

An Automated Prediction of Plant Diseases Using Leaf Images Based on Efficient Deep Learning and Image Processing

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Abstract—In all nations' economies, the agricultural sector can play a vital role through crop production. The discovery of plant diseases could be one of the most significant factors in the preservation of an agriculturally productive country. Crop farmers lose a considerable sum annually since numerous diseases have affected their plants. Various plant parts could have been contaminated by fungi, viruses, and microorganisms, but in this work, the focus is on the discovery and categorization of banana leaf disease. Improved food production quality and reduced economic losses will be achieved with an accurate early prediction of plant leaf disease. Nowadays, deep learning (DL) and artificial intelligence (AI) have been widely applied for the construction of automated systems to discover and categorize banana leaf diseases. In this paper, an automated banana leaf disease prediction system is presented by proposing an enhanced deep learning model. In this work, captured banana leaf images can be pre-processed through combined filters, in which image smoothing and noise reduction are done by a Gaussian filter, followed by a denoising process that is refined additionally using the Wiener filter scheme. Subsequently, a DL model convolutional neural network (CNN) can be exploited to extract pertinent features. In this paper, an attention and fuzzy logic-based recurrent neural network (AFLRNN) model is proposed and trained with extracted features for efficient prediction and categorization of plant leaf disease. These systems utilize image processing and computer vision techniques to analyze images of plant leaves and identify potential diseases. The proposed DL system is able to efficiently detect leaf disease in plants at an early stage. The presented scheme can learn and extract features from captured plant images to facilitate precise leaf disease discovery and categorization. This kind of early detection of leaf disease is used to provide suitable treatment and reduce crop waste. The experimental results have exposed that the proposed system has attained a above 98 % higher disease prediction accuracy that has been higher to state-of-the-art schemes.

Index Terms—Banana leaf disease detection; Image processing; Deep learning; Pre-processing and feature extraction; Leaf disease classification.

I. INTRODUCTION

In developing countries, agriculture is the main source of income and service. The agricultural area can also produce

jobs in associated industries such as food distribution, carrying, and employment [1], [2]. Economic growth has been driven through agricultural sector given those raw objects for industries and export income is produced. One of the significant divisions of the global agro-trade could be banana farming or banana trade, as bananas contain more minerals such as manganese, calcium, magnesium, potassium, and iron [3]. Bananas provide several health benefits and thus are an internationally well-liked and healthy fruit. They can be a high-quality basis for fiber, potassium, and different vitamins and minerals, which are causing increased heart strength, digestion, and largely well-being. For muscle improvement, mood improvement, and weight management, bananas have also been used [4]–[7]. Some examinations have recommended that banana fruits can play a vital role in the health of bones and kidneys. Therefore, bananas are consumed by many people worldwide because this fruit is measured as an immediate power booster [8], [9]. According to the report of the National Horticulture Board, India is the leading banana producer in the world with a yearly production of approximately 14.2 million tons. Other leading banana producing countries are Ecuador, Brazil, China, and the Philippines [10], [11]. Internationally, banana cultivation can be a considerable industry with approximately 125 million tons formed in the year 2021, and over 1,000 varieties cultivated transversely 150 countries [12], [13]. Enhanced banana forming has contributed to decreasing food insecurity and starvation, particularly in developing nations. The banana industry faces many challenges such as disease, climate variability, and soil dilapidation, which could ruin production and trades [14]–[16].

In general, banana leaf is vulnerable to numerous diseases. The most common banana leaf diseases are Fusarium wilt (Panama wilt) and Sigatoka leaf spot (both yellow and black). These types of banana leaf diseases are noticeable as lines, marks, or staining on the banana leaf, and thus it is possible to reduce photosynthesis and crop yield [17], [18]. The following types of diseases occur in banana leaves.

Yellow Sigatoka: This category of infection has appeared

as yellowish marks on the banana leaf and these might have increased and turned into a mysterious brown color, and finally, it becomes light grey with a brown circle.

Black Sigatoka: This category of infection can be crueler with dark lines and marks on the banana leaves frequently enclosed with a yellowish nimbus. These spots are combined and will lead to banana leaf death [19].

Fusarium Wilt: It appears as yellowing of lower banana leaf, beginning from the edge and succeeding heading for the midrib. Finally, yellowing has reached the central part of the leaf and thus the leaf may have broken and slid [20].

Cordana: The mark of the Cordana leaf occurs on the banana leaf by the Cordana musae fungus and it affects banana plants. It appears as round or elliptical spots with a yellow nimbus on banana leaf, and then leaf slaughter will begin and fruit quality might have reduced [21].

Pestalotiopsis: It can be fungal-based infection that has left grey or brown marks with dark boundary and golden-yellow nimbus on the banana leaf, and it increases from the centre of the banana leaf to the border. This kind of disease can lead to the destruction of the hankie, floppy and possible leaf loss, and thus the entire health of the banana plant will be destroyed [22].

The banana leaf diseases mentioned above will increase rapidly, particularly in constructive situations such as moist, warm, and wet. As a result, early-stage banana leaf disease discovery is vital to provide effective management and avoid important banana crop losses [23]. High-quality banana productions from farms are constantly dependent on infection-free banana leaves. Consequently, it could be very necessary to identify the disease at an early stage to provide an appropriate safety evaluation. Manual disease detection and categorization can take more time and involve expert suggestions. Nevertheless, the execution of an automated detection system will help this procedure in less time [24], [25]. Frequently, deep learning (DL) schemes have been utilized by many researchers for discovery and categorization of banana leaf since these contain a more powerful process than other machine learning (ML) schemes. The DL method has examined banana leaf images to find several diseases with increased accuracy. Deep learning enables automatic disease discovery, directing to more useful banana leaf disease management and to decrease yield losses [26]. In this paper, efficient image processing and enhanced deep learning methods are presented to design efficient automated predictions and categorization of banana leaf diseases. For automated disease prediction and categorization in banana leaf images, attention and fuzzy logic-based RNN DL scheme has been presented.

II. RELATED WORKS

DL schemes were exploited in [5] to ensure the accurate discovery of banana leaf diseases in an appropriate system with greater accuracy. In recent years, banana leaf disease recognition schemes could frequently be labor-intensive, time-consuming, and imprecision-prone. A very fast and lightweight convolutional neural network (CNN) structural design was designed in [6] and optimized with the Bayesian optimization scheme and has been called “BananaSqueezeNet” to discover three important banana

leaf diseases such as Sigatoka, Pestalotiopsis, and Cordana leaf mark on the banana leaf image. In [7], a comparative examination with other state-of-the-art schemes was performed to detect the image of banana leaf. In the study, the Banana Leaf-Net model was presented for disease detection in banana image and this was compared with a wide range of CNN-based structural designs such as Efficient Nets (B0, B1, B2, and B3), ResNet50, MobileNetV2, ResNets (101 and 152V), and DenseNet201 [7]. An enhanced scheme was proposed in [8] for the recognition of banana leaf infections at an early stage. The scheme presented was called the “K-scale VisuShrink algorithm” (KVA) and has been exploited to find banana leaf infections from captured images. In this examination, a novel disintegration scale K was introduced according to the middle course and semi-soft thresholds, the perfect threshold result has been attained and surrogated with the recently recognized threshold task for noise reduction in banana leaf image. Subsequently, a new network was presented to find the image known as Ghost ResNeSt-Attention RReLU-Swish Net (GR-ARNet) that was accomplished according to the Resnet50. In [9], a strategy has been presented to find disease in banana leaf at an early stage by applying pre-trained DL schemes. In the study, the cross-industry standard process for data mining (CRISP-DM) was exploited including six stages such as business perceptive, data perceptive, data training, formation, assessment, and exploitation. In [10], an efficient CNN DL model was applied for the categorization of diseases of banana leaf marks, in which the ResNet50 structural design has been applied. In the examination, the distinction between numerous factions of illnesses, together with those that occurred through ordinary banana leaf blemish diseases and those of vigorous leaves of banana plants, is highlighted.

In [11], an easy mobile application was proposed to detect Black Sigatoka and Fusarium Wilt diseases in banana leaves. This mobile application has employed a CNN model to categorize the two banana leaf diseases. This mobile application presented could provide the correct categorization of banana leaf images. In [12], a learning approach was presented to re-orient a faster region-based convolutional neural network (Faster R-CNN) for improved an discovery of improbability. In the proposed FR-CNN model, a pre-designed disease discovery scheme was utilized for a network generation that has generated accurate evaluations by the deep transfer learning (DTL) algorithm. An ensemble CNN leaf disease discovery classification model (ECNNLDD) has been exploited in [13] for leaf healthy detection. In the examination, the classification was made whether the leaf could be healthy or unhealthy, which could be a two-class problem, and this scheme was evaluated and compared with some ML classification models such as support vector machine (SVM) and decision tree (DT).

In [14], artificial neural network (ANN) was combined with scale-invariant feature transform (SIFT) scheme called “ANN-SIFT”. The leaf virus has been analyzed using ANN-SIFT with activation tasks, in which SIFT has performed the feature extraction process with multi-faceted term differentiations. Then, histogram of oriented gradients

(HOG) was incorporated with the local binary patterns (LBP) scheme and is called “HOG-LBP”. In the second integration, the HOG and LBP characteristics were applied for the discovery of the disease in leaf images. A novel technique was presented in [15] to identify diseases of banana plants by applying the image processing scheme. In the study, CNN schemes were trained on a dataset of labeled images to find and categorize banana leaf diseases. In the presented scheme, pertinent features have been extracted from banana leaf images by applying the CNN approach to provide accurate disease categorization on banana leaf images [15]. In [16], the ML technique was presented by applying the MobileNetV2 structural design for the categorization of various leaf diseases. In the examination, the images of 408 banana leaves have exploited the encomium of Black Sigatoka, Yellow Sigatoka, Bract Mosaic, Insect Pest, Panama Disease, Moko Disease, and healthy leaves. The gathered dataset has been extended to 3,264 images by image expansion for the enhancement of the efficiency of the model.

III. PROPOSED WORK

In this paper, efficient image processing and improved DL model is presented in Fig. 1 to detect and classify banana leaf diseases at an early stage. Initially, the dataset is gathered from the net sources for the training of the proposed model. Images can be pre-processed using hybrid filters (Gaussian-Weiner) for image quality improvement and make images fitting for examination. The presented banana leaf image enhancement scheme could develop the visibility of fine features associated with diseases. Afterward, image segmentation is done employing the Otsu scheme, in which the disease affected area can be segmented from the health leaf area through the Region of Interest (RoI) assortment. The DL model CNN is employed for extraction of pertinent features from the banana leaf images, such as color, texture, and shape. Finally, the proposed AFLRNN is applied to categorize the image according to the extracted features, influential in whether it illustrates a disease and probably discovering the exact banana leaf disease. The performance of the proposed model has been estimated using some evaluation metrics such as classification accuracy, specificity, precision, recall, F1-score, error rate, and false positive rate (FPR). Compared to customary schemes, the presented model will computerize the discovery of banana leaf disease to obtain faster and more precise prediction and categorization. In the presented automated banana leaf disease prediction model, the following phases are exploited.

A. Data Collection

For the discovery of banana leaf diseases, the data collection contains images of captured banana leaves (healthy and diseased images). Banana leaf images were captured in different situations (morning and evening) and at various biological sites to ensure a representative image dataset. For the proposed model training process, two typical banana disease image datasets have been collected and utilized. The first dataset is banana LSD (BLSD) that contains images of banana leaves such as healthy, Sigatoka, Pestalotiopsis, and Cordana [4], [27]. This dataset contains

two sets such as the original set that includes 937 RGB images (healthy and diseased images) and the augmented set containing 1600 images (400 images per class) that were altered by some methods such as flip, blur, contrast adjustments, cropping, cut off, conversion, and rotating shear [28]. Every image contains a normal degree of 224×224 pixels. In this paper, the augmented dataset is used for model training. Another dataset is the banana leaf dataset (BLD) that contains images of banana leaves such as healthy (6624 images), Fusarium Wilt (5877 images), and Black Sigatoka (6899 images) [29]. Figure 2 shows sample banana images collected from the dataset to test the prediction model presented for the prediction of banana leaf disease.

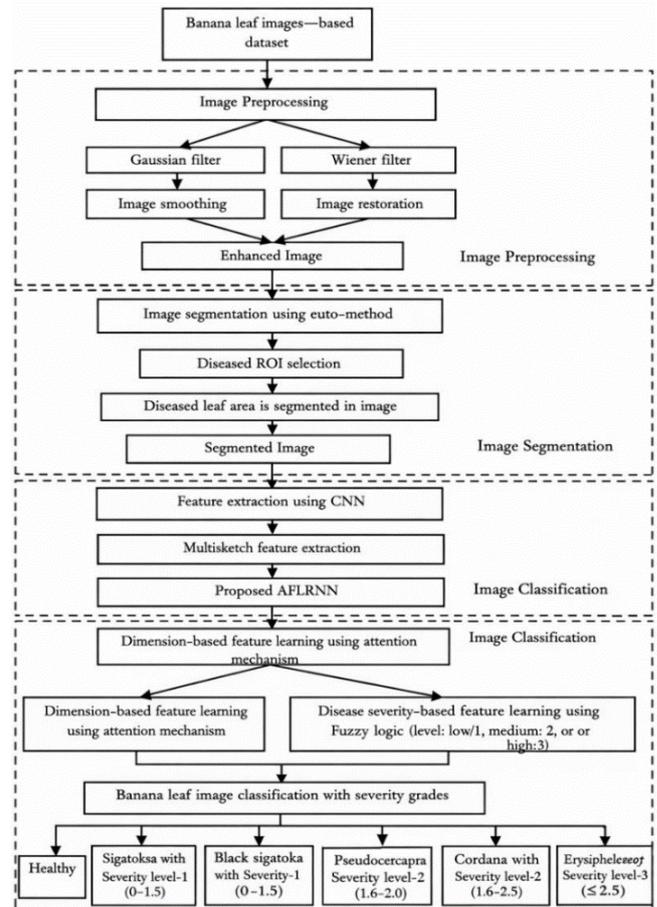


Fig. 1. Overall process of the proposed scheme.

B. Image Data Preprocessing

Initially, banana leaf image preprocessing is carried out using the Gaussian-Weiner filtering method, in which, pertinent features can be enhanced through surplus distortions elimination to improve image quality. The Gaussian filter can be exploited in banana leaf images to decrease noise and smooth. This procedure is vital since noise might have obstructed subsequent image examination phases such as image segmentation, feature extraction, and classification, and thus incorrect diagnosis of the disease can have occurred. Noises are reduced by a Gaussian filter in banana leaf images, and images could be smoothed through biased standard of adjacent pixels, wherever the weights have been established with the help of a Gaussian process. This Gaussian function is operated as a non-uniform low-pass filter, efficiently hazing out elevated frequency noise

whereas saving entire structure of banana leaf image. In the Gaussian filter, the amount of noise and hazing decrease can be maintained with the size of the Gaussian process kernel or the standard deviation (σ). For noise removal and image smoothing by Gaussian filter, the following (1), (2) are applied.

For one dimension, the Gaussian distribution with standard deviation σ is computed using (1)

$$G(a) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{a^2}{2\sigma^2}}. \quad (1)$$

Two such Gaussians are exploited in two dimensions for the noise removal and are given by

$$G(a,b) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(a^2+b^2)}{2\sigma^2}}. \quad (2)$$

In (1), (2), a denotes the distance from the source in the parallel axis, b represents the distance from the source in the perpendicular axis, and Gaussian sharing standard deviation is denoted by the symbol of σ .

Equations (1), (2) could be exploited on original banana leaf image. We can examine the filtering variations.

The presented hybrid Gaussian-Weiner filter will improve the banana leaf image quality and edges can be preserved. In the presented method, the Weiner filter has been exploited on the Gaussian filter to refine the denoising process. The consequential filter has saved the banana leaf image quality without blurring and reduced computational time is obtained for banana leaf image pre-processing. The denoising process is refined with the help of a Wiener filter through adaptive noise reduction, whereas conserving significant signal characteristics like edges of the banana leaf image. The local signs have been employed by the Wiener filter that is used for its process of adapting to every part of the image. The Weiner filter is exploited to restore the image. This category of filtering method is employed as inverse filtering, also, while incomplete knowledge might be obtainable concerning blurring process. Also, this method is exploited when there is no previous information available. The mean square error (MSE) is decreased through this filter. The squalor process and the arithmetical assets of noise can be taken into account. Uneven evaluation of the banana leaf image is discovered for MSE reduction.

The reconstructed banana leaf image $\hat{C}(u,v)$ is obtained using frequency domain restoration techniques. The degraded image is first transformed into the frequency domain as $A(u,v)$, while the distortion is represented by the degradation function $B(u,v)$

$$\frac{1}{B(u,v)} A(u,v) = \hat{C}(u,v). \quad (3)$$

Equation (3) demonstrated that when the function B might be recognized and the transform $A(u,v)$ has been taken, then the consequence could be $\hat{C}(u,v)$. The error value has not been recognized for inverse filtering. The error can be augmented when the $B(u,v)$ value is small. Such

errors might have been reduced by the Wiener filter system.

Equation (3) has been transformed into the structure of a filter and the evaluated banana leaf image $\hat{C}(u,v)$ is given by

$$\hat{C}(u,v) = \left[\frac{B^*(u,v)S_f(u,v)}{S_f(u,v)|u,v|^2 + S_n(u,v)} \right] A(u,v). \quad (4)$$

In (4), $S_f(u,v)$ denotes the image frequency spectrum, $S_n(u,v)$ represents the additive noise spectrum, and the blurring filter is represented by $B^*(u,v)$. The degradation process $B(u,v)$ will be computed when there could be a blur at a definite area in the banana leaf image. A noise $N(u,v)$ is inserted. The presented hybrid filter can be effective at decreasing several kinds of noises presented in banana leaf images. The image quality of the entire banana leaf has been enhanced through the hybrid filtering method presented. The filter parameters will be adjusted to stability noise reduction and image details savings depending on their precise necessities.

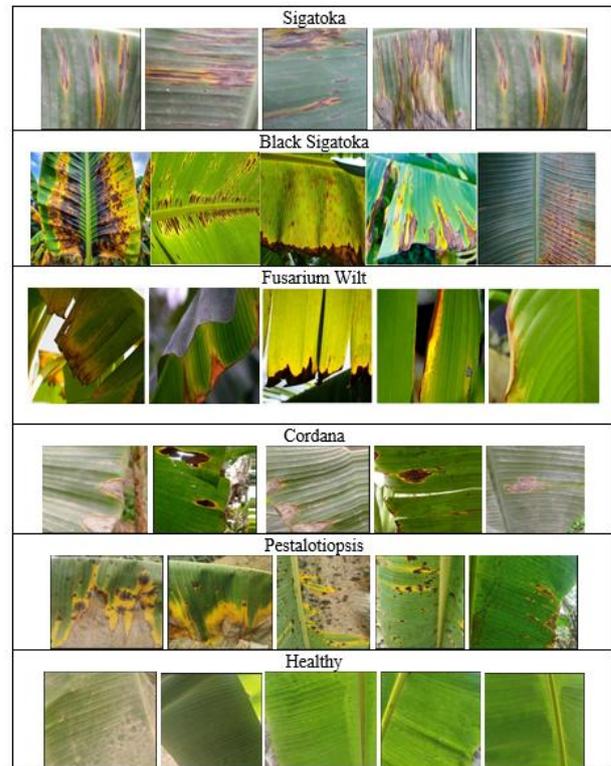


Fig. 2. Sample banana leaf images.

C. Image Segmentation and Feature Extraction

On the pre-processed banana leaf image, the Otsu technique is applied as an image segmentation scheme exploited in disease discovery in banana leaf image to divide infected areas from leaf healthy areas of the leaf through automated best threshold identification for a binary image generation. The Otsu technique is applied on a pre-processed image to its histogram for the finest threshold establishment to divide the forefront (e.g., disease marks) from the background. Subsequently, the segmented banana leaf image can be exploited for more examinations like feature extraction, disease and severity detection, and classification.

In the image segmentation process, infected ROIs are chosen in the banana leaf image with the help of the Otsu method. The hue, saturation, and brightness (HSB) settings are different by the Otsu scheme, using black as the threshold color in anticipation of the ROIs of the infected areas. The infected ROIs in the banana leaf image were segmented and provide results in reflected in “region”. This segmentation scheme can approximate the parts of the diseased ROIs and the whole banana leaf for the percentage of disease affected area estimation. The banana leaf image has been estimated by taking the ratio of the diseased area in the banana leaf to the total area in the banana leaf image. In this process, the segmented region denotes the affected area of the disease in the banana leaf and is given by

$$P(DA_a) = \frac{\text{Diseased area in banana leaf}}{\text{Total area in banana leaf}} \times 100. \quad (5)$$

After the banana leaf image segmentation, feature extraction is performed with the CNN deep learning model. Relevant features such as texture, shape, and color are extracted efficiently through the CNN model from banana leaf images.

CNNs automatically extract features such as color, texture, and shape from banana leaf images to identify diseases by pattern analysis in the banana leaf image data. CNN have utilized the layers to study hierarchical demonstrations for feature extraction. CNNs employ convolutional layers, pooling layers, and activation functions to learn and extract features. The following features can be extracted for banana leaf disease and its severity detection and classification. *Shape*: Abnormal shapes of marks, lesions, or spots presented in the banana leaf image. *Color*: Variations occur in banana leaf color due to disease. *Texture*: Abnormalities in the outside texture of the banana leaf. *Morphological Features*: Variations in the banana leaf region, edge, and width.

The following layers are used by the CNN model to extract relevant features from banana leaf images.

Convolution layer: In this layer, kernels are employed to the segmented banana leaf image for particular patterns discovery such as corners, perimeters, and color inclines. Convolution in this layer is achieved by sliding a specific size window that is called a “kernel”. In this process, sliding is done consecutively from top to bottom and from left to right, with the kernel characteristically containing identical pace in the height and thickness directions. Matrix multiplication is done in the convolution layer through kernel matrix multiplication by the pixel value x_y and f_y of the banana leaf image. After that, the resultant multiplication can be summed, and finally, a value of bias b will be added to this sum and it is computed as

$$y = \sum (x_y \times f_y) + b. \quad (6)$$

As the kernel slides over each location of the banana leaf image, it performs convolution operations to extract important features. The resulting output values form a matrix known as the feature map. In the convolution layer of the CNN model, several feature maps are obtainable; thus,

the CNN model is enabled to study various feature tasks.

Activation function: An activation function (AF) has been frequently used after every convolutional layer of CNN. This phase could be vital to initiate non-linear characteristics into the CNN approach since the convolutional layer mainly executes linear estimations such as component-wise dot product and summation. The rectified linear unit (ReLU) is commonly used as a non-linear activation function because it helps prevent the vanishing gradient problem. It also enhances training speed while maintaining high accuracy and computational efficiency. The ReLU can take the input x of the activation layer and output y is generated. The ReLU value can be either zero or one and is computed as:

$$\text{ReLU} = \max(0, x), \quad (7)$$

$$\frac{dy}{dx} = \begin{cases} 1, & x \geq 0, \\ 0, & x \leq 0. \end{cases} \quad (8)$$

Multiscale Feature Extraction: Entities in banana leaf images differ in shape and size. Therefore, feature extraction at a single-scale could not have captured every pertinent feature on entities presented in banana leaf images. But multi-scale feature extraction is done with the help of numerous convolutional kernels with various scales for entity feature capture. This method can permit a proposed AFLRNN classification model to identify entities more precisely, especially while banana leaf images illustrate entities of different sizes.

This kind of multi-scale feature extraction scheme can be an effective method to improve classifier accuracy, and enhanced performance is given to discover entities of differing sizes within banana leaf images. Multiple receptive fields are utilized by the CNN model to recognize features at different scales, enabling effective detection of patterns and variations in the input data. Local features are captured only through the network when the accessible area could be too small. On the other hand, global features could be captured when the accessible area has been too large. The size of the accessible area and multi-scale features are adjusted by the CNN model through convolutional processes controlling. Accordingly, this is used to avoid loss of information present in banana leaf images and efficiently capture characteristics at different scales. From segmented banana leaf images, multi-scale features are attained using convolution with kernels of different sizes. Numerous kernels have been applied to the input feature map for each result; in which the network can examine the feature map of a single convolutional operator. The feature map is estimated as

$$IF = \sum_{kh, kw, m} K_{kh, kw, m} \times X_{h'+kh-1, W' kw-1, m}. \quad (9)$$

In (9), the output feature map is denoted by I_F , m denotes the number of channels present in the resultant feature map, convolutional kernel can be represented by the symbol of K , and kh and kw can be the convolutional kernel height and width.

Multi-scale feature extraction can be used for banana leaf image examinations at various scales to extract pertinent

features such as color, shapes, and texture (such as spots or lesions) at every level (higher and lower levels).

Pooling Layer: In this layer, the feature maps of banana leaf images are down-sampled for dimensionality reduction to provide a more effective computation process. In this paper, the max pooling process has been employed in the pooling layer. The pooling layer is used to maintain crucial features from the feature map, decrease computational complexity, and avoid overfitting issues.

The maximum pooling process could be effective while errors occur during the process of evaluating the parameters of the convolutional layer. Errors are decreased through this method, and relevant features are highlighted. The maximum pooling is computed as

$$P(a,b) = \max_{m=0,\dots,p-1;n=0,\dots,p-1} S(a.s+m, b.s+n), \quad (10)$$

where the input feature map is denoted by the symbol of S , the resultant pooled feature map is represented by P . The size of kernel is represented by p , and stride is denoted by the symbol of s .

Feature vector: A feature vector V can be an arithmetical

demonstration of the main features of the banana leaf image. The low- and high-level representations of the learnt features that were extracted from the input banana image, such as colors, textures, and shape, are compressed through convolutional and pooling layers. For banana leaf disease discovery, a feature vector in CNN could be the outcomes of the convolutional and pooling layers that have represented the low- and high-level visual characteristics, such as texture, color, and shape, that have been extracted from the images of banana leaf. Subsequently, this feature vector can be used in the proposed AFLRNN model to classify banana leaf diseases. Most related characteristics are available in the feature vector to differentiate healthy and diseased banana leaf images and also to distinguish various kinds of disease.

D. Banana Leaf Disease Classification Using the Proposed AFLRNN

In the proposed AFLRNN, attention and fuzzy logic mechanisms are added to improve the performance of the existing RNN model to classify banana leaf images according to the extracted features (feature vector V). The architecture of the proposed AFLRNN has been illustrated in Fig. 3.

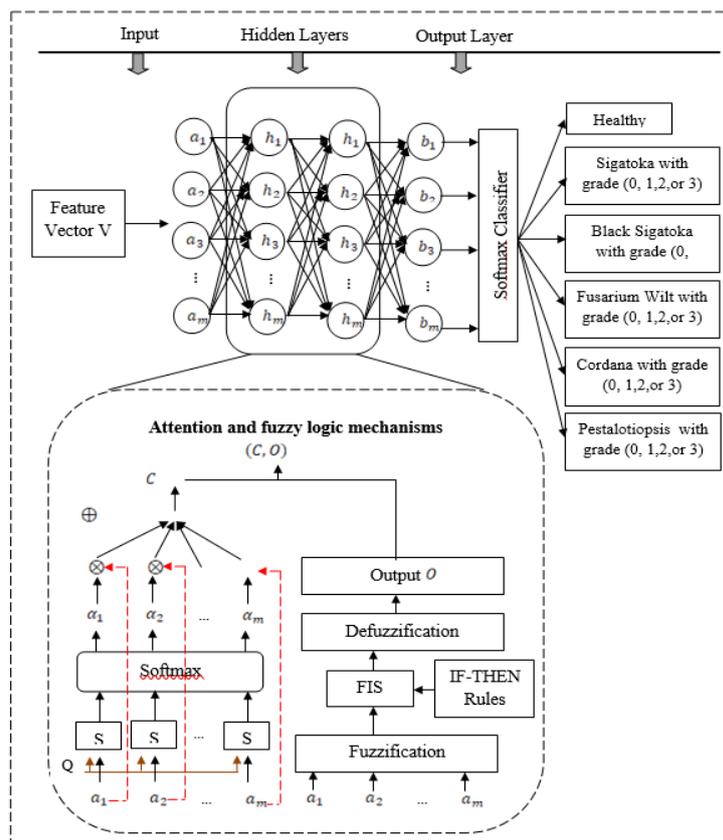


Fig. 3. Architecture of the proposed AFL-RNN.

In the proposed model, the attention mechanism is used to learn disease-based features and the fuzzy logic mechanism is used to learn severity-based features (low, medium, or high) based on the size of the infected area in banana leaf images. Accuracy of banana leaf image categorization has been improved with these hybrid approaches. The following layers are used to detect and classify the disease in banana leaf images.

Input Layer: The V feature vector is given as input to the proposed AFLRNN model. The AFLRNN can be utilized to model variations in banana leaf health over time by analysing multiple sequential observations of spectral data. The input is a series of feature vectors or where every component of the sequence characterizes a time pace t . The input to the proposed model can be $A = [a_1, a_2, \dots, a_m]$.

Hidden layer or recurrent layer: These layers contain

recurrent connections, in which the output of the hidden layer at one time step can be given back as an input to the similar hidden layer at the next time step. This kind of recurrent relationship can allow the network to preserve a “memory” or “hidden state” to obtain significant information from preceding inputs in the order. In hidden layers, every neuron utilizes the present input all along with these recurrent processes to allow the network to study banana leaf disease-related information over time.

In this layer, the RNN processes the input sequence and hidden states have been produced such as $H = [h_1, h_2, \dots, h_m]$. The temporal dependencies have been attained by the input sequence and it is estimated using (11)

$$h_t = RNN(a_t, h_{t-1}). \quad (11)$$

Attention and fuzzy logic Mechanism: The attention and fuzzy logic mechanism can be exploited to the hidden states produced through the RNN. For disease-based feature learning, the attention mechanism has estimated the resemblance flanked by every key K (significant information needed for related data estimation) and the query vector Q (AFLRNN mode what it can be searching for in the input image data). The similarity estimation function dot product is applied to estimate attention scores S and is used to discover how related every element of the input banana leaf images is. It is computed as

$$S(t, i) = \begin{cases} h_t^1 \times y_i, \\ (h_t^2)^T \omega y_i, \\ V^T \left(\omega \begin{bmatrix} h_t \\ y_i \end{bmatrix} \right). \end{cases} \quad (12)$$

In (12), encoder input hidden state is denoted by h_t at time step t , weight matrix is symbolized by ω , y_i denotes the encoder output hidden state at the location i , weight vector is represented by V . These estimated S has been passed via a Softmax function attention weights α_t discovery and it is estimated by (13)

$$\alpha_t = \text{softmax}(S(t, i)) = \frac{\exp(e_i)}{\sum_{k=1}^m \exp(e_k)}. \quad (13)$$

After that, α_t is applied for a context vector C_t estimation that could be measured as weighted sum of the hidden states and is given by

$$C_t = \sum_{i=1}^m \alpha_i h_i. \quad (14)$$

Disease-based features are learnt from the feature vector through the attention mechanism for an efficient banana leaf image classification (healthy or disease).

In the proposed model, fuzzy logic is applied to learn disease severity-based features learning according to the size or percentage of disease affected areas. Fuzzy rules are exploited for estimation of disease severity level, such as no

severity (grade 0) (healthy leaf), Low (grade 1), Medium (grade 2), and High (grade 3) through input extracted features (percentage of disease affected regions and color features). The output of fuzzy logic could be the severity of the disease with the grade. These fuzzy rules are formed as “If [Input] is [Linguistic Term] Then [Output] is [Linguistic Term],” to allow a fuzzy scheme for the handling of intrinsic vagueness and imprecision in the discovery of banana leaf disease in images.

The following elements are utilized by the fuzzy logic mechanism to discover and categorize the banana leaf disease in images: *Input Variables* - These are extracted features from banana leaf images (color features: recognized from the banana leaf image to establish the occurrence of definite color outlines, spot features: shape, size, and number of marks on the banana leaf). *Linguistic Variables*-linguistic variables have been utilized by the fuzzy logic scheme for banana leaf image data explanation that could not be accurately described, *Percentage of disease affected area $P(DA_a)$* - classified as no severity, Low, Medium or High, *Disease Grade*- Arithmetical scores are assigned as 0, 1, 2, 3 according to the infection and level, and *Output Variables* - disease severity grades.

The following functions are utilized in the fuzzy logic scheme to learn severity-based features

Fuzzification: Extracted features have been transformed into linguistic patterns by applying the pre-described membership functions. These membership functions could be processes to describe how well a feature vector value fits in to a definite linguistic pattern.

The fuzzy inference system (FIS): For linguistic input processing, fuzzy rules are utilized in FIS. The fuzzy rules can be in the form of “IF-THEN” statements that can connect the input conditions to the output ending. The following rules are utilized to discover severity level of the disease in banana leaf images:

- Rule 1: If “Percentage of disease affected region in banana leaf image IS “Low” THEN “disease-severity in grade (OUTPUT)” IS “1”.
- Rule 2: If “Percentage of disease affected area in banana leaf image IS “Medium” THEN disease-severity in grade (OUTPUT)” IS “2”.
- Rule 3: If “Percentage of disease affected area in banana leaf image “High” THEN “disease severity in grade (OUTPUT)” IS “3”.

Defuzzification: The FIS needs to be transformed to a crisp output. The fuzzified output of the FIS has been transformed to a crisp output using (15). The centre of gravity (COG) was exploited by the defuzzifier for the crisp output estimation of the FIS along the x -axis

$$X_{COG} = \frac{\sum_i \mu(x_i) x_i}{\sum_i \sum_i \mu(x_i) x_i}. \quad (15)$$

Output layer: The final layer of the proposed AFLRNN is the output layer, in which the predicted output is displayed according to the outcomes obtained from the last hidden layer. In this process, SoftMax AF is applied to handle multi-class categorization. It has transformed the logits into likelihoods and these likelihoods are shared across various

classes, and it is computed as

$$\text{softmax}(b_i) = \frac{\exp(b_i)}{\sum_j \exp(b_j)}. \quad (16)$$

In (16), b denotes the values attained from the output layer of each neuron. These values were separated through the sum of exponential values to regularize them and, after that, transformed them into likelihoods. Finally, disease and severity level are detected and categorized in banana leaf images into Healthy, Sigatoka with grade (0, 1, 2, or 3), Black Sigatoka with grade (0, 1, 2, or 3), Fusarium Wilt with grade (0, 1, 2, or 3), Cordana with grade (0, 1, 2, or 3), and Pestalotiopsis with grade (0, 1, 2, or 3) efficiently.

IV. EVALUATION METRICS

Some performance metrics have been exploited to estimate the efficiency of the presented and existing banana leaf disease detection and classification models. Such performance metrics can be classification accuracy (Acc), specificity (sp), precision (Pr), recall (re), F1 score, Error rate (Err), and false positive rate (FPR). The disease discovery model can utilize true positive (TP) and true negative (TN) to properly determine what kind of disease and its severity level in the banana leaf image. The false discovery and categorization of the disease could have been generated with false positive (FP) and false negative (FN) rates by classification models.

The first performance metric is the accuracy of the detection and classification of disease and severity level, and this metric is described as the ratio between right positive and negative consequences during the banana leaf disease detection and classification process and is estimated as

$$\text{Acc}(\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100. \quad (17)$$

The specificity performance metric has also been known as true negative rate (TNR), and it can be exploited for the estimation of the amount of exact negative cases so that the classification model is accurately found as negative and is computed as

$$\text{Sp}(\%) = \frac{TN}{FP + TN} \times 100. \quad (18)$$

Precision could be computed as a ratio between essentially classified positive consequences to TP and FP outcomes, and it is computed using (19)

$$\text{Pr}(\%) = \frac{TP}{FP + TP} \times 100. \quad (19)$$

The recall performance metric is exploited to evaluate the association between true positive categorizations and TP, and it can also be known as true positive rate (TPR) and is

computed as

$$\text{Re}(\%) = \frac{TP}{FN + TP} \times 100. \quad (20)$$

The F1-score is used as a weighted average of precision (Pr) and recall (Re) performance metrics. This kind of metric could retain the constancy between Pr and Re throughout the evaluation of positive and negative outcomes and is calculated using (21)

$$\text{F1-score}(\%) = \frac{2(\text{Precision} * \text{Recall})}{\text{Precision} + \text{Recall}} \times 100. \quad (21)$$

The error rate of the presented banana leaf disease detection model and state-of-the-art methods was computed based on the total number of incorrect segmentation of the infected region, discovery of severity level, and categorization of the disease throughout the model examination process. It is computed using (22)

$$\text{Err}(\%) = \frac{FP + FN}{TP + TN + FN + FP} \times 100. \quad (22)$$

The total negative classes incorrectly categorized as positive classes alienated through every negative class that might be the customary banana leaf image data, and it is known as the false positive rate (FPR) and is computed as

$$\text{FPR} = \frac{FP}{(FP + TN)} \times 100. \quad (23)$$

V. RESULTS AND DISCUSSIONS

The presentation of the proposed DL model has been evaluated and compared in this section using MATLAB simulation software for the detection and categorization of banana leaf disease and severity. The model presented was compared with existing state-of-the-art methods such as CNN (Sum, Saha, Nur, and Hasan 2025 [7]), GR-ARNet (Deng, Huang, Zhou, Hu, Li, and Wang (2024) [8]), Faster R-CNN (Bharathi Raja and Selvi Rajendran (2024) [12]), and ANN-SIFT (Thiagarajan *et al.* 2024 [14])) using the evaluation metrics mentioned above.

The classification accuracy of the proposed and existing DL schemes for banana leaf disease detection and categorization has been summarized and illustrated in Table I and Fig. 4. The comparison chart (Fig. 4) has demonstrated that the presented model has given the improved banana leaf disease with severity level detection and classification accuracy (more than 97 %) compared to the state-of-the-art CNN methods (Sum, Saha, Nur, and Hasan 2025 [7]), GR-ARNet (Deng, Huang, Zhou, Hu, Li, and Wang (2024) [8]), Faster R-CNN (Bharathi Raja and Selvi Rajendran (2024) [12]), and ANN-SIFT (Thiagarajan *et al.* 2024 [14]). Therefore, the presented model can provide more effective and accurate disease detection and categorization in the banana leaf image.

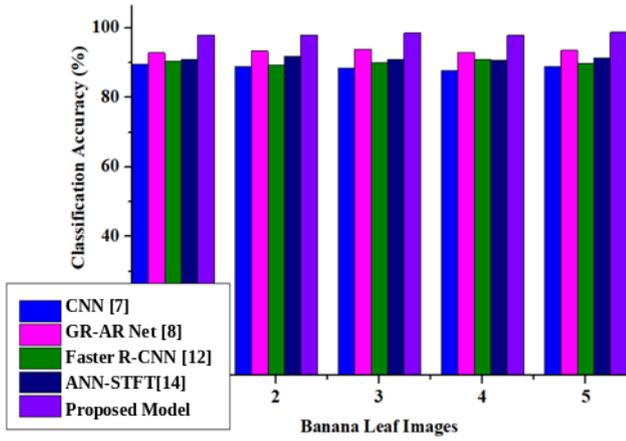


Fig. 4. Classification accuracy comparison.

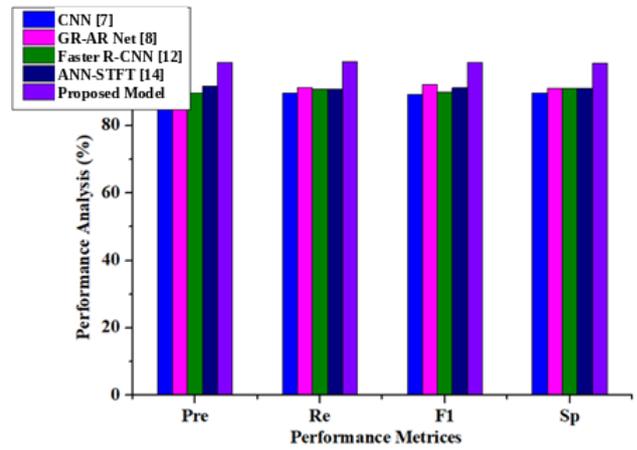


Fig. 5. Performance analysis.

The comparison of performance analysis has been demonstrated in Table II and Fig. 5. Figure 5 has exposed that the presented AFLRNN model could provide increased precision (98.75 %), recall (98.88 %), F1-score (98.81 %), and specificity (98.47 %) than state-of-the-art CNN methods (Sum, Saha, Nur, and Hasan 2025 [7]), GR-ARNet (Deng, Huang, Zhou, Hu, Li, and Wang (2024) [8]), Faster R-CNN (Bharathi Raja and Selvi Rajendran (2024) [12]), and ANN-SIFT (Thiagarajan *et al.* 2024 [14]) to detect and classify the banana leaf disease with severity level in the banana leaf image. Table III and Fig. 6 demonstrate the error rate comparison for the presented and state-of-the-art schemes. Compared to state-of-the-art CNN methods (Sum, Saha, Nur, and Hasan 2025 [7]), GR-ARNet (Deng, Huang, Zhou, Hu, Li, and Wang (2024) [8]), Faster R-CNN (Bharathi Raja and Selvi Rajendran (2024) [12]), and ANN-SIFT (Thiagarajan *et al.* 2024 [14]), the proposed scheme could give a reduced percentage of error rate (below 3 %) in the process of infected area detection and categorization in banana leaf image.

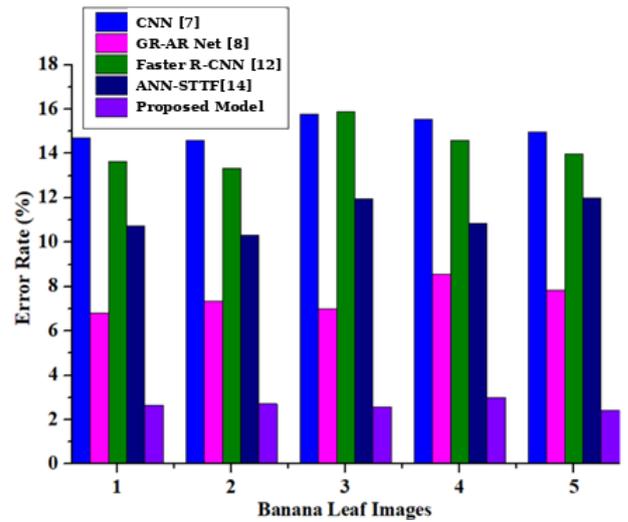


Fig. 6. Error rate.

The comparison chart of the false positive rate is demonstrated in Fig. 7.

TABLE I. CLASSIFICATION ACCURACY COMPARISON.

Banana leaf images	Classification accuracy (%)				
	CNN [7]	GR-ARNet [8]	Faster R-CNN [12]	ANN-SIFT [14]	Proposed model
1	89.47	92.88	90.39	90.99	97.99
2	88.91	93.37	89.27	91.78	98.02
3	88.53	93.92	89.99	90.85	98.53
4	87.68	92.99	90.98	90.69	97.89
5	88.97	93.58	89.72	91.33	98.72

TABLE II. PERFORMANCE ANALYSIS OF THE PROPOSED AND EXISTING CLASSIFICATION MODELS.

Performance metrics	Performance analysis				
	CNN [7]	GR-ARNet [8]	Faster R-CNN [12]	ANN-SIFT [14]	Proposed model
Pre(%)	88.64	92.99	89.73	91.62	98.75
Re(%)	89.59	91.27	90.89	90.88	98.88
F1 Score (%)	89.11	92.12	89.97	91.24	98.81
Sp (%)	89.78	90.98	90.99	90.97	98.47

TABLE III. ERROR RATE OF THE PRESENTED AND EXISTING DEEP LEARNING SCHEMES.

Banana leaf images	Error rate (%)				
	CNN [7]	GR-ARNet [8]	Faster R-CNN [12]	ANN-SIFT [14]	Proposed model
1	14.69	6.82	13.64	10.74	2.65
2	14.57	7.33	13.33	10.33	2.71
3	15.78	6.99	15.89	11.97	2.57
4	15.55	8.57	14.57	10.85	2.99
5	14.97	7.85	13.99	11.98	2.43

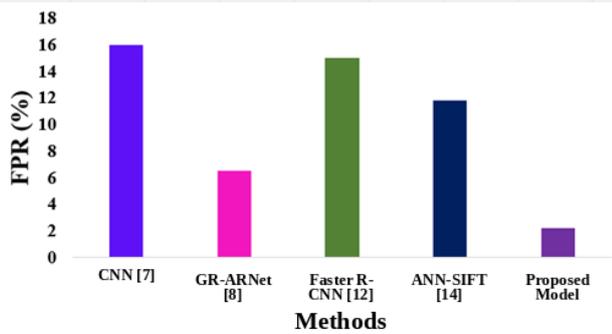


Fig. 7. FPR comparison.

Compared to the state-of-the-art methods, proposed AFLRNN obtained reduced FPR (below 3 %) in the progression of disease detection and categorization in the banana leaf image.

VI. CONCLUSIONS

In this paper, an automated banana leaf disease detection and classification has been presented using improved image processing and DL models. Initially, banana leaf images were collected. A hybrid image processing scheme was presented to enhance image quality for further processes, in which a Gaussian filter was applied to remove noise from the images and image restoration was done with the help of Weiner filtering method. Subsequently, the Otsu thresholding scheme has been exploited to segment the disease affected area in banana leaf images. Disease relevant features were extracted through the deep learning CNN. Finally, AFLRNN was presented to discover and categorize disease with its severity level in banana leaf images according to the extracted features. The presented automated banana leaf disease detection model could recognize exact diseases affecting banana leaf and it can assist farmers to take the appropriate action. Banana leaf disease can be discovered at an early stage through the presented image processing and deep learning models, allowing for appropriate involvement and probably avoiding extensive crop harm. Farmers could have obtained immediate real-time information on the health of their banana crops by incorporating this model presented into mobile applications or other platforms. Time and resources are saved through the early detection of banana leaf disease using the presented model. AFLRNN achieves enhanced accuracy to discover banana leaf diseases and misdiagnosis is decreased. This early finding of banana leaf disease and well-timed intervention will reduce banana crop losses due to diseases. In future, deep learning models will be developed and equipped with drone cameras to monitor huge regions of banana cultivated areas, allowing large-scale disease discovery.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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