A review: Detection of red palm weevil techniques

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Abstract

The red palm weevil is one of the harmful pests that affected and destroyed many palm trees all over the world, especially in the Middle East region, because of its economic impact on the countries in which it grows and its impact on the tree through growth and feeding on the fibers of the trunk of the palm and for eradication In addition, the life cycle of the red palm weevil is eggs, and the female red palm weevil lays her eggs in the cracks of the palm tree. Larval stage, after hatching, the larvae feed on the interior of the tree, forming tunnels and galleries in the bark and stem. Adult, after a few weeks, the adults emerge from the cocoon and begin feeding on the fronds and fruits of the palm tree. During the breeding phase, the adult weevil mates and the cycle begins again as the female lays her eggs in the tree. The research will look at two ways to detect and treat it because of its damage to large farms, especially those that are difficult to control. The first method is detection through sound using the machine learning algorithm Mixconvnet and the second is through images using the algorithm CNN. In this research, This paper will discuss the algorithms used in each insect detection method.

Keywords : red palm weevil ; internet of things ; machine learning ; image processing

مراجعة: تقنيات الكشف عن سوسة النخيل الحمراء

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خلاصة

تعتبر سوسة النخيل الحمراء من الآفات الضارة التي أصابت ودمرت العديد من أشجار النخيل في جميع أنحاء العالم، وخاصة في منطقة الشرق الأوسط، لما لها من تأثير اقتصادي على الدول التي تنمو فيها وتأثيرها على الشجرة من خلال نموها وتغذيتها على ألياف جذع النخلة والقضاء عليها بالإضافة إلى أن دورة حياة سوسة النخيل الحمراء هي البيض، وتضعها أنثى سوسة النخيل الحمراء البيض في شقوق النخل. مرحلة اليرقات، بعد الفقس، تتغذى اليرقات على الجزء الداخلي من الشجرة، وتشكل أنفاقًا وأروقة في اللحاء

والساق. البالغ، بعد بضعة أسابيع، يخرج البالغون من الشرنقة ويبدأون بالتغذية على سعف وثمار شجرة النخيل. أثناء مرحلة التكاثر، تتزاوج السوسة البالغة وتبدأ الدورة مرة أخرى عندما تضع الأنثى بيضها في الشجرة. البحث سوف وإلقاء نظرة على طريقتين للكشف عنه وعلاجه لما له من أضرار على المزارع الكبيرة وخاصة تلك التي يصعب السيطرة عليها. الطريقة الأولى هي الكشف من خلال الصوت باستخدام خوارزمية التعلم الآلي Mixconvnet والثانية من خلال الصور باستخدام خوارزمية CNN. في هذا البحث، ستناقش هذه الورقة الخوارزميات المستخدمة في كل طريقة للكشف عن الحشرات.

الكلمات المفتاحية : سوسة النخيل الحمراء ؛ انترنت الأشياء ؛ التعلم الالي ؛ معالجة الصورة

1. Introduction

Smart systems are frequently employed in the form of models for monitoring the environment, for example, to observe the growth of crops and to avert forest fires , due to the cost-effective and secure application of smart technology[1]. Crop disease detection technologies today primarily use spectroscopic and imaging, hyperspectral imaging, and other approaches as a result of advancements in communication and data processing. An infestation model for crop diseases can be used to diagnose and find crop diseases. In addition, due to the difficulty of manually collecting experimental samples and expensive experimental consumables, It is not appropriate for extensive agricultural disease surveillance. At present, the use of automatic image recognition for pest detection is becoming more and more common in agricultural development [2]. Agricultural monitoring requires a better understanding of the crop types in the country's agricultural regions and their respective acreage, food security analyses, as well as the formulation and enforcement of suitable legislation [3]. Palm trees are highly regarded across the globe for their economic significance. They are seen as one of the most vital trees in existence, especially in the Middle East. Figure (1) shows the top 10 countries producing dates in the world.[44,45,46]. Dates are one of the most well-known crops that require constant real-time surveillance to detect Red Palm Weevil (RPW) larval activity. Sophisticated sensing devices quickly identify any RPW threat to palm plants and send alarms [5] .

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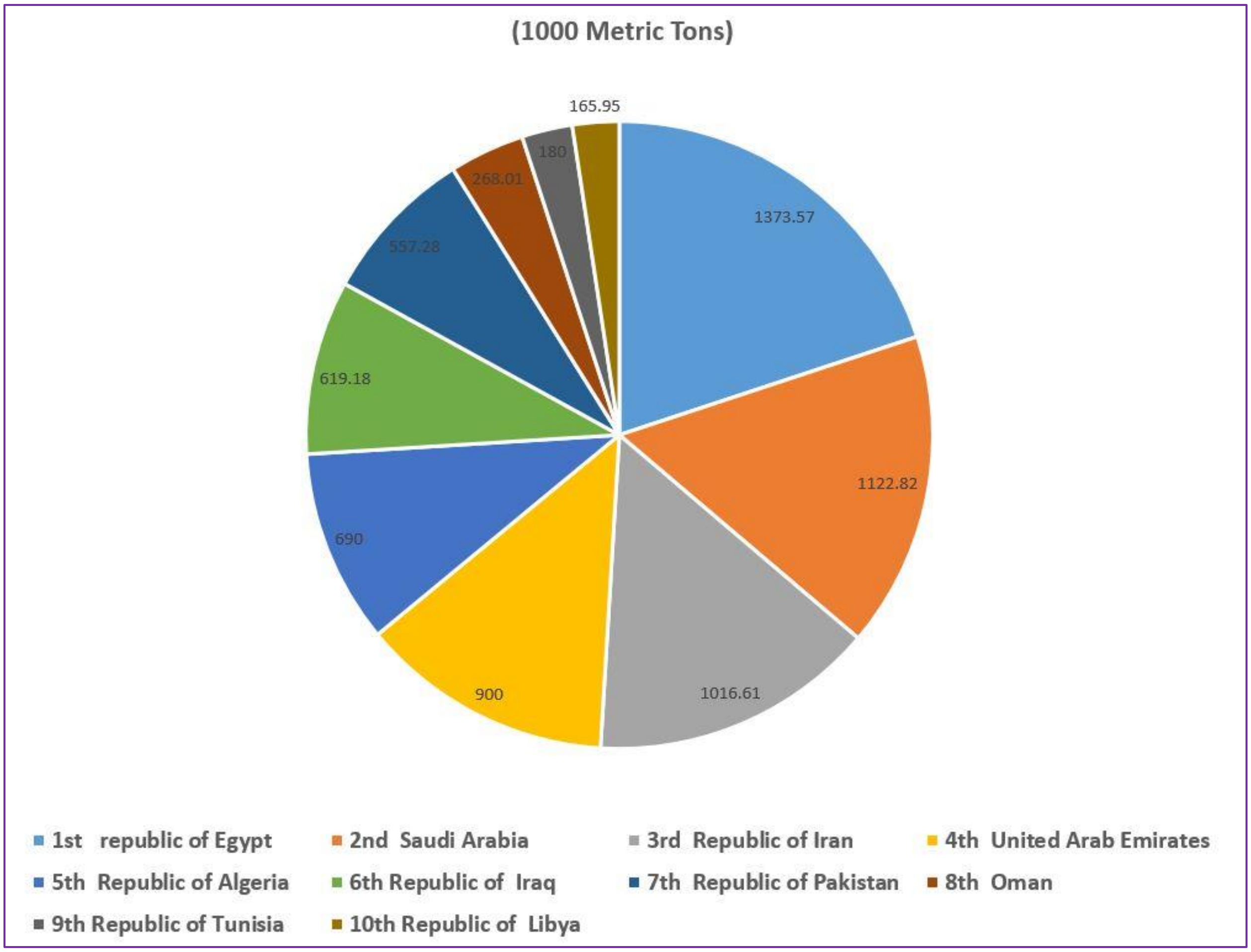

Figure (1) depicts a flow diagram representing shows the top 10 countries producing dates in the world [4].

There are many distinctive features of the red palm weevil, which show its stages of growth, as shown in Figure (2) [6] .With the help of the suggested smart detection model, it is possible to quickly obtain vital data that can identify the infected tree and prevent its destruction. In order to overcome the limitations of conventional methods and automate routine procedures and/or everyday duties for farmers, Examples of water management practices that can be implemented to improve crop health include irrigation and monitoring of crop health, smart agriculture makes use of wireless communications and information technologies [7] .

Figure 2 : RPW life cycle [6]

The Internet of Things (IoT) is a major element of smart agriculture[8,9]. Primarily, WSNs are utilized to measure and estimate various agricultural and ecological conditions, including weather temperature, soil moisture, and crop diseases [10]. This agricultural information are amenable to automatic analysis to assist farmers in making important choices like turning on irrigation pumps[8,11].Artificial intelligence (AI) tools and techniques have lately been incorporated into precision agriculture. The underlying principles of a number of AI-powered applications, such as neurosurgery and COVID-19 diagnosis, are demonstrated via machine learning and deep learning systems [12,13] . smart manufacturing [14] and secure communications [15]. Additionally, similar clever techniques have been effectively applied in agricultural applications in earlier studies, such as the diagnosis of apple leaf diseases [16]. the classification of insect pests [17]. and robotic harvesting systems [18].

In order for conventional deep learning models to finish the learning phase, huge datasets and powerful hardware like GPUs are necessary . The developers or end users may not always have access to these needs. As a result, applying transfer learning techniques offers a suitable option for smart applications with limited hardware resources and datasets[19,20]. They rely on employing the same pre-trained model and transferring knowledge from one task that is similar to another at a minimal cost of computation. Convolutional networks with many connections (Densenet) [21]. residual neural networks (Resnet)[22]. Xception [23] and MobileNetV2 [24] are four illustrations of popular transfer learning models. As a result, models of transfer learning produced accurate crop disease classification findings [25]. and other sophisticated agricultural systems [26,27]. Traditional agricultural techniques are time-consuming, costly, and unsuccessful, including manually operated insect pest detection. Farmers risk losing plants if they are unable to identify dangerous pests in time to employ effective insecticides to eradicate them [28]. The use of deep learning (DL) is extremely important, as it uses algorithms to learn from comprehensive data sets, as well as the use of CNN algorithms that help in detecting the red palm weevil [29] . In addition, the Internet of Things has become a necessity in life, enabling remote monitoring and finding applications in healthcare and smart cities [30] .We will utilize Deep Learning (DL), as it employs algorithms to learn from extensive datasets[31,32] .

Therefore, the goal of this work is to propose a new intelligent Internet of Things-based system for RPW larvae sound detection inside date palm plants. The following developments are also made possible by this study, which will help date palm farms automatically identify their infestation conditions:

- MixConvNet, a cutting-edge classifier based on transfer learning, is presented for precise sound recognition in RPW larvae.
- Integrate IoT-based technologies with deep learning models. Support expert and grower decision making with real-time crop health classification based on RPW.
- Our suggested deep learning classifier is compared with a number of models from earlier relevant research employing extensive testing and evaluation in the suggested method of RPW at the initial stages of Pressed outbreaks.

The following sections make up the remaining portions of this essay: A summary of pertinent detection techniques used in prior RPW management studies is provided in Section 2 the related work in Section 3 the Methods used to detect the

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red palm weevil . In Section 4, the research's main conclusions . The research aims to develop a method or system to detect the presence of the RPW in plants that are prone to infestation by this pest. This will involve the development of a detection system that can accurately identify the presence of the red palm weevil.

2. Related works

A summary of some of the previous work carried out by some researchers and the mechanisms they used in terms of improvement and detection of the red palm weevil. In 2008, Soroker et al. The proposed research refers to a method for automatically detecting red palm weevil activity using vector Quantization (VQ) and Gaussian mixture modeling (GMM). This confirms the importance of the automatic acoustic tool, which achieved an accuracy of 98% [33]. In Ganchev et al. 2009, The contribution of this work was to develop. Indicates the unified voltage of the vehicle. Voice recognition. From insect pests, cars show high efficiency. Cracking of the rice weevil based on the sound emitted by the larvae when eating in the trunk of a palm tree/rice storehouse. Using the provided feature extraction method, GMM, the performance or Accuracy was 99.1% accuracy [34]. This work Author, Gutiérrez et al. 2010 Presented the method of Fast Fourier Transform (FFT), studying the sound intensity around 2250 Hz, Key contributions, This work describes different stages of development dependent on sound sensors, and an electronic device to detect the eruption of red palm weevil up to 2250 Hz. the Performance or Accuracy is The infested sound intensity increases around 1 dB from 20 dB [35]. In this work Author, Rach et al. 2013 Presented the method of Filtering and amplification, feature vector quantization, and Key contributions; of this work. A vital audio sensor is designed to be installed in a palm tree to analyze audio signals over a period, with the aim of extending to large spaces and detecting red palm weevils at high rates. The Performance or Accuracy is 90% [36]. This work Authors, Amots Hetzroni et al. 2016 Presented the method of Likelihood indication by the observer, a speech recognition algorithm similar to that in Ref . , Key contributions, This work investigated the red palm weevil, using visual monitoring and a sensor-equipped covering device to capture the larvae's sound, which is distinct from external stimuli such as wind and ambient noise. Manual audio detection was enough to detect the weevil in a natural, non-protected setting in small palm trees. The data shows that audio detection must be utilized in parks and gardens. The Performance or Accuracy is 75% accuracy by humans and 80% accuracy by machine [37]. This work Author, Khawaja Ghulam Rasool et al. 2020 Presented the method of Visual analysis, the analysis of variance (ANOVA) PROC GLM procedure, the response of the leaf spectral absorbance, and Key contributions. This work made it hard to identify

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injury to the red palm tree in its early life stages. He tested the efficiency of some non-invasive optical tools, such as a thermal camera, digital imaging, magnetic DNA sensor, resistance measuring device, and stained infrared analysis, to detect this insect. This approach was used in Saudi Arabia, and after the discovery, each tree was analyzed in detail. This study revealed that all the visual tools used could identify and help detect infection with red palm weevil. The Performance or Accuracy is Accuracy: visual approach 87%, Radar 2000 77%, Radar 900 73%, resistograph 73%, thermal camera 61%, digital camera 52%, and magnetic DNA 63% [38]. This work Author, Anis Koubaa et al. 2020 Presented the method of Fast Fourier Transform (FFT), the estimation of power spectral density (PSD), peaks average difference (PAD) analysis; key contributions; this work Smart palm a system to monitor palm farms through the Internet of Things, was proposed. It allows for efficient farm management and control and is demonstrated through a prototype using smart agricultural sensors that monitor palm trees remotely, detecting red palm weevil invasion at an early stage. Performance or Accuracy is an Observable signature of the infestation [39]. This work Author, Dima Kagan et al. 2021 Presented the method CNN, faster R-CNN ResNet-50 FPN, XResNet, Key contributions, This work This research demonstrated a deep learning algorithm as a new way of detecting red palm weevils in palm trees using images. Over 100,000 images were analyzed, and 47,000 aerial photographs were mapped to detect the insect in urban areas. The Performance or Accuracy is Aerial, and street photographs can be related to actual palm trees [40].

3.Methods used to detect the red palm weevil

There are two ways to detect the red palm weevil in order to help farmers discover it. The first method is to Identifying the RPW by pictures, and the second method is to Identifying the Red Palm Weevil by sound for that insect. The two methods will be explained below:

3.1 Detection of the red palm weevil by image

The method of detecting the RPW through pictures is one of the methods for detecting the RPW insect. This method depends on the pictures taken of the tree, which is suitable because there are no side effects on the palm tree. Sometimes you have difficulty distinguishing the red palm weevil insect because some insects are similar in shape to the red palm weevil.

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similar in shape to the red palm weevil. Fig 2 To start this model, an image has to be acquired from a camera, mobile camera, or thermal camera In the input stage , [41] In Feature Extraction , This section examines the SVM model which determines whether a palm is infected with Red Palm Weevil by scanning its thermal images. By utilizing infrared thermography to produce a digitized thermal pattern known as a thermogram, the analysis of thermal images is made simpler by extracting the signals and data within them . Thermal images have two components that are represented in their features: textural and statistical. Textural features calculate the connection between pixels in a specific area, showing how the greyscale of the image changes [42]. The images were converted to black and white so that their GLCM features could be used for feature extraction. This is akin to the technique of deep learning models such as CNN, so back propagation and different filters were employed to get the most out of the photograph and improve the model . After the rotation of the images was complete, a new challenge presented itself. The images had a black background, which caused some noise and other unwanted signals. To solve this problem, the black background was removed and made transparent by adding an alpha channel, thus eliminating the noise [41] . , In Classifications , Two different types of classifiers were chosen to identify common diseases and RPW infected palms. CNN and SVM were chosen as they are known to be the most effective options for completing this task ,This text is about a method that was created to make image analysis easier. It uses mean, contrast, and standard deviation of the image pixels to extract features and predict outcomes with maximum accuracy regardless of the size or variation of the dataset. This method is also computationally inexpensive and efficient [45,46,47]. The detection of these diseases is done by taking pictures of palm trees in both normal and thermal conditions. After that, various image processing techniques are used on the acquired images. For the purpose of distinguishing between Leaf Spots and Blight Spots, a Convolutional Neural Network (CNN) is used, whereas a Support Vector Machine (SVM) is employed for the detection of Red Palm Weevil pest [41] . Fig 3 To start this model, an image has to be acquired from a camera, mobile camera, or thermal camera. In the input stage, the image is enhanced and the features of the insect are singled out to enable the model to train and categorize the illness. Finally, in the output stage, the results can be obtained [41,50] .

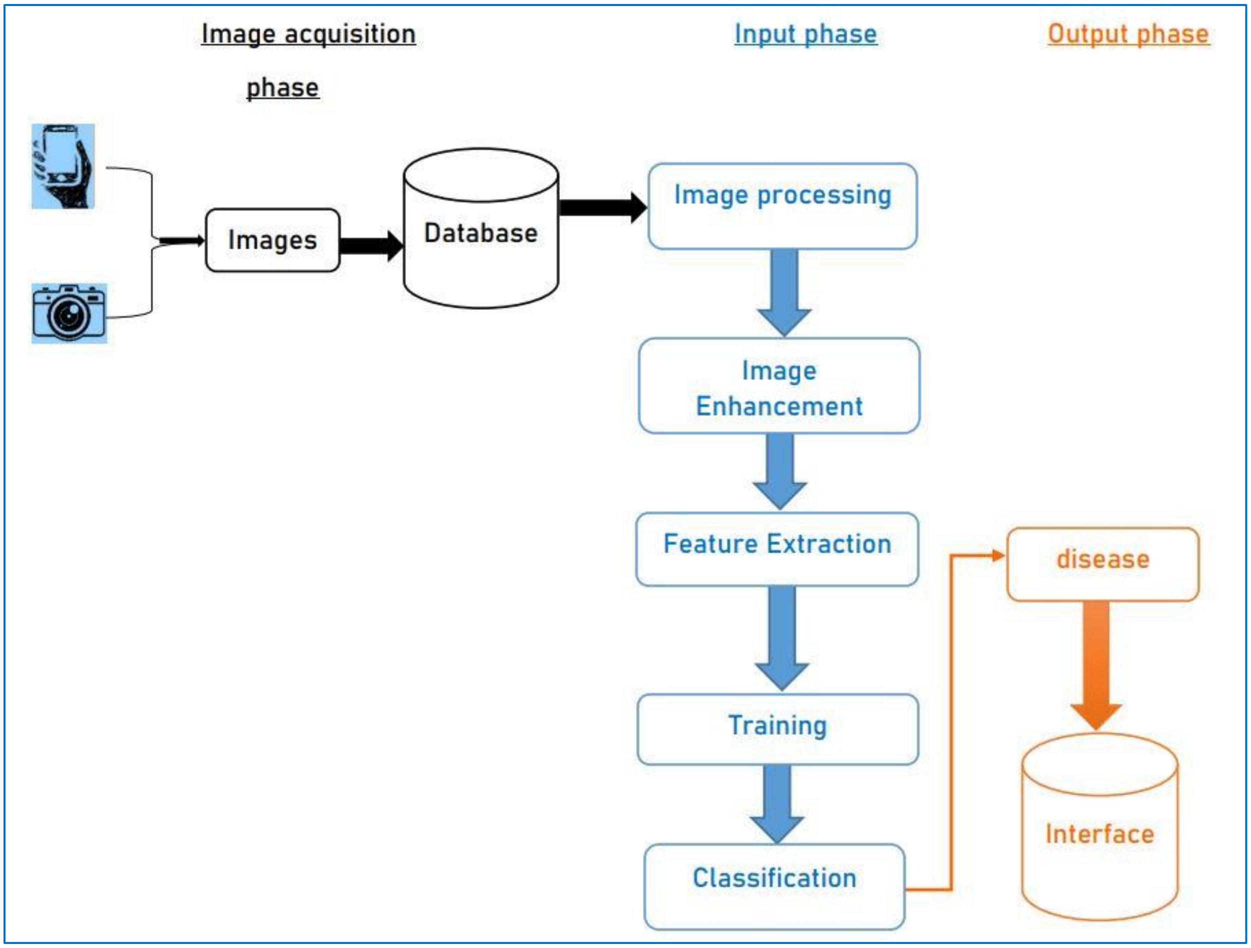

Fig.3 . Proposed System Overview[41].

3.2 Detection of the red palm weevil by sound

Initially, samples of sounds that can include the sound of the RPW are needed here by Treevibe so that the sound is analyzed and classified as shown below., respectively.

Figure 4 (right) illustrates how the TreeVibes sensing device records vibrations brought on by tree invasion using an implanted piezoelectric crystal as a microphone[43].

Collects and processes audio signals from sounds received by RPW and other borers. Then, via the proposed IoT network, these audio signals can be wirelessly saved and/or sent to a cloud-based server for additional signal processing and analysis. The average spectral sounding for three distinct RPWs is depicted graphically in Figure 4 (left)[42].

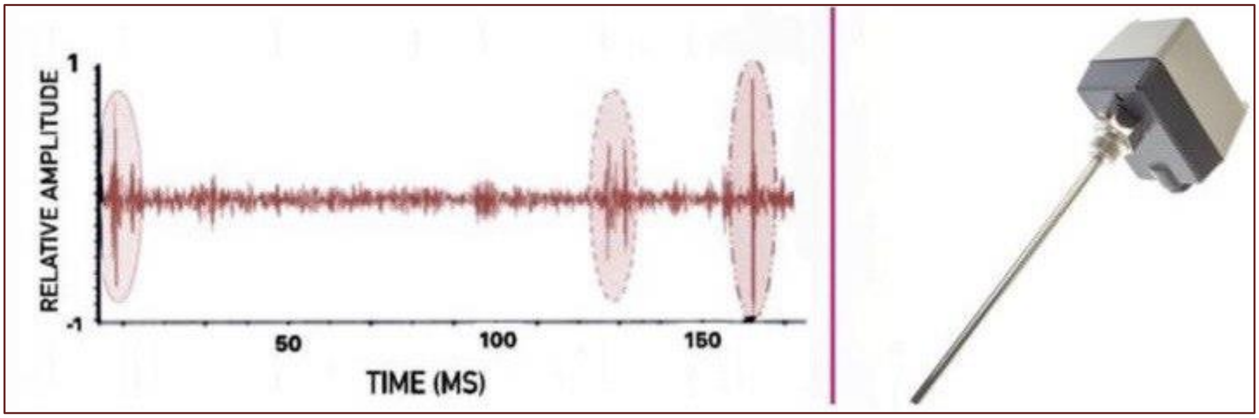

Figure 4. different RPWs (left)[43] and Tree Vibes sensing setup used to acquire moth sounds including RPW larvae (right) [42].

Figure 4 is a schematic diagram of an intelligent detection method for RPW larvae in a jujube field based on the Internet of Things platform. Three main steps constitute the detection process of the proposed RPW. To create a WSN, Attach a TreeVibe sensory sound device to each trunk of a palm tree. This network of sensors is programmed to recognize the PALM-ID of the tree, allowing it to detect any infection events in the vicinity quickly. In addition, the TreeVibe device is also equipped with a Global Positioning System (GPS) to track the palm tree's location [44]. Second, wireless audio signal analysis and protection functions are provided by cloud services. Finally, as shown in Fig. 4, the received sound signal is classified using the proposed MixConvNet classifier. In agricultural settings, a range of noises can be recorded The noise of the outdoors, from precipitation and gusts of wind to the chirps and grunts of avians , beasts, and manual workers, can be heard. This ambient noise may make the classification process of RPWs within the tree more difficult. However, RPW larval audio signals can be recovered as pulse trains from sound signals above field noise, as shown in Figure 4 (left). Therefore, these specific aspects of RPW voices are crucial for evaluating the effectiveness of the proposed MixConvNet classifier. The best way to remove noise from sound in sound detection by mixconvnet algorithm is to use a noise reduction algorithm or filter. This can be done by either using a specialised filter, such as a low-pass filter, or a more generalised approach such as a convolutional neural network (CNN). With a CNN, the input audio data is fed into a network of convolutional layers, which extract features from the sound. The features can then be used to identify and remove noise from the audio. As CNNs are highly flexible and can be trained on large datasets, they are well suited for sound detection applications [43] .

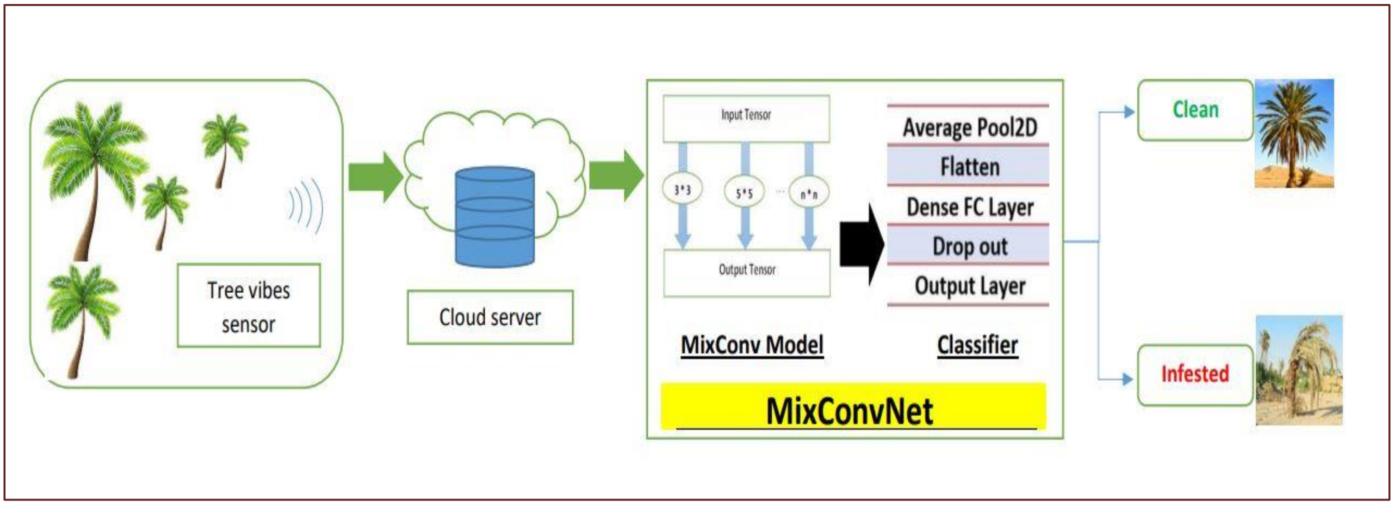

Fig. 5 Proposed RPW sound detection model in jujube tree based on IoT platform [43] .

4. conclusion

This research presents an innovative model for detecting RPW larvae in date palms based on the Internet of Things (IoT). The proposed MixConvNet classifier is atop-notch, accurate, and efficient convolutional network with different kernel sizes. It is the most reliable compared to other deep learning models through a 10-fold cross-validation evaluation. The main benefit of this research is the utilization of edge computing services integrated with lightweight deep learning models and user-friendly smartphone applications to help farmers and agricultural specialists. This system will also enable real-time visual surveillance of the palm tree's condition via surveillance cameras and motion sensors. Security and privacy concerns are taken into account in the proposed detection system, and secure transmission and analysis of audio signals captured on date palm farms over open internet and communication networks are also included to bolster the security of the model.

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