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# Smart IoT-based system for detecting RPW larvae in date palms using mixed depthwise convolutional networks

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**Abstract** Smart agriculture and Internet of Things (IoT) technologies have become the key points for many intelligent decision-making applications to support agricultural experts and farmers, especially for crop pest management and control. In this work, we present an IoT-based sound detection model for identifying red palm weevil (RPW) larvae to protect date palm trees at the early stage of infestation. The proposed detection system is mainly based on a modified mixed depthwise convolutional network (MixConvNet) as a recent deep learning classifier. The public TreeVibes dataset, which contains short audio recordings of feeding and/or moving RPWs, was successfully tested and assessed with the proposed MixConvNet classifier. There were 146 and 351 specimens of infested and clean sounds examined, respectively. The classification results showed that our proposed MixConvNet is efficient and superior to other deep learning classifiers, such as Xception and residual network (Resnet) models in previous related studies, obtaining the best accuracy score of 97.38. Moreover, the MixConvNet classifier is capable of identifying RPW infestation cases precisely with a high accuracy value of 95.90% ± 1.46, using 10-fold cross-validation. Therefore, practical implementation of our proposed IoT-enabled early sound detection system of RPWs is considered the future milestone of this study.



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## 1. Introduction

Due to the cost-effective and secure implementation of smart technologies, models based on these smart systems are frequently utilized in environmental monitoring, such as crop growth and forest fire controlling [1]. According to developments in communication and data processing, crop disease detection methods now primarily incorporate spectroscopy and imaging, hyperspectral imaging, and other technologies. The diagnosis and detection of crop disease can be accomplished by using a crop disease infestation model. Furthermore, given the difficulty for manual collection of experimental samples, expensive experimental equipment and consumables, and other factors, it is not suited for large-scale crop disease monitoring. At present time, agricultural development with technology such as automated image recognition is becoming popular for detecting crop infestations [2].

For agricultural observing and food security analysis, more understanding of crop types and their corresponding cultivated regions in national agricultural zones are required, as well as for the creation and implementation of appropriate regulations [3]. Date palms are one of the most known crops that need continuous real-time monitoring to detect the activity of the red palm weevil (RPW) larvae. The intelligent sensing technology provides early detection and alerts for any RPW threat to the date trees [4]. The suggested smart detection model allows for instant access to critical information that can pinpoint the infested tree and save it from destruction.

Smart agriculture utilizes wireless communications and information technologies in the field of agriculture to overcome drawbacks of traditional techniques and automatic routine processes and/or daily tasks for farmers, such as water irrigation and crop health monitoring [5]. Internet of Things (IoT) technology is the main core of smart agriculture [6,7]. It is based mainly on wireless sensor networks (WSNs) to estimate and accumulate agricultural and environmental status parameters, e.g., weather temperature, soil moisture, and crop diseases [8]. These agricultural data can be automatically analyzed to support farmers to make crucial decisions such as activating irrigation pumps or using specific pesticides [6,9].

Applied artificial intelligence (AI) techniques and methods in the field of agriculture become a recent trend in the framework of precision agriculture. Machine learning and deep learning models present the main algorithms of many AI-based applications such as neurosurgery and COVID-19 diagnosis [10,11], smart manufacturing [12] and secure communications [13]. Moreover, these intelligent methods have been successfully integrated in agricultural applications in previous studies, e.g., identification of apple leaf diseases [14], classification of insect pests [15], and harvesting robotic systems [16]. Nevertheless, the big datasets and high hardware resources such as graphical processing units (GPUs) are major requirements of traditional deep learning algorithms require to accomplish the training phase. These requirements are not always available at the developers or end-users. Therefore, using transfer learning approaches present a good solution for smart applications with limited datasets and hardware resources as well [17,18]. They depend on transferring the knowledge from a similar task to another task using the same pre-trained model at low computing cost. Densely connected convolutional networks (Densenet) [19], residual neural networks (Resnet) [20], Xception [21] and MobileNetV2 [22] are four examples of well-known transfer learning models. Hence, transfer learning models achieved successful results for automatic classification of crop diseases [23] and other intelligent systems in the field of agriculture [24,25].

Classical agricultural procedures and hand-operated detection of insect pests are not efficient, expensive, and time-consuming. A loss of crops may be caused if the farmers could not discover the harmful pests early to eliminate them with suitable pesticides [26]. Therefore, this study aims at proposing a new smart IoT-based detection system of RPW larvae sounds inside date palm trees. Furthermore, this paper contributes the following advancements to automatically identify the infestation conditions of date palms on the farm.

- Introducing an advanced classifier that is based on transfer learning, namely MixConvNet, to achieve precise sound detection of RPW larvae.
- Integrating deep learning models with IoT-based systems supports decision-making by experts and farmers to classify crop health status against RPWs in real-time.
- Comparing our proposed deep learning classifier with different models in preceding related works using extensive tests and evaluation to validate the proposed detection method of RPWs at the early stage of infestation.

The remainder of this paper is divided into the following sections: Section 2 gives an overview of relevant detection methods in previous studies of RPW management. Section 3 describes the public TreeVibes dataset and our proposed early detection system of RPWs using IoT. Experiments and discussions are presented in Sections 4 and 5, respectively. Finally, conclusions with the main prospects of that research work are introduced in Section 6.

## 2. Related works

Several research studies recommended each of sensors, drones, robotics, and deep learning (DL) technologies as solutions for smart farming activities [27]. Early identification of RPW infestation is one of the most pressing concerns in smart IoT-based systems, and various research works have been suggested to address this problem. Early diagnosis of RPW infestation is difficult due to the larvae's confusing feeding habits. Since there are no RPW larvae or damage visible at such early stages [28]. Although the accurate intervention of RPW infestation is difficult, it is the first step in eradicating this deadly insect. Fig. 1 shows the geographical spread of RPWs infestation as reported by the Center for Agriculture and Bioscience International (CABI) (https://www.cabi.org) in 2021.

Various approaches have been used to identify RPW infestation in date palms at the early phases of their life cycle. The study in [29] reviewed the previous research work on detecting RPWs over the last several years. According to the findings, a pheromone-based method with wide-area farmer participation offers a long-term solution to this complex problem in date palms. Using bioacoustics properties, a novel signal processing technique is designed in [30] to identify the appearance of RPW. A good number of characteristics are retrieved, including temporary roll-off and periodic distribution. The findings showed that the designed system can detect the presence of

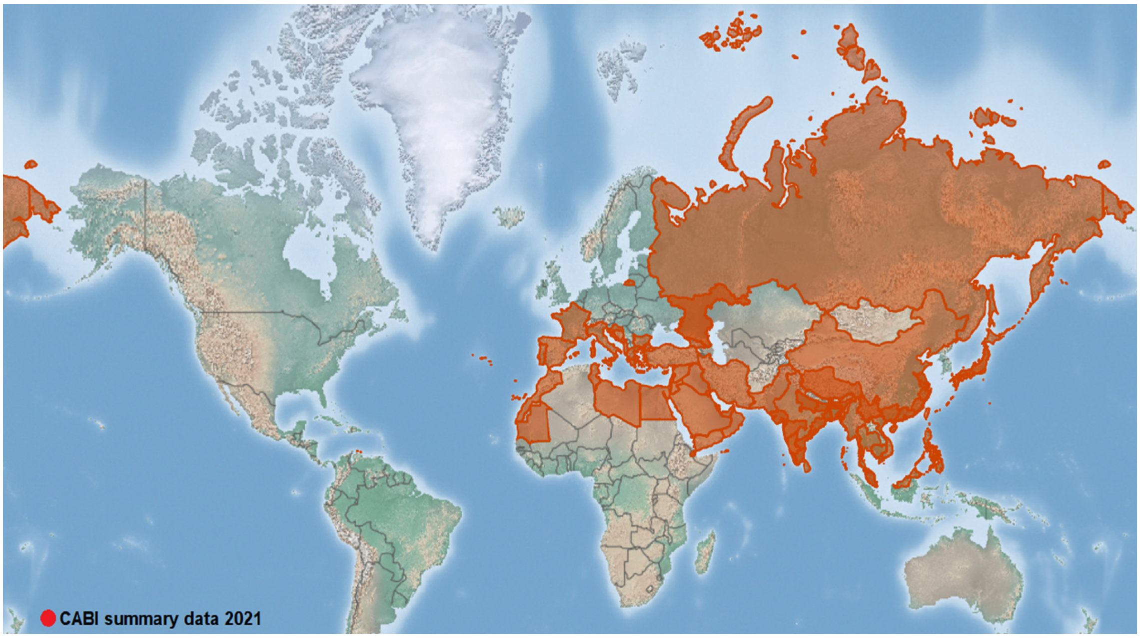


**Fig. 1** Geographical spread of Red Palm Weevils (RPWs) from Centre for Agriculture and Bioscience International (CABI) 2021.

the RPW by its feeding sound with the set frame period. In [31], the study goal was to develop software that could detect RPWs utilizing image processing and artificial neural network (ANN) methods. The experimental results showed that a three-layer ANN when using the conjugate gradient with Powell/Beale restarts tool for feed-forward supervised learning was the most effective for detecting infested cases of the RPW.

To identify the palm tree pest, a 3-axis capacitive micro-machined accelerometer is employed in [32]. The MEMS accelerometer and the digital voice recorder (DVR) were essential for RPWs detection. The authors in [33] surveyed a variety of new methodologies and ways for classifying diseased palm trees. Thermal imaging detection based on the thermal spectrum of irradiation emitted from the tree canopy and physiological changes in infested palms can produce the desired diagnosis. The effectiveness of non-invasive optical instruments such as a digital camera, thermal camera, Radar 2000, Radar 900, magnetic DNA biosensor, and near-infrared spectroscopy (NIRS) was evaluated to detect RPW infestation in date palm trees in Riyadh, Saudi Arabia [34]. Based on the obtained outcomes, the visual RPW detection strategy had the best accuracy (87%) followed by Radar 2000 (77%), Radar 900 (73%), thermal camera (61%), and digital camera (52%). The goal of the work presented in [35] is to find out if there are any RPW life stages hiding in the palm tree, such that diseased date palms are detected and treated with the use of sensors and nanoparticles. Also, the study in [35] demonstrated that the infestation of RPW can be detected in its early stages utilizing nano-techniques such as an acoustic sensor and thermal sensors as fingerprints. Leaf spots, blight spots, and RPW are considered the most frequent diseases impacting palms globally and were detected using two classifiers as presented in [36]. The accuracy ratio achievement degrees were 97.9% and 92.8% for the convolution neural network (CNN) and support vector machine (SVM) methods, respectively. The distributed acoustic sensor (DAS) of optical fiber is utilized in [37] as a paradigm technology for the early recognition of RPWs. A feeding sound produced by larvae as early as 12 days was detected by such a robust sensor in an infested tree. In [4], a suggested integrated IoT system for managing palm tree farms and early identification of the RPW is provided. The findings showed that employing both signal processing and analytical procedures are possible to establish a distinct signature of the infestation case. Researchers in [38] analyzed the effectiveness of the ten most advanced data-mining categorization algorithms to recognize RPWs in their early appearances before considerable tree destruction occurs utilizing both temperature and plant size information gathered from trees individually. Furthermore, the produced outcomes proved that data mining for RPW cases can be able employed to achieve a high accuracy and F-measure above 93%. Authors in [39] developed a strategy for initial detection of RPW in large farms practicing the integration of machine learning and fiber-optic sensor approaches. In accepted noise conditions, ANN and CNN models can be used effectively to classify the clean and infested date palm trees with the highest accuracy scores above 99.0% using temporal and spectral data, respectively.

## 3. Study materials and methods

### 3.1. TreeVibes dataset

As shown in Fig. 2 (left), the TreeVibes sensing device consists of an embedded piezoelectric crystal as a microphone to acquire the infested vibrations in the trees [40]. The acquired sounds of RPWs and also other borers are gathered and converted to audio signals. Then, these audio signals may be stored and/or wirelessly transferred via the proposed IoT networks to a server in the cloud for further signal processing and analysis. Fig. 2 (right) shows the graphical representation of mean spectral sounds for three different RPWs [26]. It is

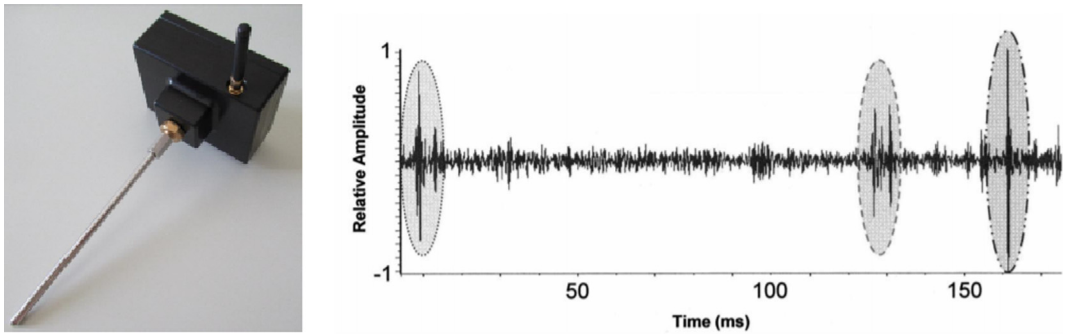


**Fig. 2** TreeVibes sensing device for acquiring sounds of borers including RPW larvae [40] (left) and mean spectral sound profile of three different RPWs [26] (right).

important to mention that the TreeVibes can only detect the feeding and movement of RPW larvae without counting them or defining their location inside the trunk of the palms tree. Hence, the placement of such a sensing device on the trunk of the date palms is considered a critical task to successfully detect the suspected sounds of RPWs and other borers within a spherical region in the range of 1.5 to 2.0 m radius.

The TreeVibes dataset includes annotated audio recordings of RPWs and other insect pests, such as Xylotrechus chinensis and Aromia bungii (Red-necked longicorn). It is an open-access database and can be freely downloaded from http://www.kaggle.com/potamitis/treevibes [40]. These sound files were stored in a wave format at a sampling frequency of 8.0 kHz. The public database of TreeVibes includes 35 annotated folders of short audio recordings, which are acquired in the field. The total number of these recordings are 2485 samples, such that 1988 and 497 samples have been used for deep classifier training and testing phases, respectively. The tested recordings of palm sounds are 351 samples for clean or healthy trees and 146 samples for infested cases. In this paper, we assumed that all infested audio recordings of feeding and moving pests are caused by the RPW larvae only.

### 3.2. Mixed depthwise convolutional kernels

CNN is the most popular architecture of deep learning classifiers in several applications [41–43]. Tan *et al.* [44] studied the impact of different kernel sizes of depthwise convolution on the efficiency and accuracy for CNNs. They proposed a new mix-up of multiple kernel sizes in a single depthwise convolution, namely (MixConv), as shown in Fig. 3. The main goal of MixConv is to easily extract different types of patterns from input signals and/or images, based on mixing-up multiple kernels with different sizes in a single depthwise convolution operation.

There are many design choices of the MixConv because of its flexible convolution operation and the group size, $g$, where $g$ determines the number of different kernels for a single tensor [44]. Therefore, the possible design choices of MixConv can be kernel size or channel size per group and dilated convolution without increasing the designed network parameters and computation budget. Three main architectures of MixNets are categorized to MixNet-small (S), medium (M), and large (L), according to the number of parameters and floating-point operations per second (FLOPS). Basically, these network architectures consist of two successive stages as follows. In the first stage, small kernels are mainly used for saving computing budgets. Then, large kernels are used in the second stage for achieving highly accurate results. In this study, we have used the architecture of MixNet-S [44], as shown in Fig. 3, because of its efficiency and accuracy concerning recognizing the health status of date palm trees while given in the following sections.

### 3.3. The proposed RPW detection system

Fig. 4 depicts an illustrative design of the proposed smart detection model of RPW larvae in the farm of date palm trees which is based on an IoT platform. The suggested RPW detection method consists of three main stages. First, the sensing sound device, i.e., TreeVibes, is placed on each trunk of the palm tree to build a WSN. The sensor nodes identify the palm-ID inside this network to recognize the infested instances easily in the farm. Also, a global positioning system (GPS) that is integrated with equipment's of TreeVibes can be also used [40]. Second, cloud services provide saving and analyzing tasks of wireless audio signals. Finally, acquired sound signals are classified using the proposed MixConvNet classifier, as shown in Fig. 4. There are many different sounds in the agricultural environment that can be recorded such as rains and wind sound, and voices of birds, animals, and human workers. These environmental sounds may be challenging the classification task of RPW inside trees. Nevertheless, audio signals of the RPW larvae are impulsive trains as depicted in Fig. 2 (right), which can be extracted from the above noisy sound signals in the farm. Consequently, these distinguishing features of the RPW sound play a significant function in the evaluation process of the performance concerning the intended MixConvNet classifier.

### 3.4. Performance analysis metrics

Our proposed MixConvNet classifier was evaluated based on classification analysis indices as follows. Cross-validation estimation [45] has been used to form a 2x2 confusion matrix. The resulted confusion matrix includes four expected results of clean and infested classes as follows: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Moreover, the classification measurement of accuracy, recall

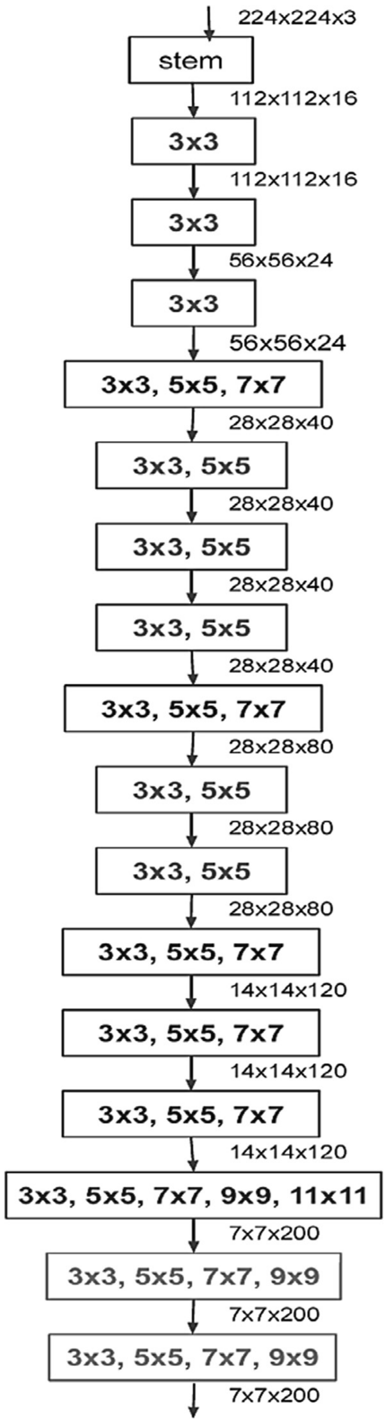


**Fig. 3** Architecture of MixConv-S model [44].

(sensitivity), specificity, precision, and F1-measure are presented by Equations (1-to-5) [45].

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

$$precision = \frac{TP}{TP + FP} \quad (2)$$

$$recall(sensitivity) = \frac{TP}{TP + FN} \quad (3)$$

$$sepecificity = \frac{TN}{TN + FP} \quad (4)$$

$$F1 - measure = \frac{2(precision \times recall)}{precision + recall} \quad (5)$$

## 4. Results and evaluation

In this study, Python code programming with the Tensorflow and Keras packages [46] have been used to implement our proposed MixConvNet classifier and other models of transfer learning. All experiments have been conducted on a laptop with Intel(R) Core (TM) i7-2.2 GHz processor, 16 GB RAM, and 4 GB NVIDIA GPU. For enhancing the classification performance of tested deep learning models, the short sound recordings of RPW and other borers [40] were preprocessed by scaling them to 224 $\times$ 224 audio window signals. We assumed that all sounds of date palm borers and RPW larvae are similar in this study. In general, all agricultural pest sounds are classified as non-clean or infested cases.

To start the training of deep learning models, the audio files of TreeVibes datasets were split 80–20% randomly, such that 20% of sound recordings have been used for validation and testing phases. The whole number of examined recording sounds are 146 for infested samples and 351 samples for clean cases. The hyperparameter values were carefully selected for our proposed MixConvNet model as follows. The learning rate is $10^{-3}$. The batch size is 60 and the number of epochs is 40. Stochastic Adam optimizer [47] has been also used during the training phase. The activation function of the output classification layer is Softmax to predict clean and infested classes for all tested sounds of date palm trees. The above values of hyperparameter are fixed for all tested deep learning classifiers in this paper to accomplish a comparison between the performance of our proposed MixConvNet classifier against other classifiers in previous studies.

The classification workflow of infested and clean date palms is automatically achieved using the fine-tuned MixConvNet classifier, as depicted in Fig. 5. Resulted confusion matrices of MixConvNet classifier and five deep learning models, specifically Resnet-50 V2, MobileNetV2, Densenet-121, EfficientNetB0, and Xception are shown in Fig. 5. The proposed MixConvNet obtained the most suitable classification accuracy score of 97.38% with only 13 misclassified samples of infested and clean cases. The most accurate model for classifying infected cases is Resnet-50 V2. However, it is failed to detect 20-clean specimens accurately. Three transfer learning models of EfficientNetB0, MobileNetV2, and Xception achieved roughly equal classification performance of 95.17 to 95.58% accuracy rates. The lowest classification accuracy is 94.77% for the Densenet-121 model.

Moreover, Table 1 illustrates evaluation results of all tested deep learning classifiers using 2-fold cross-validation, based on five performance metrics, namely accuracy, precision, sensitivity or recall, specificity and F1-score, as given in Equations (1–5). Our proposed MixConvNet showed superior performance by achieving the best values of five evaluation metrics and the accuracy score of 97.38%, while Densenet-121 model showed the lowest classification accuracy of 94.77%. The performance of Resnet-50 V2 is also verified to give the second-best classification results with 95.98% accuracy score.

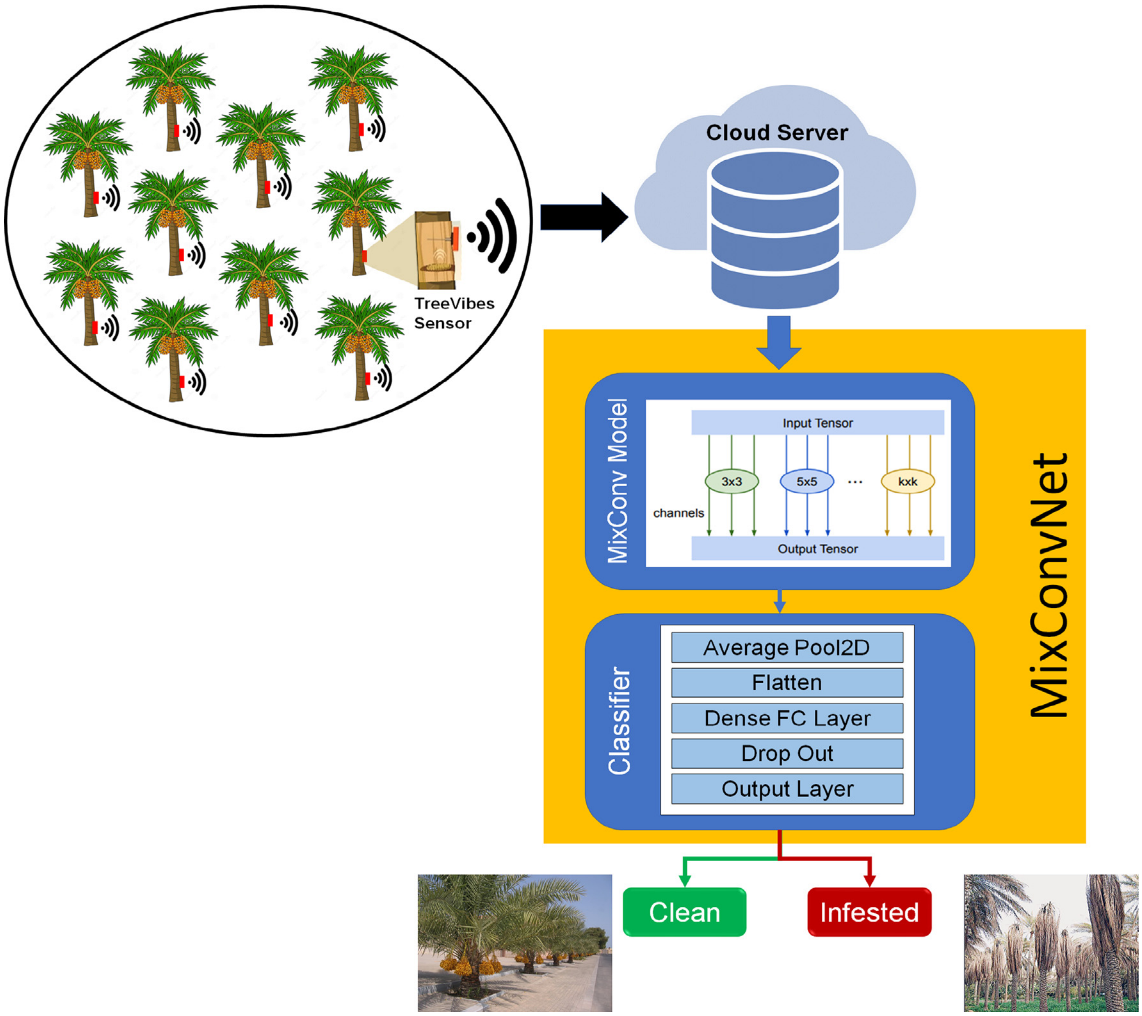


**Fig. 4** The proposed sound detection model of RPWs inside date palm trees based on IoT platform.

Furthermore, a comparison among the suggested MixConvNet and other transfer learning models in preceding related works is presented in Fig. 6 and Table 2. Using K-fold cross-validation, the MixConvNet outperforms other deep learning classifiers with the best accuracy score of 95.90%. However, Xception paradigm achieved the lowest value of standard deviation (0.99). In addition, the MobileNet-V2 presents the classifier's smallest size of 14 MB and relatively low classification accuracy of 93.65. Nevertheless, our proposed MixConvNet classifier has a moderate size of 32 MB with the highest accuracy value.

## 5. Discussions

Intelligent IoT-enabled agricultural pest management and control becomes important for protecting crops, especially for avoiding the mortality of date palm trees by harmful RPWs. Therefore, automated detection of RPW larvae at the beginning of infestation plays a major role to solve this issue in the section of agriculture. The TreeVibes device is a new tool for sensing RPW larvae and other wood borers inside trees [40]. In this study, automated vibrating sounds detection of feeding and/or moving RPW larvae inside date palms has been successfully achieved using our proposed smart IoT-based system, as depicted in Fig. 4. The fine-tuned MixConvNet classifier achieved a competitive performance against other models of transfer learning in the preceding related works to classify health status of the date palms precisely, as presented in Tables 1 and 2.

In order to support the performance of our suggested MixConvNet classifier, this study presented two evaluation comparisons as follows. First, the performance of MixConvNet and other deep learning models, i.e., Resnet-50 V2, MobileNetV2, Densenet-121, EfficientNetB0, and Xception, was evaluated using the confusion matrix in Fig. 5 and classification metrics in Equations (1–5) as given in Table 1. Second, the previous relevant work via Rigakis et al. [40] demonstrated that the Xception classifier could achieve the most accurate classification results using the same TreeVibes database. Based on K-fold cross-validation, their Xception classifier scored average accuracy of 94.16% $\pm$ 0.99, respectively, as illustrated in Table 2. However, our MixConvNet classifier showed a better accuracy score of 95.90% and also a slightly higher standard deviation of $\pm$ 1.46.

The limitations of our intended MixConvNet classifier can be its size of 32 MB and required hardware sources, e,g. GPUs, to

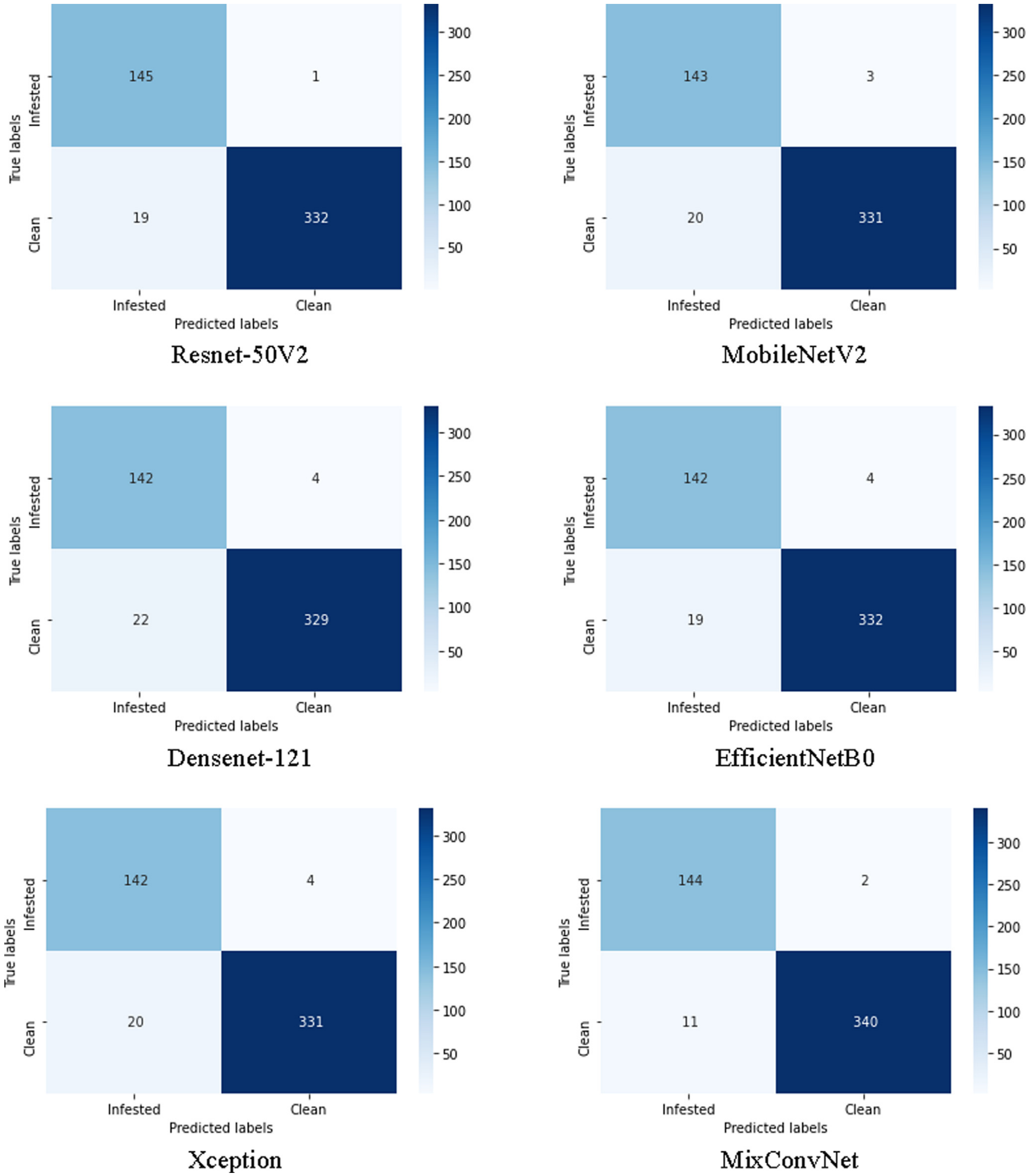


**Fig. 5** Confusion matrices for all tested deep learning model to classify RPW larvae infestation and clean trees.

accomplish the training phase of deep learning models. However, this problem can be solved by utilizing cloud computing services as shown in Fig. 4. Also, we have manually selected the hyperparameter values of all tested transfer models in this study. It is an iterative and time-consuming procedure for tuning hyperparameter values. Therefore, integrated recent optimization algorithms such as adaptive particle swarm optimization (APSO) and whale optimization algorithm (WOA) to computerize the designed parameters of deep neural networks [48–50] by an extra computing budget. However, the MixConvNet is still capable of achieving the best performance of RPW larvae sounds classification as presented in Tables 1 and 2.

**Table 1** Comparative evaluation of all tested deep classifiers in this research work.

| **Classifier** | Class | Precision | Recall(Sensitivity) | Specificity | F1-score | Accuracy |
|---|---|---|---|---|---|---|
| Resnet-50 V2 | Infested | **0.99** | 0.88 | **1.00** | 0.94 | 95.98 |
| | Clean | **0.94** | **1.00** | **0.88** | **0.97** | |
| MobileNetV2 | Infested | 0.98 | 0.88 | 0.99 | 0.93 | 95.37 |
| | Clean | **0.94** | **1.00** | **0.88** | **0.97** | |
| Densenet-121 | Infested | 0.97 | 0.87 | 0.99 | 0.92 | 94.77 |
| | Clean | **0.94** | **1.00** | **0.88** | **0.97** | |
| EfficientNetB0 | Infested | 0.98 | 0.88 | 0.99 | 0.93 | 95.58 |
| | Clean | **0.94** | 0.99 | **0.88** | **0.97** | |
| Xception | Infested | 0.97 | 0.87 | 0.99 | 0.92 | 95.17 |
| | Clean | **0.94** | 0.99 | **0.88** | **0.97** | |
| MixConvNet (ours) | Infested | **0.99** | **0.93** | 0.99 | **0.96** | **97.38** |
| | Clean | **0.94** | **1.00** | **0.88** | **0.97** | |

*Values in bold are indicated for high performance.

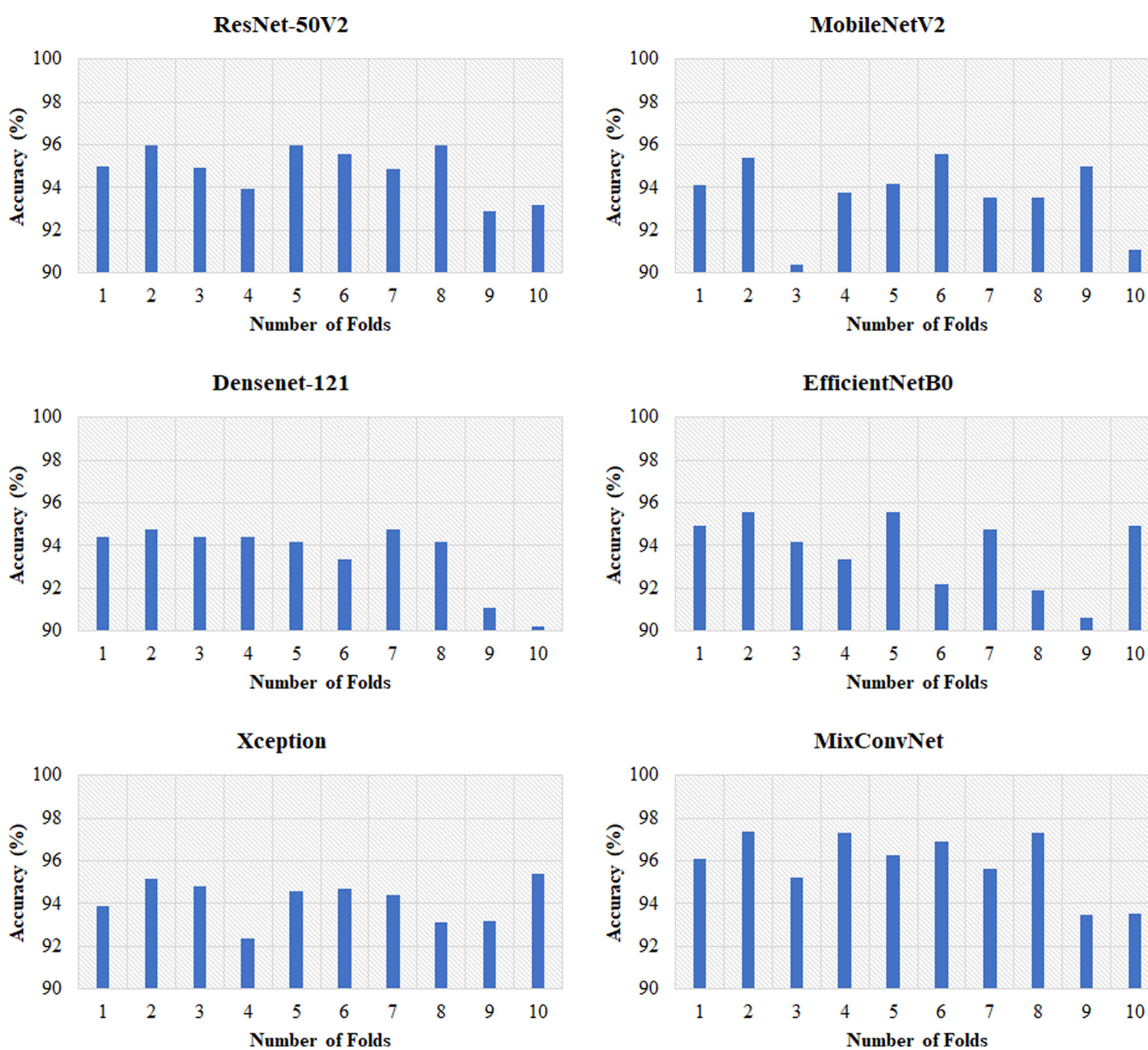


**Fig. 6** K-fold cross-validation of all tested classifiers to identify the clean and infested palm trees.

**Table 2** Comparative characteristics of the suggested RPW classifier with different models.

| Classifier of transfer learning | Size in MB | Average accuracy (%) ± standard deviation |
|---|---|---|
| Resnet-50 V2 | 98 MB | 94.83 ± 1.14 |
| MobileNetV2 | **14 MB** | 93.65 ± 1.70 |
| Densenet-121 [40] | 33 MB | 93.56 ± 1.60 |
| EfficientNetB0 [40] | 29 MB | 93.80 ± 1.71 |
| Xception [40] | 88 MB | 94.16 ± **0.99** |
| MixConvNet (ours) | 32 MB | **95.90** ± 1.46 |

*Values in bold are indicated for high performance.

Recently, safety and privacy technologies for smart agricultural systems based on IoT have been investigated such as blockchain technology and low-power wide-area networks (LPWANs) [51,52], but these technologies are not included in this study. We assumed that the security of agricultural systems based on IoT can be accomplished by current technologies of authentication, access control, and confidentiality of the stakeholders. Nevertheless, the security obligations and other sub-systems in precision agriculture, e.g., fault-diagnosis as well as reaction systems toward risks and cyberattacks [53], will be considered in future works.

## 6. Conclusions

This research work presented a new IoT-enabled sound detection model of RPW larvae inside date palm trees. The proposed MixConvNet classifier is a recent efficient and accurate convolutional network with different kernel sizes. It is successfully achieved the best accuracy among other deep learning models in previous studies, as illustrated in Table 2, using the evaluation of 10-fold cross-validation. The main prospect of this research work is utilizing edge computing services based on lightweight deep learning models [54] integrated with a developed smartphone application for guiding farmers and agricultural experts. Additionally, visual real-time monitoring of the health status of palms can be achieved by surveillance cameras and motion sensors on the farm. Furthermore, security and privacy factors [55] in our proposed detection system over open internet and communication networks will be also considered for safely sending and analyzing acquired audio signals in the date palm farms.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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