AN INTELLIGENT IDENTIFICATION OF AGRICULTURAL DISEASES USING COMPUTER VISION AND MACHINE LEARNING ALGORITHM

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Abstract:
Recognizing images of agricultural plant diseases is crucial in the field of intelligent agriculture. A number of cutting-edge machine learning methods, including deep learning and transfer learning, have started to be utilized to identify agricultural diseases in recent years as artificial intelligence technology has evolved. But there are still some significant obstacles to the implementation of these techniques. In particular, machine learning and transfer learning are studied in this work together with current developments in their application to the recognition of agricultural disease images. Transfer learning is preferable given the available agricultural disease data sets, according to analysis and comparison of these two approaches. Automatically detecting plant disease makes crop monitoring easier by allowing for the early detection of disease indications on plant leaves. Fungi, bacteria, and viruses are the primary causes in most plant diseases. Different plant diseases are detected using image processing techniques. This technique includes several processes, including input picture processing, feature extraction, and categorization using different criteria. It uses a range of classification techniques, including K Nearest Neighbour classifiers, fuzzy logic, neural networks, support vector machines, artificial neural networks, and k-means classifiers. Because the effectiveness of the results can change depending on the input data, choosing the optimum classification method can be challenging. This paper focuses on several computer methods as well as various classification algorithm for classifying agricultural diseases.

Keywords: Agriculture, Image Processing, Machine learning, Classification and Diseases

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INTRODUCTION

The agricultural land mass now functions as more than just a food source [1]. The productivity of agriculture is essential to India's economy. Therefore, it is essential to recognise plant diseases in the agricultural sector [2-3]. For recognising a plant disease in its very early stages, it is advantageous to use an automatic disease detection technique. For instance, small leaf disease, a deadly disease that affects pine trees, is a problem in the United States. The diseased tree develops slowly and dies in six years. Georgia and Alabama are both impacted, as are other Southern US states. Early identification of these s may have been advantageous [4].

According to the present method for plant disease identification, experts may recognise and detect issues with plants using nothing more than their own naked eyes [5]. When working with large farms, this necessitates a significant team of experts and ongoing plant monitoring, both of which are fairly expensive. Farmers in certain countries, meanwhile, lack access to enough resources and are even aware that they can consult experts. Specialist consultation is therefore costly and time-consuming. For keeping a watch on huge fields of crops in these situations, the suggested strategy works effectively. Automatically identifying illnesses based solely on their symptoms on plant leaves is less expensive [6-9]. This also enables machine vision to enable image-based automatic process control, inspection, and robot guiding. The many computers vision and machine learning techniques complicated and to identify the numerous agricultural diseases are listed in this survey report shown in Figure 1.

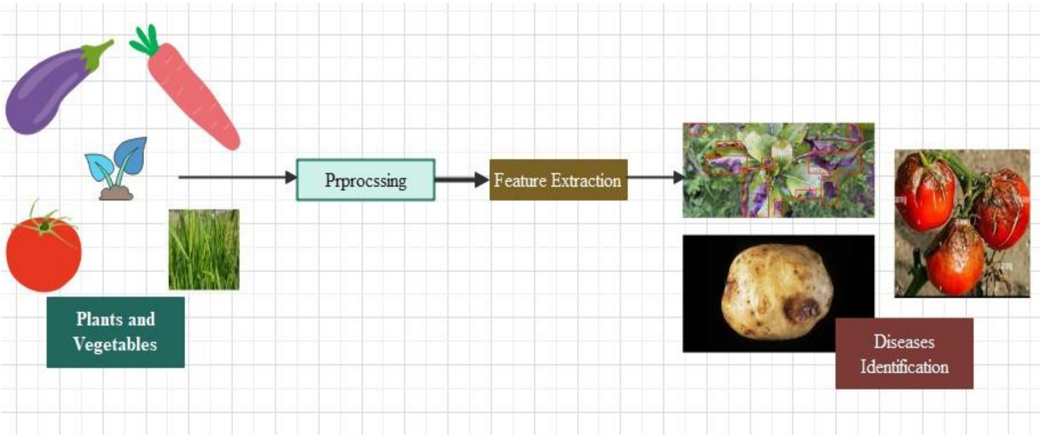

Figure 1 Process diagram- recognize diseases

LITERATURE SURVEY

Trishen Munisami (2015), developed a mobile application to recognize plant leaf, based on shape, features and color histogram to classify plant leaves using a k-nearest neighbouring classification algorithm. In this research work, the following methods as refer in Figure 1 were used. On the client-side, the user can upload the image using a high-resolution camera and it has been considered as the input image. On the server side,

they can store 20 different images for 32 different plant species. The noise and undesired information from the input image were removed in the following phase using image pre-processing techniques such rotation, grey scaling, thresholding, opening operations, inverse threshold, edge extraction, and edge filtering [10-11]. The next step is extraction of feature which is to extract the relevant information from the pre-processed output image using the following techniques such as morphological information, convex hull information, distance maps (vertical maps, horizontal maps and centroid radial maps) and color histogram to classify the different plant species using KNN classifier based on the Euclidean distance and centroid map values. The performance of the proposed system accuracy value was 83%.

Manisha Bhange (2015), developed a web tool for identifying the infected and non-infected pomegranate based on image processing methods as shown in Figure 2. In this method, user can upload the input image and it has been considered as the testing image and then resize technique is applied to avoid unwanted information from the testing image, resized size was 300 x 300 (Height, Width) pixel to extract the essential features using color, morphology and Colour Coherence Vector (CCV) feature and to group the similar features into same clusters using K-means method. To classify the infected and healthy pomegranate fruit using the SVM (Support Vector Machine) algorithm and to increase the accuracy of the proposed system based on the margin value of the linear separating image, 610 images were used as the training dataset. The overall system accuracy was 82%.

MATERIAL AND METHODS

In Figure 2 Block diagram for wheat leaf rust disease detection is presented using Root Mean Square Error (RMSE).

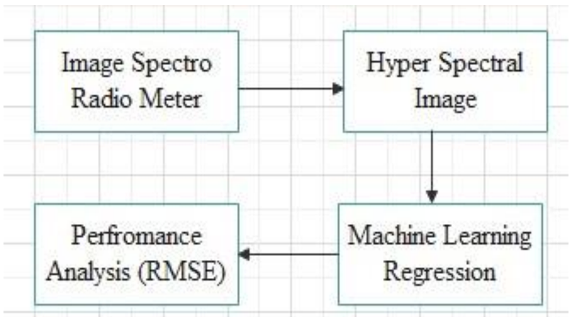

Figure 2 Block diagram for wheat leaf rust disease detection

The Root Mean Square Error (RMSE) value was utilised to evaluate the performance of the suggested system and to detect the leaf rust disease using the machine learning regression method [14-15]. Table 1 displays the RMSE values for the PLSR, VSVR, and GPR techniques.

Table 1: RMSE value for the PLSR, VSVR and GPR

Methods	PLSR	VSVR	GPR
RSME	0.6	0.03	0.05
Leaf	0.05	0.11	0.12

Aaron Partick (2017), in this research work, conveyed that the multispectral image was captured using a quad copter, based on Several Vegetation Indices (SVI). To extract the feature from the SVI processed multispectral image threshold segmentation method was used and to detect the tomato spot wilt disease the correlation method was used as shown in Figure 3. This method provides the relationship between diseased areas and the healthy area. The correlation values were manually ranked to find the relative resistance value [16]. The accuracy of this research work was above 90%.

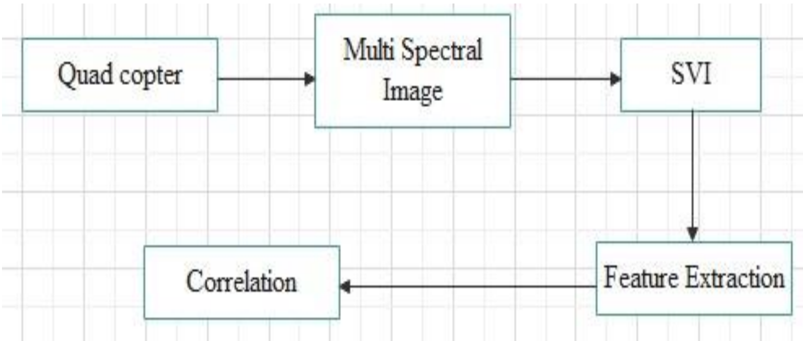

Figure 3 Block diagram to detect the tomato spot wilt disease

Peifeng Xu (2017) proposed a system to automatically detect and grade the diagnosis of wheat leaf rust as shown in Figure 4. The ARM processor was interfaced with an image sensor to capture the wheat leaf, which is transformed into an RGB color model image. In the next step, sober operator and vertical edge detection were used to convert the color RGB model image into a gray scale image and to eliminate the background information. Flood filling algorithm was used to identify the diseased area and the healthy area. The wheat leaf rust disease was diagnosed based on the ratio of disease spotted on the image [17]. The accuracy of the proposed system was 92.3%. This proposed system was used in various application fields such as classification of crop disease, detection, diagnosis and identification.

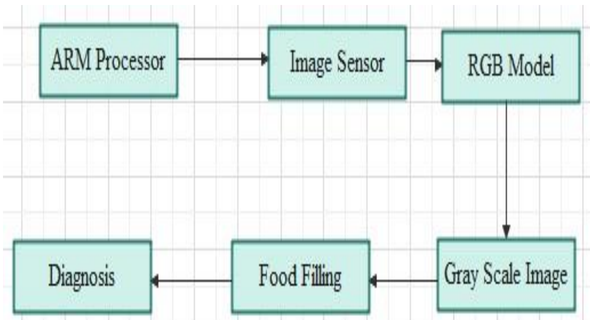

Figure 4 Block diagram for automatically detect and grade the diagnosis of wheat leaf rust

Aravind Krishnaswamy Rangarajan (2018), in this research work, they developed a software model to classify tomato crop diseases using deep learning method. The training dataset was collected from plant that consists of 6 tomato leaf diseases and captured the testing image using a mobile phone. The pre-trained Alexnet model received the test image. There are 3 fully connected layers and 5 conventional layers in it. Rectified Linear Unit (ReLU) layer was used to create 96 activation maps and apply 96 filters to the first convolution layer, which had a size of 11X11X3 (Height, Width, and Depth). Similarly, layer two has 5X5X48 (Height, Width, Depth) and 256 filters were applied, layer three has 3X3X256 (Height, Width, Depth) and 384 filters were applied, layer four has 3X3X192 (Height, Width, Depth) and 384 filters were applied and layer five has 3X3X192 (Height, Width, Depth) and 256 filters were applied. Layers 6 and 7, which comprise 4096 neurons each, are fully connected layers. The output of the completely connected layers, which were all connected to one another, categorises the diseases that affect tomato crops. The second method was a pre-trained VGG16 net model and it has 13 convoluting layers followed by the ReLU layer. The number of the testing image was 13262, and the accuracy of the alexnet model was 97.47% whereas the VGG16 model was 97.23%. The accuracy of the proposed methods, as the alexnet model, provides a slightly good accuracy with less execution time than the VGG16 model

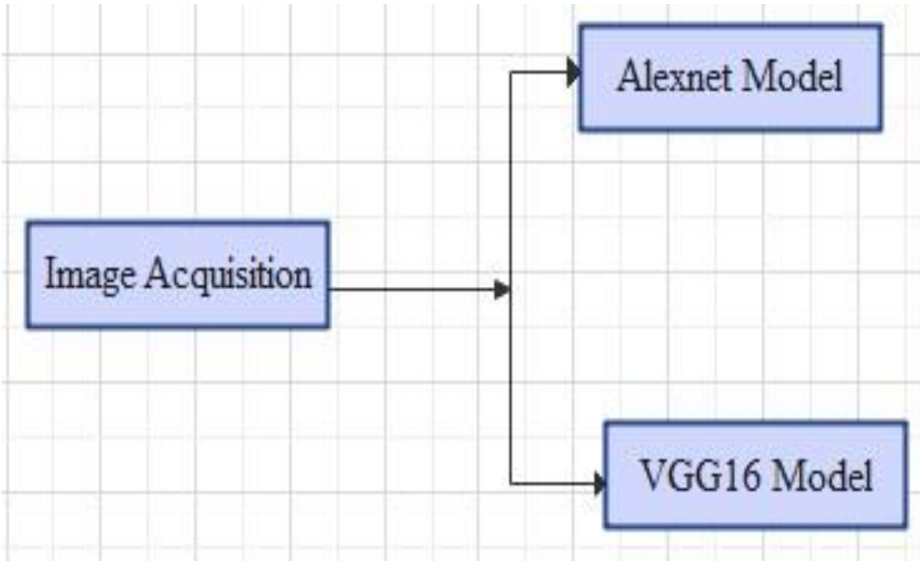

Figure 5 Block diagram for classify tomato crop diseases using deep learning method

Sukhvir Kaur (2018), in this research work, they proposed a semi-automatic method to identify and diagnosis the soybean leaf diseases as shown in Figure 5. The input image was taken using a high-resolution camera for image acquisition. The collected input image underwent pre-processing to get rid of the undesirable noise. Color and texture features were recovered throughout the feature extraction procedure using the image's pixel values. The image with the extracted features was clustered using the K-means clustering technique. The clustered image was divided into the three groups of Septoria leaf blight, downy mildew, and frog eye using a support vector machine classifier [18]. The proposed method's accuracy was 93.3%, and its error value was within acceptable bounds.

RESULTS AND DISCUSSION

In Figure 6 Machine learning algorithms are used in a contemporary method for disease detection to examine data from various acquisition systems: To identify diseases, conventional machine learning algorithms were employed. Due to their accuracy in making predictions, support vector machine (SVM) models are frequently used for plant disease identification. standard machine learning Since abiotic factors play a role in determining the health status of crops, numerous research studies have been conducted to control and monitor plants as well as forecast their health status based on particular physical sensors.

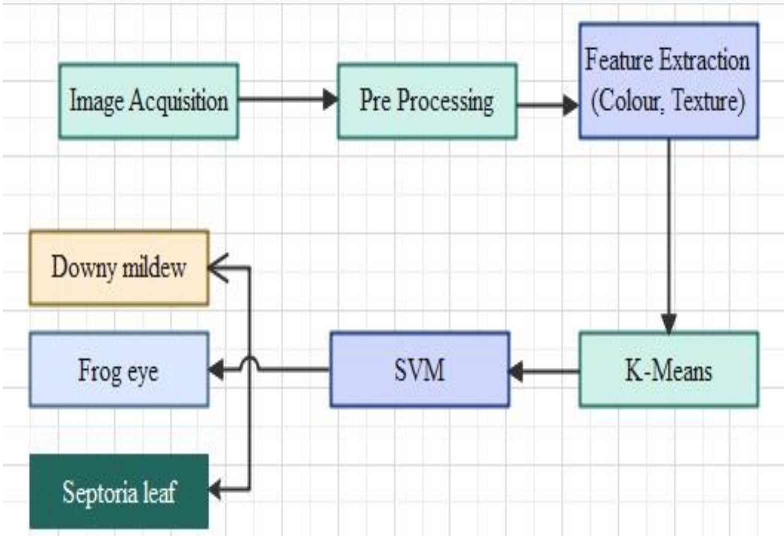

Figure 6 Block diagram for detect and classify the soybean leaf diseases

Computer vision is the ability of a machine to automatically recognise, examine, and comprehend valuable information from a single image or collection of images. With the aid of extracted data and built-in intelligence, the machine further assists the user in helping them make choices that are reliable. Smart agritech has some of the biggest effects when it comes to giving farmers the right information at the right moment. Information technology has increased the effect of smart agriculture by assisting and guiding farmers in remote locations where it is difficult or impossible to contact experts. Precision farming methods can be adopted by farmers and agrarian organisations with the aid of computer vision. The goal of precision cultivation is to boost output and effectiveness. A few techniques that set precision farming apart are soil sampling, geographic information systems, yield mapping, global positioning systems, automatic tractor navigation, and robotics. The suggested model offers greater accuracy based on the difficulties mentioned above and a combination of Computer Vision and Machine Learning (ML) approaches.

The Table 2 summarized result and observation of different crops that affected by the various diseases, which proposed by different authors. This table also inferred that the details about existing and its accuracy level.

Table 2: Summary of image processing and soft computing techniques to detect agricultural diseases

S.No	Author Name	Year	Techniques	Crop	Accuracy
1	Trishen munisami	2015	KNN classifier	32 different plant species	83
2	Manisha Bhange	2015	SVM	Pomegranate	82
3	Amar kumar dey	2016	Ostu thresholding	Vine	85
4	Vijai singh	2016	SVM, GA	Banana, lemon, beans, etc.	above 90%
5	David Ashourlo	2016	Machine learning	Multi crops	RMSE (0.03)
6	Aaron Partick	2017	Correlation	Multi crops	above 90%
7	Peifeng Xu	2017	Flood filling algorithm	Multi crops	92.3%
8	Aravind	2018	Deep learning method	Tomato	97
9	Sukhvir Kaur	2018	SVM	Soybean	93
10	Jayone Garcia Arnal	2018	Database,	21 plant species	-
11	Henrique C.diveira	2018	Morphological operator	coffee crops	90

CONCLUSIONS

The early diagnosis of disease symptoms on plant leaves is made possible by the automatic detection of plant disease, which simplifies crop monitoring. Fungi, bacteria, and viruses are the most typical culprits behind plant diseases. To identify different plant diseases, computer vision techniques are applied. This technique includes several processes, including input picture processing, feature extraction, and classification using different criteria. In specifically, machine learning and transfer learning, as well as recent advancements in their application to the recognition of agricultural disease images, are examined in this article.

FUTURE SCOPE

In recent years, as artificial intelligence technology has advanced, a number of cutting-edge machine learning approaches, such as deep learning and transfer learning, have begun to be used to identify agricultural illnesses. The use of these strategies, however, still faces some substantial challenges.

Conflict of interest. None.

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