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Machine vision techniques for identifying symptoms of *Tetranychus urticae* (Acari: Tetranychidae), *Helicoverpa armigera* (Lepidoptera: Noctuidae), and calcium deficiencies in tomato plant

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ABSTRACT

Accurate detection and identification of damaging factors are key requirements for their effective management and control. Conventional methods for detecting these pests in plants require continuous monitoring, which is a costly and time-consuming process on farms and is accompanied by unavoidable human errors. Therefore, it is necessary to use modern technologies to help farmers automatically and promptly identify key pests. In this study, a convolutional neural network with Inception_v3 architecture was used to automatically detect damage symptoms in tomato plants. A Sony DSC-WX200 camera with an effective sensor resolution of 18 megapixels was used to collect images of the symptoms caused by the pests. To evaluate the performance of the convolutional neural network with Inception_v3 architecture, the parameters of average precision, precision, and recall were used. The results showed the accuracy of the Inceptionv3 architecture in identifying the symptoms of *T. urticae* (99.47%), *H. armigera* (99.18%), and calcium deficiency (99.77%). The results indicate that our proposed system, which uses recorded images, can provide an efficient and accurate solution for identifying damaging factors in tomato plants.

KEYWORDS

Convolutional Neural Network, crop monitoring, image processing, pest detection, tomato fruit borer, two-spotted spider mite

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INTRODUCTION

Tomatoes are considered one of the most significant economic and agricultural products globally (Ponce *et al.* 2021). Based on the Iranian Agricultural Statistics for 2023, Iran ranks sixth in global tomato production, with cultivation covering more than 130,000 hectares (Ahmadi *et al.*, 2023). Throughout the planting, growing, and harvesting phases, issues such as pest attacks and nutrient deficiencies significantly affecte tomato yields across different regions (Hu *et al.* 2023).

One challenge with tomato crops is *Tetranychus urticae* Koch (Acari: Tetranychidae), which significantly impacts the quality of plants and their fruits (Al Mallah 2021). The two-spotted spider mite is a major pest of tomatoes due to its highly polyphagous nature, rapid life cycle, prolific reproduction, exceptional capacity to develop resistance to pesticides, and global distribution. More than 150 commercially important horticultural, agronomic, and ornamental plants worldwide have been documented to be affected by this species, which is known to have over 1,200 different host plants

(Abdellatif *et al.* 2023). *Tetranychus urticae* damages plant leaves by creating irregular patterns of small white spots and weaving dense webs that cover the underside of the leaves and petioles (Md Fahmid *et al.* 2024). The reduction in chlorophyll content within the leaves hampers the host plant's productivity, leading to a decline in the net rate of photosynthesis. Disruptions in a plant's physiological processes can greatly influence its growth dynamics, flowering cycles, and total yield output (Jayasinghe and Mallik 2011).

In contrast, the tomato fruit borer *Helicoverpa armigera* (Hübner) (Lep., Noctuidae) is one of the most significant threats to crop productivity (Riaz *et al.* 2021). Today, the increasing economic losses of *H. armigera* on tomatoes has become a major concern for producers of this crop in Iran and other parts of the world (Guo *et al.* 2020; Singla and Singh 2020). The larvae of this pest feed on tomato fruits, leading to significant damage and a noticeable decline in crop yield (Hossain and Tayde 2023). Damage caused by these 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 (Sousa *et al.* 2020).

In addition to the effects of various pests, tomato yield is severely affected by nutrient deficiencies. Nitrogen, phosphorus, potassium, zinc and calcium are recognized as essential nutrients for the growth of many plants, including tomatoes (Hernández-Pérez *et al.* 2020). Calcium is one of the most widely consumed elements in plants, and its role in preserving and maintaining the quality of fruits and vegetables is well known. Calcium is a vital nutrient that plays a key role in the structure of cell walls and membranes, growth and development, and fruit quality (Kadir 2004). Calcium deficiency leads to blossom end rot, which is one of the most important physiological abnormalities in tomatoes (Haleema *et al.* 2024). Blossom end rot significantly reduces the marketable yield of tomatoes. Comprehensive studies on the physiological factors of this disorder have revealed that its root causes are linked to a disrupted calcium (Ca^{2+}) balance in the blossom end of the fruit (Topcu *et al.* 2022). Tissues impacted by BER develop a dark brown color and foamy texture, potentially creating a route for secondary pathogens (Haleema *et al.* 2024).

In general, numerous damaging factors directly and indirectly affect the tomato yield. Therefore, the best 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 (Shanmugam *et al.* 2024). Machine vision and image processing technology can automatically identify, distinguish, and categorize plant damage agents. The development and application of these technologies primarily aim to enhance crop yields, minimize the use of chemicals, and reduce labor expenses (Tran *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, particularly 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 perform accurate detection. This method significantly reduces extensive damage caused by pests (Liu and Wang, 2020). Thus, different methods have been proposed for identifying and classifying image-based pests in various products. 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 could effectively identify nine different types of diseases and pests (Fuentes *et al.* 2017). Uygun and Ozguven (2024) investigated a deep-learning-based method for the early detection of damage caused by *T. absoluta* (Meyrick) in tomato plant leaves under greenhouse conditions. The results of their studies showed that the YOLOv8l-Seg model can effectively detect the damage caused by *T. absoluta*. A study was conducted to identify the damaging factors on tomatoes using a deep convolutional neural network with Inception V3. The accuracy of image classification using this model has been reported to be 87% (Devi *et al.* 2023).

The use of machine vision techniques to swiftly and accurately identify plant damage factors through visible symptoms can significantly assist farmers in improving the crop production process. Nevertheless, to date, no thorough and systematic research has been undertaken in Iran to detect and analyze the primary causes of tomato damage using an integrated approach with machine vision methods.

The primary objective of this research is to utilize a blend of machine vision techniques such as deep learning, artificial neural networks, and support vector machines (SVMs) to accurately identify and detect two-spotted spider mite and tomato fruit borer damage as well as calcium deficiencies affecting the leaves and fruit surfaces of tomato plants.

MATERIAL AND METHODS

Collection of samples

A Sony DSC-WX200 camera, equipped with a 20-megapixel effective sensor, was used to photograph the symptoms caused by *T. urticae*, *H. armigera*, and calcium deficiencies on the leaves and fruits of the plants. Images were captured at distances of 5, 10, and 15 cm from the surface of leaves and fruits. A total of 2000 images of each (leaves and fruits) were taken every 48 h**.**

Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are a specialized type of artificial neural network that is particularly effective for processing structured data, such as images. Inspired by the structure of the human visual system, CNNs have been widely used in tasks such as image recognition, object detection, and even natural language processing. CNNs are composed of interconnected neurons, each equipped with adjustable weights and biases. Each neuron processes multiple inputs, computes the weighted sum of these inputs, and applies a nonlinear activation function to generate the output (Cong and Zhou 2023). Primarily designed for image-related tasks, CNNs obtain raw pixel data from the input image and produce classification scores for each category. Structurally, CNNs are hierarchical neural networks in which convolutional layers are interspersed with pooling layers, culminating in fully connected layers that handle classification tasks. A typical CNN includes several key layers, each serving a specific purpose within the network architecture (Krichen 2023).

Architecture Used in CNN

In this study, we utilized the Inception_v3 network for transfer learning, which is a model originally developed by Google researchers (Zhang *et al.* 2024). Inception refers to a family of convolutional neural networks designed for computer vision tasks. Developed by Google researchers, it was first introduced in 2014 under the name GoogLeNet and later renamed Inception v1. This series holds historical significance as one of the pioneering CNN architectures for distinctly separating its components into three parts: the stem for data input, the body for data processing, and the head for predictions. This modular design is the foundational concept for modern CNN architectures. Inception v3, introduced in 2016, enhances its predecessor, Inception v2, by incorporating factorized convolutions to achieve better performance (Szegedy *et al.* 2016). In this research, for the purpose of data augmentation, the values rescale = 1/25, Rotation rate = 40, Zoom rate = 0.2, Width shift rate = 0.2, height shift rate = 0.2, and Horizontal flip = True were considered.

Identifying the symptoms of **T. urticae, H. armigera** *and calcium deficiencies in tomato plant*

The algorithm identifies symptoms of these damage-causing factors in tomato fruits and leaves using a three-stage process. Initially, the key features from the input image were identified and extracted through the supporting network within the CNN. In the neck section of the network, the features extracted from the image are merged, generating three feature maps organized in an S×S grid with stride sizes of 8, 16, and 32. This improvement significantly enhanced the network's capability to detect and differentiate between weak, moderate, and severe symptoms on the surfaces of leaves and fruits. Finally, the symptoms caused by *T. urticae*, *H. armigera* and calcium deficiencies within the head section of the network were identified by evaluating three bounding boxes per grid cell and selecting the most optimal box to represent the symptoms. The total count of designated bounding boxes ultimately defines the scope of the damage symptoms, whereas the dimensions of each box reflect the severity of the damage inflicted.

Error function and evaluation

The error function in the Inception v3 algorithm during training integrates several components: objectness score, class probability, and bounding box regression errors (Redmon *et al.* 2016). Within Inception v3, objectness score and class probability errors are calculated using binary cross-entropy combined with a logical error function. Meanwhile, the bounding box regression error is shared across the broader model framework to refine performance. (Rezatofighi *et al.* 2019). A confusion matrix was used to assess the performance of the algorithm. The various parameters associated with the confusion matrix are described and analyzed in detail in subsequent sections (Dyrmann *et al.* 2016).

Platforms Utilized to Develop

The proposed approach was developed in Python using the iPython platform, incorporating well-known machine-learning frameworks such as Keras and TensorFlow. The code was run on the Google Colab Cloud platform. This simulator not only serves as a platform for sharing code and utilizing deep learning frameworks but also provides users with complementary access to GPUs. This service grants each user access to an NVIDIA Tesla T4, enabling them to develop and execute applications or conduct research in the domain of deep learning. The network underwent training utilizing the Stochastic Gradient Descent with Momentum (SGDM) algorithm executed over 50 iterations. The process accounted for an initial learning rate of 0.0001, a mini-batch size of 40, and the other parameters outlined in Table 1.

Table 1. Number of parameters required for the used Inception v3 models.

Type of architecture	Parameters	Parameters Trainable	Non-Trainable
Tetranychus urticae	24778481	24779482	0
Helicoverpa armigera	2487784	24889885	0
Calcium deficiency	2874380	2879993	0

RESULTS AND DISCUSSION

Images showing the symptoms of *T. urticae*, *H. armigera*, and calcium deficiency in tomato plants were randomly split into three datasets: 70% for training, 15% for testing, and 15% for validation. Once the training phase was completed, the accuracy of the network was assessed on the test dataset using a cross-validation technique. The learning trend observed during the training phase, based on the Inception v3 architecture, for identifying the damage symptoms of two-spotted spider mites, tomato fruit borers, and calcium deficiency is illustrated in Figure 1. These images show the trend of increasing accuracy in each iteration of this architecture in the two stages of cross-validation and network testing. The upward slope is high in the first iterations and gradually decreases, which indicates the stability of this architecture in distinguishing healthy from infected plants.

Random samples from the output of the proposed model demonstrated its ability to process input images and accurately identify *T. urticae* symptoms on leaf surfaces as well as *H. armigera* and calcium deficiency on fruit surfaces (Fig. 2). The confusion matrix derived from the Inception v3 architecture for identifying two-spotted spider mites, tomato fruit worms, and calcium deficiency is outlined in Tables 2, 3, and 4, respectively. The analysis of the confusion matrices clearly indicates that the Inception v3 architecture demonstrates a strong ability to accurately identify *T. urticae* symptoms on leaf surfaces, as well as *H. armigera* and calcium deficiency on fruit surfaces.

Based on the parameters mentioned in Table 1, the results of the different classification criteria (accuracy, readability, correctness, and F1 score) are listed in Table 5. According to the results, the accuracy of this method in detecting the symptoms caused by *T. urtica* was 99.47%, *H. armigera* was 99.18%, while it was 99.77% for calcium deficiency.

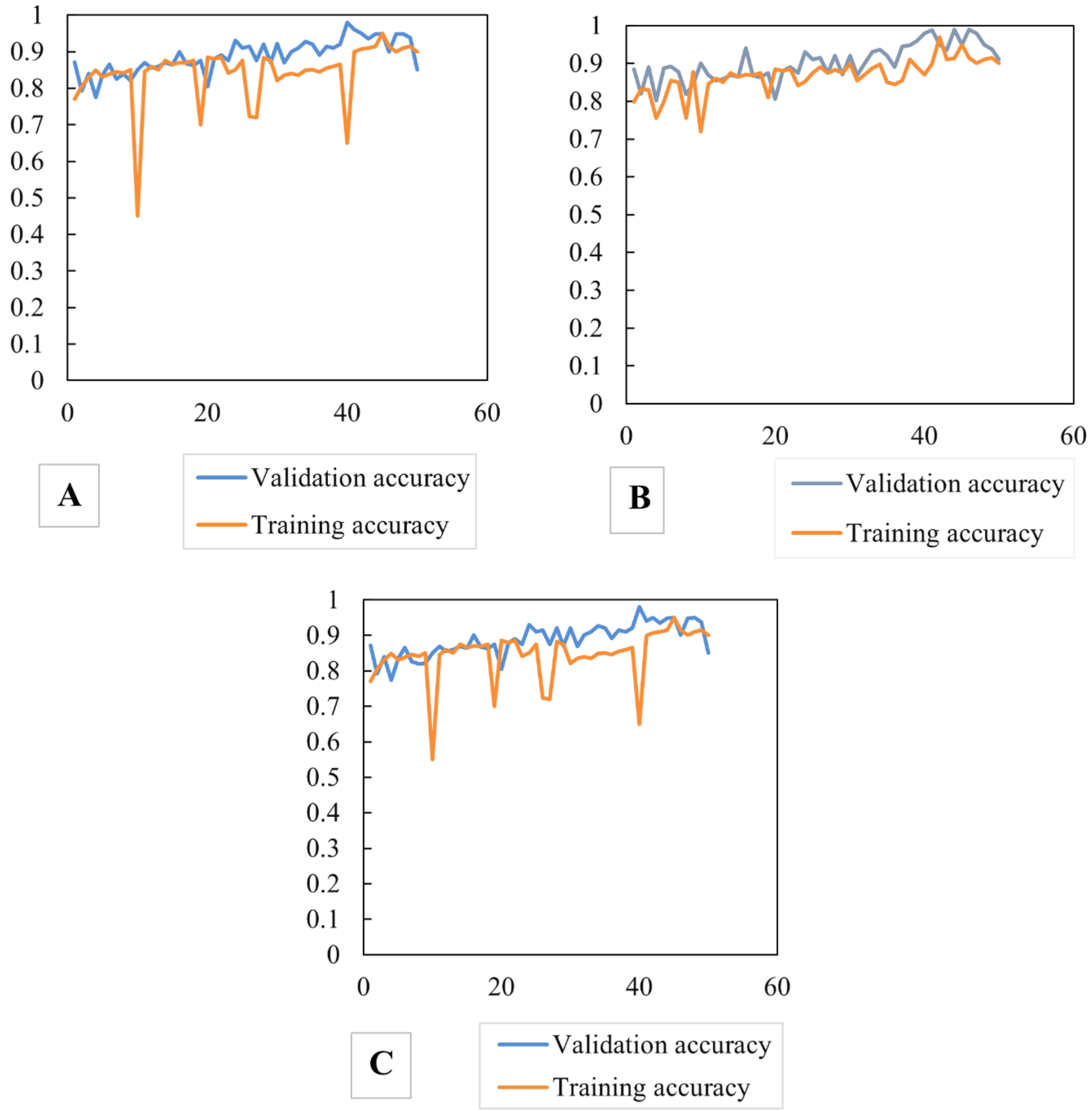

Figure 1. Accuracy of validation of the training process based on the Inception v3 architecture, for identifying damage symptoms – **A.** *Tetranychus urticae*; **B.** *Helicoverpa armigera*; **C.** Calcium deficiency.

In this study, a method for detecting the symptoms of tomato fruit borers and calcium deficiency in tomato plants was investigated. The results obtained from the test and its comparison with the results of previous studies show that this study achieved high detection accuracy. These results are in line with those 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. On the other hand, based on the findings from the architecture proposed in this study, it can be asserted that the calculated accuracy is at a much better level than the results of previous research. These results were consistent with those of Myneni and Pradeepini (2023), who used the InceptionV3 architecture to identify and diagnose diseases on the surface of tomato leaves; however, their reported accuracy was 98% .The higher accuracy of our proposed network in identifying the symptoms of pests and nutrient deficiencies can be attributed to several key factors. One reason was capturing images of the tomato plant from various distances to enable the network to calibrate itself based on distance, effectively minimizing errors associated with distance variations.

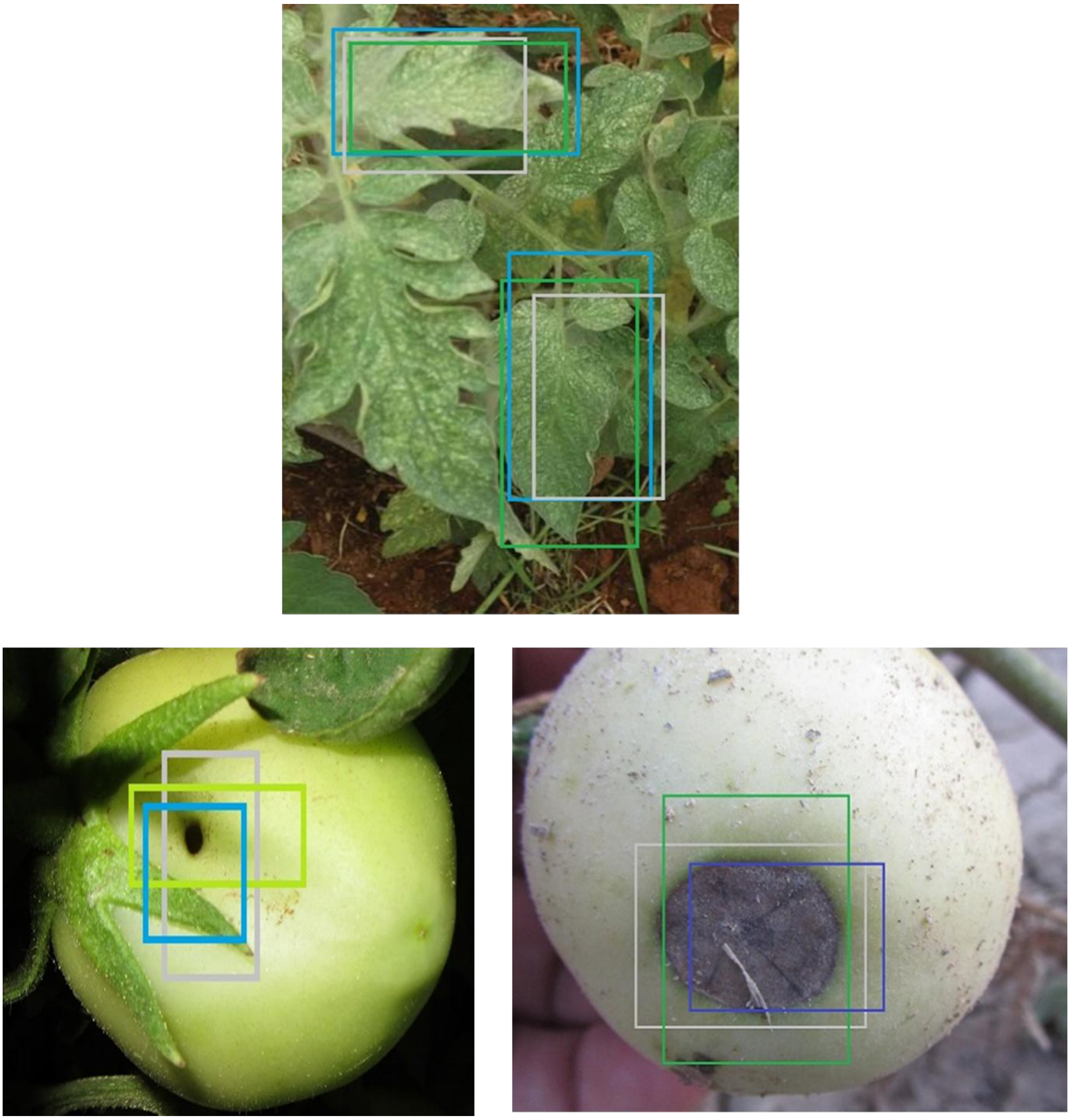

Figure 2. Identifying damage symptoms of *Tetranychus urticae* (A), *Helicoverpa armigera* (B), and Calcium deficiency (C).

Table 2. Implementation confusion matrix for *Tetranychus urticae*.

Prediction/truth	*Tetranychus urticae*	Healthy
Tetranychus urticae	99.76	0.24
Healthy	99.57	0.43

Table 3. Implementation confusion matrix for *Helicoverpa armigera*.

Prediction/truth	*Helicoverpa armigera*	Healthy
Helicoverpa armigera	99.71	0.29
Healthy	99.13	0.87

Table 4. Implementation confusion matrix for Calcium deficiency.

Prediction/truth	Calcium deficiency	Healthy
Calcium deficiency	99.78	0.22
Healthy	99.32	0.68

Table 5. Evaluation results of different categories of *Tetranychus urticae*, *Helicoverpa armigera* and Calcium deficiencies with Inception v3 architecture in percentage.

Class	Accuracy	Precision	Recall	F1-score
Tetranychus urticae	99.47	99.88	93.47	99.54
Healthy	99.66	99.93	99.55	99.87
Helicoverpa armigera	99.18	99.89	93.47	99.20
Healthy	99.16	99.11	93.78	99.48
Calcium deficiency	99/77	99.83	99.87	99.43
Healthy	99.93	99.94	99.84	99.55

Another factor is the optimization of network parameters, resulting in faster training and enhanced adaptability to handle potential noise in images. However, the most important reason for the higher accuracy of the network is the data preprocessing process, which removes poor-quality images and replaces them with better images at different spatial rotation angles.

The proposed model demonstrates that employing machine vision to identify and diagnose pests in tomato plants substantially minimizes the reliance on specialized human resources in this area. By utilizing this algorithm, farmers can simply capture images of their crops to swiftly detect damaging factors and devise more precise strategies to effectively address them. Through using proper farm management with this method, the need for chemicals can be reduced and, as a result, this would contribute to the health of the environment and society.

CONCLUSION

The use of new techniques to detect plant damage factors improves product quality and increases production. Therefore, there is an increasing need to apply and introduce new agricultural technologies. Machine vision offers a modern, efficient, and budget-friendly approach for identifying and diagnosing key pests and physiological diseases in agricultural crops, particularly in tomatoes. This technology promotes the more prudent use of pesticides, thereby lowering production costs and contributing to environmental conservation. Therefore, in this study, a model based on machine vision techniques was designed to quickly and accurately detect harmful factors in tomato plants. By examining the visible symptoms on the plant, the model offers valuable support to farmers for optimizing the crop production process.

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REFERENCES

Abdellatif, A.S., Afifi, A.M., Mahmoud, A.M.A. & Ahmed, A.M. (2023) Efficiency of some commercial stimulants in inducing tomato resistance to *Tetranychus urticae* (Acari: Tetranychidae). *Persian Journal of Acarology*, 12(1): 101–120. https://doi.org/10.22073/pja.v12i1.75453

Ahmadi, K., Ebadzadeh, H., Abdeshah, H., Kazemian, A. & Rafiei, M. (2023) *Agricultural Statistics*. Ministry of

Jihad Agriculture, Tehran, Iran, 124 pp.

Al Mallah, N.M.T. (2021) Seasonal Activity and sensitivity of some tomato cultivars to *Tetranychus urticae* Koch. *Journal of Agriculture and Veterinary Science*, 1(1): 29–37.

Cong, S. & Zhou, Y. (2023) A review of convolutional neural network architectures and their optimizations. *Artificial Intelligence Review*, 56(3): 1905–1969. https://doi.org/10.1007/s10462-022-10213-5

Devi, D., Prasanna, N., Ram, R.A.S. & Mohamed, N.N. (2023) Tomato leaves disease identification by deep convolution neural network using inception V3. *In*: Lydia, M., Ananthi, K. & Madhan Kumar, S. (Eds.), International conference on innovations in robotics, intelligent automation and control. *AIP Conference Proceedings, 14 October 2022, Coimbatore, India*, 2914: 050002. https://doi.org/10.1063/5.0176545

Dyrmann, M., Karstoft, H. & Midtiby, H. S. (2016) Plant species classification using deep convolutional neural network. *Biosystems engineering*, 151(25): 72–80. https://doi.org/10.1016/j.biosystemseng.2016.08.024

Fuentes, A., Yoon, A., Kim, A.C. & Park, D.D. (2017) A robust deep-learning-based detector for real-time tomato plant diseases and pests' recognition. *Sensors*, 17(4): 25–35. https://doi.org/10.3390/s17092022

Fuentes, A. F., Yoon, A., Lee, J. & Park, D.S. (2018) High-performance deep neural network-based tomato plant diseases and pests diagnosis system with refinement filter bank. *Front Plant Sciences*, 9(2): 11–25. https://doi.org/10.3389/fpls.2018.01162

Guo, J., Fu, X., Zhao, S., Shen, X., Wyckhuys, K.A.G. & Wu, K. (2020) Long-term shifts in abundance of (migratory) crop-feeding and beneficial insect species in northeastern Asia. *Journal of Pest Science*, 25(2): 35–47. https://doi.org/10.1007/s10340-019-01191-9

Haleema, B., Shah, S.T., Basit, A., Hikal, W.M., Arif, M., Khan, W. & Fhatuwani, M. (2024) Comparative effects of calcium, boron, and zinc inhibiting physiological disorders, improving yield and quality of *solanum lycopersicum*. *Biology*, 13(3): 66–76. https://doi.org/10.3390/biology13100766

Hernández-Pérez, O.I., Valdez-Aguilar, L.A., Alia-Tejacal, I., Cartmill, A.D. & Cartmill, D.L. (2020) Tomato fruit yield, quality, and nutrient status in response to potassium: calcium balance and electrical conductivity in the nutrient solution. *Journal of Soil Science and Plant Nutrition*, 20(7): 484–492. https://doi.org/10.1007/s42729-019-00133-9

Hossain, M. & Tayde, A.R. (2023) Efficacy and economics of biopesticides in management of tomato fruit borer *Helicoverpa armigera* (Hubner). *Annals of Plant Protection Sciences*, 31(2): 86–90. https://doi.org/10.5958/0974-0163.2023.00029.0

Hu, W., Hong, W., Wang, H., Liu, M. & Liu, S. (2023) A study on tomato disease and pest detection method. *Applied Sciences*, 13(6): 86–100. https://doi.org/10.3390/app131810063

Jayasinghe, G.G. & Mallik, B. (2011) Growth stage based economic injury levels for two spotted spider mite, *Tetranychus urticae* Koch (Acari, Tetranychidae) on tomato. *Lycopersicon esculentum* Mill. *Tropical Agricultural Research*, 22(1): 5–26.

Kadir, S.A. (2004) Fruit quality at harvest of 'Jonathan' apple treated with foliar applied calcium chloride. *Journal of Plant Nutrition*, 27(11):1991–2006. https://doi.org/10.1081/PLN-200030102

Krichen, M. (2023) Convolutional neural networks: A survey. *Computers*, 12(8): 151–159. https://doi.org/10.3390/computers12080151

Liu, J. & Wang, X. (2020) Early recognition of tomato gray leaf spot disease based on MobileNetv2-YOLOv3 model. *Plant Methods*, 16 (12): 83–96. https://doi.org/10.1186/s13007-020-00624-2

Md Fahmid, H., Uddin, M.N., Bhuyain, M.M.H., Al Bachchu, M.A., El Taj, H.F. & Ullah, M.S. (2024) Evaluation of antibiosis resistance in six tomato cultivars to *Tetranychus urticae* Koch (Acari: Tetranychidae), 26(12): 15–26. https://doi.org/ 10.21203/rs.3.rs-4981232/v1

Myneni, U. & Pradeepini, G. (2023) Prediction of tomato leaf disease using transfer learning algorithms InceptionV3 and Inception Resnetv2. *In*: Lydia, M., Ananthi, K. & Madhan Kumar, S. (Eds.), *AIP Conference Proceedings, 14 October 2022, Coimbatore, India*, 2814(1): 020009. https://doi.org/10.1063/5.0161409

Naranjo-Torres, J., Mora, M., Hernández-García, R., Barrientos, R.J., Fredes, C. & Valenzuela, A. (2020) A review of convolutional neural network applied to fruit image processing. *Applied Sciences*, 10(2): 34–43. https://doi.org/10.3390/app10103443

Ponce, H., Cevallos, C., Espinosa, R. & Gutiérrez, S. (2021) Estimation of low nutrients in tomato crops through the analysis of leaf images using machine learning. *Journal of Artificial Intelligence and Technology*, 1(1): 131–137. https://doi.org/10.37965/jait.2021.0006

Redmon, J., Divvala, S., Girshick, R. & Farhadi, A. (2016) You only look once: Unified, real-time object detection. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA*, pp. 779–788.

https://doi.org/10.1109/CVPR.2016.91.

Rezatofighi, H., Tsoi, N., Gwak, J., Sadeghian, A., Reid, I. & Savarese, S. (2019) Generalized intersection over union: A metric and a loss for bounding box regression. *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Long Beach, CA, USA*, pp. 658–666. https://doi.org/10.1109/CVPR.2019.00075

Riaz, S., Johnson, J.B., Ahmad, M., Fitt, G.P. & Naiker, M. (2021). A review on biological interactions and management of the cotton bollworm, *Helicoverpa armigera* (Lepidoptera: Noctuidae). *Journal of Applied Entomology*, 145(2): 467–498. https://doi.org/10.1111/jen.12880

Shanmugam, S.P., Murugan, M., Shanthi, M., Elaiyabharathi, T., Angappan, K., Karthikeyan, G., Arulkumar, G., Manjari, P., Ravishankar, M. & Sotelo-Cardona, P. (2024) Evaluation of integrated pest and disease management combinations against major insect pests and diseases of tomato in Tamil Nadu, India. *Horticulturae*, 5(2): 66–76. https://doi.org/10.3390/horticulturae10070766

Singla, A. & Singh, R. (2020) Estimation of avoidable yield losses in chickpea caused by *Helicoverpa armigera* (Hübner) (Lepidoptera: Noctuidae). *Phytoparasitica*, 12(6): 14–25. https://doi.org/10.1007/s12600-020-00833-4

Sousa, N., Filho, M.F., Silva, P.A. & Torres, J.B. (2020) Determination of an economic injury level for old world bollworm (Lepidoptera: Noctuidae) in processing tomato in Brazil. *Journal of Economic Entomology*, 113(2): 1881–1887. https://doi.org/10.1093/jee/toaa082

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J. & Wojna, Z. (2016) Rethinking the inception architecture for computer vision. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA*. pp. 2818–2826. https://doi.org/10.1109/CVPR.2016.308

Topcu, Y., Nambeesan, S.U. & Knaap, E. (2022) Blossom-end rot: A century-old problem in tomato (*Solanum lycopersicum* L.) and other vegetables. *Molecular Horticulture*, 14(2): 12–26. https://doi.org/10.1186/s43897-021-00022-9

Tran, T.T., Choi, J.W., Le, T.T. & Kim, J.W. (2019) A comparative study of deep CNN in forecasting and classifying the macronutrient deficiencies on development of tomato plant. *Applied Sciences*, 9(2): 16–21. https://doi.org/10.3390/app9081601

Uygun, T. & Ozguven, M.M. (2024) Determination of tomato leafminer: *Tuta absoluta* (Meyrick) (Lepidoptera: Gelechiidae) damage on tomato using deep learning instance segmentation method. *European Food Research and Technology*, 250(11): 1837–1852. https://doi.org/10.1007/s00217-024-04516-w

Verma, S., Chug, A. & Singh, A.P. (2020). Application of convolutional neural networks for evaluation of disease severity in tomato plant. *Journal of Discrete Mathematical Sciences and Cryptography*, 23(10): 273–282. https://doi.org/10.1080/09720529.2020.1721890

Zhang, A., Lipton, Z., Li, Mu. & Alexander, J. (2024) *Multi-Branch Networks (GoogleNet). Dive into deep learning*. 1st ed. Cambridge University Press, Cambridge, New York, Melbourne, New Delhi, Singapore, 574 pp.

فن بینایی ماشین برای شناسایی علایم *Tetranychus urticae* (Acari: Tetranychidae)، *Helicoverpa armigera* (Lepidoptera: Noctuidae) و کمبود کلسیم در گیاه گوجه‌فرنگی

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دبیر تخصصی
پ. لطف‌الهی

چکیده

تشخیص دقیق عوامل خسارتزای گیاهی یکی از الزامات کلیدی مدیریت و کنترل موثر آنها است. روش‌های مرسوم برای تشخیص این آفات در گیاهان نیازمند نظارت مستمر است که فرایندی پرهزینه و زمان‌بر در مزارع بوده و با خطاهای انسانی همراه است. به همین دلیل استفاده از فناوری‌های نوین برای کمک به کشاورزان در شناسایی خودکار و به‌موقع آفات کلیدی بسیار ضروری است. در این بررسی، از شبکه عصبی کانولوشن با معماری Inception_v3 برای تشخیص علائم خسارتزادر گیاه گوجه فرنگی استفاده شد. از دوربین سونی DSC-WX200 با وضوح حسگر موثر ۱۸ مگاپیکسل برای جمع‌آوری تصاویر علائم ناشی از این آفات استفاده شد. برای ارزیابی عملکرد شبکه عصبی کانولوشن با معماری Inception_v3 از فراسنجه‌های میانگین دقت، دقت و یادآوری استفاده شد. نتایج این مطالعه نشان داد که دقت معماری Inception_v3 در شناسایی علائم *Tetranychus urticae* Koch (Tetranychidae) (۹۹/۴۷٪)، *Helicoverpa armigera* (Hubner) (۹۹/۱۸٪) (Lepidoptera: Noctuidae)، کمبود کلسیم (۹۹/۷۷٪) محاسبه شد. نتایج حاکی از آن است که این سامانه پیشنهادی با بهره‌گیری از تصاویر ثبت‌شده قادر است راهکاری کارآمد و دقیق برای شناسایی عوامل خسارت‌زا در گیاه گوجه‌فرنگی ارایه دهد.

واژگان کلیدی: شبکه عصبی پیچشی، پایش محصول، پردازش تصویر، شناسایی آفت، کرم میوه، کنهٔ تارتن دو لکه‌ای.

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