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Design an Ant Lion-Based Yolo-V5 Model for Prediction and Classification of Paddy Leaf Disease

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Abstract: It is crucial to identify crop diseases early to educate farmers on how to stop the spread of diseases in their crops. However, the agriculture sector's output is impacted by the emergence of numerous crop-related diseases. Multiple methods for predicting paddy leaf diseases have been created, but they still suffer from overfitting, poor detection, and classification issues. To overcome these issues, design a novel Ant Lion-based YOLO-V5 (AL-YOLOv5) system to improve the system's functionality to detect paddy leaf disease. Paddy leaf photos were initially gathered from the internet and trained in the system. Brown spot, Leaf blast, Healthy, and Hispa are the four paddy leaf diseases the proposed model intends to classify better and identify. The dataset's noise is removed during the preprocessing stage, and the GrabCut algorithm is used to segment the impacted areas based on the pixels. The Grey-Level Co-Occurrence Matrix (GLCM), which extracts form, texture, and color features, is also used for feature extraction. Finally, utilize a YOLOv5 network to find and categorize the crop's affected diseases. The created model uses ant lion fitness to forecast paddy leaf diseases correctly. By achieving improved performance metrics, the experimental findings demonstrate the effectiveness of the designed model, and the obtained results are validated with other traditional models in terms of accuracy, precision, recall, F-score, and error rate.

Keywords: *Paddy Leaf Disease Detection, Grey-Level Co-Occurrence Matrix, Ant Lion Optimization, Principal Component Analysis, GrabCut, Segmentation. Deep Learning*

1. Introduction

One of the most recent agricultural research subjects is identifying and categorizing plant diseases by photographing the plant's leaves. Using image processing techniques to identify agricultural plant diseases will reduce the need for farmers to take extra precautions to safeguard their crops [1]. Agriculture is one of the most significant sources of income for people in many nations. Farmers gather various food plants based on the natural conditions of the area and their needs [2]. Yet, there are several issues that farmers must deal with, including natural disasters, a water deficit, plant diseases, etc. The majority of problems are reduced by offering some best technologies [3]. Furthermore, a timely approach to illness prevention may increase food production, negating the need for experts and saving time. Therefore, identifying plant disease is one of the crucial study areas in the agricultural sector [4].

Consequently, it has become challenging to identify and categorize plant diseases. India has a sizable population, and agriculture provides most of the country's food supply. Crop illnesses, insect infestations, and plant diseases are the leading causes of agricultural areas being destroyed [5]. Fungi, bacteria, viruses, or nematodes known as plant pathogens can harm plant parts like leaves, panicles, nodes, stems, and roots. Hence, one of the most recent agricultural studies is identifying and categorizing crop illnesses using photographs of plant leaves [6]. Using image processing techniques to identify plant diseases can assist farmers in preventing damage or destruction of their agricultural fields. Paddy is a staple crop for many of the world's population [7]. Therefore, early detection of symptoms of plant disease has substantial agrarian benefits. However, this endeavor is completed due to a need for integrated computer vision methods created explicitly for farming applications [8].

Moreover, many issues, such as a lack of water and plant disease, can affect agricultural productivity. Hence, one crucial activity for raising output is the early detection and prevention of plant diseases in the early phases of onset [9]. However, there are substantial restrictions on

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the accurate early-stage detection and categorization of plant diseases, and only a few researches have addressed these challenges. For instance, manually inspecting plants would be impractical because it would take time and labour [10]. Due to this, image-processing techniques have been used to identify and predict diseases based on the morphological characteristics of plant leaves.

Several methods have been used to treat common diseases of rice plants, such as leaf smut, sheath rot, leaf blast, bacterial blight, and brown spot [11]. The extraction of distinctive disease traits, such as color, size, and form, depends on the segmentation results. Yet, the wide range of plant symptoms makes categorizing these characteristics as particular disease categories difficult [12]. For example, one illness may appear as brown structures in some instances and yellow systems in others. In addition, a disease may cause the same forms and colors in a specific plant species, while other conditions may cause the same colors to appear in various shapes [13]. Despite the simplicity with which professionals can categorize plant illnesses using photographs, manual classification is far to time- and cost-intensive to provide remedies for large-scale agriculture [14].

Moreover, the manual inspection could be more accurate because it depends on individual experience. As a result, current disease examination techniques frequently produce unreliable categorization results, which have recently restricted rice production [15]. To avoid wasting money and other resources, minimize yield losses, increase treatment effectiveness, and create a healthier crop output, rice crop illnesses must be automatically detected and analyzed [16]. Every nation's economy depends heavily on agriculture, so it is essential to promote its development. In recent years, there has been an upsurge in the spread of several diseases in rice plants [17]. Many plant diseases, including bacterial, fungal, and viral, can harm the earth's various plant sections. Due to industrial and agricultural production, low yield, economic losses, and crop diseases, farmers are experiencing difficulties [18]. Therefore, it is imperative to find these diseases as soon as feasible. Most research is being done using deep learning (DL), Machine Learning (ML), and image processing.

Identifying plant diseases is crucial in preventing reductions in the number of agricultural goods produced and in yield. Disease Detection and plant health monitoring are particularly detrimental to sustainable agriculture [19]. According to studies on identifying plant diseases, illnesses are represented by observable patterns in the plants. The monitoring technique for plant diseases is more challenging when done manually [20]. The manual procedure requires excellent processing time, significant labour, and knowledge of plant diseases. Methods involving image processing are used to identify plant diseases. The image recognition processes for diagnosing diseases include picture capture, image preprocessing, image segmentation, feature extraction, and classification [21]. These procedures only are carried out on the afflicted plants' outward manifestations. Leaves are a vital source for identifying plant diseases in most plants [22]. However, the characteristics of plant diseases change depending on the type of plant. Each plant disease has unique features and varies in size, shape, and color [23]. Specific ailments are coloured yellow, whereas others are brown. While some conditions have similar forms but different colors, others have similar colors but different shapes [24]. The traits associated with the disease are retrieved following the segmentation of the afflicted and normal portions. Experts must typically diagnose plant illnesses manually, which takes more time and is more valuable on large farms. Determining the disease kind is challenging to process and occasionally results in an error [25]. Rice production has decreased recently due to inadequate treatment of leaf diseases in rice plants. A suitable and quick detection system for rice leaf disease is required. As a result, this paper suggests a novel DL technique, such as You Only Look Once (YOLO) v5, for identifying rice plant illnesses from their photographs. The main subject of this study is the four most prevalent diseases of rice plants, Brown spot, Leaf blast, Healthy, and Hispa.

The main objectives of the research article are

- To increase agricultural production by early identification and detection of paddy leaf disease.
- Create a YOLO-v5 framework based on optimization to promote the expansion of agriculture.
- To achieve superior experimental results when contrasting other models' execution times, accuracy, recall, precision, and F1-score.

2. Related Works

A few recent related works based on paddy lead disease detection are detailed below,

Deep Neural Network (DNN) with Jaya Optimization Algorithm (JOA) was proposed by Ramesh and Vydeki [26] to identify and categorize paddy leaf diseases. The photos of rice plant leaves are immediately taken for image collection from the farm field and then pre-processed to remove the backdrop. Clustering segments the data into diseased, regular, and background portions. DNN-JOA carries out disease classification. The suggested technique had a high accuracy rate of 98.9%.

Using plant picture data, Nagappan et al. [27] created a DNN classification method with the crow search algorithm (CSA) to identify paddy leaf disease. Weights and biases are optimized to reduce classification errors. Images of paddy leaves are pre-processed, and a k-means clustering technique is used to extract the regions suggestive of disease. The previously isolated sick areas are used to remove a collection of characteristics. Finally, experimental verification of the proposed DNN-CSA model's classification shows better effectiveness and efficiency.

A combination of DL models for identifying paddy leaf disease was proposed by Ganga devi and Chinnappan [28]. The photos of the input paddy leaves are gathered from common sources. Moreover, adaptive K-means clustering and Sorted-Shark Smell Optimization (S-SSO) are used to segment the strange region of the paddy leaf. Finally, the hybrid DL method using the Resnet and YOLO classifiers recognizes the disease from the segmented images. Experimental analysis is done to calculate and determine the effectiveness of the provided strategy, performance metrics, and classifier accuracy.

Samina et al. [29] use the DL model Yolov5 to produce the best and most straightforward approach for Rice leaf disease detection. Four hundred photos of the Rice leaf images dataset are obtained from the Kaggle website. The model for detecting Rice Leaf illness in this study was trained, validated, and tested using the Google Colab system. The created model makes use of 100 epochs. According to the experimental findings, the DL model built with 100 periods performed the best, with a recall of 0.94%.

A faster region-based convolutional neural network (FR-CNN) was suggested by Bifta et al. [30] for the real-time identification of illnesses affecting rice leaves. By using its original real-field rice leaf datasets and publically accessible web datasets, the FR-CNN model's robustness is increased. Also, the model had a 98.34% accuracy rate when identifying a healthy rice leaf. The FR-CNN model's results provide a very effective technique for identifying rice leaf infections that can make faster, more accurate real-time diagnoses of the most prevalent rice diseases..

A system for monitoring rice leaf disease is created using scene recognition tasks using the YOLO family techniques, which have better speed and incredible precision. Ashikur et al. [31] introduced the YOLOv5 model, which has superior results than existing DL methods for categorizing and detecting rice leaf diseases. Also, the YOLOv5 model is trained and validated using 1500 acquired data sets. The simulation results demonstrate improved object detection for the enhanced YOLOv5 network. It reaches 90% accuracy.

3. Problem Definition

The traditional methods for diagnosing leaf diseases rely on human vision. Getting expert guidance requires a lot of time and money in these situations. The human vision-based approaches have numerous areas for improvement. The eyesight of the individual or expert hired will determine the accuracy and precision of the human vision method. The best choice is made while choosing a treatment and identifying the different disorders. The fact that DL-based methods accomplish jobs more regularly than human specialists is one of its benefits. Thus, a novel DL-based classification methodology is required to address the shortcomings of existing methods. There have been minimal recent advancements in DL-based plant leaf disease detection, especially for the hardest to diagnose and classify is paddy leaf disease. Paddy leaf diseases can be identified and detected using various DL techniques. However, these methods still have limitations, including gradient explosion, vanishing problems, low accuracy, mistakes, overfitting, misclassification, and long execution times. The enormous amount of data is another issue, as is data complexity. The optimization-based YOLO-v5 framework is recommended for improving the performance of paddy plant disease diagnosis and detection.

4. Proposed Methodology

This paper suggested a novel Ant Lion-based YOLO-V5 (AL-YOLOv5) system to improve the functionality of a method used to detect paddy leaf disease. Paddy leaf photos were initially gathered from the internet and trained in the system. Brown spot, Leaf blast, Healthy, and Hispa are the four paddy leaf diseases the proposed model intends to classify better and identify. Also, the acquired dataset includes noise that is eliminated by preprocessing, which helps reduce the dataset's dimensionality and enhances the image quality using PCA. The impacted areas of the leaves are then segmented using the GrabCut algorithm based on the pixel rate and gaussian mixture. The shape, color, and texture features are extracted using GLCM feature extraction. Subsequently, the features related to color, shape, and texture were extracted using feature extraction. While detecting paddy leaf disease, the extracted features are updated to the created AL-YOLOv5 model. Update the ant lion fitness during this phase to increase the accuracy of paddy leaf disease detection. Figure 1 depicts the design model's architecture.

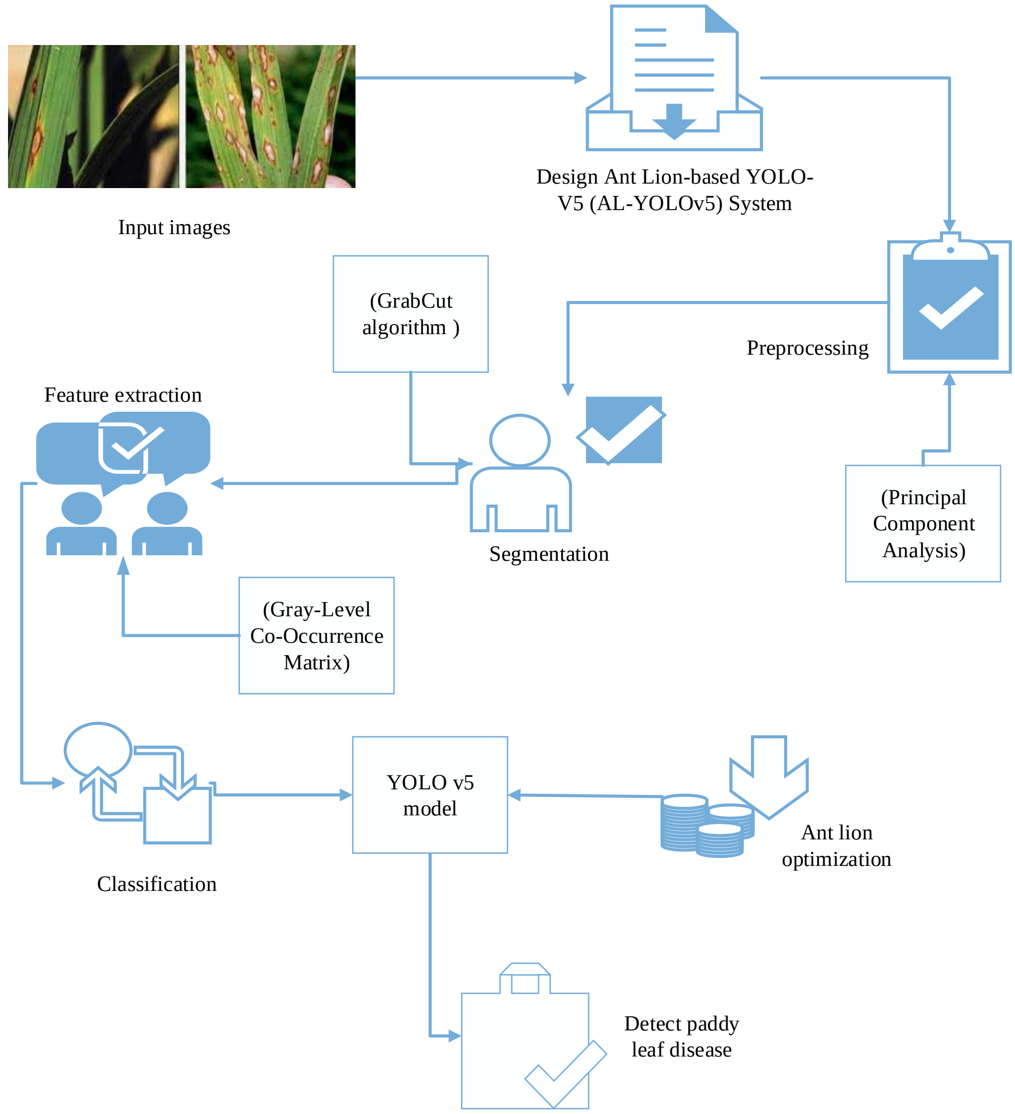

Fig.1 Architecture of the proposed methodology

4.1 Dataset description

The rice disease image dataset is collected from the Kaggle website

(https://www.kaggle.com/datasets/minhhuy2810/rice-diseases-image-dataset). The collection includes pictures of leaves that have different degrees of disease spread. The photos are taken, and a dataset is created with a total of 5447 images, including 1488 normal images, 523 images with brown spots, 565 images with Hispa, and 779 images with leaf blasts. For the training process, 400 samples are taken for each class, and for the testing process, 123 samples are considered for each category. As the number of samples considered rises, so does the training and testing accuracy. The dataset description is detailed in table.1.

Table.1 Dataset description

Labelled	Quantity	Training	Quantity	Validation	Quantity	Testing	Quantity
Brown spot	523	Brown spot	400	Brown spot	123	Brown spot	100
Hispa	565	Hispa	400	Hispa	123	Hispa	100
Healthy	1488	Healthy	400	Healthy	123	Healthy	100
Leaf blast	779	Leaf blast	400	Leaf blast	123	Leaf blast	100

As a result, out of the datasets gathered, one paddy leaf is healthy, and three have illnesses. Therefore, the acquired dataset is updated to do preprocessing, segmentation, feature extraction, and classification.

4.2 Preprocessing using Principal Component Analysis

Preprocessing techniques are used to remove the noise and obstructions present in the obtained leaf images. As a result, reliability and feature extraction are improved. Moreover, the input datasets are subjected to Principal Component Analysis (PCA) to reduce the dimensions. PCA is helpful in this situation to reduce associated features and training time. It reduces overfitting problems and transforms the high-dimensional dataset into a low-dimensional one. Eqn. (1) is used to obtain the PCA procedure.

$$p_{ca} = \bar{x} - \mu|\bar{x}| \quad (1)$$

Where, $\bar{x}$ is designated as the length of the random vector, and μ is denoted as the mean. The data are standardized using Eqn. (2).

$$s_d = \frac{\bar{x} - \mu}{\sigma} \quad (2)$$

Let, σ is represented as the standard deviation. Furthermore, segmentation updates are made to pre-processed datasets.

4.3 Segmentation

Segmentation is the process of dividing essential things into the foreground and background of digital photographs. GrabCut algorithm controls the object to be segmented through human-computer interactions and analyses the color distribution of the backgrounds and target object to use a Gaussian mixture for correctly segmenting paddy leaf affected parts.

As a result, the pre-processed image's segmentation is represented by the value of $v = (v_1, v_2, v_3 ...... v_i)$ each pixel point. As a result, when a pixel has a value of v_i is 0, it means the backdrop, and when it has a value of v_i is 1, it represents the target part, such as the damaged areas of leaves.

The vector is supplied, and the analytical solution of Gibbs in the GrabCut method is created to enable the gaussian mixture, $g = (g_1, g_2, ... g_i)$ using Eqn. (3). The Gaussian mixture is helpful for building the backdrop and the object.

$$eG(v, g, \gamma, p_v) = \bar{R}_e(v, g, \gamma, p_v) + \bar{B}_e(v, p_v) \quad (3)$$

The GrabCut algorithm is used to capture the target object segmentation. Where, eG is represented as the total energy of minimum value, and $\bar{R}_e$ is characterized as regional energy. Moreover, $\bar{B}_e$ is measured as boundary energy, p_v is denoted as the RGB value of all pixel values of images, and γ is represented as a parametric technique of gaussian mixture, which is obtained using Eqn. (4).

$$\gamma = \{f(v, g), m(v, g), \sum(v, g)\} \quad (4)$$

Let, $f(v, g)$ is characterized as the gaussian probability distribution sample weight, $m(v, g)$ is represented as the gaussian mixture, and $\sum(v, g)$ is measured as covariance.

The regional energy $\bar{R}_e$ is represented as Eqn. (5).

$$\bar{R}_e(v, g, \gamma, p_v) = \sum_{\alpha} A(v_i, g_i, \gamma, p_{vi}) \quad (5)$$

The boundary energy $\bar{B}_e$ using Euclidean distance of RGB space is obtained using Eqn. (6).

$$\bar{B}_e(v, g) = \sigma \sum_{(i, j \in B)} [v_i \neq v_j] \exp\left(-\beta \left\| p_{v\,i} - p_{v\,j} \right\|^2\right) \quad (6)$$

The GrabCut algorithm typically separates the targeted image, requiring only minimal human involvement to retrieve the boundary and colour information from the image. Additionally, it manually divides the desired elements and gradually blurs the background.

4.4 Feature extraction using Grey-Level Co-Occurrence Matrix

Also, the number of redundant data in the collection is reduced via feature extraction. The Grey-Level Co-Occurrence Matrix (GLCM) extracts the dataset's shape, color, and texture. The characteristics of the internal gradient information are extracted using the GLCM window adaptive approach. Here, GLCM techniques are used to extract the statistical features. Moreover, two-dimensional histograms composed of components (s, t) are used to perform GLCM. Then, features like shape, color, and texture are extracted; descriptions of these feature extractions are provided below, The square averaging of GLCM pixels is computed using the shape. The form value for a typical image is 1. The provided Eqn. (1) expresses the forms.

$$S = \sum_{s,t} \hat{P}(s,t)^2 \tag{7}$$

Here, $\hat{P}$ represents the pixel.

The color is expressed in Eqn. (8) and is used to calculate the values and analyze the elemental distribution within the GLCM pixel.

$$C = \sum_{s,t} \frac{\hat{P}(s,t)}{1+|s-t|} \tag{8}$$

For a typical image, the texture determines the value of various intensities in the middle of a specific pixel and its neighbor. The provided Eqn. (9) represents the texture.

$$T = \sum_{s,t} |1-t|^2 \hat{P}(s,t) \tag{9}$$

After extracting the low-level features, trained data is given to the YOLOv5 network to detect paddy leaf disease.

4.5 Classification using AL-YOLOv5 model

As a single-stage target identification method, YOLOv5 [32] has the advantages of a lower mean weight file, quicker training, and better reasoning speed based on a less drastic drop in ordinary detection accuracy. It consists primarily of the Input, Backbone, Neck, and Prediction. One uses the mosaic data augmentation method to combine four photos using random reduction, random scaling, and random arrangement, considerably enhancing the background diversity of the input image and improving the model's robustness and generalizability. Furthermore, YOLOv5 adopts the adaptable image-scaling module in input to reduce the original image to the standard size. It allows the least amount of black edge to be applied adaptively based on the original image's length-width ratio. As a result, the designed model decreases image filling, reducing the calculation cost and increasing target detection speed. In this phase, update the ant lion fitness to enhance the performance of paddy leaf disease detection. The architecture of the developed YOLOv5 with ALO is shown in fig.2. The optimized YOLOv5 model contains four layers: input, backbone, neck, and prediction layer.

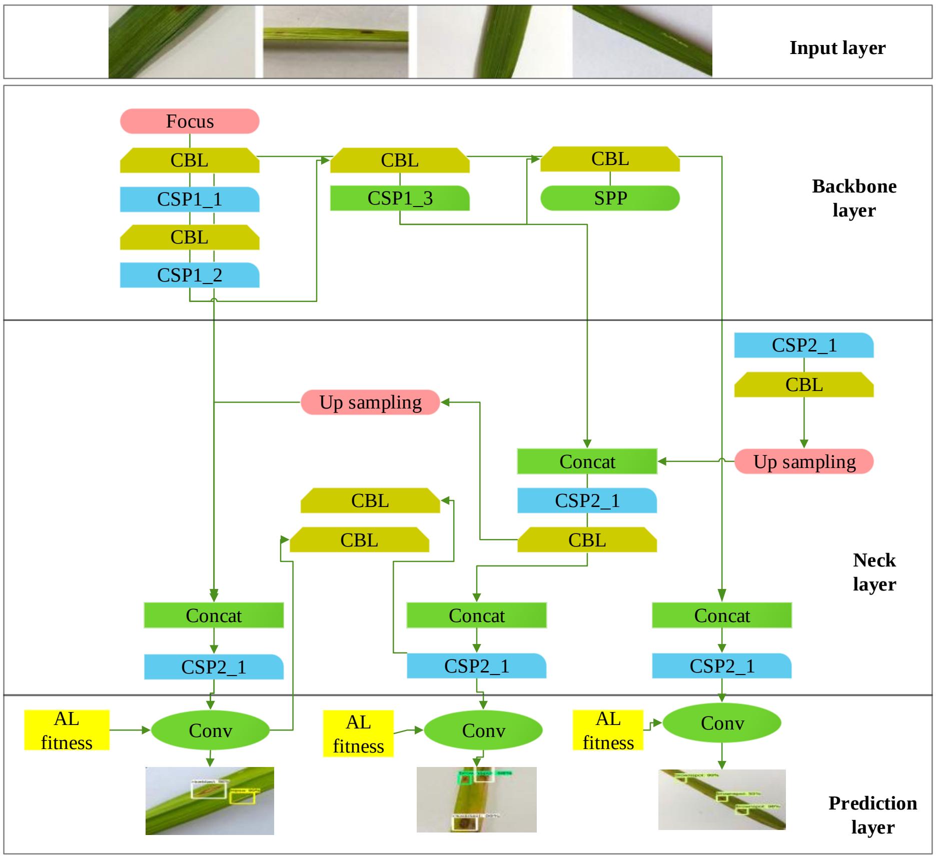

Fig.2 Architecture of developed AL-YOLOv5 model

Input layer: The mosaic data alternate solutions are put forth based on the CutMix data improvement technique's input layer. This approach adaptively determines the ideal anchor point frame based on the dataset's name and adds the least amount of black border to the scaled image.

Backbone layer: The CSPDarknet53, Focus benchmark network, and SPP structures are utilized. It makes use of the CSPDarknet53 structure. The focus phase pixels are regularly taken from high-resolution images and reassembled into low-resolution images to lessen original data and computational redundancy. The CSP architecture consists of two types: the regular CBL CSP architecture, which is given to the neck layer, and the Resunit (2 CBL convolution + residual). It is important to note that by enhancing the residual architecture, this layer improves the gradient rate of backpropagation among layers and the model's ability to generalize. Finally, the SPP structure pools kernel sizes to extract features of various scales, then performs feature fusion via stacking.

Neck layer: The series FPN + PAN structure strengthens semantic characteristics and positional information distribution by performing feature fusion and multi-scale prediction among various layers from bottom to top. The CSP2 1 component, which aids in locating the pixels to build the mask, replaces the CBL module following the Concat process.

Prediction layer: The weighted NMS approach is used to screen the target box in the YOLOv5 model, which has a superior classification result for obscured overlapping targets thanks to GIOU Loss as the loss function of the bounding box and an increased intersection scale. Upgrade ant lion fitness to raise prediction precision.

Ant lion optimization [33]: Ants' primary duty is to scout out the search area. They are expected to stroll randomly around the search area. The antlions keep the ants in their optimal position and direct their search toward the search space's most fruitful areas. The ALO algorithm imitates the random movement of ants, being trapped in an antlion pit, building a pit, moving ants to antlions, collecting prey and rebuilding the hole, and elitism for solving optimization problems. This fitness function is used to identify the affected regions from the input images and accurately classify the type of paddy leaf disease with less execution time.

Initially, the input images are equally divided into grids $g*g$. Then the images are transferred to the YOLOv5 network for detecting the target, target boundary box, and target category of every grid. At last, the designed model predicts the boundary box based on the non-maximum suppression and output dimension $g\times g(B\times 5+C)$. Thus the degree of the matching object based on the expected box is obtained using Eqn. (10).

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$$Co_i^j = P_o(C_i/O)*P_o(O)*Iou_p^t = P_o(C_i)*Iou_p^t(A_l) \tag{10}$$

Let, Co_i^j is denoted as the confidence of i th grid cell and j th boundary box, $P_o(C_i/O)$ is considered as the chance that the target falls under category i, A_l is denoted as ant lion fitness function, and $P_o(O)$ is represented as the chance that an object is present in the current box. Moreover, Iou_p^t is considered as a proportion of the projected box's union and intersection with the actual box, and $P_o(C_i)$ is denoted as the chance of occurring i-th category.

The IOU tracker assumes that every object is monitored once every frame, with minimal to no lag time among detections. Similarly, when an item is detected in subsequent frames, the IOU expects a more significant overlap for intersection over joints. The IOU metric computation, which serves as the foundation for this method, is provided in Eqn (11).

$$Iou_p^t = \frac{A_r(t)\cap A_r(p)}{A_r(t)\cup A_r(p)} \tag{11}$$

The most excellent IOU value is detailed in Eqn. (11) is used to track objects if the IOU tracker does not reach a predetermined threshold. Since this study aims to monitor objects, cancelling tracks that do not satisfy a predetermined threshold time length and where no identified objects exceed the necessary IOU threshold can improve IOU performance. Remembering that the IOU tracker heavily depends on how well object recognition models can identify items is crucial. Hence special attention is paid to training these models efficiently.

Let, $f_{al}(t)$ is denoted as the fitness of antlion optimization, T_h is considered as the threshold value of each pixel, W_f is represented as an assigned weighted function, and $h(m)$ is regarded as the harmonic mean. The threshold functions of the crop images are obtained using Eqn. (12).

$$T_h = \begin{cases} diseases & if\left(T_h \geq C_l(d)\right) \\ healthy & if\left(T_h < C_l(d)\right) \end{cases} \tag{12}$$

Finally, classify the affected diseases of each plant and improve the results with better performance. Thus the designed model attains better efficiency by detecting and classifying crop diseases. The flow chart of the developed model is shown in fig.3.

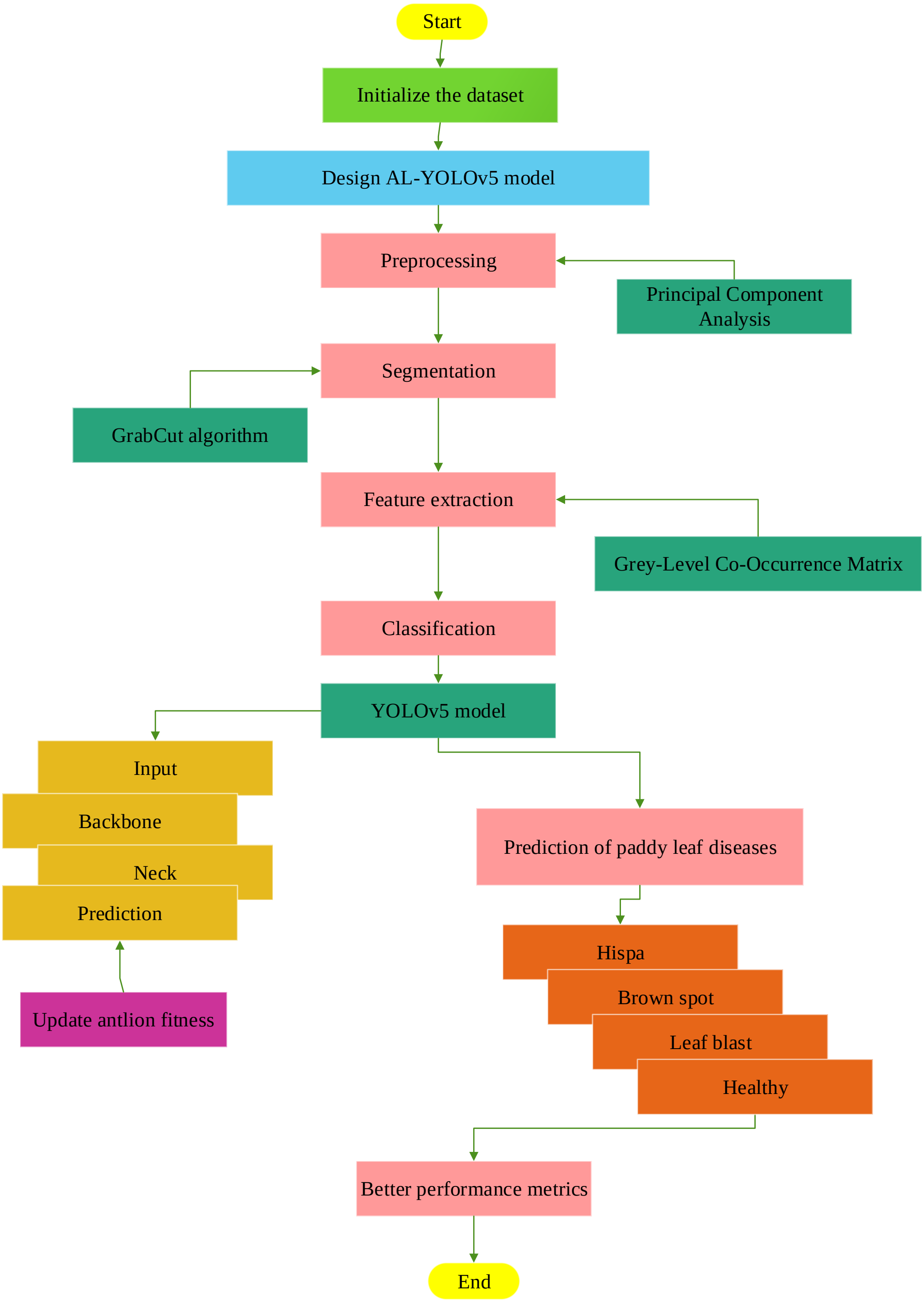

Fig.3 Flow chart of the proposed model

5. Results and Discussions

The AL-YOLOv5 model uses a python program to predict and classify paddy leaf diseases. Additionally, the YOLOv5 system has updated the ant lion fitness function to increase the precision of paddy leaf disease identification. Further, the dataset's noise is removed during the preprocessing step. Furthermore, feature extraction removes unnecessary features and takes essential data from the dataset. The plant community dataset, which includes images of both healthy and diseased plants, is where the designed model datasets are gathered. Finally, based on the segmented findings, the developed model diagnoses and categorizes the affected illnesses.

5.1 Performance analysis

The obtained findings are tested with other widely used conventional models to demonstrate the effectiveness of the created model. Also, the developed model's accuracy, precision, recall, F-score, and error rate performance measures are contrasted. Thus the existing techniques are DNN-JOA [26], DNN-CSA [27], YOLO v5 [29], and FR-CNN [30].

5.1.1 Accuracy

Accuracy is evaluated using closed measurements of the accepted or actual value. Accuracy is used to assess how close to the genuine or desired value is. Accuracy is measured using Eqn. (13).

$$A_c = \frac{t_p^* + t_n^*}{t_p^* + f_p^* + t_n^* + f_n^*} \tag{13}$$

Let, t_p^* denoted as the true positive rate of detected and classified paddy leaf diseases, t_n^* is considered the true negative rate of detected and classified paddy leaf diseases. Moreover, f_p^* and f_n^* are represented as the false positive and false negative rates of detected and classified paddy leaf diseases. The graphical representation of the accuracy is shown in fig.4.

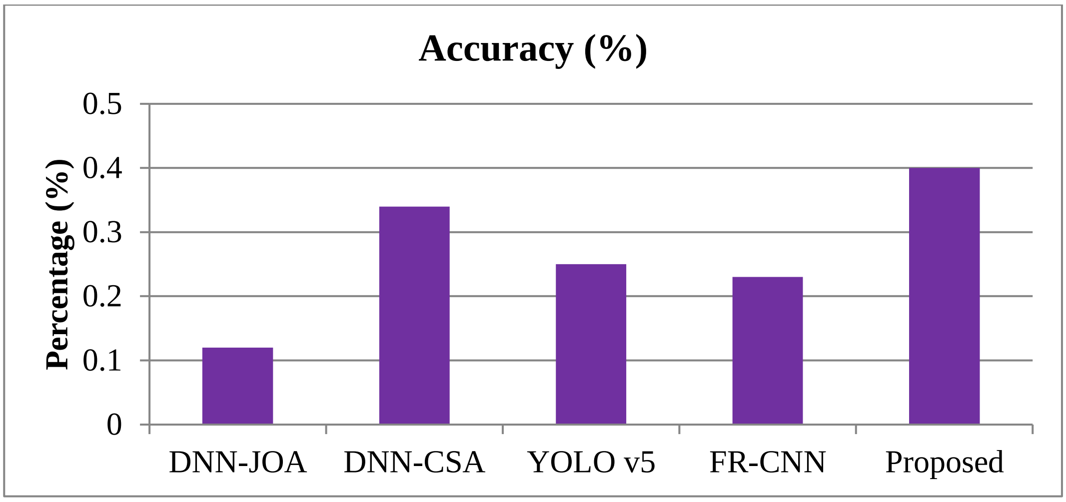

Fig.4 Comparison of accuracy

The proposed model increased accuracy results are compared to popular models like DNN-JOA, DNN-CSA, YOLO-v5, and FR-CNN. Moreover, the accuracy rates for DNN-JOA and DNN-CSA were 98.9% and 85%, respectively. Similar results were obtained by the YOLO-v5 model (94% accuracy) and the FR-CNN approach (98.34% accuracy). Eventually, the created model achieved an accuracy of 99.87%. Compared to other models, the designed one achieves higher accuracy ratings.

5.1.2 Precision

Moreover, precision is determined using the closed measurements of similar things next to one another. Precision is separate from accuracy and becomes more reliable when measured by repeated outcomes. Precision is measured using Eqn. (14).

$$P_r = \frac{t_p^*}{t_p^* + f_p^*} \tag{14}$$

The outcomes of the developed model's increased precision are validated using findings from other popular models like DNN-JOA, DNN-CSA, YOLO-v5, and FR-CNN. The precision rates for DNN-JOA and DNN-CSA were also 96.4% and 80%, respectively. In accordance, the FR-CNN technique achieves 98% precision, while the YOLO v5 model gained 93.5% precision. Eventually, the developed model achieves a precision of 99.34%. Compared to other models, the designed one achieves higher precision scores. Fig.5 displays a graphical representation of precision.

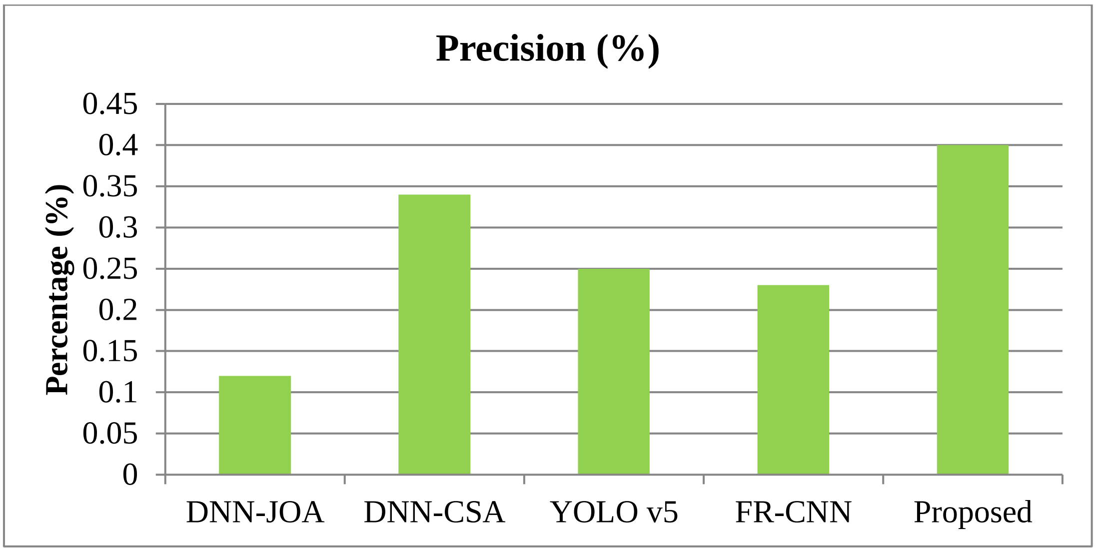

Fig.5 Comparison of precision

5.1.3 Recall

The recall is a count of all relevant documents retrieved and appropriate in some way. It is the designed model's capacity to locate every pertinent case in the dataset. In addition, it is calculated by dividing the total number of true positives by the sum of true positives and false negatives. The recall is measured using Eqn. (15).

$$R_e = \frac{t_p^*}{t_p^* + f_n^*} \tag{15}$$

The acquired recall outcomes of the developed model are validated using various widely used models, including FR-CNN, YOLO-v5, DNN-JOA, and DNN-CSA. Moreover, the recall rates for DNN-JOA and DNN-CSA were 98% and 80%, respectively. Similar results were obtained by the YOLO-v5 model (94.7%) and the FR-CNN method (98.21%). Eventually, 99.66% of recall is achieved by the designed model. Figure 6 displays a graphic illustration of recall.

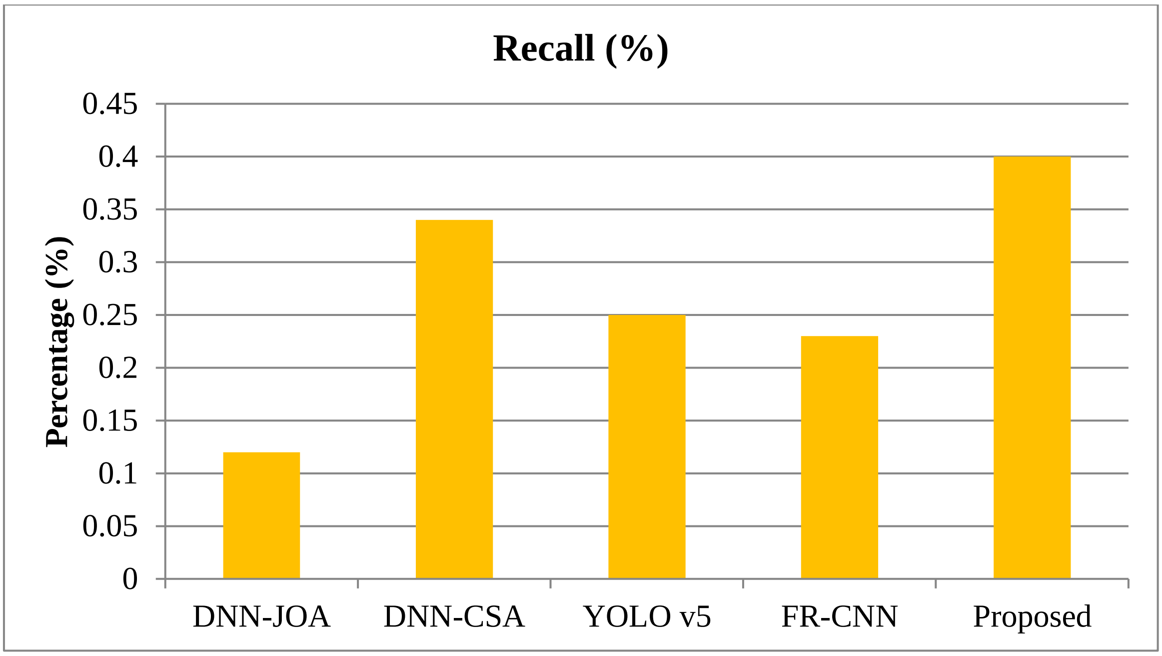

Fig.6 Comparison of recall

5.1.4 F-score

The single sum of the classification measures is used to produce the F-score. F-score takes into account the precision and recall of the scoring method. The greater F-score demonstrates the categorization measures' accurate predicting ability. The F-score is calculated using Eqn. (16).

$$F_s = 2 \times \frac{P_r \times R_e}{P_r + R_e} \tag{16}$$

Where, P_r is denoted as precision and R_e is represented as recall.

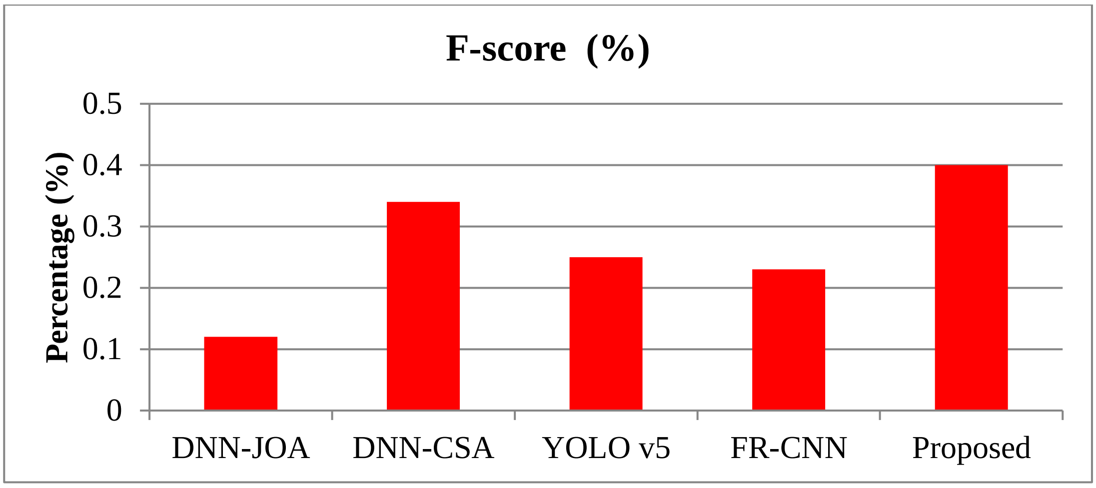

Fig.7 Comparison of F-score

The developed model's F-score results are validated against other widely used models, including DNN-JOA, DNN-CSA, YOLO-v5, and FR-CNN. The F-score rates for DNN-JOA and DNN-CSA were also 96.4% and 76.8%, respectively. In accordance, the FR-CNN technique achieves a 97% F-score, whereas the YOLO-v5 model obtained a 92% F-score. Eventually, 99% of the F-score is achieved by the designed model. Compared to other models, the designed one achieved higher F-scores. Figure 7 shows a graphic representation of the F-score.

5.1.5 Error rate

The error rate is a phrase used to describe how accurately the proposed model predicts the actual model. Moreover, it is the proportion of incorrect data units to the total number of data units communicated. Eqn. (17) is used to calculate the error rate.

$$E_r = \frac{\left(f_p^* + f_n^*\right)}{p + n} \tag{17}$$

Let, p is denoted as a positive value and n is represented as a negative value. The graphical representation of the error rate is shown in fig.8.

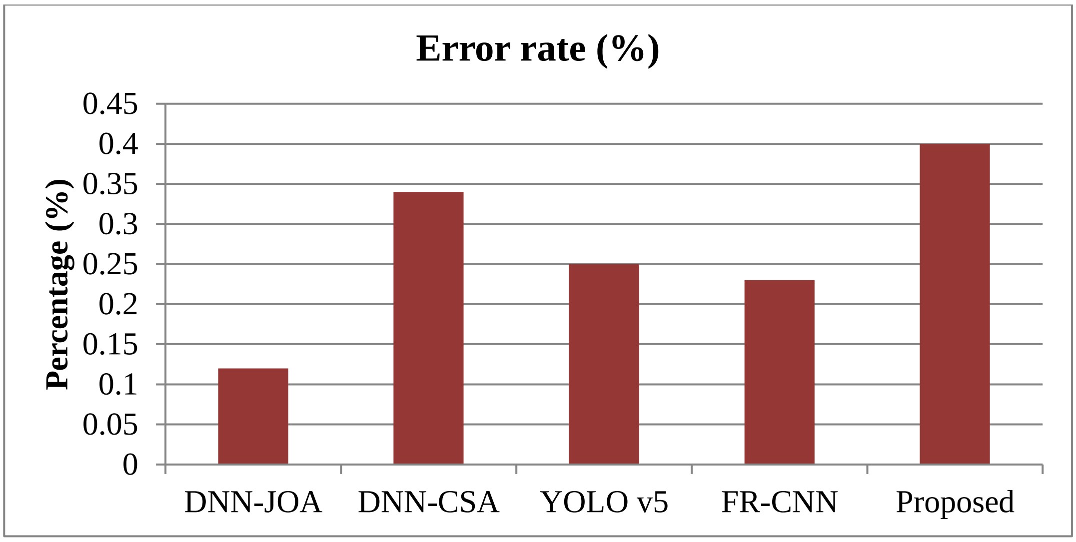

Fig.8 Comparison of error rate

The results of the proposed model's acquired error rate are verified against those of other widely used models like DNN-JOA, DNN-CSA, YOLO-v5, and FR-CNN. The error rates for DNN-JOA and DNN-CSA were 0.12% and 0.34%, respectively. In line with this, the YOLO-v5 model achieved an error rate of 0.25%, while the FR-CNN method achieved an error rate of 0.23%. Eventually, the developed model achieves an error rate of 0.4%. Compared to other models, the designed model has a lower error rate.

5.2 Discussions

The developed model performed better in terms of accuracy, precision, recall, F-score, and error rate. In addition, compared to other models, the time needed to identify and categorize paddy leaf diseases is also shorter. The performance of the developed model is finally validated using 20, 40, 60, 80, and 100 epochs. Table 2 provides specifics about the model's outcomes.

Table.2 Overall performance

No.of. Epochs	Performance assessments				
	Accuracy	**Precision**	**Recall**	**F-score**	**Error rate**
20	99.87	99.34	99.66	99	0.4
40	99.60	99.20	99.50	98.78	0.5
60	99.42	99.04	99.43	98.50	0.7
80	99.12	98.88	99.18	98.31	0.8
100	99	98.56	99.04	98.11	0.9

Also, the YOLOv5 model, which correctly and efficiently classifies paddy leaf illnesses, has upgraded antlion fitness. Furthermore, 30% of datasets are utilized for testing, while 70% are used for training. As a result, the designed model attained better results in identifying and detecting paddy leaf disease, reaching 99.87%, 99.60%, 99.42%, 99.12%, and 99% accuracy, 99.34%, 99.20%, 99.04%, 98.88%, and 98.56% precision, 99.66%, 99.50%, 99.43%, 99.18%, and 99.04% recall, 99%, 98.78%, 98.50%, 98.31%, and 98.11% F-score, and 0.4%, 0.5%, 0.7%, 0.8%, and 0.9% error rate for 20, 40, 60, 80, and 100 epochs. As a result, the developed model produces improved results for reliably classifying paddy leaf diseases. The created model aids farmers in spotting illness at an early stage and boosts agricultural development.

6. Conclusion

A novel Ant Lion-based YOLO-V5 (AL-YOLOv5) method is suggested in this study for the precise identification and classification of paddy leaf diseases. The datasets used in this research are collected from the Kaggle website. The Python tool implements the specified model. First, the PCA method is used to eliminate noise and achieve dimensionality reduction. Next, the impacted areas are divided based on the pixels using the GrabCut algorithm. The most crucial features are further fed into the YOLOv5 model using feature extraction, which uses the GLCM method. Finally, use threshold values and ant lion fitness to identify and categorize the crop-affected diseases. With preventative measures, the model's obtained findings enable the accurate detection and classification of plant diseases. The findings show the dominance of the designed model, and the experimental results are also validated using other traditional approaches. The proposed model achieves 99% F-measure, 99.87% accuracy, 99.34% precision, and 99.66% recall. As a result, the created model is effective at identifying and classifying paddy leaf diseases.

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