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Intelligent IoT-Aided Early Sound Detection of Red Palm Weevils

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Abstract: Smart precision agriculture utilizes modern information and wireless communication technologies to achieve challenging agricultural processes. Therefore, Internet of Things (IoT) technology can be applied to monitor and detect harmful insect pests such as red palm weevils (RPWs) in the farms of date palm trees. In this paper, we propose a new IoT-based framework for early sound detection of RPWs using fine-tuned transfer learning classifier, namely InceptionResNet-V2. The sound sensors, namely TreeVibes devices are carefully mounted on each palm trunk to setup wireless sensor networks in the farm. Palm trees are labeled based on the sensor node number to identify the infested cases. Then, the acquired audio signals are sent to a cloud server for further on-line analysis by our fine-tuned deep transfer learning model, i.e., InceptionResNet-V2. The proposed infestation classifier has been successfully validated on the public TreeVibes database. It includes total short recordings of 1754 samples, such that the clean and infested signals are 1754 and 731 samples, respectively. Compared to other deep learning models in the literature, our proposed InceptionResNet-V2 classifier achieved the best performance on the public database of TreeVibes audio recordings. The resulted classification accuracy score was 97.18%. Using 10-fold cross validation, the fine-tuned InceptionResNet-V2 achieved the best average accuracy score and standard deviation of 94.53% and ±1.69, respectively. Applying the proposed intelligent IoT-aided detection system of RPWs in date palm farms is the main prospect of this research work.

Keywords: Red palm weevils; smart precision agriculture; internet of things; artificial intelligence

1 Introduction

Date palm trees are not only food but also one of the main income sources in the Arab world countries, especially in Saudi Arabia [1]. Although date palm is the oldest known cultivated tree, it is recently confronted with several contemporary issues. The red palm weevil (RPW) or *Rhynchophorus ferrugineus*, which originated in Asia and was first discovered in the Gulf region in the 1980s, has caused enormous losses to date palm farmers [2]. Over the last four decades, RPW has steadily extended its global influence. This species quickly spread across the Middle East's Gulf area, North Africa's Maghreb countries, and Europe's Mediterranean basin countries as shown in Fig. 1. The elimination of highly infested trees alone costs the Gulf countries and the Middle East around 8 million dollars per year as reported by the Food and Agriculture Organization (FAO) [3].

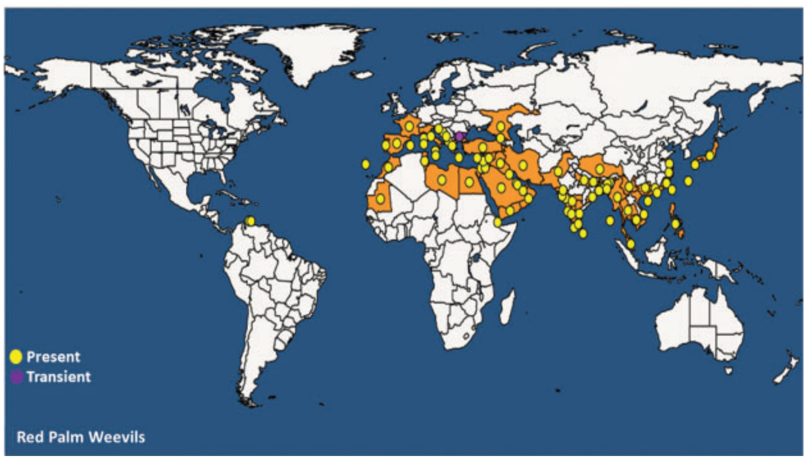


Figure 1: The red palm weevil (RPW) global geographical distribution

As a result, seeking a cost-effective solution to the RPW dilemma would not only save the "blessed" palm tree but will also assist farmers and governments in reversing the mounting financial losses that have arisen. Decision-makers, academics, and farmers generally believe that early recognition could save thousands/millions of healthy trees by using easy steps to quarantine infested trees and secure non-infested trees and offshoots [4]. Accordingly, primary disease discovery could theoretically assist in the victory over the RPW. Since obvious early symptoms of invasion occur only once it is too late to save the tree, the red palm weevil poses a significant threat to palm tree preservation. The weevil's vague behavior and inherent biological characteristics have made it very difficult to be recognized and thereby managed. There are multiple characteristics of the RPW characterize its growing stages as depicted in Fig. 2 [5]. Nowadays, the elements of RPW management systems have many weaknesses and difficulties. Early recognition of the weevil infestation, limitations of biological control measures in field circumstances, and a lack of farmer engagement in control operations are some of these issues [6]. Therefore, the early detection of such predators does provide the best chance of eradicating them and minimizing the likelihood of palm tree damages. Fortunately, with the advancement in artificial neural networks (ANN) technology, the detection possibility of RPW in its early stages could be achieved [7].

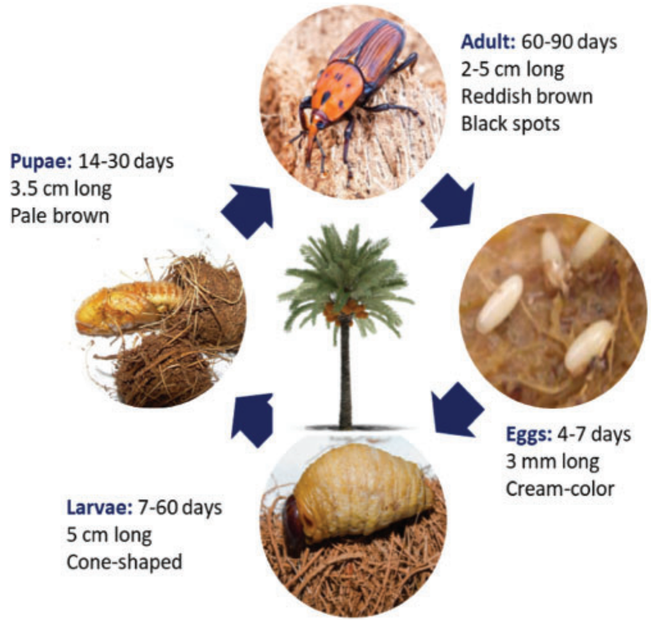


Figure 2: RPW life cycle

Visual examination of the tree for symptoms appearance, identification of the sound made by nourishment larvae as well as chemical analysis of volatile signatures generated by infested date palms are considered the most known RPW early detection approaches [8]. Also, thermal imaging to monitor temperature changes in invaded palms is another classical method to detect RPW. The most expensive approach is sound detection and the most reliable one is based on the observation of symptoms [9]. So instead of focusing on conventional detection approaches, there is a need to develop computational solutions for finding and controlling RPW species that are both accurate and permanent. It is also important to figure out what main characteristics to look for when identifying plagued palm trees. Lately, a fusion of computer science, sensors, and advanced electronic technology is being used to construct reasonable and fast mechanisms for automatic recognition of RPW. Acoustic devices, X-ray imaging, remote sensing tools, and radio telemetry are among the most significant and promising new trends to control the RPW [10].

Smart precision agriculture exploits modern information and wireless communication technologies to achieve challenging agricultural processes and/or regular tasks automatically [11,12]. For instance, Internet of Things (IoT) has been applied in real-life applications of agriculture, such as precision management of water irrigation, crop diseases and insect pests [13–15]. IoT mainly relies on wireless sensor network (WSN) to measure and collect environmental parameters like soil moisture and humidity. Then, these collected data can be saved or analyzed to assist decisions of specialists or famers, and/or to operate water irrigation pumps [11]. Artificial intelligence (AI) techniques such as machine learning and deep learning models [16,17] have been recently employed to analyze acquired agricultural and environmental data. Crop health monitoring presents a major aspect of smart precision agriculture [18], specifically identifying the infectious status of insect pests in the farm. Traditional techniques and manual detection of insect pests are insufficient, time-consuming and relatively expensive. Therefore, early detection of the plant pests is a high priority for farmers to use suitable pesticides, avoiding the loss of crops [19]. Hence, the focus of this study is proposing a new solution for continuous health monitoring of date palm trees against RPWs by using IoT and deep learning models. Transfer learning approach overcomes the drawback of traditional deep learning methods in case of small dataset and limited resources for training phase. The main idea of this approach is transferring the knowledge from a similar task, and again using the pre-trained deep learning model for achieving another task with minimal computation power [20]. Advantages of transfer learning technique have been widely exploited in several applications, e.g., medical and healthcare systems [21,22], industrial manufacturing [23], and robotic systems [24]. Moreover, transfer learning models showed significant results of achieving smart water irrigation [11] and plant diseases and pest's classification [25] in the field of agriculture. Convolutional neural networks (CNNs) are still the most popular deep learning method. Residual neural networks (Resnet) [26], MobileNet [27] and Xception [28] are three of well-known pretrained models based on transfer learning approach. This paper presents a new IoT-based sound detection system of RPWs using deep transfer models of residual inception networks. The main contributions of this study are presented as follows.

- Proposing a new intelligent detection system of RPW sounds at early stage of infectious date tree palms using IoT.
- Developing a transfer learning-based classifier to accomplish accurate sound identification of RPWs.
- Conducting extensive tests and comparative study of our proposed method with other methods in previous studies to validate the advanced capabilities of our early detection system of RPW.

The reminder of this paper is divided into the following sections. Section 2 introduces a review of previous studies including different machine and deep learning models for identifying RPWs. The public sound dataset of RPWs, architecture of transfer learning models and description of our proposed RPW detection system are presented in Section 3. Evaluation results and discussions of deep learning classifiers to detect clean and infested palm trees are given in Sections 4 and 5, respectively. Section 6 presents conclusions and outlook of this study.

2 Related Works

Deep learning (DL) is a cutting-edge machine learning (ML) technology that does quite well in various tasks such as image classification, scene analysis, fruit detection, yield estimation, and many others [29]. DL can create new features from a restricted range of features in the testing dataset, which is considered one of the key advantages over other ML algorithms. Convolutional Neural Networks (CNN), Fully Convolutional Networks (FCN), Recursive Neural Networks (RNN), Deep Belief Networks (DBN) and Deep Neural Networks (DNN) are examples of DL architectures that have been widely deployed to a variety of research domains [30]. Recently, several DL techniques have been applied to different agricultural-based methods with increasing significance. Researchers in [31] performed a survey of several DL techniques applied to different agricultural issues. The authors examined the models employed, the data source, the hardware utilized, and the probability of real-time deployment to investigate future integration with autonomous robotic mechanisms.

The authors in [9] tested the ability of ten cutting-edge data mining classification models to forecast RPW infections in its early phases, before major tree damage occurs, using plant-size and temperature measurements obtained from individual trees. The experimental results demonstrated that using data mining, RPW infestations could be expected with an accuracy of up to 93%, a precision of above 87%, a recall of 100%, and an F-measure of greater than 93%. To identify the presence of RPW using its own bioacoustics features, a new signal processing platform has been designed [32]. An analysis of the parameters for selecting the best time frame length as well as window feature is given. The findings indicate that the established method with the selected representative characteristics is more effective. The authors in [33] proposed a study to create algorithms that can classify the RPW and differentiate it from other insects present in palm tree habitats using image recognition and artificial neural network (ANN) techniques. It was discovered that an ANN of three-layer using the Conjugate Gradient with Powell/Beale Restarts method is the most effective for identifying the RPW. In [34], the normal and thermal images of palm trees have been used to detect RPW, blight spots and leaf spots diseases. CNN was used to distinguish between blight spots and leaf spots infection, and support vector machine (SVM) was used to distinguish between the leaf spots and RPW pests. The accuracy ratio success rates for the CNN and SVM algorithms were 97.9% and 92.8 percent, respectively. Based on remote images from the Alicante area in Spain, researchers in [35] introduced the first region-wide geographical collection of *Phoenix dactylifera* and *Phoenix canariensis* palm trees. The presented detection model, which was created using RetinaNet, offers a quick and easy way to map isolated and densely dispersed date and canary palms and other Phoenix palms as well. In order to monitor palms remotely, an IoT-based smart prototype has been also suggested for the early detection of red palm weevil invasion [36]. The data is collected using accelerometer sensors, then signal processing and statistical methods are applied to analyze this data and define the attack fingerprint. In [37], a solution for early identification of RPW in large farms is presented using a hybrid of ML and fiber-optic distributed acoustic sensing (DAS) system. The obtained results showed that ANN with 99.9% and CNN with 99.7% accuracy values can effectively distinguish between healthy and infested palm trees. Tab. 1 summarizes the related work review and their main characteristics. It is evident from the literature that image-based methods had high accuracy values compared sound-based ones. This motivates this work to consider the improvement of sound detection models.

3 Materials and Methods

3.1 TreeVibes Device and Dataset

Sounds of RPW and other borers are collected using the TreeVibes recording device, as depicted in Fig. 3 [38]. It is a public database and is freely available at http://www.kaggle.com/potamitis/treevibes (last accessed on 20 February 2021). The piezoelectric crystal as an embedded microphone has been used for sensing the vibrations inside the trees, i.e., sounds of the borers including the RPWs. The acquired signal can be converted to short audio signals to be stored and transmitted through wireless IoT networks and a cloud server. An example of mean spectral profile for three different sounds of a RPW is shown in Fig. 3b [39]. The TreeVibes device cannot count the number of borers or their location in the palm tree, but it is able to detect their feeding sounds within 1.5 to 2 m radius of a spherical region [38]. Therefore, the positioning of TreeVibes sensing device on the trunk of palm tree is crucial to achieve the expected early detection performance.

The TreeVibes database includes 35 folders with short and annotated audio recordings. The sampling frequency of these recordings is 8.0 kHz. All tree vibration sounds have been saved in a wave format. The proposed classifier was trained and tested on 26 and 9 folders, respectively. The infested data represent the potential sounds of feeding and/or moving wood-boring pests, such as *Rhynchophorus ferrugineus* (Red palm weevil), *Aromia bungii* (Red necked longicorn) and *Xylotrechus chinensis* [35]. In this study, we assumed the infested status of date palm trees is caused by RPWs only.

Table 1: Related work comparison

Reference	Presented method	Dataset	Accuracy
Kurdi et al. [9]	Data mining classification algorithms	90 RPW infested date palm trees	93%
Hussein et al. [32]	Bioacoustics recognition and Sound wave	Sound frames, 3750 batches of length 0.8 sec	94%
Al-Saqer et al. [33]	Image recognition and Artificial neural network	319 images of RPW and 93 images of other insects	99.5%
Alaa et al. [34]	Thermal images	2400 thermal images	92.8%
Culman et al. [35]	Convolutional neural networks	RGB images	86%
Koubaa et al. [36]	Advanced signal processing and probabilistic methods	Acoustic signals	—
Wang et al. [37]	Machine learning and fiber optic distributed acoustic sensing	Digital accelerometer sensor	99.9%

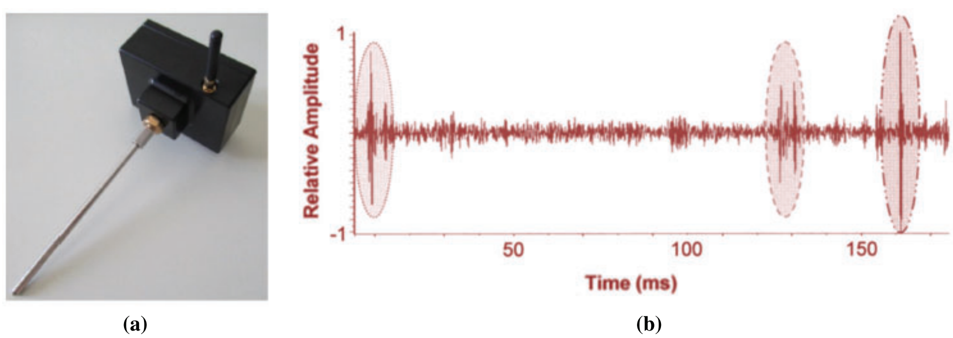


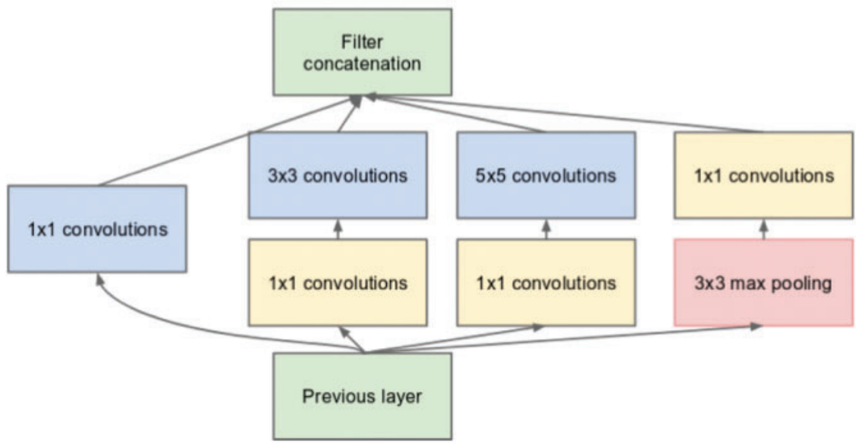
Figure 3: (a) TreeVibes device for recording palm tree sounds of pests [35], and (b) Graphical representation of three different impulses of detected RPW sounds

3.2 Transfer Learning Models

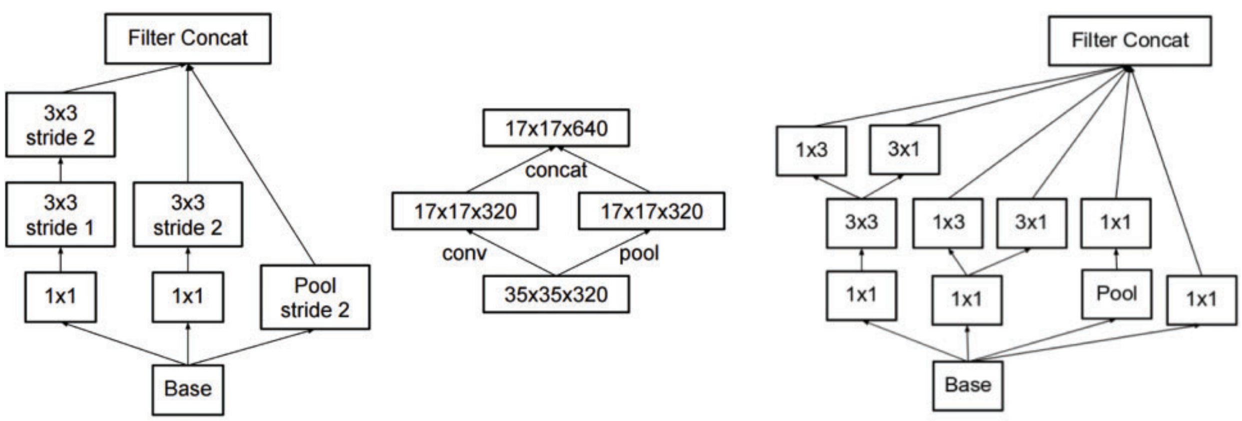
This section gives an overview of the proposed transfer learning models for identifying the health status of palm trees as follows. First, different version architectures of Inception models are described, highlighting the main features of each transfer learning model. Second, merging between Inception and Resnet architectures in the Inception-Resnet model is also presented, showing a comparison between two structures of Inception-Resnet-V1 and V2.

3.2.1 Inception Models

Fig. 4 depicts main architectures for two versions of Inception model. The first version of Inception classifier was introduced by Szegedy et al. [40] to achieve advancement over the state-of-the art classifiers on the ImageNet Large-Scale Visual Recognition Challenge 2014 (ILSVRC14). Inception-V1 improved the accuracy performance of detection and classification by increasing the depth and width layers of the CNN model at constant computational cost. The optimized Inception-V1 architecture was based on the Hebbian principle and multi-scale processing. Inception-V1 with a dimension reduction of 22 layers CNN is also called GoogleNet [40], as shown in Fig. 4a.



(a)



(b)

Figure 4: (a) Inception-V1 with dimensions reduction (GoogleNet) [40], and (b) Inception-V2 [41]

Inception-V2 and V3 were introduced in 2016 by the same Google research group, as shown in Fig. 4b [41]. The 5 × 5 convolution module of Inception-V1 was replaced by two 3 × 3 convolutions in these advanced Inception models. However, Inception-V3 added other capabilities to enhance its network architecture as follows. First, factorizing 7 × 7 convolutions and RMSProp optimizer are used. Second, auxiliary classifiers are batch normalized. Third, label smoothing is provided to prevent overfitting in the deep network.

3.2.2 Inception-ResNets

Inception-ResNet and Inception-V4 were presented to validate the positive influence of residual connections on deep learning-based classification [42]. Here, these models of Inception were modified through "Reduction Blocks", changing the width and the height of its grid network architecture. The functionality of reduction blocks was inspired by the outstanding performance of residual neural network, namely ResNet [26]. The hybrid Inception and ResNet module resulted two sub-versions, namely InceptionResNet-V1 and V2 [42], as depicted in Fig. 5.

Both InceptionResNet-V1 and V2 have the same structural modules and reduction blocks. Nevertheless, the computational costs of Inception-ResNet-V1 and V2 are similar to the computing budgets of Inception-V3 and Inception-V4, respectively. The hyper-parameter settings such as optimizer and batch size present the only difference between these two Inception-ResNets.

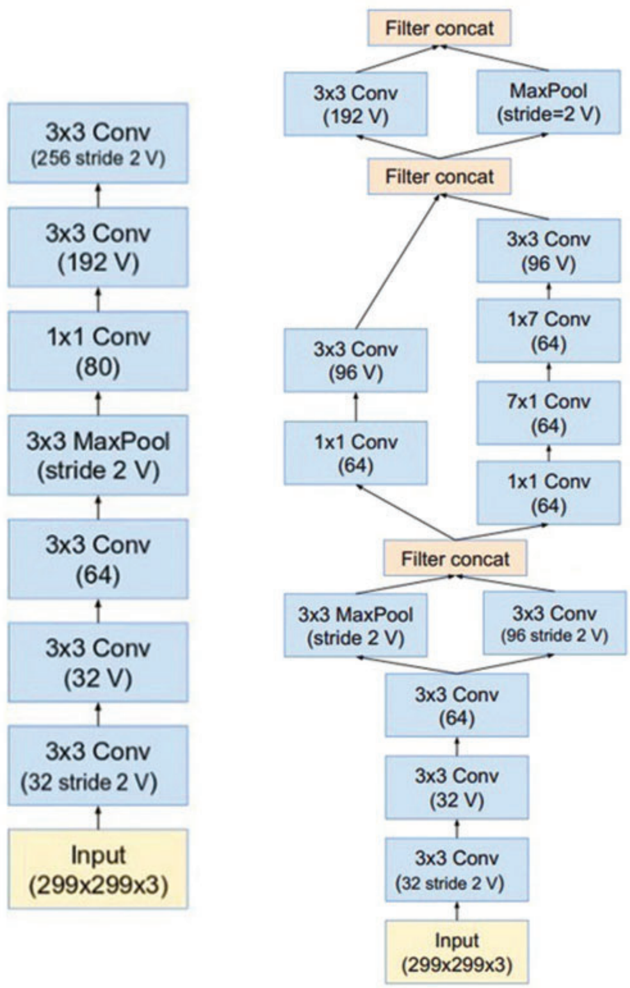


Figure 5: Architectures of InceptionResNet-V1(left), and InceptionResNet-V2 (right) [42]

3.3 Proposed RPW Detection System

Schematic diagram of our proposed intelligent IoT-aided detection system of RPWs is shown in Fig. 6. The proposed RPW detection system includes three main modules as follows. First, TreeVibes sensor devices are carefully mounted on each palm trunk to setup wireless sensor network in the farm. Palm trees are labeled based on the sensor node number in the wireless network to identify the infested cases successfully. Moreover, the infested tree location can be monitored on the farm map by using a global positioning system (GPS) associated with the TreeVibes device [38]. Second, a cloud server received wireless acquired sound signals of palm trees. These audio data on the cloud server can be stored for further on-line analysis by our fine-tuned deep transfer learning model, i.e., InceptionResNet-V2, as depicted in Fig. 6. Third, the binary classification task of clean and infested trees can be automatically done either on the cloud server or by a computer system of the user. In the field, there are many different sounds that can be recorded. For instance, agricultural environment includes bird or animal vocalizations, rains and wind sounds, and voices of farm workers. Therefore, it may be a challenging task to extract sounds of RPW inside trees from these external noisy signals in the field. However, characteristics of generated audio signal by the RPW borers are distinguished impulsive trains (see Fig. 3b). That plays an important role to enhance the accurate performance of proposed Inception-ResNet-V2 classifier, as presented in Section 4.

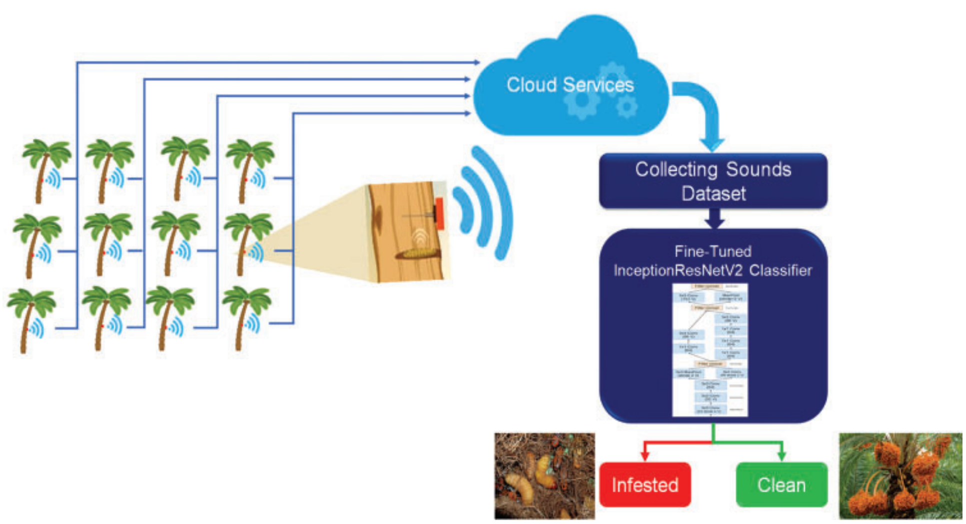


Figure 6: Schematic diagram of proposed IoT-based detection system of RPW sounds using fine-tuned InceptionResNet-V2 Classifier

3.4 Performance Analysis Metrics

The performance of fine-tuned InceptionResNet-V2 classifier was analyzed for identifying the RPW infestation using the following evaluation metrics. The cross-validation estimation [43] is used to build a confusion matrix. A 2 $\times$ 2 confusion matrix contains the following possible results of hypothesis testing for two predicted classes: True Positive (TP), True Negative (TN), False

Positive (FP), and False Negative (FN). In addition, the classification measures of accuracy, recall or sensitivity, precision, and F1-score are given in Eqs. (1)–(4), respectively.

$$accuracy\,(\%) = \frac{TP + TN}{TP + FP + FN + TN}\,100\% \tag{1}$$

$$precision = \frac{TP}{TP + FP} \tag{2}$$

$$recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = \frac{2\,(precision \times recall)}{precision + recall} \tag{4}$$

4 Evaluation Results

All sounds of RPW and other borers collected from the public dataset [38] have been scaled to 224 × 224 audio window signals to enhance the performance of tested classifiers. In this study, we assumed that the sounds of pest borers inside trees are similar to the feeding and/or moving sounds of RPW larvae. They are classified as infested cases generally. The proposed InceptionResNet-V2 classifier and other transfer learning models have been implemented using open-source Python programming language with the packages of Tensorflow and Keras [44]. Implemented RPW sound classifiers were executed using a 4 GB NVIDIA GPU and 16 GB RAM on Intel(R) Core(TM) i7-2.2 GHz processor laptop.

Classification procedure of infested and clean palm trees has been automatically done using the proposed InceptionResNet-V2 model, as shown above in Fig. 6. The sound recordings of pests database have been randomly 80%–20% split for conducting training, validation and test phases. The value of each hyperparameter is carefully tuned for the proposed InceptionResNet-V2 as follows. Number of epochs and batch size are 40 and 60, respectively. The learning rate is 0.001. An update of stochastic Adam optimizer [45], namely Adamax has been applied to accomplish targeted convergence during training step. Softmax activation function of the output classifier layer was used to identify infested and clean classes of palm tree sounds. Moreover, these hyperparameter values have been also used for other transfer learning models to justify the classification performance of our proposed InceptionResNet-V2 model with other deep learning classifiers in this study.

Fig. 7 shows the resulted confusion matrics of six transfer learning models, which are Resnet-50, MobileNet, Densnet-121, EfficientNetB0, Xception and our proposed InceptionResNet-V2. The total number of tested recoding sounds are 497 such that infested and clean sounds are 146 and 351 samples, respectively. Our proposed InceptionResNet-V2 showed superior classification performance with the highest accuracy score of 97.18% and 14 samples of infested and clean are only misclassified. Resnet-50 presents the most accurate classifier of infested cases, but it fails to identify 20 clean samples correctly. Three models of Densenet-121, EfficientNetB0 and Xception showed approximately equal classification accuracy rates of 95.58%, 95.37% and 95.17%, respectively. MobileNet represents the second-best RPW sounds classifier with accuracy score of 96.78%.

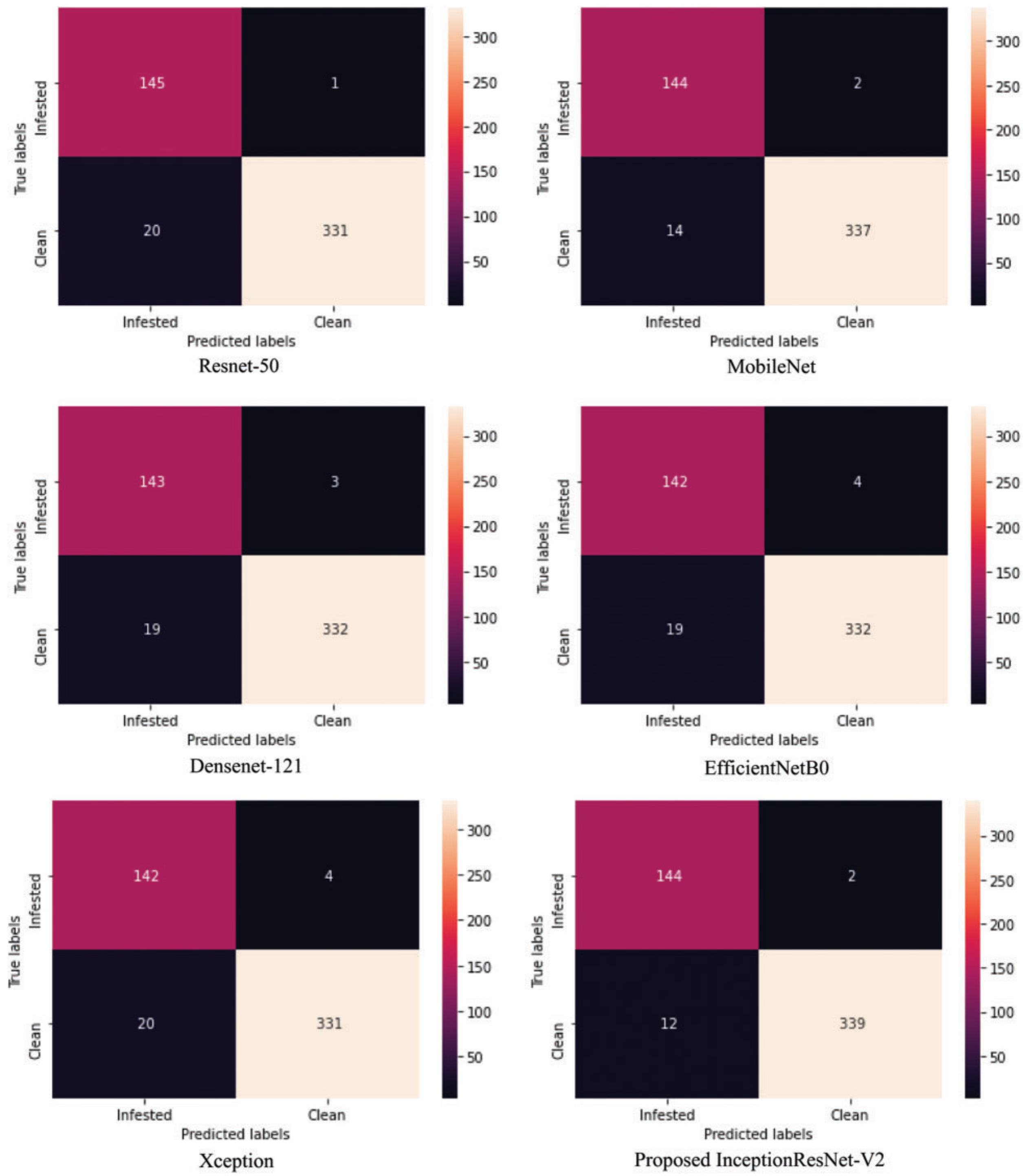


Figure 7: Confusion matrix results of all tested transfer learning classifiers for identifying RPW infestation and clean palm trees

Results of four performance evaluation metrics, which are accuracy, precision, recall and F1-score in Eqs. (1)–(4) are reported for each transfer learning classifier, as illustrated in Tab. 2. Our proposed Inception-ResNet-V2 showed the best values for all tested infested and clean cases with accuracy score of 97.18. MobileNet is still the second-best classifier and achieved accuracy score of 96.78%, while Xception model showed relatively the lowest value of classification accuracy 95.17%.

Furthermore, Tab. 3 illustrates a comparison between our proposed classifier and five deep learning models in previous studies to identify the health monitoring status of palm trees. InceptionResnet-V2 outperforms other methods in previous studies, but its size is large (215 MB). Xception model showed minimum value of standard deviation (±0.99). Nevertheless, the MobileNet classifier constitutes a smallest-size advantage of 16 MB and a good average accuracy of 93.84 ± 1.72.

Table 2: Performance metrics comparison of transfer learning classifiers in this study

Transfer learning classifier	Class	Precision	Recall (sensitivity)	F1-score	Accuracy (%)
Resnet-50	Infested	**0.99**	0.88	0.93	95.77
	Clean	0.94	**0.99**	0.96	
MobileNet	Infested	**0.99**	0.91	**0.95**	96.78
	Clean	0.96	**0.99**	**0.98**	
Densenet-121	Infested	0.98	0.88	0.93	95.58
	Clean	0.95	**0.99**	0.97	
EfficientNetB0	Infested	0.97	0.88	0.93	95.37
	Clean	0.95	**0.99**	0.97	
Xception	Infested	0.97	0.87	0.92	95.17
	Clean	0.94	**0.99**	0.97	
Our proposed InceptionResNet-V2	Infested	**0.99**	**0.92**	**0.95**	**97.18**
	Clean	**0.97**	**0.99**	**0.98**	

Notes: *Best performance values are indicated in bold.

Table 3: Comparative average accuracy of proposed RPW classifier with other deep learning models in previous studies using 10-fold cross validation

Transfer learning classifier	Size	Average accuracy (%) ± standard deviation
Resnet-50	98 MB	93.40 ± 1.76
MobileNet	**16 MB**	93.84 ± 1.72
Densenet-121	33 MB	92.80 ± 1.80
EfficientNetB0	29 MB	93.76 ± 1.61
Xception [38]	88 MB	94.16 ± **0.99**
Our proposed InceptionResNet-V2	215 MB	**94.53** ± 1.69

Notes: *Best performance values are indicated in bold.

5 Discussions

Advanced IoT-based health monitoring of the date palm trees becomes essential for saving crop productivity and preventing high tree mortality caused by RPWs. Automatic early detection of RPW infestation can be achieved by acquired vibrating sounds of feeding and/or moving RPWs via the TreeVibes sensing device [38], as shown in Fig. 6. In addition, deployed deep learning models such as fine-tuned InceptionResNet-V2 classifier can achieve a good classification performance to identify infestation and clean tree status accurately, as illustrated in Tabs. 2 and 3.

In this study, our proposed InceptionResNet-V2 classifier was compared with five transfer learning models, namely Resnet-50, MobileNet, Densenet-121, EfficientNetB0 and Xception. These five models have been previously investigated by Rigakis et al. [38], showing that Xception model is the top rank classifier of pest sounds inside trunks of trees. It achieved average classification accuracy of 94.16% with minimal standard deviation of ± 0.99 based on 10-fold cross validation. In contrast, the fine-tuned InceptionResNet-V2 demonstrated a competitive classification accuracy of 94.53% with higher standard deviation of ± 1.69, as presented in Tab. 3. The only limitation of our proposed classification model is its large size of 215 MB. That required additional resources to accomplish the early detection task of RPWs in the proposed IoT network framework, as depicted in Fig. 6. However, using cloud computing services can solve the above problem of limited hardware resources and the availability of GPUs at end users.

Although security and privacy issues of IoT-based smart farming have been discussed in recent studies [12–14], these issues are not considered in this study. Because a single security protocol of IoT-systems in agriculture is still not sufficient to prevent leakage of information [12]. However, basic requirements of secure IoT-based agricultural systems can be fulfilled, i.e., authentication, access control and confidentiality of the stakeholders. Other integrated sub-systems such as protection, fault-diagnosis and reaction systems against danger and cyberattacks should be also considered in the security model of smart precision agriculture systems. The above security requirements and sub-systems will be considered in the future version of our proposed intelligent IoT-based detection system of RPW sounds.

In addition, selecting the hyperparameter values of transfer learning models is an iterative complicated process to accomplish the targeted task. Therefore, recent studies suggested the utilization of bio-inspired optimization techniques such as whale optimization algorithm (WOA) [46] and adaptive particle swarm optimization (APSO) [47] to automate the design of deep neural networks, with increasing required training computing cost. Nevertheless, our proposed InceptionResNet-V2 still achieved best classification performance for RPW sounds detection, as illustrated in Tabs. 2 and 3.

6 Conclusions

In this study, a new IoT-based early detection system of RPWs has been developed based on acquired sounds of palm trees. The TreeVibes sensing device was used to acquire and record short vibration sounds of RPWs inside palm trees. Here, the role of cloud services is to save these recoding sounds and forward them for deep learning classifiers at the end user, as shown in Fig. 6. Deep transfer leaning model, namely InceptionResNetV2 was fine-tuned to distinguish between clean and infested trees, as depicted in Fig. 5. Using 10-fold cross validation, the developed classifier showed a superior performance over other transfer learning models in previous studies, achieving accuracy score of 94.53 ± 1.69 as given Tab. 3.

In future work, we aim to minimize the computing power resources by exploiting cloud computing services [48] to accomplish the early detection task of RPWs on a developed mobile application for guiding specialists and farmers. Also, we are working on enhancing the classification accuracy of our proposed system by using other advanced deep learning models, e.g., generative adversarial neural networks (GANs) [49], considering the security and privacy aspects of open IoT network communications [50,51] for sending sound data of date palm trees safely.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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