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RESEARCH ARTICLE

Enhancing Red Palm Weevil Detection Using Bird Swarm Algorithm With Deep Learning Model

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ABSTRACT In recent times, mostly in the Middle East region, Red Palm Weevils (RPW) are one of the most dangerous pests of palm trees worldwide. The RPW causes significant harm to several palm species. The existing detection method includes the symptoms detection of RPW through sound or visual assessment and chemical recognition of volatile signatures created by diseased palm trees. However, an effective recognition of RPW disease at earlier stages is assumed that a very complex problem for cultivating date palms. This is another reason why the use of state-of-the-art technologies is supported in the avoidance of the spread of the RPW on palm trees. Several researchers are working on determining the correct process for the localization, classification, and detection of RPW pests. Therefore, this paper presents an intelligent Red Palm Weevil Detection using the Bird Swarm Algorithm with Deep Learning (IRPWD-BSADL) model. The major aim of the IRPWD-BSADL technique focuses on the identification and classification of RPW using CV and DL models. Primarily, the bilateral filtering (BF) approach can be utilized to remove the noise that exists in the images. In the presented IRPWD-BSADL technique, an improved ShuffleNet model can be applied for feature extraction purposes. To enhance the recognition results, the IRPWD-BSADL technique makes use of BSA for the hyperparameter tuning process. For RPW detection and classification, an extreme gradient boosting (XGBoost) classifier can be used. The simulation analysis of the IRPWD-BSADL method can be tested on the RPW dataset. An extensive comparison study stated the improved performance of the IRPWD-BSADL algorithm on the RPW detection method.

INDEX TERMS Computer vision, machine learning, pest detection, agriculture, hyperparameter tuning, crop productivity.

I. INTRODUCTION

The red palm weevil (RPW), Rhynchophorus ferrugineus, is an important pest of palm trees, causing substantial harm to the trees and leading to considerable economic loss for the agriculturalists [1]. RPW has reflected between more damaging pests, which threaten palms around the world. Approximately, $2 million contribution has been provided by Saudi Arabia to assist the worldwide efforts to destroy RPW [2]. However, numerous restrictions are required that can be overcome, particularly in the agricultural field. Generally, farmers did not have some automatic method that offers evident indicators around infected palm trees to lead to 25-40% loss of yielding because of uncontrolled processes. Control of the RPW introduces an important challenge for entomologists because of the starting of current farming,

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specifically in the earlier identification of infected palms [3]. Visual analysis of palms is one of the major adaptable methods to detect infected palms. For detecting palm diseases, farmers can be required to provide a substantial quantity of currency to employ a palm tree contagion adept for every annum.

Visual analysis of the tree for the presence of signs, detection of the sound developed by nourishment larvae along chemical study of volatile signs produced by infected date palms are examined as the most recognized RPW earlier identification methods [4]. Moreover, an alternative standard technique of thermal imaging for monitoring temperature variations in diseased palms has to identify RPW. The most valuable method is sound recognition and highly dependable one can be depends on the observance of signs. In contrast with considering standard identification techniques, it is required to make computational determinations for controlling and identifying RPW types, which are both permanent and accurate [5]. This can also be significant in finding out what key features to appear for when detecting plagued palm trees.

Smart precision agriculture employs current information and wireless transmission techniques to attain stimulating automatic consistent activities and agricultural methods [6]. For example, the Internet of Things (IoT) is implemented in real-time applications of farming namely insect pests, accuracy management of water irrigation, and crop disease. IoT mostly depends on wireless sensor networks (WSNs) for detecting and gathering the surrounding conditions such as humidity and soil moisture [7]. Subsequently, this gathered information could be analyzed and stored to function water irrigation pumps as well as support the decisions of experts or cultivators. Artificial intelligence (AI) systems like DL and ML methodologies are presently utilized for analyzing obtained environmental and agricultural data [8]. Crop health observation offers a key component of smart precision agriculture, particularly detecting the infective condition of insect pests in the agricultural region. Conventional methods and manual identification of insect pests have been inadequate, time-saving, and comparatively high-cost [9]. Consequently, earlier identification of the plant pests has a higher importance for agriculturalists to utilize appropriate pesticides, preventing crop loss [4]. Therefore, this analysis aims to develop an innovative solution for continuously monitoring the health of date palm trees against RPWs by implementing DL and IoT frameworks [10]. The transfer learning (TL) method addresses the limitations of standard DL algorithms in the condition of smaller databases and insufficient resources for the training stage [11]. The basic concept of this method is forwarding the information from the same activity, and again exploiting the pretrained DL technique to attain different tasks with the lowest computational efficiency [12].

This study presents an intelligent Red Palm Weevil Detection using the Bird Swarm Algorithm with Deep Learning (IRPWD-BSADL) algorithm. Primarily, the bilateral filtering (BF) approach can be utilized to remove the noise that exists in the images. In the presented IRPWD-BSADL technique, an improved ShuffleNet model can be applied for feature extraction purposes. To enhance the recognition results, the IRPWD-BSADL technique makes use of BSA for the hyperparameter tuning process. For RPW detection and classification, an extreme gradient boosting (XGBoost) classifier can be used. The simulation analysis of the IRPWD-BSADL algorithm can be tested on the RPW dataset. An extensive comparison study stated the improved performance of the IRPWD-BSADL method on the RPW detection technique.

The rest of the paper is organized as follows. Section II provides the related works and section III offers the proposed model. Then, section IV gives the result analysis and section V concludes the paper.

II. RELATED WORKS

In [13], an effective method for the earlier identification of RPW was developed. This technique depends on RPW sound actions being analyzed and verified. The primary stage includes the change of sound data into images derived from chosen feature sets. The secondary stage contains the integration of images from similar sound data, however, calculated through various features as a single image. The final stage comprises the use of diverse DL methods for classifying resultant images. Karar et al. [14] introduced a novel IoT-based model for earlier sound identification of RPWs applying modified TL methods such as InceptionResNet_V2. Palm trees could be labelled depending on the count of sensor nodes. Later, the obtained audio signals were analyzed with the help of fine-tuned deep-TL (DTL) techniques like InceptionResNet_V2. In [15], an IoT-based sound identification method was introduced for detecting RPW larvae. This presented detection method is majorly dependent upon an adapted mixed depthwise convolution network (MixConvNet) as a current DL method.

Singh et al. [16] designed an end-to-end architecture by implementing image processing and DL approach. The customized deep 2D- CNN was trained to forecast. Moreover, the recent Keras pre-trained CNN algorithms InceptionResNetV2, Xception, NASNetMobile, VGG19, VGG16, InceptionV3, DenseNet201, and MobileNet are fine-tuned for classifying the images. Aladhadh et al. [17] introduced an effective pest identification technique that precisely identified the pests and classified them by their preferred class labels. The YOLOv5s framework was adapted in many methods namely expanding the cross-stage partial network (CSP) unit, enhancing the select kernel (SK) from the attention mechanisms, and adapting the extraction feature approach that performs an important part in the classification and identification. In [18], 2 techniques of DL such as Residual Network (ResNet) and TL of InceptionResNet were designed. The effectiveness of image classification by employing the ResNet method was improved especially, plant leaf disease classification. Besides, difficulties for example, inter-class similarity, difference of luminance and background, and various image scales are processed.

Maray et al. [19] implemented an AI-Enabled Coconut Tree Disease Detection and Classification (AIE-CTDDC) algorithm. Initially, the AIE-CTDDC technique implements MF-based noise removal. Subsequently, the Bayesian fuzzy cluster-based segmentation approach was deployed and the CapsNet algorithm could be utilized as a feature extraction. The Harris Hawks Optimizer (HHO) with GRU technique was also employed for identification. Azfar et al. [20] recommended real-time identification of Cotton Flying Moths (CFMs) employing an IoT-based technique in the farming sector. This introduced model comprises a Zigbee-based communication element, unmanned aerial vehicle (UAV), gateway device, collection of strong infrared sensors, lithium polymer battery, and Arduino 2560 Mega board for responding as a pesticide-sprayer against the identified pests.

Saleh and Ertunç [21] introduce an ML algorithm based on image processing to identify these insect species for people who do not know them. The fundamental concept is to develop a neural network model that uses image processing to detect RPW and discriminate it from other insects found in palm tree habitats. Parvathy et al. [22] propose a Convolutional Autoencoder based DL approach for the detection of RPW acoustic emissions from other background noise. Mel spectrogram of acoustic samples was selected as the extracted feature for the proposed model. The proposed Convolutional Autoencoder was trained using Mel spectrogram images of RPW acoustic activities which are considered the normal instances.

A significant research gap in the field of RPW detection using DL is the imperative need for comprehensive hyperparameter tuning methods. While DL algorithms have shown promise in RPW detection, the effective optimization of hyperparameters tailored to the intricacies of RPW detection remains an understudied area. Achieving the maximum possible accuracy and generalization in pest detection, particularly in complex environmental conditions, demands a dedicated exploration of hyperparameter tuning methods specially developed for RPW detection techniques and models. Addressing this research gap is critical for harnessing the full potential of DL in the context of RPW recognition and promoting its practical applicability in real-time pest management scenarios. Thus, in this work, we focus on the design of BSA for the hyperparameter tuning process.

III. THE PROPOSED MODEL

In this paper, we have designed an automated RPW detection approach called as IRPWD-BSADL approach. The main objective of the IRPWD-BSADL technique is mainly concentrated on the identification and classification of RPW using CV and DL models. It comprises several subprocesses namely BF-based pre-processing, improved ShuffleNet feature extractor, BSA-based hyperparameter tuning, and XGBoost classification. Fig. 1 exemplifies the working flow of the IRPWD-BSADL algorithm.

A. BF BASED PRE-PROCESSING

To pre-process the input images, the BF approach can be used. BF is a common approach utilized in image processing for distinct tasks comprising image pre-processing. It can be an edge-preserving, non-linear smoothing filter that reduces noise while maintaining the sharpness of edges in the image. BF is effective in reducing distinct kinds of noise from the images namely salt-and-pepper noise or Gaussian noise. It smoothens the image while retaining edges, making it well-suited for applications where noise reduction is required.

B. FEATURE EXTRACTION USING IMPROVED SHUFFLENET MODEL

In this work, an improved ShuffleNet model can be applied to the feature extraction process. ShuffleNet is an effective CNN architecture used mainly for the tasks of target detection and image classification [23]. ShuffleNet is represented by the reduced computational complexity and number of parameters while preserving its reliability. These features can be attained by using two crucial methods: channel shuffle and group convolution. Group convolution lowers the model's effectiveness once the input mapping feature data is considered. For these problems, a channel shuffle model has been added among 2 group convolutions to interrupt the channel order, such that data is exchanged between various groups.

For ShuffleNetV2, the researchers proposed four guidance summaries: reducing element-level operations, balancing the dimensional channel of input and output via 1x1 convolutions, paying more attention to the different groups using group convolution, and avoiding network fragmentation. The researchers studied the limitations of the ShuffleNetV1 model and assimilated improvements to generate ShuffleNetV2. The channel split technique is the central development established in the V2 version that includes splitting the input mapping features into 2 different parts from the channel size. The right branch has three consecutive convolutional layers with similar input and output channels, followed by guidance 1, whereas the left branch of separate is equally mapped. Moreover, during the V2 version, the prior group convolutional is used for 1x1 convolutions and is replaced by the standard convolutional, aligning with guidance 2.

The model efficiency and accuracy are a pair of contradictory indicators. ShuffleNet has attained a higher efficiency. In the subsequent two aspects, the specific improvement was reflected:

The DW convolution contributes comparatively few computation costs, however, most of the computation focused on the 1x1 convolutional layer. Thus, each 3x3 DW convolution layer was replaced by the 5x5 DW convolutional layers. Also, this will increase the model accuracy but it will not increase the computation weight too much.

In deep CNN (DCNN), the feature selection (FS) channel is vital to increase the effectiveness. However, the classical NN frequently doesn't assume the relationships between channels while processing the weight of the FS channel, thus failing

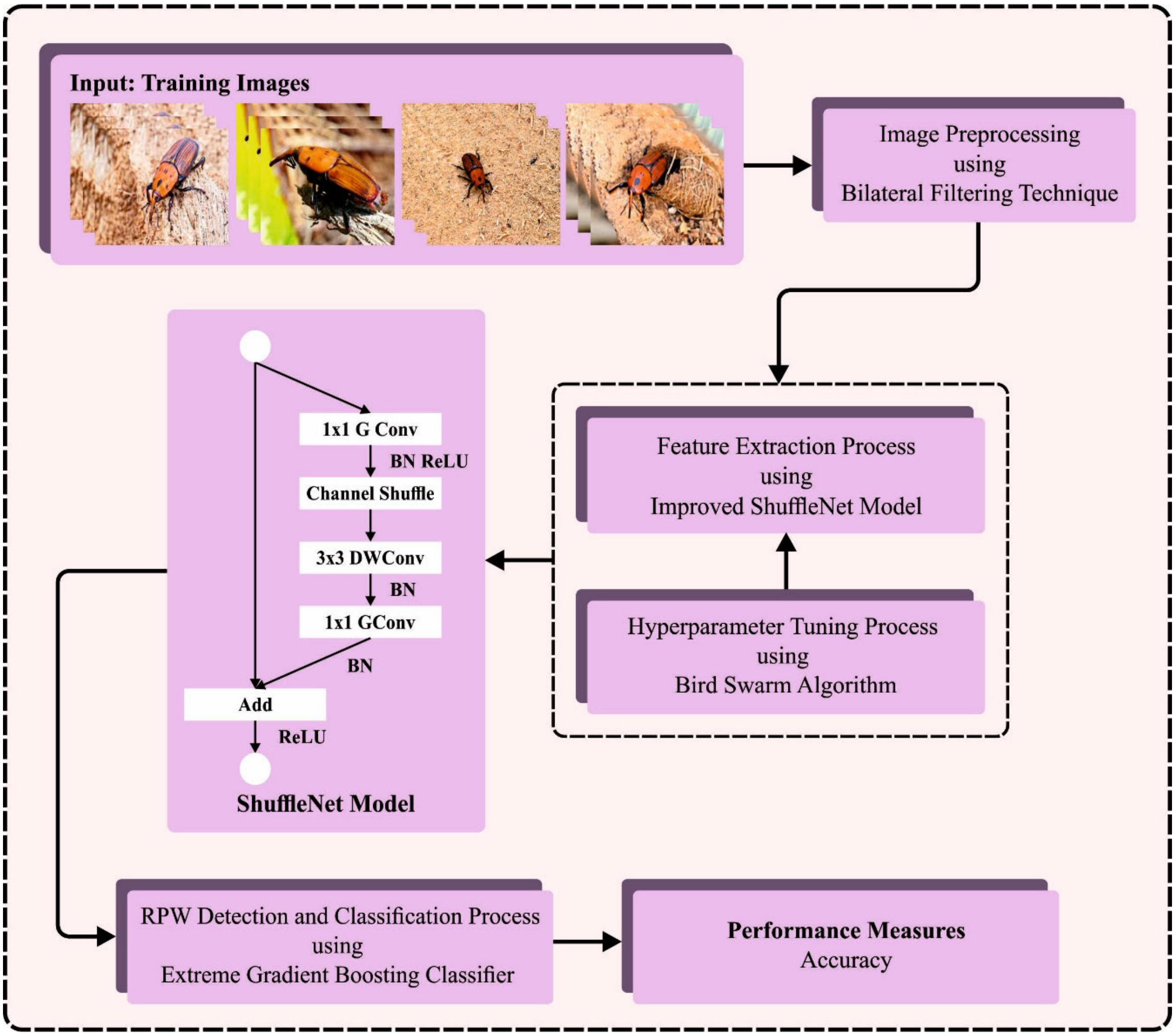

FIGURE 1. Workflow of IRPWD-BSADL algorithm.

to apply the data among FS channels. To overcome these problems, Hu et al. 2018 developed a channel attention module that depends on the squeeze-and-excitation (SE) model, named SENet.

The channel attention module of SENet is used to learn the significance of all the channels, thus establishing the feature channel from the network and suppressing the irrelevant ones. First, the global average pooling layer has been carried out by the squeeze function to attain the global average of all the channels. Then, the excitation function is carried out by using two FC layers to learn the weight of all the channels by mapping *thec*-weight coefficient. Lastly, this weight is multiplied by all the channels from the input mapping features to attain the mapping features adapted by the channel attention model.

C. HYPERPARAMETER OPTIMIZATION USING BSA

For the hyperparameter tuning process, the BSA is applied. The BSA aims to mimic the vigilance, flight, and foraging behaviours based on interaction and social behaviours to resolve the optimization problem [24]. The BSA algorithm is given below:

Foraging: The individuals within the swarm might vary their behaviours. It can be modelled by the stochastic decision once they perform vigilance or foraging.

It uses the existing and its own experience within the swarm when the bird searches for food. These behaviours are analyzed by the following equation:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + \left(p_{i,j} - x_{i,j}^{t}\right) Crand\,(0, 1) + \left(g_j - x_{i,j}^{t}\right) Srand\,(0, 1)\,, \tag{1}$$

In Eq. (1), g_j is the best previously shared location in the swarm. $rand(0, 1)$ is a uniform distribution of random numbers in [0, 1]. $p_{i,j}$ denotes the prior best location of $thei_{th}$ bird, S and C are the coefficient values of social and cognitive acceleration, correspondingly, $j \in [1, \ldots, D]$,

Birds can update and recall the best experience individually; along with sharing social information instantly amongst the entire swarm based on the food patches when they engage in foraging behaviours.

Birds are individually updated and recall the optimum experience within the swarm based on the food patches when they are engaged in foraging behaviours. Social info is instantaneously shared amongst the complete swarms.

Vigilance: The birds attempt to move towards the swarm centre to fight with other individuals, however, they will not directly move towards the swarm centre as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + A1\left(mean_j - x_{i,j}^{t}\right) \times rand\,(0,1) + A2\left(p_{k,j} - x_{i,j}^{t}\right) \times rand\,(-1,1) \quad (2)$$

$$A1 = a1 \times \exp\left(-\frac{pFit_i}{sumFit + \varepsilon} \times N\right) \quad (3)$$

$$A2 = a2 \times exp\left(\left(\frac{pFit_i - pFit_k}{|pFit_k - pFit_i| + \varepsilon}\right)\frac{N \times pFit_k}{sumFit + \varepsilon}\right) \quad (4)$$

Now $a1$ and $a2$ are the 2 positive constants within zero and two. $A1$ and $A2$ denote the outcomes generated by the interference while the birds move towards the swarm centre. *sumFit* refers to the sum of optimum fitness values (FV) from the swarm. $pFit_i$ is the better FV in the i^{th} location; k is a positive integer in $[0,N]$, and ε is preventing an error of zero-division.

The individual bird from the swarm attempts to move to the centre. Individuals with a small supply can occupy relatively peripheral positions, while individuals with a large food supply are inclined to place themselves near the swarm centre.

Flight: The birds fly to other places periodically and can be scroungers or producers. The birds with the large food reserve are the producers, and the birds with the lower reserve are the scrounge. Birds with intermediate reserves can shift among producers and become scroungers. These behaviours are mathematically modelled in the following:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + randn\,(0,1) \times x_{i,j}^{t}, \quad (5)$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + \left(x_{k,j}^{t} - x_{i,j}^{t}\right) \times PL \times rand\,(0,1), \quad (6)$$

Now the positive integer FQ shows that the individuals may move to other places all the FQ range. $FL(FL \in [0,2])$ shows the scrounger follows the producer to find food. $randn(0,1)$ indicates the Gaussian-distributed arbitrary integer with a standard deviation of 1 and a mean of 0.

Within the BSA framework, Birds can engage in various activities. Scrounger randomly follows the producers in search of food, while Producers are involved actively in foraging for food.

The fitness optimum is a key feature of the BSA system. An encoded solution has been deployed to develop a better solution for candidate performances. Presently, the accuracy value is a primary condition deployed to design an FF.

$$Fitness = \max\,(P) \quad (7)$$

Algorithm 1 BSA Pseudocode

Input N: the bird counts (individuals) from the populatio
M: the maximum iteration counter
FQ: the frequency of birds' flight performance
P: the probability of searching for foo
$C, S, al, a2, FL$: 5 constant parameter
$t = 0$, z Initializing the population and determining the related paramete
Assess the FV of N individuals, and determine the optimum performance
While ($t < M$)
I($t\%FQ \neq 0$)
For $i = l{:}N$
If rand (0, 1) $<P$
Birds search for food
Els
Birds preserve vigilance
End_if
End_for
Els
Separate the swarm into producer and scrounger.
For $i = 1 : N$
If *iz* is a produce
Producing
Els
Scrounging
End_If End_Fo
End_If
Calculate the novel solutio
If the novel solution is greater than the prior one, then update
Find the optimum solution
$t = t+1$, · End while
Output: the individuals with the optimum main function

$$P = \frac{TP}{TP + FP} \quad (8)$$

whereas, *FP* and *TP* imply the false and true positive values.

D. XGBOOST CLASSIFIER

At the final stage, the XGBoost classification model can be applied for an automated RPW detection process. XGBoost is a classical ML approach for the classification of land use and land cover [25]. XGBoost model improves the efficiency and accuracy of ML algorithms. The underlying principle of XGBoost is to train weak learners and assimilate them into final learners to accomplish better predictive performance. Fig. 2 illustrates the framework of XGBoost. Consider the training dataset as $= (p_1, y_1), (p_2, y_2), \ldots, (p_n, y_n)$, where p_i refers to the i^{th} input feature vectors and y_i denotes the respective target output. The objective is to learn a function $F(p)$ which maps input features into the output target. The function $F(p)$ is signified as a sum of M weak learner $(p, \theta m)$, where M represents the number of weak learners in the final model, and θm shows the parameter of m^{th} weak learners.

$$F(p) = \sum m = 1^M f(p, \theta m) \tag{9}$$

By using the XGBoost model, the weak learner is trained. During each iteration, the algorithm tries to fit weak learners $h(p)$ to a negative gradient of loss function $(y, F(p))$ that is shown below:

$$g_i = -\left[\frac{\partial(L(y_i, F(p_i)))}{\partial(F(p_i))}\right] \tag{10}$$

The weak learner $h(p)$ is trained to minimalize the loss function as follows

$$Lm = \sum i = 1^n [y_i - (Fm - 1(p_i) + hm(p_i))]^2 + \Omega(hm) \tag{11}$$

Now, $Fm-1(p)$ indicates the output of the model at $(m-1)-th$ iteration and $\Omega(hm)$ shows the regularization term that penalizes the complication of weak learners. The learning rate is represented as η and controls the contribution of all the weak learners to the last model.

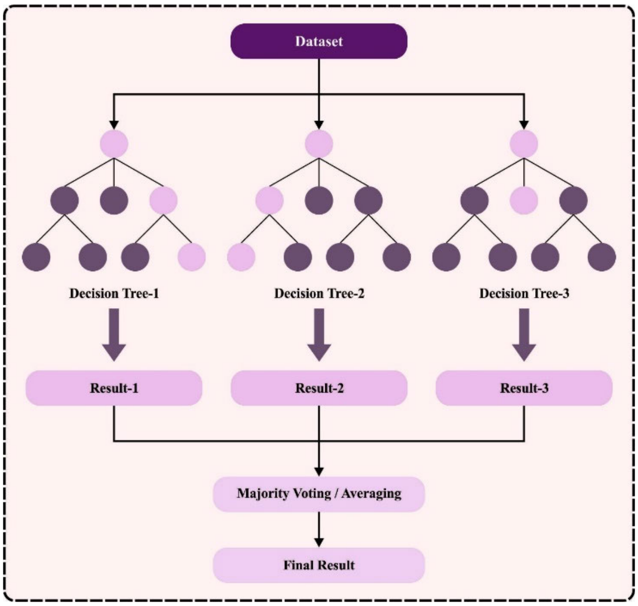

FIGURE 2. XGBoost structure.

Lastly, the updated model at *the* m^{th} iteration is shown below:

$$Fm(p_i) = Fm - 1(p_i) + \eta hm(p) \tag{12}$$

Briefly, XGBoost is a robust model that makes use of gradient boosting to reiteratively train weak learners and add them to the last strong learners

IV. RESULTS AND DISCUSSION

In this section, the simulation validation of the IRPWD-BSADL approach can be tested utilizing the RPW image database [26]. In Table 1, the RPW detection outcomes of the IRPWD-BSADL method can be examined under distinct

TABLE 1. RPW detection outcome of IRPWD-BSADL algorithm under distinct test images.

No. of Epochs						
Test Images	500	1000	1500	2000	2500	3000
Img-1	99.44	99.10	99.27	99.54	98.59	98.82
Img-2	99.56	98.77	98.75	98.45	98.89	99.38
Img-3	99.03	99.43	98.73	98.20	98.81	99.61
Img-4	98.75	99.47	99.40	98.58	99.13	99.20
Img-5	99.20	99.06	98.57	99.00	98.58	99.41
Img-6	99.55	98.23	99.27	98.25	98.46	99.35
Img-7	99.58	98.68	99.56	98.72	99.09	99.59
Img-8	99.71	99.14	99.68	98.75	98.29	99.54
Img-9	99.28	99.59	98.58	99.05	98.71	99.66
Img-10	99.07	98.30	98.70	99.24	98.81	99.77
Average	99.32	98.98	99.05	98.78	98.74	99.43

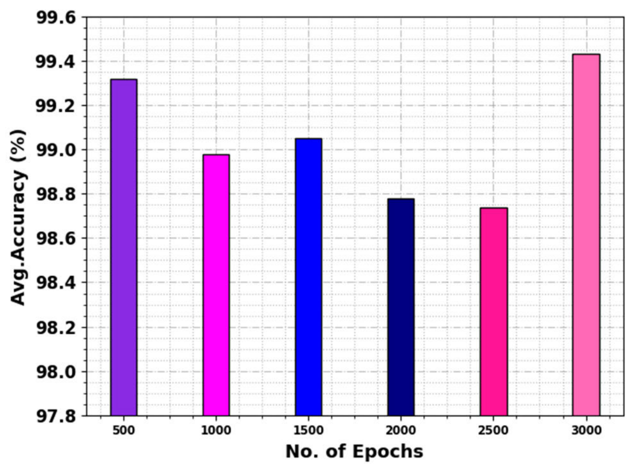

FIGURE 3. Average of IRPWD-BSADL technique under varying epochs.

test images. The simulation values implied that the IRPWD-BSADL system reaches effectual performance under several epochs. For instance, with Img-1, the IRPWD-BSADL technique offers 99.44%, 99.10%, 99.27%, 99.54%, 98.59%, and 98.82% under epochs 500-3000 respectively. Besides, with Img-2, the IRPWD-BSADL approach attains 99.56%, 98.77%, 98.75%, 98.45%, 98.89%, and 99.38% under epochs 500-3000 correspondingly. Additionally, with Img-4, the IRPWD-BSADL method offers 98.75%, 99.47%, 99.40%, 98.58%, 99.13%, and 99.20% under epochs 500-3000 respectively. Meanwhile, with Img-6, the IRPWD-BSADL system achieves 99.55%, 98.23%, 99.27%, 98.25%, 98.46%, and 99.09% under epochs 500-3000 correspondingly. Furthermore, with Img-8, the IRPWD-BSADL methodology gains 99.71%, 99.14%, 99.68%, 98.75%, 98.29%, and 99.54% under epochs 500-3000 respectively. Simultaneously, with Img-9, the IRPWD-BSADL approach attains 99.28%, 99.59%, 98.58%, 99.05%, 98.71%, and 99.66%

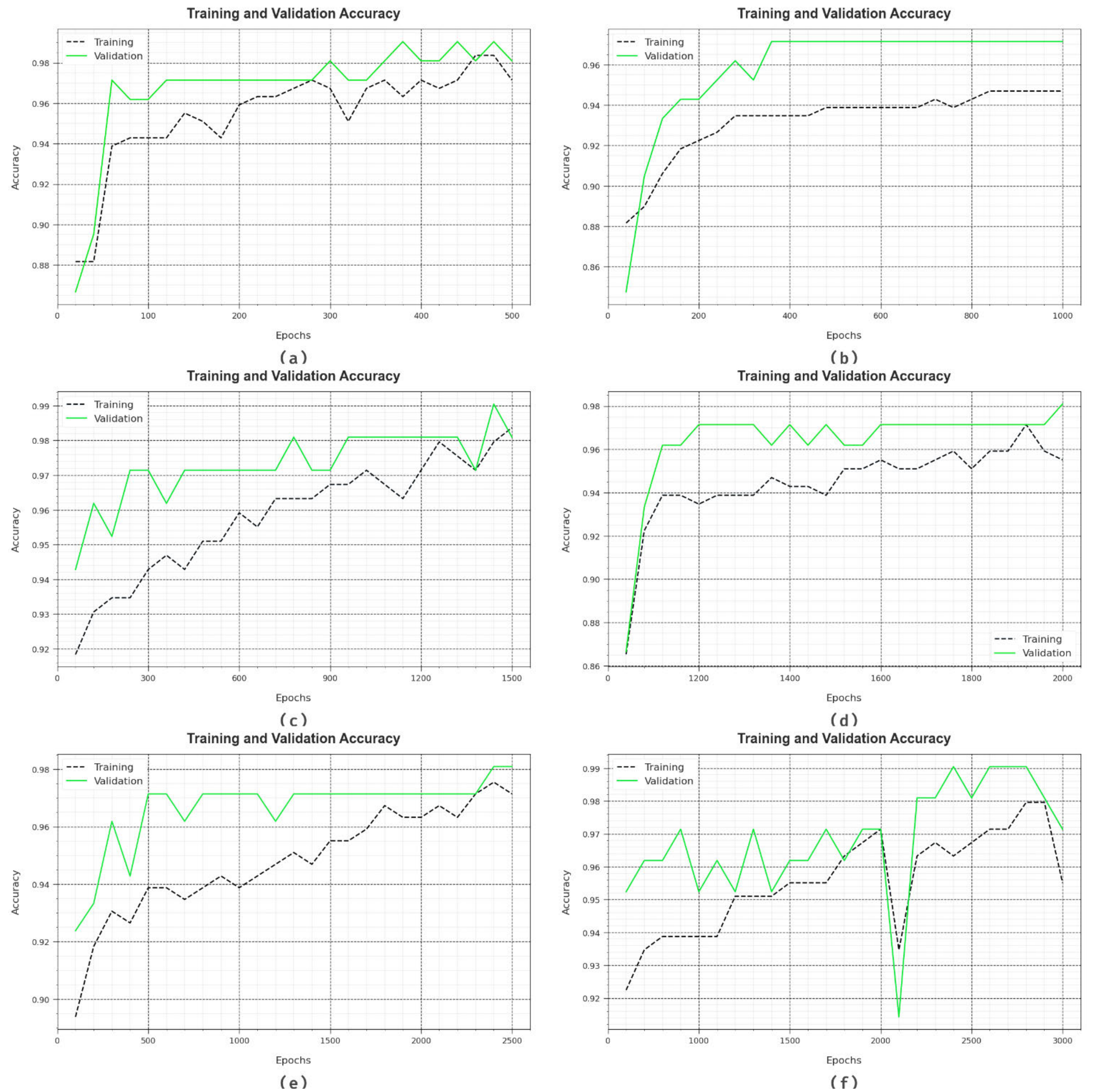

FIGURE 4. *$Accu_y$* **curve of IRPWD-BSADL algorithm (a) 500 epoch, (b) 1000 epoch, (c) 1500 epoch, (d) 2000 epoch, (e) 2500 epoch, and (f) 3000 epoch.**

under epochs 500-3000 respectively. Finally, with Img-1, the IRPWD-BSADL technique gains 99.07%, 98.30%, 98.70%, 99.24%, 98.81%, and 99.77% under epochs 500-3000 correspondingly.

In Fig. 3, the average RPW detection outcome of the IRPWD-BSADL algorithm can be tested under distinct epochs. The outcome demonstrated that the IRPWD-BSADL methodology reaches effectual outcomes under several epochs. It is perceived that the IRPWD-BSADL system reaches an average $accu_y$ of 99.32%, 98.98%, 99.05%, 98.78%, 98.74%, and 99.43% under epochs 500-3000 respectively.

To calculate the performance of the IRPWD-BSADL approach, TR and TS $accu_y$ curves are determined, as depicted in Fig. 4. The TR and TS $accu_y$ curves establish the performance of the IRPWD-BSADL approach over several epochs. The figure offers meaningful details regarding the learning task and generalization capabilities of the IRPWD-BSADL approach. With an increase in epoch count, it is observed that the TR and TS $accu_y$ curves get improved.

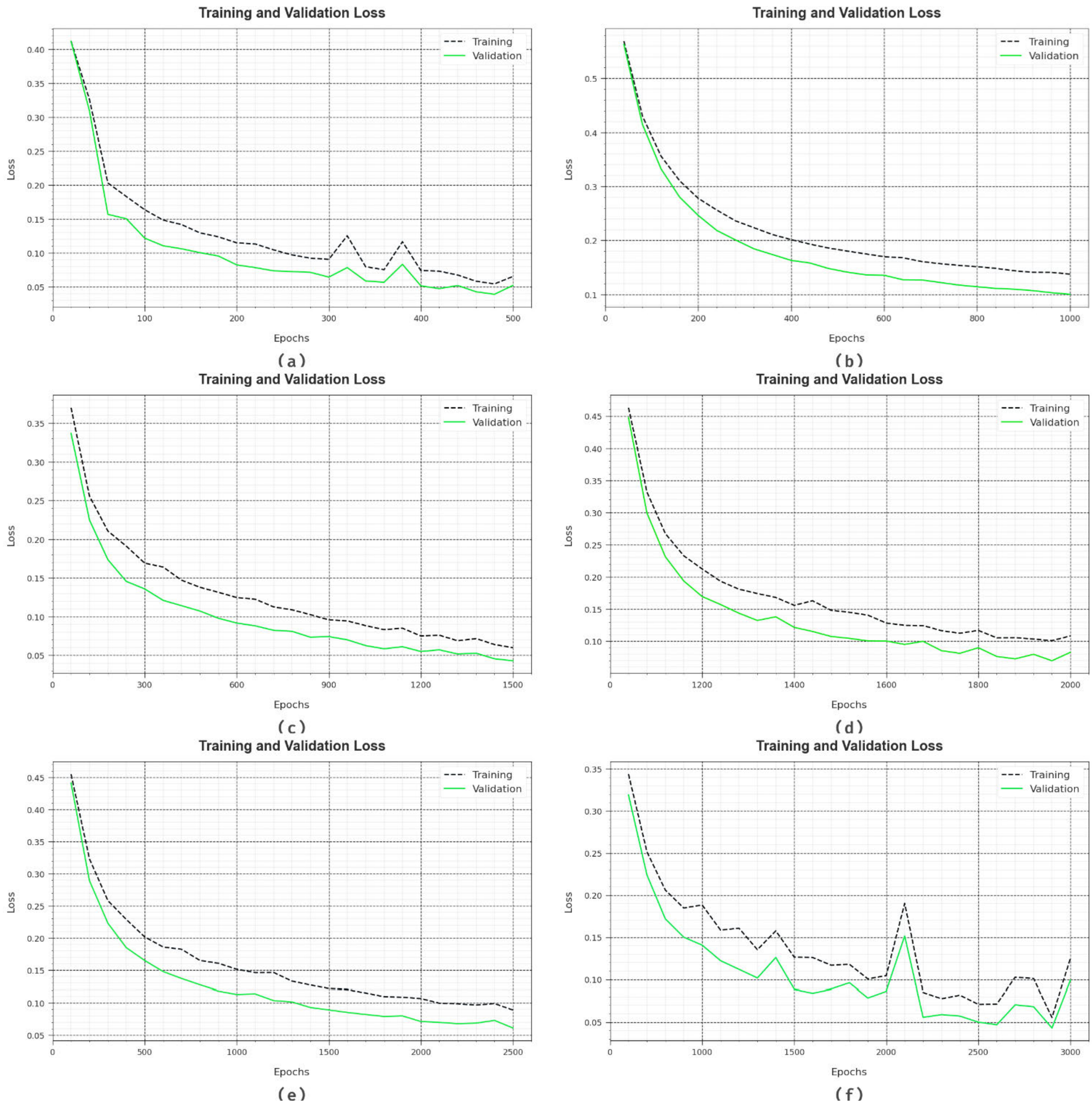

FIGURE 5. **Loss curve of IRPWD-BSADL approach (a) 500 epoch, (b) 1000 epoch, (c) 1500 epoch, (d) 2000 epoch, (e) 2500 epoch, and (f) 3000 epoch.**

It is observed that the IRPWD-BSADL system achieves higher testing accuracy, which can recognize the patterns in the TR and TS data.

Fig. 5 exhibits the overall TR and TS loss values of the IRPWD-BSADL algorithm over epochs. The TR loss portrays the model loss as lesser over epochs. Primarily, the loss values get reduced as the method modifies the weight to decrease the prediction error on the TR and TS data. The loss curves demonstrate the extent to which the model fits the training data. It is detected that the TR and TS loss steadily decreased and portrayed that the IRPWD-BSADL method efficiently learns the patterns exhibited in the TR and TS data. It is also observed that the IRPWD-BSADL approach adjusts the parameters to reduce the discrepancy between the prediction and the original training label.

Finally, Fig. 6 and Table 2 represent a comprehensive comparative result of the IRPWD-BSADL technique with recent approaches [27]. The simulation values stated that the NB algorithm reaches the least outcome with a minimal $accu_y$ of 82.60%. At the same time, the RF, MLP, SVM,

TABLE 2. ***$Accu_y$* outcome of IRPWD-BSADL algorithm with existing approaches [27].**

Methods	Accuracy
SVM Model	93.11
NB	82.60
RF	93.09
MLP Algorithm	93.07
AdaBoost	93.10
Faster R-CNN	99.03
RPWE-GTODL	99.27
IRPWD-BSADL	99.43

and AdaBoost approaches have obtained slightly improved performance with $accu_y$ of 93.09%, 93.07%, 93.11%, and 93.10% correspondingly.

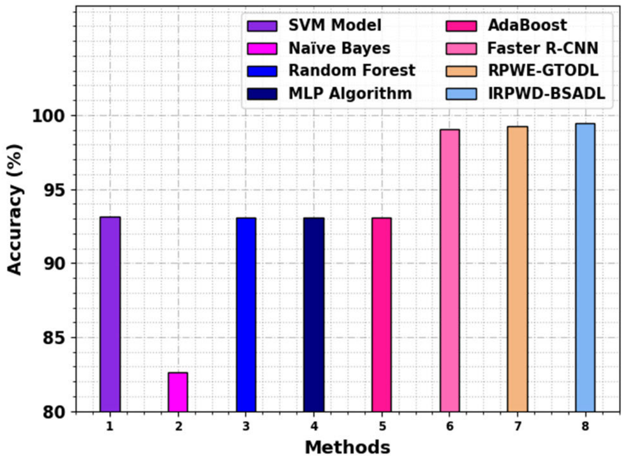

FIGURE 6. ***$Accu_y$* outcome of IRPWD-BSADL algorithm with existing approaches.**

Meanwhile, the Faster CNN and RPWE-GTODL techniques have reported near-optimal performance with closer $accu_y$ values of 99.03% and 99.27% respectively. However, the IRPWD-BSADL technique gains maximum performance with an improved $accu_y$ value of 99.43%. These results highlighted that the IRPWD-BSADL technique reached enhanced performance over other models on automated RPW detection and classification.

V. CONCLUSION

In this paper, we have designed an automated RPW detection approach called as IRPWD-BSADL approach. The major aim of the IRPWD-BSADL technique is mainly concentrated on the identification and classification of RPW using CV and DL models. It comprises several subprocesses namely BF-based pre-processing, improved ShuffleNet feature extractor, BSA-based hyperparameter tuning, and XGBoost classification. In the presented IRPWD-BSADL technique, an improved ShuffleNet model can be applied for feature extraction purposes. To enhance the recognition results, the IRPWD-BSADL technique makes use of BSA for the hyperparameter tuning process. For RPW detection and classification, the XGBoost classifier can be used. The simulation validation of the IRPWD-BSADL algorithm can be tested on the RPW database. An extensive comparison study stated the improved solution of the IRPWD-BSADL algorithm on the RPW detection process with maximum accuracy of 99.43%. The practical implications of the IRPWD-BSADL technique are profound, as it empowers the early and accurate detection of RPW infestations in palm trees, particularly in regions like the Middle East. By combining computer vision and deep learning, this model facilitates precision agriculture practices, enabling targeted pest management and reducing the need for widespread chemical treatments. Its application translates to safeguarding valuable palm crops, minimizing economic losses, and promoting sustainable agriculture while contributing to scientific advancements in pest detection and management methods. Future work can focus on the computation complexity examination of the proposed model.

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