Automated Insect Detection and Classification using Pelican Optimization Algorithm with Deep Learning on Internet of Enabled Agricultural Sector

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Abstract

Recently, the combination of Deep Learning (DL) methods within the Internet of Things (IoTs) has developed in the agricultural field, especially in the domain of pest management. This study considers the implementation and development of an innovative method for Insect Detection and Classification using DL within the environment of the IoTs in agriculture. The developed system advantages advanced DL approaches for analysing images captured by IoT-enabled devices, enabling real-time identification and categorization of insect pests. By continuously incorporating these technologies, these research goals to increase the efficiency and precision of pest monitoring, finally providing to sustainable agricultural technologies and increased crop yield. This study presents an Automated Insect Detection and Classification using Pelican Optimization Algorithm with Deep Learning (AIDC-POADL) technique on Internet of Enabled Agricultural Sector. The main objective of the AIDC-POADL system is to identify and categorize various types of insects exist in the agricultural field. In the primary stage, the AIDC-POADL technique involves DenseNet-121 model to learn complex features in the input images. Also, the hyperparameter choice of the DenseNet-121 algorithm developed by the POA. At last, multilayer perceptron (MLP) model can be applied to discriminate the insects into various classes. To validate the enhanced performance of the AIDC-POADL algorithm, a series of simulations are involved. The experimental outcomes stated that the AIDC-POADL technique offers enhanced recognition results over other approaches.

Keywords: Internet of Things; Insect Detection; Pelican Optimization Algorithm; Deep Learning; Agricultural region

1. Introduction

IoT (Internet of things) connectivity helped agriculture in many ways such as analysis, data collection and automation. IoT comes with numerous benefits but frightens agricultural manufacturing's scientific structure and devices [1]. Detection of pest involves discovering as well as tracking pests that threaten property, animals, humans, or environment. Pest detection aids in order to defend dangerous systems like farming. Sound analytics capable to achieve pest populations in huge agricultural regions [2]. Artificial Intelligence (AI) as well as Machine learning (ML) can detect pests by employing huge datasets that contain sounds, photographs, and environmental facts. It portrays pests like rats and flies on agriculturalists' fields [3]. AI aid to enhance pest control by generating analytical techniques for pest eruptions as well as dispersal patterns. For early pest detection, insect monitoring is very necessary to avoid extreme use of insecticides [4]. Currently, Integrated pest management (IPM) system has been proposed by research community in order to decrease overuse of insecticides, observing plagues and applies exact amounts when required [5]. The main aim of insect monitoring is to deliver agriculturalists with an effective decision making device, donating to optimisation of their harvests, growing environmental sustainability, and enhances quality as well as harvest of production [6]. One of the main procedure of monitoring is discovering and with pests that are involved to tricks dispersed besides farming fields where the insects will be captured. A usual

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monitoring approach complete by experts, who identify and physically calculate pests that trapped in setup [7]. However, this task is actually time consuming as well as inclined to errors and sometimes each trap have numerous number of insects in dissimilar species.

Smart pest monitoring (SPM) developed with fast advances in AI and IoT, which permits automatic data acquisition, decision-making, data processing and remote transmission. AI algorithms develop data processing as well as suggest theories for precise decision-making [8]. AI is a common field that includes ML and deep learning (DL). ML is major types of AI that employs algorithms as well as arithmetical techniques in order to permit a system to enhance its act of exact task [9]. In addition, ML also lets a system to learn from data without obviously programmed. DL is a precise kind of ML that includes usage of neural networks which are processes stimulated by structure of brain [10]. These algorithms made up of several layers of interconnected nodes and capable to learn difficult patterns in data.

This study presents an Automated Insect Detection and Classification using Pelican Optimization Algorithm with DL (AIDC-POADL) technique on Internet of Enabled Agricultural Sector. The main objective of the AIDC-POADL system is to identify and categorize various types of insects exist in the agricultural field. In the primary stage, the AIDC-POADL technique involves DenseNet-121 model to learn complex features in the input images. Also, the hyperparameter choice of the DenseNet-121 algorithm designed by the POA. At last, multilayer perceptron (MLP) model can be applied to discriminate the insects into various classes. To validate the increased performance of the AIDC-POADL approach, a series of simulations are involved.

2. Related works

In [11], a fine-grained insect detection technique built on a graph pyramid attention; CNN (GPA-Net) has been developed in order to stimulate agricultural manufacture effectiveness. Initially, CSP backbone system built to get feature map. Next, a cross-stage trilinear attention element created for removing plentiful fine-grained features of discernment parts of insect objects. Furthermore, a multi-level pyramid structure mainly intended to absorb multi-scale spatial features as well as graphical dealings to improve identification of insects and illnesses. In [12], ADSNN-BO method has been developed based on augmented attention device and MobileNet framework. Furthermore, Bayesian optimization (BO) model applied in order to tune hyper-parameters. Cross-validated detection tests conducted depend on a public rice illness dataset by 4 groups. The activation map, feature analysis, and filters visualization model also conducted in order to check interpretability of presented technique.

In [13], an IoT-assisted pest identify and classify model developed. Firstly, IoT sensors employed to gather essential images. Then, Yolov3 used for detection of object. In addition, discovered images fed into technique of “CNN,” which deep features realized, then lastly assumed like input for classification method of “Convolution Neural LSTM (CNLSTM),” in turn few hyperparameters altered by “Adaptive Honey Badger Algorithm (AHBA).” In [14], an automated technique has been presented for precise detect and classify illnesses from a complete image. This model receives a CV–based technique, which implements ML, image processing, and DL models in order to decrease trust on conventional approaches to guard paddy yields from illnesses. A combination of SVM and CNNs models employed to identify and classify exact variations of crop plant diseases.

In [15], chili insect and disease features removed by employing customary technique equated with features extracted by employing a DL-based t. Whereas, six traditional feature-based techniques as well as six DL feature-based models employed to remove important insects and illness features from chili leaf pictures. Then, extracted features served into 3 ML techniques namely RF, SVM, and ANNs for task of identification. In [16], numerous important DL-based object recognition techniques such as Faster R-CNN, EfficientDet, CenterNet as well as SSD applied depend on Tensorflow Object Detection structure. Many major systems like EfficientNet, Inception_ResNet_V2, ResNet101_V1, MobileNet_V2, and HourGlass104 used for feature extraction.

3. The proposed method

In this article, we have presented an innovative AIDC-POADL system on Internet of Enabled Agricultural Sector. The main aim of the AIDC-POADL method has been detected and categorized various kinds of insects exist in the agricultural field. Fig. 1 demonstrates the workflow of AIDC-POADL technique.

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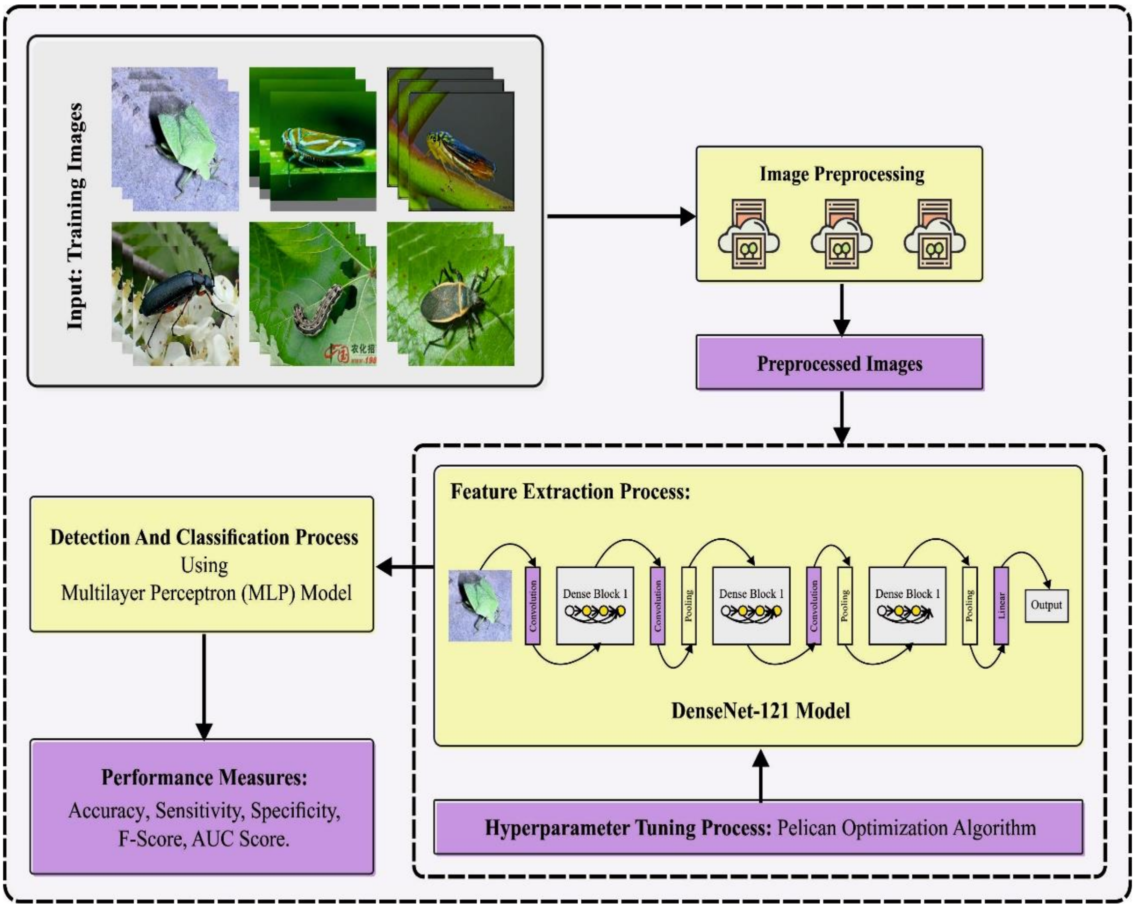

Figure 1. Workflow of AIDC-POADL technique

3.1. Feature extraction

Initially, the AIDC-POADL technique involves DenseNet-121 model to learn complex features in the input images. DenseNet make certain amendments in the interconnections amongst the layers based on other frameworks, such as the Highway Network, ResNet, Fractal Network, etc [17]. In DenseNet, each layer is directly connected and uses the feature-reprocessing concept, which supports for decreasing the overall amount of parameters. Another problem in DNN model arises during training as they follow the flow of data and gradients. To resolve these issues, DenseNet provides the opportunity to each layer for directly retrieving the gradients by relating the loss function.

For the deep architecture, some data acquire at the input layer till the output layer is so long that, the data path from the gradient and input to output which travels the reverse way develops very huge, it obtains lost before it gets the goal.

The classical FFNN bridges the outcome of layer to its adjacent layer by carrying out certain operation.

$$L_i = H_i(L_{i-1}) \tag{1}$$

Eq. (1) modified as Eq. (2) in ResNet.

$$L_i = H_i(L_{i-1}) + (L_{i-1}) \tag{2}$$

DenseNet concatenate the maps rather than summing the outcome feature map of each block. Thus, the equation is given as

$$L_i = H_i([L_0, L_1, L_2, \dots \dots, L_{i-1}]) \tag{3}$$

Since the concatenation of feature map cannot be simultaneously done due to their size variance, therefore DenseNet is divided into different blocks (DenseBlock). In every block, dimension of map is fixed, while, filter number changes continuously. The Transition Layers (TL) is Layers between two blocks that assist in down sampling with BN, convolutional and a 2×2 pooling-layers. In this work, the DenseNet-121 model was implemented.

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3.2. POA based hyperparameter tuning

At this stage, the hyperparameter selection of the DenseNet-121 architecture designed by the POA. In 2022, Dehghani & Trojovský have proposed a new technique called POA [18]. This technique mainly concentrates on pelicans' social performance as well as hunting strategies. Pelicans have long beaks and huge pouch in their throats that they utilize to trick and swallow their prey. Pelicans commonly survive in large groups and are members of population. The members of population randomly modified by employing equation as follows:

$$x_{i,j} = l_j + rand.\left(u_j - l_j\right), \quad i = 1,2, \dots, N, j = 1,2, \dots, m \tag{4}$$

Whereas $x_{i,j}$ signifies value of jth variable definite by ith candidate solution, N and m signify number of population and problem variables, rand refers to random number in [0 and1]. While u_j and l_j represents upper and lower boundaries of problem variables, respectively.

The population matrix formed to recognize population members in POA utilizing Eq. (5).

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,m} \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \tag{5}$$

A main function defined from Eq. (6)

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times m} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times m} \tag{6}$$

Whereas F refers to objective function vector and F_i denotes objective function value of i^{th} candidate solution. Pelicans' hunting procedure separated into dual stages such as exploitation and exploration. An exploitation stage includes flying on water surface while exploration stage involves going near prey. During 1st step, pelican's tactic prey after identifying its place. As prey position randomly produced, this leads to enhance in exploration power of POA. The 1st stage arithmetically showed in Eq. (7):

$$x_{i,j}^{P_1} = \begin{cases} x_{i,j} + rand.\left(-l.x_{i,j}\right), F_p < F_i; \\ x_{i,j} + rand.\left(x_{i,j} -\right), else, \end{cases} \tag{7}$$

Whereas $x_{i,j}^{P_1}$ denotes ith pelican's novel status in jth dimension depend on 1st phase, l represents random number equivalent to one or two, p_j signifies prey's location in jth dimension, F_p states prey's objective function rate. In POA, a pelican's novel location established if objective function's value improved in that location. This is highly denoted as effective upgrade and it delays model from arriving into non-optimal areas. The mathematically Eq. (8) is mentioned below:

$$X_i = \begin{cases} X_i^{P_1}, F_i^{P_1} < F_i; \\ X_i, \quad else, \end{cases} \tag{8}$$

where $X_i^{P_1}$ refers ith pelican's novel status and $F_i^{P_1}$ denotes pelican's objective function value depend on 1st stage. At time of 2nd phase, pelicans lift fish up by increasing their wings on surface of sea and catch prey in their throat. As an outcome, pelicans grab more fish. This stage improves POA's exploitation possible as procedure meets superior solutions in hunting zone. The below mentioned equation is a mathematical representation of hunting procedure:

$$x_{i,j}^{P_2} = x_{i,j} + R.\left(1 - \frac{\tau}{T}\right).(2.rand - 1).x_{i,j} \tag{9}$$

where $x_{i,j}^{P_2}$ refers ith pelican's new status in jth dimension depend on 2nd stage, $R = 0.2$ is a constant, $R.(1 - t/T)$ denotes neighborhood radius of $x_{i,j}$, t signify an iteration counter and T refers maximal amount of iterations. Effective upgrading used at this phase to receive or drop novel pelican location, Eq. (10):

$$X_i = \begin{cases} X_i^{P_2}, F_i^{P_2} < F_i; \\ X_i \ else, \end{cases} \tag{10}$$

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where $X_i^{P_2}$ means ith pelican's new status and $F_i^{P_2}$ denotes pelican's objective-function value. When all members of population upgraded, next iteration starts as well as numerous phases depend on Eqs. (7) to (10) are repeated until whole implementation is accomplished.

The POA method acquires a FF for achieving superior classification effectiveness. This can find a positive integer to signify the enriched performance of the candidate solutions. The reduction of the classification error rate can be calculated as the FF that specified in Eq. (11).

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{number\ of\ misclassified\ instances}{Total\ number\ of\ instances} * 100 \quad (11)$$

3.3. Classification using MLP model

Eventually, MLP model can be applied to discriminate the insects into various classes. As a variant of NN architecture, the FFNN stimulates the neurons of human brain based on the knowledge being a series of layers [19]. All the layers are interconnected to the next layer to generate the learning objective. The FNN contains a 3 successive layers: input, hidden, and output. The input layer can be the data features. The hidden layer applies the required process for detecting the accurate output of input features. The output layer is the predictable types of various series inputs.

MLP has a variant of FNN method where the information must be transmitted from the input to the output layers. The MLP contains hidden, input, and output layers. The MLP parameter is the weight (w), the bias (b), and the features (input). Fig. 2 displays the framework of MLP. The output of MLP is computed by using the following steps:

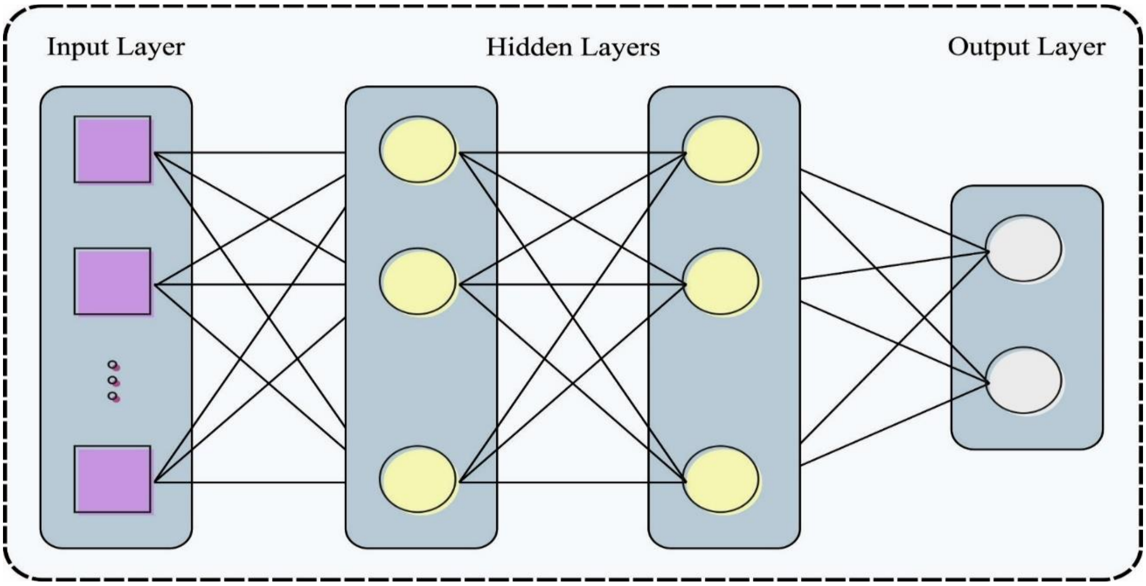

Figure 2. MLP architecture

Initialization: all the inputs in MLP is allocated the weighted sum score and it can be mathematically modelled as follows:

$$S_j = \sum_{i=1}^{n} (w_{ij}.X_i) - \beta_j, j = 1,2, \dots, h \quad (12)$$

Where the amount of inputs in MLP is n, the connected weight vector to i^{th} input at j^{th} hidden neuron is W_{ij}. The input number i is X_i and β_j is bias of j^{th} hidden neurons.

Using activation function: the sigmoid function was utilized for processing the output of weighted vector. Next, the output vector generated could be fed into the subsequent layer. Sigmoid output ranges from zero to one; hence, it is not utilized in this work. A more suitable activation function is used for predicting the Leaky ReLu function as it generates the output in the range $[-\infty, +\infty]$.

$$LekcyReLU = max(\alpha x, x) \quad (13)$$

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In general, the hyperparameter value α ranges within [0.01,0.1].

Lastly, the output of final layer is calculated by the following expression.

$$y = \sum_{i=1}^{m} w_{kj} f_i + b_k \tag{14}$$

Where the connection weight taken from j^{th} hidden to output neurons is w_{jk}. The bias of k^{th} output neurons is b. The vector of weight and bias are the cornerstone for the estimation of MLP last output. In search of optimum value of weight and bias vectors can be a crucial stage in stimulating the efficiency of MLP. It may leads to obtaining a best classification performance.

4. Result analysis

The experimental validation of the AIDC-POADL technique can be examined employing the IP102 database [20].

Fig. 3 portrays the classifier performance of the AIDC-POADL methodology with 70:30 of TRPH/TSPH. Figs. 3a-3b shows the confusion matrices attained by the AIDC-POADL system. The figure represented that the AIDC-POADL technique can be precisely identified and categorized with 6 classes. Afterward, Fig. 3c exposes the PR curve of the AIDC-POADL methodology. This outcome defined that the AIDC-POADL system gains better PR effectiveness with each class. Nevertheless, Fig. 3d demonstrates the ROC curve of the AIDC-POADL algorithm. The outcome displayed the AIDC-POADL model lead to proficient solutions with great ROC values on diverse classes.

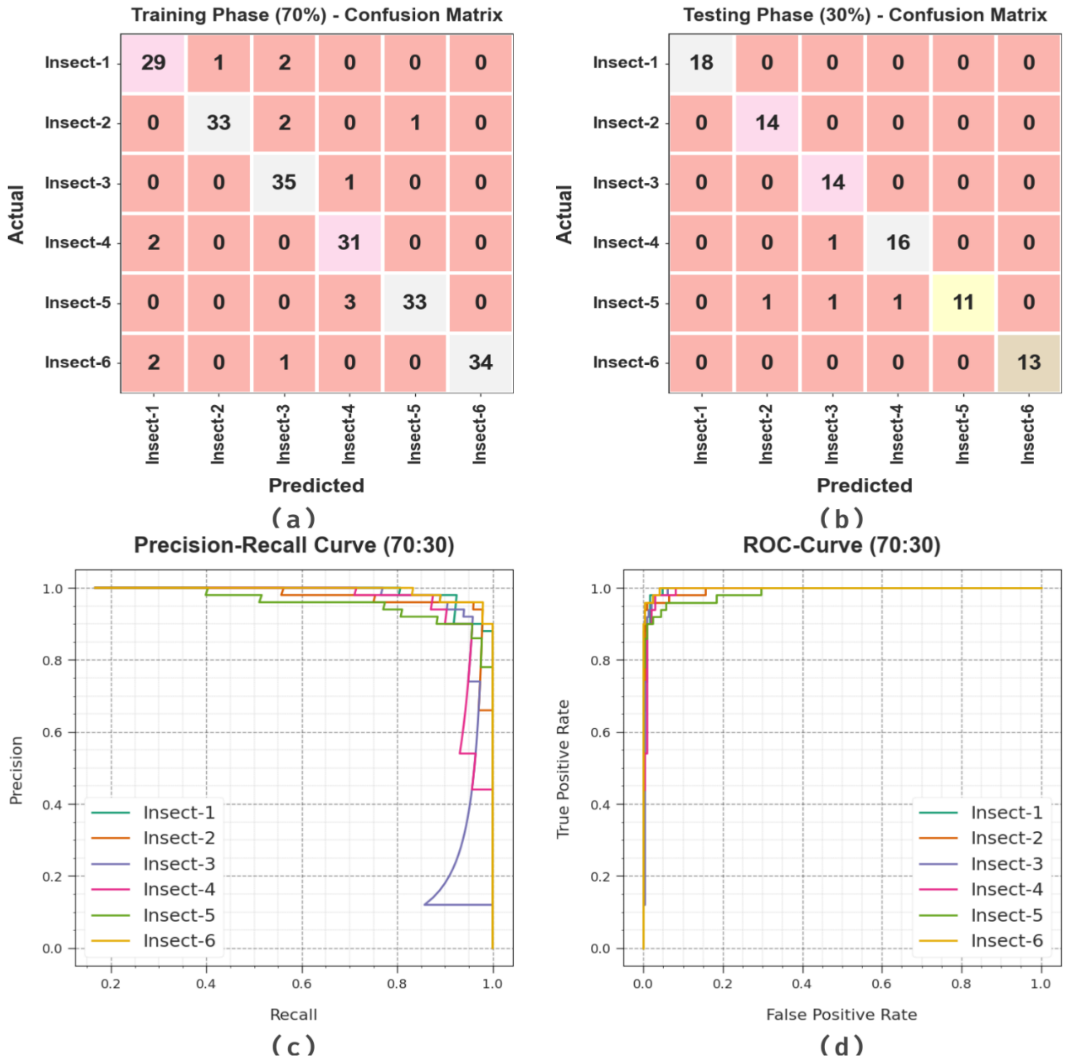

Figure 3. 70:30 of TRPH/TSPH (a-b) Confusion matrices and (c-d) PR and ROC curves

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In Table 1 and Fig. 4, the analysis of the AIDC-POADL algorithm is clearly depicted. On 70% of TRPH, the AIDC-POADL technique provide average $accu_y$, $sens_y$, $spec_y$, F_{score}, and AUC_{score} of 97.62%, 92.84%, 98.58%, 92.81%, and 95.71%, respectively. Also, with 30% of TSPH, the AIDC-POADL approach offer average $accu_y$, $sens_y$, $spec_y$, F_{score}, and AUC_{score} of 98.52%, 95.45%, 99.11%, 95.33%, and 97.28%, correspondingly.

Table 1: Classifier outcome of AIDC-POADL technique at 70:30 of TRPH/TSPH

Class Labels	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}	AUC_{Score}
Training Phase (70%)					
Insect-1	96.67	90.62	97.75	89.23	94.19
Insect-2	98.10	91.67	99.43	94.29	95.55
Insect-3	97.14	97.22	97.13	92.11	97.17
Insect-4	97.14	93.94	97.74	91.18	95.84
Insect-5	98.10	91.67	99.43	94.29	95.55
Insect-6	98.57	91.89	100.00	95.77	95.95
Average	**97.62**	**92.84**	**98.58**	**92.81**	**95.71**
Testing Phase (30%)					
Insect-1	100.00	100.00	100.00	100.00	100.00
Insect-2	98.89	100.00	98.68	96.55	99.34
Insect-3	97.78	100.00	97.37	93.33	98.68
Insect-4	97.78	94.12	98.63	94.12	96.37
Insect-5	96.67	78.57	100.00	88.00	89.29
Insect-6	100.00	100.00	100.00	100.00	100.00
Average	**98.52**	**95.45**	**99.11**	**95.33**	**97.28**

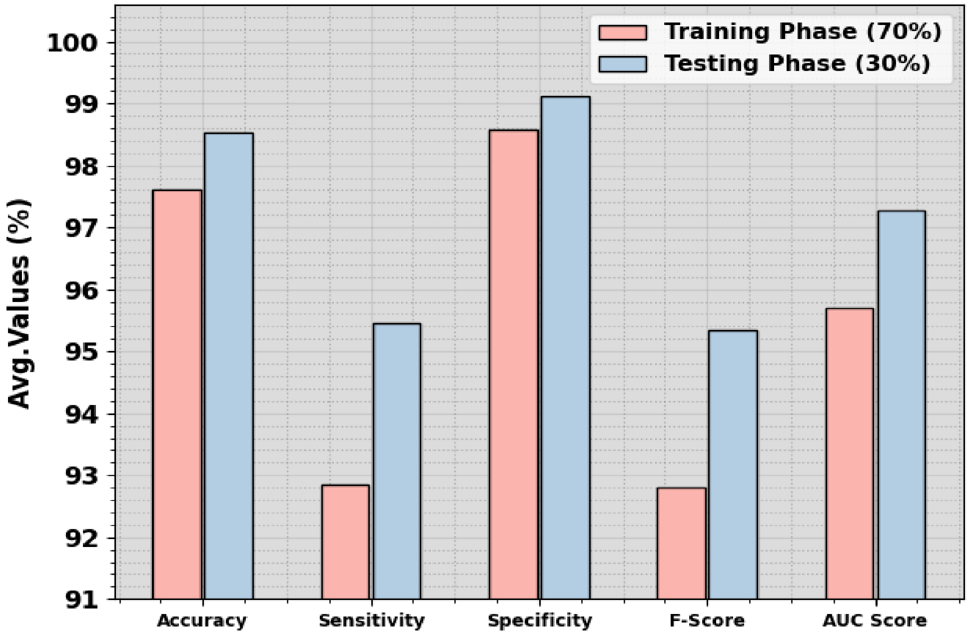

Figure 4. Average of AIDC-POADL technique on 70:30 of TRPH/TSPH

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Fig. 5 shows the classifier outcomes of the AIDC-POADL methodology on 60:40 of TRPH/TSPH. Figs. 5a-5b describes the confusion matrices achieved by the AIDC-POADL system. The figure refer that the AIDC-POADL system is correctly identified and categorized with six classes. Additionally, Fig. 5c displays the PR analysis of the AIDC-POADL methodology. The figure stated that the AIDC-POADL approach gets higher PR rate on 6 classes. However, Fig. 5d displays the ROC analysis of the AIDC-POADL model. This figure exposed that the AIDC-POADL technique gives efficient solutions with improved ROC rates with 6 classes.

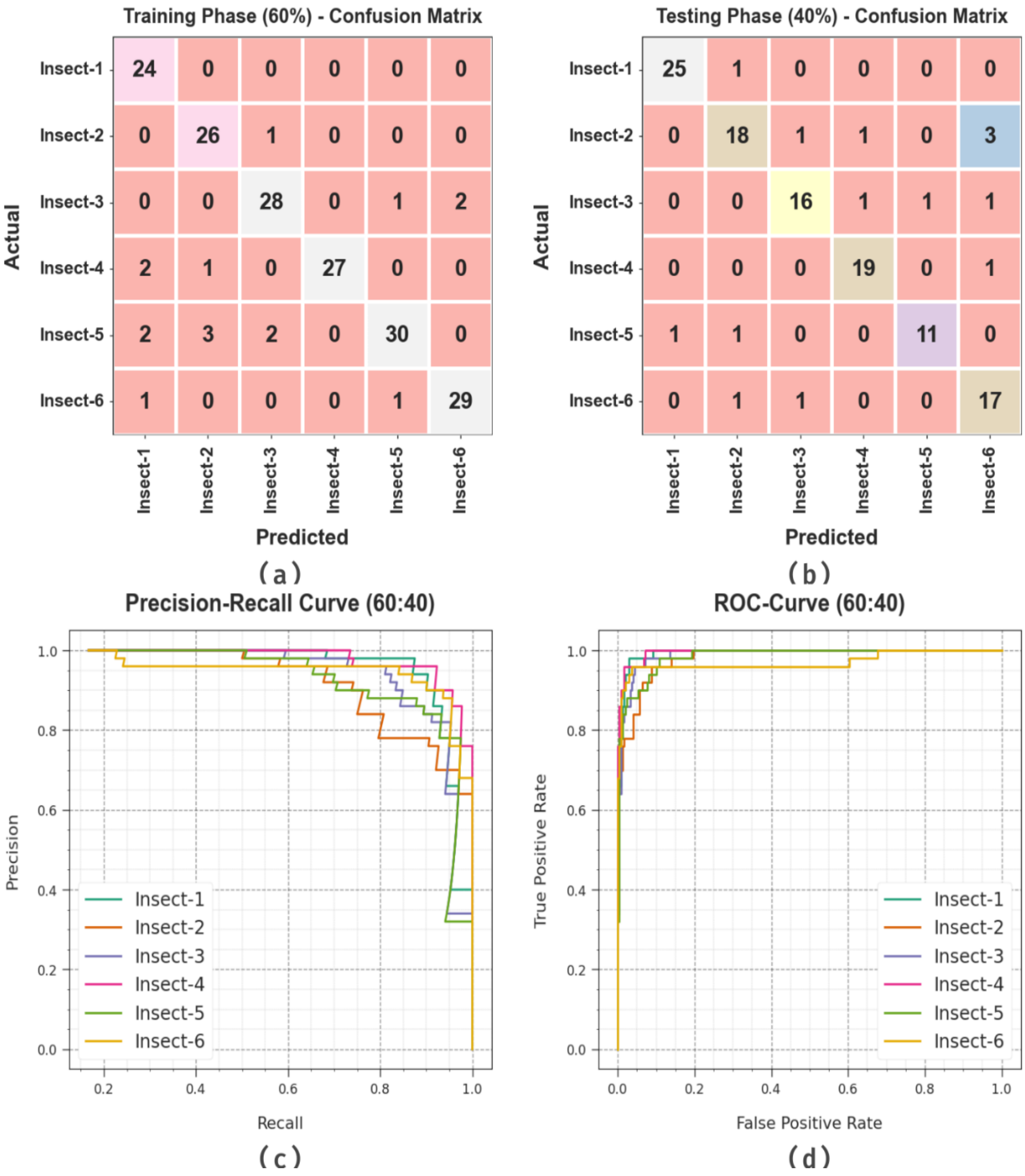

Figure 5. 70:30 of TRPH/TSPH (a-b) Confusion matrices and (c-d) PR and ROC curves

In Table 2 and Fig. 6, the analysis of the AIDC-POADL system can be evidently represented. According to 60% of TRPH, the AIDC-POADL method provide average $accu_y$, $sens_y$, $spec_y$, F_{score}, and AUC_{score} of 97.04%, 91.87%, 98.24%, 91.23%, and 95.06%. Besides, on 40% of TSPH, the AIDC-POADL system offer average $accu_y$, $sens_y$, $spec_y$, F_{score}, and AUC_{score} of 96.11%, 87.95%, 97.66%, 88.01%, and 92.81%, correspondingly.

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Table 2: Classifier outcome of AIDC-POADL methodology at 60:40 of TRPH/TSPH

Class Labels	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}	AUC_{Score}
Training Phase (60%)					
Insect-1	97.22	100.00	96.79	90.57	98.40
Insect-2	97.22	96.30	97.39	91.23	96.84
Insect-3	96.67	90.32	97.99	90.32	94.15
Insect-4	98.33	90.00	100.00	94.74	95.00
Insect-5	95.00	81.08	98.60	86.96	89.84
Insect-6	97.78	93.55	98.66	93.55	96.10
Average	**97.04**	**91.87**	**98.24**	**91.23**	**95.06**
Testing Phase (40%)					
Insect-1	98.33	96.15	98.94	96.15	97.55
Insect-2	93.33	78.26	96.91	81.82	87.58
Insect-3	95.83	84.21	98.02	86.49	91.12
Insect-4	97.50	95.00	98.00	92.68	96.50
Insect-5	97.50	84.62	99.07	88.00	91.84
Insect-6	94.17	89.47	95.05	82.93	92.26
Average	**96.11**	**87.95**	**97.66**	**88.01**	**92.81**

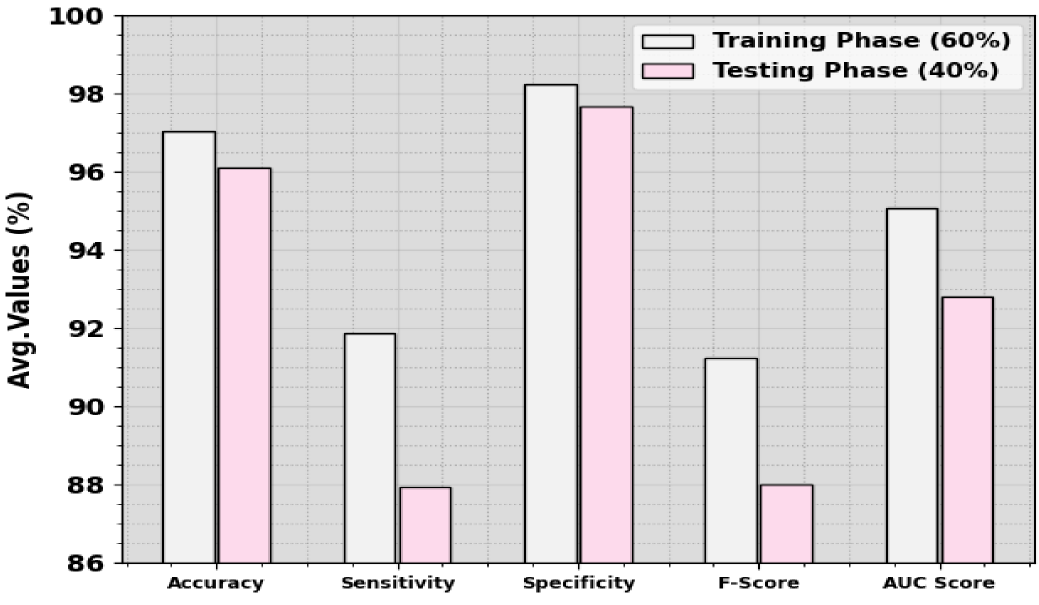

Figure 6. Average of AIDC-POADL system at 70:30 of TRPH/TSPH

Fig. 7 reveals the classifier analysis of the AIDC-POADL methodology on 70:30 and 60:40. Figs. 7a-7c represents the accuracy analysis of the AIDC-POADL algorithm. This figure reports that the AIDC-POADL methodology gains boosting $accu_y$ values at improving epochs. Likewise, the raising validation $accu_y$ over training $accu_y$ exposes that the AIDC-POADL system learns professionally on the test database. Lastly, Figs. 7b-7d shows the loss curve of the AIDC-POADL algorithm. The obtained outcomes specify that the AIDC-POADL method acquire nearer values of training and validation loss. This can be seen that the AIDC-POADL system learned effectively under the test datasets.

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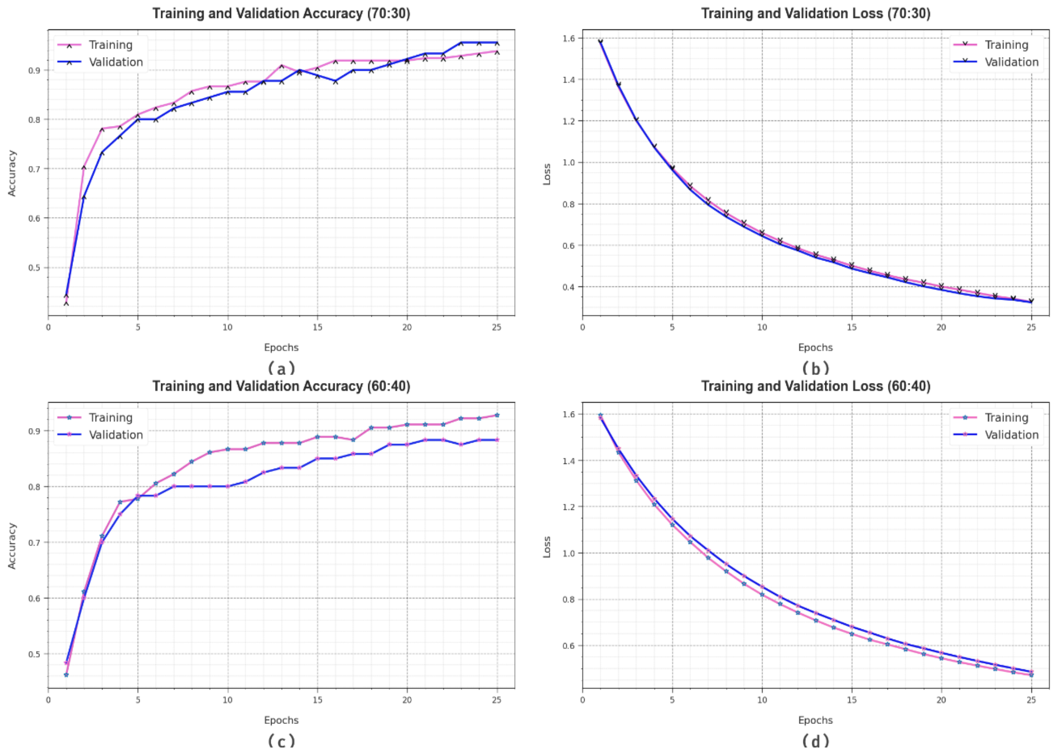

Figure 7. (a-c) $Accu_y$ curve on 70:30 and 60:40 and (b-d) Loss curve on 70:30 and 60:40

In Table 3 and Fig. 8, a wide-ranging comparison result of the AIDC-POADL technique is provided under TRPH [21]. The values highlighted that the AIDC-POADL technique reaches improved $accu_y$ of 97.62%. On the other hand, the IAEODL-IDC, Convolutinal NN, Artificial NN, Naïve Bayes, AlexNet, ShuffleNet, SqueezeNet, Log. Regression and FFGWO-CNN models offer decreased $accu_y$ values of 96.34%, 94.90%, 94.79%, 94.85%, 94.05%, 92.13%, 94.54%, 94.96%, and 95.46% respectively.

Table 3: $Accu_y$ outcome of AIDC-POADL technique with other models under TRPH

Training Phase	
Methods	**Accuracy (%)**
AIDC-POADL	97.62
IAEODL-IDC	96.34
Convolutinal NN	94.90
Artificial NN	94.79
Naïve Bayes	94.85
AlexNet	94.05
ShuffleNet	92.13
SqueezeNet	94.54
Log. Regression	94.96
FFGWO-CNN	95.46

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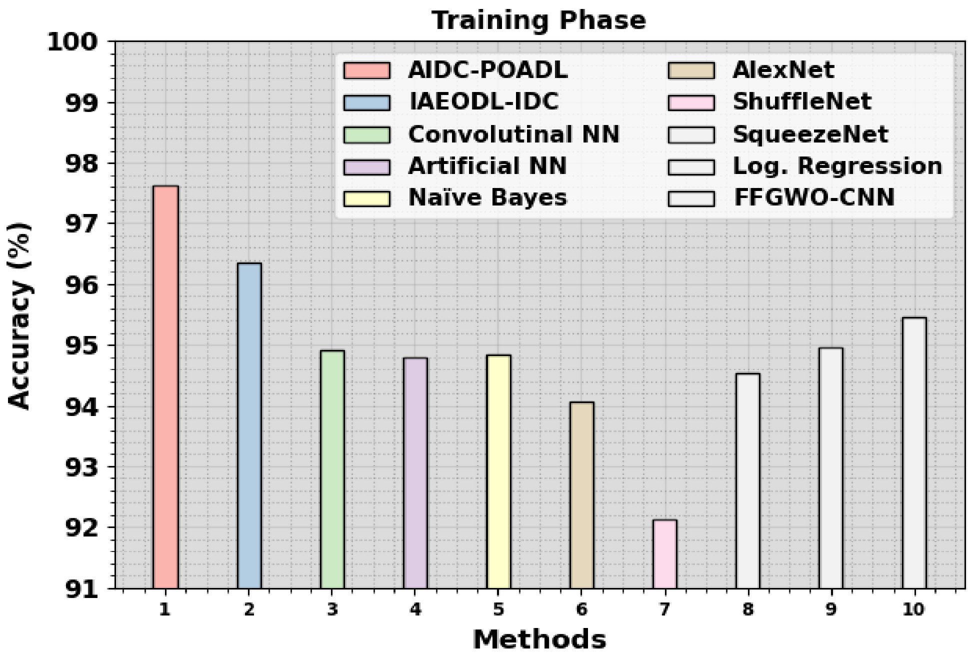

Figure 8. $Accu_y$ analysis of AIDC-POADL technique under TRPH

In Table 4 and Fig. 9, an extensive comparison outcome of the AIDC-POADL system is described under TSPH. The achieved value displays the AIDC-POADL method gets better $accu_y$ of 98.52%. Conversely, the IAEODL-IDC, Convolutinal NN, Artificial NN, Naïve Bayes, AlexNet, ShuffleNet, SqueezeNet, Log. Regression, and FFGWO-CNN methodologies gives diminished $accu_y$ values of 97.93%, 92.57%, 92.62%, 92.25%, 96.10%, 96.22%, 96.62%, 97.06%, and 94.80%, correspondingly.

Table 4: $Accu_y$ outcome of AIDC-POADL technique with other models under TSPH

Testing Phase	
Methods	**Accuracy (%)**
AIDC-POADL	98.52
IAEODL-IDC	97.93
Convolutinal NN	92.57
Artificial NN	92.62
Naïve Bayes	92.25
AlexNet	96.10
ShuffleNet	96.22
SqueezeNet	96.62
Log. Regression	97.06
FFGWO-CNN	94.80

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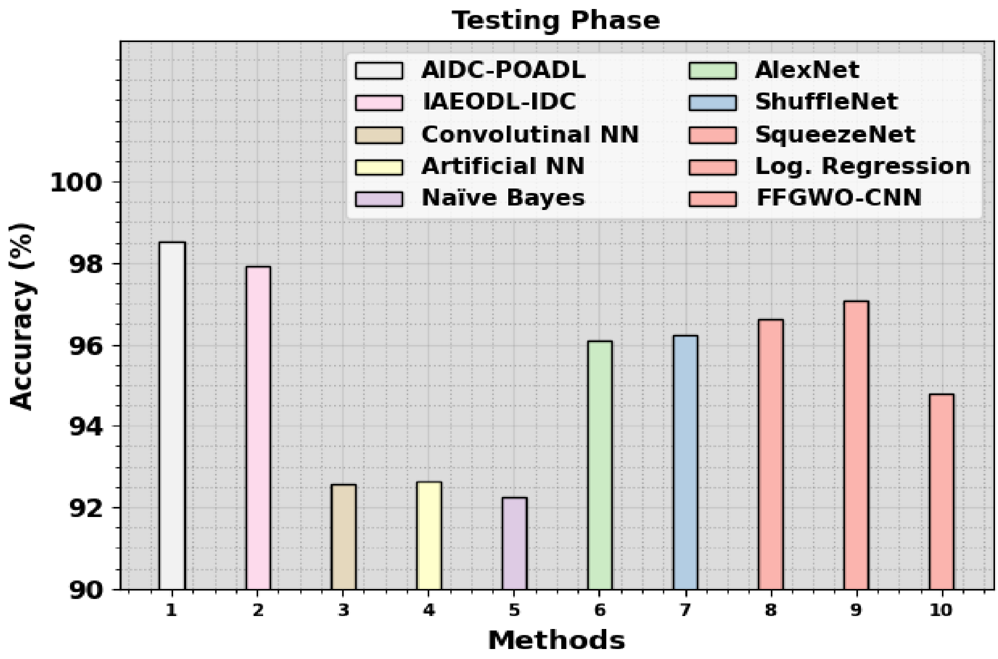

Figure 9. $Accu_y$ Outcome of AIDC-POADL technique under TSPH

5. Conclusion

In this article, we have presented an innovative AIDC-POADL technique on Internet of Enabled Agricultural Sector. The main objective of the AIDC-POADL method is to identify and categorize various types of insects exist in the agricultural field. Initially, the AIDC-POADL technique involves DenseNet-121 model to learn complex features in the input images. Also, the hyperparameter choice of the DenseNet-121 system designed by the POA. At last, MLP model can be applied to discriminate the insects into various classes. To validate the increased performance of the AIDC-POADL system, a series of simulations were involved. The experimental outcomes stated that the AIDC-POADL technique offers enhanced recognition results over other approaches.

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