model

4.1 Image Acquisition

Image acquisition is the first step in the framework. Stacking an image is a computerized image measure that captures an image with a high-resolution camera and stores it on high-resolution media. The camera is used to capture noise and diseased pictures. The efficacy of the photographs is determined by their type.

4.2 Image Pre-Processing

The primary goal of picture pre-processing is to improve the image and remove undesired twists using image upgrading processes such as RGB to gray scale transformation, RGB to HSI conversion, and dynamic image size, among others. Structure, noise filtering, picture alteration, and morphological activities are all examples of morphological activities.

4.3 Image segmentation

The process of dividing a digitized picture into several pieces is known as image division. To organize the image, it is segregated into distinct pieces. We use the K-Means cluster approach to divide the photos into groups, with at least one portion of the cluster containing an image of the cluster's unhappy section. For a cluster of highlights, the K-means group algorithmic standard is used to organize objects into distinct classes.

4.4 Feature extraction

For include extraction, the GLCM (Gray-Level Co-Inference Matrix) approach was used, which addressed the spatial organization and distance framework. The GLCM capabilities depict the picture's surface, create a matrix, and extract factual measurements from it by determining how frequently a pair of pixels with specific attributes appears in the image in a certain spatial relationship. The mean, standard deviation, distinction, skewness, kurtosis, contrast, strength, homogeneity, zone, boundary, centroid, aspect proportion, eccentricity, entropy, and entropy are among the quantifiable highlights that have been deleted.

4.5 Classification

The preparation and testing of datasets are both done with classifiers. A random forest timberland categorization completes the pattern. This method is used to examine and compare the leaves of healthy and ill plants.

V. SEGMENTATION AND FEATURES

5.1 Segmentation Methods

5.1.1 Thresholding method

It is the most basic method of image segmentation, which divides picture pixels according to their intensity level. The picture histogram's peak can be used to calculate the threshold value. It is the most basic method of image segmentation, which divides picture pixels according to their intensity level. The picture histogram's peak can be used to calculate the threshold value. It is the most basic method of image segmentation, which divides picture pixels according to their intensity level. The picture histogram's peak can be used to calculate the threshold value.

5.1.2 Region Based Method

Picture segmentation is a fundamental technique for dividing image pixels into groups based on their intensity level. The picture histogram's limit may be used to calculate the edge value. The primary approach for separating picture pixels by their force level is image

Volume: 13 Issue: 04 Pages: 5057-5062(2022) ISSN: 0975-0290

division. The photo histogram's limit can be used to establish the limit worth. The basic approach for dividing picture pixels by their intensity level is called picture division. The picture histogram's limit may be used to calculate the edge value.

As a result, the affiliation and adjacent pixels are separated. It operates on the principle that consecutive pixels within a particular area have relative attributes and are not linked to pixels in other locations. It is flexible enough to choose between intuitive and automated picture division processes. The stream from the inward emphasise the external district's most visible material boundaries. When compared to other techniques, it produces more exact results. In nature, more computation time, memory, and sequencing are necessary. The client's exuberant seed selection results in faulty dividing. The zone partitioning the square has a separating plan.

5.1.3 Clustering Method

Pixels in the picture with similar features are partitioned into separate clusters using this approach. Depending on the picture highlights, divide the image into several regions. This technique frequently uses the K-Means computation. It is simple to obtain uniform zones. This method is significantly faster. For a more modest estimate of k, the k-mean comes out faster. This necessitates clusters of comparable size, so the duty of arranging the neighbouring group site is appropriate.

5.1.4 Edge based technique

In this technique, all of the edges are located first, and then the edges are associated with the appropriate limitations to frame the article's bounds. It is dependent on edge breakdown recognition. It's ideal for photographs with a lot of contrast between locations. Never seemed right for a photo with a lot of high edges. It's difficult to choose the right article edge.

5.1.5 Fractional differential condition based apportioning strategy

They are rapid and cost-effective for time-sensitive applications. It is dependent on the condition of the differential. The higher the computing complexity, the faster the technique.

5.2 Colour Feature Extraction Methods

5.2.1 L*a*b

The other two channels, A and B, are termed chromaticity layers in this colour space. One channel is for brightness, while the other two are for chromaticity layers. The softness measurement is L, while the colour contrast measures are A and B. In this hue and intensity, perform independently. It is capable of calculating minor colour differences. The single problem is similar to the other nonlinear change.

5.2.2 HSV Histogram

The intensity may be represented as the focus vertical axis, and HSV can be addressed as a hexagon in three measures. It's all about the tone and saturation. Colours are depicted in depictions, and brightness is more important for consistent usage. Light contrasts aren't as noticeable.

5.2.3 RGB

This is a colour space that is based on the RGB colour scheme. It is made up of three independent picture planes, one each for red, green, and blue. As a result, colour is useless for image processing.

5.2.4 UV

As retinal bar cells, main channel radiance describes light power. Colour information is conveyed via the chrominance segments U and V. Colour data isolates this strikingly contrasted colour.

5.3 Configuration highlights extraction strategies -

5.3.1 Gray level co-occurrence grids

As a grey level co-event lattice, this is a factual technique for analysing the spatial connectivity of pixels. The length of the highlight vector is short. In order to create a colour co-event network that may be used in a different colour space, Many grids that are not vulnerable with rotation and scaling should be processed.

5.3.2 Wavelets transformation

In the recurrent domain, it performs better than in the spatial domain.

5.3.3 Free Component Analysis

This is a method of computing that divides a multivariate signal into smaller subunits. It isn't used very often.

5.3.4 Gabor Filter

It is a multi-resolution and multi-scale filter that is used to explicitly deconstruct the image's distinctive recurring content in the vicinity of the region of interest.

VI. CLASSIFIERS

6.1 Naive Bayes Classifier

This is a random order. The hypothetical estimation of assumption is independent of the estimation of any other element due to the strong freedom of a given component.

6.2 K-Nearest Neighbours

It can distribute quantifiable and non-parametric grouping loads to neighbour are commitments, allowing the nearest neighbours to contribute more than the distance between them. Extremely sensitive testing is time-consuming due to the fact that every realised event necessitates a distance estimate.

6.3 Sector Vector Machine

It is based on decision planes, which define the choice's boundaries. Its job is divided into two phases: i. Offline measurement and ii. Online measurement.

As a cluster of parallel vector machines, a multi-class support vector machine is used for preparation and characterization.

This is particularly useful in high-dimensional regions since the order exactness is superior to that of other characterization approaches. SVM is a robust algorithm, albeit the preparatory models are a little hazy. With a large amount of informative gathering to plan the initial information to the high dimensional information choice of the kernel function, preparation time is long and kernel boundaries are difficult.

6.4 Decision tree

It divides the work zone into smaller subsections by identifying its characteristics. The class marks are represented by the leaves, and the credits that go to those classes are represented by the branches. For some, simple informative indexes with precision compared with different ordering, little estimated trees may be easily defined. With loud order capabilities, some datasets may be more feasible.

Artificial neural network: It is based on the human natural neuron framework, which consists of two datasets, one for preparation and the other for testing. It is tough and can handle a lot of noise in the information.

VII. CONCLUSION

In this paper we describe a research in which we used several machine learning and image processing approaches to characterise diverse farmed product illnesses. We've discussed the merits and downsides of several colour and texture-based element extraction methods. In addition, we reviewed several division tactics, as well as their benefits and drawbacks. In addition, the study briefly discusses a number of other segment tactics as well as their pros and drawbacks. We will use some of the approaches discussed in this paper in our study later on.

REFERENCES

[1] H. Park, J. S. Eun and S. H. Kim, "Image-based disease diagnosing and predicting of the crops through the deep learning mechanism", *In Information and Communication Technology Convergence (ICTC) IEEE 2017 International Conference on*, pp. 129-131, 2017.

[2] K. Elangovan and S. Nalini, "Plant disease classification using image segmentation and SVM techniques", *International Journal of Computational Intelligence Research*, vol. 13, no. 7, pp. 1821-1828, 2017.

[3] S. H. Lee, C. S. Chan, S. J. Mayo and P. Remagnino, "How deep learning extracts and learns leaf features for plant classification", *Pattern Recognition*, vol. 71, pp. 1-13, 2017.

[4] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis", *Computers and Electronics in Agriculture*, vol. 145, pp. 311-318, 2018.

[5] Sandesh Raut and Amit Fulsunge, "Plant Disease Detection in Image Processing Using MATLAB", *IJIRSET*, vol. 6, no. 6, 2017.

[6] Sonal P Patel and Arun Kumar Dewangan, "A Comparative Study on Various Plant Leaf Diseases Detection and Classification", *(IJSRET)*, vol. 6, no. 3, March 2017.

[7] Prakash M. Mainkar, Shreekant Ghorpade and Mayur Adawadkar, "Plant Leaf Disease Detection and Classification Using Image Processing Techniques", *IJIERE*, vol. 2, no. 4, 2015.

[8] C.V. Giriraja, C. M. Siddharth, Ch. Saketa and M. Sai Kiran, "Plant health analyser", *Advances in Computing Communications and Informatics (ICACCI) 2017 International Conference on*, pp. 1821-1825, 2017.

[9] D. W. Zhang and J. Wang, "Design on image features recognition system of cucumber downy mildew based on BP algorithm", *Journal of Shenyang Jianzhu University (Natural Science)*, vol. 25, pp. 574-578, May 2009.

[10] D. T. Zhao, Y. H. Chai and C. L. Zhang, "Inspection of soybean frogeye spot based on image procession", *Journal of Northeast Agricultural University*, vol. 41, pp. 119-124, April 2010.

[11] Y. W. Tian and Y. Niu, "Applied research of support vector machine on recognition of cucumber disease", *Journal of Agricultural Mechanization Research*, vol. 31, pp. 36-39, March 2009.

[12] G. L. Li, Z. H. Ma and H. G. Wang, "Image recognition of grape downy mildew and grape powdery mildew based on support vector machine", *CCTA*, pp. 151-162, 2011.

[13] R. C. Shinde, J. Mathew C and C. Y. Patil, "Wood defects classification using laws texture energy measures and supervised learning approach", *Adv. Eng. Informatics*, vol. 34, no. September, pp. 125-135, 2017.

[14] A. S. Setiawan, Elysia, J. Wesley and Y. Purnama, "Mammogram Classification using Law's Texture Energy Measure and Neural Networks", *Procedia Comput. Sci.*, vol. 59, pp. 92-97, 2015.

[15] M. Rachidi, A. Marchadier, C. Gadois, E. Lespessailles, C. Chappard and C. L. Benhamou, "Laws' masks descriptors applied to bone texture analysis: An innovative and discriminant tool in osteoporosis", *Skeletal Radiol.*, vol. 37, no. 6, pp. 541-548, 2008.

[16] N. Kaur and V. Devendran, *Research Article Plant leaf disease detection using ensemble classification and feature extraction,* Turkish Journal of Computer and Mathematics Education, vol. 12, no. 11, pp. 2339-23352, 2021.

[17] Smita Naikwadi and Niket Amoda, "Advances in Image Processing for Detection of Plant Diseases", *International Journal of Application or Innovation in Engineering & Management (IJAIEM)*, vol. 2, no. 11, November 2013.

[18] A. Adedoja, P. A. Owolawi and T. Mapayi, "Deep Learning Based on NASNet for Plant Disease Recognition Using Leave Images", *2019 International Conference on Advances in Big Data Computing and Data Communication Systems (icABCD)*, pp. 08851029, August 2019.

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