Koc. J. Sci. Eng., 5(1): (2022) 1-4 https://doi.org/10.34088/kojose.871289

Kocaeli University

Kocaeli Journal of Science and Engineering

http://dergipark.org.tr/kojose

# Development of a Neural Network Model for Recognizing Red Palm Weevil Insects Based on Image Processing

Radhwan Ali Abdulghani SALEH [1,*], H.Metin ERTUNÇ [2]

[1] *Department of Mechatronics Engineering, Kocaeli University, Kocaeli, 41380, Turkey,* ***ORCID:*** *0000-0001-9945-3672*
[2] *Department of Mechatronics Engineering, Kocaeli University, Kocaeli, 41380, Turkey,* ***ORCID:*** *0000-0003-1874-3104*

**Article Info**

**Research paper**

*Received : January 30, 2021*
*Accepted : July 07, 2021*

**Keywords**

*ANN*
*Color Moments Features*
*Image Classification*
*Image Enhancement*
*Image Segmentation*
*Red Palm Weevil Recognition Texture*

**Abstract**

The red palm weevil (RPW) is an invasive pest insect that attacks palm trees and threatens their existence. Accordingly, RPW causes significant and massive economic losses during the last two decades. This issue makes the early detection of RPW is a hot research topic. This study proposes a machine learning technique based on image processing to easily recognize these insect species for people who do not know them. The basic idea of the proposed research is to develop a neural network model that can use image processing to identify RPW and distinguish it from other insects found in palm tree habitats. This model consists of three stages: image pre-processing (image enhancement and segmentation using Otsu's thresholding), feature extraction (texture and color moments features), and classification (artificial neural network). The dataset used in this study includes 913 images, where 448 are RPWs' images, and the rest are ants' images. The experimental results of the ten-fold cross-validation show that the accuracy of the proposed model is 92.22%.

## 1. Introduction

Many pests have adverse effects on plants, where some of them may damage the trees and cause many losses in agriculture production. This fact leads to economic loss and high rates of poverty. Although various kinds of pests infest trees, such as bacteria, viruses, insects, and harmful parasites, the Red Palm Weevil (RPW) is one of the most destructive insects in infested trees. RPW is considered a global disease, destroying trees, raising the temperature of the tree, and creating water stress. It places the eggs inside the tree trunk, continues to feed on the tree's tissue, and starts moving into it until the tree dies, then moves onto the following plants. It is not easy to diagnose this weevil early; the noticeable signs of the infection only occur when the disease is in a dangerous stage.

In literature, different detection methods are used to discover the infected trees, such as Acoustic Detection, Chemical Detection, Thermal remote sensing, and Visual Inspection. In [1] survey article, these techniques were discussed in detail. And they concluded that there are drawbacks in each of these techniques, and there is a need to propose a novel model to detect RPW early.

In the literature, a limited number of studies have used image processing techniques to identify RPW. In [2] paper, a novel model is proposed. This model is based on image processing techniques and artificial neural networks. In this paper, nine features are extracted from each image (three from the regional properties technique and six from the Zernike moments technique). Then artificial neural networks are used as a classification model. The data set used in this paper consists of 326 RPW and 93 other insects' images. Two separate training algorithms have been used to train the neural network: Conjugate Gradient with Powell/Beale restarts (CGB) and Scaled Conjugate Gradient (SCG). The results obtained in this paper are 100% identification rates for RPW's images and 93% for other insects' images. The same author has published another article using the same data set and image

* Corresponding Author: redhwan9191@gmail.com

2667-484X © This paper published in Kocaeli Journal of Science and Engineering is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License

processing techniques. But instead of using artificial neural networks for classification, he has used the Support Vector Machine (SVM) with the polynomial kernel. The suggested method succeeded in detecting RPW and other insects by rates of 97% and 93%, respectively [3]. In 2020, the Linear SVC algorithm was used for the early detection of RPW. The proposed model has achieved 92.8% of accuracy [4]. Despite numerous attempts and research to combat this pest, none of them have been successful enough to discuss a way for detecting RPW in its early phases [5].

This study proposed an artificial intelligence technique to recognize RPW for people who do not understand easily. The proposed model consists of three stages. The first stage is called image pre-processing. This stage aims to enhance the quality of images and segment the body of the insects into separate images. In order to enhance images, Erodes and Dilates filters are used [6]. In contrast, Otsu's thresholding method is used for segmentation tasks [7]. The second stage is called feature extraction, which is an essential step in machine learning. In this stage, four texture and nine color moments features are extracted from the segmented images [8]. The final stage is called the classification stage, done by artificial neural networks (ANN).

The rest of the paper is organized as follows. First, the proposed image processing techniques are introduced. Then the proposed feature extraction techniques are presented. After that, the proposed classification model is illustrated. Finally, the obtained results are discussed.

## 2. Materials and Methods

In this section, we discuss our model in detail. In order to do that, we divide this section into three main subsections as the following.

### 2.1. Pre-processing

This stage focuses on enhancing the image to increase the classification accuracy and decrease the blur that happened by morphology operations. In this stage, the sample images are enhanced using Erodes and Dilates filter after resizing them into 256×256. The techniques of image rescaling are applied due to the lack of the same and standard size of images as our data set is collected from different sources. We can see the original image and the image after enhancement in Figures 1 and 2, respectively. We have also plotted the histograms in order to show whether it is possible to segment the background from the foreground of the image or not. After that, the image is passed to the segmentation method concerned with extracting the insects' bodies from the inserted image. It is clear in the histogram figures that it is possible to segment the insect region from the background by finding the optimal threshold. However, this is not the case in all images, which may negatively affect the performance of the proposed model. Therefore, we have used Otsu's thresholding method to find the optimal threshold for each image. Then we have used this threshold value to convert the image into a binary image representing the mask filter that will be used to segment the image, as shown in Figure 3. The obtained mask is then multiplied by the three-color channels (Red, Green, and Blue) to extract the region of interest, as is shown in Figure 4. Finally, we have extracted the proposed features from the segmented image that is shown in Figure 4.

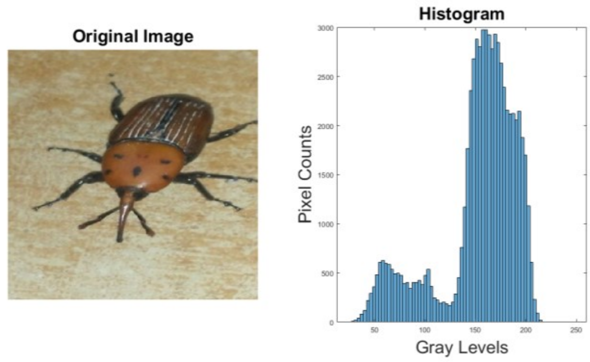


**Figure 1.** Sample of the dataset with its histogram.

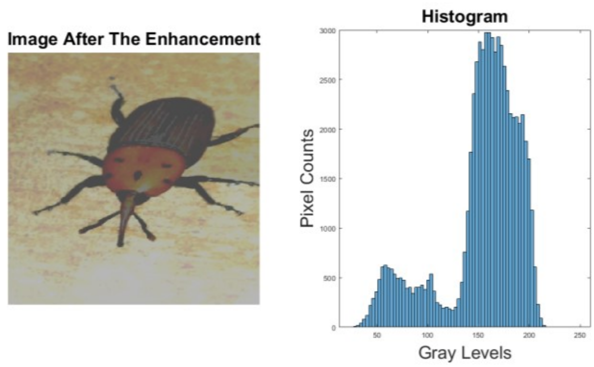


**Figure 2.** Results after the enhancement step.

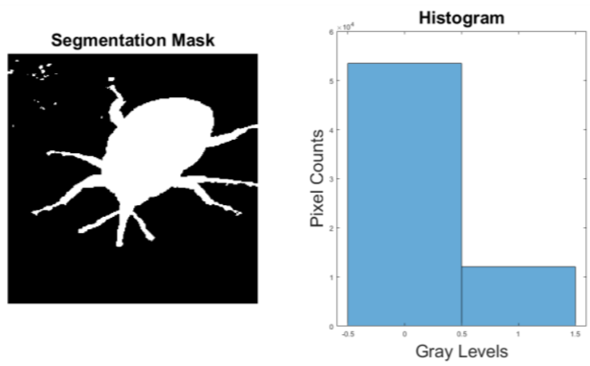


**Figure 3.** Binary mask obtained by Otsu's method.

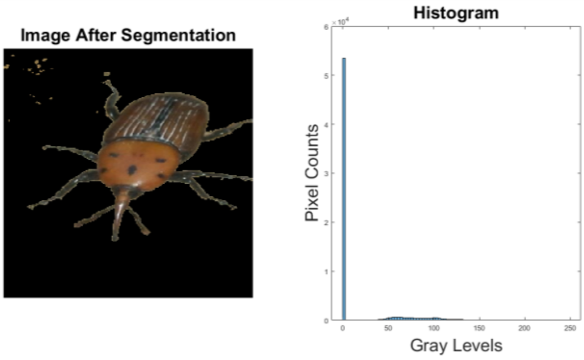


**Figure 4.** Results after the segmentation step.

### 2.2. Feature Extraction

This stage concentrateson transforming the input images from a matrix of pixels into a specific number of features. Those features arethen used as inputs to the classification models and help differentiate between input patterns (in this project, help distinguish between PRW and Ant). This study proposed hybridizing texture features (four features) with color moments features (nine features). Since insects differentiate from each other in texture and color, the proposed feature extraction model concurrently calculates each kind of feature. In order to extract texture features, Gray Level Co-Occurrence Matrix (GLCM) should be calculated from the segmented image. Then, there are many statistics exist that can be derived from GLCM [9]. But in our study, we have just used four texture properties: Energy, Contrast, Correlation, and Homogeneity. Concurrently, the Red Green Blue (RGB) image isseparated into three layers wherein three-color moments are extracted. These moments are called first, second, and third moments and their equations are shown in Eqs. (1-3).

$$M = \frac{1}{N}\sum_{j=1}^{N} P(i,j) \quad (1)$$

$$\sigma = \sqrt{\frac{1}{N}\left(\sum_{j=1}^{N}(P(i,j) - M)^2\right)} \quad (2)$$

$$S = \sqrt[3]{\frac{1}{N}\left(\sum_{j=1}^{N}(P(i,j) - M)^3\right)} \quad (3)$$

### 2.3. Classification

This stage focuses on training the artificial neural networks to classify whether the input features are for RPW or ant. ANNs can identify and learn correlated patterns between input data sets and corresponding target values. The configuration of ANNs used in this study is one input layer with 13 nodes, one hidden layer with 92 nodes, and one output layer with 2 nodes. The trial and error method is used to find the optimal number of hidden layer nodes, as it is suggested in [10]. The training algorithm used in training is Levenberg-Marquardt backpropagation [11].

## 3. Results and Discussion

Due to the lack of data set of PRW images in the literature, we have collected a new data set. The collected data set consists of 913 images, where 448 are RPWs' images, and the rest are Ants' images. Since our problem is a classification problem, and our data set is balanced, the accuracy metric is enough to test the performance of the proposed model. However, a confusion matrix is also used in order to test the performance of the proposed model. Moreover, the classification model was trained for 30 independent runs and tested using 10-fold cross-validation to study the stability and variance of the model. Table 1 shows the Best, the Mean, and Standard Deviation of the classification accuracy metric over the 30 runs of ANNs. Table 2 shows the confusion matrix of the best run for ANNs.

**Table 1.** Classification accuracy results of the 30 runs.

| Model | Best% | Mean% | Standard Deviation% |
|---|---|---|---|
| ANN | 92.2217 | 87.7475 | 1.7215 |

**Table 2.** Confusion matrix of the best run for ANNs.

| | | Actual | | |
|---|---|---|---|---|
| | | RPW | Ant | Sum |
| Predicted | RPW | 421<br>46.11% | 44<br>4.82% | 465<br>90.54% |
| | Ant | 27<br>2.96% | 421<br>46.11% | 448<br>93.97% |
| | Sum | 448<br>93.97% | 465<br>90.54% | 913<br>92.22% |

The 10-fold cross-validation means the dataset is randomly partitioned into ten equal subsamples, and the proposed model is trained ten times using nine parts of the dataset, wherein each time is tested using a different part of the ten parts. After that, the average of the ten times represents the accuracy of this run. We have used 10-fold cross-validation as a performance measurement metric to ensure no bias in the dataset. Moreover, we have examined the model's performance for 30 runs to check the stability of the results.

As it is shown in Table 1, the proposed model archives competitive accuracy on 10-fold cross-validation experiments (92.22%). Moreover, the mean accuracy of the 30 runs proves that the proposed model can be generalized and used in real-time applications with high accuracy. The standard deviation that is shown in Table 1 proves that the proposed model has low variance. Furthermore, if the model is trained again, it will give a similar performance. The results shown in the confusion matrix tell us that the accuracy rate for RPWs' images is 93.97% and 90.54% for Ants' images. That means our model can identify RPWs' images so efficiently.

## 4. Conclusions

This study proposed an artificial intelligence model to easily recognize RPW insects to decrease the massive economic losses that occur due to the damage happened to the trees because of the RPW. In this model, each image has to go through the following steps. First, the image is enhanced using erodes and delites filters. Next, the insect region is segmented using Otsu's method. Then, four texture and nine color moments features are extracted from the segmented part of the image. Finally, the artificial neural network is used to recognize whether the image is RPW or not. The experimental results of the 10-fold cross-validation show that the accuracy of the proposed model is very competitive, and that is 92.22%. Moreover, the proposed model can be used in real-world applications since we have used a new dataset that consists of images with different backgrounds. However, in future studies, we are planning to collect more images in order to be able to use deep learning techniques like Convolutional Neural Networks. Furthermore, other kinds of machine learning models could be proposed, such as using different types of features. If there were enough images and deep learning techniques were used, the accuracy would exceed 95%.

## Declaration of Ethical Standards

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

## Conflict of 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.

## References

[1] Ahmed H., 2020. Red Palm Weevil Detection Methods: A Survey. Journal of Cybersecurity and Information Management (JCIM), **1**(1), pp. 17-20.

[2] Al-Saqer S. M., 2012. A reliable identification system for red palm weevil. American Journal of Applied Sciences, **9**(8), p. 1150.

[3] Hassan G. M., Al-Saqer S. M., 2012. Support vector machine based red palm weevil (Rynchophorus ferrugineous, Olivier) recognition system. American Journal of Agricultural and Biological Sciences, **7**(1), pp. 36-42.

[4] Alaa H., Waleed K., Samir M., Tarek M., Sobeah H., Salam M. A., 2020. An intelligent approach for detecting palm trees diseases using image processing and machine learning. Int. J. Adv. Comput. Sci. Appl., **11**(7), pp. 434-441.

[5] Eldin H. A., Waleed K., Samir M., Tarek M., Sobeah H., Salam M. A., 2020. A Survey on Detection of Red Palm Weevil Inside Palm Trees: Challenges and Applications. In Proceedings of the 2020 9th International Conference on Software and Information Engineering (ICSIE), Cairo, Egypt, 11-13 November, pp. 119-125.

[6] Haralick R. M., Shapiro L. G., 1992. Computer and robot vision. Vol. 1. Reading: Addison-wesley.

[7] Otsu N., 1979. A threshold selection method from gray-level histograms. IEEE transactions on systems, man, and cybernetics, **9**(1), pp. 62-66.

[8] Saleh R. A. A., Rüştü A. K. A. Y., 2019. Classification of melanoma images using modified teaching learning based artificial bee colony. Avrupa Bilim ve Teknoloji Dergisi, pp. 225-232.

[9] Haralick R. M., Shanmugam K., Dinstein I. H., 1973. Textural features for image classification. IEEE Transactions on systems, man, and cybernetics, (6), pp. 610-621.

[10] Saleh N. A., Ertunç H. M., Saleh R. A., Rassam M. A., 2021. A Simple Mask Detection Model Based On A Multi-Layer Perception Neural Network. In 2021 International Conference of Technology, Science and Administration (ICTSA), 22-24 March, pp. 1-5. IEEE.

[11] Moré J. J., 1978. The Levenberg-Marquardt algorithm: implementation and theory. In Numerical analysis, pp. 105-116. Springer, Berlin, Heidelberg.