Crop Field Monitoring and Disease Detection of Plants in Smart Agriculture using Internet of Things

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***Abstract*—The Internet of Things can be defined as the network of physical objects that have sensors, software, and other technologies built into them in order to communicate and exchange data with other systems and devices over the internet. In intelligent agricultural advancements to increase the quality of agriculture, the Internet of Things (IoT) can be used. The manual monitoring of plant diseases is quite challenging. It demands enormous effort, expertise in the diseases of plants and the considerable time required for processing. The idea of automation in Smart Agriculture is implemented using the Internet of Things (IoT). They help monitor the plant leaf conditions, control water irrigation, gather images using installed IoT system which includes NodeMCU, cameras, soil moisture, temperature sensors and detect diseases in plants on the datasets collected from leaves. To detect plant diseases, image processing is applied. The detection of diseases comprises the acquisition of images, image pre-processing, segmenting an image, extracting and classifying features. In addition, the performance of two machine-learning techniques, such as a linear and polynomial kernel multi hidden extreme machine (MELM) and a support vector machine (SVM), has been studied. This paper discussed how plant diseases could be detected via images of their leaves. This analysis seeks to validate a proposed system for an appropriate solution to the IoT-based environmental surveillance, water irrigation system management and an efficient approach for leaf disease detection on plants. The proposed multi hidden layers extreme machine classification delivers good performance of 99.12% in the classification of leaf diseases in comparison to the Support Vector Machine classification, which gives 98%.**

***Keywords*—Image acquisition; segmentation; feature extraction; Internet of Things; plant disease**

I. Introduction

Agriculture is the primary livelihood of Indian villagers; more has been done to boost yields and help farmers address issues like agriculture and plant disease. There have been significant mechanical and chemical advances. In this industry, however, there is little or less digitization. With the IoT growth, it is hoped that the farmers will make a digital agriculture system that will assist farmers in making educated decisions on their farms and help them address undesirable issues earlier. It will therefore avail to increase crop quality and will also benefit farmers. This will help—early disease detection, which in agriculture is a great challenge. IoT sensor nodes play a significant role in collecting real-time information play a significant role in collecting real-time information [1], [2]. These nodes can make the system highly practical by gathering data from crop fields in real-time to specify the agriculture system precisely. Presently to make agriculture system more practical with the help of machine learning techniques. All of them are more beneficial in different domains. Multiple applications are developed in precision agriculture to update the farmers about the condition of the crop [3]. The precision agricultural model is usually made up of three primary phases, as illustrated in Fig. 1. In the first phase, the availability of the IoT sensor nodes and their monitoring conditions can be obtained for crop. Later in the second phase, the data gathered from all the sensors are sent to the fog node with a wireless module to further process the data for higher levels where it can be monitored. Finally, the analytic methods are applied in the third phase of architecture to understand the status of the fields.

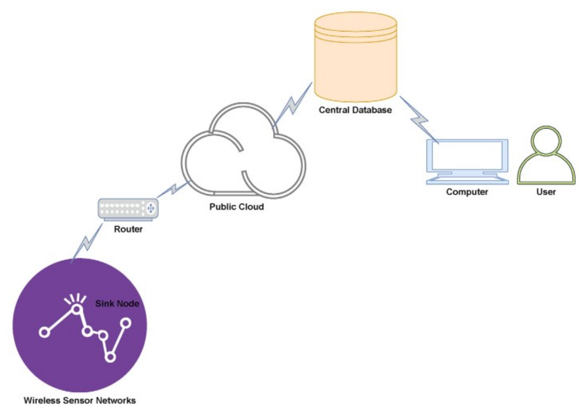

Fig. 1. Precision Agriculture Model.

An alert data is passed to the farmers to make them alert and take necessary precautions if any abnormal conditions are met, like dryness in the crop field, any leaves affected by diseases, with the help of deployed sensors. Therefore, there is continuous communication with the selector, which switches the dipping system on or off to allow the water for all the areas of the ground. Later, the farmers can use the required nitrogen, potassium, and phosphorus fertilizer to sustain plant growth and achieve crop yield. The response system is initiated by using analytics and actuators when any crucial situation is recognized (sensed/predicted). There are several IoT and WSN applications [4], some of which are discussed here. The applications for precision farming are shown in Fig. 2. The different implementation of greenhouses leads to specific significant planting problems and minor technical problems for the global conservation systems [5]—one of the primary issues employing temperature preservation. Pest insects and

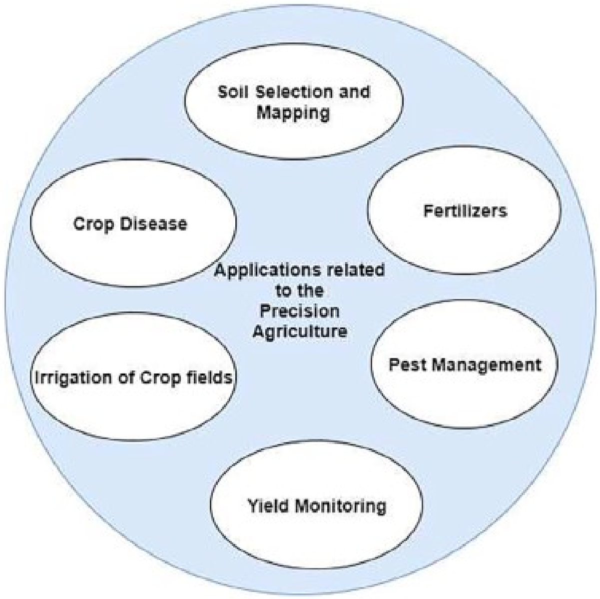

Fig. 2. Applications Related to Precision Agriculture.

flies have also damaged greenhouses because they are covered in a structure that generates turbulence in the covered sheet for any reptile or flies. This turbulence can eventually cause a reduction in plant health, and even their growth can be affected. Because of these issues, the greenhouse practice has to be evaluated and technology integrated to address these concerns. This paper emphasises applying the internet of things (IoT) to solve temperature monitoring and leaf dataset detection in the plant. It will allow agribusiness, farmers, horticultural companies and potential investors to transform the internet from an existing greenhouse into an innovative greenhouse.

II. Related Work

Various literature works on the cloud and edge in the health service have emerged. A software approach for the automatic detection and classification of plant leaf diseases was suggested and experimentally verified in [6]. The proposed system developed includes four fundamental steps. In the first step, most of the coloured pixels are detected. Those pixels are subsequently masked using the Otsu method depending on specific threshold values, and predominantly green pixels are masked. The second step is to remove pixels with red, green, and blue nulls and the pixels on the edges of the infected cluster. The experiment results show that the technique provided is a robust method for detecting diseases from plant leaf images. The efficiency of the proposed algorithm may successfully detect and classify the diseases studied with accuracy from 83In [7], the authors trained a deep convolutional neural network to detect 14 plant classes and 26 diseases from 54,306 images of unhealthy and healthy plant leaf taken under controlled conditions (or absence thereof). The trained model obtains a 99.35% accuracy with a stable test set, which shows the practicality of the technique. The model still reaches an accuracy of 31.4% when tested on a collection of images acquired from reputable web sources, i.e. under conditions different from those for training. Although this accuracy is substantially higher than that due to random selection (2.6%), additional training data are required to improve overall accuracy. Essentially, the technique of deep learning models in increasingly large and open-ended image data sets presents a holistic path toward that massive global diagnosis of smartphone-assisted plant disease. In [8], the authors integrated thermal and visible light image data with information on the depth. They custom-made a machine learning system for remotely detecting plants with Oidium neolycopersici powdery tomato fungus. The results make evident that, by integrating this information with the depth data, the detection accuracy of unhealthy plants has improved dramatically from the image data. Furthermore, it has been demonstrated that a new feature set may detect plants that were not initially injected with the fungus at the beginning of the experiment but became diseased through standard transmission. In [9], the authors studied several computer vision ways that resulted in the detection of multiple algorithms. Phase one was taken using a typical digital camera to gather images of banana leaves. Phase two involves using several extraction methods to collect essential data for phase three when images are healthy or unhealthy. Extremely randomized trees have done their best in detecting diseases with 0. 96 AUC in banana bacterial wilts and 0.91 in the case of banana black Sigatoka (BBS) among the seven classifiers used in this study. Finally, based on the area under curve (AUC) analysis, the performance of various classifiers was evaluated, and the optimum approach for the automatic diagnosis of these banana conditions was then selected. In [10], the nonexistence of farmers in a country where around 58 percent of the people participates in farming, the best crop for the land is decided on by traditional and non-scientific techniques. Farmers were sometimes unable to choose the suitable soil crops, season and geographical location. This leads to suicide, to an abandonment of agriculture and urban living conditions. The authors have presented a technique to help farmers select the crop to overcome this problem by considering all elements, such as the soil's season and the crop's location. Moreover, precise agriculture is practised in emerging countries with current agriculture techniques, focusing on site-specific crop management. In order to accurately separate the disease symptoms from the clutter background, manual selection of the input dataset was utilised at the same time. In [11], Textual features can be extracted in two different methods. One method for calculating the energy, inertia, entropy, and homogeneity of textual features is to utilise a grey level co-occurrence matrix. The Gabor transform can also be used. Some studies employ descriptors based on colour. Area, perimeter, centroid, and diameter were once taken into consideration for shapes. Due to its high accuracy and reduced dimensionality problem, Support Vector Machine (SVM) is a favoured classification method. In [12], the CNN is a neural network technology that is frequently used today to train or analyse visual data. Convolution's matrix format is intended to filter the images. The input layer, convo layer, fully connected layer pooling layer, drop-out layer to form CNN, and finally linked dataset classification layer are all used in the Convolution Neural Network for data training. In [13], to extract the distinctive elements from an image, segmentation is an approach that takes into account the texture and colour of the image. In [14],the adoption of deep learning, more specifically Convolutional Neural Network (CNN), as a substitute method for creating a model for classifying diseases. In [15], in order to extract local features, the convolution layer convolves the input image (or the output of the previous layer) using configurable weight filters, or kernel. CNN extracts shiftand scale-invariant local features from the input by using various weight filters. The object's translation invariance is acquired by the pooling layer, which summarises the results of the preceding layer. In [16], color, texture, and shape are some of the features that were taken from the image. Information about boundaries, spots, and broken areas is contained in the colour feature. The percentage of the lesion and its type are also included in the shape attribute. Uniformity, contrast, probability, variance, and correlation are all aspects of texture. The database is split into two sets of photos for training and testing using the identified features. In [17], building a model that can be utilised by developers to build smartphone or online applications to detect tomato leaf diseases using convolutional neural networks in order to illustrate, categorise, and provide solutions for plant problems. In [18], the tool for classification is a neural network. Target data is provided to the neural network as a class vector, and seven extracted features—Contrast, Correlation, Energy, Homogeneity, Mean, Standard Deviation, and Variance—are given as input. In this case, the data was classified using a back propagation neural network. Following the network's training, it displays the performance plot, confusion matrix, and error histogram plot. In [19], a pixel's intensity in relation to its surrounding pixels throughout the entire image is measured as contrast. The basis for contrast in visual observations of the real world is how the colour and brightness of an object change in comparison to other objects in the frame of reference. A constant image has a contrast value of 0.

III. Materials and Methods

In this work, we concentrate on monitoring humidity, temperature, and water flow to know the environmental conditions of the crop field with the help of IoT sensors connected to the server. In addition, the work involves the early detection of plant leaf diseases by capturing images periodically with the proper deployment of cameras and applying image processing techniques. Our work mainly contributes two-fold: Initially, a standalone system for monitoring and irrigation, as shown in Fig. 3. Second, the analysis and detection for plant leaf disease as shown in Fig. 4. Different sensors such as soil moisture, temperature, and camera are used to detect diseases on a leaf. Data from sensors is collected and transmitted to NodeMCU via wired or wireless devices. Data are checked and matched to the ideal data values such as temperature, humidity, and soil moisture on the server-side (Cloud database). If there is a discrepancy in the threshold value, send the notification on the mobile or website to the farmer. In the webpage and farmer, the output of the sensors is generated.

A. NodeMCU

NodeMCU is an IoT platform open source. The ESP-12 module includes both firmware that operates on the ESP 8266 Wi-Fi SoC and hardware. A 32-bit RISC CPU is clocked at 80 MHz and supports up to 16MB external flash storage for a significant RAM supplement. Thanks to its small size and built-in Wi-Fi capability, the gadget is particularly ideal for IoT applications.

B. DHT11 Temperature and Humidity Sensor

For hotness measurement and environmental impact, a temperature sensor is utilized. Humidity is the amount of water vapour in the air that the hygrometer can measure. For this, we used the DHT11 sensor, which can measure the temperature and humidity data. This sensor has compactness and operates at low voltages of 2.2V, and draws a few mA currents, thus suited for all temperatures and humidity conditions at a long transmission distance of 20m.

C. Water Flow Sensor

The water flow sensor has a plastic valve design, a Hall Effect sensor and a water rotor. The motion of the rotor with a changing rate of flow alters as the water flows along with the rotor rolling unit for each revolution. The process of recording the output 5 to 6 pulses for every litre of liquid that flows for 60secs. In this current work, we used a water flow sensor with a 20mm diameter and water pressure of 1.75 MPa and a flow range of 1 25L per minute.

D. Soil Moisture Sensor

Understanding the soil moisture in our fields is critical for optimal irrigation scheduling for precision irrigation. That's why we use intelligent and precise soil moisture sensors, which may be used to water our plants just when they're dry, avoiding over-or under-watering. A standard soil moisture sensor consists of two parts: A fork-shaped probe with two bare conductors inserted into the soil or anywhere else that water content is to be recorded. As previously stated, it operates as a variable resistor, with resistance that varies depending on soil moisture. An electronic module is also included with the sensor, which couples the probe to the NodeMCU. The module generates an output voltage based on the probe's resistance and provides access via an Analog Output (AO) pin. The module comes with a built potentiometer for adjusting the digital output's sensitivity. Using a potentiometer, we can configure a threshold setpoint such that when the moisture level is above the predefined threshold, the module will output level '0' (LOW), otherwise '1'. (HIGH). This design is highly beneficial when we want to initiate an action when a given limit is met. We can, for instance, activate a relay to start pumping water when the moisture level in the soil reaches a certain level.

E. VGA Camera Module

The operation of the installed camera in the crop field permits regular access with a 24-7 clock visual display of the crop field and plant conditions. A compact image sensor, low voltage module 'OV7670 Camera' allows a single chip, a VGA camera and an image processor to complete. The sensor can deliver the full-frame, samples, and different resolutions of up to eight data bits with SCCB bus controls. With the VGA image that has been inserted, it is possible to obtain frame rates of up to 30 frames per second. It takes the leaf images with high resolution in a suitable format that may be extensively controlled and effectively measured. This procedure includes image processing features, including the white balance and correction in saturation levels interface. SCCB programming interface.

F. Disease Detection Framework

This subsection shows how the leaf diseases detection process can be done on leaf dataset images by applying image processing operations using Matlab application. All the gathered images are in RGB format.

G. Image Acquisition

The camera captures the images of the plant leaf. In RGB (Red, Green and Blue), this image has been generated. For the RGB image, a colour transformation structure is constructed, and a device-independent colour transformation is performed to the design of colour transformation.

H. Image Pre-Processing

Different preprocessing methods are proposed to eliminate noise from the image or other object removal. Cropping of the image, i.e. leaf image, to get the region of interest (ROI) of the image relevant. Image smoothing is done with filter smoothing. Enhance the effectiveness to increase the contrast. The RGB images are converted into grey images by the equation (1).

$$f(x) = 0.2989 * R + 0.5870 * G + 0.114. * B \tag{1}$$

The histogram equalization that distributes the image intensities is then applied to improve images of plant disease. Intensity levels are distributed by a cumulative distribution function [20].

I. Image Segmentation

Segmentation implies dividing the image into different parts or with certain similarities. Segmentation can be performed with several approaches such as Otsu, k-means, RGB-image conversion in HIS, etc.

J. Segmentation using Boundary and Spot Detection Algorithm

The image of RGB is transformed into a HIS segmentation model. Identifying the boundary and spots helps discover the part of the infected leaf [21]. In this current study, the 8-pixel connection is considered for boundary detection, and the algorithm for boundary detection is used.

K. Adaptive K-Means Clustering Algorithm (AK-Means)

This approach uses the maximum connected domain technique for the K-means segmentation method to determine K values. After many tests, the K value ranges typically from 2 to 5. The K-means strategy solves the problem of "Maximization of Expectations" to apply the assignment mechanism to the necessary information points for the closest cluster, as shown in equation (2). We can also observe from equation (4), that when the data points belong to a cluster of xi, they belong to other clusters of k. Likewise, μ_j term denotes explicitly cluster centre xi. Interestingly, for the sake of closed clusters, we used Adaptive K-Means for the clustering process of leaf images which are unhealthy for further processing.

$$C = \sum_{i=1}^{y} \sum_{j=1}^{z} w_{ij} x^i - \mu_j^2 \tag{2}$$

$$\frac{\partial C}{\partial w_{ij}} = sum_{i=1}^{y} \sum_{j=1}^{z} x^i - \mu_j^2 \tag{3}$$

$$w_{ij} = \begin{cases} 1 if k = argmin_i x^i - \mu_j^2 \\ \\ 0 else \end{cases} \tag{4}$$

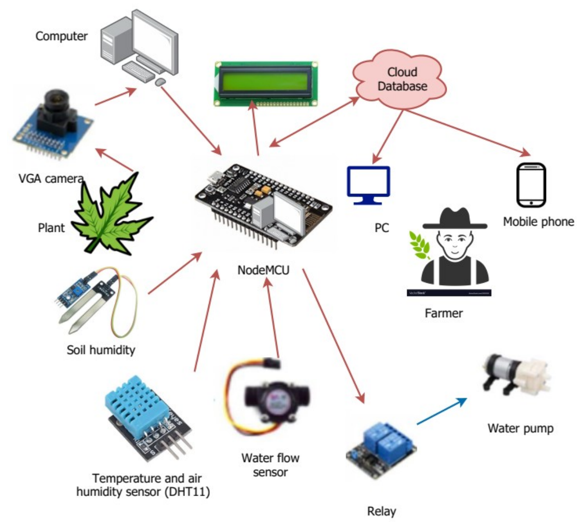

Fig. 3. Overview of Automated Monitoring and Irrigation System Hardware Design Architecture.

L. Feature Extraction

The extraction of features is a crucial element in object identification. The images were then removed by the Color Co-occurrence Method (CCM). The images were taken. The CCM consists of a matrix of pixel values distributed in the same way by the images at the provided offsets (grey scales or colours) in eq. (9). The features that can be employed to diagnose plant diseases are colour, texture, morphology, edges, etc. This method takes into consideration both colour and texture to create a unique image. The RGB is transformed to HSI translation for this purpose.

$$H = \begin{cases} \theta if B < G \\ \\ 360 - \theta, B > G \end{cases} \tag{5}$$

$$S = 1 - \frac{3}{(R + G + B)} [min (R, G, B)] \tag{6}$$

$$I = \frac{1}{3} (R + G + B) \tag{7}$$

The CCM approach employs SGDMs in which the CCM grey level is applied for doing the sampling process. The grey level is sampled in a way that is mainly associated with the other grey levels.

$$(p, q) = \sum_{x=1}^{n} \sum_{y=1}^{m} \begin{cases} if l(x,y) = p, \\ \qquad 1, l(x + \Delta x, y + \Delta y = q)_{0else} \end{cases} \tag{8}$$

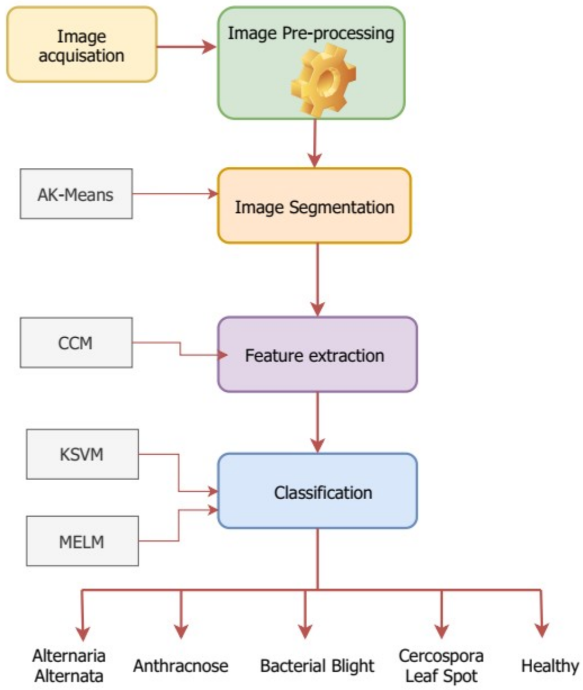

Fig. 4. Plant Leaf Disease Detection Process.

M. Leaf Color Extraction using H and B Components

Using an anisotropic diffusion approach, the input image is improved to preserve information of affected pixels before colour is separated from the base [22]. H and B components from the colour space of HIS and LAB are considered to discriminate between the grape leaf and the non-grape leaf.

N. Classification

After extracting features, the learning images from the learning database are classified using two separate machine learning algorithms: support vector machine and extreme learning machine. In addition, the SVM was used with two different kernels, linear and polynomial.

O. Support Vector Machine

The SVM supports a binary classifier that falls under machine learning. SVM is a binary classifier. The learning model is supervised and examines classification and regression data. Consequently, the most efficient hyperplanes selected for the SVM Classifier have been chosen, separating every input sample into two classes based on the two-class binary classification issue.

$$X = \left\{ \left(y^1, z^1\right), \left(y^2, z^2\right), ., \left(x^n, y^n\right) \right\} \tag{9}$$

The classification line is derived as:

$$X\left(n\right) = \left(w, n\right) + a \tag{10}$$

where z denotes X class label, and n is the high dimensional space-represented sample vector. The equation of the classification line is achieved with the help of w and a parameter. This work used 150 images of 5 different kinds of leaves to develop the SVM-based supervised machine learning classification with two different kernels. The test images of the NodeMCU and the camera were used to investigate the performance of the specified classifiers after the training procedure.

P. Proposed Multihidden-Layer ELML (MELM)

Fig. 5 illustrates the structure of the MELM (choose, for instance, the 3-level hidden layer ELM). Fig. 6 shows the workflow of the 3-level hidden layers using the MELM approach. To train the network, we provided the samples $\left\{X, T\right\} = \left\{xi, ti\right\}\left(i = 1, 2, 3, ..., Q\right)$ and constructed the network topology with hidden layers $\left(therearethreelayersineachofwhichhashiddenneurons\right)$ with activation function $g\left(x\right)$. Input layer, three hidden layers and output layer are available for the 3 level hidden layer structure of ELM. In this present work, we used three hidden layers placed with each other as two hidden layers. Thus the weight matrix β_{new} can be obtained from the second and output layers of the network. We can employ β weights, which enhance the overall ability of the network, depending on the number of actual samples. Then the MELM divides the previously combined three hidden levels and has three hidden layers for the MELM structure. This allows the predicted results of the third hidden layer $H3 = t\beta^+_{new}$ The β^+_{new} weight matrix is generalized inversely. The third MELM denotes the required matrix $W_H E1 = \left[B_2 W_2\right]$ allows for the calculation of the formula (12) and formula $H3 = g\left(H_2 W_2 + B_2\right) = g\left(W_{HE1} H_{E1}\right)$ acquired by the parameters of the third layer.

$$W_{HE1} = g^-1\left(H_3\right) H^1_{E1} \tag{11}$$

While H_2 denotes the second layer actual output, W_2 denotes the weight present in the second and the third hidden layer, B_2 denotes the third layer biasing factor, and H^+_{E1} denotes the inverse of the $H_{E1} = \left[1H_2\right]^T$ generation T, 1 is a one-column size Q vector with scalar unit elements 1. The $g^-1\left(x\right)$ notation denotes the opposite of $g\left(x\right)$ activation function. We use several activation functions for classification and regression to test the performance of the proposed MELM algorithm. We generally use the $g\left(x\right) = \frac{1}{\left(1+e^-x\right)}$ logistic sigmoid function. This determines the actual output of the third hidden layer:

$$H_4 = g\left(W_{HE1} H_{E1}\right) \tag{12}$$

Finally, the output new weights matrix $\beta_n ew$ can be obtained from the third hidden and the output layer, the computation is as follows: If the number of hidden layer neurons is lower than the number of training samples β can be indicated as continues to follow:

$$\beta_{new} = \left(\frac{1}{\lambda} + H^T_4 H_4\right)^- 1 H^T_4 T \tag{13}$$

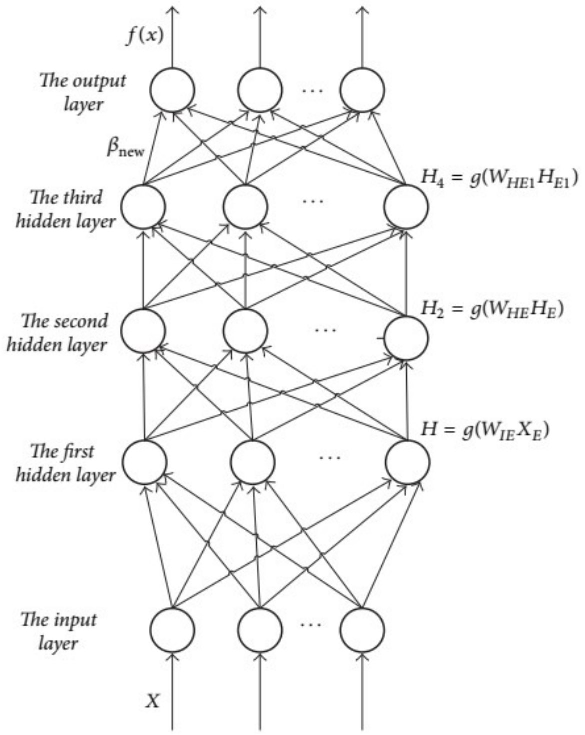

Fig. 5. Network Layers with 3-Level ELM

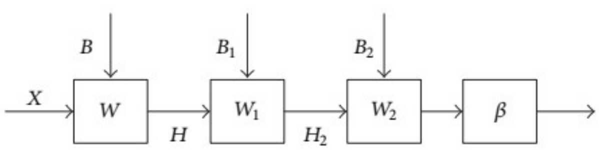

Fig. 6. The Workflow of the 3-Level Hidden-Layer of the ELM.

If the number of neurons in the hidden layer exceeds the number of training data, β is the following:

$$\beta_{new} = H_4^T \left(\frac{1}{\lambda} + H_4^T H_4\right)^{-} 1T \tag{14}$$

The actual output of the ELM network with three hidden levels can be described below:

$$f(x) = H_4 \beta_{new} \tag{15}$$

The operation phase is adjusting the network structural parameters from the second hidden layer to guarantee for Final hidden layer output be close to the estimated hidden layer performance for the total training time. Above is the estimated parameter for the ELM network of 3-level hidden layers, but our present work is intended to compute the ELM network variables from the multiple hidden layers and the final output of the MELM underlying network. The actual output of the ELM network of three hidden layers is as follows:

$$f(x) = H_4 \beta_{new} \tag{16}$$

The operation process optimises the network structure terms from the second hidden level to ensure that the actual hidden layer result is close to the estimated hidden layer output during the complete training time.

IV. Results and Discussion

In this study, the testing prototype and detecting plant leaf diseases are two phases of execution. The experimental prototype consists of the primary configuration and functioning of hardware components for necessary applications. Likewise, the analysis of plant leaf diseases detecting diseases from the images of the leaf dataset in question. There are two parts of system design, the primary is the sensor monitoring process, and the secondary is to predict the leaf diseases. The heart of the architecture is the NodeMCU microcontroller. The sensors are connected to the microcontroller, and gathered data is sent to the controller and received data will be further processed by the Matlab application for leaf disease detection. The sensors must capture the current environmental data. The early diagnosis of a disease depends on the image captured from the actual crop field using the MATLAB simulation tool. These images are the test cases for the identification process of plant disease.

A. Evaluation

The evaluation involves implementing a system of environmental monitoring sensors, including a software package required for deployed VGA cameras in the crop field to have precise agriculture for farmers. Database Description: The databases comprise 237 plant disease images from the leaf. The two most excellent plant disease image database websites collect five categories of images affected. Arkansas Plant Database and Reddit Plant Leaf Data Sets [14] [15] are used to acquiring images of diseases affected. Fig. 7 shows sample images of each form of plants leaf disease.

B. Evaluation of Segmentation

Two parts address the result section: first is the output of the segmentation of leaf diseases and the performance comparison of the segmentation in different parameters. The second part is detecting diseases from the collected images of the leaf dataset for the MELM and SVM classifications. For performance evaluation between the MELM segmentation output and the manual segmentation output, the Dice similarity coefficient (DSC), the mean square error (MSE) and the structural similarity index measure (SSIM) parameters were determined.

For the ten leaf samples, the average performance of the segmentation output, as shown in Table I, illustrates that the three parameters are acceptable for leaf disease detection.

TABLE I. Performance Parameter Values of the Segmentation Result

Disease Type	***DSC***	***MSE***	***SSIM***
Alternaria Alternata	0.97	0.014	0.97
Anthracnose	0.98	0.021	0.98
Bacterial Blight	0.95	0.047	0.96
Leaf Spot	0.96	0.011	0.94
Healthy	0.97	0.010	0.99

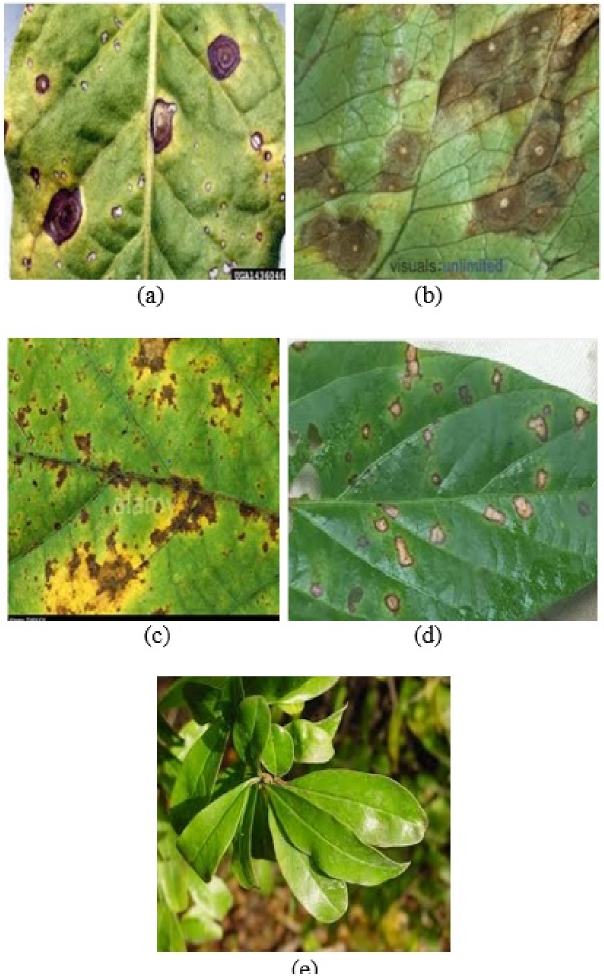

Fig. 7. Sample Images from the Database of Plant Disease: (a) Alternaria Alternata (b) Anthracnose (c) Bacterial Blight (d) Leaf Spot (e) Healthy

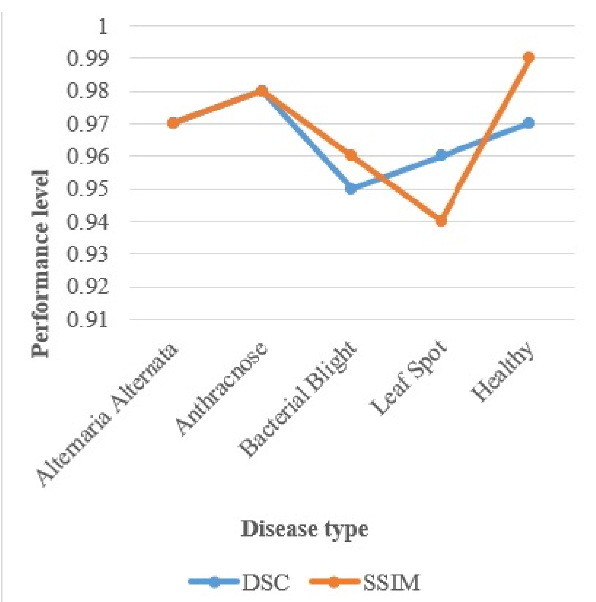

Fig. 8. Segmentation Result of the Parameters DSC and SSIM.

Fig. 8 shows that good segmentation with the proposed MELM techinique for five types of plant diseases having high DSC and SSIM values.

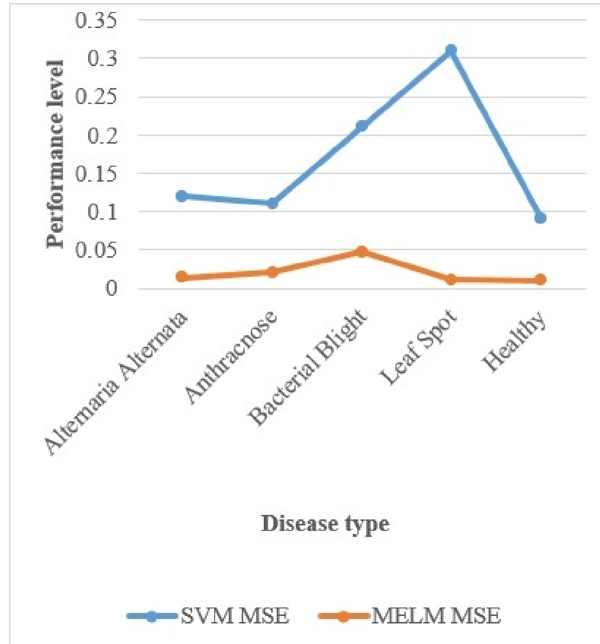

Fig. 9. Segmentation Result of the Parameter MSE of Two Classifiers

Fig. 9 illustrates good segmentation of five classes of plantation diseases with the minimum MSE values by the proposed MELM technique when SVM is poorly functioning owing to overfitting.Table II shows that the proposed MELM classification performs in classifying leaf diseases with other available approaches.

TABLE II. PERFORMANCE PARAMETER VALUES OF THE CLASSIFICATION RESULT OF TWO CLASSIFIERS

Disease Type	*KSVM Accuracy*	*MELM Accuracy*
Alternaria Alternata	98.28	99.12
Anthracnose	97.32	98.92
Bacterial Blight	96.21	98.31
Leaf Spot	97.81	98.21
Healthy	98.21	99.14

The performance was evaluated of the two classifying models on the test data set, and the accuracy parameters for the performance assessment were calculated. The test data set includes 37 images with five different types of diseases. Fig. 10 demonstrates that the average five-class performance represents the average classification performance based on the test dataset after the individual classification performance is computed. The proposed multi hidden layers extreme machine classification delivers good performance of 99.12 in the classification of leaf diseases in comparison to the Support Vector Machine classification, which gives 98%.

V. CONCLUSION

The idea of detecting and monitoring leaf diseases of environmental conditions and irrigation systems is put into

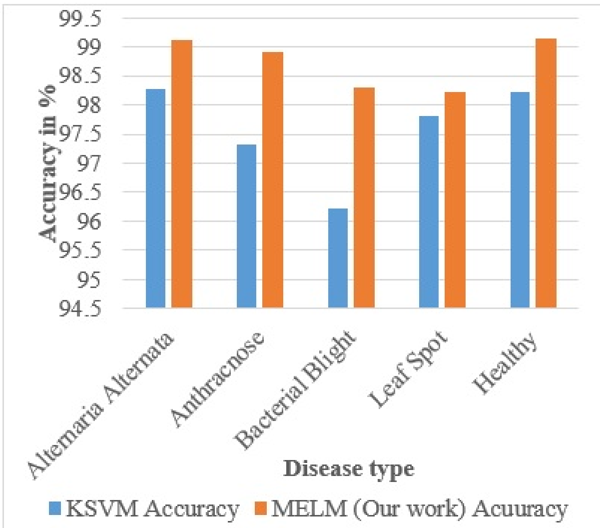

Fig. 10. Comparison of Classification Result of the Two Classifiers.

practice. For successful cultivation of crops, the correct detection and classification of the plant disease are crucial, and this may be done with image processing. This present study dealt explicitly with the adaptive K-Means clustering technique via various techniques for segments of the diseased part. This paper also explored several colour co-occurrence and classification methods for extracting the features of the diseased block and plant disease classification. The deployment of Multihidden Extreme Learning Machines can be efficiently employed for the classification of diseases in plants. The overall accuracy is considerably more significant for the multiple classifications than the ELM network structure. The MELM improves the network structure's performance in certain instances. In future, the data collected from Unmanned Ground Vehicles and Unmanned Aerial Vehicles can be applied to different ensemble algorithms.

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