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Intelligent detection of citrus fruit pests using machine vision system and convolutional neural network through transfer learning technique

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ABSTRACT

Plant pests and diseases play a significant role in reducing the quality of agricultural products. As one of the most important plant pathogens, pests like Mediterranean fruit fly cause significant damage to crops and thus annually farmers face a lot of loss in their products. Therefore, the use of modern and non-destructive methods such as machine vision systems and deep learning for early detection of pests in agricultural products is of particular importance. In this study, citrus fruit images were taken in three stages: 1) before pest infestation, 2) beginning of fruit infestation, and 3) eight days after the second stage, in natural light conditions (7000–11,000 lux). A total of 1519 images were prepared for all classes. To classify the images, 70% of the images were used for the network training stage, 10% and 20% of the images were used for the validation and testing stages. Four pre-trained CNN models, namely ResNet-50, GoogleNet, VGG-16 and AlexNet as well as the SGDm, RMSProp and Adam optimization algorithms were used to identify and classify healthy fruit and fruit infected with the Mediterranean fly. The results of evaluating the models in the pest outbreak stage showed that the VGG-16 model with the help of SGDm algorithm had the best efficiency with the highest detection accuracy and F1 of 98.33% and 98.36%, respectively. The evaluation of the third stage showed that the AlexNet model with the help of SGDm algorithm had the best result with the highest detection accuracy and F1 of 99.33% and 99.34%, respectively. AlexNet model using SGDm optimization algorithm had the shortest network training time (323 s). The results of this study showed that convolutional neural network method and machine vision system can be effective in controlling and managing pests in orchards and other agricultural products.

1. Introduction

Nowadays, pest and disease control are crucial steps in reducing crop losses. One of the most destructive pests that affect agricultural products such as citrus fruits is the Mediterranean fruit fly (MFF) [1]. With its high reproduction rate, adaptation to different climatic conditions, lack of natural enemies and the existence of more than 350 species of hosts (fruits and vegetables) for it, this pest has been able to spread rapidly around the world [2,3]. The life cycle of this pest is between 21 and 30 days and can be described in four consecutive stages which consist of 1) the penetration of the female fly's bite into the fruit and laying eggs inside it, 2) conversion of eggs into larva that feed on the fruit, resulting in gradual spoilage due to the penetration of fungi and bacteria through the tunneling created in the fruit, 3) exit of larva from the fruit to pupate and its fall on the soil and 4) passing the maturation stage in the soil and departure from the soil; beginning to mate after five days [4,5]. Successive generations of flies are born after several months due to the availability of hosts. Common methods for controlling this pest in the world are the use of insecticides, protein bait spraying [6], trapping in the contaminated environment [7] and sterilization of male insects [8]. Currently, this pest is controlled by using trapping or spraying methods in some gardens of Mazandaran province, Iran (Fig. 1).

Since using these methods has not been able to definitively prevent MFF from invading citrus fruits, early and non-destructive identification of infected fruits (in the larva stage) and prompt implementation of management activities are essential to effectively control it and prevent the birth of its next generation. Only by continuous monitoring of citrus fruits and accurate pest diagnosis, can the cost of control and crop losses

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be reduced [1,9]. The time of flies' attack to citrus and the onset of damage depends on the host fruit and the area's climate. However, not all farmers have timely access to experts [10]. To be able to supply the demand for agricultural products, agricultural problems should be addressed by advanced techniques. Thus, agricultural industries are focusing on the application of artificial intelligence methods [11,12,38]. Several traditional machine learning (ML) algorithms have been used to classify plant diseases. However, after the evolution of deep learning (DL), many state-of-the-art architectures, including AlexNet, Visual Geometry Group (VGG), DenseNet, Inception-v4 and ResNet, showed promising results for the classification of plant diseases [13–16]. This is due to the automatic feature extraction capability of the DL algorithms. One of the architectures of interest in the DL method is the CNN, which has been widely used in digital image processing [17–19]. Among different methods used to tackle agricultural problems, the successful classification of plant diseases is vital in improving the quality/quantity of agricultural products and reducing an undesirable application of chemical sprayers such as fungicides/herbicides. Thus, advancing automated plant disease detection is an emerging research topic. However, it is a very complex process due to the resemblance of the plants affected by diseases [16]. Therefore, several studies have been conducted to improve the classification of plant diseases using CNN (Table 1). The aim of this study was to automatically detect citrus fruits infected with Mediterranean fruit fly larvae using machine vision system and convolutional neural network through transfer learning technique. Early detection of this disease in the early stages of its emergence (physical symptoms of the pest on the fruit) can minimize damage to crops and prevent the spread of the disease in orchards. Early detection of this pest can also be very effective in reducing costs in other agricultural activities.

2. Materials and methods

2.1. Imaging

In this study, 1519 images of citrus orchards located in Mazandaran province in Iran were prepared. Images were taken in three different stages at three different times 1) before pest infestation, 2) beginning of fruit infestation or when fruit discoloration starts to occur, 3) 8 days after the second stage. The images were taken using a mobile phone camera (Samsung, J5 Model with a camera resolution of 13 megapixels) at a distance of about 30 cm from the tree (Table 2 and Fig. 2). A lux meter device (Lutron-TEM 8820) was used to measure the ambient light intensity range. Imaging took place in natural light conditions (7000–11000 LUX) with a size of 2322 × 4128 pixels and a resolution of 72 dpi.

2.2. Pre-processing images

In this research, images have a large size (2322 × 4128 pixels) and this reduces the speed of image analysis and processing. Therefore, to achieve the highest classification accuracy, the image size was changed to 224 × 224 and 227 × 227 pixels. Image resize is carried out due to the following reasons [30,31].

- The number of network parameters decreases.
- The number of local connections decreases.

Table 1
Brief report of research results to compare diagnostic accuracy between different CNN models.

Authors	Application	Number image	Algorithm	Accuracy (%)
Ramalingam et al. [20]	Remote insects trap monitoring	200	Faster RCNN ResNet- 50	94
Sushmitha et al. [21]	Eggplant diseases	1747	AlexNet Google Net ResNet-101 DenseNet-201	97.4 99.9 97.8 99.8
Pham et al. [22]	Pest detection on traps	3000	SSD + VGG-16	86
Xing et al. [23]	Citrus pests and diseases recognition	12,561	VGG-16 SENet-16 Weakly DenseNet-16 MobileNet-v2	93 88.71 93.42 87.97
Xia et al. [24]	Insect detection	4800	VGG-19 + RPN	89.22
Liu et al. [25]	Grape leaf diseases identification	7660	VGG-16 GoogleNet ResNet-34 SVM	88.96 94.25 94.67 67.82
Saleem et al. [16]	Plant disease classification	54,306	VGG-16 AlexNet ResNet-50 DenseNet-121 Improved GoogleNet Inception ResNet v2	81.89 95.78 94.23 95.80 95.21 90.91
Dasgupta et al. [26]	Potato disease	2152	ResNet-50 ResNet-101 DenseNet121 VGG-16	99.43 99.43 100 98.87
Tetila et al. [27]	Diagnosis of soybean plant pests	5000	ResNet-50 VGG-16 VGG-19 Exception	93.82 91.80 91.33 90.52
Jiang et al. [28]	Apple leaf diseases	26,377	AlexNet GoogleNet VGG-16 ResNet-34 ResNet-50 ResNet-101 InceptionV3	95.78 94.85 96.10 93.17 92.43 91.16 95.49
Luaibi et al. [29]	Citrus leaf diseases	200	ResNet-50 AlexNet	95.83 97.92

Fig. 1. Common types of traps for catching MFF.

Table 2
Number of images recorded in three imaging steps.

Steps	Imaging time	Number of images
1	Healthy fruit (22 days before discoloration of the fruit)	500
2	Observe the beginning of the color change in the fruit	512
3	Imaging 8 days after step 2	507
Total number of images		**1519**

- Network training speed increases.

2.3. Implementing models on CNN

In order to achieve the highest classification accuracy, four different pre-trained models on CNN, namely AlexNet, GoogleNet, VGG-16 and ResNet-50 and three different optimization models, i.e. SGDm, RMSProp and Adam were used in this study. The number of layers used in these models is reported in Table 3.

2.4. Transfer learning and pre-trained models on CNN

In this study, transfer learning approach was applied to retrain DL models and the citrus fruit pests classification tasks are evaluated in terms of accuracy and efficiency. DL models contain layered architecture with different layers to learn complex features of the citrus fruit pests images and finally, all these layers are connected to a fully connected layer to get the final results. In transfer learning, this layered architecture is allowed to use the pre-trained models such as AlexNet, ResNet and VGG-16 without its final classification layer as fixed feature extractor to achieve better citrus fruit pests classification performance with less training time. We mainly explore four DL models based on CNN such as AlexNet, ResNet, GoogLeNet and VGGNet for classification of citrus fruit pests via transfer learning. The contribution of this work is an effective learning methodology, which is used to tackle the citrus fruit pests classification problem. The DL models that are adopted to train on different datasets using transfer learning are explained detail in the next subsections.

2.4.1. AlexNet model

The AlexNet model is an eight-layer neural network designed by Hinton. The model, which consists of five convolution layers and three fully connected layers with 60 million parameters and 650,000 neurons, won the Image Net competition in 2012 [32,33]. The size of the input images required in this model is 227 × 227 × 3.

2.4.2. GoogleNet model

This model consists of 22 layers and has 7 million parameters, and like other CNN models, uses the ReLU function instead of tangential and sigmoid functions in neural network structures, which speeds up training [32,33]. The size of the input images required in this model is 224 × 224 × 3.

2.4.3. VGG model

This model was introduced by the University of Oxford in 2014. Several versions of VGG with variable layers have been developed under the names VGG-11, VGG-13, VGG-16 and VGG-19. The VGG-16 model consists of 13 convection layers and 3 complete connection layers with 133 million parameters. In this model, instead of annular (circular) cores with the sizes of 11 × 11 and 7 × 7, a small size of 3 × 3 was used to increase the depth of the network [32]. The size of the input images required in this model is 224 × 224 × 3.

2.4.4. ResNet model

This model was introduced by He Kaiming in 2015. In this model, the advantage of increasing the network depth (i.e. increasing the number of circular layers) is used to extract meaningful features. Therefore, the deeper the network, the more complex output characteristics are learned by the network [32,33]. The size of the input images required in this model is 224 × 224 × 3.

2.5. Optimization algorithms

In recent studies, various optimization algorithms have been used to achieve better results in the DL method. These algorithms have improved DL models by updating weight and loss parameters. Stochastic Gradient Descent with Momentum (SGDm) is one of the most widely used optimization algorithms for deep neural networks. This method uses the same numerical learning ratio for the parameters that are effective in the development of education, and offers good performance

Table 3
Number of layers for the different CNN models.

CNN models	AlexNet	VGG-16	GoogleNet	ResNet-50
Number of Layers	8	16	22	50

Fig. 2. Sample images recorded in three stages A) Healthy fruit B) Pest outbreak and the beginning of fruit discoloration at the site of fly bite C) eight days after stage B.

[32]. Root Mean Squared Propagation (Rmsprop) algorithm is based on adaptive learning, which considers a separate learning speed for each parameter [32]. Adaptive Moment Estimation (Adam) is an adaptive optimization algorithm that uses a combination of the heuristic properties of SGDM and RMSProp algorithms [32].

2.6. Training, validation and testing of the networks

To avoid overfitting, the dataset is divided into three categories: training, validation, and testing: 70%, 10%, and 20%, respectively [16, 27]. Therefore, in each stage, 70% of the images were considered for network training, 10% of the images were considered for validation, and 20% of the images were considered for testing. To achieve the best results, SGDm, RMSProp and Adam optimization algorithms were used to train the networks.

2.7. Evaluation metrics

Standard statistical metrics such as Accuracy, Precision, Recall, and F1 are used to evaluate the diagnostic performance and classification of algorithms [30,34,35]. The metrics are calculated using Equations (1)–(4). In this study, each simulation is done five times and the mean, and standard deviation of the results are reported.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

where:

TP: The number of infected images that the system has correctly detected.

TN: The number of healthy images that the system has correctly detected.

FN: The number of healthy images identified by the system as infected fruit.

FP: The number of infected images that the system has detected as healthy.

3. Results and discussion

In this study, the deep learning approach was used for early detection of the MFF infection. At first, the collected images were pre-processed and classified in terms of size. Then, the pre-processed images were given as input to the pre-trained AlexNet, ResNet-50, GoogleNet and VGG-16 models for feature extraction. Some well-known optimization algorithms such as SGDm, Adam and RMSProp were also used in the training process. In this section, we present a comparative analysis of the four models' performance, the results of which led to the selection of the best model and the appropriate optimization algorithms for the current problem.

The performance of different CNN models using evaluation criteria for healthy fruit images is reported in Table 4. The results show that among the evaluated models, the AlexNet model with Adam and SGDm optimization algorithms performed best with the accuracy of 98.80% and 98.75%, respectively. The lowest network training time in AlexNet model using Adam and SGDm optimization algorithms was 483 and 347 s, respectively. The comparison of the accuracy of different CNN models for healthy fruit detection is shown in Fig. 3. The results show that the use of SGDm optimization algorithm in different CNN models increases the detection accuracy. The lowest detection accuracy (94.56%) corresponds to the VGG-16 model using the RMSProp optimization algorithm and the highest detection accuracy (98.80%) corresponds to the AlexNet model using the Adam optimization algorithm.

Table 4
Comparison of testing phase results for ResNet-50, Google Net, Alex Net and VGG-16 models (Healthy fruit).

Pre-trained models	Optimizers	Precision	Recall	F1-score	Accuracy	Train time (Second)
ResNet-50	SGDm	97.92 ± 0.90	97.90 ± 0.93	97.91 ± 0.92	97.89 ± 0.88	2702
	RMSProp	96.65 ± 1.72	96.61 ± 1.70	96.63 ± 1.71	96.50 ± 1.65	2984
	Adam	97.73 ± 2.78	97.75 ± 2.81	97.74 ± 2.79	97.70 ± 2.78	2909
Google Net	SGDm	98.73 ± 0.39	98.70 ± 0.35	98.72 ± 0.37	98.65 ± 0.38	983
	RMSProp	96.86 ± 0.77	96.84 ± 0.74	96.85 ± 0.76	96.77 ± 0.75	1023
	Adam	97.97 ± 0.62	97.91 ± 0.56	97.95 ± 0.58	97.88 ± 0.59	1065
Alex Net	SGDm	**98.78 ± 0.67**	**98.74 ± 0.63**	**98.76 ± 0.65**	**98.75 ± 0.62**	**347**
	RMSProp	96.79 ± 2.87	96.86 ± 2.81	96.84 ± 2.84	96.77 ± 2.83	502
	Adam	**98.85 ± 0.97**	**98.80 ± 0.93**	**98.83 ± 0.95**	**98.80 ± 0.95**	**483**
VGG-16	SGDm	97.11 ± 0.82	97.03 ± 0.75	97.05 ± 0.79	96.98 ± 0.68	4317
	RMSProp	94.65 ± 3.13	94.62 ± 3.11	94.64 ± 3.12	94.56 ± 3.20	4586
	Adam	97.15 ± 1.21	97.12 ± 1.23	97.13 ± 1.22	97.07 ± 1.03	508

Table 5 shows the results of the evaluation metrics for different CNN models in the pest outbreak stage (beginning of fruit discoloration in the bitten area). The results obtained from Precision, Recall, F1 and accuracy criteria using different models show that the efficiency of the VGG-16 model that uses the SGDm algorithm with the acquisition values of 98.39%, 98.34%, 98.36% and 98.33%, respectively, is better in comparison to other models (Figs. 4 and 5). In cases where there is an unbalanced distribution of data classes, the F1 criterion is a suitable metric to show the model's ability in the classification task [16]. For example, in a dataset, the number of the images of the fruits infected with MFF is less than the number of the images of the healthy fruits. Therefore, the

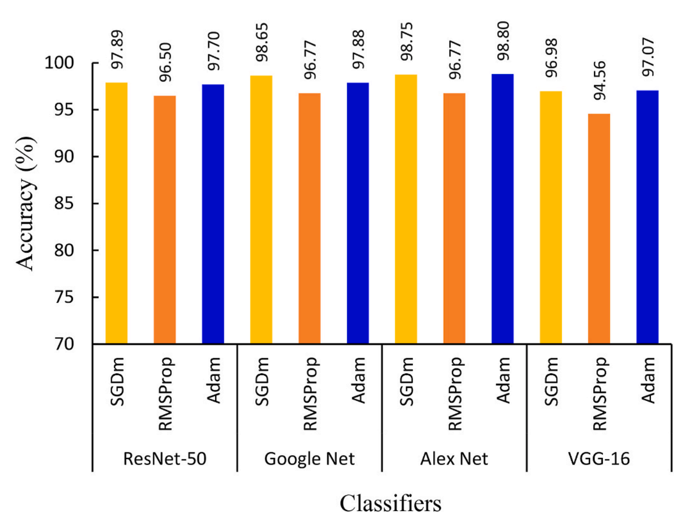

Fig. 3. Comparison of diagnostic accuracies of the pre-trained models (Healthy fruit).

Table 5
Comparison of testing phase results in the ResNet-50, GoogleNet, Alex Net and VGG-16 models in the early stages of the outbreak.

Pre-trained models	Optimizers	Precision	Recall	F1	Accuracy	Train time (Second)
ResNet-50	SGDm	96.69 ± 0.32	96.66 ± 0.35	96.68 ± 0.33	96.68 ± 0.33	3062
	RMSProp	96.25 ± 1.68	96.01 ± 2.07	96.26 ± 1.88	96.02 ± 2.06	3321
	Adam	96.51 ± 2.25	96.44 ± 2.02	96.49 ± 1.94	96.44 ± 2.01	3409
Google Net	SGDm	97.22 ± 1.16	97.18 ± 1.16	97.20 ± 1.15	97.17 ± 1.15	1073
	RMSProp	97.37 ± 1.29	97.34 ± 1.26	97.37 ± 1.25	97.34 ± 1.27	1117
	Adam	97.83 ± 1.53	97.92 ± 1.74	97.75 ± 1.63	**97.67 ± 1.74**	1183
Alex Net	SGDm	97.56 ± 0.46	97.50 ± 0.50	97.54 ± 0.51	97.50 ± 0.50	366
	RMSProp	97.40 ± 0.98	96.83 ± 1.04	97.37 ± 1.03	96.83 ± 1.04	421
	Adam	96.07 ± 1.72	95.75 ± 2.02	95.91 ± 1.87	95.75 ± 2.02	389
VGG-16	SGDm	**98.39 ± 0.61**	**98.34 ± 0.67**	**98.36 ± 0.63**	**98.33 ± 0.67**	5236
	RMSProp	84.03 ± 4.20	82.18 ± 5.39	84.42 ± 3.89	**82.09 ± 5.40**	5448
	Adam	88.67 ± 5.55	90.90 ± 6.27	89.93 ± 7.67	91.13 ± 6.51	5432

value read from the F1 criterion in using the VGG-16 model shows that this model is more appropriate in terms of classification than the other models followed by the GoogleNet and AlexNet models with slight differences. The shortest network training time was achieved with the AlexNet model using SGDm algorithm during a training time of 366 s. The elapsed time shows that the training process in the AlexNet model is faster than the other models. Comparison of detection accuracy between CNN models in the MFF outbreak stage (Fig. 5) shows that the use of the SGDm optimization algorithm increases detection accuracy in most cases. The lowest detection accuracy occurred using the RMSProp algorithm in the VGG-16 model.

The results of the evaluation criteria for different CNN models are shown eight days after the outbreak of the pest (Table 6). Among the evaluated models, the AlexNet model with the SGDm algorithm and the GoogleNet model with Adam algorithm had the best performance, with the respective detection accuracies of 99.33% and 99.25% (Figs. 6 and 7). Also, the highest F1 for the AlexNet model with the SGDm algorithm and the GoogleNet model with the Adam algorithm were 99.34% and 99.28%, respectively. The lowest network training time in the AlexNet model was obtained using the SGDm optimizer algorithm with 323 s.

The evaluation results of the models at the beginning of the pest outbreak (Table 5) shows that all the models have good performances if the optimized algorithms are selected correctly for detecting the infected fruit. For example, the highest detection accuracy among the evaluated models was 98.33% and belonged to the VGG-16 model that used the SGDm algorithm, while the lowest detection accuracy with the value of 82.09% was obtained through the VGG-16 model that used the RMSProp algorithm. At this stage, GoogleNet, AlexNet and ResNet-50 models were slightly different from the VGG-16 model in accuracy. This is due

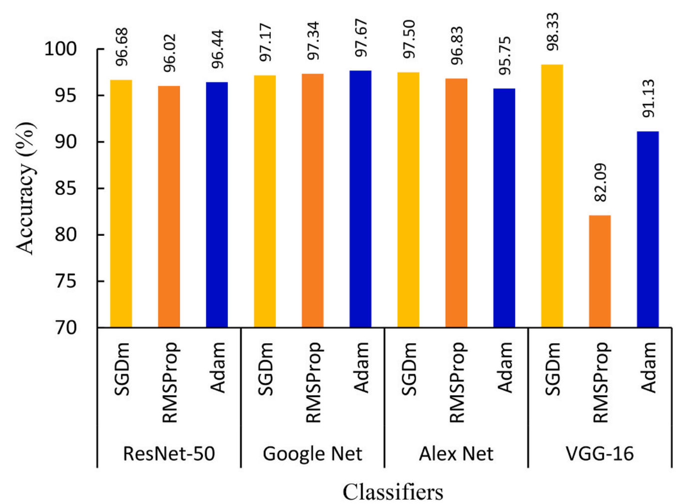

Fig. 5. Comparison of detection accuracy in pre-trained models in the early stages of the outbreak.

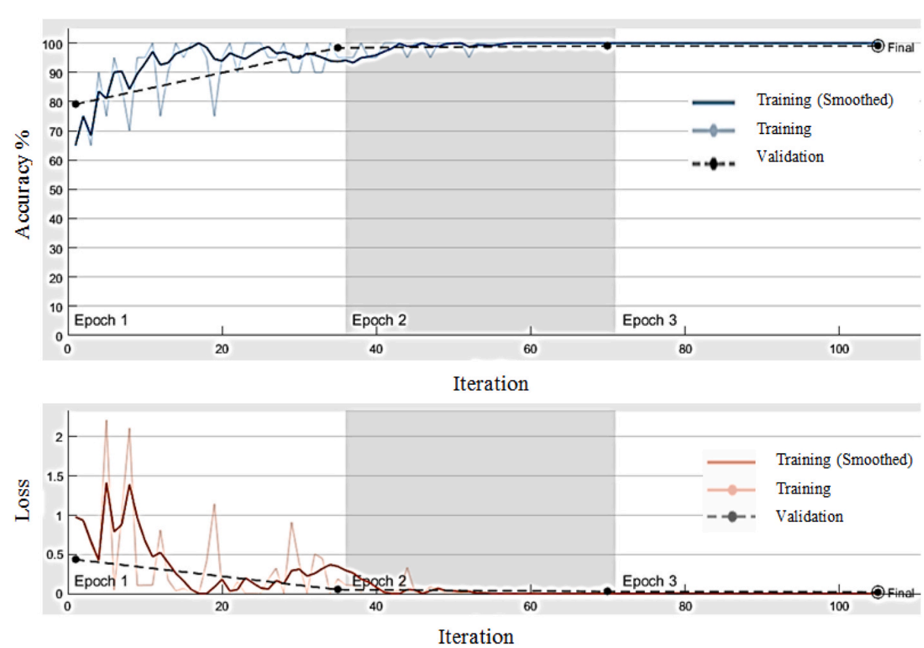

Fig. 4. Diagram of detection accuracy and loss in the VGG-16 model using the SGDm optimization algorithm.

Table 6
Comparison of testing phase results for ResNet-50, Google Net, Alex Net and VGG-16 models (eight days after the outbreak stage).

Pre-trained models	Optimizers	Precision	Recall	F1	Accuracy	Train time (Second)
ResNet-50	SGDm	97.63 ± 0.95	97.60 ± 0.94	97.62 ± 0.93	97.59 ± 0.95	2899
	RMSProp	97.55 ± 1.39	97.51 ± 1.44	97.53 ± 1.42	97.50 ± 1.44	3210
	Adam	93.99 ± 3.87	93.84 ± 3.94	93.92 ± 3.87	93.85 ± 3.94	3221
Google Net	SGDm	98.84 ± 0.25	98.83 ± 0.28	98.85 ± 0.26	98.83 ± 0.28	1043
	RMSProp	99.04 ± 0.77	99.01 ± 0.81	99.02 ± 0.79	99.01 ± 0.81	1052
	Adam	99.27 ± 0.62	99.24 ± 0.41	**99.28 ± 0.53**	**99.25 ± 0.47**	1082
Alex Net	SGDm	99.35 ± 0.52	99.33 ± 0.53	**99.34 ± 0.58**	**99.33 ± 0.52**	**323**
	RMSProp	98.19 ± 2.93	98.26 ± 3.21	98.19 ± 2.93	98.26 ± 3.21	426
	Adam	99.26 ± 0.76	99.25 ± 0.75	99.26 ± 0.76	99.25 ± 0.75	416
VGG-16	SGDm	98.55 ± 0.78	98.50 ± 0.82	98.53 ± 0.80	98.51 ± 0.83	4632
	RMSProp	84.37 ± 6.90	84.56 ± 6.91	84.51 ± 6.91	84.56 ± 6.92	4867
	Adam	92.87 ± 3.91	91.44 ± 4.87	92.15 ± 4.39	91.47 ± 4.85	5201

to the high ability of the pre-trained models to extract image features and the small differences among the numbers of layers of these models, which has led to close results. These results are in line with the results reported by Jiang et al. [28] and Dasgupta et al. [26].

The values reported for eight days after the outbreak stage of the pest in Table 6 show that the criteria have increased compared to the results of the previous stage. At this stage, the images were recorded at a time when the discoloration and rot of the fruit at the larvae location was more visible than in the previous stage. These conditions caused the models to achieve more accurate diagnoses than the previous stage by better use of the color and texture features. The evaluation results showed that the highest detection accuracy (99.33%) was obtained by the AlexNet model using SGDm and with the lowest calculation time (323 s). Similarly, Saha & Neware [36] achieved a 88.89% accuracy in diagnosing citrus fruit disease using a proposed model. In a recent study, the transfer learning technique was used in a field of citrus fruits and the highest accuracy of diagnosis for citrus leaf disease was reported to be 97.92% obtained by the AlexNet model [29]. The results of this study indicate the ability of the pre-trained models and the advantage of their application in extracting image features since good results were obtained with access to a small number of images. According to the results of this study, it can be suggested that the AlexNet and GoogleNet models be used in similar research due to their low number of layers and shorter computation time.

Fruit (like oranges) have many nutritional benefits and usually contain several essential vitamins and minerals for humans that are not found in other foods. Eating healthy fruit energizes humans and delivers a wide range of vitamins, minerals, and antioxidants to the human body, ultimately improving their health. Therefore, due to the importance of fruit consumption, achieving simple, rapid, and non-destructive

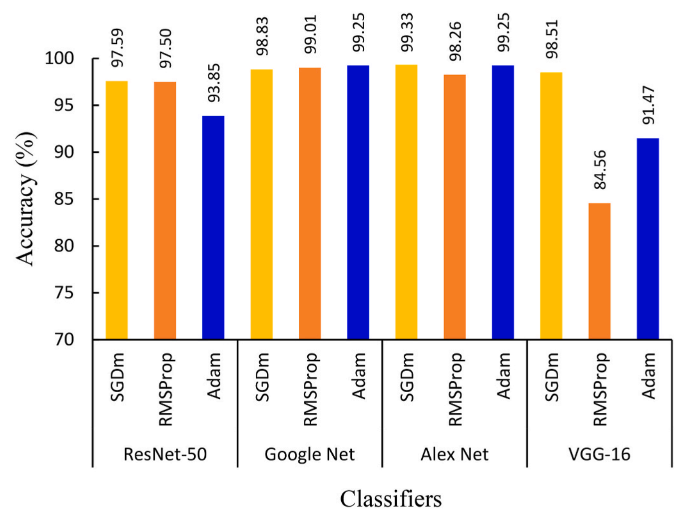

Fig. 7. Comparison of diagnostic accuracies of the pre-trained models (eight days after the outbreak stage).

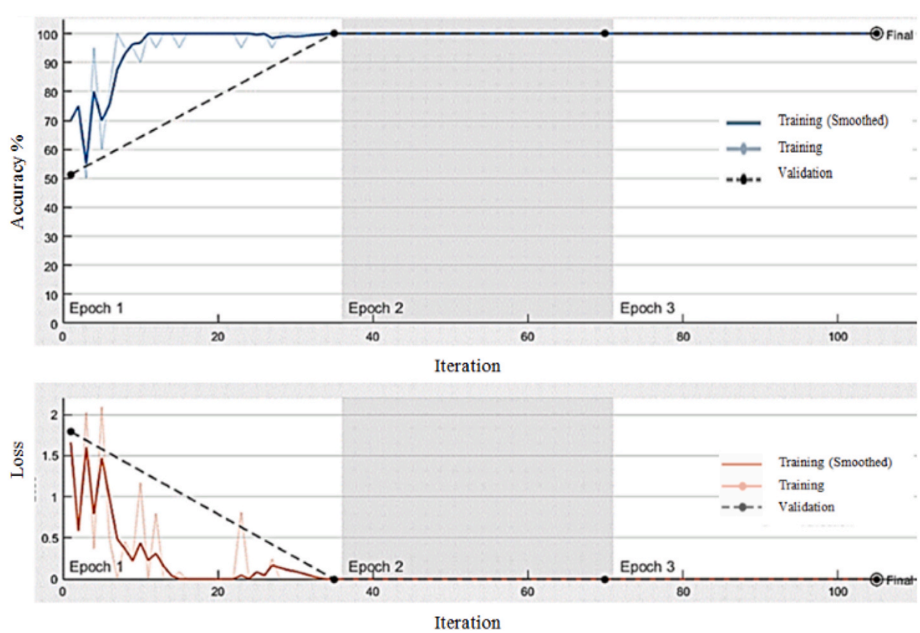

Fig. 6. Diagram of accuracy of detection and loss with AlexNet model using SGDm optimization algorithm (eight days after the outbreak stage).

methods for quality control and fruit grading is of particular importance. Different qualities of an orange fruit (such as orange infected with pests) must be identified and classified before packing. Due to the unique characteristics of orange fruit and many operations such as harvesting, warehousing, transportation, etc. carried out to deliver the product from the field to be consumed, providing a healthy and high-quality product is challenging. Therefore, according to the quality of the fruit in terms of disease-free, orange fruit can be graded from the tree to reduce waste and increase marketability, and then harvest only the healthy, high-quality fruit. This study showed that image processing techniques and the CNN method were very effective and useful for this type of research. The methods used in this research can identify pests infected fruit, and then the farmer can prevent their losses by performing targeted spraying operations. Development of fruit disease detection and classification system can be done in perspective of remote monitoring of the crop to take timely decision and improve fruit quality. Real-time and reliable pest classification and detection are very important in pest and disease monitoring for fruit protection [13,37].

4. Conclusion

In this study, the deep learning method was used to detect fruits infected with MFF larvae and the aim of the study, was timely management of the pest in order to control it and prevent the emergence of its next generation. Images were recorded in natural conditions with a light intensity of 7000–11000 lux in three stages (before the outbreak, at the beginning of the outbreak and eight days after the outbreak). Four pre-trained CNN models, i.e. ResNet-50, GoogleNet, VGG-16, and AlexNet, were used to distinguish between infected fruits and healthy fruits by extracting image features. In addition, in order to achieve the best results, SGDm, RMSProp and Adam optimization algorithms were used for training the networks. The results of model evaluation showed that in the pest outbreak stage, the VGG-16 model that used the SGDm algorithm and the GoogleNet model that applied the Adam algorithm had the best performance with 98.33% and 97.67% detection accuracies, respectively. Also, the evaluation results in the next stage (eight days after the outbreak stage) showed that the AlexNet model using the SGDm algorithm and the GoogleNet model using the Adam algorithm had the best performance with 99.33% and 99.25% detection accuracies, respectively. The values for the precision and recall criteria in the pest outbreak stage using VGG-16 model (above 98%) and in the next stage with AlexNet and GoogleNet models (above 99%) showed that the selected models perform well despite the lack of data. The shortest network training time was obtained with the AlexNet model using SGDm. Since the in-depth features were extracted from pre-trained models on large databases like ImageNet, there is no need for a complex training process. As a result, time and hardware resources are saved. In addition, despite the small number of training data, high diagnostic accuracy has been achieved. Based on the results obtained, it can be said that the use of the transfer learning method in deep structures can be effective in diagnosing pests. Future studies can work on other agricultural products.

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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