Artificial Intelligence Techniques for Plant Disease Detection: A Review

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ABSTRACT: Disease identification in crops is one of important job that every farmer practice and takes required action for eliminating them since they are damaging to not only crops but also to farmers, customers, and environment too. Quality or safety of agricultural goods is one of key issues in today's situation. In previous times farmers contacts specialists or use their own expertise for detection of illnesses in their crops but now days intelligent methods are progressively replacing the monitoring of crops since they are more reliable, accurate, quick and cheap in comparison to earlier ways. This article covers several methods based on machine learning or image processing that were provided by researchers all over the globe for detection of illnesses in crops, subsequent comments are given that may be useful for advancements in this area. This study would assist other academics and practitioners to review different methods utilized for the process of disease detection in plants and limitations of existing systems.

KEYWORDS: Artificial Intelligence, Classification, Disease Detection, Image Processing, Image Capture.

1. INTRODUCTION

Farmers have begun using smart farming methods, which has resulted in increased food yields, thanks to advances in agricultural practices. Earlier methods were time consuming, expensive, and needed more work, but today many jobs may be completed in a short amount of time. Smart farming is a farming method that is used to identify plant diseases, weeds, classify land cover, and grade fruits, among other things. However, very little progress has been made in adapting these techniques because the majority of farmers still rely on traditional agricultural techniques, particularly in Asian and African countries, where agriculture employs around 50% of the population. However, this sector pays a high price because 30 to 40% of annual production is lost due to disease[1].

Previously, disease detection was entirely reliant on manual techniques, with farmers relying on their own expertise or hiring experts to identify signs so that illness could be diagnosed and appropriate preventative action could be done. Traditional methods have disadvantages, such as relying only on the expert's vision, being time consuming, bulky, labor demanding, and lacking precision. As a result, there is a pressing need to replace manual disease detection methods with automated ones as soon since possible, as the quality and safety of agricultural products is a significant issue. It is critical to identify infections early on, since their spread may be readily managed without compromising crop quality or production. This survey presents a variety of illness detection methods suggested by researchers from all around the world. The architecture of plant disease identification systems is given after a review of several literatures. The following section gives an overview of a few systems suggested by various researchers for various crops.

1.1 Techniques for Detecting and Recognizing Plant Diseases Using Artificial Intelligence:

Previously, farmers utilized their own expertise or paid experts to do manual disease inspections. However, there were several disadvantages to this method, including the fact that it was a time-consuming process because a person had to inspect the plant at each stage, that it lacked accuracy because several diseases have nearly identical symptoms, and that it was completely reliant on the person's or expert's eyesight. For illness diagnosis and identification, machine learning and image processing methods are extensively utilized. Image Acquisition, Image Preprocessing, Image Segmentation, Feature Extraction, and Classification or Recognition are five modules that may be included in such a system. A disease identification system with a general framework and several methods utilized in each module.

1.2 Image Capture:

The system's accuracy is entirely dependent on this module for training. Several studies utilized datasets (Plant Village, IPM Photos, and the APS image database), while others used scanned images acquired under controlled circumstances. The quality of recorded picture samples may be reduced by dew drops, insect feces, dust, and other contaminants present on plant components, which can cause shadow and noise effects. These effects can be eliminated using a variety of filters or contrast enhancement techniques. A digital camera and the internet were used to collect 40 picture samples of sick paddy leaves, which were subsequently saved in JPEG format. For picture acquisition, a 3-CCD color camera was positioned at a height of 60mm above the wheat leaves, and over 300 image samples were acquired. In natural lighting circumstances, a 640*481 resolution Nikon D80 camera was utilized to capture 800 picture samples of four wheat leaves with the backdrop set to black. To create an RGB picture, a flatbed scanner was used to scan the leaves of the betel vine plant. The photos were then digitized at 300 dpi resolution. Images of different phases of soybean plant growth were taken using a mobile phone camera. The mobile phone camera was selected because it is inexpensive, readily available, and accessible to farmers. A Sonny digital color camera with a resolution of 16 mega pixels was used to gather picture samples in natural light, and the photos were subsequently saved in jpeg format. a digital mobile camera was utilized to gather picture samples for the identification and categorization of cotton leaf spot infections. Image capture was done using a digital camera and the internet, and the samples were saved in jpeg format[2].

1.3 Preparation of images:

Because the pictures obtained may include noise and therefore be unsuitable for processing directly, preprocessing methods are used on the data. Cropping, enhancing, filtration, smoothing, and color conversion are examples of these methods. This process improves the optical examination of picture samples. They transformed the picture samples to HSV color space, retrieved the S component, conducted histogram equalization, and sharpened the images using Laplacian filters. The diseased areas of picture samples were clipped, then the images were transformed to their appropriate gray levels, and lastly the Laplacian filter was used to improve the image. Because diseased areas of plant leaves had greater intensity values than other portions, picture samples were transformed to HIS color space [8] trimmed acquired pictures for maximum CPU usage, quicker processing time, and efficient disk storage. As a result, 30% of storage space was saved, CPU speed was increased 1.4 times, and no area of interest was lost. After converting RGB picture samples to YCbCr color space and extracting the Y, Cb, and Cr components, the background was removed from the recorded images. A disease identification system with a general framework and several methods utilized in each module[3].

1.4 Segmentation of Images:

It is used to acquire an area of interest and can be useful in distinguishing between sick or healthy parts of image samples, since it divides them into clusters with infected portions in one cluster as well as healthy portions in another. Preprocessed pictures are split into many smaller areas in this module so that features may be extracted quickly. For segmentation of wheat leaves, the Fuzzy C-Means clustering method was used using a collection of intensity values from picture samples. For extracting regions of interest from picture data, we utilized basic threshold segmentation. For the segmentation of betel vine leaves, the Otsu thresholding technique was used. First, the RGB picture was transformed to HSV color space, or then the Otsu method has been applied to the “H” component for segmentation. For segmentation, a color filtering operation was used, resulting in a bi-level picture, with white areas indicating diseased regions and black regions indicating healthy and background region. Several morphological procedures were then performed[4].

1.5 Extraction of Features:

Different characteristics may be retrieved from the segmented picture in this module, and these features can be used to identify items from each other. Its goal is to decrease picture data by measuring certain characteristics of segmented image samples. This phase takes into account three kinds of characteristics: color, texture, and form. Color is often described by moments and histograms, whereas texture may be associated with a variety of characteristics such as homogeneity, entropy, variance, contrast, and shape aspects such as roundness, concavity, area, and eccentricity. For extracting characteristics including texture, color, and shape from picture sample, fractal descriptor were employed.

Multiple characteristics (inertia, energy, correlation, and homogeneity) were recovered from segmented picture samples utilizing co-occurrence matrix texture based features Color (saturation moments, hue moments intensity moments) and form (entropy, median, mode, variability, number of 0's in binary picture, standard deviation, and so on) were also retrieved. Deviation, Color features (Average, Correlation, Entropy, Variance, Energy of color histogram, etc.) were extracted using two color spaces texture features (Energy, Entropy, Moment of Inertia, Local Smooth, Correlation, etc.) were extracted in four directions using GLCM after converting RGB spot image to Gray, and finally shape features were extracted using edge detection. Gabor filters were employed on each picture sample to extract texture characteristics. Color characteristics were extracted using the color channel, while texture features including energy, correlation, contrast, and homogeneity were extracted using the GLCM.

Texture characteristics were retrieved using the Gabor filter, while color features were extracted using the H, S (HSI color space) and Cr (YCbCr) component. Contrast, uniformity, max probability, homogeneity, inverse differential moment of order 2, differential variation diagonal volatility, entropy, as well as correlation were extracted using GLCM. extracted shape features based on parameters such as lesion area, geometrical center, rectangle degree, roundness degree, and figure complexity, color information parameters such as H component of HIS color space, third order order accuracy of B component of RGB color space, and third order accuracy of H component of HIS color space, as well as texture features parameters such as energy, entropy or texture complexity Complex, roundness, long axis ratio, as well as degree of rectangle characteristics were utilized to extract shape data; texture features were retrieved using GLCM's energy, entropy, and contrast parameters while color feature were extracted by computing the average of RGB component of the lesion region[5].

1.6 Classification of Images:

Image Recognition is another name for it. Labels are given to the objects based on the extracted characteristics and descriptions, which will aid in the identification of a specific attribute of the item. The classifier is initially trained on the training set before being used to recognize pictures from the test set. PNNs (Probablistic Neural Networks) were utilized to recognize illnesses in paddy crops, with 5-cross fold validation used to separate training or test data as well as a confusion matrix used to further analyze the results.

PNN was used to identify diseases. It contains four layers: an input layer, a pattern layer, a summation layer, as well as an output layer. It also has a quicker training speed than the BPNN. For image classification, a three-layered Back Propagation Artificial Neural Network was used, with the first layer containing 22 neurons describing the features of image samples retrieved during the feature extraction phase, the third layer containing only one neuron during training, and the hidden layer containing four neurons. Color SVMs, Shape SVMs, Texture SVMs, and Meta level SVMs were utilized for picture recognition, with Meta level SVMs making the final classification decision. This greatly enhanced the performance of the suggested system. SVM was used to classify tomato leaves, and the results were assessed using the k-fold cross validation technique. After extracting texture and color characteristics, SVM kernels (linear, polynomial, radial basis function, and quadratic) were used to identify sugarcane illnesses. The linear kernel was suggested owing to its accuracy in detecting sugarcane diseases. For the detection of grape leaf diseases, multiclass SVMs were used. used Back propagation neural networks were used to recognize powdery or downy mildew illness in grape leaves, using nine neurons (nine texture characteristics) in the input layer and two neurons in the output layer (downy mildew or powdery mildew). On conventional neural networks, an enhanced PSO-based method was used; the input layer of neural network had 20 neurons (extracted features), the output layer contained three neurons (diseases to be identified), as well as the hidden layer contained 19 neurons (combined with Kolmogorov algorithm). For three cucumber illnesses, the Minimum Distance classifier was employed.

1.7 Image Preprocessing:

The gathered samples of pictures may include noise and may not be appropriate for processing directly so preprocessing methods are applied to data. These methods are cropping, enhancement, filtering, smoothing, color transformation etc. This procedure improves the quality of optical examination of the image examples.

Transformed the picture samples to HSV color space, extracted component from these, they also conducted histogram equalization and utilized Laplacian filters for sharpening pictures. Diseased region in picture samples was clipped then photos were transformed into their matching gray levels and lastly Laplacian filter was applied by for picture enhancement. According to infected areas of plant leave exhibit greater intensity levels in comparison to other parts thus obtained picture samples were transformed HIS color space. Acquired pictures were cropped by for maximum use of CPU, quicker processing time and economical disk storage therefore 30 percent of storage space was saved, CPU speed was increased 1.4 times and there was no loss of area of interest. RGB picture samples were transformed into YCbCr color system, extracting Y, Cb and Cr component later background was separated from the recorded pictures. generic structure of a disease identification system with various methods employed in each module[6].

2. LITERATURE REVIEW

Diego Inácio Patrcioa et al. conducted research on the world economy relies heavily on grain production. In this regard, the need for efficient and safe food manufacturing techniques is growing. One of the instruments for achieving this goal is information technology. We highlight computer vision systems coupled with artificial intelligence algorithms that have achieved significant achievements in the identification of patterns in pictures among the current tools. In this respect, this paper provides a systematic study aimed at determining the application of computer vision in precision agriculture for the production of the world's five most widely consumed grains: maize, rice, wheat, soybean, and barley. In this regard, they offer 25 articles over the past five years that use a variety of methods to disease detection, grain quality, and phenotyping. The systematic review's findings reveal significant possibilities, such as the use of GPUs (Graphics Processing Units) and sophisticated artificial intelligence techniques like DBNs in the development of robust computer vision systems for precision agriculture[7].

Kamlesh Golhani and colleagues investigated this article examines advanced Neural Network (NN) methods for hyperspectral data processing, with a focus on plant disease diagnosis. To begin, we give an overview of the NN mechanism, kinds, models, and classifiers that analyze hyperspectral data using various methods. The present status of imaging as well as non-imaging hyperspectral data for early illness detection is then discussed. The use of a hybridized NN hyperspectral method to identify and diagnose illness has shown to be a valuable tool. The Spectral Illness Index (SDI) is the ratio of pure disease spectra's various spectral bands. Following that, we present NN methods for fast SDI creation. We also discuss hyperspectral data's present problems and potential trends[8].

Jayme Garcia et al. studied about the issue connected with automated plant disease diagnosis utilizing visible range pictures has received significant attention in the past two decades, but the methods suggested so far are generally restricted in their breadth and reliant on perfect capture circumstances in order to function effectively. This seeming lack of substantial advances may be partly explained by several tough difficulties presented by the subject: presence of complex background which can be easily removed from the region of interest , boundaries of the symptom often are not well characterized, uncontrolled capture conditions may reveal features that make the image task more difficult, certain illnesses produce symptoms with a variety of characteristics, the symptom created by various diseases may be very comparable, and they may be present simultaneously. This article offers an examination of each one of those difficulties, highlighting both the problems that they may create and how they may have possibly impacted the methods presented in the past. Some potential methods capable of addressing at least some of those difficulties are suggested[9].

Patrizia Busato et al studied about Machine learning has developed alongside big data technologies and high-performance computing to offer new possibilities for data intensive research in the multi-disciplinary Agri-technology domain. In this article, we provide a thorough overview of research devoted to applications of machine learning in agricultural production system. The works examined were classified in (a) agricultural management, including application on yield prediction, disease detection, weed identification crop quality, and species identification; (b) livestock management, including applications on animal welfare as well as livestock production; (c) water management and (d) soil management. The filtering categorization of the provided papers show how agriculture can benefit from machine learning technologies. By applying machine learning to sensor data, farm management systems can developing into real time machine learning powered applications that offer rich suggestions Providing insight for farmer decision - making and action[10].

3. DISCUSSION

Farmers have begun using smart farming methods, which has resulted in increased food yields, thanks to advances in agricultural practices. Earlier methods were time consuming, expensive, and needed more work, but today many jobs may be completed in a short amount of time. Smart farming is a farming method that is used to identify plant diseases, weeds, classify land cover, and grade fruits, among other things. Disease identification in crops is one of important job that every farmer practice and takes required action for eliminating them since they are damaging to not only crops but also to farmers, customers, and environment too. Quality and safety of agricultural goods is one of key issues in today's situation. In previous times farmers contacts specialists or use their own expertise for detection of illnesses in their crops but now day's intelligent methods are progressively replacing the monitoring of crops since they are more reliable, accurate, quick and cheap in comparison to earlier ways. This study addressed various Machine Learning and Image Processing approaches which are helpful in detecting and categorizing illnesses of different crops but still there is lot of potential of development in this area so that manual disease detection methods may be substituted for benefit of everyone. For future study big and high-quality picture samples may be utilized for presenting a robust and dependable method which can overcome limitations of current techniques.

4. CONCLUSION

Digital pictures are more dependable for illness identification in comparison to human eyes, many diseases have identical characteristics at times it is tough for human eyes for recognizing them furthermore recognition is entirely reliant on eyesight of human expert. This study addressed various Machine Learning and Image Processing approaches which are helpful in detecting and categorizing illnesses of different crops but still there is lot of potential of development in this area so that manual disease detection methods may be substituted for benefit of everyone. For future study big and high-quality picture samples may be utilized for presenting a robust and dependable method which can overcome limitations of current techniques. This article covers several methods based on machine learning and image analysis that were provided by researchers all over the globe for detection of illnesses in crops, subsequent comments are given that may be useful for advancements in this area. This study would assist other academics and practitioners to review different methods utilized for the process of disease detection in plants and limitations of existing systems

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