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Article

Deep-learning techniques for symptoms' detection of *Aculops lycopersici* (Acari: Eriophyidae) and *Tuta absoluta* (Lepidoptera: Gelechiidae) on tomato

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ABSTRACT
Accurate pest detection is the most fundamental requirement in the management of damage-causing factors. Traditional methods of identifying and counting pests in plants require continuous monitoring, which is very costly and time-consuming in large farms, and involves uncontrollable human errors. It is necessary to help farmers identifying key pests automatically and at the beginning phase of the infestation with the help of new technologies. Therefore, deep-learning techniques and a convolutional neural network with VGG Net-16 architecture were used in this study for the automatic detection of the symptoms of two key tomato pests in Iran: *Tuta absoluta* (Myrick) (Lepidoptera: Gelechiidae) and *Aculops lycopersici* (Tryon) (Acari: Eriophyidae). A Sony DSC-WX200 camera with an effective sensor resolution of 18 megapixels was used to collect images of the symptoms caused by these pests. To evaluate the performance of the convolutional neural network with VGG Net-16 architecture, the parameters of average precision, precision, and recall were used. To evaluate counting performance, a linear regression curve and the coefficient of determination were used. The detection parameters for the symptoms of *T. absoluta* and *A. lycopersici*, including average precision (99.51% and 99.89%, respectively), accuracy (100 for both pests), and recall (100 for both pests), demonstrated the high performance of the convolutional neural network in detecting these two pests. Additionally, the coefficients of determination (0.99 for both pests) indicated the high accuracy of the network in detecting the symptoms of these pests. The results showed that our proposed system can provide a practical solution for the accurate detection of these pests in tomato crops using captured images.

KEYWORDS: Convolutional Neural Network, symptoms, tomato russet mite, tomato leaf miner, VGG Net-16.

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INTRODUCTION

Today, the solanaceous crop tomato, *Solanum lycopersicum* (L.) is an important vegetable farmed globally to meet the demands of fresh markets and processing industries (Shanmugam *et al*. 2024). Tomato cultivation holds a significant place in Iran's agriculture. Iran is the seventh largest producer of tomatoes in the world (Ashtari *et al*. 2020). Various factors, especially pests, lead to a reduction in the yield of tomatoes. The tomato russet mite, *Aculops lycopersici* (Tryon) (Acari: Eriophyidae), and the tomato leaf miner, *Tuta absoluta* (Meyrick) (Lep.: Gelechiidae), are currently spreading and established across the country. The tomato russet mite is a key pest in commercial tomato crop worldwide. This mite feeds on the cell surface of leaves, stems, and fruits. It causes leaves and fruits

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to appear rusty, and it can lead to the death of the plant in severe infestations (Pfaff and Böckmann 2024). Plant infestation is usually detected in the presence of initial symptoms. Early symptoms like light chlorosis on the leaves or light gray and brown shades on the stems are easily overlooked. Also, later more obvious symptoms like browning of stems and leaves may be mistakenly attributed to other pests such as fungi and viruses (Pfaff *et al*. 2019). Overall, no efficient monitoring method for *A. lycopersici* has been developed (Pfaff *et al*. 2020). On the other hand, the tomato leaf miner is considered a key pest of tomatoes in Iran and other parts of the world (Pandey *et al*. 2023). It is a multi-generational pest with high reproductive potential and a short life cycle, causing significant damage to tomato in the country due to the lack of precise information on the pest's biology, absence of effective natural enemies, and unavailability of efficient management tools to control its population (Dehghani *et al*. 2024). Under suitable climatic conditions and without the implementation of appropriate management programs, the damage caused by this pest can lead to the destruction of 90% of the crop in both field and greenhouse conditions (Potting *et al*. 2009).

The damage caused by these two pests in major tomato-growing areas has led farmers to overuse chemical pesticides. This can result in the development of resistance, elimination of biological control agents, pesticide residues on the product, environmental pollution, and increased production costs (Abdelmaksoud *et al*. 2020; Vervaet *et al*. 2021). Therefore, the best and most appropriate way to prevent crop yield reduction and minimize pesticide use is to identify and diagnose plant-damaging factors in a timely manner, which is an important and challenging topic in the field of agriculture (Liu and Wang 2020). Although expert observation is the main approach adopted in practice for pest detection and identification, this approach requires continuous monitoring, which can be costly in large farms. Therefore, it is necessary to help farmers identify and count pests automatically by analyzing digital images.

Computer tools based on advanced machine vision techniques have undergone significant development in the field of agriculture to improve agricultural quality and increase crop yield. Deep learning methods are among the latest technologies in the world and have penetrated all sciences with their advent (Tran *et al*. 2019). In the agricultural sciences, deep-learning models can be used to predict and classify various plant damage factors, like crop management, weed detection, agricultural land management, etc. and can increase the efficiency of the agricultural industry by reducing labor costs and also minimizing the use of chemical pesticides and environmental pollution (Mokhtar *et al*. 2015; Zheng *et al*. 2019). Convolutional Neural Networks (CNN) are one of the most common deep-learning methods for solving machine learning problems and have been widely used in image and video processing (Naranjo-Torres *et al*. 2020). CNNs in agriculture have expanded research in the field of pest management, especially for tomato plants, and have provided a practical strategy for developing better detection methods (Fuentes *et al*. 2018). CNNs can be used to train prediction model results, which not only can save time and labor but also can perform accurate detection and counting. This method significantly reduces the extensive damage caused by pests (Liu and Wang 2020). Thus, different methods for identifying and classifying image-based pests in various products have been proposed. A deep learning-based approach to identify diseases and pests in tomato plants using images captured by cameras with different resolutions was proposed, and the results demonstrated that the proposed system can effectively identify nine different types of diseases and pests (Fuentes *et al*. 2017). Uygun and Ozguven (2024) investigated a deep learning-based method for early detection of damage caused by *T. absoluta* in tomato plant leaves under greenhouse conditions. The results of their studies showed that the YOLOv8l-Seg model and method can effectively detect damage caused by *T. absoluta*.

Although with the rapid development of deep learning technology in recent years, many researchers have conducted numerous studies at home and abroad to improve the accuracy in identifying and diagnosing plant diseases and pests, to date there has been no comprehensive and systematic study to diagnose and enumerate tomato pests in Iran using deep-learning methods, and it seems necessary to provide an approach based on deep learning techniques for accurate detection and enumeration of these pests. Therefore, the primary objective of this study was to apply deep learning techniques to automatically detect and identify the symptoms of tomato russet mites and tomato leaf miner.

MATERIALS AND METHODS

Collection of samples

To capture images of the symptoms of the tomato russet mite and the tomato leaf miner on fruit and leaves of the plant, a Sony DSC-WX200 camera with an effective sensor resolution of 20 megapixels was used. Images were taken from distances of 5, 10, and 15 centimeters from the surface of the leaves and fruit, with 2000 images of each (leaf and fruit) taken every 48 h.

Convolutional Neural Networks (CNN)

CNNs consist of neurons with learnable weights and biases. Each neuron receives several inputs and calculates the product of the weights and inputs, and uses a nonlinear activation function to provide the result. CNNs are typically used for image inputs, where on one side they take the raw pixels of the input image and on the other side they provide scores for each category. A CNN is generally a hierarchical neural network in which convolutional layers are alternated with pooling layers, followed by several fully-connected layers for classification (Shin *et al*. 2016). Therefore, in general, each CNN comprises several main types of layers, each with a different function (O'Shea and Nash 2015).

Convolutional layers

The convolutional layer is the core building block of a convolutional neural network comprising a set of learnable filters. The filters slide across the width of the input, computing the dot product between the filter values and the input values, and passing the result to the next layer.

Pooling layers

The main purpose of this layer is to down sample the input image to reduce the computational load and memory usage. There are different types of pooling, such as average pooling and max pooling. In max pooling, the maximum value is taken, and in average pooling, the average value is taken within each sampling region.

Flattening layer

The flattening layer is typically used before the first fully connected layer and converts the information obtained from the previous layers into a vector.

Softmax layer

This layer is responsible for classification, using the output from the flattening layer and applying specific algorithms such as weighting and voting systems to perform the classification and provide the output.

Architecture used in CNN

In this study, the VGG Net-16 network was used for transfer learning. This architecture was introduced by researchers from the Visual Graphics Group at Oxford (Pattnaik *et al*. 2020). This network is best known for its pyramid-like shape, where layers closer to the image are wider, and layers farther away are deeper. The reason for using this architecture is that it is an excellent design for evaluating specific tasks. In addition, pre-trained VGG networks are freely available on the internet, which explains their popularity in many fields (Al-Ruzouq *et al*. 2020).

Detection of symptoms of the russet mite and tomato leaf miner on leaves and fruits of tomatoes

Identification of the symptoms of these pests in tomato fruits and leaves is performed using this algorithm in three stages. First, valuable features from the input image are extracted using the supporting network of the CNN. Then, in the neck part of the network, these features extracted from the image are combined, producing three feature maps in an S × S grid with strides of 8, 16, and 32. This enhancement improves the network's ability to identify weak, moderate, and extensive symptoms on the surface of leaves and fruits. Finally, the detection of these pests' symptoms in the head part of the network is performed by considering three bounding boxes for each grid cell and assigning the best box to the symptoms. The number of designated bounding boxes at the end determines the range of the pest's symptoms, and the size of each box indicates the extent of damage caused by the pest.

Error function

The error function of the VGG Net-16 algorithm during training is a combination of the objectless score, class probability, and bounding box regression scores (Redmon *et al*. 2016). The objectless score indicates the probability of the object being within the bounding box, the class probability score indicates the probability of correctly labeling each object, and the bounding box regression score determines the overlap between the predicted bounding box and the ground truth box. In VGG Net-16, the object score error and class probability are obtained through the binary cross entropy along with the logical error function and bounding box error by sharing around the general community (Rezatofighi *et al*. 2019).

Evaluation

A confusion matrix was used to evaluate the algorithm performance. The parameters of the confusion matrix are introduced and examined in the following sections.
Accuracy criterion: This criterion indicates the ratio of the correct predictions to the total predictions and is obtained using equation (1):

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn} \quad \text{Equation (1)}$$

where:
t_p: the number of images in which the presence of pests was correctly detected,
t_n: the number of images whose health is correctly detected,
fp: the number of images that are mistakenly identified as pests.
f_n: the number of images that are wrongly recognized as healthy.

Therefore, the fraction form means the sum of the principal diameters in the confusion matrix. The denominator of the fraction means all the images (including both correctly identified images and wrongly classified images). In other words, accuracy means the ratio of correctly identified samples to the total number of samples.

Other important metrics for evaluating classifiers include precision, readability, and the F1 score. The accuracy measure represents the ratio of the number of correct predictions in a given class to the total number of predictions for the same class. The readability criterion expresses the ratio of the number of correctly classified data with correct predictions in a given class to the total number of data in that class. In addition, the F1 score represents the harmonic mean between the precision and readability measures. These criteria are given in equations 2–4 (Dyrmann *et al*. 2016).

$$precision = \frac{tp}{tp + fp} \quad \text{equation (2)}$$

$$Recall = \frac{tp}{tp + fn} \qquad \text{equation (3)}$$

$$f1 - score = 2\frac{precision \times Recall}{precision + Recall} \qquad \text{equation (4)}$$

Tools and implementation environments

The proposed method was implemented in Python on the iPython platform using machine learning frameworks such as Keras and TensorFlow. The code was executed using the Google Colab cloud service. In this simulator, in addition to providing a platform for sharing code and using deep learning frameworks, users are also offered free access to GPUs. In this service, each user is provided with an Nvidia Tesla T4, which the user can use to develop and implement applications or research in the field of deep learning. The network was trained using the Stochastic Gradient Descent with Momentum (SGDM) algorithm and 50 repetitions. Additionally, an initial learning rate of 0.0001, minibatch size of 40, and the other parameters listed in Table 1 were considered.

Table 1. Number of parameters required for the used models.

Type of architecture	parameters	Trainable parameters	non-trainable parameters
VGG Net -16 *Tuta absoluta*	25555041	24555041	0
VGG Net -16 *Aculops*	26777122	26777122	0

RESULTS AND DISCUSSION

Images related to the symptoms of tomato russet mites and tomato leaf miner moth were randomly divided into three datasets: training (70%), testing (15%), and validation (15%). After training, the network accuracy was evaluated on the test data using the cross-validation method. Accordingly, the learning trend during the training phase of the proposed model for the VGG Net-16 architecture for the symptoms of *T. absoluta* and *A. lycopersici* can be observed in Figures 1 and 2.

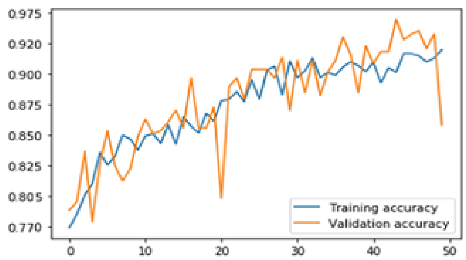

Figure 1. Accuracy of validation of the training process for VGG Net-16 for *Tuta absoluta* architecture. Blue line shows accuracy on training set, orange line shows accuracy on validation set.

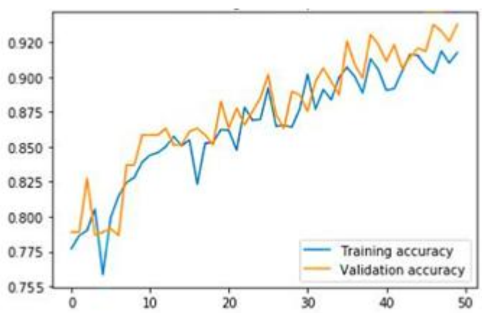

Figure 2. Accuracy of validation of the training process for VGG Net-16 for *Aculops lycopersici* architecture. Blue line shows accuracy on training set, orange line shows accuracy on validation set.

Random samples can be seen from the output of the proposed model, which took input images and correctly predicted the symptoms of *T. absoluta* on the leaf surface and those of *A. lycopersici* on the fruit surface (Fig. 3).

Figure 3. **A.** Symptoms of *A. lycopersici*; **B.** Symptoms of *T. absoluta.*

The confusion matrix for the VGG Net-16 architecture is presented in Tables 2 and 3. The clear conclusion that can be drawn from the confusion matrices is the appropriate capability of the VGG Net-16 architecture for identifying the symptoms of tomato russet mites and tomato leaf miner moth, as well as the absence of these symptoms on leaves and fruits. A high recorded value indicates successful performance of the proposed architecture.

Table 2. implementation confusion matrix.

Prediction/truth	with *Tuta absoluta*	healthy
with *Tuta absoluta*	99/51	0.49
healthy	99.02	0.98

Table 3. implementation confusion matrix.

Prediction/truth	with *Aculops lycopersici*	healthy
with *Aculops lycopersici*	99/89	0.11
healthy	99.62	0.38

According to Table 2, the network error in detecting the symptoms of the tomato leaf miner moth was 0.98%, for detecting the absence of its symptoms, it was 0.49%, and according to Table 3, for the tomato russet mite, it was calculated as 0.1% and 0.3%, respectively.

Based on the parameters mentioned in Table 1, the results of different classification criteria (accuracy, readability, correctness, and F1 score) are shown separately in Tables 4 and 5. According to the results, the accuracy of this method in detecting the symptoms caused by *T. absoluta* was 99.51%, and the accuracy for detecting *A. lycopersici* was 99.89%. These results are consistent with the studies conducted by Durmuş *et al*. (2017) and Suryawati *et al*. (2018), who used deep-learning techniques with the VGG Net-16 architecture to identify and diagnose tomato pests and diseases as their reported accuracy was 97.2% and 95.24%, respectively.

Table 4. Evaluation results of different categories of *Tuta absoluta* with VGG Net-16 architecture in percentage.

Class	Accuracy	Precision	Recall	F1-score
with *Tuta absoluta*	99/51	100	100	100
healthy	99.02	100	100	100

Table 5. Evaluation Results of different categories of *Aculops lycopersici* with VGG Net-16 architecture in percentage.

Class	Accuracy	Precision	Recall	F1-score
with *Aculops lycopersici*	99/89	100	100	100
healthy	99.62	100	100	100

To more accurately evaluate the algorithm's performance in detecting the presence and absence of pest symptoms, a linear regression curve was used between the presence of each sample and the network's detection (Figs. 4, 5).

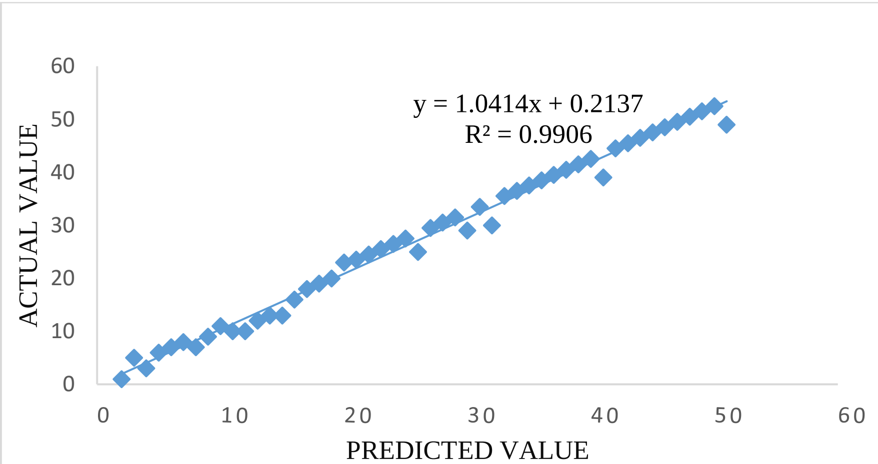

Figure 4. Linear regression relationship and the coefficient of determination between the presence and absence of *Tuta absoluta* symptoms as detected by the VGG Net-16 model.

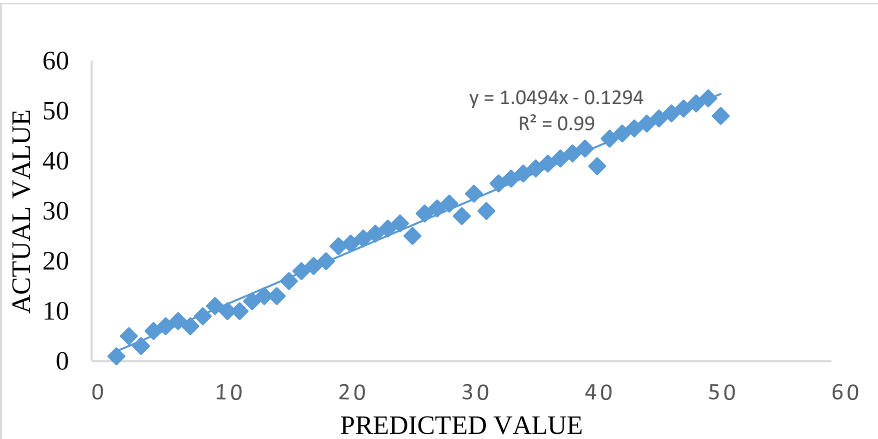

Figure 5. Linear regression relationship and the coefficient of determination between the presence and absence of *Aculops lycopersici* symptoms as detected by the VGG Net-16 model.

These results show the high generalization capability of the VGG Net-16 network for detecting the symptoms of tomato leaf miner moth on leaves (R2 = 0.99) and for detecting the symptoms of tomato russet mite on fruit (R2 = 0.99). These results are in line with the studies of Verma *et al*. (2020) and Fuentes *et al*. (2017), who presented a deep learning-based approach to identify pests in tomatoes using images captured by camera devices with different resolutions.

CONCLUSION

For successful and proper cultivation of agricultural products, accurate pest detection is essential. Fast pest detection in plants can assist in the timely development of control methods, significantly reducing economic losses. Recent advancements in deep learning have allowed researchers enhancing the accuracy of detection systems. One of the primary advantages of using deep learning to detect pest damage symptoms is the significantly reduced time required. Additionally, using artificial intelligence to detect pests in plants is cost-effective, and in some cases, farmers can perform this for free.

The findings of this study suggest that deep learning models have high capability for accurately detecting *T. absoluta* and *A. lycopersici* using captured images. Pest detection methods based on intelligent systems are more efficient than conventional methods. The primary advantage of deep learning over previous methods is that deep learning can identify the type of pest directly from raw images without preprocessing. With an increase in the amount of training data, the recognition power of these models also increases. On the other hand, considering advancements in artificial intelligence and deep-learning, the development of systems for detecting plant pests and diseases remotely and around the clock will become possible in the near future. These systems can automatically identify diseases and pests and take the necessary measures to eliminate them.

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تکنیک یادگیری عمیق برای تشخیص علایم ***Aculops lycopersici*** **(Acari: Eriophyidae)** و ***Tuta absoluta*** **(Lepidoptera: Gelechiidae)** روی گوجه فرنگی

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چکیده

تشخیص دقیق آفات، اساسی‌ترین ضرورت در مدیریت کنترل عوامل خسارت‌زا است. چرا که روش‌های معمول شناسایی و شمارش آفات درگیاهان، نیاز به نظارت مداوم دارد که در مزارع بزرگ بسیار پرهزینه و زمان‌بر و در عین حال دارای خطاهای انسانی غیر قابل کنترل است. کمک به کشاورزان در شناسایی خودکار و به هنگام آفات کلیدی با کمک فناوری‌های نوین، بسیار ضروری است. بنابراین در این پژوهش از تکنیک یادگیری عمیق و شبکه عصبی پیچیده با معماری VGG Net-16، برای تشخیص خودکار علایم *Tuta absoluta* (Myrick) (Lepidoptera: Gelechiidae) و *Aculops lycopersici* (Tryon) (Acari: Eriophyidae) که از آفات کلیدی گیاه گوجه‌فرنگی در ایران به شمار می‌روند، استفاده شد. برای جمع‌آوری تصاویر علایم خسارت این آفات از دوربین عکاسی سونی مدل DSC-WX200 با دقت موثر حسگر ۱۸ مگاپیکسل، استفاده شد. برای ارزیابی عملکرد شبکه عصبی پیچیده با معماری VGG Net-16 از فراسنجه‌های دقت متوسط، دقت و یادآوری استفاده شد. برای ارزیابی عملکرد در شمارش، از منحنی رگرسیون خطی و ضریب تبیین استفاده شد. فراسنجه‌های تشخیص علایم *T. absoluta* و *A. lycopersici* شامل دقت متوسط (۹۹/۵۱٪ و ۹۹/۸۹٪)، دقت (۱۰۰ و ۱۰۰) و یادآوری (۱۰۰) و (۱۰۰)، عملکرد بالای شبکه عصبی پیچیده در تشخیص این دو آفات را نشان داد. همچنین ضریب تبیین (۰/۹۹ و ۰/۹۹) دقت بالای شبکه را در تشخیص علایم این آفات داشت. به طور کلی نتایج نشان داد که سامانهٔ پیشنهادی می‌تواند راه‌حلی کاربردی برای تشخیص دقیق این آفات در گوجه‌فرنگی با استفاده از تصاویر گرفته شده ارایه کند.

کلمات کلیدی: شبکه عصبی پیچیده، علایم، شب‌پره مینوز گوجه فرنگی، کنهٔ حنایی گوجه فرنگی و شبکهٔ VGG Net-16.

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