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Leveraging Pattern Recognition based Fusion Approach for Pest Detection using Modified Artificial Hummingbird Algorithm with Deep Learning

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Abstract: Pest detection is a vital feature of agriculture and ecosystem organization, intended to classify and mitigate the power of harmful organisms on crops and the atmosphere. By automating the recognition procedure, researchers and farmers can improve accuracy in pest organization, enhance resource allocation, and finally donate to sustainable and strong farming practices. Leveraging innovative technologies like computer vision (CV) and machine learning (ML), pest recognition techniques can examine images and sensor information to recognize the presence of pests in agricultural areas. Pest classification utilizing pattern detection and DL contains the growth of sophisticated methods to mechanically recognize and classify numerous pests. This incorporated technique connects the powers of traditional pattern detection approaches and the learning abilities of deep neural networks (DNNs). DL, particularly Convolutional Neural Networks (CNNs), has shown amazing victory in learning complex patterns straight from raw data. By using DNNs, the method can mechanically learn hierarchical representations, enabling it to discern complex features and relationships in pest-related data without clear feature engineering. In this aspect, this study introduces a fusion of the Modified Artificial Hummingbird Algorithm with Deep Learning-based pest detection and classification (MAHADL-PDC) technique. The MAHADL-PDC technique aims to effectually recognize distinct pests' types. The input image quality is enhanced by the adaptive median filtering (AMF) approach. In addition, feature extraction using the EfficientNet-B4 model is performed to learn complex features, and its hyperparameters were chosen by utilizing MAHA. The MAHADL-PDC method uses the deep belief networks (DBNs) model to detect and classify pests. To highlight the significant performance of the MAHADL-PDC method, a series of experiments were made. The performance validation of the MAHADL-PDC approach portrayed superior outcome over existing models.

Keywords: Pest Detection; Agricultural Crops; Plant Disease; Artificial Hummingbird Algorithm; Deep Learning.

1 Introduction

Agriculture is described as the support of the economy that provides for the country's financial development and controls living standards [1]. The agricultural and food processing industry is a most significant field in all countries and performs a crucial role in increasing the export quality of agricultural and food products. In evolving states, an improvement in food processing alterations is a major one owing to the effect of export rates and domestic market requirements [2]. In particular cases, it needs storage, continuous preservation of equipment, and highly frequent workspaces. Pest attack is a major important issue in the agricultural field that leads to a reduction in crop quality [3]. Weeds, pests, and germs cause huge damage to crops and lead to less market for the last crops. Finding novel methods to get even slight improvement in effectiveness will produce the variance amongst turning them into a loss or profit [4]. This is taking into account the pest attacks under harvests that affect the development of the field crops. An extremely vital cash crop mainly provides for large quantities of production. The insects become a major source after crop quality degeneration and minimize the production of crops [5]. Thus, analyzing and monitoring the damages caused by insects can be required to ensure crop quality and protectively in agriculture.

Plant diseases and pests are a type of natural phenomena that affect the regular development of plants and cause plant death in the complete evolution processes of plants from seed evolution to seedling and to seedling

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development [6]. During machine vision processes, plant diseases and pests tend to be the idea of human involvement instead of simple mathematical functions. In real intricate environmental surroundings, plant diseases and pests detection will be handled with several problems such as smaller variance among the lesion regions and the contextual, lower contrast, huge dissimilarities in the measure of the lesion areas and diverse categories, and various noise in the lesion imageries [7]. Additionally, varieties of disruptions even gather plant diseases and pests images in natural light settings. Currently, the standard classical algorithms recurrently perform without support, and this is complex for accomplishing higher efficient detection outcomes [8]. Recently, the effectiveness of deep learning (DL) applications characterized by CNNs in several fields of CV, for example, scenario text identification, face identification, medical image recognition, traffic detection, and emotion identification [9]. Several plant diseases and pests recognition methods that are dependent upon DL are employed in real-time agriculture and a few domestic and foreign organizations have established a multiple of DL-based plant diseases and pests detection [10].

This study introduces a fusion of the Modified Artificial Hummingbird Algorithm with Deep Learning-based pest detection and classification (MAHADL-PDC) technique. The MAHADL-PDC technique aims to effectually recognize distinct pests' types. The input image quality is enhanced by the adaptive median filtering (AMF) approach. In addition, feature extraction using the EfficientNet-B4 model is performed to learn complex features, and its hyperparameters were chosen by utilizing MAHA. The MAHADL-PDC method uses the deep belief networks (DBNs) model to detect and classify pests. To highlight the significant performance of the MAHADL-PDC method, a series of experiments were made.

2 Related Works

Sanghavi et al. [11] presents a Hunger Games search-based deep-CNNs (HGS-DCNNs) method. An advanced convolutional layer has been developed. This research was managed in dual stages. A new adaptive cascaded filter (ACF) approach is employed for pre-processing. The developed filtering method has been split into decision-based guided image filtering (GIF) and median filtering (MF) techniques. Arun and Umamaheswari [12] introduced an innovative end-wise DeepPestNet architecture for identifying and categorizing pests. The developed method comprises eleven learnable layers, eight convolutional and three fully connected (FC) layers. This technique employed image rotation methods for increasing the sizes of the dataset and image augmentation algorithms for examining the generalizability of this developed DeepPestNet method. Unhelkar and Chakrabarti [13] projected an improved CNN with an Adaptive Particle Swarm Optimizer with the LSTM (ICNN-APSO-LSTM) technique. The mathematical form can be obtained through a main function, integrating pest recognition and pesticide recommendation employing CNNs and machine vision. This method also employs soil NPK sensors for obtaining soil nutrient parameters and evaluating to suggest proper fertilizers.

Albattah et al. [14] developed a lightweight drone-based method such as a modified CornerNet technique with DenseNet100 as a main network. This architecture encompasses 3 phases. The region of interest (RoI) was first achieved by developing sample annotations after being utilized in the training model. A modified CornerNet could be developed at the subsequent stage by utilizing the DenseNet-100 for computing the significant key points. The first phase detector CornerNet detects and classifies diverse pests in the ending stage. Ananyasreya and Subhija [15] aimed to develop an automatic pest classification method employing DL techniques. Input data was augmented and pre-processed by utilizing histogram equalization. DL was employed for extracting the features and features have been offered to traditional methods. In [16], the PestLite system is dependent upon the YOLOv5 architecture. The study also developed a Multi-Level Spatial Pyramid Pooling (MTSPPF) technique. By employing a light-weight component, it combines normalization, activation, and convolution processes. Furthermore, the technique presented the ECA mechanism for improving the context of knowledge.

In [17], a two-phase DCNN method was utilized for plant and citrus disease identification by employing leaf imageries. The developed model includes two major phases; (a) developing the possible target diseased areas employing a region-developed network; and (b) categorization of the more possible targeted regions for the respective disease types by employing a classifier. In [18], an innovative DL method named the Faster-PestNet was developed. An enhanced Faster-RCNN technique was devised by employing the MobileNet as its main system and changed under the pest instances for identifying the pests of diverse kinds and provided the term Fatser-PestNet. Primarily, the MobileNet was implemented to remove a distinct group of instance features, after being identified by a two-stage locator of the enhanced Faster-RCNN architecture.

3 The Proposed Method

In this research, a fusion of the MAHADL-PDC methodology is proposed. The MAHADL-PDC methodology aims to effectually recognize the distinct types of pests. The MAHADL-PDC methodology comprises processes like AMF-based preprocessing, EfficientNet-B4-based extraction, MAHA-based tuning, and DBN-based classification. Fig. 1 illustrates the structure of the MAHADL-PDC method.

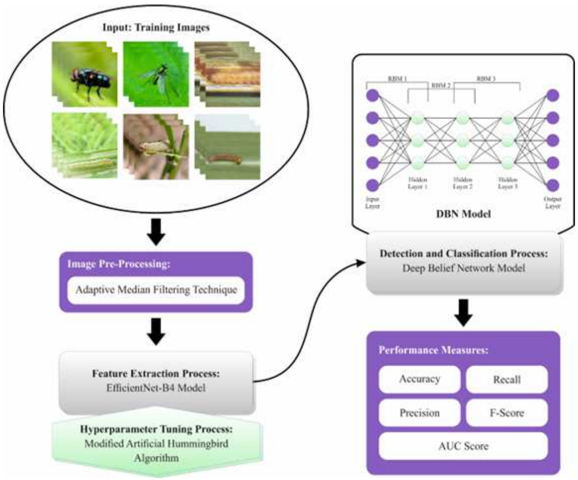

Fig. 1: Overall workflow of MAHADL-PDC model

3.1 Preprocessing

Initially, the MAHADL-PDC methodology undergoes the input image quality can be boosted by the AMF approach. The MF removes noise from the image while preserving its sharpness [19].The median value of closer pixels modifies each pixel and a3×3 window was utilized.

This filter removes the speckle noise and is the optimum filter in traditional filters. The AMF maintains the edges and construction of the images. Based on each pixel, the window size varies in the AMF. When the AMF improved, structural metrics could be moderately decreased, by this, an image can be slightly blurred. The given Eq. (1) signifies the probability density function:

$$p(y)=\begin{cases} pu, & \text{y=u;} \\ pv, & \text{y=v;} \\ 0, & \text{other.}\end{cases} \quad . \tag{1}$$

From Eq.1 , pu and pv are given as probability relevant to u and v, and the $u=0$ and $v=255$ have been the black-and-white noise points. The next Eq.2 indicates the MF mathematical form:

$$L(i,j)=Median(m(s)). \tag{2}$$

Now, m denoted as the category of gray value sequences, s is described as the number of pixels, i indicated as the pixel vertical coordinate, and j is shown as the pixel horizontal coordinates. When the noise probability $p(y)>20$, the filtering impact will reduce in the conventional MF. The noise fact changes the median point once the window inappropriate noise point is greater than 50%, this produces the significance of filter loss. The AMF finds the conditions for distinguishing if the changed MF becomes a noise point or not and it can be valuable for preventing the complexity of MF.

3.2 EfficientNet-B4-based Feature Extractor

At this level, feature extraction using the EfficientNet-B4 model is performed to learn complex features. In the deep transfer learning (DTL) model, the researchers try to create an efficient model with more resolution, or by making them so deeper and wider [20]. However, this provides false results and makes the model to be saturated for the classification problems. In EfficientNet architecture, in terms of resolution, depth, and width, the scaling can be done in a controlled and effective manner to achieve better outcomes. Specifically, the EfficientNetB4 technique is used for the identification of pest detection. Thereby obtaining a greater balance between the model performance and size. This is a reversed residual block and MBConv characterizes the mobile inverted convolution block. This provides depthwise convolution operation on the input, also helps to learn features from the mammogram input, and needs fewer parameters with robust computation. Fig. 2 demonstrates the infrastructure of the EfficientNet-B4 technique. Thus, the MBConv block of EfficientNetB4 architecture provides an effective representation of the feature vector. Then, the feature map is passed into the global average pooling (GAP). This assists in attaining an improved global representation and reduced spatial dimension of feature maps.

$$GAP(x)=\frac{1}{H\star W}\star\sum x(i,j), \tag{3}$$

Where $GAP(x)$ indicates the GAP results, W specifies the width, H denotes the height, $x(i,j)$ show the feature map value at (i,j) position. The GAP block is interconnected next to the convolution block. This will help to capture high-level representation and reduce the feature dimension. The FC layer output acts as a deep feature extracted from the mammogram image of $N\times1792$. A sample visualization of intermediate activation of EfficientNetB4 architecture for input Mammogram of CBIS-DDSM database. This illustrates the intermediate activation of the '*block2a_expand_activation*' layer of EfficientNetB4 for visualization. Here, it demonstrates how the DL is providing a strong feature vector.

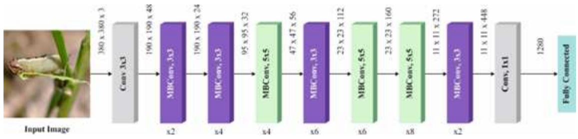

Fig. 2: Architecture of EfficientNet-B4 model

3.3 Hyperparameter Tuning utilizing MAHA

In this paper, the MAHA model is used for hyperparameter tuning. The reconnaissance aspects of hummingbirds include the superiority of definite flowers, nectar amount, and replenishment rate to select suitable sources from the various food sources [21]. Unique flying and foraging strategies of hummingbirds are the main inspiration for this algorithm. The details of the mathematical formula of the classical AHA is given below:

Initialization

A swarm of hummingbirds'n is the random location to n food source and it is defined as follows:

$$X_o = Low + r \times (Up - Low),\ o = 1, ..., n. \tag{4}$$

In Eq. (4), X_o denotes the food source location, r depicts the randomly produced integer in $[0,1]$, and U_P and Low refers to the upper and the lower boundaries. The following expression is used to construct the visit table:

$$VT_{oj} = \begin{cases} 0 & if \quad o \neq j \\ null, & if \quad o = j \end{cases},\ o, j = 1, ..., n. \tag{5}$$

If $o \neq j$, then the VT_{oj} value becomes zero which means j^{th} the food source is newly searched by 0^{th} hummingbirds in the existing iteration. If $o = j$, then the VT_{oj} value becomes null which implies the hummingbird is gathering food from its specific source.

Guided foraging

Every individual tends to the food source to forage with nectar amount which means an envisioned source should own a wide-ranging interlude without any visit and high nectar replenishment rate. Diagonal, axial, and omnidirectional are the three kinds of flying strategies of hummingbirds that provide direction. This determines whether d=dimension direction is reachable or not. In swarm, birds fly towards the omnidirectional but they glide axially and diagonally. The axial fight is represented as follows

$$D^{(0)} = \begin{cases} 1 & \text{if } o = \text{rando}([1,d]) \\ 0 & \text{else} \end{cases} \qquad o = 1, \ldots, d \tag{6}$$

The diagonal fight is described by:

$$D^{(0)} = \begin{cases} 1 & \text{if } o = P(j\cdot), j \in [1,k], P = \text{rand}\, p(k), k \in [2, [r_1^*(d-2)] + 1] \\ 0 & \text{else} \end{cases} \tag{7}$$

$o = 1, \ldots, d$

The omnidirectional flight is denoted by:

$$D^{(o)} = 1,\ o = 1, ..., d. \tag{8}$$

In Eq.8,rand $p(k)$ and rando$[1,d]$ are a set of permutation ranges from 1 to k and 1 to d, r_1 indicates the random numbers within $[0,1]$:

$$v_o(t+1) = x_{o,tr}(t) + a \times D \times (x_o(t)\text{-}x_{o,tr}(t)), \tag{9}$$

$$a \sim N(0,1), \tag{10}$$

In Eq. (9), $x_{o,tr}$ denotes the location of 0^th hummingbirds for intended the food source, $x_o(t)$ indicates the location of 0^th food sources at reconnaissance t time interval, a shows the factor of coxswained, N(0,1) refers to the uniform distribution factor with a variance of 1 and a mean of 0. Furthermore, Eq. (9) repeats directed foraging in hummingbirds by employing various flying patterns and enables the food source to update the location in terms of food sources:

$$x_o(t+1) = \begin{cases} x_o(t), & \text{f}(x_o\ \text{(t)}) \leq \text{f}(v_o\ \text{(t+1)}); \\ v_o(t+1), & \text{f}(x_o\ \text{(t)}) > \text{f}(v_o\ \text{(t+1)}). \end{cases} \tag{11}$$

In Eq. (11), f denotes the fitness function (FF). If the candidate nectar replenishing rate is better than the present one, then the hummingbird avoids the present source and takes from the candidate source.

Territorial foraging

Once the flower nectar is exhausted, a hummingbird chooses to follow the novel sources, thereby visiting the other food sources. Thus, it easily migrates towards the nearby position to find the new food source as follows:

$$v_o(t+1) = x_o(t) + b \times D \times x_o(t), \tag{12}$$

$$b \sim N(0,1), \tag{13}$$

Where b refers to the territorial factor and $N(0,1)$ represents the uniform distribution with mean and variance between zero and one.

Migration foraging

If the iteration exceeds the prior migration coefficient factor, then hummingbirds have a low replenishing rate of nectar and discover a new food source inside their region.

$$x_{wr}(t+1) = low + r \times (Up - Low), \tag{14}$$

In Eq. (14), x_{wr} represents the food source with a low replenishing nectar rate, so the succeeding preference is applied for the migration coefficient to swarm size.

$$M = 2n. \tag{15}$$

The main shortage related to the analytical model is that this method can easily stuck in local optima and is hardly applicable in a large-scale system. The proposed MAHA has the advantage of unique exploitation and exploration search capability to discover the global optimum solution.

It is noteworthy that the initial tactic is an arbitrary drive of objectives assigned with the density probability function of Levy's fight and is used to improve the search abilities where the swarm jumps towards the novel location that is distant from the optimum solution and evades stagnation issue:

$$x_o(t+1) = x_o(t) + s.\frac{u}{|v|^{1/\beta}}.(x_o(t) - x_{0,tr}(t)), \tag{16}$$

$$\begin{aligned} u &\sim N(0, \sigma_u^2), \\ v &\sim N(0, \sigma_v^2), \end{aligned} \tag{17}$$

$$\sigma_{ij} = \left\{ \frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma((1+\beta)/2)\beta 2^{(\beta-1)/2}} \right\}^{\frac{1}{\beta}}, \tag{18}$$

where β indicates the constant factor set as 1.5. s denotes the scaling parameter. u and v are normal distribution random numbers, σ_v is equal to one and Γ refers to the Gamma function.

The MAHA model generates a fitness function (FF) to achieve superior classifier performance. It uses a positive value to depict the higher performance of a candidate solution. Furthermore, the error rate reduction of the classifier is expressed through the fitness function, as defined in Eq. (19).

$$\begin{aligned} \text{fitness}(x_i) &= \text{Classifier Error Rate } (x_i) \\ &= \frac{\text{No.of misclassified samples}}{\text{Overall samples}} \times 100, \end{aligned} \tag{19}$$

Classification utilizing DBN Model

Finally, the MAHADL-PDC model utilizes the DBN model to detect and classify the pests. The DBNs is developed by stacking numerous Restricted Boltzmann Machine (RBM) with one another and including the regression layer over the top RBMs [22]. In this study, the DBN with dual RBM has been devised in a voltage degradation feature extractor. Moreover, the Gaussian-Bernoulli RBM (GBRBM) was employed as the structure of DBN. With the help of Eqs. (2) and (3), the training data have been applied to contribute to the training procedures of the DBNs, comprising dual models such as fine-tuning of supervised and pre-training of unsupervised.

The RBM stands for a stochastic neural network (SNN) that can be learned from the possibility distribution in the visible layer (VL) to the hidden layer (HL). Now, the input layer (V) and HL (H1) can be described as RBM1, and then the two adjacent HLs (H1, H2) are defined as RBM2. Conversely, the neurons among various layers are FC by the weight W. The hidden units h_j, a_i and b_j defined as biases of visible unit $v_{i,n}$, and m denote the neuron counting of VL and HL. The RBMs will be learned through the energy function $E(v,h)$ that is measured as given below

$$E(v,h) = \sum_{i=1}^{n} \frac{(v_i - a_i)^2}{2\sigma^2} - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n}\sum_{j=1}^{m} \frac{v_i}{\sigma^2} h_j w_{ij}, \tag{20}$$

Now, σ signifies the standard deviation. The probability distribution $p(v,h)$ will be described for every set of neurons (v,h) by subsequently employing the energy function:

$$p(v,h) = \frac{\Sigma_h \ e^{-E(v,h)}}{\Sigma_{v,h} \ e^{-E(v,h)}}, \tag{21}$$

The activation probability of h_j provided the visible vector v will be derived by:

$$p(h_j = 1|v) = sigm\left(b_i + \sum_{i=1}^{n} \frac{v_i}{\sigma^2} w_{ij}\right), \tag{22}$$

Here, $sigm(\bullet)$ represents the sigmoid function. Likewise, the activation probability of v_i specified the hidden vector h will be measured as:

$$p(v_i = 1|v) = N\left(a_i + \sum_{i=1}^{m} h_i w_{ij}, \sigma^2\right), \tag{23}$$

whereas $N(\bullet)$ refers to the Gaussian distribution.

4 Performance Validation

The pest detection outputs of the MAHADL-PDC approach are assessed on the IP102 database [23] comprising 700 images with 7 classes as definite in Table 1. Fig. 3 shows the sample images.

Table 1: Dataset specification

Label	Classes	Insect Numbers
C1	Rice Leaf Roller	100
C2	Rice Leaf Caterpillar	100
C3	Paddy Stem Maggot	100
C4	Asiatic Rice Borer	100
C5	Yellow Rice Borer	100
C6	Rice Gall Midge	100
C7	Rice Stemfly	100
Total No. of insects		700

Fig. 3: Sample images

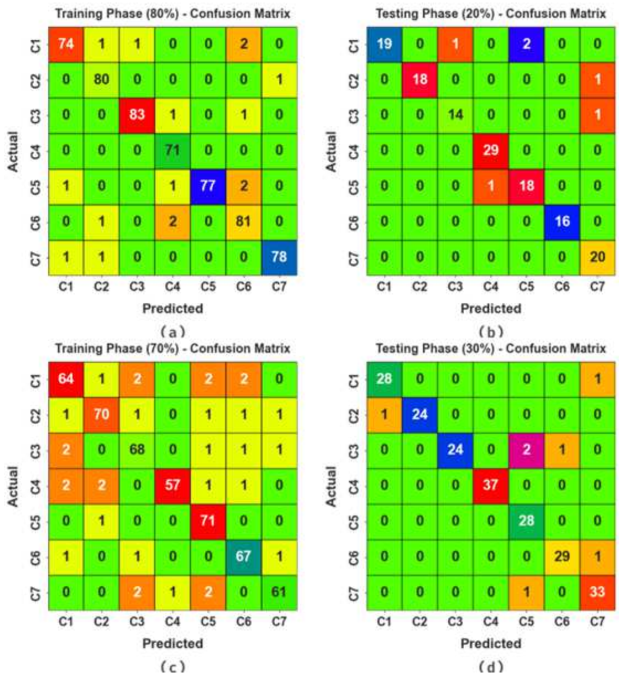

Fig. 4: Confusion matrices of (a-c) 80:70 of TRAPH and (b-d) 20:30 of TESPH

Fig. 4 portrays the confusion matrices of the MAHADL-PDC technique under 80:20 and 70:30 of TRAPH/TESPH. The results shows that the MAHADL-PDC technique has effectual detection and classification of all seven classes accurately.

In Table 2 and Fig. 5, the pest detection results of the MAHADL-PDC approach are portrayed with 80:20 of TRAPH/TESPH. The experimental outputs inferred that the MAHADL-PDC technique reaches effectual recognition of distinct types of pests. With 80% of TRAPH, the MAHADL-PDC technique reaches an average accu_y of 99.18%, prec_n of 97.16%, reca_l of 97.18%, F_score of 97.15%, and AUC_score of 98.35%. Also, with 20% of TESPH, the MAHADL-PDC model attains an average accu_y of 98.78%, prec_n of 95.84%, reca_l of 95.60%, F_score of 95.59%, and AUC_score of 97.44%.

In Table 3 and Fig. 6, the pest recognition outputs of the MAHADL-PDC approach are represented with 70:30 of TRAPH/TESPH. The MAHADL-PDC approach attains effectual detection of different types of pests. With 70% of TRAPH, the MAHADL-PDC approach achieves an average accu_y of 98.13%, prec_n of 93.65%, reca_l of 93.41%, F_score of 93.48%, and AUC_score of 96.16%. Also, with 30% of TESPH, the MAHADL-PDC model gets an average accu_y of 99.05%, prec_n of 96.83%, reca_l of 96.45%, F_score of 96.55%, and AUC_score of 97.95%.

The performance of the MAHADL-PDC method under an 80:20 split of TRAPH/TESPH is presented in Fig. 7, showing the training accuracy (TRAA) and validation accuracy (VALA) curves. The figure provides valuable insight into the behavior of the MAHADL-PDC technique across different epochs, illustrating its learning process and generalization capabilities. Notably, the figure shows a consistent increase in both TRAA and VALA as the epochs progress, highlighting the adaptive behaviour of the MAHADL-PDC method in the pattern

Table 2: Pest detection outcome of MAHADL-PDC technique under 80:20 of TRAPH/TESPH

Class Labels	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	AUC_{Score}
TRAPH (80%)					
C1	98.93	97.37	94.87	96.10	97.23
C2	99.29	96.39	98.77	97.56	99.07
C3	99.46	98.81	97.65	98.22	98.72
C4	99.29	94.67	100.00	97.26	99.59
C5	99.29	100.00	95.06	97.47	97.53
C6	98.57	94.19	96.43	95.29	97.69
C7	99.46	98.73	97.50	98.11	98.65
Average	99.18	97.16	97.18	97.15	98.35
C1	97.86	100.00	86.36	92.68	93.18
C2	99.29	100.00	94.74	97.30	97.37
C3	98.57	93.33	93.33	93.33	96.27
C4	99.29	96.67	100.00	98.31	99.55
C5	97.86	90.00	94.74	92.31	96.54
C6	100.00	100.00	100.00	100.00	100.00
C7	98.57	90.91	100.00	95.24	99.17
Average	98.78	95.84	95.60	95.59	97.44

Table 3: Pest detection outcome of MAHADL-PDC method under 70:30 of TRAPH/TESPH

Class Labels	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	AUC_{Score}
TRAPH (80%)					
C1	97.35	91.43	90.14	90.78	94.35
C2	98.16	94.59	93.33	93.96	96.18
C3	97.76	91.89	93.15	92.52	95.86
C4	98.57	98.28	90.48	94.21	95.12
C5	98.37	91.03	98.61	94.67	98.47
C6	98.37	93.06	95.71	94.37	97.26
C7	98.37	95.31	92.42	93.85	95.86
Average	98.13	93.65	93.41	93.48	96.16
TESPH (30%)					
C1	99.05	96.55	96.55	96.55	98.00
C2	99.52	100.00	96.00	97.96	98.00
C3	98.57	100.00	88.89	94.12	94.44
C4	100.00	100.00	100.00	100.00	100.00
C5	98.57	90.32	100.00	94.92	99.18
C6	99.05	96.67	96.67	96.67	98.06
C7	98.57	94.29	97.06	95.65	97.96
Average	99.05	96.83	96.45	96.55	97.95

detection process for both TRA/TES data. The upward trend in VALA emphasizes the MAHADL-PDC technique's ability to effectively adapt to the TRA data and accurately classify unseen data, demonstrating its strong generalization performance.

Fig. 8 demonstrates the training loss (TRLA) and validation loss (VALL) outcomes of the MAHADL-PDC methodology under 80:20 of TRAPH/TESPH over dissimilar epochs. The steady lessening in TRLA emphasizes the MAHADL-PDC methodology improving the weights and reducing the classification error on the TRA/TES data. The figure offers a clear insight into the MAHADL-PDC model's connection with the TRA data, underscoring its efficiency in capturing patterns across both datasets. Remarkably, the MAHADL-PDC model constantly increases its parameters in decreasing the changes between the actual and prediction TRA classes.

The PR curve in Fig. 9 shows that the MAHADL-PDC technique, under 80:20 of TRAPH/TESPH, consistently achieves improved PR values for each class. This demonstrates the enhanced capability of the MAHADL-PDC approach in classifying and detecting various classes effectively.

Furthermore, in Fig. 10, the ROC curves of the MAHADL-PDC technique under 80:20 of TRAPH/TESPH portrays superior performance in

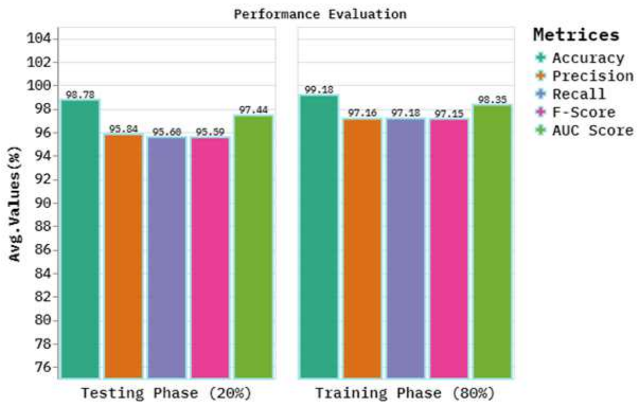

Fig. 5: Average of MAHADL-PDC technique under 80:20 of TRAPH/TESPH

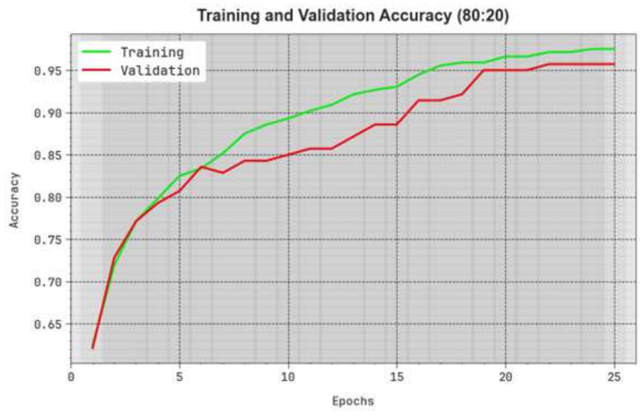

Fig. 7: Accu$_y$ curve of MAHADL-PDC method under 80:20 of TRAPH/TESPH

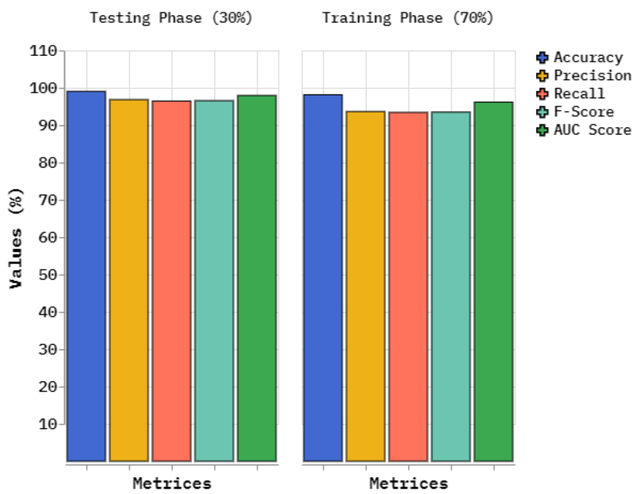

Fig. 6: Average of MAHADL-PDC method under 70:30 of TRAPH/TESPH

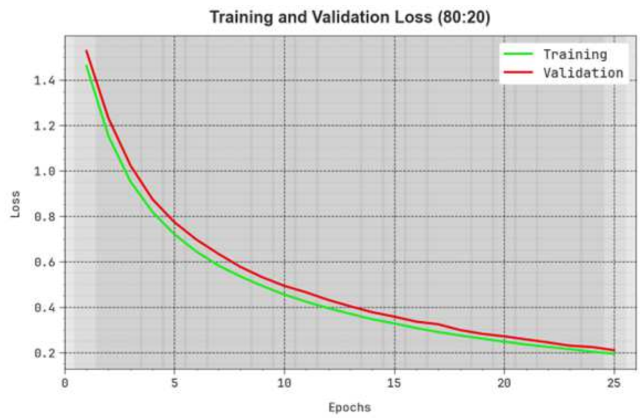

Fig. 8: Loss curve of MAHADL-PDC model under 80:20 of TRAPH/TESPH

classifying diverse labels. The figure illustrates a comprehensive understanding of the tradeoff between TPR/FPR across varying detection threshold values and epochs. It accentuates the improved classification outputs of the MAHADL-PDC technique for all classes, demonstrating its effectualness in addressing a wide range of classification challenges.

The pest recognition results of the MAHADL-PDC approach is compared with present models in Table 4 and Fig. 11 [24]. The outputs indicate the promising outcomes of the MAHADL-PDC technique. It is observed that the ANN, SVM, KNN, NB, and CNN models have appeared to accomplish ineffectual performance. Simultaneously, the MMTL-IPCAC method has reached slightly boosted outcomes. It is shown that the MAHADL-PDC technique attains a maximum accu_y of 99.18%, prec_n of 97.16%, reca_l of 97.18%, and F_score of 97.15%. Thus, the MAHADL-PDC approach is used for the automatic pest detection process.

5 Conclusions

In this research, a fusion of the MAHADL-PDC technique was presented. The MAHADL-PDC technique aimed to effectually recognize distinct pests' types. The MAHADL-PDC methodology involved different types of processes such as AMF-based preprocessing, EfficientNet-B4-based extraction, MAHA-based tuning, and DBN-based classification. Initially, the input image quality was improved by the AMF approach. In addition, feature extraction using the EfficientNet-B4 model was performed to learn complex features, and its

Table 4: Comparative evaluation of MAHADL-PDC approach with other methods

Class Labels	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}
MAHADL-PDC	99.18	97.16	97.18	97.15
MMTL-IPCAC	98.80	94.51	94.39	94.42
ANN Algorithm	89.89	89.16	90.50	88.12
SVM Algorithm	89.39	90.67	86.60	86.49
KNN Algorithm	92.63	89.68	89.87	86.52
NB Algorithm	89.46	89.12	86.65	88.50
CNN Algorithm	92.07	90.49	90.27	89.73

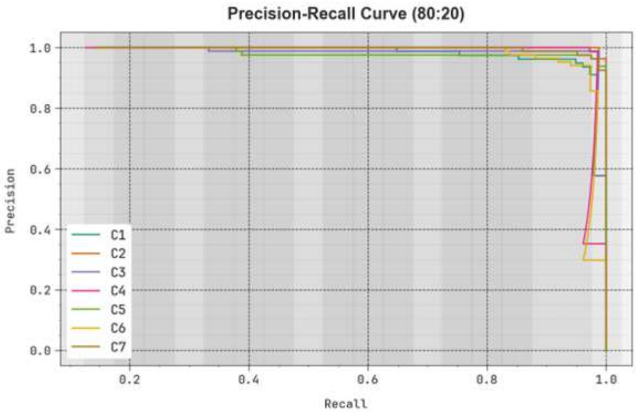

Fig. 9: PR curve of MAHADL-PDC model under 80:20 of TRAPH/TESPH

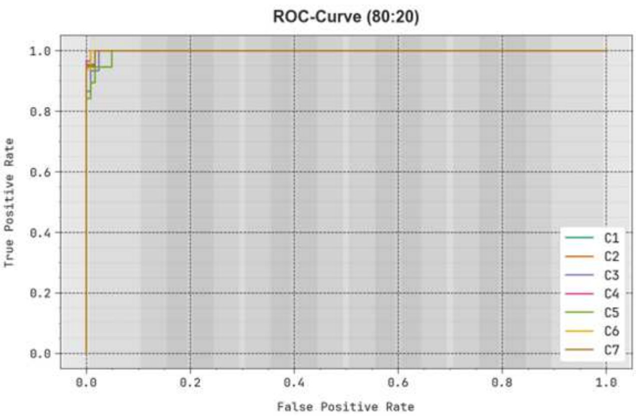

Fig. 10: ROC curve of MAHADL-PDC technique under 80:20 of TRAPH/TESPH

hyperparameters were chosen by utilizing MAHA. For the pest recognition and identification procedure, the MAHADL-PDC method employed the DBN approach. To highlight the significant performance of the MAHADL-PDC method, a series of experiments were

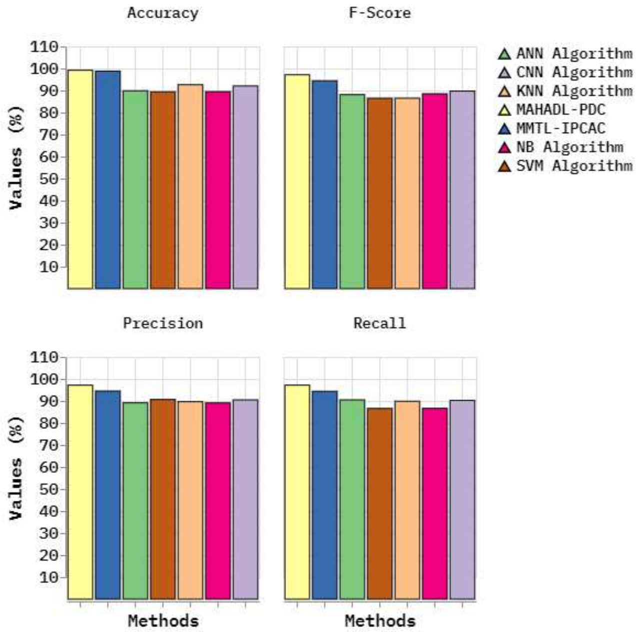

Fig. 11: Comparative evaluation of MAHADL-PDC approach with other methods

made. The performance validation of the MAHADL-PDC approach portrayed superior outcome over existing models.

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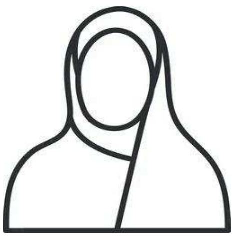

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