IoT-enabled Pest Identification and Classification with New Meta-Heuristic-based Deep Learning Framework

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Research Article

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IoT-enabled Pest Identification and Classification with New Meta-Heuristic-based Deep Learning Framework

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***Abstract*-The insect pests and crop diseases are the most critical factors that affect agricultural production, which reduces the sustainable development of agriculture. While detecting the pest, it is inconsistent to place the surveillance cameras near the target pests and the captured images from the Internet of Things (IoT) monitoring equipment at a constant location that is mostly insufficient for pest detection. IoT is a well-known advanced technology and an analytics system incorporated in diverse industries based on its unique abilities and flexibilities over a particular environment like agriculture. There is a demand for the IoT in agricultural areas to reduce the chemical crop protection agents and fertilizers to manage the efficient crop state and crop production. Hence, the data collection is through the IoT devices in this research model. This research aims to develop a pest identification and classification model to detect and identify the pests in the images. Initially, the IoT platform is created, and IoT devices conduct the data collection. Then, object detection is performed using Yolov3 to detect the pests in the images from the gathered images. The detected images are subjected to the Convolutional Neural Network (CNN) for gathering the deep features, which are then forwarded to the enhanced classifier, termed Convolution Neural Long Short-Term Memory (CNLSTM) for getting the classified outcomes as pest details, in which the optimization of parameters is done by Adaptive Honey Badger Algorithm (AHBA). These results demonstrated that the proposed method shows enhanced performance by rapidly collecting the information in agriculture and ensures the technical indication for population estimation and pest monitoring.**

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I. INTRODUCTION

Identifying and classifying crop pests is one of the vital challenges in agriculture [9]. Insects are an essential factor in causing damage to crops and reducing crop productivity. Insect classification is a complex task due to its complex structure and high similarity in appearance among the distinct species [10]. It is essential to recognize and classify the insects present in the crops earlier by providing highly effective pesticides and biological control methods for preventing the spread of insects that causes crop diseases [11] [12]. The traditional way of identifying insects is considered inefficient, time-consuming, and labor-intensive. The vision-based computerized system of image processing has been implemented based on machine learning to accurately perform the classification and identification of insects to overcome the conventional problems in agriculture research.

IoT is a well-known revolutionary technology for future communications and computing. The people in the world are highly dependent on agriculture for income and food resources. Therefore, intelligent Information Technology (IT) technologies are necessary for overcoming the challenges of traditional agricultural approaches. IoT makes it easier for the farmers in agriculture by providing many techniques to achieve sustainable and precise agriculture production for facing the challenges in the agricultural field [13]. IoT technology supports farmers in collecting information regarding realistic scenarios like soil fertility, temperature, moisture, and weather. Crop online monitoring system enhances agricultural productivity, and crop growth finds the animal intrusion into a field and helps detect the weed, pest, and water levels [14]. IoT enables farmers to monitor their agricultural fields anywhere in the world. The main intention of the IoT is to extend the network by concatenating various kinds of connected devices [15 [16]. IoT mostly focused on three perspectives like cost-saving, automation, and communication in the system. IoT encourages people to pursue their routine activities based on the internet and saves the cost and time for making the productive [17].

An automated insect identification system is implemented to interpret seven geometrical features. It utilizes deep learning and machine learning algorithms to obtain better results by considering less number of insect classes [24] [25]. When involving the machine learning algorithms, the classification accuracy mainly relies on the structure of the extracted features. So, the optimal features are chosen for the machine learning, which maximizes the complexity of computation [18]. In addition, the accuracy needs to be improved by incorporating deep learning algorithms for categorizing huge image datasets [19]. The deep learning algorithm is used to perform the automated feature extraction by using the raw data that decreases the challenges of the hand-crafted features and addresses the highly complex issues related to image classification [23]. Recently, the deep learning approaches have been investigated with the help of Convolutional Neural Networks (CNNs) that ensure promising solutions for the existing challenges [20]. Compared to machine learning techniques, deep learning techniques are helpful in automatically obtaining the representative features from the training dataset, which avoids complex image processing steps and labor-intensive feature engineering for satisfying diverse outdoor conditions [21] [22]. An effective deep CNN model is developed to classify the insect species of field-crop insect images, which provides higher classification accuracy. Thus, deep learning techniques have great potential for pest detection in practical applications. Hence, it is significant to develop a new IoT-enabled pest identification and classification model with the help of a deep learning approach.

The main contributions of the research works are given as follows.

- To develop a new IoT-based pest identification and classification model for accurately detecting the pest in the crop field and reducing their effects at the earlier stage for improving the crop production in the agricultural areas.
- To integrate an enhanced deep architecture named CNLSTM for extracting the deep features from the YOLOv3-based detected images and classifying the extracted features along with the parameter optimization using the suggested AHBA to identify the type of pest present in the images.
- To introduce an improved meta-heuristic algorithm named AHBA for optimizing the hidden neurons of the LSTM to enhance the performance of the optimal pest classification in the proposed model.
- To examine the suggested pest identification and classification model with existing meta-heuristic algorithms and classifiers using diverse performance measures.

The remaining section of the developed model is described as follows. Section II explains the related works and the problems. In section III, the proposed pest identification and classification model is depicted. In section IV, dataset collection and YOLOv3-based pest detection are carried out. Section V introduces the extracted deep features for CNLSTM-based classification and the proposed algorithm. In section VI, the attained results of the proposed model are discussed. In section VIII, the developed pest identification and classification model is summarized.

II. Literature Survey

A. Related Works

In 2021, Kumar *et al.* [1] introduced an enhanced model for identifying the pests affecting the rice at the time of crop productivity. Here, the IoT-based mechanism passed the rice pest images to the cloud storage and provided the pest information. When the pest was identified, the information regarding the presence of the pest was sent to the farmers or owners to take respective actions. The analysis results have shown that the proposed approach has minimized the rice wastage in the productivity field through the continuous monitoring of the pests in the rice field. In 2020, Chen *et al.* [2] implemented a deep learning-based model for obtaining the insect locations and analyzing the environmental information from the weather stations for getting the pests information in the field with the help of an enhanced deep learning approach. The experimental results have shown that the proposed system has secured better identification accuracy. Precise identification of the insects and pests has decreased the amount of pesticide usage and minimized the pesticide damage to the soil.

In 2021, Turkoglu *et al.* [3] presented two classification approaches with the help of deep feature extraction obtained from the pre-trained CNN. The proposed model was validated with the help of diverse diseases and pest images. It was observed that the accuracy scores were better with the majority of the ensemble model and provided improved performance than the existing models. In 2019, Liu *et al.* [4] developed an end-to-end method for classifying and detecting huge multi-class pests with the help of deep learning. The three major parts of the proposed framework were a novel module with an attention-based approach, the developed neural network for ensuring the region proposals, and a score map for classifying the pest and bounding box regression. The experimental analysis was carried out to demonstrate the effectiveness of multi-class pest detection through the proposed model.

In 2021, Li *et al.* [5] have involved a novel technique for enhancing the accuracy of small pest detection. The suggested framework was trained with the help of a transfer learning methodology using the tiny pest training set. The developed deep learning architecture has provided better performance than other approaches. The analysis has shown that the proposed method has ensured robust performance in detecting the tiny pests at varied light reflections and pest densities. In 2018, Yue *et al.* [6] proposed an enhanced residual-based network to detect crop field problems. The proposed method was correlated with the traditional approaches and demonstrated the developed model's high power capacity for image reconstruction. The analysis results have shown that the proposed approach has revealed an enhanced recall rate for pest detection.

In 2021, Wang *et al.* [7] have developed an efficient deep learning model in the pest monitoring system for automatically detecting and counting the pest in the rice planthoppers. Here, the proposed approach was developed to extract the high-quality regions in the pest images, even the tiny ones. The analysis results have shown that the suggested method has improved recognition recall compared with the state-of-the-art approaches. In 2019, Thenmozhi *et al.* [8] implemented an elevated deep learning network for classifying the insect species through the three available datasets. The suggested approach was validated with the other deep learning architectures under the insect classification. Further, this model has included transfer learning for tuning the pr-trained models. The experimental results have shown that the suggested model effectively classified the different types of insects and applied them in the agricultural sector for crop protection.

B. Problem statement

Plant pests are the most important factor for causing the huge loss in agricultural production along with the social, ecological, and economic implications. It is essential to recognize and classify the insects present in the crops at the early stage. This prevents the insect spread into the harvest, resulting in crop diseases by choosing the efficient biological control and pesticide approaches. Numerous features and challenges of Agriculture pest detection are reviewed in Table 1. Artificial Intelligence [1] decreases rice wastage at the time of production by monitoring the pests at the regular interval of time. However, an improved technique needs to be developed for better performance. YOLOv3, LSTM [2] reduces the damages caused to the environment by involving enormous usage of pesticides and increases crop quality. Yet, there is a requirement for enhancing the perspectives in the images to solve the issues related to insufficient training samples. Ensemble learning [3] ensures high robustness. But, it cannot handle the imbalance problem of training data. CNN, Channel-spatial attention [4] are more robust for detecting the tiny pests on the image.

On the other hand, the sample size must be maximized in diverse external scenarios to gain better results. TPest-RCNN [5] helps to improve the performance by maximizing the replacement frequency of traps. However, this model is technically difficult because of the limits of computer vision. Deep CNN [6] is used to reduce the density of the monitoring cameras employed for the surveillance. But, there is a need to improve the model against images with motion blur or noise through DnCNN, Deblur GAN and other image enhancement approaches. CNN [7] performs well on small size pest detection. However, this model achieves poor accuracy. CNN [8] has more potential for pest detection, especially in outdoor applications. But, it requires more time to process a large number of data. Therefore, a new pest detection model using deep learning is required to develop, considering these above mentioned drawbacks.

TABLE I. FEATURES AND CHALLENGES OF AGRICULTURE PEST DETECTION

Author [citation]	Methodology	Features	Challenges
Kumar *et al.* [1]	Artificial Intelligence	• It decreases the rice wastage during the production time by monitoring the pests at the regular interval of time.	• However, an improved technique needs to be developed for better performance.
Chen *et al.* [2]	YOLOv3, LSTM	• It reduces the damages caused to the environment by involving enormous usage of pesticides and increases crop quality.	• Yet, there is a requirement for enhancing the perspectives in the images to solve the issues related to insufficient training samples.
Turkoglu *et al.* [3]	Ensemble learning	• It ensures high robustness.	• But, it cannot handle the imbalance problem of training data.
Liu *et al.* [4]	CNN, Channel-spatial attention	• It is more robust for detecting the tiny pests on the image.	• On the other hand, the sample size must be maximized in diverse external scenarios to gain better results.
Li *et al.* [5]	TPest-RCNN	• It helps to improve the performance by maximizing the replacement frequency of traps.	• However, this model is technically difficult because of the limits of computer-vision technology based on visible-range images.
Yue *et al.* [6]	Deep CNN	• It is used to reduce the density of the monitoring cameras employed for the surveillance.	• But, there is a need to improve the model against images with motion blur or noise through DnCNN, Deblur GAN and other image enhancement approaches.
Wang *et al.* [7]	CNN	• It performs well on small-size datasets for pest detection.	• However, this model achieves poor accuracy.
Thenmozhi *et al.* [8]	CNN	• It has more potential for pest detection, especially in outdoor applications.	• But, it requires more time to process a large number of data.

III. A NOVEL DEEP LEARNING FRAMEWORK FOR IOT-ENABLED PEST IDENTIFICATION AND CLASSIFICATION

A. Proposed Architecture and Description

The remote monitoring mechanism with IoT devices is a vital technique involved in diverse applications like object tracking in smart cities, healthcare, human surveillance, modern farming, etc. With the help of IoT, insect control can be monitored and managed from anywhere in the world. In [30], the IoT network is used along with the wireless imaging system for developing the remote greenhouse pest monitoring system. The imaging system uses blob counting and k-means color clustering algorithms to automatically count the insects and pests present in the trap sheet. Similarly, in another research, the IoT-based innovative farm field management methodology is implemented to monitor crop growth, detect insects in the crop field, and determine the appropriate pesticide to manage crop pests.

On the other hand, the automated identification of insects and pests is a significant challenge in pest monitoring systems. Hence, deep learning and machine learning algorithms are used for decision-making and object detection in diverse insect control mechanisms. In [31], the adequate performance of the machine learning, deep learning, and computer vision algorithms are utilized for pest detection, especially in tomato farms. This study has shown that the deep learning architecture provides enhanced performance compared to three considerations. From the literature works, it is clear that IoT is more essential for the pest monitoring systems, where the deep learning techniques are known to be the optimal approach for detecting and classifying the insects and pests from the crop images. Thus, IoT and deep learning are combined into the pest identification and classification model to offer more benefits to the farmers, and the architecture is diagrammatically represented in Fig. 1.

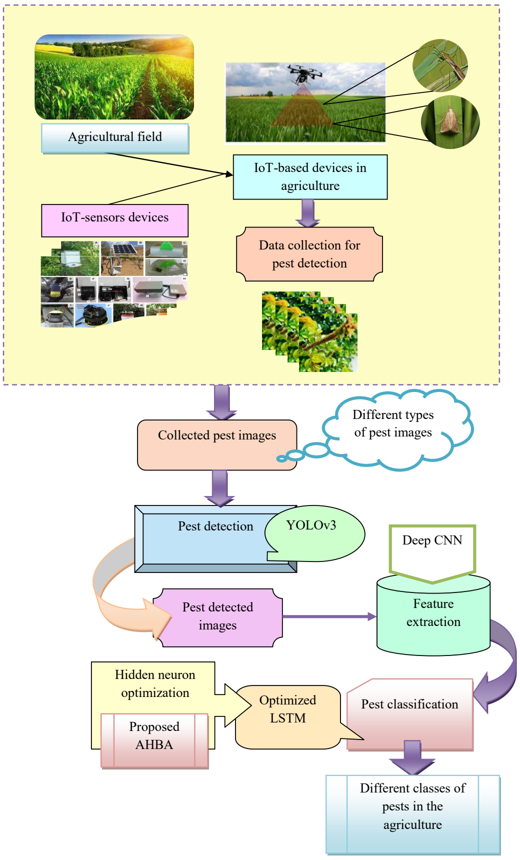


Fig. 1. Proposed pest identification and classification architecture with IoT and deep learning approach

New pest identification and classification model with IoT using the deep learning architecture is developed to identify and classify the pests in the crops to reduce the usage of fertilizers and increase crop production by preventing the problems at an earlier stage of crop growth. The IoT technology collects the required crop images from the agricultural fields through the sensors. These collected images are considered for the object detection phase, where the YOLOv3 detector is used to detect the pest regions in the given input images. The detected images from the YOLOv3 are given to the CNLSTM network, where the CNN framework is used for extracting the essential features of the pest detected images. The pest features are passed towards the developed LSTM network, where the LSTM is used for classifying the feature into different pest classes in the agricultural field. The proposed AHBA further enhances the performance of the classification model in conducting the optimization in the hidden neurons of the LSTM network, which intends to achieve the maximization of accuracy in the classification phase in the proposed optimal pest classification model.

B. IoT-enabled Pest Detection and Smart Agriculture

Agriculture is a science of crop production, animal husbandry, and soil cultivation, where the resultant products need to be marketed effectively. The food demand has been increasing abundantly both in the qualitative and quantitative aspects, which can be satisfied by incorporating computer technology into agricultural practices. Owing to the world's population growth, it is also necessary to increase crop production regarding the requirements of food in terms of nutrition. Crop production can be mainly affected by various diseases that are caused due to certain factors like the presence of insects and pests in the crop field. It needs to be prevented to enhance crop production by reducing the disease-affected crop in the agricultural areas. Hence, the IoT technology is required for automatically detecting the insects and pests through the IoT sensor devices, which helps the farmers monitor and remove the pest that affects the crops at the earlier stage of the crop growth. Traditionally, the insects and pests are determined manually by the medical experts, which takes high time consumption and may result in inaccurate results. To avoid such inaccurate results and time-consuming processes, automatic and remote identification of pests can be applied through IoT. IoT-based agricultural systems provide accurate results when determining the pest regions in the crop field. Here, the sensors need to be correctly installed and maintained in the agricultural areas. The sensors act as the assistance of the farmers in finding the target locations of the fields affected by the insects and pathogens. Initially, the sensors collect the data transferred into the centralized platforms through the wireless medium. This helps the farmers from distant locations monitor and protect their crops from insects and pest attacks, which also reduces the possibility of environmental contamination and crop intoxication and minimizes the usage of pesticides in the crop field. Thus, it is essential to incorporate IoT technology with agriculture to detect the insects and pests in the crops. The IoT-based pest detection in intelligent agriculture is shown in Fig. 2.

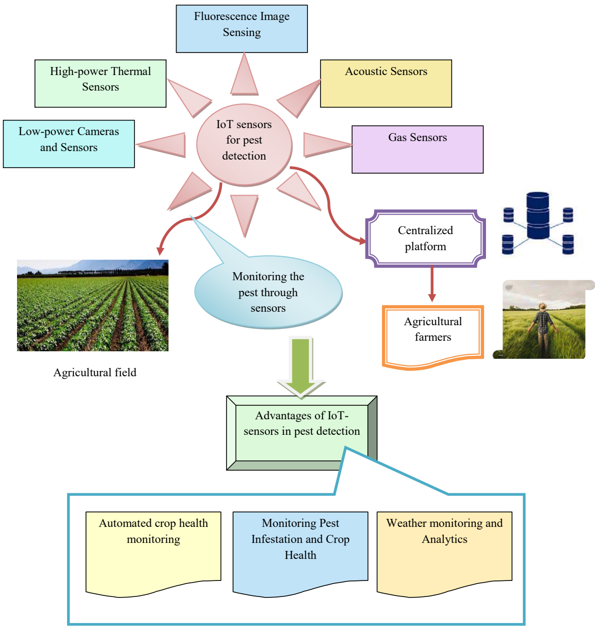


Fig. 2. IoT-based pest detection in intelligent agriculture

IV. PEST DETECTION FROM IOT GATHERED DATA USING YOLOV3 WITH DEEP FEATURE EXTRACTION.

A. Dataset Description

The proposed pest detection model with IoT requires the pest images collected from "https://github.com/xpwu95/IP102: access date: 2022-01-12". Here, the dataset comprises more than 75k images that are considered under the number of 102 classes. Additionally, the number of 19k images is presented with bounding boxes for performing object detection. The collected pest images are represented by mg_m^{input} where $m = 1,2,\ldots,M$ M and how the total number of pest images for 102 classes of pests. The sample images with different courses of pests from the dataset are shown in Fig. 3.

Pest description	**Images**	**Pest description**	**Images**
Rice leaf roller		Rice water weevil	
Rice leaf caterpillar		Rice leafhopper	

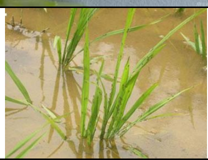
Paddy stem maggot		Grain spreader thrips	
Asiatic rice borer		Rice shell pest	
Yellow rice borer		Grub	
Rice gall midge		Mole cricket	
Rice stem fly		Wireworm	
Brown plant hopper		White margined moth	
White-backed plant hopper		Black cutworm	
Small brown planthopper		Large cutworm	

Fig. 3. Sample images for the pest detection from the dataset

B. Pest Detection using Yolov3

The proposed pest detection model with IoT utilizes the YOLOv3 [32] for detecting the pest region from the input images mg_m^{input}. YOLO classifier is one of the deep learning-based networks utilized for object classification and detection in the input pest images. Object detection is carried out by finding the object's location using the respective bounding boxes in the given input image. Here, the latest version of the YOLO-V3 classifier is used to achieve more accurate results better than the previous versions of YOLO classifiers. The YOLO-V3 can get additional semantic information on the input pest images in the training process. Even though the YOLO-V3 requires more time consumption in the training process, it also gives more re-grained information obtained from the previous feature map. This provides superior performance even for the smaller objects in the YOLOv3. Finally, the YOLOv3 detects the pest from input images, and the detected images $mg_m^{\det}$ are further considered for the deep feature extraction phase.

C. Deep Features Extraction from Detected Pest

The image features are extracted from the detected images $mg_m^{\det}$ using CNN [2] in the proposed pest identification and classification model. CNN extracts the learning features from the detected images $mg_m^{\det}$ and sorts these features according to the feature map in the hidden neurons of the convolutional layer. Here, the feature map gives equivalent weights for all the neurons with the same feature map, and at the same time, different weights will be given to the neurons with different feature maps. The c^{th} output of the feature map is computed based on Eq. (1).

$$O_c = af\left(Fe_c * mg_m^{\det}\right) \tag{1}$$

The terms $mg_m^{\det}$ a Fe_c re described here as the input images and the convolutional filter in the c^{th} output feature map. The 2D convolutional filter is employed to compute each location's filter model in the input features. The non-linear features are extracted using the activation function, which is represented as $af(\cdot)$. Further, the pooling layer decreases the spatial resolution, gains the input noise's spatial inconsistency, and transfers them to the feature map. The maximum features collected in the pooling layer lead to the maximum value for the receptive field, which is depicted in Eq. (2).

$$(OP)_{cst} = \max_{(x,y)\in T_{st}} \left(mg_m^{\det}\right)_{cxy} \tag{2}$$

The output of the pooling regions is shown as $(OP)_{cst}$, which is located at the c^{th} feature map, and the element present in the pooling layer is denoted as $\left(mg_m^{\det}\right)_{cxy}$ in the location (x, y). The output of the pooling layer is given into the LSTM for pest detection. The extracted features from the DCNN are represented as FT_f^{ext}.

V. Modified CNN-LSTM network for optimal pest classification with IoT

A. CNN-LSTM model

The extracted features FT_f^{ext} are utilized in the developed CNLSTM approach for classifying pest images to avoid crop diseases through IoT's suggested optimal pest classification model. The classification phases are made stronger by the recurrent structures of the deep learning algorithm, and so, the external memories are needless for storing the output. The recurrent structures of the LSTM classifiers provide less complexity in computation. The four components, such as "cells, input gate, output gate, and forget gate," are presented in the LSTM [2] network. The cell carried the data and passed it to the input and output gate. The forget gate is initially used to determine the information given through the network shown in Eq. (3).

$$c_t = \sigma\left(B_c \cdot \left[k_{t-1}, \left(FT_f^{ext}\right)_t\right] + w_c\right) \tag{3}$$

Here, the terms σ a k_t re correspondingly shown as sigmoid activation function and the output of the hidden respect. The weight matrices are described B_c, B_g, B_h, B_q, and the input variable is given FT_f^{ext}. Then, the cell output, output gate, and forget gate are represented g_t q_t G_t, respectively. The biased values of these gates are portrayed w_c, w_f, w_h, w_q. The input gate is formulated in Eq. (4).

$$g_t = \sigma\left(B_g \cdot \left[k_{t-1}, \left(FT_f^{ext}\right)_t\right] + w_f\right) \tag{4}$$

Further, it updates new cell states using a sigmoid function that generates the new vector $\widehat{G}_t$ shown in Eq. (5).

$$\widehat{G}_t = \tan k\left(B_h \cdot \left[k_{t-1}, \left(FT_f^{ext}\right)_t\right] + w_h\right) \tag{5}$$

For updating the old cell into a new one, the earlier state is integrated with forget gate and added more parameters given in Eq. (6).

$$G_t = g_t * G_{t-1} + c_t * \widehat{G}_t \tag{6}$$

Finally, the output gate provides the cell state using the output of the sigmoid of output gates that are given in Eq. (7) and Eq. (31).

$$q_t = \sigma\left(B_q \cdot \left[k_{t-1}, \left(FT_f^{ext}\right)_t\right] + w_q\right) \tag{7}$$

$$k_t = q_s * \tan k(d_t) \tag{8}$$

The sigmoid activation function of the LSTM classifier is represented as σ with hyperbolic tangent $\tanh$. Finally, the classified outcomes for the proposed pest identification and classification model are obtained from the developed CNLSTM approach.

B. Proposed AHBA

The proposed pest identification and classification model is performed using the suggested AHBA for optimizing the hidden neurons of LSTM to improve the accuracy of the classification process. HBA [26] is chosen in the proposed pest identification and classification model as it has a high convergence rate with the minimum time consumption. It also contains the improved explorative ability owing to the ample population diversity over the search process. On the other hand, it is necessary to resolve other practical scale optimization issues. Therefore, the proposed AHBA algorithm is improved for overcoming the existing challenges. In the proposed AHBA, the random variable rr s are computed by the new fitness-based concept for enhancing the convergence performance of the proposed algorithm.

$$rr = \frac{(a-(a-5))*(1-0)}{[(a+5)-(a-5)]} + 0 \tag{9}$$

$$a = \alpha * \frac{bestfit}{worstfit} \tag{10}$$

Here, the term a s are denoted as the variables determined based on the fitness concept in the proposed algorithm, which is used to determine the random variables rr established randomly in the conventional algorithm. Term $bestfit$ and $worstfit$ denotes the best fitness value and worst fitness value. HBA is the meta-heuristic optimization algorithm motivated by the foraging (food searching) behavior of the honey badger. This animal finds their prey by smelling and digging or following the honeyguide bird. This algorithm runs under two searching modes and honey mode. It includes the exploration and exploitation phase. The population of the solutions present in the algorithm is computed through Eq. (11).

$$pP = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1d} \\ y_{21} & y_{22} & \cdots & y_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{md} \end{bmatrix} \quad (11)$$

Here, the j^{th} position of the solution is indicated $y_j = \left[y_j^1, y_j^2, \ldots, y_j^d\right]$. The position of the honey badgers is determined by Eq. (12).

$$y_j = Lb_j + rr_1 \times \left(Ub_j - Lb_j\right) \quad (12)$$

Here, the upper and lower bounds are represented by Ub_j and Lb_j, respectively, and the j^{th} random number indicate y_j s the position of the honey badger expressed rr_1 that lies in the interval of $(0,1)$. Then, the inverse square law is involved in determining the intensity of the smell of the prey. When the high smell intensity is computed, then the movement of the honey badger will be fast. The computation of the smell intensity of the prey is given in Eq. (13).

$$S_{in} = rr_2 \times \frac{ST}{4\pi D_{in}^2} \quad (13)$$

$$ST = \left(y_j - y_{j+1}\right)^2 \quad (14)$$

$$D_{in} = y_{prey} - y_j \quad (15)$$

Here, the term S_{in} indicates the smell intensity of the prey, D_{in} shows the distance between the j^{th} solution and prey, and ST represents the concentration strength or source strength. Further, the density factor α ies are the constraint for the exploration transition to the exploitation phase. The density factor is computed through Eq. (16).

$$\alpha = c \times \exp\left(\frac{-itr}{itr_{mx}}\right) \quad (16)$$

Here, the term c expresses the constant value, and the maximum number of iterations is denoted itr_{mx}. Then, the new position y_{new} for the search agents (honey badgers) is determined through the digging and honey phases. In the digging stage, the propagation of the honey badger is based on the Cardioid motion represented in Eq. (17).

$$y_{new} = y_{pry} + f \times \beta \times S \times y_{pry} + f \times rr_3 \times \alpha \times D_{in} \times \left|\cos(2\pi rr_4) \times \left[1 - \cos(2\pi rr_5)\right]\right| \quad (17)$$

Here, the random parameters are indicated by rr_3, rr_4 and rr_5. The position of the prey (best position) is shown by y_{pry}, and the distance between in^{th} honey badger and prey is represented by D_{in}. The badger may get specific disturbance f by altering the search directions shown in Eq. (18).

$$f = \begin{cases} 1 & if\ rr_6 \le 0.5 \\ -1 & else \end{cases} \quad (18)$$

T α he term indicates the time-varying search influence factor. When considering the honey phase, the honey badger is guided by the honeyguide bird to reach the new position y_{new} shown in Eq. (19).

$$y_{new} = y_{pry} + f \times rr_7 \times \alpha \times D_{in} \quad (19)$$

Here, the prey location and new position are indicated y_{pry} y_{new}, respectively. That shows the random number rr_7 lies in the interval of $(0,1)$.

Algorithm 1: Proposed AHBA
Initialize the population with its parameters
Evaluate the fitness of all honey badgers with the objective function
While $(itr \le itr_{mx})$
Upgrade the decreasing factor with Eq. (16).
For $(in = 1\ to\ pP)$
Compute the intensity S_{in} using Eq. (12).
Determine the random variables rr using Eq. (9)
If $(rr < 0.5)$
Use Eq. (17) for updating the position of the solution.
Else
Use Eq. (19) for updating the position of the solution.
End if
Validate new position and set to the fitness fn_{new}
If $(fn_{new} \le fn_{in})$
Declare $(y_{in} \le y_{new})$ and $(fn_{in} \le fn_{new})$
End if
If $(fn_{new} \le fn_{pry})$
Declare $(y_{pry} \le y_{new})$ and $(fn_{pry} \le fn_{new})$
End if
End for
End while
Return the best optimal solution
End

The improved algorithm named AHBA enhances the overall performance of the proposed pest classification model with better efficiency in detection accuracy. The flowchart of the suggested AHBA is given in Fig. 4

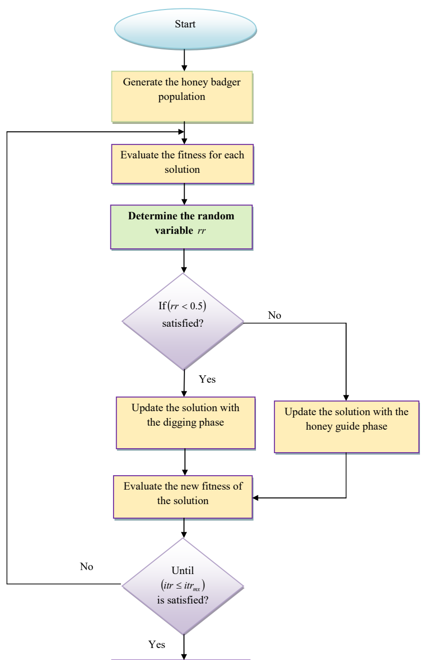


Fig. 4. Flowchart of the developed AHBA

C. Modified CNN-LSTM model

The proposed optimal pest classification model with IoT develops a hybrid deep learning approach named CNLSTM by optimizing the hidden neurons of LSTM using the suggested AHBA algorithm for achieving better classification performance with less time requirement. CNN can analyze the high-level features based on statistical learning even with the huge data volume to attain better prediction results. Similarly, LSTM is used to solve the vanishing gradient problem and ensures the relative insensitivity to the gap length, which is comparatively better than other sequence learning approaches in diverse applications. Therefore, an enhanced and hybrid version of CNN and LSTM is developed named CNLSTM for enhancing the performance of feature extraction and classification in the proposed optimal pest classification model. The extracted features from CNN are considered in the developed optimized LSTM for identifying the pest types. This would prevent crop disease and enhance crop production. The objective function FF of the proposed optimal pest classification model is to maximize the accuracy that is shown in Eq. (20).

$$FF = \underset{\{HN_b^{lstm}\}}{\arg\min}\left(\frac{1}{accy}\right) \tag{20}$$

Here, the term HN_b^{lstm} is represented as hidden neurons of the LSTM. The developed AHBA optimizes the number of hidden neurons in the range of $[5,255]$. Accuracy $accy$ is measured as the "closeness of the measurements to a specific value," as given the Eq. (21).

$$accy = \frac{\left(T^p + T^n\right)}{\left(T^p + T^n + F^p + F^n\right)} \tag{21}$$

Here, the true positive and true negative values are shown as T^p and T^n, respectively, and false positive and false negative values are given as F^p and F^n, respectively. The developed CNLSTM classifier for optimal pest classification is diagrammatically represented in Fig 4.

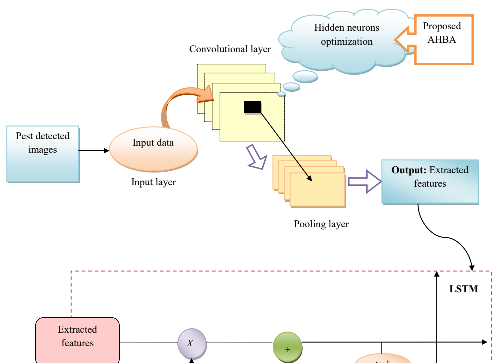


Fig. 5. Developed CNLSTM classifier of the proposed optimal pest classification model

VI. Results and Discussions

A. Experimental setup

Python platform was utilized for developing the pest identification and classification model, and it was evaluated through experimental analysis. The experimental investigation was conducted based on specific quantitative measures by comparing the proposed model with certain existing meta-heuristic algorithms and classifiers for estimating the performance of the proposed model. This experimental analysis was undergone with a population count of 10 and maximum iterations of 25 for the proposed pest identification and classification model. The proposed AHBA-CNLSTM was compared with other meta-heuristic algorithms like "Particle Swarm Optimization (PSO) [27], Tunicate Swarm Algorithm (TSA) [28], Deer Hunting Optimization Algorithm (DHOA) [29], HBA [26] and deep learning algorithms like CNN [7], deep-CNN [6], RCNN [5] and LSTM [2]".

B. Performance metrics

The performance of the proposed pest identification and classification model is evaluated using various quantitative measures that are given as follows.

(a) FPR F_{pr} is defined as "the ratio between the numbers of negative events wrongly categorized as positive (false positives) and the total number of actual negative events," as given in Eq. (22).

$$F_{pr} = \frac{F^p}{F^p + T^n} \tag{22}$$

(b) Specificity S_{spcty} is "the proportion of negatives that are correctly identified," as represented in the Eq. (23)

$$S_{spcty} = \frac{T^n}{T^n + F^p} \tag{23}$$

(c) Sensitivity $S_{senstvy}$ is "the proportion of positives that are correctly identified," as denoted in Eq. (24)

$$S_{senstvy} = \frac{T^p}{T^p + F^n} \tag{24}$$

(d) F1-score F_{score} is determined as “the measurement of the accuracy in the conducted test” as given in Eq. (25)

$$F_{score} = 2 \times \frac{2T^p}{2T^p + F^p + F^n} \tag{25}$$

(e) FNR F_{nr} is “the proportion of positives which yield negative test outcomes with the test," as given in Eq. (26)

$$F_{nr} = \frac{F^n}{F^n + T^p} \tag{26}$$

(g) NPV N_{pv} is described as “the sum of all persons without disease in testing," as denoted in Eq. (27)

$$N_{pv} = \frac{T^n}{T^n + F^n} \tag{27}$$

(h) MCC M_{cc} is "a measure of the quality of binary classifications of testing," as given in the Eq. (28)

$$M_{cc} = \frac{T^p \times T^n - F^p \times F^n}{\sqrt{(T^p + F^p)(T^p + F^n)(T^n + F^p)(T^n + F^n)}} \tag{28}$$

(i) FDR is "a method of conceptualizing the rate of errors in testing when conducting multiple comparisons," as denoted in Eq. (29)

$$F_{dr} = \frac{F^p}{F^p + T^p} \tag{29}$$

Precision $prsn$ is explained as "the fraction of relevant instances among the retrieved instances," as given in Eq. (30).

$$prsn = \frac{T^p}{T^p + F^p} \tag{30}$$

C. *Detection results*

The resultant images of the pest detection using the YOLOv3 approach in the proposed pest identification model are depicted in Fig 6.

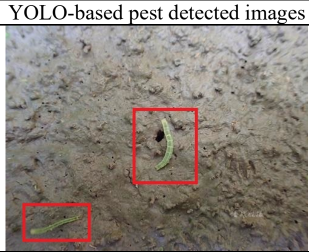
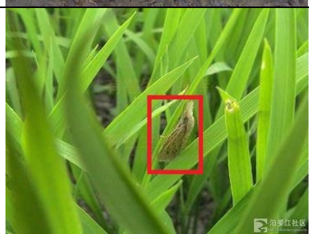
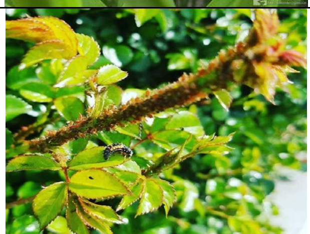
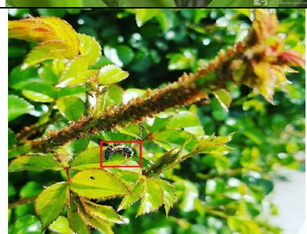
Description	Actual images	YOLO-based pest detected images
Image 1		
Image 2		
Image 3		
Image 4		

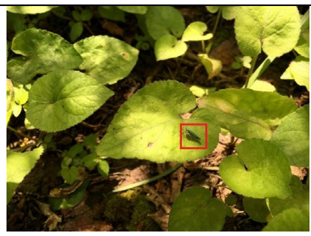
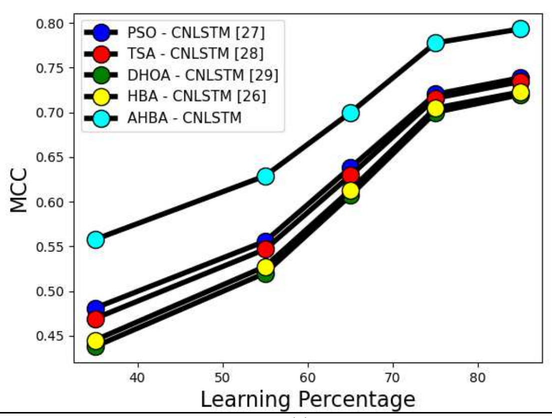
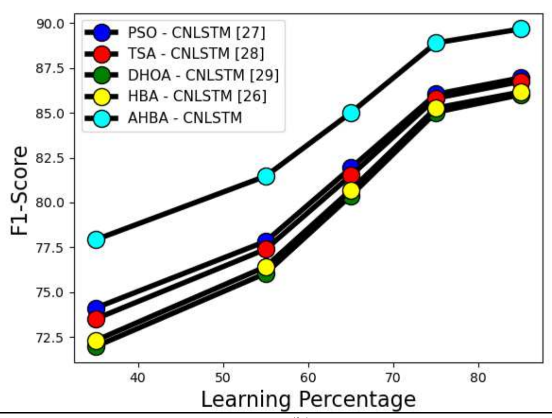
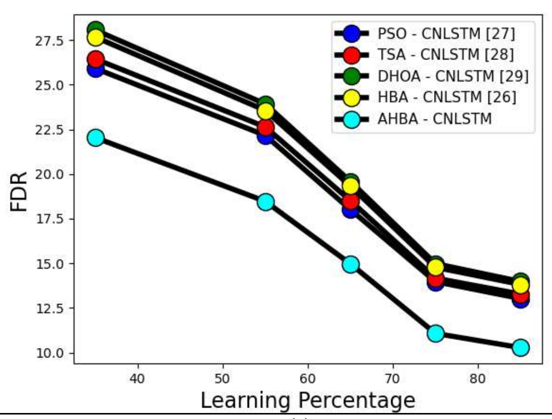
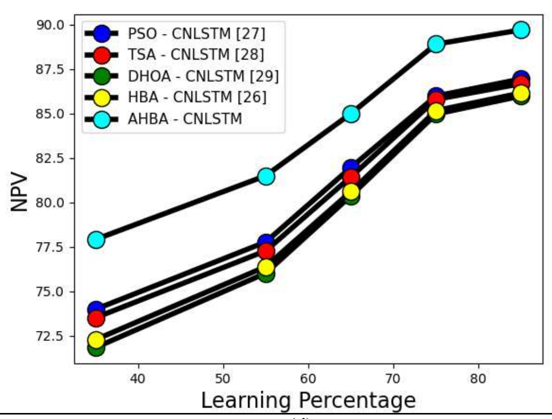
Image 5		
Image 6		

Fig. 6. Detected Images of the Proposed Pest Identification Model

D. Algorithmic analysis of proposed model

The performance of the proposed pest identification and classification model based on developed FS-SSO is evaluated at varying learning percentages with different heuristic-based algorithms, as shown in Fig 7. The proposed AHBA-CNLSTM shows 0.3%, 0.3%, 0.35% and 0.41% higher accuracy than the PSO-CNLSTM, TSA-CNLSTM, HOA-CNLSTM and HBA-CNLSTM, respectively at the learning rate of 70. While observing the FNR of the proposed AHBA-CNLSTM, it always lies at the lowest error value in all the learning percentages. At the same time, it is increasing the learning percentage to 65, which is better than the other existing algorithms. Therefore, the proposed pest identification and classification model with implemented AHBA-CNLSTM is superior to the conventional meta-heuristic algorithm-based methods.

	
(a)	(b)
	
(c)	(d)

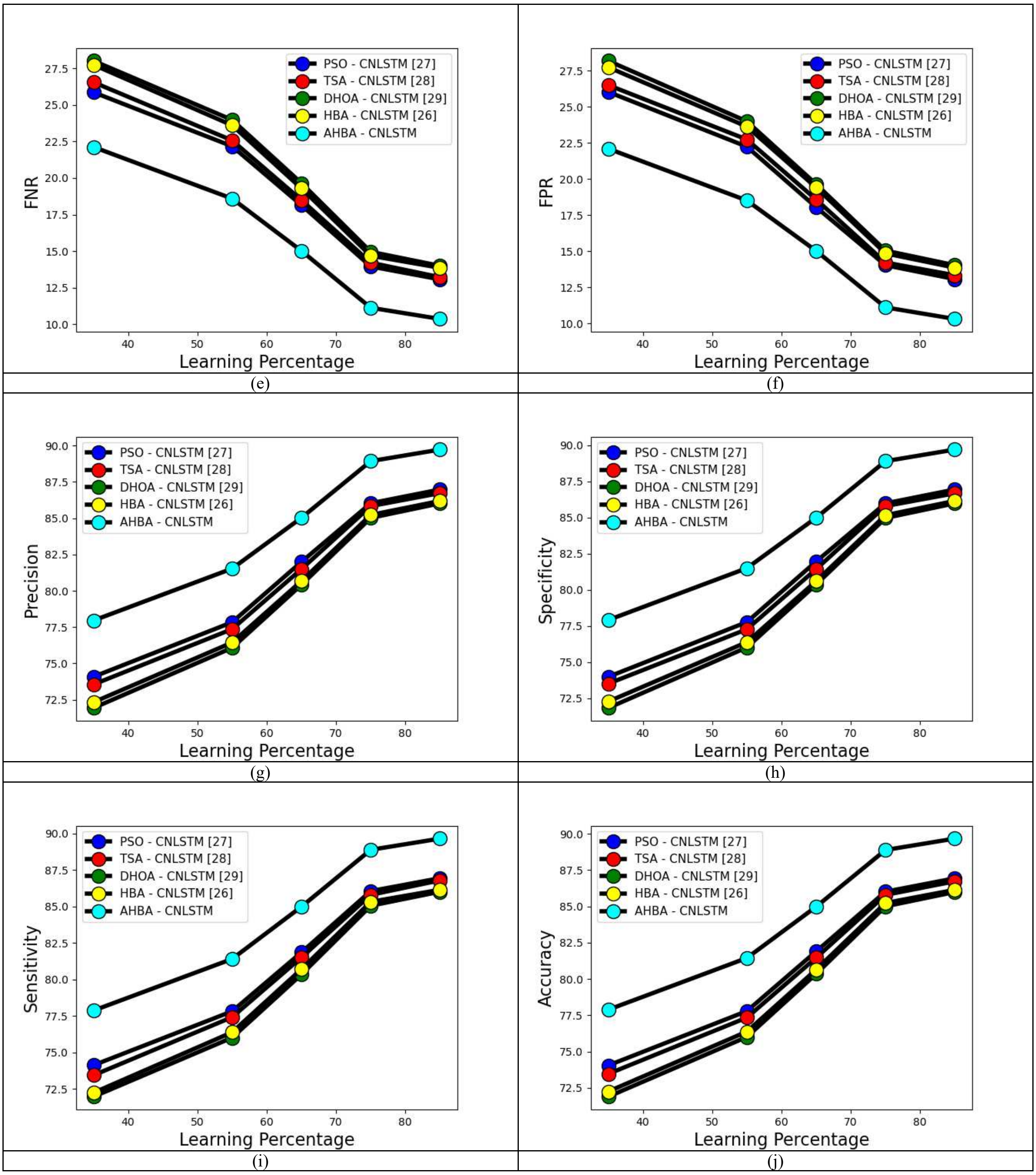
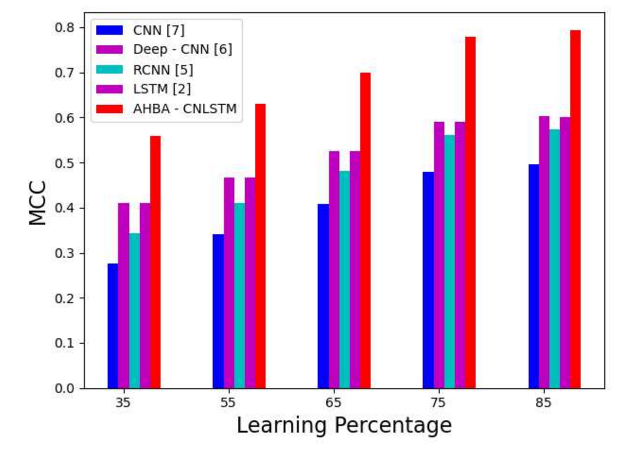


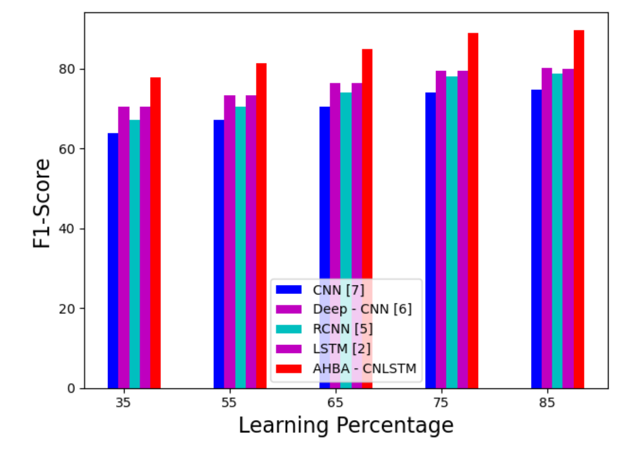
Fig. 7. Performance analysis on proposed pest identification and classification model with different meta-heuristic algorithms in terms of (a) MCC, (b) F1-Score, (c) FDR, (d) NPV, (e) FNR, (f) FPR, (g) precision, (h) specificity, (i) sensitivity and (j) accuracy

E. Classifier analysis on proposed model based on optimal pest classification

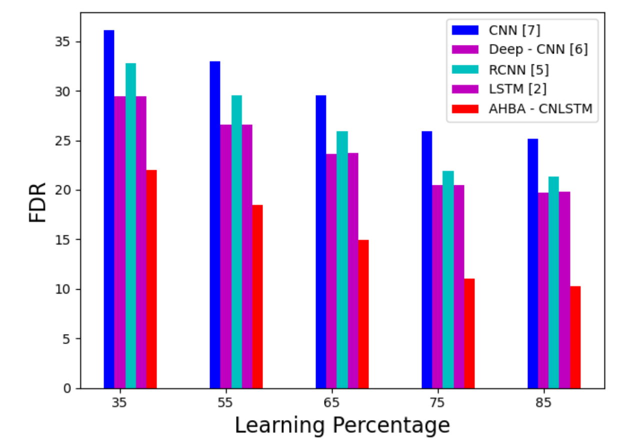
The performance of the proposed pest identification and classification model using the developed AHBA-CNLSTM is tested at varying learning percentages with different classifiers, as shown in Fig 8. The proposed AHBA-CNLSTM gives 34.6%, 27.2%, 29.6%, and 48.9% improved MCC values than the CNN, Deep-CNN, RCNN, and LSTM, respectively, at the learning rate of 65. The proposed AHBA-CNLSTM secures a very low error rate with improved performance observed through this classifier analysis in all the quantitative measures. Therefore, the proposed pest identification and classification model with implemented AHBA-CNLSTM provides enhanced performance to the conventional classifier methods.


MCC
Learning Percentage
CNN [7]
Deep - CNN [6]
RCNN [5]
LSTM [2]
AHBA - CNLSTM

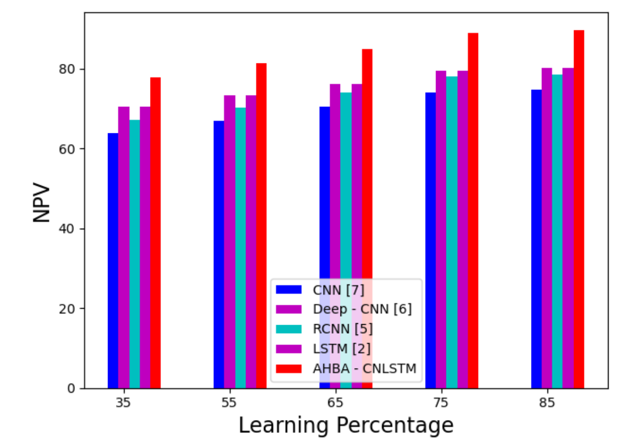
(a)


F1-Score
Learning Percentage
CNN [7]
Deep - CNN [6]
RCNN [5]
LSTM [2]
AHBA - CNLSTM

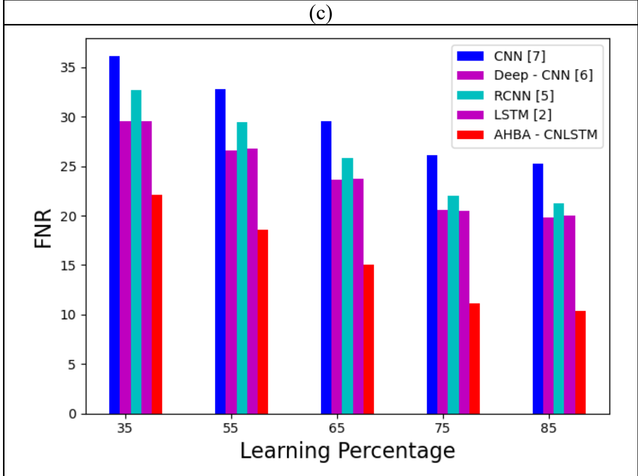
(b)


FDR
Learning Percentage
CNN [7]
Deep - CNN [6]
RCNN [5]
LSTM [2]
AHBA - CNLSTM

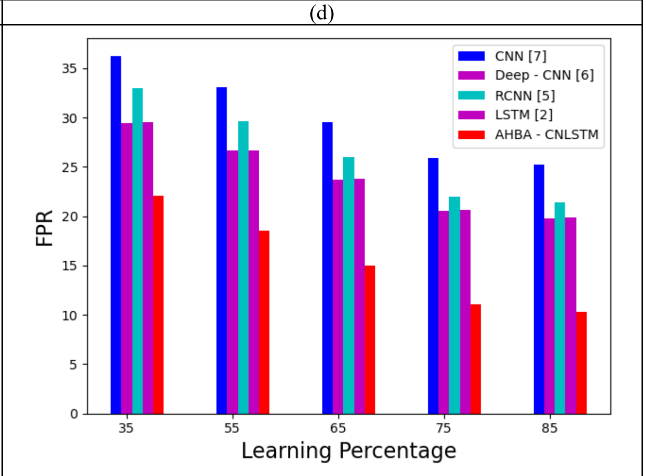
(c)


NPV
Learning Percentage
CNN [7]
Deep - CNN [6]
RCNN [5]
LSTM [2]
AHBA - CNLSTM

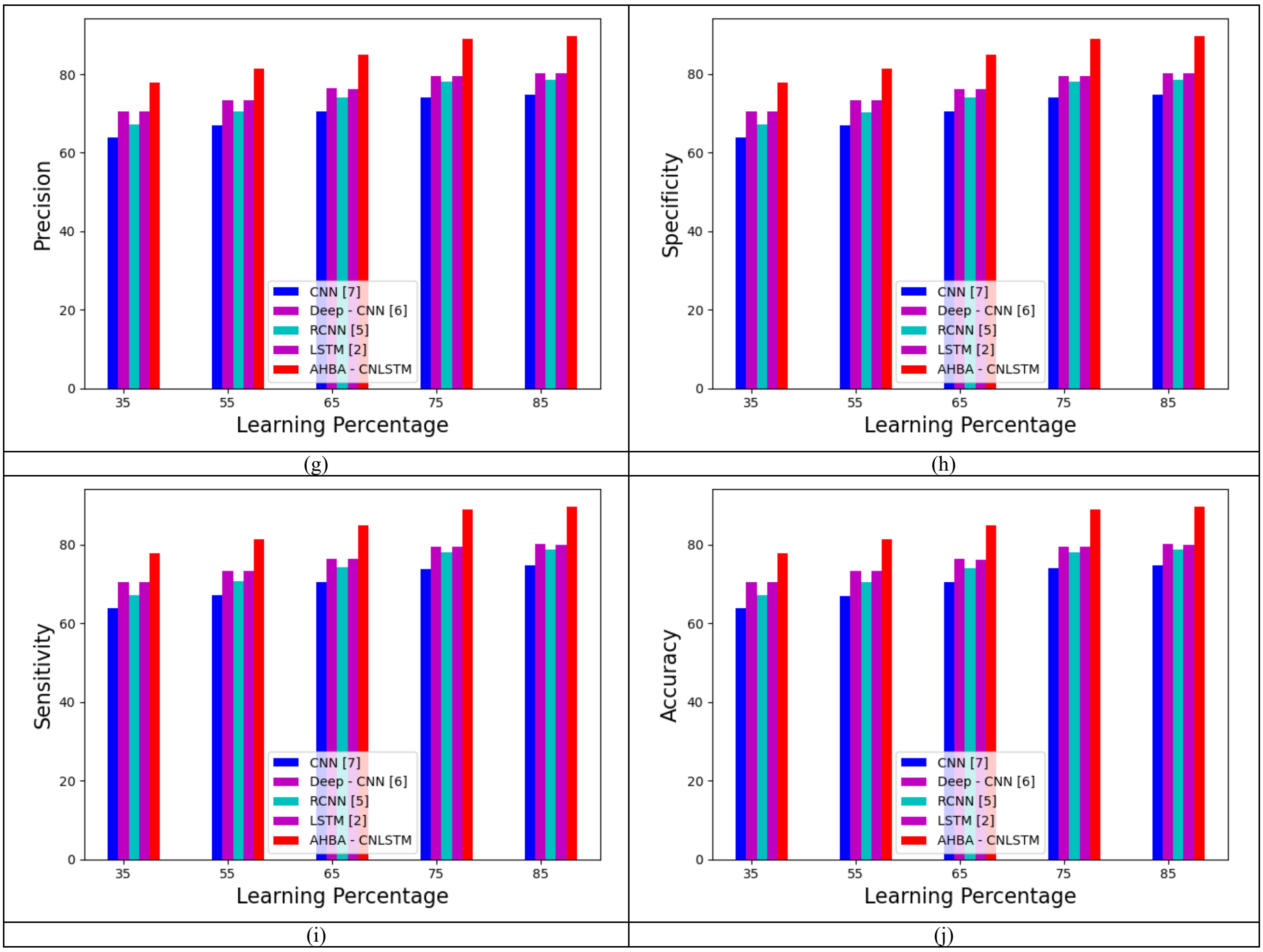
(d)


FNR
Learning Percentage
CNN [7]
Deep - CNN [6]
RCNN [5]
LSTM [2]
AHBA - CNLSTM

(e)


FPR
Learning Percentage
CNN [7]
Deep - CNN [6]
RCNN [5]
LSTM [2]
AHBA - CNLSTM

(f)



(g) (h)

(i) (j)

Fig. 8. Performance analysis on proposed pest identification model with different classifiers in terms of (a) MCC, (b) F1-Score, (c) FDR, (d) NPV, (e) FNR, (f) FPR, (g) precision, (h) specificity, (i) sensitivity and (j) accuracy

F. Overall performance analysis based on different meta-heuristic algorithms

The proposed pest identification and classification model is compared with various meta-heuristic algorithms and is shown in Table II for computing its performance based on the dataset. The performance of the proposed AHBA-CNLSTM is 0.06%, 0.03%, 0.12%, and 0.13%, correspondingly improved in terms of F1-score than the PSO-CNLSTM, TSA-CNLSTM, HOA-CNLSTM, and HBA-CNLSTM. The proposed AHBA-CNLSTM indicates superior performance by decreasing pest detection errors by observing the comparative analysis of optimization algorithms. Therefore, the proposed pest identification and classification model has enhanced its performance among all other existing methods.

TABLE II. COMPARATIVE ANALYSIS OF PROPOSED PEST IDENTIFICATION AND CLASSIFICATION MODEL USING EXISTING META-HEURISTIC ALGORITHMS

Measures	PSO [27]	TSA [28]	DHOA [29]	HBA [26]	AHBA-CNLSTM
“Accuracy”	0.860187	0.85794	0.850084	0.85241	0.888902
“Sensitivity”	0.860571	0.857969	0.850511	0.853218	0.888812
“Specificity”	0.859802	0.857911	0.849655	0.851599	0.888992
“Precision”	0.860319	0.858334	0.850218	0.852268	0.889308
“FPR”	0.140198	0.142089	0.150345	0.148401	0.111008
“FNR”	0.139429	0.142031	0.149489	0.146782	0.111188
“NPV”	0.859802	0.857911	0.849655	0.851599	0.888992
“FDR”	0.139681	0.141666	0.149782	0.147732	0.110692
“F1-score”	0.860445	0.858152	0.850364	0.852743	0.88906
“MCC”	0.720373	0.71588	0.700167	0.704819	0.777804

G. Overall performance analysis based on different classifiers

The overall performance analysis is made on the proposed pest identification and classification model for estimating its performance among different classifiers portrayed in Table III. The proposed AHBA-CNLSTM based on the MCC value gives 26.8%, 18.8%, 4.77%, 3.14%, and 56.33%, correspondingly better performance than the CNN, Deep-

CNN, RCNN, and LSTM. The proposed AHBA-CNLSTM provides a lower value in the negative measures and a higher value in the positive measures, which confirms the enhanced performance of the proposed model based on various quantitative measures. Therefore, the proposed pest identification and classification model improves its performance to the existing methods.

TABLE III. COMPARATIVE ANALYSIS OF PROPOSED PEST IDENTIFICATION AND CLASSIFICATIONMODEL WITH EXISTING CLASSIFIERS

Measures	CNN [7]	Deep-CNN [6]	RCNN [5]	LSTM [2]	AHBA-CNLSTM
"Accuracy"	0.740076	0.794595	0.779958	0.794595	0.888902
"Sensitivity"	0.738792	0.794293	0.779536	0.79509	0.888812
"Specificity"	0.741364	0.794897	0.780382	0.794098	0.888992
"Precision"	0.74135	0.795328	0.780779	0.794858	0.889308
"FPR"	0.258636	0.205103	0.219618	0.205902	0.111008
"FNR"	0.261208	0.205707	0.220464	0.20491	0.111188
"NPV"	0.741364	0.794897	0.780382	0.794098	0.888992
"FDR"	0.25865	0.204672	0.219221	0.205142	0.110692
"F1-score"	0.740069	0.79481	0.780157	0.794974	0.88906
"MCC"	0.480157	0.58919	0.559917	0.589188	0.777804

VII. CONCLUSION

This research has developed a novel pest identification and classification model with implemented AHBA for achieving the accurate detection of the pest in the crop field. Initially, the pest images were collected through the IoT technology with the sensors. The collected images were subjected to the object detection phase, where the YOLOv3 detector was utilized to detect the pest regions in the given input images. The detected images were obtained from the YOLOv3 that were further given into the CNN framework to extract the significant features from the pest images. The extracted features were considered for the developed CNLSTM network. The optimal feature classification with proposed AHBA was performed that has classified into different classes of pests in the agricultural field. The performance analysis showed that the accuracy of the proposed AHBA-CNLSTM was 2.08% more improved than CNN, 4.2% enhanced than Deep-CNN, 4.2% enriched than RCNN, and 5.3% elevated than the LSTM classifier. Therefore, the overall performance of the proposed pest identification and classification model with implemented AHBA-CNLSTM was superior to the other conventional techniques.

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