Detecting Plant Stress using Low-Cost Object Recognition Systems and Machine Learning Methods

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Abstract

Agriculture is one of India's primary economic pillars because so many people in the country work in it. Early identification of plant stress is a key advantage in intelligent agriculture. To improve the quality and productivity of food crops and to minimise plant damage, it is crucial to recognise plant stress using environmental indicators. Visual sensors in conjunction with environmental sensors help by spotting the leaf colour change early on, at which point further harm can be avoided. A trustworthy framework for identifying plant stress is proposed with the goal of making it easy for farmers to implement. The system uses a camera to take pictures of the leaves in the field, and then uses machine learning to determine if the leaves are healthy or not.

Keywords—Machine learning, Leaves Stress Detection ,Agriculture ,Deep learning , convolutional neural network ,crop stress , precision phenotyping, quality of food crop, Identify color change.

1.INTRODUCTION

The language for technical computing with the lowest overall performance is MATLAB. It combines computation, visualisation, and programming in a user-friendly environment where problems and solutions are expressed using well-known mathematical notation. The acronym MATLAB stands for matrix laboratory, and it was originally created to provide easy access to matrix software that had been enhanced using LINPACK (linear system bundle) and EISPACK (Eigen system package deal deal) duties. In order to quickly address various technical computing challenges, particularly those involving matrix and vector formulations, MATLAB is built on a foundation of advanced matrix software programme application. The key component of this array is that it does not require pre-dimensioning.

The features are retrieved from the expert's end and applied to machine learning algorithms for disease classification. Experts offer remedies to the farmers based on the classification. By processing only the leaf tissue impacted by the disease, this method lessens the hardware's complexity. Knowing where the infected plants are in the field will allow farmers to apply the appropriate amount of insecticides, halting the spread and increasing production. In plant disease detection systems, image processing plays a clear role because pre-processing and segmentation aid in precisely identifying the damaged area.

As a result, the proposed framework employs SVM for classification purposes. In this investigation, plant stress is detected in its earliest stages through a careful analysis of the foliage. In order to train the proposed technique, GLCM features from both healthy and diseased plant leaf samples are used. The camera captures images in the field, then applies a segmentation threshold to identify damaged leaves, before sending those images and the extracted characteristics to a cloud service for storage and analysis. Using a support vector machine, we can put the data into "healthy" or "ill" categories. The performance of the suggested prototype will be evaluated using criteria including precision, recall, stress detection accuracy, and classification accuracy.

2.RESEARCH ELABORATIONS

Crop diseases are the primary cause of global agriculture industry productivity declines and financial losses. To stop the development of illnesses and conduct efficient management, it is essential to monitor the health state of crops. This study presents an in-field automatic diagnosis system for wheat diseases based on weakly supervised deep learning, or deep multiple instance learning, which integrates disease localization and identification of wheat diseases using only image-level annotation for training images in natural settings.

We tested 10 photograph samples, each ordinary and suffering from Mars domestica. The pattern is captured first, then colour and texture capabilities are applied, and the classifier is used to extract the beneficial capabilities wished to differentiate the affected photograph pattern from the everyday photograph pattern. In the future, Bayesian, K-manner clustering, and predominant thing classifiers may be analyzed for class purposes.

I. Algorithm

Plant stress detection using computer vision systems and machine learning techniques algorithms is helpful in understanding the model in detail. The step-by-step algorithm can be seen below:

Step-1: Start

Step-2: Measure plant features like contrast, energy, correlation, homogeneity, entropy.

Step-3: Monitor the measured data of plant leaf will be health or unhealthy.

Step-4: Display measured features of the leaf on the graph.

Step-5: End

II. Flow Chart

The stream chart to control the robot vehicle with an Android-based versatile application is shown in below Fig. 1.

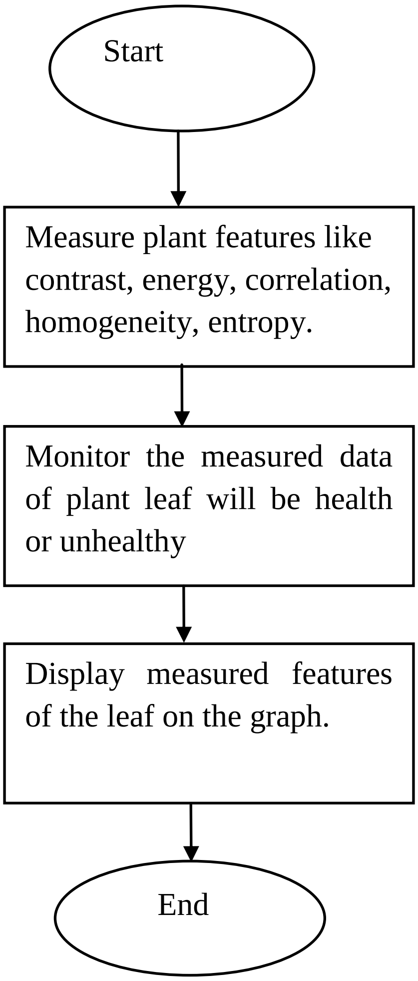


Fig.1 Flow chart of system

3.RELATED WORK

Digital photo processing is the use of algorithms to carry out image processing of virtual pics. As a subcategory or place of virtual signal processing, virtual photo processing has many blessings over analog photo processing. It permits a loads wider variety of algorithms to be carried out to the enter records and can save you troubles inclusive of the construct-up of noise and signal distortion for the duration of processing. Considering that photos are described over dimensions (possibly more) virtual photo processing may also be modelled inside the kind of multidimensional programs.

4.PROPOSED METHOD

This section describes a method that can automatically identify leaf stress in plants. A method that has been devised and put into practise to detect plant stress in agricultural settings. The process flow of the proposed framework is shown in fig.1. Vision sensors are used to capture images in the field. The image is preprocessed to increase the accuracy of the feature extraction procedure. The GLCM characteristics based on texture are extracted from the preprocessed leaves. The plants will be photographed at regular intervals or if there is a significant change in their surrounding environment.Temperature, humidity, illumination, soil moisture, precipitation, and other environmental factors can be tracked using sensors. For ease of use in subsequent applications, the taken image is shrunk in size as part of the pre-processing phase. Before converting the scaled image from RGB to L*a*b* colour space, the contrast is raised, which aids in the segmentation process. The LAB colour space is preferred over the RGB colour space for use in visual applications. New segmentation technique (NSP) is used to separate the damaged part of the leaf. The GLCM matrix will then calculate energy, homogeneity, contrast, and entropy from the segmented leaf.It has been found that texture-based GLCM features, which consider the connection between two pixels, are very effective for classification tasks. The cloud storage system receives these characteristics for the purpose of archiving. The agricultural consultant utilised the SVM algorithm after retrieving the attributes to determine whether or not the leaves were healthy. Both the training data and the characteristics of the captured image are sent into the classifier. Unhealthy leaf types are a good indicator of plant stress. Third, analysing and verifying the results through experimentation.Considering the prevalence of diseases on brinjal leaves, a validation dataset consisting of 1,000 disease-free photographs and 1,000 diseased photos was assembled for use in training.Kaggle images were utilised for both testing and training, including 500 healthy and 500 unhealthy examples. The efficiency of the system is evaluated by metrics including recall, precision, stress detection rate, and classification accuracy. Photos of brinjal leaves were scaled down to 256 by 256 from the original database size for convenience of use. The image is complete once the contrast has been adjusted and the RGB primary colours have been converted to L*a*b*. Color correction will be followed by thresholding with an NSP-created algorithm. The parameter threshold would be calculated by averaging the differences between neighbouring pixels in the L* component image. The texture-based energy, homogeneity, contrast, and entropy properties will be determined by the GLCM matrix after segmentation is complete (Table 1). Thing Speak will feature the aforementioned texture-based features. The agricultural expert will classify the plants' health using MATLAB software, where the SVM code runs, after extracting characteristics from the thin speech at the monitoring station. pictures of healthy brinjal leaves that have been preprocessed and segmented as part of an experimental study. Photos of damaged brinjal leaves that were experimentally pre-processed and segmented are shown in Figs. 3 and 4. Data can be stored and analysed in the cloud using Thin Communicate, which has a MATLAB interface.

Using the block diagram, this is where the experiment's foundations and features are triggered. The block diagram shows us what components and processes are employed. The cloud where things have their say receives the extracted features.

4.1Requirements

- Operating System:Windows
- Coding Language: Python 3.7

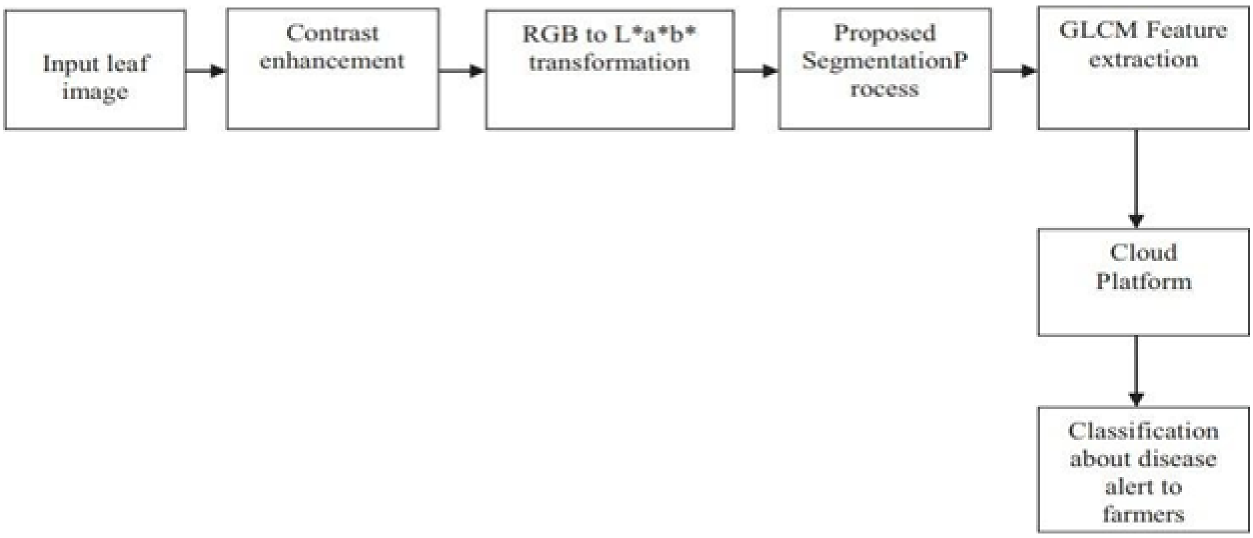


Fig. 2 ProposedPlantStressDetection(PSD)Framework

Table 1 Features

Features	**Values**
Contrast	0.6354,0.6554,0.6484
Energy	0.7354,0.7868,0.7779
Correlation	0.922,0.9284,0.9997
Homogeneity	0.6985,0.6636,0.6883
Entropy	0.8704,0.8657,0.8088

Setting where one's values can be organised in a moral flowchart. It reveals the cloud-based capabilities that have been attained. Using the method described in Evaluation metrices, we assess the proposed machine's performance in terms of accuracy and recall. Accuracy, or precision, is the degree to which a classifier's predictions match up with actual results. Recall is the percentage of correct, good results obtained from all available samples. The Harmonic Analysis The F1 Score is the midpoint between the precision and recall metrics. Classifier accuracy is represented by the F1 Score's range of values between 0 and 1, which is [0, 1].

F1 Score can range from 0 to 1, indicating the classifier's high degree of accuracy. Extreme specificity is provided by a low consider value, which overlooks a large number of times that are otherwise impossible to categorise. The greater the prototype's F1 Score, the better it performs. Precision, deliberation, and F1 score values are suggested. The accuracy of stress detection is calculated by use of an equation. The efficiency with which stress is detected is an important indicator of how soon damage to a plant can be discovered, regardless of whether or not the leaves show signs of stress. SDA =PT 100% The classifier's strain detection accuracy is indicated in Table 1 for monitoring brinjal plants' leaf fitness reputation.

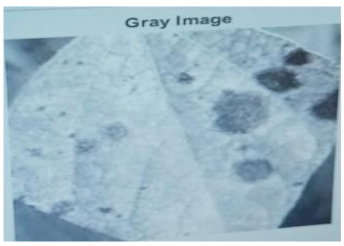
Artificial intelligence (AI) could be the silver bullet to all of the problems with modern plant strain phenotyping if it were included into improved computerised phenotyping structures. Now, with the advent of cutting-edge sensors, high-throughput phenotyping (HTP), and superior statistics analytics via ML, as well as the ever-present availability of computational infrastructure and resources, there is hope for resolving previously intractable problems with plant strain phenotyping.

In contrast, modern unsupervised learning methods can be taught without the aid of annotated images. Removing the need for human involvement in the annotating process saves time and money while also increasing objectivity because human error is eliminated along with the subjective nature of the process. Large datasets can be used more effectively in model training without the time and cost restrictions of labelling education data, improving scalability and rule performance.

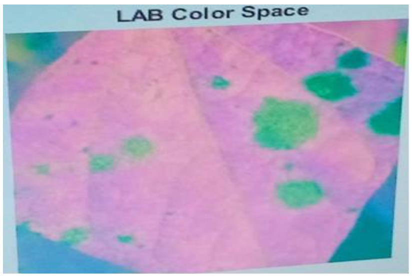
5.RESULT

Image Acquisition: can be carried out with the use of a digital camera, digital scanner, or the camera on a smart tele cell smartphone. For the dataset, it was used to take pictures of both diseased and healthy plant leaves. At this stage, images are resized, smoothed, assessed for growth, and enhanced, among other things, to remove unwanted elements and reduce noise. K-means, converting RGB to L*a*b*, and other techniques are used in image segmentation, which is the process of splitting the image into several parts with the same feature. Extracting salient features: Grey Level Co-incidence Matrix (GLCM), Blend Imagination, and Device Intelligence can all be used to extract the colours, shapes, and textures that are unique to a plant's disordered parts. Extracted features undergo feature analysis, a Machine Learning version, and a fuzzy rule-primarily based class for disease detection and classification. Common machine learning models include the Support vector machine (SVM), Random Forest, K-nearest neighbour, and others. The model is put to the test in one of two ways: either by utilising the image with disorder and running it through the aforementioned steps in the hopes that the classifier will correctly label the disorder, or by examining a pattern of functions left for testing the model. The version's correctness is also checked at this point. By observing the result we are seeing the different stage of the experiment process in following Fig. 2 and Fig. 3.

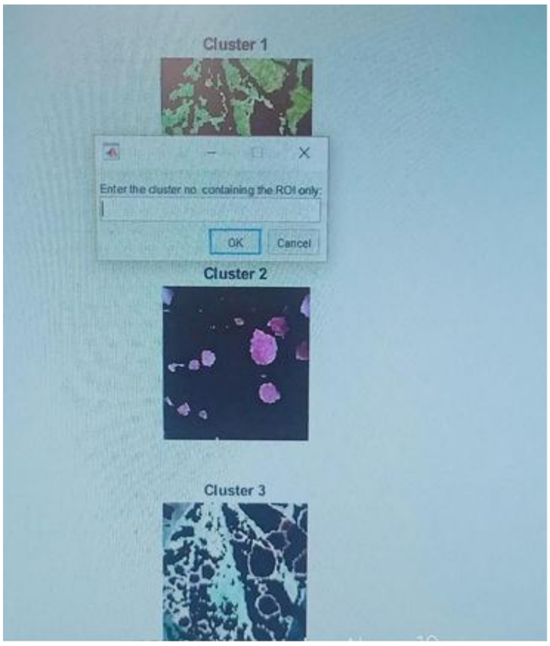
(a)



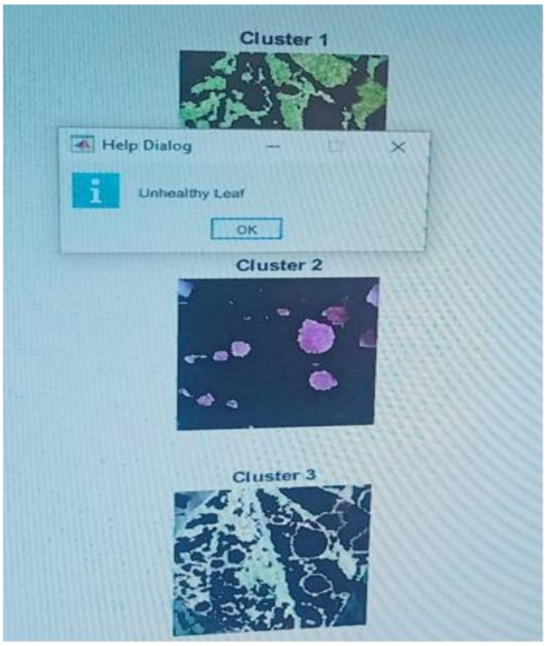
(b)



(c)



(d)

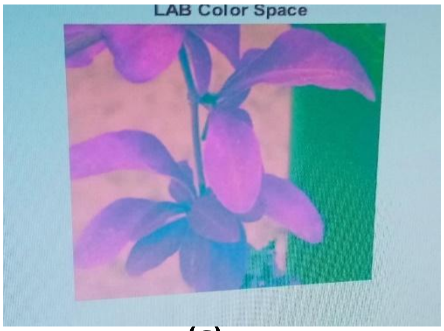


(e)

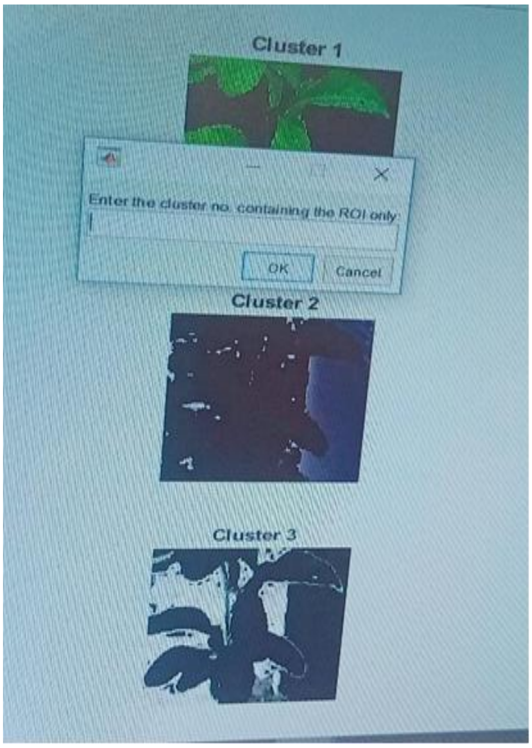
Fig. 2.(a) Input Image 1 (b) RGB Conversion (c) LabColorTransformation (d) ClusterNumber Selection (e) OutputImage

(a)

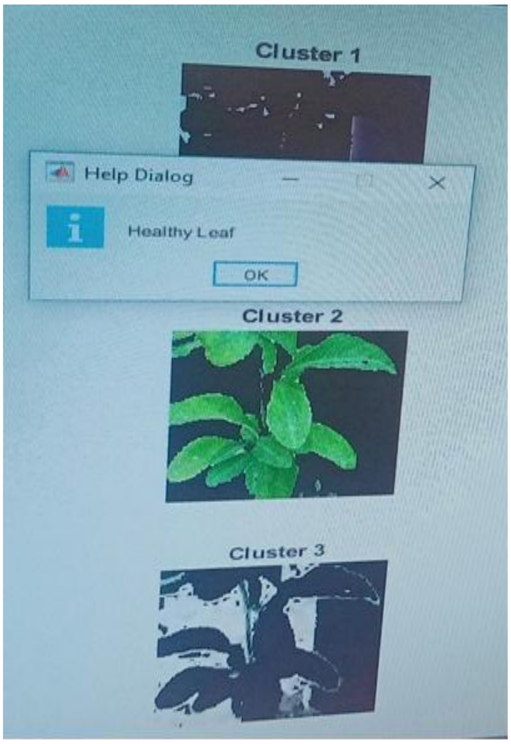
(b)



(c)



(d)



(e)

Fig. 3. (a) Input Image 2 (b) RGB Conversion (c) LabColorTransformation (d) ClusterNumber Selection (e) OutputImage

6.CONLUSION

Tracing plant health and increasing the country's economic output both rely heavily on plant strain detection. Therefore, it is crucial to detect plant strain early in order to protect the blossoms from damage. A digital camera is used to take pictures in the field for the suggested framework, and these pictures are then preprocessed to aid in the feature extraction procedure. It was possible to extract GLCM characteristics from the segmented image and send them to the cloud. The agricultural representative uses a support vector machine (SVM) classifier to alternately retrieve the functions of retrieving healthy and unhealthy leaves. The early detection of plant strains allows agricultural representatives to provide equal replies to farmers. The results look good, and eventually a hardware prototype will be used to prove the framework works. The prototype could be used in a real-world setting for verification and testing. We anticipate our high-throughput framework will aid in increasing the value of genetic benefit by providing a solid, extensible foundation for a wide variety of abiotic and biotic stressors. Additionally, we foresee this procedure incorporated into a high-throughput phenotyping ground vehicle and unmanned aerial vehicle to provide real-time, automated pressure trait detection and quantification for plant research, breeding, and pressure scouting.

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