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Research Article

Plant Monitoring System Using Gray Level Co-occurrence Matrix and Weight Based Artificial Neural Network Algorithm over Internet of Things

V. P. Arul Kumar [1*], M. Vigenesh [2]

[1] Research scholar, Department of CSE, Karpagam Academy of Higher Education, Coimbatore, India
[2] Associate Professor, Department of CSE, Karpagam Academy of Higher Education, Coimbatore, India
* **Corresponding Author:** arulkumarssk@gmail.com

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ABSTRACT

The potential deployment of the plant monitoring system in cutting-edge technologies is currently generating a great deal of interest. A new IoT-based technology is used to track both the development and wellness of the plant. Setting up cross-device connectivity over the internet is the idea underlying IoT devices. It is a sizable network that links people and various interconnected elements in order to gather and transmit data. This research article aims to generate a manufacturing Internet of Things (IoT) based plant monitoring system that uses IoT sensors to detect environmental conditions. The IoT term is used to link objects to the internet and make it easier for consumers to obtain data. The technology can accurately perceive the surroundings in agriculture and convey the data to users. The system keeps track of several factors like soil moisture, temperature, and light intensity. The method begins with the collection of plant images and noise reduction pre-processing. Once the images have been segmented, they are done so utilizing the Region based K-Means Clustering (RKMC) technique. Following that, Gray Level Co-occurrence Matrix (GLCM) is utilized to extract features, with a focus on extracting the more informative characteristics like color, texture, and shape features. The classifying process is completed by utilizing Weight based Artificial Neural Network (WANN) algorithm for improving the plant monitoring system performance significantly. It offers IoT-based solutions to categorize plant illnesses and observe variables including soil moisture, air temperature, and pH values. Te findings of the suggested GLCM-WANN algorithm show better performers than existing methods for obtained values of computation complexity, accuracy, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE).

Keywords: Plant Monitoring System, Gray Level Co-occurrence Matrix (GLCM), Region based K-Means Clustering (RKMC) Algorithm, Weight based Artificial Neural Network (WANN) Algorithm.

INTRODUCTION

A stable food chain and the ecological cycle are both critically dependent on crops. In India, agriculture has always been a key industry. There is an obligation to manage factories through automation because of how quickly the world is developing and how much of it is automated (Hidayanti, Rahmah, & Sahro, 2020). Each crop has some unique requirements that must be met if it is to survive. Thus, a framework must be created so that crops can interact with users via IoT. Additionally, it's important to evaluate, gather, and effectively employ variables for state categorization.

IoT is significant in various sectors. The numerous benefits that can be derived from IoT have increased its use. The sector demands to be developed to be able to meet the necessities and serve a substantial section of the population. Low rainfall is a major problem in the majority of the region, and even if there is sufficient rainfall, water is wasted because of inadequate storage structures (Siddagangaiah, 2016). To give the crop optimal irrigation, IoT uses a variety of strategies. IoT devices can also be utilized at home for real-time garden monitoring.

Agronomic crops comprise a significant portion of the economy. Given the rapid population growth of the twenty-first century, agronomic crops and plants are imperative. Modern development demands that its realm be created gradually without expanding. Reusing a comparable plot of land is one technique to boost production, although this strategy isn't always effective because of the terrain's unpredictability (Farooq, Hussain, Ul-Allah, & Siddique, 2019). a few issues with land reuse for higher production. Their primary purpose is to decompose and pollute, thus they damage the farms from the inside out.

Every year, three million hectares of agricultural land are lost to soil deterioration and bursting, rendering it unusable (Rizk & Habib, 2018). One of the effects is the disease of crops and plants. This is the condition that hinders productivity the most. Technology such as IoT used to agronomic crops and plants may have a big impact. Plant illness must be carefully detected since plant diseases are often encountered. Conversely, if the right actions are not followed, it affects plants and lowers crop and plant output in terms of quantity, quality, or productivity. One advantage of using a pre-programmed system to identify plant diseases is that it saves time when inspecting big product farms. An automated method for image processing that is used to identify and categorise plant leaf diseases automatically. Research on various disease assessment techniques that may be used to determine plant leaf diseases is also included. This algorithm not only measures the infection but also employs image processing to assess the quality of the soil in relation to plant health, a crucial step in identifying the infection location in cases of plant leaf disease.

Crop disease poses a serious risk to sufficient crop supply and has catastrophic effects on producers. Particularly those who need healthy crops for their income and have small farm areas (Lee, Wei, & Zhu, 2021). The newest discipline in engineering, precision agriculture (PA), uses information technology image processing methods to enhance the agricultural production process. Cost reduction for crop disease detection is one of PA's key benefits, and when these procedures are used, crop diseases may be quickly and accurately diagnosed. It enables the prompt dissemination of crucial knowledge for disease prevention and treatment, improving crop output.

IoT developments can be applied to Effective cultivation to raise the level of agriculture which drives the Indian economy and its expansions. Agricultural productivity is poor by worldwide standards as outdated farming technologies are used. Villagers/Farmers commute to towns to pursue lucrative industries instead of focusing on farming. Although farming has always been innovative, IoT, a system of sensors that, indirectly or directly connects users to the Internet (Thorat, Kumari, & Valakunde, 2017) can covert farming to the next level. With IoT sensors, they may collect precise, up-to-date information on greenhouse characteristics such as temperatures, illumination, soil quality (Kotkar, 2021; Akhter & Sofi, 2022). In addition to gathering environmental data, forecasting stations have the autonomy to adjust the environment to reflect the stated standards.

The plant monitoring system employing WANN in IoT is the focus of this study as very few plant monitoring systems are accurate. The shortcomings of the current methods include subpar food crops and incorrect classification outcomes. The efficiency of the plant monitoring system as a whole is improved by the GLCM-WANN algorithm, which addresses these issues. This work uses pre-processes, segmentations, feature extractions, and classifications on the provided plant dataset where innovative techniques provide accurate outcomes.

The residue of the research is structured as follows: In section 2, a summary of some of the literature on preprocesses, segmentations, feature extractions, and classifications. In section 3, the suggested technique for the GLCM-WANN scheme is described. Section 4 provides the experimental findings and an overview of the outcome. Finally, Section 5 reviews the outcomes.

LITERATURE REVIEW

Singh, Srivastava, and Mishra (2020) suggested encouraging smart farming methods and lowering hazards in the agricultural sector. Utilizing an IoT-based monitoring system, the impact of physical factors like soil temperature, moisture, and light intensity is tracked. Various sensor modules, including the LDR, DHT11, DS18B20, Noir cameras, soil moisture sensed by sensors, and Application Programming Interfaces (APIs) collect the data necessary for measuring plants' developments. Fluctuations in plant growth relative to received sunshine were found to be under 1000 lx–1200 lx, category-2 (best). The retrieved variables are analyzed utilizing several

Machine Learning (ML) techniques. For analyzing the physical factors influencing marigold cultivation, Gradient Boosting Classifier, the Logistic Regression, and Linear Support Vector Classifier (SVC) methods are shown to be the most effective.

Hanumann et al. (2022) discussed the most crucial duty in agriculture-based settings is the plant monitoring system. An automated IOT-based irrigation system that uses temperature, moisture, humidity, and light intensities for preserving farms' needed soil moisture. According to the evaluation of their sensor results, farmers can choose which farm will suit a given piece of land. Automation will help farmers make better crop decisions, grow more crops, and make the best use of water resources (some regions have drought-stricken areas). The automatic IOT-based irrigation system uses resources effectively and produces excellent temperature precision with a working Arduino UNO. In total, it lowers financial outlay and human interference.

Kumar and Saini (2022) presented an architecture with cloud computing and IoT for monitoring hydropower plants where historical plant data comparisons with recent data were used to identify correlations on the Thing Speak cloud. The states of Hydro turbine had R2-values of 0.9693 and MAPE of 0.67% at 0.89% for RMSE, and power sand with an R2-value of 0.9503 and MAPE of 0.798% at 0.91% for RMSE, demonstrated model's predictive capacity.

Mudholkar et al. (2022) introduced Plant health care which is known for identification and treatment of biological procedures that impede crops from developing to reach their genetic capacity for usage such as ornaments, and food. Crop management is one of the important duties in any environment that is purely related to agriculture: the setup of a program for tracking plant health is described; which will assess many environmental elements, including temperatures, humidities, and light intensities, that impact plants and restore soils' moistures. These Arduino Uno development boards send this data to the Ubidot IoT cloud platform. The user's phone will be notified if there is a discrepancy between the sensor nodes in the data and the real number.

Tangworakitthaworn, Tengchaisri, Rungsuptaweekoon, and Samakit (2018) focused on the use of a game-based learning system that is built on IoT technology to encourage individuals to take care of trees and plants. Caring for plants, game-based learning, and IoT are essential parts. An inventive method for combining these three components is described and put into practice. The experimental evaluation of how satisfied learners were with using the game in practical settings has been published for an established game-based learning system.

Sethy, Behera, Kannan, Narayanan, and Pandey (2021) provide a structure for setting up a system for remote crop observation. The images and data from the sensor and camera are transferred through the IoT for data gathering and analyses for additional processing. The two deep learning algorithms that were created using vgg16 and Support Vector Machine (SVM) effectively detect paddy leaf diseases and calculate nitrogen levels. For recognizing four different leaf diseases and forecasting nitrogen levels, transfer learning methods of vgg16 provided 79.86% and 84.88%, respectively. The recommended designs also offer key information and needed set up systems for monitoring paddy fields remotely where prototypes practically track all elements that impact crop production, including soil and rice plants.

A. Kohli, Kohli, B. Singh, and Singh (2020) discussed the necessity of plants for ecological cycle maintenance, healthy development which can be maintained through regular monitoring. Hence, the study automated IoT to build a smart plant monitoring system which includes many characteristics like intelligent decisions that were made based on real-time data on soil moisture using level, DHT11 and soil moisture sensors, etc. The moisture content of various plants was measured by soil moisture sensors and when levels fell below marginal values, signals were transmitted to the Arduino board, causing pumps to water plants. The pumps were turned off when moisture levels reached expected levels based on level sensor data. Level sensors detect water levels in tanks and transmitt data about water levels to the Arduino board and subsequently all monitored data is sent to cloud servers.

Shibani, Sendhil Kumar, and Siva Shanmugaml (2020) suggested two sections where first section used sensors and IoT simulations to monitor plant requirements. Sensors were used to gather data, which was then transmitted to Blynk app. Only when moisture contents dropped below certain levels the automated water controllers turned on. Plants were categorized as healthy or diseased. The second section analysed gathered Blynk data. The study compared classification performances of logistic regressions, random forests, and SVM.

METHODOLOGY

Here, Weight based Artificial Neural Network (WANN) algorithm is recommended to enhance the plant monitoring performance. Pre-processing, segmentation, feature extraction, and classification are the three primary processes of the suggested approach. **Figure 1** displays the recommended framework's overall block architecture.

Data Collection

Images of the leaf diseases alternaria alternata, anthracnose, Cercospora leaf spot, bacterial blight, and diplocarpon rosae from tomato, cucumber, and eggplant plants are gathered from the internet. Each dataset contains 50 images, 25 of which are utilised for training and the remaining 25 for testing. Furthermore, distinct images are obtained using the image capturing device designed to capture the tomato plant within the controlled chamber (de Luna, Dadios, Bandala, & Vicerra, 2020). The acquired image is in the JPEG format, with a consistent dimension of 680×480 and a horizontal and vertical resolution of 96 dots per inch (dpi). It has a bit depth of 24 as well. The system harvests tomato plants at 8:00 a.m., 12:00 p.m., and 5:00 p.m. to collect data on the plant under varying natural lighting conditions. In order to get higher-quality fruit images, the camera is placed 0.65 metres away from the intended plant. A number of gathered image datasets is 277 and the number of sample images used for training is 231. Pre-processing is done on these images to make segmentation and feature extraction easier. A suggested IoT-enabled gadget uses the GLCM-WANN technique to categorize diseases by sending Current environmental data and a image of a plant leaf are added to a database.

Pre-processing via Adaptive Median Filtering (AMF) Algorithm

AMF algorithm eliminates noises, and is designed specifically for image graphs of plant leaves. It is mostly utilized to provide a solid and efficient model for enhancing image outcomes when their noises are present. To determine an image's pixels affected by noises, AMF performs spatial processes (Verma, Singh, & Thoke, 2015). By analyzing each pixel on a plant leaf to its neighbors, the AMF determines if a pixel is noisy or not. The analogy parameter can be changed, as can the neighborhood's size (Ibrahim, Kong, & Ng, 2008). A pixel that varies significantly from its neighbors is referred to as noise while also being different from most of its neighbors. The mean pixel values of neighborhoods that succeeded in noise labelling tests are utilized to substitute these noise pixels. Hence, image quality is improved by reducing noises in images.

The window size of an adaptive filter is increased as a result of the quantity of noise candidates in locations. Window sizes in regions are determined by Equation (1) using noisy pixel counts across all regions. After thorough models that guarantee the highest quality outcomes based on MSE thresholds for altering window sizes are based on noisy pixel counts in locations.

$$W(M)=\sum_{p} C(p,D_P)+\sum_{q \int N_p} T\left[\left|M_P-M_q\right|=1\right]+\sum_{q \int N_p} T\left[\left|M_P-M_q\right|>1\right] \tag{1}$$

W indicates the window matching function, and *M* for *W*'s best outcome. The real pixel in the provided image is *p*, and *q* represents *p*'s neighboring pixel. N_P stands for groups of pixels immediately surrounding *p*. The letters M_P and M_q, accordingly represent estimated matching windows of *p* and *q*. *C* stands for the price of a specific matching window. The logic function $T[\bullet]$ tests the assertions it contains, yields 0 if they are false and 1 if they are true. Increase the window size in Equation (1) before if the window doesn't have a noise-free pixel or if window's averages are noisy pixels. The adaptive nature of window sizes employed to filter image pixels cause them to increase when specified requirements are not satisfied. If the case is true, the pixel is processed utilizing the window's median. Let I_{ij} is the pixel of the corrupted image, $I_{\min}$ represents min. pixel values, $I_{\max}$ represents max. pixel values of windows, W are window sizes, $W_{\max}$ represent max. window sizes that can be achieved while I_{med} implies assigned window medians.

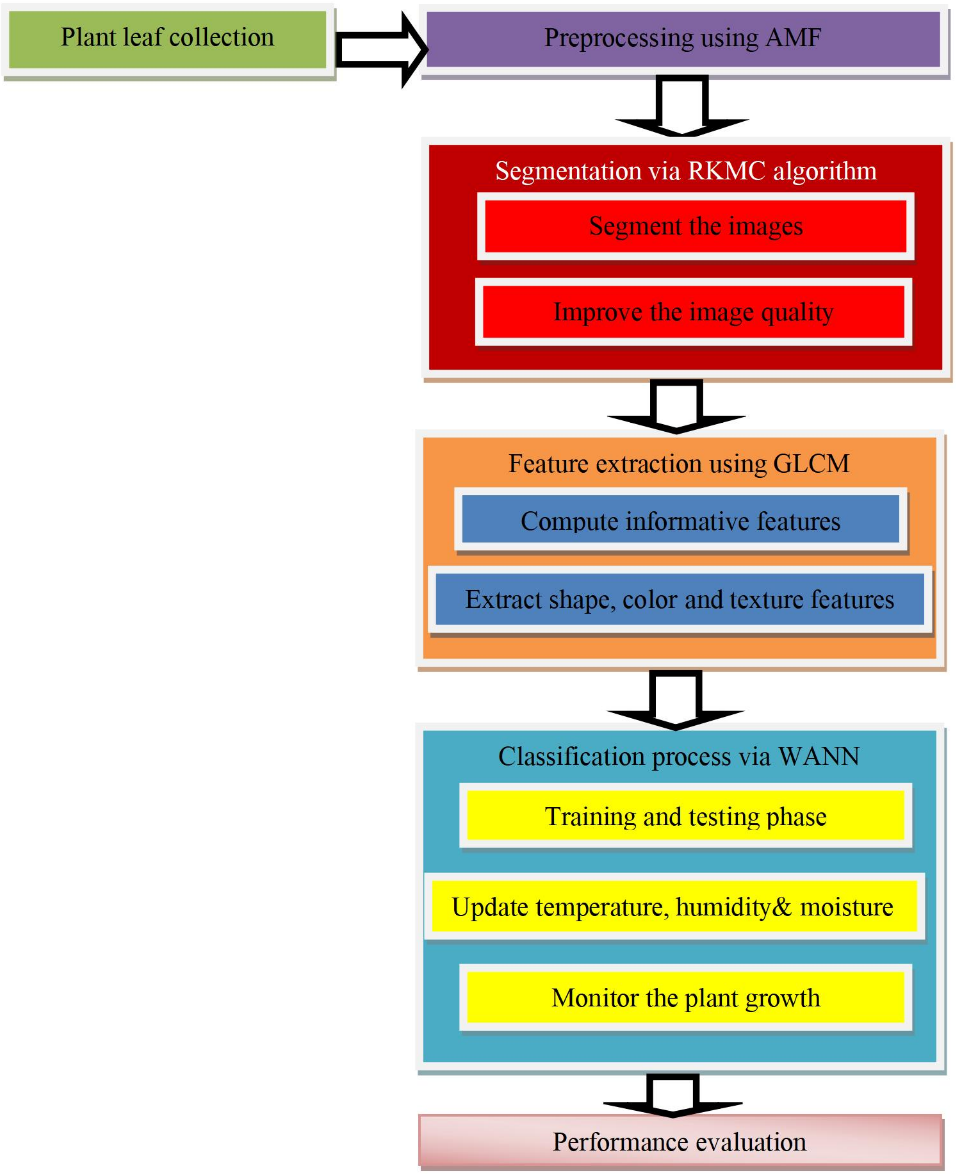

Figure 1. Overall Block Diagram of the Proposed System

Segmentation via RKMC Algorithm

RKMC technology segments plant leaves efficiently. The damaged leaf sections may be segmented by using a color-based segmentation method and region-based k-mean clustering. Which creates three groups based on colour variations. First, RGB source images are converted into L*a*b* colour spaces (Sulaiman & Isa, 2010), a* and b* stand for chromaticity layers, or colour falls along blue-yellow and red-green axes, respectively, and L stands for brightnesses. This method divides the data into segments and accurately places n perceptions into one of k clusters with defined centroids. The means of clusters are then calculated, and point clusters are then set to the closest ones using squared Euclidean distances. The technique labels each pixel based on the k-mean result and categorizes the colors in a*b*. As an outcome, clustered images are produced that are segmented from the primary image and distinguish between the leaf's damaged and unaffected portions.

KMC clusters are useful for splitting similar information into sets by using centroids of clusters. The clusters' centroids are determined based on the Euclidean distance concept. The method continually determines the present cluster's centers (i.e., mean vectors of clusters in data spaces) starting with an arbitrary partitioning, and (ii) repositions every piece of data in the nearest cluster to its center. Upon the cessation of all transfers, it ends. By performing, the squared difference between the linked cluster centers and the data characteristics, or the intra-cluster variance, is locally reduced. The KMC technique is demonstrated in **Figure 2**.

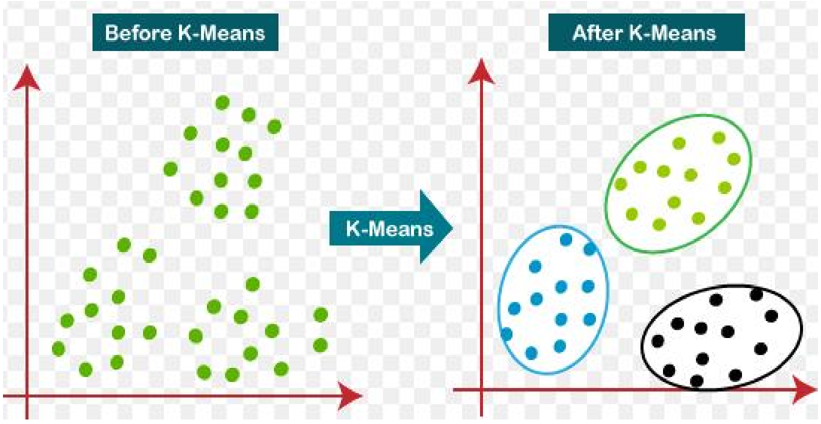

Figure 2. Example of KMC Algorithm

The technique is a pixel-driven image segmentation approach where initially seed points are selected. This segmentation technique, determines if pixels that are close to the initial seed points, should be added to the region by examining those pixels. Area splitting and region merging are iterative processes. Generally, the initial phase of region splitting, involves dividing an image into numerous regions as is feasible. The regions merged to produce segmented renditions of initial images presume that adjacent pixels within the same regions will have similar intensity levels.

Efficiencies of K-means implementations and their linear runtimes are two main advantages. The number of clusters in this study is equal to classes. The formula below determines Euclidean distances in order to determine cluster centroids.

$$d(i,j) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{2}$$

Here, x_i and y_i are two points in Euclidean n-space.

Algorithm 1: RGKMC algorithm

1. Select a number of clusters k from plant leaf database (D).

2. Set cluster centers µ1,...µk and segment plant leaf images.

3. Select k data points, place cluster centers on top of them, and then take beginning seeds from those clusters.

4. assigning points to clusters at arbitrarily, calculating the clusters' means, and finally locating the nearest pixels.

5. Compute distances between data points and cluster centres closest to them with Equation (2).

6. Confirm pixels for region grows with Equation (2) and select nearest pixels.

7. On comparisons of pixel similarities, closely connected seed areas are updated, and data points allocated to clusters.

8. Re-calculate cluster centers and find the affected regions based on luminosity and chromaticity.

9. Identify the earlier prediction probability of plant leaf images.

10. Stop on lack of fresh reassignments.

RKMC technique generates clusters of full pixels from the whole database set. Hence, selected pixels fill feasible values in regions. It is employed to clearly identify the initial phase of impacted images. Images are initially divided according to the healthy and damaged marks. The recently included pixels are verified to see if they have been assembled in the right class after applying RKMC on the plant leaf database from the resulting clusters. If it is in the right cluster, the given value is made permanent, after that the procedure is repeated for the next pixel. The following possible values will be assigned and assessed, if pixels are in erroneous clusters, and continued until the right clustering values for pixels are determined. As an outcome, this research increases the accuracy of previous plant leaf prediction, and it also uses the RKMC technique to raise image classification accuracy.

Feature Extractions Using GLCM

Following segmentation of the problematic area, attributes according to color, texture, and shape are then retrieved. The gray comatrix function in Matlab has been used to apply the GLCM approach to textures that take pixel spatial relationships into account (Mohanaiah, Sathyanarayana, & GuruKumar, 2013). For Grey level co-occurrence matrix (GLCM) implementation, the segmented RGB parts of affected leaves are converted to grayscale images. Furthermore, a colour co-occurrence matrix is created from each pixel map in order to collect statistical information about textures. Colour moments, or mean and root mean squares, are calculated after converting to HSI colour space in order to display colour dispersion. Texture attributes include correlation, homogeneity, contrast, energy, and entropy.

The impacted part's area is calculated as an element of form. If y, x indicates the column and row position indices of pixels, P_{xy} is an assessment of the likelihood that points match the elements of the GLCM, L implies distinctgray level counts, σ^2 stands for variances, m for pixels' mean values in specific segmented regions, i implies intensity values, I signifies average intensities P_i are probable intensity values, i_{xy} represent images' x and y intensities, and the following features are extracted:

Homogeneity: Homogeneity evaluates similarities amongst pixels. It has a fixed range of 0 to 1. Its component parts add up to one. For a diagonal GLCM, homogeneity equals 1. Combined probable occurrences of pixel pairs with defined spatial connections and grey level values r and c in images are represented by elements (r,c) in normalised GLCM.

$$\text{Homogeneity}=\sum_{i,j}\frac{P(i,j)}{1+|i-j|} \tag{3}$$

Where $1+|i - j|$ specifies i pixels are separated from j pixels and 1 is added for diagonal GLCM.

Correlation: Correlation depicts the relationship among pixels and their neighbors, with values ranging from -1 to 1. It calculates the image's intensity linear dependency.

$$\text{Correlation}=\frac{\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i\sigma_j} \tag{4}$$

Energy: It serves as a gauge for uniformity. For a constant image, energy has a value of 1, and its full range is from 0 to 1. Modify the template as follows to override the default.

$$E=\sum_{i,j=0}^{N-1}p_{i,j}^2 \tag{5}$$

Where p refers to GLCM matrix counts

Contrasts: To measure intensity contrasts, the equation below is used.

$$\text{Contrast}=\Sigma\Sigma(i-j)^2\,p(i,j) \tag{6}$$

Entropy: It is described as comparing the different intensity levels that each pixel can select. The measure of order in an image is called entropy. The entropy equation is,

$$\text{Entropy}=-\Sigma\Sigma\,p(i,j)\log p(i,j) \tag{7}$$

Mean: To determine images' average intensity levels, utilized means, total pixel counts are divided by sums of pixel values.

$$m=\sum_{x=1}^{L-1}i(P_i) \tag{8}$$

Intensity: The equation that follows calculates intensity,

$$i=\frac{R+G+B}{3} \tag{9}$$

Classification Using Weight based Artificial Neural Network (WANN) Algorithm

Here, the WANN algorithm is suggested for the classification and plant monitoring systems. ANN is employed for knowledge acquisition through learning. Input, output, and hidden layer, are the three stages of an ANN. The input layer gathers input data features, and after processing them, produces 'n' inputs. These procedures follow a set of weights. Weights are the data that neural network issues are solved with De Luna et al. (2017). After some useful hidden extraction, the hidden information is taken from the input layers and sent to output layers. WANN is utilized in this instance to classify the dataset. Training the plant leaf dataset using WANN and in testing state features are classified. The ANN is improved with Multilayer Perceptron (MLP) via sigmoid function which is called WANN. **Figure 3** shows the ANN architecture.

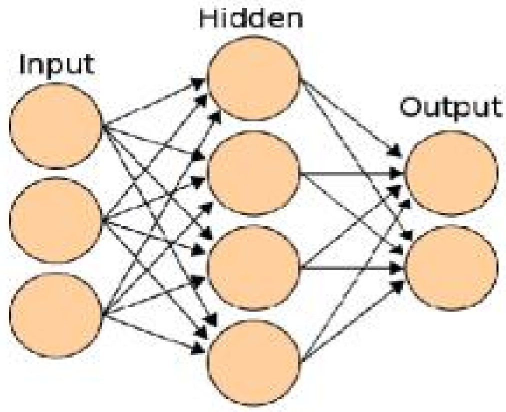

Figure 3. Architecture of ANN

Input Layer—The network's input layer contains the details of the chosen properties of plant leaves. At first, the data is a little undeveloped.

Hidden Layer—The fundamental function of the hidden layer is to transform the input layer's raw dataset data into a form that the output layer can utilize. One or more hidden levels may be present in the WANN design.

Output Layer—The output layer processes the data it receives from the hidden layer in order to deliver the intended outcomes (higher classifier accuracy and lower execution time).

The most popular Feedforward Neural Network (FNN) is aMLP model in which neurons are grouped in a cascade. A minimum of two layers make up MLP. In MLPs, there is no data transfer among the neurons that make up a layer; instead, the ith layer's outputs are inputs to the i+1th layer's neurons. The node counts in input layers correspond to characteristic counts in input vectors, whereas node counts in input layers correspond to output class counts.

$$Y_n = f(\sum_{m=1}^{h}(w_{nm}, f(\sum_{l=1}^{i} v_{ml} X_l + \theta_{vm}) + \theta_{wm} \tag{10}$$

$$n = 1,\ldots..,o$$

Where Y_n is the output layer's nth node output, X_l is the input layer's lth node input, w_{nm} are connective weights amongst nodes of m hidden and n output layers, v_{ml} represents connective weights amongst nodes of nodes of l hidden layers while θ_{vm} and θ_{wm} represent bias thresholds of output layers' nodes n, and hidden layers' nodes m, in transfer functions f.

Plant diseases to track and categorize IoT is necessary for sending imagegraphs and providing feedback. A suggested IoT device delivers plant images for disease classification and updates environmental variables including humidity, air temperature, and soil moisture.

This Internet of Things (IoT) supported gadget transmits environmental factors in real time, which is crucial to support plant health. This device provides information on soil pH, soil moisture, and air temperature. When considering plant health, these values are presented. It makes calculations for the soil moisture, humidity, and temperature. It serves as an example of how temperature and humidity affect plant disease. The temperature value obtained from the chosen environment aids in monitoring temperature differences concurrently, which is beneficial for the wellbeing and development of plants. The smart plant monitoring system can use IoT technologies. This is an appropriate way to assess the soil's qualities, which aid in the beginning of greater plant growth. It might aid in reducing water consumption.

The fact that WANN has no assumptions about class distribution inside the class is a major benefit of utilizing WANN. In WANN, if the weighted sum of the inputs is greater than a programmable cutoff value, also known as an activation function, the perceptron model transmits the output 1. Each neuron's output is the weighted sum of its inputs, with its bias. The weights and input neuron, accordingly, are denoted by "w" and "x".

$$\sum_{i=1}^{m} bias + \left(w^i x^i\right) \tag{11}$$

One of the functions mentioned in the activation function is the sigmoid function.

$$f\left(x\right) = sigmoid = \frac{1}{1+\exp\left(-x\right)} \tag{12}$$

The network weights are formed up of the connection weights and each neuron bias terms. The method of updating the network weights and determining the right weights and biase values is known as "neural network training," and it is thought to be the efficient way to get desired outputs from inputs.

This work aims to develop different farming uses and learn how to use rainwater gathering in this sector. The wellness of plants has a big impact on growth, output, and the standard of farm goods. The goal is to use sensors like humidity, temperature, and color to construct an automated system that can recognize the presence of disease in plants through variations in leaf health conditions. IoT Users can program the irrigation system to plants automatically by considering a number of parameters, eliminating the need for them to water the plants manually each day.

Algorithm 2: WANN

Input: Selected features from plant leaf dataset

Output: Better classification results

1. Procedure WANN (input, neurons, repeat)
2. Connect IoT device
3. Create input database
4. Input←database with all possible combinations
5. Train WANN
6. For input = 1 to end of input do
7. For neurons =1 to n do
8. For repeat = 1 to n do
9. Train WANN
10. WANN-storage ←save value with highest accuracy features
11. End for
12. End for
13. Check the temperature, humidity and soil moisture via IoT device
14. Moniot plant heath condition
15. WANN-storage←save best prediction of WANN depending on inputs
16. End for
17. Return WANN-storage → Result with best classification of WANN for every feature combinations

RESULTS

In this work, the plant monitoring system is implemented via MATLAB. The efficiency of the suggested GLCM-WANN algorithm is compared with the present SVM and ANN algorithms. The performance metrics are considered such as accuracy, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and technical difficulty. The suggested study categorizes plant illnesses by acquiring images using a Raspberry pi 3 enabled IoT-based device together with critical environmental information from various farms. Images are delivered to the database by utilizing this IoT device, where the RKMC technique is used to segment the impacted part after scaling the image to 256×256 and conducting preprocessing. The plant leaf dataset is taken from the Internet which is shown in **Figure 4**.

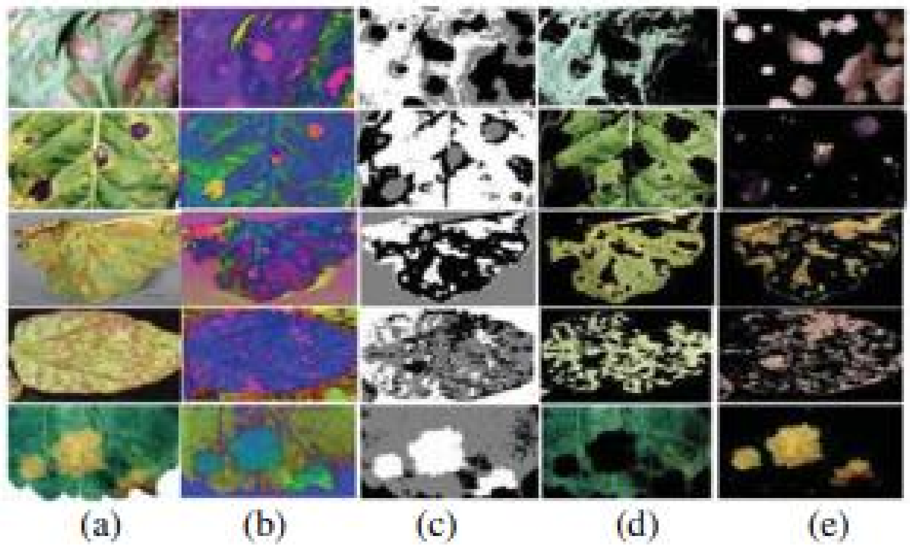

Figure 4. (a) Input Image, (b) Converted in HSI Color Space, (c) Labeled Image Clustered Index, (d) Uninfected Portions, (e) Segmented Infected Portions

Accuracy

The entire actual classification parameters ($T_p + T_n$) are estimated for the accuracy of the algorithm, which, is split by the total of the categorization parameters ($T_p + T_n + F_p + F_n$). It is determined as follows:

$$\text{Accuracy} = \frac{T_p + T_n}{\left(T_p + T_n + F_p + F_n\right)} \tag{13}$$

Here, T_p is true positive, T_n is true negative, F_p is false positive and F_n is false negative.

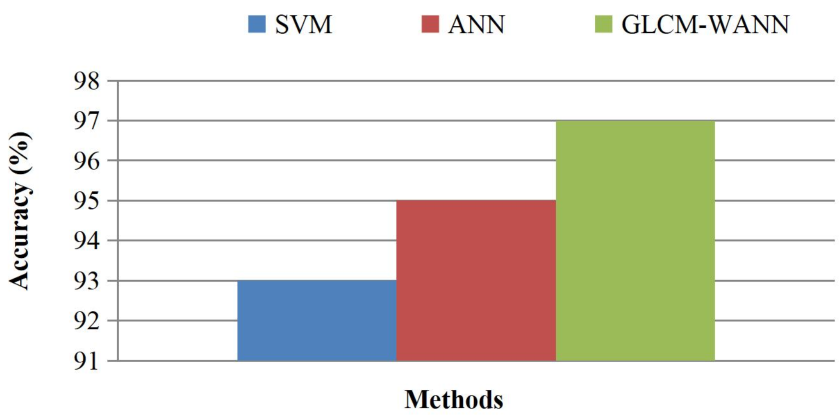

Figure 5. Accuracy

Figure 5 depicts the evaluation accuracies of methods where x-axis forms methods, and y-axis depicts accuracy values. The recommended GLCM-WANN algorithm outperforms standard approaches like SVM and ANN techniques in terms of accuracy for the presented plant leaf datasets. By using nearby pixels, the suggested region-growing centered segmentation technique enhances image quality. WANN extracts more informative features which increases the plant monitoring system performance. Training samples are used to create the color-based, region-based, and WANN segmentation algorithms. Ten seconds were allotted for training to obtain required accuracy for input plant image detections. The outcome concluded the suggested ensemble GLCM-WANN system increase the overall performance.

RMSE

Conventional performance assessments use RMSE as reference-based statistics. The following can be used to calculate RMSE amongst images:

$$RMSE = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\left(R(m,n) - F(m,n)\right) \tag{14}$$

$f(m, n)$ is the value of a pixel in the fused image at position (m,n).

RMSE is an indicator of image quality where high values denote low-quality merged images. If the fused image's RMSE value is smaller than the original image's, its value is preferred.

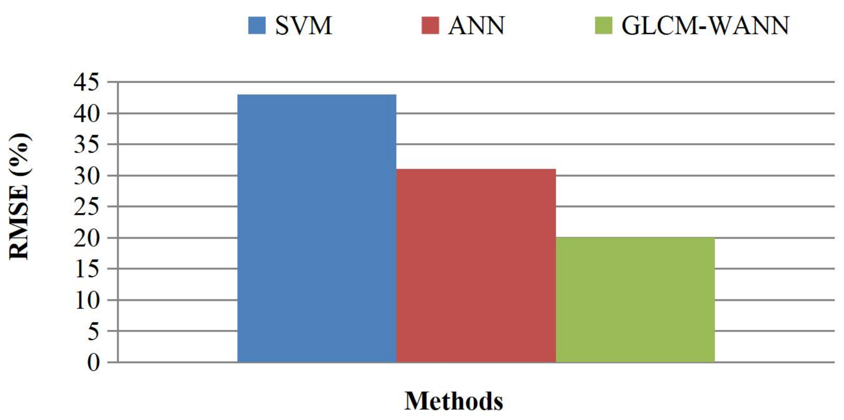

Figure 6. RMSE

It is clear from the previous **Figure 6** that the comparative metric is evaluated by means of RMSE utilizing present techniques. The method is displayed on x-axis, and the RMSE value is displayed on the y-axis. The current SVM and ANN methods have a larger RMSE than the suggested GLCM-WANN technique. To demonstrate the outcomes of applying the trained model to the identification of specified inputs in various test images, experiments are carried out. The trained model's accuracy in producing the predicted outputs is then determined by computing its per cent accuracy. The results show that the plant monitoring system operates more efficiently thanks to the use of the GLCM-WANN technique.

Mean Absolute Error (MAE)

The average difference between a dataset's significant values and its projected values is known as the MAE. The formula for the mean absolute error is

$$MAE = \frac{\sum_{i=1}^{n}\left|y_i - x_i\right|}{n} \tag{15}$$

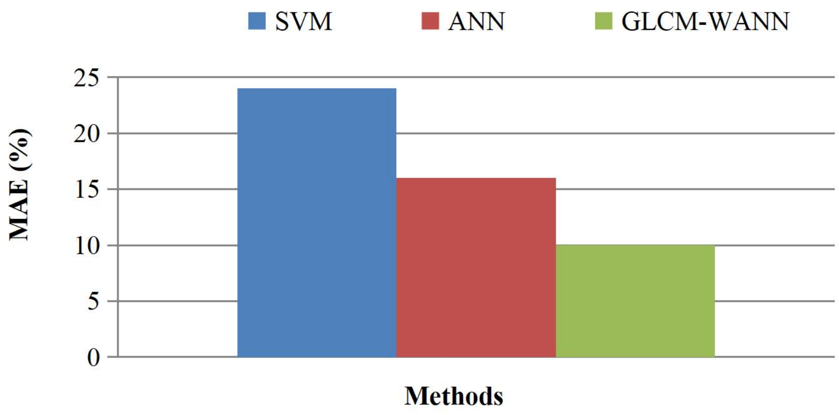

Figure 7. MAE

Figure 7 depicts evaluation accuracies of methods where x-axis forms methods, and y-axis depicts MAE values. The conventional SVM and ANN technique offers higher, but the suggested GLCM-WANN method offers lower MAE. In order to determine the ideal values for parameter tuning, feature extraction is also carried out using GLCM. To determine the optimal dataset division and WANN model, models are evaluated by using the testing dataset. When feature extraction and segmentation are carried out, WANN models perform noticeably better than when the default parameter values are used. The findings indicate that the introduced GLCM-WANN approach enhances the efficiency of the plant monitoring system.

Computational Complexity

When the suggested approach offers less computational complexity, it performs better.

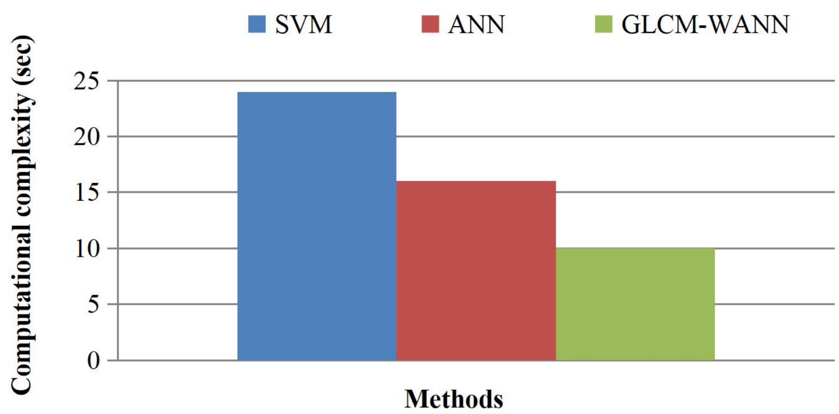

Figure 8. Computational Complexity

Present techniques are used to evaluate the computational complexity of the comparison measure from **Figure 8**. The x-axis displays methods, while the y-axis displays the computational complexity value. The current SVM and ANN approach has a larger computational complexity than the suggested GLCM-WANN method, which has a lower computational complexity. The existing SVM and ANN algorithms show the execution time of 24 sec and 16 sec as higher and the proposed GLCM-WANN was trained for 10 seconds to acquire required accuracy of given monitoring system for input images. Hence, proposed algorithm is better in terms of computational complexity rather than the existing algorithms. The findings indicate that the introduced GLCM-WANN approach enhances the efficiency of the plant monitoring system.

CONCLUSION

The GLCM-WANN technique is suggested in this study to enhance the effectiveness of plant monitoring system for provided plant leaf images. Data collection, segmentation, feature extraction, and classification are some of the four primary modules of this research. Images of plant leaves are first pre-processed to enhance their quality before being segmented using the RKMC technique. The GLCM technique is utilized for feature extractions, which effectively extract more useful elements. Then the plant monitoring and classification is performed via WANN algorithm. Therefore, categorizing diseases and examining environmental factors aid farmers in effectively monitoring plant growth for increased output. Experimental findings indicate that, compared to the existing methods, the suggested GLCM-WANN algorithm offers improved accuracy, reduced RMSE, MAE, and execution time. In future, it can be developed autonomously by applying the technology to unmanned Ariel vehicles or drones.

CONFLICT OF INTEREST

The authors have no conflicts of interest to declare. All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report.

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