Indonesian Journal of Electrical Engineering and Computer Science
Vol. 27, No. 1, July 2022, pp. 92~101
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v27.i1.pp92-101

Olive trees cases classification based on deep convolutional neural network from unmanned aerial vehicle imagery

Noor Abdulhafed Sehree[1], Abdulsattar Mohammed Khidhir[2]
[1]Technical Engineering College, Northern Technical University, Mosul, Iraq
[2]Computer Systems Technology, Mosul Technical Institute, Mosul, Iraq

Article Info

Article history:

Received Feb 21, 2022
Revised May 16, 2022
Accepted May 31, 2022

Keywords:

Deep convolutional neural network
Deep learning
Remote sensing
Transfer learning
Unmanned aerial vehicle

ABSTRACT

Unmanned aerial vehicles (UAVs) are one of the various aerial remote sensing platforms with ease of use and cost-effectiveness it can deliver high-resolution imaging, obtained using a variety of sensors. Photogrammetric data is derived by the use of unmanned aerial systems (UAS, which consists of a UAV, sensor(s), and base station). As a result of these types, vegetation monitoring is conceivable. Deep neural networks have had a lot of success with image classification tasks, especially in the remote sensing field. In this paper, we demonstrate how deep neural networks can be used to classify olive trees status from aerial images. We have addressed a multi-class classification problem. In this work five different neural network architectures: VGG16, ResNet50, MobileNet, Xception, and VGG19 had been compared. Transfer learning had been accomplished using training of the fully connected layer(s) at the end of the deep learning layers. We used metrics such as accuracy, precision, recall, and confusion metric to evaluate the results. With accuracy, our model achieves the best results using ResNet50 with an accuracy is (97.2%).

Corresponding Author:

Noor Abdulhafed Sehree
Department of Computer Engineering, Northern Technical University
Mosul, Iraq
Email: noorsehree7@gmail.com

1. INTRODUCTION

Nowadays computer-aided techniques are used for fast processing unmanned aerial vehicles (UAVs) are one of the various aerial remote sensing platforms that are available. Combined this technique with a convolutional neural network (CNN) is used in the deep learning (DL) model. The features are extracted to automatically classify images using a fully connected network or more. Olives are one of the most cultivated plants in the world, and they are susceptible to a variety of diseases that reduce crop productivity. Diseases primarily influence the state and color of olive tree leaves. Diseases have similar patterns, and making them visible is a major challenge [1]. As per the food and agriculture organization (FAO), pests cause a 20 to 40% loss in global crop production each year. As a result, smart agriculture is the best option for farmers to use artificial intelligence techniques combined with modern information [2].

In 2019, Aravind *et al.* [3] presented a transfer network based on VGG16 with the other transfer network model AlexNet. The dataset was captured from six smartphones. The best accuracy obtained of VGG16 is 93.33%. Then modified VGG16 by adding a fully connected layer with 4096 neurons to the last fully connected layer. The accuracy is 96.70%. Alruwaili *et al.* [4] employed two pre-trained DL models AlexNet and GoogLeNet for plant disease classification. An accuracy of 99.35% percent was attained using the plant village dataset of damaged and healthy plant leaves. Zhao *et al.* [5] proposed a new method for assessing rice lodging which is based on a deep learning U-shaped network (UNet) architecture images. Dataset was taken by the UAV fitted with a multispectral camera and a high-resolution digital camera.

According to the results, the dice coefficients on the RGB and multispectral datasets reach 0.9442 and 0.9284, respectively. Alruwaili *et al.* [1] discussed convolutional neural network (CNN) AlexNet, for olive disease detection and classification. Its key contribution is to increase the accuracy of diagnosing olive illnesses. In Wu [6] utilized the imaging plants in the field. Small UAV are used with a Sony Alpha 6000. The camera was mounted to a DJI Matrice. The first two stages of three-stage's CNN pipeline were used to create the image analysis method. Barbedo [7] used the (Jayme Garcia Arnal Barbedo) created in 2017. There are other studies for classifying plant diseases using images taken with a variety of sensors (smartphones, compact cameras, and DSLR cameras) and deep learning techniques (GoogleLeNet).

In 2020 the Uğuz [8] use a single shot detector, researchers developed a technique to identify olive peacock spot disease (SSD) the average accuracy (AP) value achieved was 96% percent. Ainiwaer *et al.* [9] used a fixed-wing UAV for red–green–blue (RGB) imaging and (CNN)-based VGG16 and VGG19 models. The classification accuracy was 95.6%.to classify plant communities. Dubey and Shanmugasudaram [10] worked to develop a classification system for plant diseases like (Early and late blight of potato and tomato, Tomato target spot) on Lenet-5 architecture images of crop plant leaf disease were obtained from the plant village repository, and the validation accuracy 99%. Barman *et al.* [11] presented a citrus leaf disease classification system using the MobileNet CNN and CNN architecture. Which are More helpful and accurate for smartphone image-based citrus leaf disease classification. Zhang *et al.* [12] worked to test unmanned aerial vehicle UAV for aerial imagery with three different CNNs (simple convolutional neural network, VGG-16, and GoogLeNet) for wheat lodging detection. Tetila [13] introduced five deep learning architectures to classify soybean pests (inception-v3, Resnet-50, VGG-16, VGG-19, and Xception). The highest classification accuracy obtained was up to 93.82% of the dataset captured in the field using UAV.

In 2021, Safonova *et al.* [14] presented mask RCNN to detected olives tree using UAV remote sensing. In their work, they reached, that the use of RGB or NDVID or GNDVI not important was not important, also the increase in the number of data did not affect the accuracy result of the accuracy of mask RCNN. Also has been done, several studies were conducted to discover plant diseases based on deep learning and CNN networks, which adopted a database whose data is available on the internet a (plant village) [15]. Another study was done to discover some diseases that affect trees, from the ultra spectrum linear scanner thermal images RGB and hyperspectral images are useful, but the cameras which were used to collect data over drones were large and bulky [16]. Dhaka *et al.* [17] introduce a survey of previous studies that used pre-trained deep learning networks to predict various plant diseases such as (tomatoes, maize, and rice) was presented during this survey, the accuracy of each type of neural network used in the classification and prediction of diseases on different crops was shown. Sun *et al.* [18] introduced approach achieves based on a deep transfer learning neural network (ResNet, and DenseNet) database from plant village for identification plant diseases. Margapuri *et al.* [19] used the convolutional neural networks (ResNet-100 VGG-16, and classification seed phenotyping from UAV imagery. The better accuracy has been achived by ResNet-101.

These reviews demonstrated the ability of commonly used deep learning models to cope with a variety of objectives, as well as the usage of artificial intelligence in agriculture by implementing various neural network models. In this study, a database of aerial images spotted by the drone was adopted, which is the most prominent modern technology for remote sensing. These pictures were taken from different heights, and they are real field pictures that were taken of the olive groves of a village in the city of Mosul, Northern Iraq. The purpose of the study is to classify four cases of olive trees (healthy, dead, healthy high density, and disease olive trees) due it is an important crop and affects the agricultural economy and is included in industrial agriculture.

2. AN OVERVIEW ON ARTIFICIAL INTELLIGENCE

2.1. Artificial neural networks (ANNs)

Over the last two decades, artificial neural networks have been employed in a variety of applications including classification, pattern recognition, regression, and forecasting. Between the input and output layers of an ANN are hidden layers [20] as seen in Figure 1. All global patterns in the input space are learned in an ANN, while CNN's are useful. In contrast to ANNs, which learn global patterns, CNNs learn key local patterns detected in the input [21] as seen in Figure 2.

2.2. Machine learning (ML)

Many fields employ ML techniques. Machine learning is a term that describes the processes that allow computers to think using various learning approaches. It's also known as a domain, and it's a subset of artificial intelligence (AI). In recent years, deep learning (DL) has emerged as a promising, novel, and cutting-edge technology for data processing. It's a better form of artificial neural networks (ANN), which is one of today's most prominent AI technologies [22], [23].

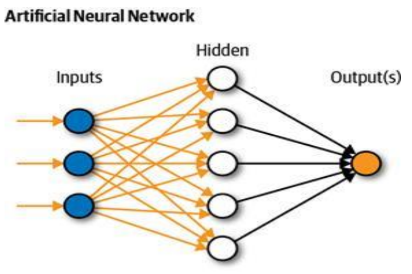


Figure 1. Artificial neural network

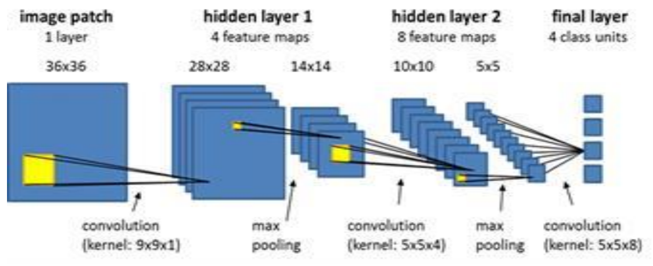


Figure 2. Main architecture of CNN

2.2.1. Machine learning and deep learning in agriculture

With the rise of big data technologies and high-performance computers, machine learning and DL algorithms have opened up new possibilities for data-intensive science in agri-technologies (agricultural crop management) which included applications such as yield prediction, disease detection, crop quality, species recognition uses: machine learning to sensor data, is evolving into real-time artificial intelligence-enabled algorithms, that provide insights for farmer decision support [2]. Remote sensing (RS) aircraft are used, which are unmanned aircraft, with techniques digital image images processing in the detection and identification of the most important problems related to agriculture. In this research paper, the focus is on the classification of olive trees cases through images of UAV.

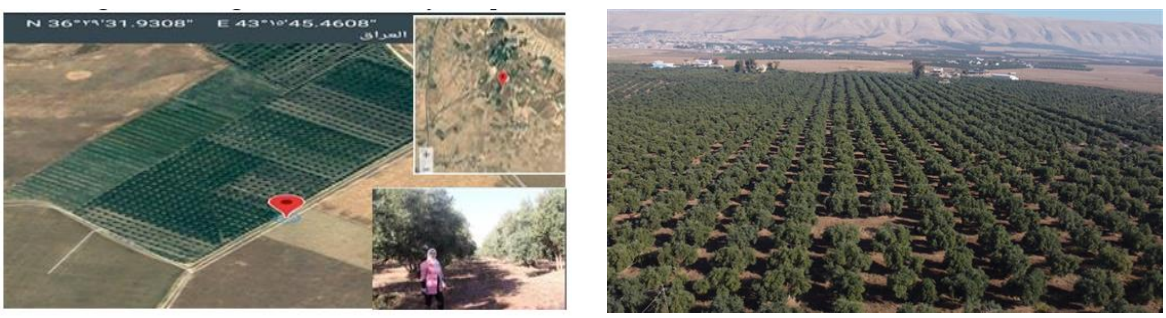
3. APPLICATION OF UAV IN AGRICULTURE

UAVs can revolutionize agriculture, and this platform has grown in importance as the digital farming era unfolds. Where traditional satellite sensing is still unsatisfactory, but UAV imaging could improve or even replace routine data assessments. In recent years, Data science has advanced significantly [24]. This technology is used in agriculture to help monitor crops from afar, making it easier to make decisions about the state of the field. There are various types of UAVs for different agricultural operation purposes to monitor and detect different plant diseases based on deep learning networks and convolutional neural networks such as DJI s1000, DJI s800, and phantom 4 pro [25].

4. MATERIAL AND INFORMATION

4.1. Research topic and data

In this study, a field study area was chosen to capture aerial photographs of olive groves trees to form the researcher's dataset as seen in Figure 3 using DJI (Mavic ari2) UAVs in Al-Fadiliyah, one of the largest villages in Nineveh Governorate, northern Iraq, with a geographical location is (N 36°29' 31.9308" E43°15'.408") as seen in Figure 3(a) which was used in this study, and the application of deep learning networks. The total number of aerial images is 1705 which were collected in this study Figure 3(b) shows the sample of the aerial image. Each image resized of 296 by 296 pixels.



(a) (b)

Figure 3. Form researcher's dataset, (a) study area location and (b) aerial image of trees olives for the study area

5. WORK METHOD AND RESULT

5.1. Researcher method

The work methodology used in this study takes place in obtaining data through aerial photography from drones pre-processing the data, and designing the artificial network algorithm, the deep learning model was fed with the collected data sets, which are the data set for healthy trees, high and low density, the data set for trees affected by Verticillium wilt disease, as well as the data set for dead trees. and then practical application of the data on it. After that, the performance of the network is evaluated through the results obtained for each type of deep convolutional neural network (DCNNs) models.

5.2. Data augmentation (DA)

DA techniques improve classification accuracy the process of increasing data is closely related to the improvement of the accuracy and stability of deep learning network models. This increase includes the generation of new data to expand the available dataset [26], and this method has proven its effectiveness in the fields of image processing and object recognition, giving the network high accuracy as a result of the increased number of data and extraction of more information from the original data. DA will help the field produce high-quality, reproducible results by training DL algorithms on datasets.

5.3. Deep learning transfer modeling

Several algorithms have been used to detect crop diseases [27], the most well-known of which are the visual geometry group algorithms (VGG19 [28] diagram seen in Figure 4. VGG16 [28], [29] diagram seen in Figure 5). Other networks for learning transfer include the residual neural network (ResNet50 [28], [29], [30] diagram seen in Figure 6). Previously trained these networks on a large dataset (ImageNet). This type of deep learning transfer network is useful in the field of image classification because it transfers learning and training to the image classification state, resulting in more effective results than if the training was started from the beginning [31]. In addition to ResNet50 VGG16 and VGG19, they trained and tested under the same conditions other, well-known, deep learning models: MobileNet shown in Figure 7 which is used for classification and detection. It converts a basic convolution into a depth-wise convolution by factoring it [32]. And Xception show in Figure 8, data is compressed into a few chunks by Xception packages [33]. Al network, in this work, the field data obtained from the UAV for olive trees orchard will be applied to the mentioned learning transmission networks. The accuracy of the results for each networks will be compared.

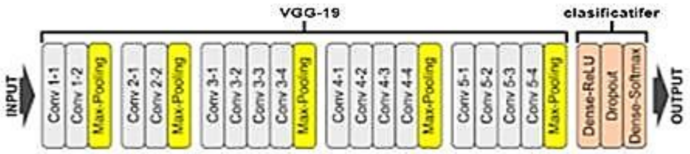


Figure 4. Schematic diagrams architecture of vgg19

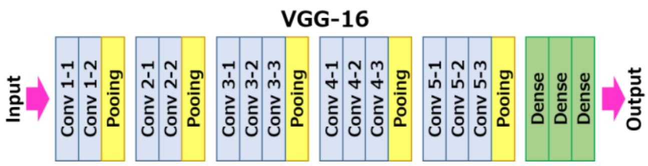


Figure 5. Schematic diagrams architecture of vgg16

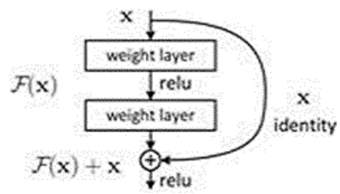


Figure 6. Schematic diagrams architecture of ResNet50

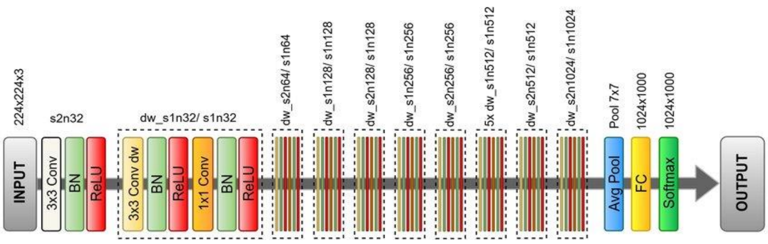


Figure 7. Schematic diagrams architecture of MobileNet

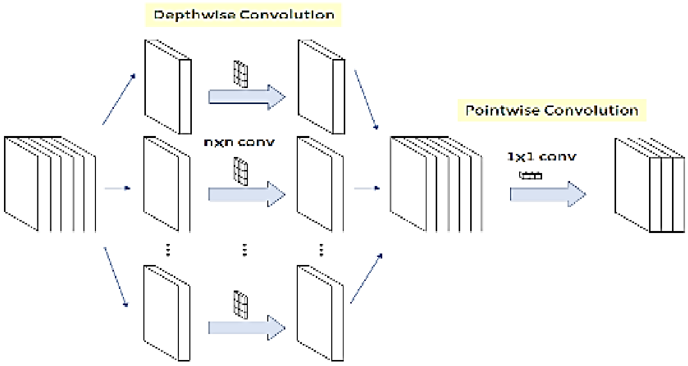


Figure 8. Schematic diagrams architecture of Xception

5.4. Researchers' method

The dataset was obtained in the field, which in this case was a sequence of aerial images captured by the DJI Mavic ari2 drone. Olive groves were depicted in the aerial shots, which totaled (1705). The goal of this research work is to find and distinguish between infected and healthy olive trees (the disease in question), also to determine whether healthy olive trees have a high density or not, as the photos were divided into four groups to conduct the study and apply deep learning networks, which are a sort of transfer on deep learning networks. The researchers work seen in Figure 9.

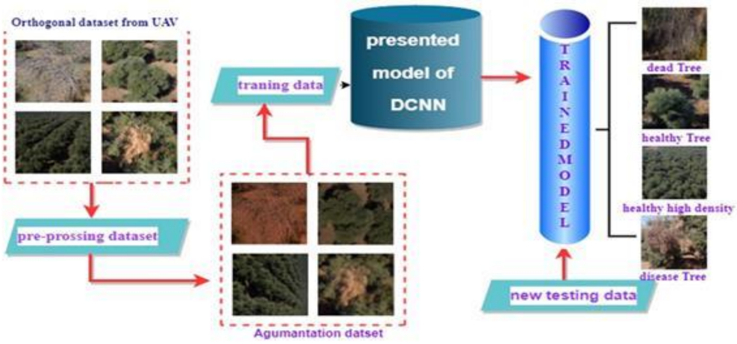


Figure 9. Researchers work

In this work, two fully connected (FC) layers were added to each transfer learning network which was used to classification olive trees case to obtain better accuracy. A new fully connected layer is simply a feed-forward neural network. Fully connected layers are found at the very bottom of the network. A fully connected layer receives input from the output layer of the final pooling or convolutional layer, which is flattened before it is used as input flattening the output entails unrolling all values obtained from the output after the last pooling or convolutional layer as a vector (3D matrix). The proposed DCNN show in Figure 10 as a vector (3D matrix).

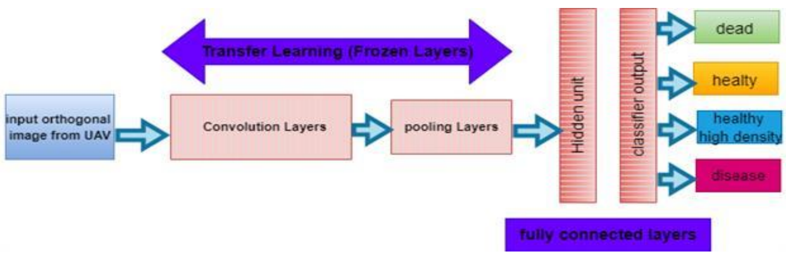


Figure 10. Proposed deep CNN

6. RESULT

After choosing the deep learning check model, applying our data to these networks, and implementing each type of network at a rate of 100 epochs, where the size of the images used in this study was (296 x 296) pixel, as the results obtained were as follows for each type of network used in this study. Table 1. The model of deep learning ResNet50 that given the high accuracy than other models. The accuracy for each model was calculated from (1), the result of the confusion matrix and Training and validation accuracy for each model of DCNN. The results of training the neural networks for each model are illustrated by Figures 11-15, which are listed for each type of networks used in this study. These figures show the results of training the networks (Xception, MobileNet, VGG19, VGG16 and ResNet50) sequentially, where the subfigures (a) represent the confusion matrices and subfigures (b) represent the training and validation accuracies. Furthermore the calculation of recal, precision and selectivity are given in (2)-(4) respectivley, given that (TP) is the true positive, (FP) is the false positive, (FN) is the false negative and (TN) is the true negative. The results are shown in Table 2.

$$Accuracy\ (\%) \quad = \frac{TP+TN}{TP+FP+FN+TN} 100\% \tag{1}$$

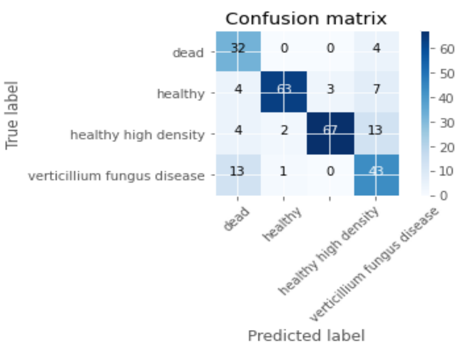
$$Recall \quad = \frac{TP}{TP+FN} \tag{2}$$

$$Precision \quad = \frac{TP}{TP+FP} \tag{3}$$

$$specivity \quad = \frac{TN}{TN+FP} \tag{4}$$

Table 1. Accuracy results for deep learning networks

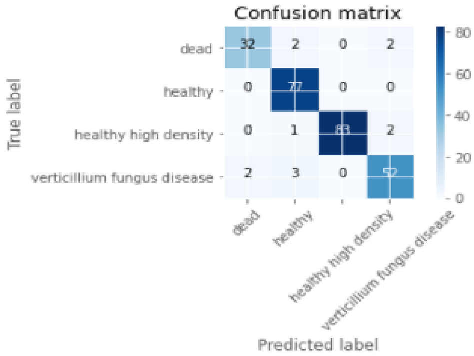
Model DCNN	Accuracy%
Xception	80
MobileNet	95.3
VGG19	94.5
VGG16	95.3
ResNet50	97.2



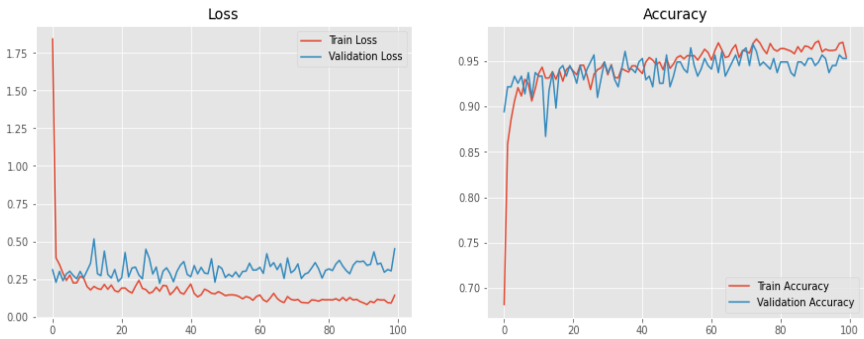
(a)

(b)

Figure 11. Xception network results, (a) confusion matrix and (b)Training and validation accuracy

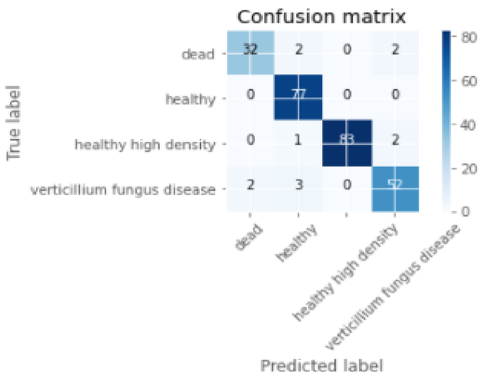


(a)

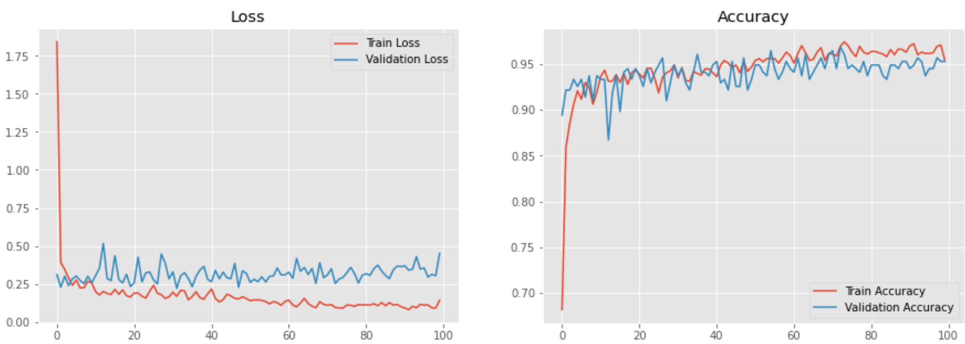


(b)

Figure 12. MobileNet network results, (a) confusion matrix and (b) training and validation accuracy

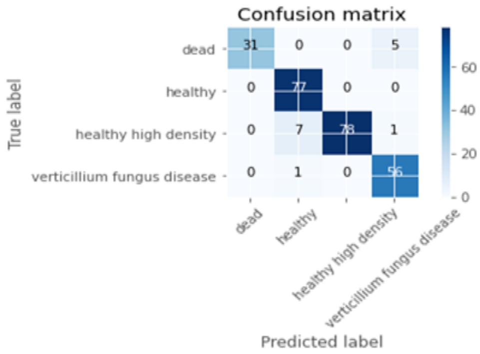


(a)



(b)

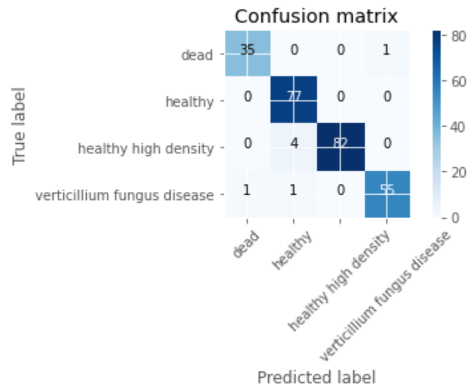
Figure 13. VGG16 network results, (a) confusion matrix and (b) training and validation accuracy



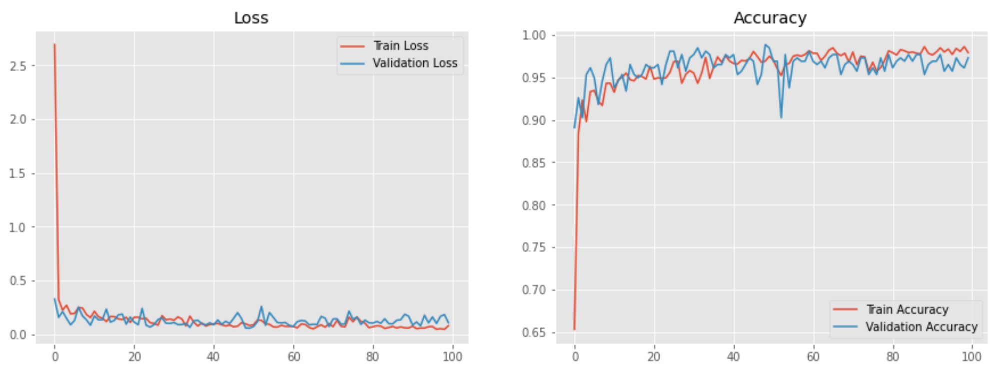
(a)

(b)

Figure 14. VGG19 network results, (a) confusion matrix and (b) training and validation accuracy



(a)



(b)

Figure 15. ResNet50 network, (a) confusion matrix and (b) training and validation accuracy

Table 2. Result of DCNN models

Olive tree classification	Model of DCNN	Xception	MobileNet	VGG16	VGG19	ResNet50
Dead	Precision	0.60	0.94	0.94	1	0.97
	Recall	0.88	0.91	0.88	0.86	0.97
	Specivity	0.90	0.99	0.99	1	0.99
Healthy	Precision	0.95	0.91	0.92	0.90	0.93
	Recall	0.81	0.98	1	1	1
	Specivity	0.97	0.96	0.95	0.95	0.97
Healthy high density	Precision	0.95	0.98	1	1	1
	Recall	0.77	1	0.96	0.90	0.95
	Specivity	0.97	0.99	1	1	1
Verticillium fungus disease	Precision	0.64	0.96	0.92	0.90	0.98
	Recall	0.75	0.85	0.91	0.98	0.96
	Specivity	0.98	0.98	0.97	0.97	0.99

7. CONCLUSION

The data that was adopted in this study were aerial photographs of olive orchard trees that were obtained in the field by the drone camera. The purpose of the study is to distinguish the condition of the trees if they are healthy or healthy with a high density or if they are infected with verticillium wilt disease or if the trees are dead as a result of infection with wilt disease. Five models of the deep learning network were applied modified Xcepion, MobileNet, VGG19, VGG16, and ResNet50 in this study, and it was found from the results obtained that the network of ResNet50 is the best. It obtains a higher accuracy than the other models, and the classification accuracy reached (97.2%). The objective is to apply this model to classify the types of diseases affecting olive trees. For future extension of this work, it is recommended to increase the dataset captured from drone, this is expected to increase the learning ability of neural network model to accomplish high accuracy detection.

REFERENCE

[1] M. Alruwaili, S. Alanazi, S. A. El-Ghany, and A. Shehab, "An efficient deep learning model for olive diseases detection," *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 8, pp. 486–492, 2019, doi: 10.14569/ijacsa.2019.0100863.

[2] M. E. Karar, F. Alsunaydi, S. Albusaymi, and S. Alotaibi, "A new mobile application of agricultural pests recognition using deep learning in a cloud computing system," *Alexandria Eng. J.*, vol. 60, no. 5, pp. 4423–4432, 2021, doi: 10.1016/j.aej.2021.03.009.

[3] K. R. Aravind, P. Raja, R. Ashiwin, and K. V. Mukesh, "Disease classification in Solanum melongena using deep learning," *Spanish J. Agric. Res.*, vol. 17, no. 3, 2019, doi: 10.5424/sjar/2019173-14762.

[4] M. Alruwaili, S. A. El-Ghany, and A. Shehab, "An enhanced plant disease classifier model based on deep learning techniques," *Int. J. Eng. Adv. Technol.*, vol. 9, no. 1, pp. 7159–7164, 2019, doi: 10.35940/ijeat.A1907.109119.

[5] X. Zhao, Y. Yuan, M. Song, Y. Ding, F. Lin, and D. Liang, "Use of unmanned aerial vehicle imagery and deep learning unet to extract rice lodging," *Sensors*, vol. 19, no. 18, pp. 1–13, 2019, doi: 10.3390/s19183859.

[6] H. Wu, "Autonomous detection of plant disease symptoms directly from aerial imagery," *Plant Phenome J.*, vol. 2, no. 1, pp. 1–9, 2019, doi: 10.2135/tppj2019.03.0006.

[7] J. G. A. Barbedo, "Plant disease identification from individual lesions and spots using deep learning," *Biosyst. Eng.*, vol. 180, no. 2016, pp. 96–107, 2019, doi: 10.1016/j.biosystemseng.2019.02.002.

[8] S. Uğuz, "Automatic olive peacock spot disease recognition system development by using single shot detector," *Sak. Univ. J. Comput. Inf. Sci.*, vol. 3, no. 3, pp. 158–168, 2020, doi: 10.35377/saucis.03.03.755269.

[9] M. Ainiwaer, J. Ding, and N. Kasim, "Deep learning-based rapid recognition of oasis-desert ecotone plant communities using UAV low-altitude remote-sensing data," *Environ. Earth Sci.*, vol. 79, no. 10, pp. 1–11, 2020, doi: 10.1007/s12665-020-08965-w.

[10] A. Dubey and M. Shanmugasudaram, "Agricultural plant disease detection and identification," *Int. J. Electr. Eng. Technol.*, vol. 11, no. 3, pp. 354–363, 2020, doi: 10.34218/IJEET.11.3.2020.038.

[11] U. Barman, R. D. Choudhury, D. Sahu, and G. G. Barman, "Comparison of convolution neural networks for smartphone image-based real time classification of citrus leaf disease," *Comput. Electron. Agric.*, vol. 177, no. January, p. 105661, 2020, doi: 10.1016/j.compag.2020.105661.

[12] Z. Zhang, P. Flores, C. Igathinathane, D. L. Naik, R. Kiran, and J. K. Ransom, "Wheat lodging detection from UAS imagery using machine learning algorithms," *Remote Sens.*, vol. 12, no. 11, 2020, doi: 10.3390/rs12111838.

[13] E. C. Tetila, "Detection and classification of soybean pests using deep learning with UAV images," *Comput. Electron. Agric.*, vol. 179, no. May, 2020, doi: 10.1016/j.compag.2020.105836.

[14] A. Safonova, E. Guirado, Y. Maglinets, D. Alcaraz-Segura, and S. Tabik, "Olive tree biovolume from UAV multi-resolution image segmentation with mask r-CNN," *Sensors*, vol. 21, no. 5, pp. 1–17, 2021, doi: 10.3390/s21051617.

[15] K. Manjula, S. Spoorthi, R. Yashaswini, and D. Sharma, "Plant disease detection using deep learning," in *Lecture Notes in Electrical Engineering*, vol. 783, pp. 1389–1396, 2022, doi: 10.1007/978-981-16-3690-5_133.

[16] F. Sabrina, S. Sohail, S. Thakur, S. Azad, and S. Wasimi, "Use of deep learning approach on UAV imagery to detect mistletoe infestation," *2020 IEEE Reg. 10 Symp. TENSYMP 2020*, no. January, pp. 556–559, 2020, doi: 10.1109/TENSYMP50017.2020.9230971.

[17] V. S. Dhaka *et al.*, "A survey of deep convolutional neural networks applied for prediction of plant leaf diseases," *Sensors*, vol. 21, no. 14, 2021, doi: 10.3390/s21144749.

[18] Y. Sun, Y. Liu, H. Zhou, and H. Hu, "Plant diseases identification through a discount momentum optimizer in deep learning," *Appl. Sci.*, vol. 11, no. 20, 2021, doi: 10.3390/app11209468.

[19] V. Margapuri, N. Penumajji, and M. Neilsen, "Seed classification using synthetic image datasets generated from low-altitude UAV imagery," *International Conference on Machine Learning and Applications (ICMLA)* 2022, pp. 116–121, doi: 10.1109/icmla52953.2021.00026.

[20] M. A. Alamir, "An artificial neural network model for predicting the performance of thermoacoustic refrigerators," *Int. J. Heat Mass Transf.*, vol. 164, p. 120551, 2021, doi: 10.1016/j.ijheatmasstransfer.2020.120551.

[21] H. Quang and N. Vo, "Realization and verification of deep learning models for fault detection and diagnosis of photovoltaic modules," *Translational Engineering* 2020.

[22] F. Bal and F. Kayaalp, "Review of machine learning and deep learning models in agriculture," *Int. Adv. Res. Eng. J.*, vol. 5, no. 2, pp. 309–323, 2021, doi: 10.35860/iarej.848458.

[23] K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine learning in agriculture: A review," *Sensors (Switzerland)*, vol. 18, no. 8, pp. 1–29, 2018, doi: 10.3390/s18082674.

[24] L. R. do Amaral, C. Zerbato, R. G. de Freitas, M. R. B. Júnior, and I. O. P. da Silva Simões, "UAV applications in agriculture 4.0," *Rev. Cienc. Agron.*, vol. 51, no. 5, pp. 1–15, 2020, doi: 10.5935/1806-6690.20200091.

[25] K. Neupane and F. B.-Gurel, "Automatic identification and monitoring of plant diseases using unmanned aerial vehicles: A review," *Remote Sens.*, vol. 13, no. 19, 2021, doi: 10.3390/rs13193841.

[26] E. Lashgari, D. Liang, and U. Maoz, "Data augmentation for deep-learning-based electroencephalography," pp. 1–55. *Journal of neurocsience*, doi: 10.1016/j.jneumeth.2020.108885.

[27] J. Potgieter, M. H. Saleem, and K. M. Arif "Plant disease detection and classification by deep learning," *plants*, pp. 32–34, 2019, doi: 10.3390/plants8110468.

[28] K. Thenmozhi and U. S. Reddy, "Crop pest classification based on deep convolutional neural network and transfer learning," *Comput. Electron. Agric.*, vol. 164, no. June, p. 104906, 2019, doi: 10.1016/j.compag.2019.104906.

[29] D. T. R. R. Sedamkar, "Detecting affect states using VGG16, ResNet50 and SE - ResNet50 Networks," *SN Comput. Sci.*, pp. 1–7, 2020, doi: 10.1007/s42979-020-0114-9.

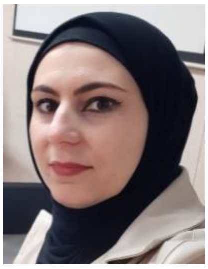
[30] E. Rezende, G. Ruppert, T. Carvalho, F. Ramos, and P. De Geus, "Malicious software classification using transfer learning of ResNet-50 deep neural network," *Proc. - 16th IEEE Int. Conf. Mach. Learn. Appl. ICMLA 2017*, vol. 2017-Decem, 2017, pp. 1011–1014, doi: 10.1109/ICMLA.2017.00-19.

[31] X. Han and R. Jin, "A small sample image recognition method based on resnet and transfer learning," *Proc. - 2020 5th Int. Conf. Comput. Intell. Appl. ICCIA 2020*, 2020, pp. 76–81, doi: 10.1109/ICCIA49625.2020.00022.

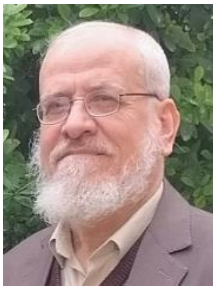
[32] U. Kulkarni, S. M. Meena, S. V Gurlahosur, and U. Mudengudi, "Classification of cultural heritage sites using transfer learning classification of cultural heritage sites using transfer learning," no. September, 2019, doi: 10.1109/BigMM.2019.00020.

[33] K. Hasan, T. Tanha, O. Faruk, and S. Aljahdal "Cataract disease detection by using transfer learning-based intelligent methods," *hinawi* vol. 2021, 2021, doi: 10.1155/2021/7666365.

BIOGRAPHIES OF AUTHORS



Noor Abdulhafed Sehree BSc.in Computer Engineering in 2006 from College of Electronics Engineering College/Mosul, now she is a post-graduate student for the master degree in Computer Engineering (Vegetation's Classification Based on Deep CNN from UAV Imagery) in Technical College/Mosul. She published research in computer science. She can be contacted at email: noorsehree7@gmail.com.



Abdulsattar M. Khidhir is an assistant professor at Mosul Technical Institute - Northern Technical University in Iraq. He obtained his B.Sc. (1981), M.Sc. (1989) and Ph.D. (2000) in Electronics and communications engineering from University of Mosul. He published many researches in various fields of science and engineering. He can be contacted at email: abdulsattarmk@ntu.edu.iq.