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An Efficient Approach for Coffee Leaf Disease Classification and Severity Prediction

Santhosh Kumar S[1]* **B.K Raghavendra[2]**

[1]*Department of Information Science & Engg, Don Bosco Institute of Technology, Bengaluru, Visvesvaraya Technological University,Belagavi Karnataka- 560074,India*
[2]*Information Science and Engineering,Don Bosco Institute of Technology, Bengaluru, Visvesvaraya Technological University, Karnataka 560074,India.*
* Coresponding author's Email: santhoshkumars.cs@gmail.com

Abstract: Coffee is used by about two-thirds of the population in their daily life in one way or the other. However, their significance is greatly affected by the diseases that occur in the coffee leaves. This work proposes a colour-based filtering technique to determine the diseases that arise in the coffee leaves. Initially, the image obtained from the dataset is pre-processed, and contrast enhancement takes place using top–hat transform-contrast limited adaptive histogram equalization (THT-CLAHE) to enhance the visual characteristics. Next, the background present in an image is removed and the leaf is filtered depending on its colour into healthy and diseased leaves via supremum distance-fuzzy C means (SD-FCM) machine learning technique. Then, to obtain minute details, patches are extracted from the diseased leaf. Afterward, by employing double adaptive weight strategy-mexican axolotl optimization (DAWS-MAO), feature extraction is carried out followed by the selection of crucial features. For the classification of leaf diseases, the selected features are further fed into the tuned hard sigmoidal-multi-layer perceptron neural network (Tuned HS-MLPNN). In the end, based on the area of disease prediction, the severity of the disease thus classified is predicted using machine learning. The proposed Tuned HS-MLPNN method achieves the classification accuracy of 98.65%. Finally, the superiority of the proposed model is analysed with the Support Vector Machine (SVM), Naïve Bayes (NB), and artificial neural network (ANN).

Keywords: Disease prediction, Severity, Classification, Feature, Extraction, Coffee leaf, Machine learning.

1. Introduction

Coffee, which acts as a significant source of income for the countries of its production, is the second most traded and the most used drink after water in the commodity [1]. Thus, it is essential for farmers to continuously monitor the quality of coffee production to meet the economic status of developing countries [2]. Disease, which causes characteristic damage to the plant, is one of the significant factors that affect the quality and production of coffee. The disease commonly occurs in the leaf part of coffee production. Thus, it is necessary to determine the symptoms, their severity, and the causative agents for effective management of the disease that arises in the coffee plant [3]. Via recurrent observation of the flowers, stems, leaves, and fruits of the coffee plant, disease identification is usually done by farmers [4]. Generally, in coffee production, the leaf of the coffee plant acts as a significant source. Thus, to reduce the losses that occur in the coffee leaves, early detection and prevention of diseases are crucial. Recurrent monitoring and identification of disease are not possible in the case of large-scale coffee production, which in turn results in a severe outburst of the disease [5]. Now, farmers use poisonous chemicals to eradicate the diseases caused by bacteria, fungi, or pests to maintain coffee production which in turn cause numerous health hazards. Hence, in the coffee leaf disease classification, disease identification, and control measures are hot topics [6].

Previously, with the help of agricultural

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organizations, disease prediction and classification were carried out which in turn was not effective due to the limited availability of human and logical resources [7]. For the effective prediction and classification of the diseases in the coffee leaf, various techniques were utilized. Data collection, effective handling of the changing weather condition, and sprinkling pesticides periodically are the steps adopted by farmers in conventional coffee production [8].

However, the classification accuracy was affected since the techniques couldn't offer better outcomes. Thus, machine learning (ML) approaches are adopted. To make appropriate decisions and predictions depending on new data, ML techniques are generally trained with the relevant data. Some of the ML approaches utilized for the classification phenomena are artificial neural networks (ANN), support vector machines (SVM), decision trees (DT), etc. Machines make a decision in ML regarding the diseases that arise in the coffee plant on behalf of humans [9]. But the existing research methodologies classified the coffee leaf disease by processing only the region of interest (ROI) areas, which resulted in inefficient disease classification phenomena. Thus, by using the T-HS-MLPNN classification technique, color-based filtering of the healthy and diseased leaves is proposed. The most adapted neural network for better classification and easy prediction of diseases is MLPNN [10].

1.1 Problem statement

Despite the various advantages offered by traditional methodologies, there exist certain downsides that are enlisted below,

- In existing research techniques, severity prediction is based on the pixel count produced invalid results.
- The presence of a background in an image resulted in inherent bias during feature extraction.
- Accurate disease prediction is not possible, since the coffee leaf images are taken under different illumination conditions.

Hence, to alleviate the afore-said issues, this paper proposes color-based filtering of healthy and diseased leaves via patch extraction using the T-HS-MLPNN technique and its main contributions are,

- Here, color-based severity prediction is done.
- The background subtraction performed in this work resulted in the effective extraction of crucial features.
- The patch extraction phase proposed in this work provided minute details to aid in the better disease classification process.

The remaining part is arranged as: the literature survey is evaluated in section 2; the proposed methodology is elucidated in section 3; the result and discussion are exhibited in section 4; the paper is wrapped up with the future work in section 5.

2. Literature Survey

Naïve Bayes algorithm [11] is not able to perform prediction when the dataset has a categorical variable and it assumes that all features are independent, random forest [12] uses many decision trees, it requires lot of memory and algorithm suffers from overfitting that directly affect the overall forest. Decision tree [13] requires more time to train the model and it uses unstable algorithm when there is small variation in the data. Regression model [14] is the machine learning (ML) technique that have been focused on the coffee plants disease prediction. Peripheral support is essential for this model, which also takes an extensive time to make a valuable decision. Moreover, in the accurate as well as timely detection of coffee leaf disease prediction, soft computing played an important role. However, they lack efficiency and have a lower success rate [15]. The authors [16] propounded a real model that could slice and classify several sorts of leaf lesions and estimate the stress severity in coffee leaves utilizing a convolution neural network (CNN). But this system required regular internet for its operation. The proffered a strategy [17] that created masks for deep leaves classification. After that, exploiting semi-automated segmentation (SAS) of leaves along with disordered regions, the consequences were labelled and are able to mount segmentation accuracy. However, the author cited glitches regarding several misclassified cases of illuminated areas that were further predictable as infections. Inspected biotic stresses [18] in coffee leaves for estimating the few-shot learning's performance in classification along with severity estimation tasks. The training time required by triplet networks model was higher when analogized to others. The authors [19] explored an approach that employed transfer learning and the number of pre-trained CNN models that abstracts deep channel features as of the coffee plant leaves' images. finally, the mined deep features were collected by numerous DL models that conquered higher validation. Yet, the DL essential large amounts of information for training the network. Surveyed the vegetation indexes [20] of healthy coffee leaves owing to necrosis, which instigated early leaf falling and diminished the plant's harvest and lifespan. The images were attained from the farm directly and computed for spectral bands exploiting Raster Calculator, which was effective. Still, it was not appropriate to a wide variety of datasets. [21] noticed coffee leaf disease, namely Hemileiavastatrix, which was owing to climate variation that mounted the cases of this disease. This disease was found due to employing an artificial intelligence-centric application. Yet, model accuracy was much lower and also it focused on one disease only. The authors [22] extended a DL-centric object detection method that achieved k-means clustering and RGB value quantification. It attempted to spot the coffee leaf disease's severity and then the infection phases were also predicted. But, with less indications of the disease, five clusters conquered a more favourable outcome since the symbols of the diseases were minor and required a more substantial number of clusters to be detected. [23] explicated transfer learning along with several pre-trained CNN models that are exhibited for mining deep features as of coffee leaves' images. Deep features were takeout deeply; also, the ensemble architectures were accomplished for detecting the classification. But these models required a greater number of training data. The authors [24] presented a Deep Learning centered semantic segmentation technique for disease identification in coffee leaves. For efficient mapping of features, the input image obtained was fed into the CNN. Hence, background complexity was avoided effectively by the usage of semantic segmentation. Nevertheless, overlapping lesions weren't classified. The authors [25] developed a probabilistic patch model for rust disease prediction in coffee leaves. Here, for within-patch transmission, probabilistic cellular automated model (PCMA) was utilized; also, by employing canopy cover-based spore movement (CCSM), the between-patch transmission was modelled. However, this technique just aimed at the coffee rust disease, whereas other disease types were not considered. The authors [26] explored a '2' stage DL segmentation technique for disease quantification in coffee leaves. To extract the leaves from the complex background, '3' segmentation networks were wielded. The stages involved were location, identification, and Lesion area determination. Hence, the utilization of the '3' stage network helped in the effective identification of the lesion in coffee leaves. But the severity estimation was not accurate and resulted in increased computational complexity. The author [27] developed a few-shot learning (FSL) centered methodology for the stress classification of coffee leaves. Thus, the data sparsity problem was avoided by the usage of the meta-learning paradigm. But the system's ability was highly limited by the number of training data. Research in [28] recommended deep-transfer learning (DTF) centered disease identification technique in coffee leaves. Here, for the disease identification process, ImageNet and Inception module was utilized. By using ImageNet, the weight values were initialized. But infeasible results were produced by the disease prediction in the particular area of the coffee leaf. The authors [29] explored convolutional autoencoder (CAE), and CNN-based disease detection techniques. Here, for the effective classification of healthy and diseased leaves, the input data was initially encoded into a compressed domain and fed into the CNN. Hence, the disease identification time was minimized by the usage of compressed representations. Yet, the major downside was the requirement of a prominent loss function for reconstruction loss. The authors [30] examined ResNet-deep neural network (DNN) for coffee leaf disease classification. The several stages involved were pre-processing, background subtraction, contrast enhancement, and classifications. Hence, the system's efficacy was augmented by the usage of diverse activation functions in several layers of the deployed DNN. Yet, for real-world applications, this system was not suitable. Research in [31] explored an ML-centric system for the effective detection of coffee leaf disease. Primarily, the leaves were resized and the input image's quality was improved by utilizing histogram equalization (HE). Followed by the effective extraction of the leaf boundary, the image was clustered using KMA and fed into support vector machine (SVM) for classification. Hence, the disease in coffee leaves was minimized by the usage of cutting-edge techniques. But ineffectual outcomes were generated by the disease prediction centered on the leaf boundary. The authors [32] built a hybridized neutral methodology for the effective determination of coffee leaf disease. Several stages involved were pre-processing, feature extraction, feature selection, and classification. Hence, to assist in the disease detection process, the strains were analysed effectively. This system failed to determine the disease in coffee leaves with no lesions in them. The authors [33] deployed Multispectral radial characteristics centered detection of disease in coffee leaves. Here, grounded on the average leaf growth percentage, the leaves were detected employing classification techniques. Also, for the effective detection of disease, the non-destructive method was wielded. Hence, by employing this system, the vascular tissue characteristics were detected effectively. However, this system doesn't aim for biotic stress, which minimized coffee production. The author [34] explored the chal lenges in coffee leaves disease segmentation and identification on various factors that would influence the efficiency of image analysis techniques. The authors [35] addressed research issues to develop an efficient approach to find and diagnose the plant diseases would assist agricultures and pathologist in prospect exploration. The paper depicts the importance of image processing in agriculture field and considering the type of disease for further research work. The authors [36] proposed a JFCM-centric multi-disease prediction in coffee leaves with a reliable G-YOLOv3 segmentation. For image enhancement, the PRUF technique is utilized. also, for the coffee leaf disease prediction, JFCM is wielded. In the comparative analysis, the prediction of multiple diseases in the coffee leaves attained a 98% accuracy level, which is higher than the prevailing works.

3. Proposed color-based filtering of coffee leaf disease

In the agricultural field, significant changes are brought about by the recent advancements in technology. The quality and quantity of plants are hugely affected by the disease in modern farming. Thus, to assess the severity of the disease and also to measure coffee production, color-based filtering of the diseased leaves is proposed. In Fig. 1 the structure of the proposed framework is displayed.

3.1 Pre-processing

Primarily, the image required for the effective prediction of diseases in the coffee leaves is obtained from the coffee leaf image dataset. Now, these images undergo pre-processing. Since the raw image obtained from the dataset contains unwanted noise, it is necessary to pre-process such images to make them useful for further analysis. The two different pre-processing steps involved in the disease prediction process are:

(i) Noise removal

The input coffee leaf image $(f(x,y))$ contains some noisy components (n_0) within it and is modelled in (2). Here, noise is the intensity variations that occur during the image acquisition

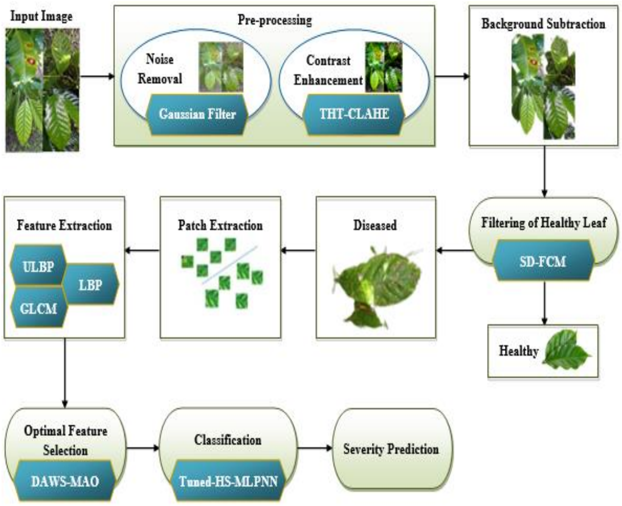

Figure. 1 Structure of the proposed framework

process. Thus, Gaussian filter (GF) is utilized in this work to alleviate the noisy components present in an image without adversely affecting its features. The most popular denoising approach is the Gaussian filter. It removes noise and details related to the noise by applying the Gaussian function. It also removes the noises due to the image taken in low light and makes the edges smooth. The mathematical formulation for the Gaussian function $\left(G^{(\bar{f})}\right)$ is given below.

$$G^{(\bar{f})} = \frac{1}{\sqrt{2\pi\eta^2}} \exp^{-\frac{f(x,y)^2}{2\eta^2}} \tag{1}$$

$$f(x,y) = f_{im}(x,y) + n_0 \tag{2}$$

Where, $f_{im}(x,y)$ implies the image component present in the input. Hence, the output obtained after noise removal is $f^*(x,y)$.

(ii) Contrast enhancement using THT-CLAHE

After suppressing the unwanted noises present in an input image, contrast enhancement takes place. To enhance the quality of $f^*(x,y)$, contrast enhancement is generally carried out to obtain every fine detail present in it. Here, by employing THT-CLAHE, contrast enhancement is performed. Initially, the noise-removed image $(f^*(x,y))$ is split into equally-sized regions. The resultant image obtained is defined in (3)

$$f^*(x,y) = g(1) + g(2) \tag{3}$$

Here, $g(1)$and $g(2)$ implies rectangular-shaped continuous and non-overlapping regions.

3.2 Background subtraction

The mean background intensity $\left(B\left(I^{(m)}\right)\right)$ is utilized for replacing similar background areas after the removal of the background present in the contrast-enhanced image $\left(I^{(m)}\right)$. Hence, the resultant image $\left(\bar{B}^{i}\right)$ is defined as,

$$\bar{B}^{i} = \bar{B}^{1}, \bar{B}^{2}, \bar{B}^{3}, \ldots, \bar{B}^{I} \tag{4}$$

Where, $i = 1,2,3,\ldots,I$ implies the I −number of background-subtracted images.

3.3 Filtering of healthy leaf by SD-FCM

The most widely accepted technique used for the effective filtering of the diseased leaf is termed fuzzy C means (FCM) clustering. To calculate the distance between pixels and the initial centroid, it uses euclidean distance (ED). The supremum distance (SD) is used instead of ED since the calculation of ED is complex and it degrades the clustering accuracy. This amalgamation of SD in the conventional FCM is renamed as SD-FCM. The SD-FCM filtering is detailed as follows,

- Initially, the pixel (j) present in the background subtracted image $\left(\bar{B}^{i}\right)$ is discussed below,

$$\bar{B}_{j}^{i} = \left\{\bar{B}_{1}^{i}, \bar{B}_{2}^{i}, \bar{B}_{3}^{i}, \ldots, \bar{B}_{J}^{i}\right\} \tag{5}$$

Here, J implies the number of pixels in the image $\left(\bar{B}^{i}\right)$.

- Then, the random selection of $N -$ number of cluster centroids (C^{n}) from $\bar{B}_{j}^{i}$ takes place and is modelled as,

$$C^{n} = C^{1}, C^{2}, C^{3}, \ldots.., C^{N} \tag{6}$$

Here, $n = 1,2,3,\ldots,N$ points to the $N -$ number of cluster centroids.

- Next, the Supremum Distance $\left(SD\left(\bar{B}_{j}^{i}, C^{n}\right)\right)$ is evaluated between the initial pixels $\left(\bar{B}_{j}^{i}\right)$ and the randomly selected cluster centroids (C^{n}). The distance evaluation is detailed below.

$$SD\left(\bar{B}_{j}^{i}, C^{n}\right) = \lim_{w\to\infty}\left(\sum_{j=1}^{J}\sum_{n=1}^{N}\left|\bar{B}_{j}^{i} - C^{n}\right|^{w}\right)^{w^{-1}} \tag{7}$$

Here, w implies a supremum constant.

- Using the SD computation, the objective function (Obj^{ε}) of the SD-FCM is computed using the upcoming expression,

$$Obj^{\varepsilon} = \sum_{j=1}^{J}\sum_{n=1}^{N}\left(\omega^{jn}\right)^{a} \cdot \left[SD\left(\bar{B}_{j}^{i}, C^{n}\right)\right]^{2} \tag{8}$$

Where, a implies the fuzzy control parameter and ω^{jn} symbolizes the membership function.

- The fuzzy membership function $\left(\omega^{jn}\right)$ is defined by,

$$\omega^{jn} = \sum_{l=1}^{L}\left\{\frac{\left\|\bar{B}_{j}^{i} - C^{l}\right\|}{\left\|\bar{B}_{j}^{i} - C^{n}\right\|}\right\}^{\left[\frac{-2}{a-1}\right]} \tag{9}$$

Here, C^{l} delineates the cluster centroid selected from C^{n}. Hence, until the following condition is met, the process is repeated by the effective optimization of the objective function (Obj^{ε}) and reassignment of the cluster centroids.

$$\left\|\omega^{jn}(L) - m^{jk}(L+1)\right\| \leq Q \tag{10}$$

Here, Q implies a constant and L signifies the number of iterations. In the end, the diseased and healthy leaves are separated based on the distance and objective function for further identification and analysis.

Pseudocode of proposed SD-FCM

Input: Background subtracted image $\bar{B}^{i}$
Output: Filtered leaves
Begin
  Initialize pixels B_{J}^{I}, N
    For input pixels **do**
     Determine Centroid (C^{n})
     Perform $\lim_{w\to\infty}\left(\sum_{j=1}^{J}\sum_{n=1}^{N}\left|\bar{B}_{j}^{i} - C^{n}\right|^{w}\right)$ with Supremum distance
     Compute objective function Obj^{ε}
     Update ω^{jn}
     Update cluster until $\left\|\omega^{jn}(L) - m^{jk}(L+1)\right\| \leq Q$
   End For
   Return filtered pixels
End

3.4 Patch extraction of diseased leaf

Then, to classify the disease, effective processing of the diseased leaf by means of patch extraction takes place. By extracting patches, even minute features of the diseased leaf can be processed. Thus, to evaluate minor changes in the coffee leaf, the patch extraction approach is adopted, and the steps involved in the patch extraction phase are detailed further down.

- Primarily, the mean value of each pixel in the extracted patch of the diseased leaf is determined.
- Next, the sorting operation is performed. Here, the patches are sorted depending on the energy of each pixel contained in it.
- Finally, the patches are reshaped into columns to form $\hat{\varphi}_u^d$.

The process involved in the patch extraction $\left(P(\varphi^d)\right)$ phenomenon is detailed as,

$$P(\varphi^d) = P(\hat{\varphi}_u^d|u)^{1/v} \tag{11}$$

Here, $\hat{\varphi}_u^d$ implies the extracted patches from the diseased leaf (φ^d), v depicts the size of the patch, and is greater than 0. Next, by multiplying the probability of the neighbouring patches, the similarity between the patches extracted (δ) is obtained and is formulated below,

$$\delta = \Gamma\left(P(\hat{\varphi}_{u_\hbar}^d|u_\hbar)^{1/v_\hbar}\right) \tag{12}$$

Where, Γ implies the product of the patch probability between $\hbar$ neighbouring patches. The $b-$ number of patches extracted from the diseased leaf (ρ^v) is modelled as,

$$\rho^v = \rho^1, \rho^2, \rho^3, \ldots, \rho^b \tag{13}$$

3.5 Feature extraction

After the extraction of patches from the diseased leaf, feature extraction takes place for the classification of coffee leaf disease. The extraction of the most dictating and delicate characteristics of an image is done by means of this process. It is described as follows.

(i) ULBP

The ULBP $\left(ULBP(\rho^v)\right)$ is responsible for obtaining local and global texture details from the central and diagonal pixels. It provides minute details from the vascular tissue of the leaf by reducing computational complexity. The area is one of the crucial features obtained using ULBP. It is formulated as,

$$ULBP(\rho^v) = \sum_{v=1}^{v/2} D\left(\rho^v, \rho^{v+(v/2)}\right) \cdot 2^{v-1} + 2^{(v/2)+1} D(\rho^0 - \rho^v) \tag{14}$$

(ii) LBP

LBP is used to extract the texture feature from the extracted patches of the diseased leaf. It concatenates the normalized histograms of all pixels. The resultant binarized pixels $\left(LBP(\rho^v)\right)$ are expressed below,

$$LBP(\rho^v) = \sum_{v=1}^{b} 2^{v-1} D(\rho^v - X) \tag{15}$$

Here, $D(\rho^v)$ implies the pixel intensity and X signifies the center pixel of an image.

(iii) GLCM

GLCM, which determines the texture feature by computing the relationship between each pixel in an image, is the most widely used traditional feature extraction technique. Some of the texture features extracted are contrast, skewness, homogeneity, mean, entropy, etc. Hence, the $t-$ number of features extracted (y_z) via the above descriptors is modelled as,

$$y_z = (y_1, y_2, \cdots\cdots, y_t) \tag{16}$$

3.6 Optimal feature selection via DWAS-MAO

The selection of optimal features takes place using the DWAS-MAO algorithm from the extracted features. A metaheuristic algorithm inspired by the ability of the axolotls to alter their colour and body parts to protect them from predators is Mexican axolotl optimization (MAO). The axolotl is known for its extraordinary ability to regenerate amputated limbs and other organs and tissues of the body. The crucial characteristic of the axolotl is the ability to regenerate their limbs with all their bones, muscles, and nerves within a week in suitable places. The four different stages involved in MAO are larvae to adult transformation, Injury and restoration, reproduction, and assortment. Nevertheless, the ability of the axolotls to change their colour is limited, which affected the convergence rate, and also, the random behaviour of the axolotl to regenerate its body part resulted in the local optimum problem. Thus, to alleviate this issue, a double adaptive weight strategy (DAWS) is imposed. This introduction of DAWS in the existing MAO is the so-called DAWS-MAO.

Step 1*: *Initialization

Initially, all the axolotls (Extracted features) (y_z) in the $D-$ dimensional search space are initialized and formulated as,

$$y_z = (y_1, y_2, \cdots\cdots, y_t) \tag{17}$$

Step 2: Fitness determination

After successful initialization, each individual in the population is assigned male or female and their fitness (Classification accuracy) value is determined. The fitness determination $\left(f(y_z)\right)$ is expressed as,

$$f(y_z) = \vartheta(y_1, y_2, y_3, \ldots, y_t) \tag{18}$$

Here, ϑ implies the fitness function.

Step 3: Adult transformation

Usually, the male axolotl lives in water and undergoes an adult transformation with the proper adjustments in their body parts. The one with the best fitness value is provided with better camouflage using DAWS. One of the weight strategies added to improve the global search ability is $\varpi^{(1)}$, which is defined as,

$$\varpi^{(1)} = \left(1 - \frac{\vartheta(y_z)}{z}\right)^{1-\tan\left(\pi\times(rnd-0.5)\right)} \tag{19}$$

Step 4: Accident and restoration

Now, adults have the ability to move in the water. During their movement, there is a possibility of getting hurt. It results in the loss of certain body parts of the axolotl. In the proposed approach, $\varpi^{(2)}$ is utilized for the effective restoration of their body parts and is defined as,

$$\varpi^{(2)} = \left(2 - 2\times\frac{\vartheta(y_z)}{z}\right)^{1-\tan\left(\pi\times(rnd-0.5)\right)} \tag{20}$$

Here, rnd implies the random variable.

Step 5: Reproduction and Assortment

Next is the reproduction stage. For reproduction, the most fitted male is selected for the respective female using the tournament selection technique. Here, for egg formation, the genetic information of both the male and female axolotl is utilized. Then, hatching begins. The assortment is initiated once hatching is done. The newly formed individuals compete with their parents in the assortment phase. The parent axolotl will be replaced by their ward if the fitness value of the new individual is better than their parents. The process is repeated until the optimal solution is obtained and the optimal features (ζ^s) obtained are modelled as,

$$\zeta^s = \zeta^1, \zeta^2, \zeta^3, \ldots., \zeta^S \tag{21}$$

Here, $s = 1,2,3,\ldots,S$ implies the $S-$ number of selected optimal features.

Pseudocode of proposed DAWS-MAO

Input: Features y_z
Output: Selected features

Begin
Initialize MA population (extracted features), population size (t), D, $iter_{\max}$
Set $iter = 1$
While $(iter \leq iter_{\max})$ **do**
Calculate $fit(ma)$
Perform sub-population classification
Perform adult transformation state
Select the best axolotl using $\left(1 - \frac{\vartheta(y_z)}{z}\right)^{1-\tan\left(\pi\times(rnd-0.5)\right)}$ of DAWS.
Perform accident and restoration process when the $p(M,F)$ is damaged
Perform reproduction and assortment for young larva
If $(p(M,F) > rand)$**{**
Update position
} Else {
Change colour
}
End If
End While
$iter = iter + 1$
Return optimal feature (ζ^S)
End

3.7 Classification using Tuned-HS-MLPNN

For the effective classification of disease, the selected features are then fed into the Tuned-HS-MLPNN classifier. MLPNN is a feed-forward neural network with an input layer, hidden layer, and output layer. It is the most widely used neural network for the easy prediction of diseases in coffee leaves because of its highly flexible nature to map the input to its corresponding output. But, the fully connected nature of the MLPNN increased the parameter required for the effective training of MLPNN which in turn increased the training time of the network. To reduce parameter requirement, a tuned intensification operator and hard sigmoidal activation function are used and thereby the training time of the network is also reduced with the corresponding reduction in the computational cost. Also, to trigger the neurons in the MLPNN, the HS activation function is used. This amalgamation of the tuned intensification operator and HS activation function in the MLPNN is the so-called Tuned-HS-

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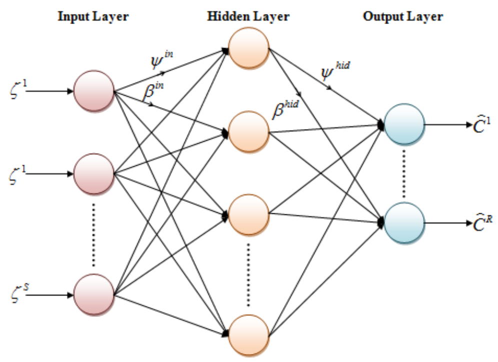

Figure. 2 Structure of proposed Tuned- HS-MLPNN

MLPNN. In Fig. 2, the architecture of Tuned-HS-RMLPNN is cited.

The process involved in Tuned-HS-MLPNN is detailed below,

(i) Input layer: The optimal features are given as input to the input layer. Moreover, to initiate the classification process, each layer is provided with numerous neurons by utilizing the bias and the weight values provided. The input applied to the input layer is forwarded to the hidden layer $(\Im^{in})$ and is modelled as,

$$\Im^{in} = \sum_{s=1}^{S} \zeta^{s} \psi^{in} + \beta^{in} \tag{22}$$

Where, ψ^{in} and β^{in} implies the weight and bias values in the input layer.

(ii) Hidden layer: Then, effective processing of the features takes place in this layer. All the node in the hidden layer is highly interconnected with all the other nodes in the network. A tuned intensification operator $(\aleph^{r})$ is used to tune the parameters in the network. It splits the incoming features into three different channels with the consecutive determination of the threshold value and membership function of each channel. Hence, the output obtained at the hidden layer (H^{in}) is,

$$H^{hid} = \Omega\left(\sum_{s=1}^{S} (\Im^{in} * \aleph^{r}) \psi^{hid} + \beta^{hid}\right) \tag{23}$$

Here, Ω implies the hard sigmoidal activation function, and ψ^{hid}, β^{hid} signifies the weight values and bias function of the neural network.

(iii) Hard Sigmoidal (HS) activation function: The mathematical formulation for the HS activation function is expressed below,

$$\Omega = \max\left(0, \min\left(1, \frac{\left(\sum_{s=1}^{S} (\Im^{in} * \aleph^{r}) \psi^{hid} + \beta^{hid}\right)}{2}\right)\right) \tag{24}$$

(iv) Output layer: The output obtained at the output layer of Tuned- HS-MLPNN (O^{out}) is represented.

$$O^{out} = \Omega\left(\sum_{s=1}^{S} H^{hid} \psi^{out} + \beta^{out}\right) \tag{25}$$

In the end, the error that arises in the network is determined as,

$$\bar{\varepsilon} = \frac{1}{S} \sum_{s=1}^{S} (\widehat{D} - O^{out}) \tag{26}$$

Here, $\widehat{D}$ implies the desired output and O^{out} signifies the output obtained. Hence, the classifier classifies various diseases $(\mathcal{C}^{q})$ that occur in the coffee leaf. To predict the severity of the diseases in the coffee leaf, this classified result will further be used and the classified result is,

$$\mathcal{C}^{q} = \mathcal{C}^{1}, \mathcal{C}^{2}, \mathcal{C}^{3}, \ldots, \mathcal{C}^{R} \tag{27}$$

Here, $q = 1,2,3, \ldots, R$ depicts the $R-$ number of classified diseases.

3.8 Severity prediction

After classification, severity prediction taking place. The depending on the area (extracted feature) of the extracted region, the severity of the disease in the leaf is predicted. The severity prediction $(\wp)$ is detailed below.

Thus, it is considered as less severe if 25% of the total leaf area is affected. In case, 25% to 50% of the total area in the leaf is affected then it is considered as medium severe, whereas if the area affected is greater than 50%, then it is considered as highly severe and needs immediate treatment. The four different classes of disease predicted by the proposed method are Miner, Rust, Phoma, and Cercospora. Thus, the proposed methodology effectively determines the disease and its severity based on the area.

$$\varphi = \begin{cases} low\ severe\ if\ the\ disease\ symptoms < 25\%\ total\ leaf\ area \\ Medium\ severe\ if\ the\ disease\ symptoms\ 25\%\ to\ 50\%\ of\ total\ leaf\ area \\ Highly\ severe\ if\ the\ disease\ symptoms > 50\%\ of\ total\ leaf\ area \end{cases}$$

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4. Results and discussion

Regarding performance metrics, the proposed technique's superiority is evaluated. The proposed methodology is implemented in the working platform of PYTHON.

4.1 Database description

In this section, we deliberate the experimental results obtained by the Tuned-HS-MLPNN methods in the context of plant disease classification and severity estimation. Also, we present the datasets used in the research and discusses the results. In this research work we were used the dataset developed by Krohling [37]. The data consists of images of coffee leaves affected by common biotic stresses. The author divides the data into Leaf dataset and symptoms dataset. The labelled dataset has 1685 images representing the major stress and its severity. In this research the dataset is divided into four biotic stress classes are leaf miner, rust, brown leaf spot and cercospora leaf spot, one healthy class. Fig. 3 shows sample examples of images from the dataset. These images are mainly for classification of different types of disease that occurs in the coffee leaves.

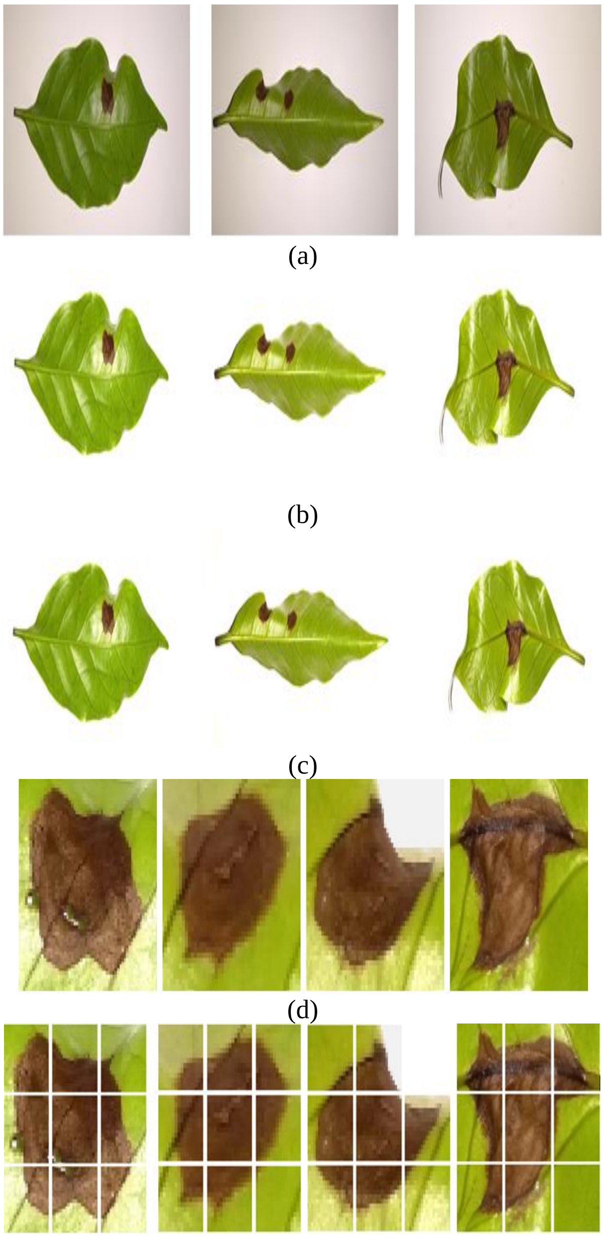

Figure. 3: (a) Sample images from the coffee leaf image dataset and the output attained for different steps such as, (b) pre-processing, (c) Background subtraction, (d) Filtering of healthy and diseased leaf, and (e) patches extracted.

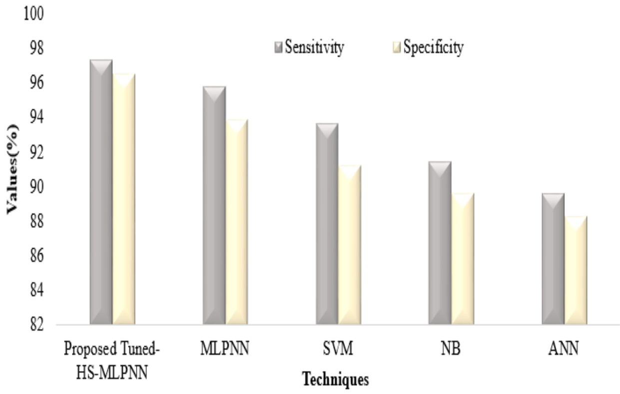

Figure. 4 Performance measurement of the proposed technique.

Table 1. Comparative assessment of the proposed Tuned-HS-MLPNN

Techniques	Performance metrics (%)		
	Precision	Recall	F-Measure
Proposed Tuned-HS-MLPNN	98.13	97.52	93.99
MLPNN	95.23	94.21	94.16
SVM	93.18	93.52	91.89
NB	90.01	91.93	89.48
ANN	88..52	89.67	86.67

4.2 Performance measure of the proposed Tuned-HS-MLPNN

The performance of the proposed method is evaluated and compared with the existing methods are MLPNN, support vector machine (SVM), Naïve Bayes (NB), and artificial neural network (ANN).

The proposed Tuned-HS-MLPNN's performance measure regarding sensitivity and specificity is depicted in Fig. 4. The proposed Tuned-HS-MLPNN provides better performance by achieving 97.37% of sensitivity, and 96.58% of specificity, whereas the existing MLPNN, SVM, NB,

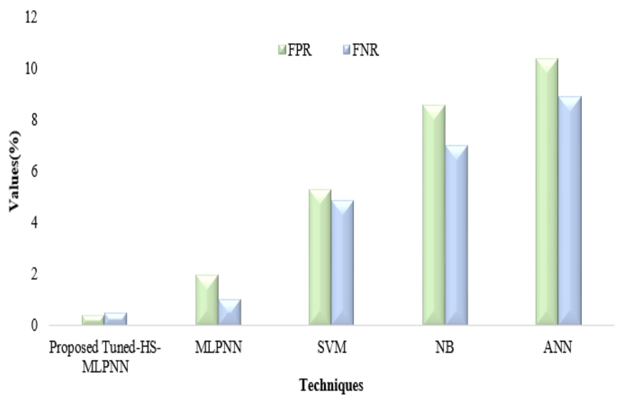

Figure. 5 Graphical representation of proposed Tuned-HS-MLPNN

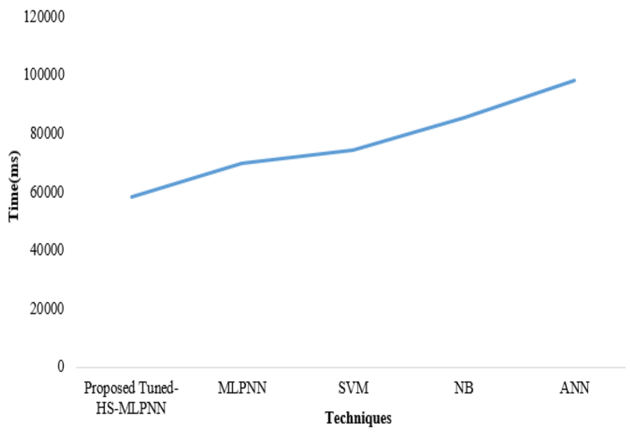

Figure. 6 Performance measure of proposed Tuned-HS-MLPNN

and ANN attained the values at the range of (95.83%,93.92%), (93.71%. 91.25%), (91.47%, 89.63%) and (89.66%,88.32%). Thus, the usage of the tuned intensification operator in the developed approach accurately classifies the disease from the coffee leaf.

The proposed Tuned-HS-MLPNN is evaluated centered on precision, recall, and F-Measure in Table 1. For precision, recall, and F-Measure, the Tuned-HS-MLPNN achieves 98.13%, 97.52%, and 99.04%; whereas, the prevailing MLPNN, SVM, NB, and ANN attain low values that range between 86.67%-95.23%. Thus, the usage of the HS activation function in the proposed technique tends to avoid uncertainties as compared to the existing models.

Regarding false positive rate (FPR), and false negative rate (FNR), the proposed methodologies' performance is evaluated in Fig.5. The Tuned-HS-MLPNN's FPR and FNR rates are 0.41% and 0.52%. But the ANN achieves FPR and FNR at the rate of 10.41% and 8.92%, respectively. Similarly, certain

Table 2. Severity prediction of the proposed framework

Predicted class	Severity level (%)		
	Low	Mild	Severe
Class I Minor	47	3.21	51
Class II Rust	73	Nill	27
Class III Phoma	70	29	1
Class IV Cercospora	60	12	28

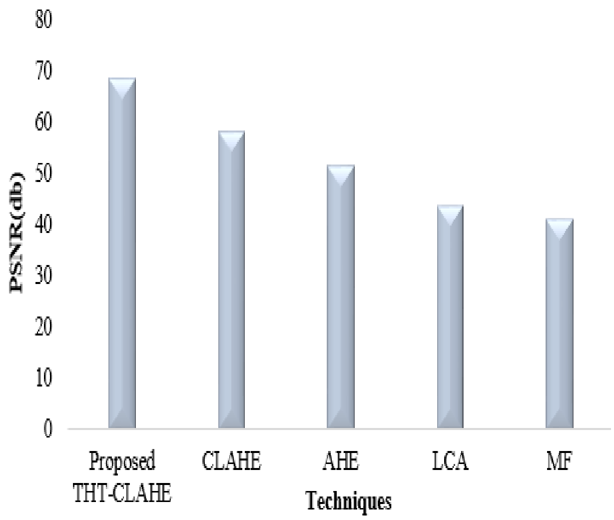

Figure. 7 Performance evaluation of proposed THT-CLAHE

other methods also achieve lower FNR and FPR rates. Thus, when contrasted with the prevailing techniques, the Tuned-HS-MLPNN offers more reliable results.

In Fig. 6, the training time required by the proposed classification technique is revealed. 57982ms is the training time of the Tuned-HS-MLPNN; while existing systems have MLPNN (69812ms), SVM (74012ms), NB (85201), and ANN (98031). Hence, the Tuned-HS-MLPNN takes less time to complete the training process with accurate detection of coffee leaf disease.

The severity results achieved by the proposed coffee leaf prediction framework in terms of a minor, rust, Phoma, and Cercospora based on the affected area are depicted in Table 2. Four different types of diseases like minor, rust, Phoma, and Cercospora that occur in diseases are considered. Thus, the proposed approach detected 47%, 3.21%, and 51% of low, mild, and severe risk levels of disease. Likewise, all the other classes are also effectively predicted by the proposed methodology.

4.3 Performance evaluation of proposed THT-CLAHE

Here, regarding peak signal to noise ratio

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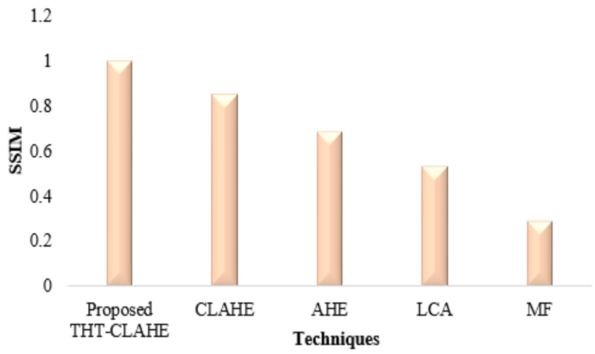

Figure. 8 Performance assessment based on SSIM

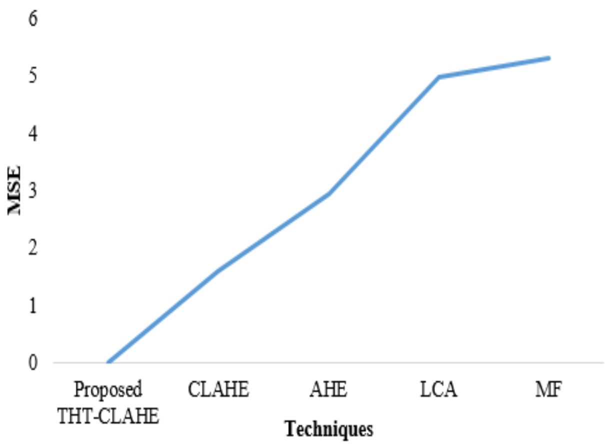

Figure. 9 Graphical representation of proposed THT-CLAHE

(PSNR), mean square error (MSE), and structural similarity index measure (SSIM), the proposed THT-CLAHE's performance is contrasted with the prevailing CLAHE, adaptive histogram equalization (AHE), linear contrast adjustment (LCA), and median filter (MF).

The PSNR obtained by the proposed technique is depicted in Fig. 7. The PSNR value obtained by the proposed THT-CLAHE is higher (68.49db), whereas the existing CLAHE, AHE, LCA, and MF obtain 58.32db, 51.47db, 43.84db, and 41.25db, which are lower. Thus, the usage of the THT in the traditional CLAHE technique avoided over amplification and resulted in a better-enhanced image.

In Fig. 8, the superiority of the proposed THT-CLAHE based on SSIM is displayed. The proposed approach achieves a better SSIM of about 0.9969. On the other side, the SSIM achieved by the existing CLAHE is lower (0.8501). Similarly, the SSIM varies for other methods also. Hence, the proposed approach outperforms all the other existing algorithms.

The graphical representation of the proposed THT-CLAHE is depicted in Fig. 9. The THT-CLAHE attains an MSE of about 0.0095. While, the existing systems acquire CLAHE (1.5897), AHE (2.9354), LCA (4.9870), and MF (5.321) are lower. Thus, the proposed system is superior to the existing algorithms.

Table 3. Comparative assessment of proposed SD-FCM

Techniques	Time(ms)
SD-FCM	1147
FCM	1522
KM	2258
K-Medoid	2897
MS	3580

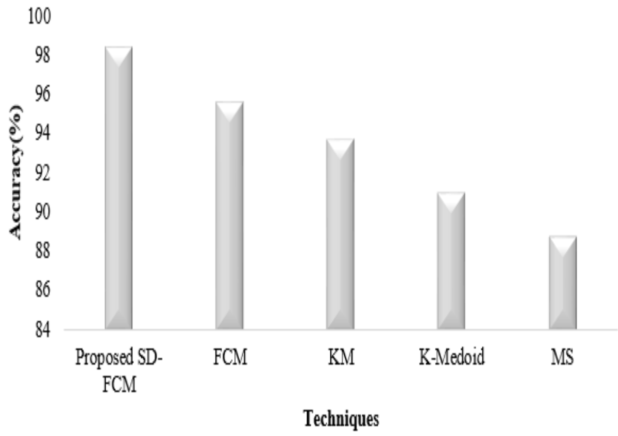

Figure. 10 Clustering accuracy of proposed and existing methods

4.4 Performance measurement of proposed SD-FCM

Here, the proposed SD-FCM filtering's performance is compared with the existing FCM, K-means (KM), K-medoid, and mean shift (MS).

The comparative measure of the proposed SD-FCM technique is illustrated in Table 3. The SD-FCM has a lower clustering time of 11474 ms; while, the prevailing techniques have 1522ms for FCM, 2258ms for KM, 2897 for K-Medoid, and 3580ms for MS. Hence, the usage of the SD in the conventional FCM has reduced the clustering time and aided in the better filtering of the healthy and diseased leaf based on the color.

The clustering accuracy of the proposed SD-FCM is depicted in Fig. 10. The SD-FCM provides effective filtering of diseased and healthy leaves with 98.43% accuracy; while the prevailing FCM, KM, K-Medoid, and MS have lower clustering accuracy of the order of 95.68%, 93.79%, 91.04%, and 88.84%, respectively. Hence, the proposed system is better than the other baseline techniques.

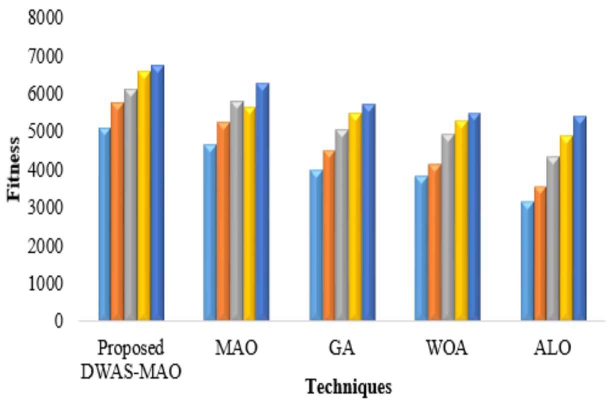

Figure. 11 Performance analysis based on fitness value

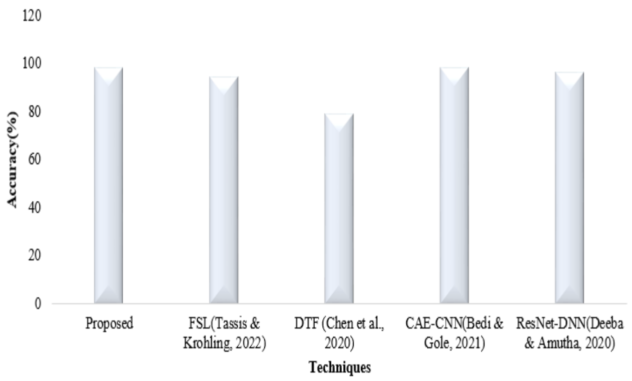

Figure. 12 Performance evaluation of the proposed methodology

4.5 Performance measurement of proposed DWAS-MAO

Here, the proposed technique's effectiveness is evaluated with prevailing Mexican axolotl optimization (MAO), genetic algorithm (GA), whale optimization algorithm (WOA), and ant lion optimization algorithm (ALO).

Fig. 11 unveils the fitness value of the proposed DWAS-MAO technique. When the number of iterations is 5, the fitness values achieved by the existing MAO is 4633, GA is 3991, WOA is 3798, and ALO is 3154. These values are lower than the proposed system i.e. 5057. Similarly, the fitness value also rises as the number of iterations increases. When the number of iterations is 10, the fitness value of the proposed system is 6725, which is higher than the traditional methods. Thus, the usage of the DAWS in the traditional MAO approach avoided the local optimum problem, and hence the proposed system performs superior to the existing techniques.

4.6 Comparative measure with literature papers

Here, the proposed disease classification methodology's superiority is evaluated with the conventional FSL [27] achieved an accuracy of 93.25% in the severity estimation task, DTF [28] achieves a validation accuracy of 91.83% on the public dataset, CAE-CNN [29] model achieved 98.38% testing accuracy, ResNet-DNN [30] model achieved 96.6% testing accuracy.

The graphical representation of the proposed methodology is depicted in Fig. 12. The proposed method obtains a higher accuracy (98.65%), whereas, the existing ResNet-DNN has an accuracy of 96.6%. Hence, an effective disease prediction strategy is caused by the color-based filtering of the healthy and diseased leaf followed by the patch extraction phenomena. Thus, the proposed classification technique accurately classifies the disease present in the coffee leaf.

5. Conclusion and future scope

This paper proposes an efficient disease classification and severity prediction model based on the color-based filtering of the diseased and healthy leaf. The various processes involved in the proposed technique is are pre-processing, Background subtraction, Filtering of the healthy and diseased leaf using SD-FCM, patch extraction, feature extraction, optimal feature selection, and classification. Next, based on the feature (area) extracted, the severity of the classified disease is predicted. Also, the superiority of the proposed framework is estimated by comparing it with some other existing techniques. As per the experimental outcomes, the proposed model attains an accuracy of 98.65%. Thus, when weighed against the prevailing techniques, the proposed system is more efficient and achieves more accurate results. Nevertheless, filtering the diseased leaf based on the clustering is not effective. Thus, this work will be improved in the future by considering certain other factors for disease classification using advanced neural networks. considering certain other factors for disease classification using advanced neural networks.

Conflicts of interest

There are no conflicts of interest declared by any of the authors.

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Author contributions

Authors proposed a Multi-Disease Classification, prediction framework on Coffee Plane Leaves Datasets Using CNN Model to overcome the problem of existing models and tested data sets and results obtained are expected. The paper background work, conceptualization, methodology, dataset collection, implementation, result analysis and comparison, preparing and editing draft, visualization have been done by first author. The supervision, review of work has been done by second author.

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Notation	Parameter
$(f(x,y))$	Input Coffee Leaf Image
(n_0)	Noisy Components
$(G^{(\bar{f})})$	Mathematical Formulation of Gaussian Function
$f_{im}(x,y)$	Image Component Present in the Input
$f^*(x,y)$	Noise Removal
$f^*(x,y)$	Contrast Enhancement
$(f^*(x,y))$	Noise-Removed Image
$g(1)$	Rectangular-Shaped Continuous
$g(2)$	Non-overlapping regions
(ς)	Determination of the Clip Limit
$\circ, \bullet$	Opening and Closing Operation
G	Clip Factor
$\varsigma(\Pi), \varsigma_W(\Pi)$	White and Black Top-Hat Transform
$(\gamma(\varsigma))$	Cumulative Distribution Function
h	Pixel Gray Level
$\kappa(\varsigma)$	Gray Level Redistribution Function
$\chi(\varsigma)$	Delineates the Color Transformation
ς^{max}	Elucidates the Maximum Pixel Value
$I^{(m)}$	Resultant Contrast Enhancement Image
$(B(I^{(m)}))$	Mean Background Intensity
$(I^{(m)})$	Contrast Enhanced Image
$(\bar{B}^i)$	Background Removed Image
$I -$	Number of background-subtracted images
(j)	Initial Pixel
J	Number of Pixels in the Image
$N -$	Number of Cluster Centroids
(C^n)	Cluster Centroids
(Obj^{ε})	Objective Function
a	Fuzzy Controller Parameter
ω^{jn}	Symbolizes the Membership Function.
(ω^{jn})	Fuzzy Membership Function
C^l	Delineates the Cluster Centroid
Q	Constant
L	Number of Iterations
$\hat{\varphi}_u^d$	Patches are Reshaped into Columns
$(P(\varphi^d))$	Patch Extraction
(φ^d)	Diseased Leaf
$\hat{\varphi}_u^d$	Extracted Patches from The Diseased Leaf
v	Size of the Patch
(δ)	Patches Extracted
Γ	Patch Probability
$\hbar$	Neighbouring Patches
$b -$	Number of Patches Extracted from the Diseased Leaf
(ρ^v)	Diseased Leaf
$(ULBP(\rho^v))$	Upgraded Local Binary Pattern
X	Center Pixel of an Image
$t -$	Number of Features Extracted
GLCM	Gray-Level Co-occurrence Matrix
$D(\rho^v)$	Pixel Intensity
(y_z)	Extracted Features
$t -$	Number of Features Extracted
$D -$	Dimensional Search Space
$(f(y_z))$	Fitness Determination