Research Article
Hittite Journal of Science and Engineering, 2023, 10 (3) 249-257
ISSN NUMBER: 2148-4171
DOI: 10.17350/HJSE19030000314

Investigation of Deep Learning Approaches for Identification of Important Wheat Pests in Central Anatolia

Tolga Hayit[1] Sadik Eren Kose[2]
[1]Yozgat Bozok University, Department of Computer Engineering, Yozgat, Türkiye
[2]Yozgat Bozok University, Department of Computer Technology, Yozgat, Türkiye

ABSTRACT

Artificial intelligence-based systems play a crucial role in Integrated Pest Management studies. It is important to develop and support such systems for controlling wheat pests, which cause significant losses in wheat production is of strategic importance, particularly in Turkey. This study employed various pre-trained deep learning approaches to identify key wheat pests in the Central Anatolia, namely *Aelia* spp., *Anisoplia* spp., *Eurygaster* spp., *Pachytychius hordei*, and *Zabrus* spp. The models' classification success was determined using open and original datasets. Among the models, the ResNet-18 model outperformed others, achieving a classification success rate of 99%. Furthermore, each model was tested with original images collected during field studies to assess their effec-tiveness. The results demonstrate that pre-trained deep learning models can be utilized for the identification of important wheat pests in Central Anatolia as part of Integrated Pest Management.

Keywords:
Important wheat pests; Insect classification; Deep learning; CNN; Transfer learning; ResNet-18

Article History:
Received: 2023/05/26
Accepted: 2023/09/13
Online: 2023/09/30

***Correspondence to**: Tolga Hayit,*
Yozgat Bozok University, Computer Engineering, 66900, Yozgat, TÜRKİYE
E-Mail: tolga.hayit@bozok.edu.tr;
Phone: +90 354 217 8991/1120;
Fax: +90 354 217 8991.

INTRODUCTION

For human beings to survive, there are basic needs such as breathing, shelter, and nutrition [1]. Agricultural production holds strategic importance in meeting the nutritional requirement of these needs. However, agricultural production faces various risks from production to marketing. The ability of agriculture to effectively meet nutritional needs is directly linked to controlling these risks. Crop losses caused by diseases, weeds, and pests are significant risks in production. Effective measures are required to mitigate these risks, which are considered plant protection issues. Failure to combat diseases, pests, and weeds results in an average yield loss of 36.5% (10.2% caused by insects) [2]. Integrated Pest Management (IPM) studies, incorporating the use of the least harmful methods to humans and the environment, are crucial in preventing losses caused by pests. Artificial intelligence-based fields such as computer vision, data mining, and expert systems play a pivotal role in IPM.

Artificial intelligence-based systems developed for plant health protection are particularly valuable for the production of economically significant cereal crops. Among these crops, wheat holds the top position globally as well as in Turkey in terms of cultivation area and production volume, highlighting its strategic importance. According to Polat [3], data from the United States Department of Agriculture (USDA) indicates that wheat production accounts for 28% of the world's grain production, totaling 2.7 billion tons. The same study also highlights Turkey's crucial role in global wheat exports, ranking ninth during the 2019-2020 production season. Compared to other cereal crops, wheat, which occupies the top position among 162 crops worldwide, is an indispensable commodity due to its substantial production volume and trade value [4]. These facts underscore the significance of wheat for the global economy, particularly for Turkey.

In order to sustain wheat production, it is crucial to develop production techniques that increase the yield per unit area and effectively mitigate product losses. Wheat pests have garnered the attention of researchers due to their detrimental impact on wheat production, resulting in economic challenges and yield reductions.

Cite as:
Hayit T, Kose S E. Investigation of Deep Learning Approaches for Identification of Important Wheat Pests in Central Anatolia. Hittite Journal of Science and Engineering 2023;10(3): ***249-257****. doi:10.17350/hjse19030000314*

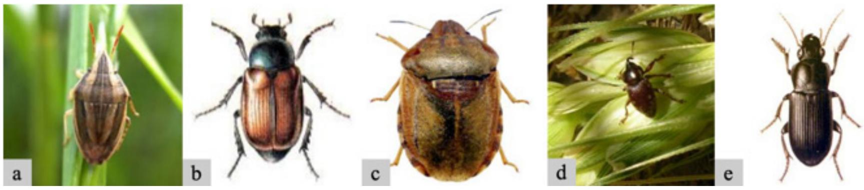

Figure 1. The important wheat pests in Central Anatolia, a: *Aelia* spp., b: *Anisoplia* spp., c: *Eurygaster* spp., d: *Pachytychius hordei*, e: *Zabrus* spp. [7].

There exist significant wheat pests that adversely affect both the yield and quality of wheat. In regions with a high population density, these pests, if left uncontrolled, can cause crop losses of up to 100% [5]. The Agricultural Control Technical Instructions provide a clear overview of the definition, life cycle, economic significance, distribution, and control measures for wheat pests [6]. Researchers and producers rely on these instructions to effectively manage major wheat pests. Fig. 1 presents images of these key wheat pests.

In recent years, significant progress has been made in using Machine Learning (ML) for pest detection and identification for crop protection. These works encompass both traditional approaches and modern Deep Learning (DL) techniques, such as Convolutional Neural Networks (CNN). CNN, being a prominent DL method, has gained extensive popularity, particularly in object identification tasks involving images [8-10]. CNN models possess a deep neural architecture comprising convolutional, pooling, and connected layers. Current agricultural studies based on deep learning provide evidence that CNN can effectively recognize diseases and pests in plant protection [11-22].

The successful outcomes of deep learning-based studies have served as the motivation for this research. However, the development of a successful and high-quality CNN model necessitates a well-curated dataset. Unfortunately, limited data availability and insufficient open access datasets pose as restricting factors when training CNN models.

This study employed modern deep learning approaches to identify crucial wheat pests in the Central Anatolia, including *Eurygaster* spp., *Aelia* spp., *Anisoplia* spp., *Pachytychius hordei*, and *Zabrus* spp. The classification success of the models was evaluated using pre-trained deep learning models, namely AlexNet, ResNet-18, and InceptionV3 CNN networks. Open access datasets containing images of these significant wheat pests were utilized to train the models. The contributions of this study are evident in its application of modern deep learning techniques, its emphasis on identifying crucial wheat pests, the evaluation of deep learning models, its utilization of open-access and original datasets, and its potential to enhance agriculture and advance agricultural research in the Central Anatolia.

The remainder of the paper is organized as follows: the second section provides a detailed description of the dataset and methodology employed, the third section discusses the findings and presents a comparative performance analysis, and the final section presents the concluding remarks on the study.

MATERIAL AND METHODS

Dataset

The Agricultural Control Technical Instructions [6] provide a comprehensive overview of the definition, life cycle, economic significance, distribution, and control measures for wheat pests. Through field surveys, original images of the *Eurygaster* spp. pest were obtained and used for the final testing of the best model. However, the limited quantity and diversity of the original data hindered the ability to train and validate the models effectively. To address this issue, open data sets have been employed.

The Global Biodiversity Information Facility (GBIF) is an international data network funded by governments, aiming to provide open access to various life-related data [23]. GBIF encompasses numerous data sets. In this study,

Table 1. The raw dataset statistics [24-28].

Aelia	*Anisoplia*	*Eurygaster*	*Pachytychius*	*Zabrus*	TOTAL
333	301	310	108	183	1235

Figure 2. Sample images from the dataset, (a): *Aelia* [24], (b): *Anisoplia* [25], (c): *Eurygaster* [26], (d): *Pachytychius* [27], (e): *Zabrus* [28].

Hayit T. and Kose S. E. / Hittite J Sci Eng, 2023; 10 (3) 249-257

Table 2. Final dataset statistics.

	Aelia	*Anisoplia*	*Eurygaster*	*Pachytychius*	*Zabrus*	*TOTAL*
Training	350	350	350	350	350	**1750**
Validation	50	50	50	50	50	**250**
Test	100	100	100	100	100	**500**
TOTAL	**500**	**500**	**500**	**500**	**500**	**2500**

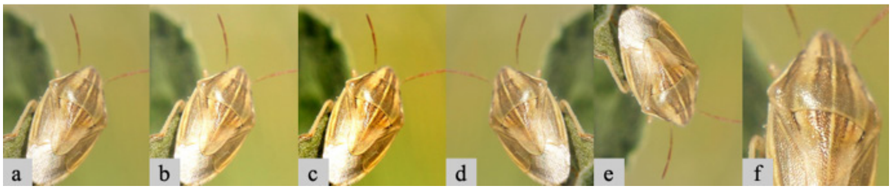

Figure 3. Augmented forms of a sample *Aelia* image: (a) original image, (b) brightness modified, (c) contrast modified, (d) horizontal flipped, (e) vertical flipped, (f) random rotated.

the raw data utilized for training, validation, and testing of the models were obtained from GBIF open data sets. Table 1 presents the statistics of the raw data set, while Fig. 2 showcases sample images for each pest species. In the experimental studies, each pest was denoted by its scientific name.

The number of data sets was sufficient for training the deep learning models. However, in order to avoid issues such as overfitting and underfitting, it was necessary to balance the amount of data in each class. Particularly, due to the disparity in the amount of data between the *Pachytychius* and *Zabrus* classes, data augmentation techniques were employed, which are widely used in such cases [29-31]. This approach helped equalize the number of images in each class and achieve a balanced distribution of data across classes.

The final data set, created through data augmentation, was divided into three groups: training (70%), validation (10%), and test (20%). The models developed during the training and validation process were subsequently tested using the independent test dataset (20%), and the results were compared with the validation outcomes. Table 2 provides details regarding the number of final datasets generated as a result of the data augmentation process, while Fig. 3 showcases augmented versions of a sample *Aelia* image.

In addition, a total of 423 original *Eurygaster* images were collected through field surveys conducted in March 2022. These images served as the original dataset for the study and were used for testing the models, in addition to the designated test dataset. Note that due to field and weather conditions, only images of *Eurygaster* could be acquired. Sample images from the original Eurygaster dataset are presented in Fig. 4.

Convolutional Neural Networks and Transfer Learning

A Convolutional Neural Network (CNN) is a deep learning model composed of interconnected layers that can automatically learn features from images within different classes. CNNs are extensively utilized, particularly in multi-class image classification tasks. Recent research demonstrates that CNN approaches can mimic human learning from images, achieving performance on par with or even surpassing human capabilities.

A CNN network can be trained from scratch or use "pre-trained" models that have been trained on large-scale datasets for specific tasks. This technique, known as "Transfer Learning," allows for improved performance with reduced training time, especially for tasks that require extensive datasets [32]. Numerous pre-trained CNN models, such as AlexNet [33], ResNet-18 [34], and InceptionV3 [35], are available, each suitable for identifying important wheat pests. In this study, we employed the AlexNet, ResNet-18, and InceptionV3 models.

AlexNet, introduced by Krizhevsky et al. [33], demonstrated superior performance in the ImageNet image classifi-

Figure 4. Sample images of the *Eurygaster* original dataset.

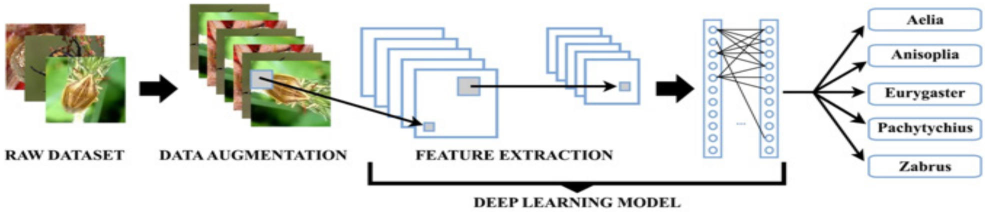

Figure 5. Proposed model workflow: pest images are passed to the CNN (Deep Learning Model), which automatically learns features and classifies pests.

cation task. AlexNet achieved victory in the 2012 ImageNet competition by attaining a top-5 error rate of 15.3%, surpassing the second-place error rate of 26.2%. It has a total of 8 learned layers. These layers include 5 convolutional layers and 3 fully connected layers. The activation function used on the AlexNet network is ReLU (Rectified Linear Unit), and maximum pooling is employed to reduce the dimensionality of the hidden layers. The output of the last fully connected layer is fed into the SoftMax function for class prediction.

ResNet [34], introduced by He et al., achieved first place in the ImageNet classification with a top-5 error rate of 3.57% in 2015. ResNet-18 consists of 18 layers in total, out of which 16 layers are trainable. The other two layers are the input layer and the final fully connected layer. ResNet-18, an enhanced version of the basic model.

Inception [36], also known as GoogLeNet, outperformed other models in the ImageNet classification task, achieving a top-5 error rate of 6.67% in 2014. InceptionV3 [35], an improved and optimized version of GoogLeNet, and it has a total of 48 trained layers. These layers include convolutional layers, pooling layers, fully connected layers, and auxiliary classifiers. InceptionV3 offers higher efficiency compared to previous models and requires less computational cost.

Freezing Layers

During training, specific layers' weights within the CNNs are immobilized, remaining unchanged throughout the fine-tuning process. This technique is commonly employed for the initial layers, which primarily capture fundamental features. In opposition, the upper layers concentrate on extracting task-specific discriminative features and therefore remain unfrozen.

The Proposed Model

This paper presents a deep learning model based on transfer learning, utilizing pre-trained CNN models. The task involves the identification of important wheat pests in the Central Anatolia. The pre-trained CNN models used in this study include AlexNet, Res-Net-18, and InceptionV3. Data augmentation was performed using the Python programming language and the OpenCV (Open Computer Vision) library, while MATLAB software was employed for training, validation, and testing of the models.

The training process involved utilizing 1750 pest images of significant wheat pests obtained from open datasets. During training, each model was validated using 250 images. The final models were created upon completion of the training process. Fig. 5 provides a visual representation of the main steps in the workflow of the proposed deep learning-based classification model.

Performance Metrics

To assess the performance of the CNN models, a confusion matrix was computed to evaluate both the average and classwise performance. As the proposed model predicts one of the five pest types, the resulting confusion matrix, denoted as C(m,n), is a 5x5 matrix. Based on the confusion matrix, various performance metrics were measured to determine the accuracy, precision, sensitivity, and F1-Score values of the models, providing insights into their overall performance and class-specific performance.

RESULTS

Throughout the experiments, the AlexNet, ResNet-18, and InceptionV3 CNN models were trained and validated using the open dataset. However, it was observed that the models based on ResNet-18 and InceptionV3 achieved the highest accuracy values. The validation accuracy of these models is presented in Table 3.

From the analysis of Table 3, it is evident that the ResNet-18 and InceptionV3 models performed comparably well. However, in this case, the focus shifts towards the complexi-

Table 3. The validation accuracy rates (%).

Model	Accuracy
AlexNet	97.6
ResNet-18	**99.6**
InceptionV3	99.2

Table 4. Hyperparameters of the models: Hyperparameters were defined such as the learning rate was assigned 0.00001, and also *Adam* was used as an optimizer.

Optimizer	Adam
Loss function	Categorical cross entropy
Momentum	0.9
Initial Learning rate	1.0000e-05
Early stopping patience	10
Maximum epoch	20
Mini batch size	8
Shuffle	Every epoch

ties of the models and the associated workloads rather than their success rates. Despite InceptionV3's strong performance in previous studies, it possesses a more complex structure when compared to the ResNet-18 architecture. Additionally, considering the number of layers (ResNet-18 has 18 layers, while InceptionV3 has 48 layers), ResNet-18 offers a lightweight architecture. Herein, it is worth noting that the training of the ResNet-18 model was completed in approximately 12 minutes, whereas the InceptionV3 model required around 84 minutes for training. Thus, despite the close average accuracy values between the models, the ResNet-18 model is considered more successful due to its shorter training time and lightweight architecture.

The parameter settings of the learners used for training and testing in this study are presented in Table 4. The main parameters employed for configuring the learners' settings include InitialLearnRate, MaxEpoch, and MiniBatchSize. In the domain of machine learning and statistics, the learning rate serves as a critical tuning parameter within optimization algorithms, governing the magnitude of each step taken during iterations to approach the minimum of a loss function. One MaxEpoch entails a complete iteration of a training algorithm across the entire training dataset. Conversely, a MiniBatchSize refers to the number of images processed within each individual iteration.

Following multiple rounds of experimentation, the chosen MaxEpoch for this research is 20. Given the limited quantity of training datasets, the mini-batch size is typically opted to be small, falling between 4 to 64, preferably in powers of 2. This selection aims to ensure effective utilization of the datasets while minimizing wastage. As a result, the MiniBatchSize designated for this study is 8.

After each fully connected layer, batch normalization and dropout techniques are implemented. Hyperparameters, including a learning rate of 0.00001, along with the utilization of the Adam optimizer, were defined. While the initial 12 convolutional and separable convolution layers remained unchanged (frozen) throughout the training process, the upper layers underwent fine-tuning.

Both training and validation accuracy graphs were plotted using categorical cross-entropy as the loss function for ResNet-18, see Fig. 6.

During the training process, it was observed that both the training and validation accuracy consistently improved over time. Furthermore, a loss graph was generated to visualize the training process, as depicted in Fig. 7. The training loss and validation loss graphs demonstrate a decreasing trend throughout the training iterations, and their behavior closely resembles each other.

Relying solely on average accuracy is not sufficient to determine the success of CNN models. To address this limitation, a separate test was conducted for each model using 500 pest images (20% of the total dataset) listed in Table 2. These images were not encountered by the models during the training process. It was observed that the test performance of all models closely aligned with their average accu-

Figure 6. The ResNet-18 model was trained for 20 epochs and the training-validation accuracies were presented after each epoch.

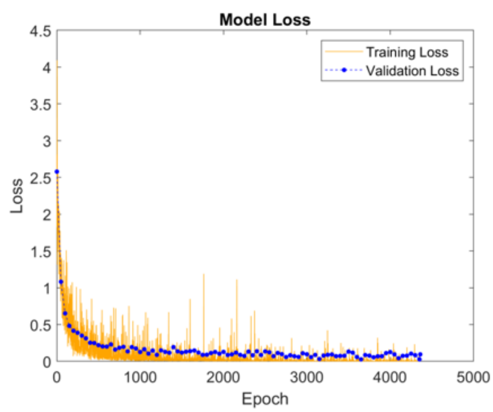

Figure 7. The ResNet-18 model was trained for 20 epochs and the training-validation loss values were presented after each epoch.

Hayit T. and Kose S. E. / Hittite J Sci Eng, 2023; 10 (3) 249–257

Table 5. The test accuracy rates (%).

Model	Accuracy	Precision	Recall	F1-Score
AlexNet	97.6	0.97	0.98	0.97
ResNet-18	**99.4**	**0.99**	**0.99**	**0.99**
InceptionV3	99.0	0.99	0.99	0.98

racy performance (Table 5). This result indicates that each model exhibited good generalization capabilities for the given problem. Note that the ResNet-18 model, which demonstrated the best performance in terms of training time, achieved an average test accuracy (99.4%) that was almost identical to the average accuracy.

The confusion matrix, is a table commonly used to visualize the performance of supervised learning algorithms in ML. Each row of the matrix corresponds to instances in a true class, while each column represents instances in a predicted class. For classification problems, the confusion matrix summarizes the count or percentage of correct and incorrect predictions. The term 'confusion' in the name arises from the matrix's ability to reveal whether the system is causing confusion between classes.

In Fig. 8, we present the confusion matrix, providing a detailed analysis of the performance of the most successful models for each class. The diagonal cells, highlighted in blue within the confusion matrix, indicate the number of accurate classifications made for each respective class. Note that the InceptionV3 model misclassified 3 images belonging to the *Eurygaster* pest class. However, both models achieved 100% accuracy in recognizing the *Aelia* pest class.

On the other hand, the confusion matrix was utilized to calculate the average test accuracy, as well as metrics such as precision, recall, and F1-Score. These metrics, along with the average accuracy, consistently supported the notion that the models were capable of effectively classifying the important wheat pests. A comprehensive breakdown of the performance of the ResNet-18 model for each class can be found in Table 6.

The models were subsequently subjected to testing using the original dataset of 423 *Eurygaster* images (see 'Dataset' section). The experimental results revealed that the best-performing models, ResNet-18 and InceptionV3, achieved accuracies of 97% and 92% respectively. These findings demonstrate that the models exhibit robust generalization capabilities and can be effectively applied to real-world scenarios.

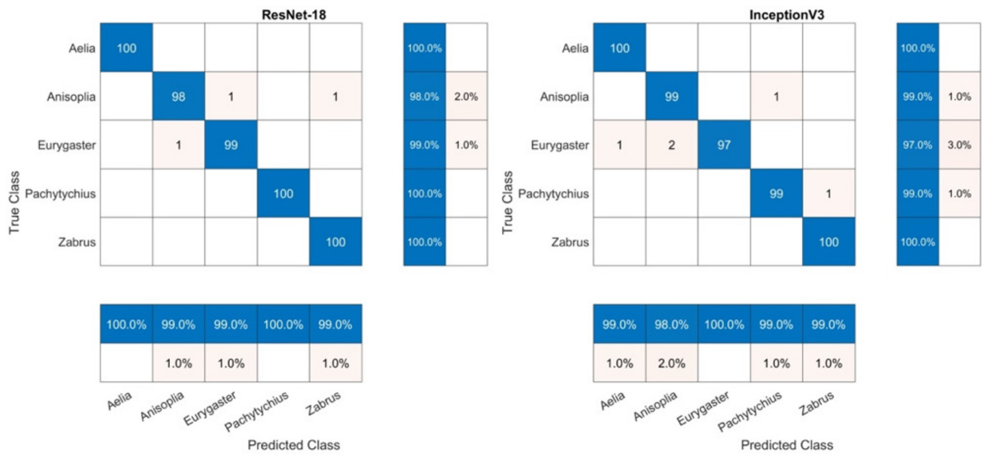

Figure 8. The confusion matrix for the best models trained on the dataset, on the left by ResNet-18 and on the right by InceptionV3.

Table 6. Classwise performance comparison for ResNet-18.

Metric	*Aelia*	*Anisoplia*	*Eurygaster*	*Pachytychius*	*Zabrus*	TOTAL
Precision	1.0	0.98	0.99	1.0	1.0	0.99
Recall	1.0	0.99	0.99	1.0	0.99	0.99
F1-Score	1.0	0.98	0.99	1.0	1.0	0.99

DISCUSSION

Based on the experimental results, it is evident that the pre-trained CNN models successfully identified significant wheat pests in Central Anatolia. The dataset, comprising five crucial pests, was utilized across all methodologies. The best performance achieved was 99.4%. The same hyperparameters were employed for all classifications to ensure a fair comparison.

The confusion matrix provided a detailed analysis of the performance of the models for each class. Therefore, it can be concluded that the models successfully classify each class.

Utilizing transfer learning (TL) as a deep learning technique involves employing a pre-trained model from an extensive dataset for a specific task within a certain domain. This pre-trained model serves as a foundation for tackling a different task within a similar domain, even when there is limited labeled data available. Models based on transfer learning (pre-trained) require a shorter training duration when compared to models trained entirely from scratch [32]. The popular pre-trained CNN classification models are documented in the literature [37], including AlexNet, ResNet, and Inception. These models are robust methods for image classification and effective object identification [33-36]. It has also been demonstrated that these models exhibit better accuracy and computational efficiency compared to other CNN models in some studies. The pre-trained CNN models most frequently employed in pest classification studies [11-22] serve as the foundation of our deep learning strategy.

Finally, the results of this paper and related studies are presented in Table 7. The contribution of deep models to classification performance is evident in both other studies as the study. Consequently, CNN models can serve as a foundational component of a portable system integrated with hardware, which can be utilized by farmers or researchers to identify various pest species in real-world environments.

Pest classification is a novel and increasingly popular field within the realm of computer vision. While there exist methodological similarities, our study exhibits notable distinctions when considering the dataset employed. Importantly, we assert that our research carries national significance, as it identifies critical pest species within the Central Anatolia. Furthermore, the chosen pest species are those that impose the most substantial damage upon wheat.

CONCLUSION AND SUGGESTIONS

This study demonstrated the effectiveness of pre-trained CNN models for the identification of important wheat pests in Central Anatolia. The results of the analysis, which involved a five-way classification task using transfer learning, indicated an average test accuracy of approximately 99% (see Table 5). Furthermore, metrics such as precision, recall, and F1-Score, provided in Table 6, further supported the success of the models.

Comparing the accuracy and loss graphs, as well as considering the performance on the original dataset, it can be concluded that CNN models integrated into mobile systems for real-world applications can be reliably employed to identify significant wheat pests in Central Anatolia. Future works could involve testing and comparing the performance of these models using original datasets that include other pests. Additionally, it would be valuable to explore the use of traditional models alongside deep learning models and compare their performances. Encouraging the continuation of similar research endeavors is crucial for effectively managing factors that pose a serious threat to wheat production.

Table 7. Related work and accuracy results (%) summary.

Study	*Other CNN*	*AlexNet*	*ResNet*	*Inception*	*Class*
Proposed work	**-**	**97.6**	**99.4**	**99**	**5**
Zhu et al. [11]	99.60	100	-	-	22
Xia et al. [13]	89.22	-	-	-	24
Thenmozhi and Reddy [16]	97.47	94.23	95.95	-	24
Nanni et al. [18]	92.10	92.43	-	90.77	10
Ayan et al. [19]	98.81	-	92.18	97.06	40
Visalli et al. [20]	98.39	-	-	-	11
Kasinathan et al. [21]	91.5				9
Kasinathan et al. [21]	90	-	-	-	24
Zheng et al. [22]	98.4	89.0	92.0	-	30

Note: Best results of the studies were represented; models (if used) and their performance are presented for each study.

ACKNOWLEDGEMENT

This study was supported by project 1919B012107851 no. within the scope of the 2209-A University Students Research Projects Support Program carried out by the Science Fellowships and Grant Programmes Department (TUBİTAK BİDEB). We also thank the Directorate of Plant Protection Central Research Institute, the Republic of Türkiye Ministry of Agriculture and Forestry for support in obtaining the original dataset.

CONFLICT OF INTEREST

The authors declare that they have no potential conflict of interest.

AUTHOR CONTRIBUTION

Tolga Hayit designed the models and analysed the data, and also wrote the manuscript and read and approved the final manuscript. Sadik Eren Kose collected original images and contributed image processing work.

References

1. Maslow AH. A theory of human motivation. Psychol Rev. 1943 50(4):370-396.
2. Agrios NG. Plant pathology. San Diego (USA): Elsevier Academic Press; 2005.
3. Polat K. Tarım Ürünleri Piyasaları [Internet]. Turkey (SGB): Tarımsal Ekonomi ve Politika Geliştirme Enstitüsü; 2021 [reviewed 2022 Dec 15; cited 2022 Dec 20]. Available from: https://arastirma.tarimorman.gov.tr/tepge/Belgeler/PDF%20Tar%C4%B1m%20%C3%9Cr%C3%BCnleri%20Piyasalar%C4%B1/2021-Ocak%20Tar%C4%B1m%20%C3%9Cr%C3%BCnleri%20Raporu/Bu%C4%9Fday,%20Ocak%202021,%20Tar%C4%B1m%20%C3%9Cr%C3%BCnleri%20Piyasa%20Raporu.pdf
4. FAO. World Food and Agriculture – Statistical Yearbook 2022. Rome: https://doi.org/10.4060/cc2211en; 2022.
5. Babaroğlu NE, Akci E, Çulcu M, Yalçın F. Süne ve Mücadelesi. Ankara (TR): Tarım ve Orman Bakanlığı Gıda ve Kontrol Genel Müdürlüğü; 2020.
6. Zirai Mücadele Teknik Talimatları Cilt 1. Ankara (TR): Gıda Tarım ve Hayvancılık Bakanlığı Tarımsal Araştırmalar ve Politikalar Genel Müdürlüğü Bitki Sağlığı Araştırmaları Daire Başkanlığı; 2008.
7. Hububat Zararlıları [Internet]. [place unknown: publisher unknown]; [reviewed 2022 Dec 16; cited 2022 Dec 20]. Available from: https://arastirma.tarimorman.gov.tr/zmmae/Belgeler/Sol%20Menu/Zirai%20M%C3%BCcadele%20Rehberi/Hububat/Hububat-Zararl%C4%B1.pdf
8. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521(7553):436-444.
9. Hayit T, Erbay H, Varçın F, Hayit F, Akci N. Determination of the severity level of yellow rust disease in wheat by using convolutional neural networks. JPP. 2021;103(3):923-934.
10. Hayıt T, Erbay H, Varçın F, Hayit F, Akci N. The classification of wheat yellow rust disease based on a combination of textural and deep features. Multimedia Tools and Applications. 2023:1-19.
11. Zhu LQ, Ma MY, Zhang Z, et al. Hybrid deep learning for automated lepidopteran insect image classification. Oriental Insects. 2017;51(2):79-91.
12. Lim S, Kim S, Kim D. Performance effect analysis for insect classification using convolutional neural network. In 2017 7th IEEE International Conference on Control System, Computing and Engineering. 2017; Penang, Malaysia; 2017. p. 210-215.
13. Xia D, Chen P, Wang B, Zhang J, Xie C. Insect detection and classification based on an improved convolutional neural network. Sensors. 2018;18(12):4169.
14. Marques ACR, Raimundo MM, Cavalheiro EMB, et al. Ant genera identification using an ensemble of convolutional neural networks. Plos One. 2018;13(1):e0192011.
15. Lu CY, Rustia DJA, Lin TT. Generative adversarial network based image augmentation for insect pest classification enhancement. IFAC-PapersOnLine. 2019;52(30):1-5.
16. Thenmozhi K, Reddy US. Crop pest classification based on deep convolutional neural network and transfer learning. Comput Electron Agric. 2019;164(104906).
17. Hansen OL, Svenning JC, Olsen K, et al. Species-level image classification with convolutional neural network enables insect identification from habitus images. Ecol Evol. 2020;10(2):737-747.
18. Nanni L, Maguolo G, Pancino F. Insect pest image detection and recognition based on bio-inspired methods. Ecol Inform. 2020;57(101089).
19. Ayan E, Erbay H, Varçın F. Crop pest classification with a genetic algorithm-based weighted ensemble of deep convolutional neural networks. Comput Electron Agric. 2020;179(105809).
20. Visalli F, Bonacci T, Borghese NA. Insects image classification through deep convolutional neural networks. Prog Artif Intell. 2021:217-228.
21. Kasinathan T, Singaraju D, Uyyala SR. Insect classification and detection in field crops using modern machine learning techniques. Inf Process Agric. 2021;8(3):446-457.
22. Zheng T, Yang X, Lv J, Li M, Wang S, Li W. An efficient mobile model for insect image classification in the field pest management. IJEST. 2023;39(101335).
23. GBIF.org. What is GBIF? [Internet]. Copenhage (DK); 2022 [reviewed 2023 Jan 05; cited 2023 Jan 20]. Available from: https://www.gbif.org/what-is-gbif
24. GBIF.org. Aelia images. Copenhage (DK); 2023 [reviewed 2023 Jan 10; cited 2023 Jan 10]. Available from: https://doi.org/10.15468/dl.x52gxq
25. GBIF.org. Anisoplia images. Copenhage (DK); 2023 [reviewed 2023 Jan 08; cited 2023 Jan 08]. Available from: https://doi.org/10.15468/dl.3k29je
26. GBIF.org. Eurygaster images. Copenhage (DK); 2023 [reviewed 2023 Jan 08; cited 2023 Jan 08]. Available from: https://doi.org/10.15468/dl.7sz7cp
27. GBIF.org, Pachytychius images. Copenhage (DK); 2023 [reviewed 2023 Jan 08; cited 2023 Jan 08]. Available from: https://doi.org/10.15468/dl.fh8q57
28. GBIF.org. Zabrus images. Copenhage (DK); 2023 [reviewed 2023 Jan 05; cited 2023 Jan 05]. Available from: https://doi.org/10.15468/dl.tpq3zy
29. Moreno-Barea FJ, Jerez JM, Franco L. Improving classification accuracy using data augmentation on small data sets. Expert Syst Appl. 2020;161(113696).
30. Tian X, Ding CH, Chen S, Luo B, Wang X. Regularization graph convolutional networks with data augmentation. Neurocomputing. 2021;436:92-102.

31. Oyelade ON, Ezugwu AE. A deep learning model using data augmentation for detection of architectural distortion in whole and patches of images. Biomed Signal.2021;65(102366).
32. Mohanty SP, Hughes DP, Salathé M. Using deep learning for image-based plant disease detection. Front Plant Sci. 2016;7(1419).
33. Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. Commun. 2017;60(6):84-90.
34. He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. Proceedings of the IEEE conference on computer vision and pattern recognition; 2016; Las Vegas, NV, USA.
35. Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z. Rethinking the inception architecture for computer vision. Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 2818-2826.
36. Szegedy C, Liu W, Jia Y, et al. Going deeper with convolutions. Proceedings of the IEEE conference on computer vision and pattern recognition; 2015. p. 1-9.
37. Sultana F, Sufian A, Dutta P. Advancements in image classification using convolutional neural network. In 2018 Fourth International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN). 2018 Nov. p. 122-129.