Selcuk Journal of Agriculture and Food Sciences
https://dergipark.org.tr/tr/pub/selcukjafsci
Research Article

(2024) 38(3), 414-426 DOI:10.15316/SJAFS.2024.037 e-ISSN: 2458-8377 Selcuk J Agr Food Sci

Identification of Leaf Diseases from Figs Using Deep Learning Methods

Yilmaz Karatas[1], Elham Tahsin Yasin[2], Talha Alperen Cengel[1], Bunyamin Gencturk[2], Muslume Beyza Yildiz[1], Yavuz Selim Taspinar[3], Osman Ozbek[4], Murat Koklu[1,*]

[1]Selcuk University, Technology Faculty, Department of Computer Engineering, Konya, Türkiye

[2]Selcuk University, Graduate School of Natural and Applied Sciences, Konya, Türkiye

[3]Selcuk University, Doganhisar Vocational School, Konya, Türkiye

[4]Selcuk University, Faculty of Agriculture, Department of Agricultural Machinery and Technologies, Konya, Türkiye

- HIGHLIGHTS
- Early detection of plant diseases is crucial for agricultural health and productivity.
- The study uses AI for early fig plant disease detection to minimize agricultural losses.
- Fig leaves dataset includes 1350 diseased and 971 healthy leaf images.
- The study compares DarkNet-19, ResNet50, VGG-19, and other algorithms for disease detection.
- VGG-19 achieved the highest accuracy at 93.32%, highlighting AI's potential in agriculture.

Abstract

Early detection of plant diseases is of great importance for agricultural production and plant health. Early detection is important to prevent the spread of diseases and reduce agricultural losses. The aim of this study is to use artificial intelligence technologies for the early detection of diseased fig plants and reduce agricultural losses. The fig leaf dataset used in the study has two classes: healthy and diseased leaves. There are a total of 2321 images in the dataset. Among these images, there are 1350 images representing diseased leaves and 971 images representing healthy leaves. The dataset is divided into 80% training data and 20% test data. DarkNet-19, ResNet50, VGG-19, VGG-16, ShuffleNet, GoogLeNet, MobileNet-v2, EfficientNet-b0, and DarkNet-53 algorithms were used to analyze the fig leaves dataset using a MATLAB graphical user interface (GUI). The classification accuracy values of each algorithm are as follows: DarkNet-19 90.3%, ResNet50 90.95%, VGG-19 93.32%, VGG-16 92.89%, ShuffleNet 89.44%, GoogLeNet 87.5%, MobileNet-v2 87.5%, EfficientNet-b0 85.56%, and DarkNet53 91.59%. These results evaluate the usability and performance of different algorithms for the early detection of plant diseases. The research emphasizes the importance of the effective use of artificial intelligence technologies in the agricultural industry.

Keywords: Data Analysis; Deep Learning Methods; Disease Detection; Image Classification; Fig Leaves Diseases

Citation: Karatas Y, Yasin ET, Cengel TA, Gencturk B, Yildiz MB, Taspinar YS, Ozbek O, Koklu M (2024). Identification of Leaf Diseases from Figs Using Deep Learning Methods. *Selcuk Journal of Agriculture and Food Sciences*, 38(3), 414-426. https://doi.org/10.15316/SJAFS.2024.037
Correspondence: mkoklu@selcuk.edu.tr
Received date: 02/07/2024
Accepted date: 09/09/2024

1. Introduction

Plant diseases are a growing challenge in the global agricultural industry, causing significant economic losses (Kursun et al. 2024). Monitoring plant health and detecting diseases early is used to prevent disease spread and facilitate effective management practices (Martinelli et al. 2015). Early detection of plant diseases can facilitate the treatment of diseased plants and increase the productivity of plant production (Kursun et al. 2023b). This helps to minimize the damage caused by disease in the agricultural sector and to obtain healthy products.

Detection of diseases with image processing in the agricultural sector is becoming increasingly popular. With the developing image processing techniques, the use of image processing in the agricultural sector is increasing and developing (Yasin et al. 2023). This technology enables the processing of images captured by computers using various analysis techniques and producing the desired information. Image processing plays a role in solving many problems in the agricultural sector (Kursun et al. 2023a). In particular, it facilitates agriculture in issues such as the classification and detection of crop diseases. With these techniques, diseased plant parts such as leaves can be identified, affected areas can be measured and diseases can be diagnosed (Alzoubi et al. 2023).

Especially the protection of fruits against diseases is of great importance, such as figs, which are widely consumed and play an important role in agricultural production. Early detection of fig leaf diseases is important for efficient production. What artificial intelligence and image analysis techniques can be used for fast and accurate detection of fig leaf diseases is examined. Artificial intelligence-based systems and computerized image processing methods can play an important role in the identification and classification of diseases in fig fields. The integration of these technologies can enable fig producers to respond to diseases faster and increase agricultural productivity (Sharma et al. 2020).

The classification of fig leaves represents a significant area of focus in agricultural research, driven by the objective of enhancing productivity and minimizing human errors. The correct identification and classification of fig leaves can lead to improved disease detection, better crop management, and ultimately, higher yields. In this study, we explore the application of convolutional neural network (CNN) classification algorithms to achieve accurate fig leaf classification. The algorithms tested on the used interface include a diverse array of models: DarkNet-19, ResNet50, VGG-19, VGG-16, ShuffleNet, GoogLeNet, MobileNet-v2, EfficientNet-b0, and DarkNet-53. Each of these models has been selected for their proven efficacy in image classification tasks and their varying architectural approaches, which provide a comprehensive comparison of their performance in the context of fig leaf classification.

This research aims to use deep learning techniques to develop a robust system for the automatic classification of fig leaves. By evaluating the performance of multiple CNN architectures, the study seeks to identify the most effective algorithm in terms of accuracy, computational efficiency, and adaptability to different environmental conditions. The implications of this research are far-reaching, offering potential advancements in precision agriculture where accurate plant classification can inform better decision-making and resource allocation.

This work represents a thorough investigation into the use of deep learning for fig leaf classification. By systematically comparing the performance of various CNN models, we aim to determine the optimal algorithm that not only achieves high classification accuracy but also demonstrates practical applicability in real-world agricultural settings. This study is poised to contribute significantly to the field of agricultural informatics, paving the way for more intelligent and automated farming practices.

Presently, the classification of healthy and diseased plant leaves is becoming an important area of research in the food industry and agriculture. In particular, studies on plant materials such as fig leaves, as well as leaves of other vegetables and fruits, are of importance for plant health and consumer health. Research in this field is also carried out on many other plant species, for example tomato, cotton, rice, or various fruit leaves.

Bari et al. (2021), used the Faster R-CNN algorithm for real-time detection of rice leaf diseases. Faster R-CNN presents an advanced region recommendation network (RPN) architecture for detection. This model is trained with publicly available online resources and real field rice leaf datasets and achieves good results in terms of accuracy. The proposed deep learning-based approach is able to automatically diagnose distinctive rice leaf diseases such as rice blast, brown spot, and hispa with accuracies of 98.09%, 98.85%, and 99.17%, respectively. Moreover, the model is able to identify healthy rice leaves with 99.25% accuracy.

De Luna et al. (2018), trained a deep learning-based convolutional neural network for the detection of diseases such as Phoma Rot, Leaf Miner and Target Spot in a specific tomato variety, Diamante Max. Using a dataset of 4,923 images of healthy and diseased tomato leaves, they developed a system to detect the presence or absence of these diseases. The trained convolutional neural network was successfully used to detect diseases in tomato plants. The anomaly detection model trained with F-RCNN produces 80% accuracy, while the disease recognition model trained with Transfer Learning achieves 95.75% accuracy. Using an automatic image capture system, they achieved 91.67% accuracy in recognizing diseases in tomato plant leaves.

Kumari et al. (2019), used the K-means clustering method to perform image segmentation of agricultural diseases. With this method, they identified the regions affected by the disease and extracted various features from these regions. The extracted features were used to classify the diseases. For cotton leaf diseases, the accuracy rates for bacterial leaf spot and target point detection were 90% and 80%, respectively. For tomato leaf diseases, they obtained 100% accuracy rate for septoria leaf spot and leaf mold detection.

In the study by Ozguven and Adem (2019), they highlighted the consequences of leaf spot disease (*Cercospora beticola* Sacc.) in the field causing yield loss in sugar beet. Timely detection of disease symptoms is important; disease progression can cause a loss of 10% to 50% of sugar yield. Therefore, early detection of disease symptoms and prompt treatment measures are necessary. The method proposed in this study was developed by modifying the R-CNN architecture. This method, which uses image-based expert systems, was trained and tested with 155 images. According to the test results, the overall correct classification rate of the proposed model was 95.48%.

Iqbal and Talukder (2020) emphasized that detecting Early Blight (EB) and Late Blight (LB), two important foliar diseases that commonly affect potato plants and inhibit growth, in the early stages can increase the productivity of potato crops. In this study, they propose an automated system based on image processing and machine learning that aims to identify and classify potato leaf diseases. In the study, they performed segmentation on 150 healthy, 150 Early Blight and 150 Late Blight potato leaf images obtained from a publicly available plant database. These images were processed with seven (Random Forest (RF), Logistic Regression (LR), k-Nearest Neighbors (KNN), Decision Trees (DT), Naive Bayes (NB), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM)) classifier algorithms to recognize and classify diseased and healthy leaves. As a result of the analysis, they determined that the Random Forest classifier performed the best with an accuracy rate of 97%.

Zhong and Zhao (2020) proposed three regression methods based on DenseNet-121 deep convolutional network, multi-label classification and focus loss function for apple leaf disease identification. They used an apple leaf image dataset containing 2462 images of apple leaf diseases for data modeling and method evaluation. The proposed methods achieved 93.51%, 93.31% and 93.71% accuracy on the test set, respectively. These results showed that they outperformed the cross-entropy loss function (92.29% accuracy) based on traditional multiple classification methods.

Zhang et al. (2019), addressed the limitations of existing image-based crop disease recognition algorithms. The limitations of the proposed approach in the classification process are focused on segmenting diseased leaf images with K-means clustering, extracting shape and color features from lesion information, and classifying diseased leaf images using sparse representation (SR). In this study, they compared the proposed approach with four other feature extraction-based methods (probabilistic neural networks (PNNs), sparse representation classification (SRC), Deep CNNs (DCNNs), and AlexNet) using a leaf image dataset focusing on cucumber diseases. The results show that the proposed approach has an accuracy of 85.7% in recognizing seven major cucumber diseases.

Yıldız et al. (2024), examined the use of different algorithms such as k-Nearest Neighbors (KNN), Random Forest (RF), Logistic Regression (LR), Support Vector Machine (SVM) and Neural Networks (NN) on a dataset created from images of tomato leaf diseases. An algorithm developed in Python provided the highest accuracy. They obtained the highest accuracy rate of 95.6% in the classification process. In addition, classification with the deep learning model was performed with an accuracy rate of 96%.

Using a dataset of fig leaves, a study compares the performance of different deep learning models to classify healthy and diseased leaves. This study aims to help in the rapid detection of diseased leaves in the agricultural sector. The rapid detection of diseased leaves contributes to faster treatment of diseased plants, thus increasing agricultural productivity (Yasin & Koklu 2023; Yasin et al. 2024).

2. Materials and Methods

In this study, various deep learning algorithms were applied to classify healthy and sick fig leaves using fig leaves dataset from Mendeley Data. The deep learning models used include DarkNet-19, ResNet50, VGG-19, VGG-16, ShuffleNet, GoogLeNet, MobileNet-v2, EfficientNet-b0 and DarkNet-53. The dataset is divided into 80% training and 20% test dataset. This separation of training and test sets provides a consistent testing environment to evaluate the performance of the models. Each deep learning algorithm was trained on the training data and validated on the test data to classify healthy and sick leaves. The results are analyzed and compared according to performance metrics such as classification accuracy, precision and sensitivity of the different algorithms (Hafi Saad et al. 2023). The steps to be applied in the study process are given in Figure 1.

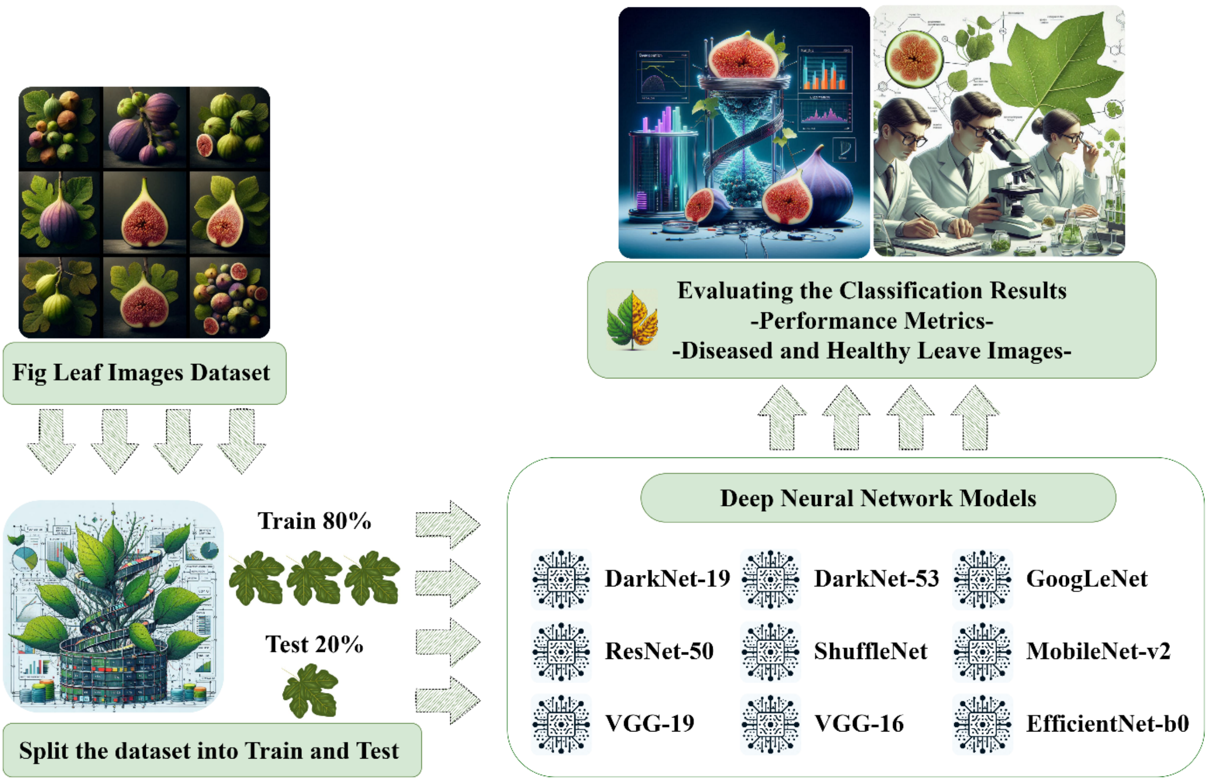

Figure 1. Fig leaf disease detection flow diagram

2.1. Dataset Description

"Fig Leaves Dataset" was used in this study. The dataset included healthy and diseased fig leaves, which were associated with Ficus leafworms. The dataset, obtained using the methods described in the paper, was used to study the health status of fig leaves and their association with Ficus leafworms. This dataset consists of high-resolution images that were precisely managed and acquired during the fruiting season. In total, the dataset contains 2321 images, with 1350 images representing infected leaves and 971 images depicting healthy ones. The images were acquired using a random sampling approach to ensure a balance between data from different fig trees and a detrimental mix of diversity. Sample images of the dataset are shown in Figure 2 (Hafi et al. 2024).

Healthy fig's leaves (a) **Diseased fig's leaves (b)**

Figure 2. Sample images of fig dataset

2.2. Convolutional Neural Network

The Convolutional Neural Network (CNN) is making significant achievements in the field of deep learning and attracting great attention in industry and academia. CNN is achieving impressive successes in image processing, natural language processing and many other areas. These achievements allow computers to understand and analyze complex visual data (Cinar & Taspinar 2023). CNN's wide range of applications and impressive performance have increased and are increasing its popularity in deep learning research and industrial applications (Li et al. 2021).

ResNet-50: ResNet is an important type of deep learning neural network introduced by Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun in 2015 in the paper "Deep Residual Learning for Image Recognition". This neural network has attracted attention by using a "residual learning" approach to facilitate the training of deeper networks. Compared to the ResNet-152 model, which had 152 layers in its first implementation, ResNet-50 has a smaller layer architecture. ResNet-50 has been trained in more than one million images and uses high-quality features learned from the ImageNet database. This model is a CNN and has a depth of 50 layers (Saritas et al. 2023). From one layer to the next, it passes the values needed to reach the result through predictions. To improve prediction accuracy, ResNet-50 has a special block structure that improves the quality of the results (Hayta et al. 2023; He et al. 2016).

EfficientNet-b0: EfficientNet is based on a base network developed using the AutoML MNAS framework. This network is fine-tuned to achieve maximum accuracy, but the computational load of the network is penalized if it is too large. Also penalized is the slow inference time, which is the time required for the network to make predictions. The architecture uses a mobile reverse bottleneck convolution similar to MobileNet-v2, but much larger in size due to the FLOPS (Total Loss Per Operation) increase. This base model is designed by a scaling strategy used to achieve a family of scaled EfficientNets. EfficientNet-b0 is a CNN algorithm developed to provide high performance and efficient computation in modern deep learning systems (Tan & Le 2019).

ShuffleNet: ShuffleNet is a highly efficient Convolutional Neural Network (CNN) model introduced in the paper "ShuffleNet: An Extremely Efficient Convolutional Neural Network for Mobile Devices" is a highly efficient Convolutional Neural Network (CNN) model. This model is specifically designed for use on mobile devices and aims to provide high accuracy while minimizing computational cost. ShuffleNet is optimized for mobile applications and works effectively in mobile environments with features such as low memory usage, low computational cost and fast inference time (Zhang et al. 2018).

DarkNet-19: DarkNet-19 is a convolutional neural network 19 layers deep. The network works with images of size 256x256 pixels. This network has been trained on more than one million images from the ImageNet database. Using a pre-trained model, it is able to classify images of 1000 object categories such as keyboard, mouse, pencil and many animals (Baygin et al. 2022).

GoogLeNet: "Going Deeper with Convolutions" is a research paper published in 2014 in collaboration between Google and several universities. In this paper, GoogLeNet (or Inception V1), a new architecture for increasing the depth of convolutional neural networks, was introduced. This architecture achieved great success by winning first place in the ILSVRC 2014 image classification competition (Cinar 2023). The overall architecture of Google Net has a depth of 22 times and is designed to prioritize computational efficiency. The basic idea of the architecture is that it can be run efficiently even on individual devices with low computational resources. It also includes two auxiliary classifier layers based on the Inception (4a) and Inception (4d) layers (Szegedy et al. 2015).

MobileNet-v2: MobileNet is a lightweight computer vision model. Open-sourced by Google, this computer vision model is specifically designed for training classifiers. MobileNet-v2 leverages deep convolutions using significantly fewer parameters compared to other networks, leading to a lightweight and efficient deep neural network. MobileNet-v2 is the first mobile computer vision model from TensorFlow (Howard et al. 2017; Koklu et al. 2022).

DarkNet-59: DarkNet-59 is a deep learning algorithm designed for computer vision applications. This algorithm is optimized for object recognition, classification and detection. DarkNet-59 is a customized version of the Darknet network architecture that underpins the YOLO (You Only Look Once) object detection systems. The DarkNet-59 algorithm is a 59-layer deep convolutional neural network. This network is designed with a special focus on speed and efficiency (Redmon & Farhadi 2018).

VGG-16: VGG-16 is an important convolutional neural network (CNN) model in the field of deep learning and computer vision. It was developed by the Visual Geometry Group (VGG) at the University of Oxford. VGG-16 is considered a fundamental reference point among deep convolutional neural networks and has a wide range of applications, especially in image classification tasks. VGG-16 model is a deep convolutional neural network with 16 layers (Koklu et al. 2023). These layers include 13 convolutional layers and 3 fully connected layers (Butuner et al. 2023; Simonyan & Zisserman 2014).

VGG-19: VGG-19 is a deep learning model for computer vision and was developed by the Visual Geometry Group (VGG) at the University of Oxford. The VGG-19 model is an extended version of the VGG-16 model and includes more convolutional layers. VGG-19 model is a deep convolutional neural network with a total of 19 layers (Koklu et al. 2023). These 19 layers include 16 convolutional layers and 3 fully connected layers (Simonyan & Zisserman 2014; Taspinar et al. 2022; Unal et al. 2022). The parameter values determined in all the algorithms used are shown in Table 1. These parameters follow common practices from earlier research and meet the needs of the models used. We also considered results from early tests, practical limits like computer power, and advice from experts.

Table 1. Parameter values used for fig leaf disease classification.

Parameter	Value
Validation Frequency	5
Max Epochs	8
Mini batch size	32
Initial learn rate	0.0001
Solver	sgdm
L2 Regularization	0.0001

2.3. Confusion Matrix and Performance Metrics

Confusion matrix is a type of matrix used to evaluate the performance of the model in classification problems. This matrix visualizes the relationship between the actual class labels and the class labels predicted by the model. Confusion matrix is used to analyze the accuracy, precision, recall rate and other performance measures of the model (Deng et al. 2016; Gencturk et al. 2024; Yildiz et al. 2024).

True Positive (TP): Represents true healthy outcomes. That is, the number of truly healthy samples that the model correctly predicts as healthy.

False Positive (FP): Represents samples that are truly diseased, but the model incorrectly predicts as healthy.

True Negative (TN): Represents true patient outcomes. That is, the number of truly sick samples that the model correctly predicted as sick.

False Negative (FN): Represents samples that are truly healthy but that the model incorrectly predicts as sick. These are missing healthy samples (Kursun et al. 2022; Yasin et al. 2023). An example table is shown in Table 2.

Table 2. Sample of binary confusion matrix.

		Actual Class	
		Healthy	**Infected**
Predicted	**Healthy**	**TP**	**FP**
Class	**Infected**	**FN**	**TN**

Confusion matrix is a tool used to evaluate the performance of classification models in more detail. This matrix visually shows the relationship between the model's actual class labels and the predicted class labels. By calculating various performance metrics with the values obtained from the confusion matrix, the performance of the model is analyzed in detail (Erdem et al. 2023; Koklu et al. 2012; Stehman 1997).

Accuracy: Indicates the proportion of correctly predicted samples in total samples. Accuracy measures the overall performance of the model.

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

Precision: Indicates the proportion of samples that the model predicts as healthy that are actually healthy. Precision focuses on reducing false positives (FP).

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

Recall: Indicates the proportion of samples that the model predicts as healthy that are actually healthy. Precision is focused on reducing false positives (FP).

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

F1-Score: The harmonic average of Precision and Recall. It is a balanced performance metric and focuses on both Precision and Recall in a balanced way.

$$\textbf{F1-Score} = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{3}$$

3. Results

Two classes of fig data were used in this study. This dataset contains healthy and diseased fig leaves. In total, the dataset contains 2321 images, of which 1350 images represent infected leaves, and 971 images represent healthy leaves. The dataset is divided into 80% and 20%. 80% of the parts is used as training data and the algorithms are trained on this dataset. During the training process, the algorithms learn from the dataset and recognize patterns in it. After the training is complete, a 20% data set is used to test the performance of the model. This test data set is different from the data set used in the training process and is used to evaluate the generalization ability of the model.

The application is realized with deep learning methods. The deep learning algorithms used include DarkNet-19, ResNet50, VGG-19, VGG-16, ShuffleNet, GoogLeNet, MobileNet-v2, EfficientNet-b0 and DarkNet-53. These algorithms are used to accurately classify and understand the health status of fig leaves.

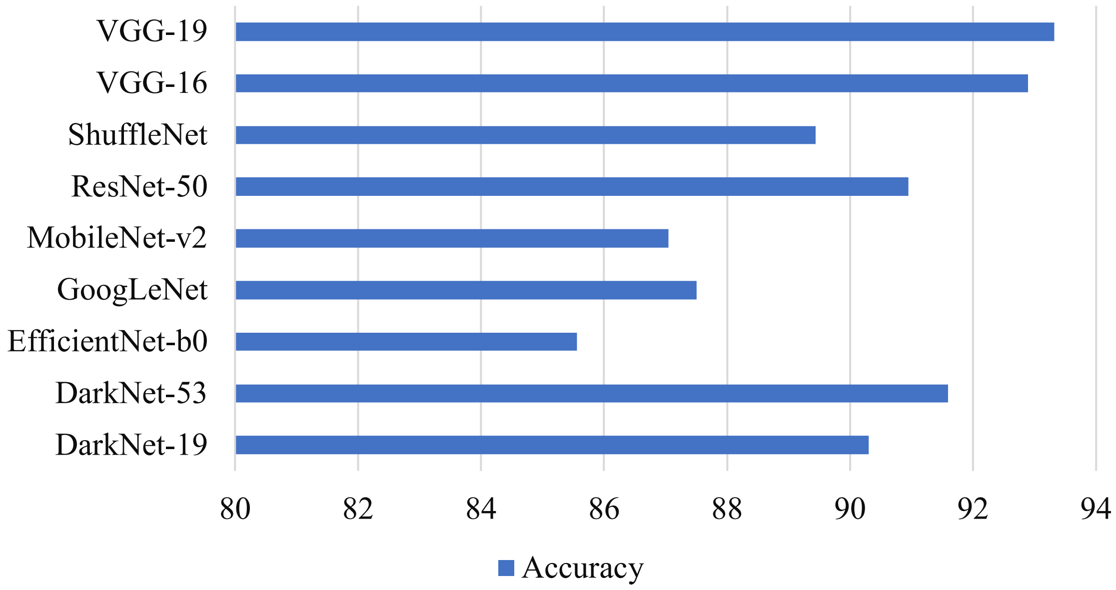

Figure 3. Accuracy values for the applied algorithms

In the deep learning methods, popular models such as DarkNet-19, ResNet50, VGG-19, VGG-16, ShuffleNet, GoogLeNet, MobileNet-v2, EfficientNet-b0, and DarkNet53 are evaluated. The classification accuracy values of each algorithm are as follows: DarkNet-19 90.30%, ResNet50 90.95%, VGG-19 93.32%, VGG-16 92.89%, ShuffleNet 89.44%, GoogLeNet 87.5%, MobileNet-v2 87.5%, EfficientNet-b0 85.56%, and DarkNet-53 91.59%.

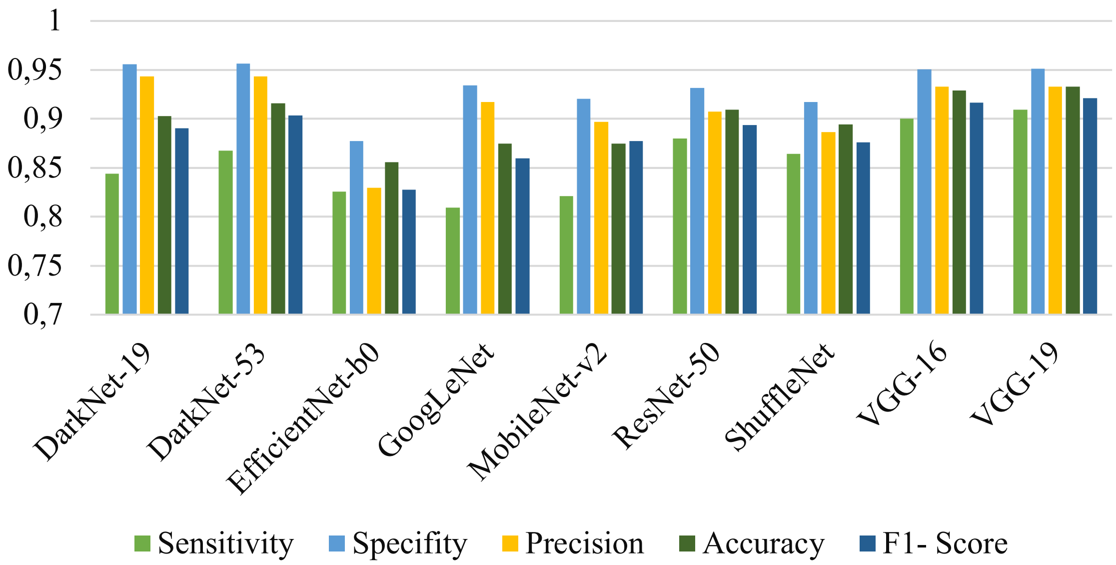

Figure 4. Performance metrics of the algorithm

Figure 4 shows performance metrics such as accuracy, precision, sensitivity and F1-score using the confusion matrix when working on a dataset of fig leaves classified as healthy or unhealthy. These values will help us to objectively evaluate the performance of your classification model. Each metric shows how successfully the model can distinguish between healthy and unhealthy classes and how reliable it can produce results.

In this study, it is noteworthy that the lowest accuracy results were obtained by GoogLeNet and MobileNet-v2 when deep learning algorithms such as GoogLeNet and MobileNet-v2 were applied to the dataset. The low accuracy performance of the GoogLeNet algorithm may be due to the complexity of the model's architecture. The GoogLeNet architecture has a depth of 22 times and has a complex and deep convolutional neural network structure. One of the reasons for such low results of GoogLeNet is the overall complexity of the model and its high demand on computational resources. Especially for lighter and simpler applications, lighter models such as MobileNet-v2 are preferred over GoogLeNet. MobileNet-v2 has an optimized architecture with low computational layers and can run more efficiently on mobile and local devices.

These results demonstrate the effectiveness of deep learning models for automatic recognition of leaf diseases. Models such as VGG19 and VGG16 have high accuracy and F1-Score ratios. These findings suggest that deep learning techniques can be successfully used in agricultural applications to diagnose fig leaf diseases and monitor the health of fig fruit. Table 3 shows the confusion matrix and metrics.

Table 3. Confusion matrix and performance metrics of algorithms

ALGORITHMS	CONFUSION MATRIX		ACCURACY	PRECISION	SENSITIVITY	F1-SCORE
DarkNet-19	183	11	0.903	0.9433	0.8443	0.8905
	34	236				
DarkNet-53	183	11	0.9159	0.9433	0.8673	0.9037
	28	242				
EfficientNet-b0	161	33	0.8556	0.8556	0.8256	0.8278
	34	236				
GoogLeNet	178	16	0.875	0.9175	0.8091	0.8599
	42	228				
MobileNet-v2	174	20	0.875	0.8969	0.8208	0.8771
	38	232				
ResNet-50	176	18	0.9095	0.9072	0.88	0.8934
	24	246				
ShuffleNet	172	22	0.8944	0.8866	0.8643	0.8759
	27	243				
VGG-16	181	13	0.9289	0.933	0.9005	0.9165
	20	250				
VGG-19	181	13	0.9332	0.933	0.9095	0.9211
	18	252				

The main reasons for the high accuracy of the VGG-19 algorithm are the following: This model is a deep convolutional neural network with 19 layers, and this depth provides the ability to learn more features and complexity. The main reasons why the VGG-19 algorithm has a high accuracy value are: This model is a deep convolutional neural network with 19 layers, and this depth provides the ability to learn more features and complexity. Moreover, the successive convolutional layers used in VGG-19 repeatedly extract different features from the input images, enabling deeper and more complex features to be identified. Furthermore, the small size (3x3) filters used in the model help to learn more localized features and provide overall better performance. Models like VGG-19 are usually pre-trained on large datasets and learn general features from large datasets. This allows for higher accuracy with impulsive training on a new dataset. Finally, various regularization techniques can be used in VGG-19 to avoid overfitting, which increases generalizability and leads to better accuracy. Combining all these features, VGG-19 is generally highly accurate, especially on large and diverse datasets.

4. Conclusions

Overall, the study emphasizes the importance of timely detection of plant diseases as a key component in controlling the spread of plant diseases and maintaining agricultural productivity and plant health. Using artificial intelligence technologies, specifically neural network algorithms, this research aims to identify diseased fig leaves with the highest degree of accuracy. An examination of a variety of algorithms shows that they can be effective and practical in the early detection of disease, ultimately resulting in less agricultural loss as a result of the process. This study highlights the importance of using advanced AI techniques in farming to increase crop yields and better manage diseases. The results of this study show that artificial intelligence can be used to detect fig plant diseases early. By comparing different algorithms like VGG-19, ResNet50, and DarkNet-53, the research shows how AI can reduce crop losses and manage diseases. In the farming industry, these results demonstrate the value of AI models in identifying healthy and diseased fig leaves. There can be a lot of potential for future work to extend the dataset to include a broader variety of plant species and disease types, as well as exploring the integration of these AI models with real-time surveillance systems for even more timely and efficient disease management in the future.

Author Contributions: Conceptualization, Yilmaz KARATAS, Talha Alperen CENGEL, Bunyamin GENCTURK, Elham Tahsin YASIN, Osman OZBEK, and Murat KOKLU; methodology, Yilmaz KARATAS, Talha Alperen CENGEL, Bunyamin GENCTURK, Elham Tahsin YASIN, Muslume Beyza YILDIZ, Yavuz Selim TASPINAR, Osman OZBEK, and Murat KOKLU; software, Yilmaz KARATAS, Yavuz Selim TASPINAR, and Elham Tahsin YASIN; validation, Yilmaz KARATAS, Yavuz Selim TASPINAR, Elham Tahsin YASIN, Osman OZBEK, and Murat KOKLU; formal analysis, Yilmaz KARATAS, Elham Tahsin YASIN; investigation, Yilmaz KARATAS, Yavuz Selim TASPINAR, and Elham Tahsin YASIN; writing—original draft preparation, Yilmaz KARATAS, and Elham Tahsin YASIN, Yavuz Selim TASPINAR; writing—review and editing, Yavuz Selim TASPINAR, Elham Tahsin YASIN, Osman OZBEK, and Murat KOKLU; visualization, Yavuz Selim TASPINAR, Yilmaz KARATAS, and Elham Tahsin YASIN; supervision, Yavuz Selim TASPINAR, Osman OZBEK, and Murat KOKLU. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The dataset used in this study, which was performed to help diagnose fig leaf diseases, can be accessed at: https://data.mendeley.com/datasets/f7dk2yknff/2

Conflicts of Interest: The authors declare no conflict of interest.

References

Alzoubi S, Jawarneh M, Bsoul Q, Keshta I, Soni M, Khan MA (2023). An advanced approach for fig leaf disease detection and classification: Leveraging image processing and enhanced support vector machine methodology. *Open Life Sciences 18*(1): 20220764.

Bari BS, Islam MN, Rashid M, Hasan MJ, Razman MAM, Musa RM, Ab Nasir AF, Majeed APA (2021). A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework. *PeerJ Computer Science 7*: e432.

Baygin M, Yaman O, Barua PD, Dogan S, Tuncer T, Acharya UR (2022). Exemplar Darknet19 feature generation technique for automated kidney stone detection with coronal CT images. *Artificial Intelligence in Medicine 127*: 102274. https://doi.org/10.1016/j.artmed.2022.102274

Butuner R, Cinar I, Taspinar YS, Kursun R, Calp MH, Koklu M (2023). Classification of deep image features of lentil varieties with machine learning techniques. *European Food Research and Technology 249*(5): 1303-1316. https://doi.org/10.1007/s00217-023-04214-z

Cinar I (2023). Detection of chicken diseases from fecal images with the pre-trained Places365-GoogLeNet model. *2023 IEEE 12th International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS)*.

Cinar I, Taspinar YS (2023). Detection of fungal infections from microscopic fungal images using deep learning techniques. *Proc Int Conf Adv Technol., August 17-19, 2023,* Istanbul, Turkiye.

De Luna RG, Dadios EP, Bandala AA (2018). Automated image capturing system for deep learning-based tomato plant leaf disease detection and recognition. *TENCON 2018-2018 IEEE Region 10 Conference*.

Deng X, Liu Q, Deng Y, Mahadevan S (2016). An improved method to construct basic probability assignment based on the confusion matrix for classification problem. *Information Sciences 340*: 250-261. https://doi.org/10.1016/j.ins.2016.01.033

Erdem K, Yildiz MB, Yasin ET, Koklu M (2023). A Detailed analysis of detecting heart diseases using artificial intelligence methods. *Intelligent Methods In Engineering Sciences 2*(4): 115-124.

Gencturk B, Arsoy S, Taspinar YS, Cinar I, Kursun R, Yasin ET, Koklu M (2024). Detection of hazelnut varieties and development of mobile application with CNN data fusion feature reduction-based models. *European Food Research and Technology 250*(1): 97-110. https://doi.org/10.1007/s00217-023-04369-9

Hafi S, Mohammed MA, Hamed D, Alaskar H, Abir H (2023). *fig leaves dataset, Mendeley Data,* Version 2, https://doi.org/10.17632/f7dk2yknff.2

Hafi SJ, Mohammed MA, Abd DH, Alaskar H, Alharbe NR, Ansari S, Aliesawi SA, Hussain AJ (2024). Image dataset of healthy and infected fig leaves with Ficus leaf worm. *Data in Brief 53*: 1-5. https://doi.org/10.1016/j.dib.2023.109958

Hayta E, Gencturk B, Ergen C, Koklu M (2023). Predicting Future Demand Analysis in the Logistics Sector Using Machine Learning Methods. *Intelligent Methods In Engineering Sciences 2*(4): 102-114. https://doi.org/10.58190/imiens.2023.70

He K, Zhang X, Ren S, Sun J (2016). Deep residual learning for image recognition. *Proceedings of the IEEE conference on computer vision and pattern recognition, In Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770-778.

Howard AG, Zhu M, Chen B, Kalenichenko D, Wang W, Weyand T, Andreetto M, Adam H (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861*. https://doi.org/10.48550/arXiv.1704.04861

Iqbal MA, Talukder KH (2020). Detection of potato disease using image segmentation and machine learning. *2020 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET)*, Chennai, India, 2020, pp. 43-47. https://doi.org/10.1109/WiSPNET48689.2020.9198563.

Koklu M, Cinar I, Taspinar YS (2023). Analysis of Hybrid Artificial Intelligence Models Determining Properly Wear a Face Mask. *Authorea Preprints*.

Koklu M, Kahramanli H, Allahverdi N (2012). A new approach to classification rule extraction problem by the real value coding. *International Journal of Innovative Computing, Information and Control 8*(9): 6303-6315.

Koklu M, Unlersen MF, Ozkan IA, Aslan MF, Sabanci K (2022). A CNN-SVM study based on selected deep features for grapevine leaves classification. *Measurement 188*: 110425. https://doi.org/10.1016/j.measurement.2021.110425

Kumari CU, Prasad SJ, Mounika G (2019). Leaf disease detection: feature extraction with K-means clustering and classification with ANN. *2019 3rd International Conference on Computing Methodologies and Communication (ICCMC).*

Kursun R, Yasin ET, Koklu M (2023a). The effectiveness of deep learning methods on groundnut disease detection. *11th International conference on advanced technologies (ICAT'23)*, Istanbul, Turkiye, pp. 4-20, https://doi.org/10.58190/icat.2023.11.

Kursun R, Yasin ET, Koklu M (2023b). Machine learning-based classification of infected date palm leaves caused by dubas insects: a comparative analysis of feature extraction methods and classification algorithms. 2*023 Innovations in Intelligent Systems and Applications Conference (ASYU)*, Sivas, Türkiye, pp. 1-6, https://doi.org/10.1109/ASYU58738.2023.10296641

Kursun R, Yasin ET, Koklu M (2024). Classification of Sugarcane Leaf Disease with AlexNet Model. *Proceedings of International Conference on Intelligent Systems and New Application*s, Liverpool, UK, pp. 32-37. https://doi.org/10.58190/icisna.2024.86.

Li Z, Liu F, Yang W, Peng S, Zhou J (2021). A survey of convolutional neural networks: analysis, applications, and prospects. *IEEE Transactions on Neural Networks and Learning Systems 33*(12): 6999-7019. https://doi.org/10.1109/TNNLS.2021.3084827

Martinelli F, Scalenghe R, Davino S, Panno S, Scuderi G, Ruisi P, Villa P, Stroppiana D, Boschetti M, Goulart LR (2015). Advanced methods of plant disease detection. A review. *Agronomy for Sustainable Development 35*: 1-25.

Ozguven MM, Adem K (2019). Automatic detection and classification of leaf spot disease in sugar beet using deep learning algorithms. *Physica A: Statistical Mechanics and its Applications 535*: 122537. https://doi.org/10.1016/j.physa.2019.122537

Redmon J, Farhadi A (2018). Yolov3: An incremental improvement. *arXiv preprint arXiv:1804.02767*. https://doi.org/10.48550/arXiv.1804.02767

Saritas MM, Taspinar YS, Cinar I, Koklu M (2023). Railway Track Fault Detection with ResNet Deep Learning Models, pp. 66-72. E-ISBN: 978-605-72180-3-2.

Sharma P, Hans P, Gupta SC (2020). Classification of plant leaf diseases using machine learning and image preprocessing techniques. 1*0th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, Noida, India, pp. 480-484. doi: 10.1109/Confluence47617.2020.9057889.

Simonyan K, Zisserman A (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*. https://doi.org/10.48550/arXiv.1409.1556

Stehman SV (1997). Selecting and interpreting measures of thematic classification accuracy. *Remote sensing of Environment 62*(1): 77-89. https://doi.org/10.1016/S0034-4257(97)00083-7

Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, Erhan D, Vanhoucke V, Rabinovich A (2015). Going deeper with convolutions. *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1-9.

Tan M, Le Q (2019). Efficientnet: Rethinking model scaling for convolutional neural networks. *International Conference on Machine Learning*.

Taspinar YS, Dogan M, Cinar I, Kursun R, Ozkan IA, Koklu M (2022). Computer vision classification of dry beans (*Phaseolus vulgaris* L.) based on deep transfer learning techniques. *European Food Research and Technology 248*(11): 2707-2725. https://doi.org/10.1007/s00217-022-04080-1

Unal Y, Taspinar YS, Cinar I, Kursun R, Koklu M (2022). Application of pre-trained deep convolutional neural networks for coffee beans species detection. *Food Analytical Methods 15*(12): 3232-3243. https://doi.org/10.1007/s12161-022-02362-8

Yasin E, Koklu M (2023). Utilizing Random Forests for the Classification of Pudina Leaves through Feature Extraction with InceptionV3 and VGG19. *Proceedings of the International Conference on New Trends in Applied Sciences*.

Yasin ET, Kursun R, Koklu M (2023). Deep learning-based classification of black gram plant leaf diseases: A comparative study. 1*1th International Conference on Advanced Technologies (ICAT'23)*, Istanbul-Turkiye.

Yasin ET, Kursun R, Koklu M (2024). Machine Learning-Based Classification of Mulberry Leaf Diseases. P*roceedings of International Conference on Intelligent Systems and New Applications*.

Yildiz MB, Hafif MF, Koksoy EK, Kursun R (2024). Classification of diseases in tomato leaves using deep learning methods. *Intelligent Methods In Engineering Sciences 3*(1): 22-36. https://doi.org/10.58190/imiens.2024.84

Yildiz MB, Yasin ET, Koklu M (2024). Fisheye freshness detection using common deep learning algorithms and machine learning methods with a developed mobile application. *European Food Research and Technology* 1-14. https://doi.org/10.1007/s00217-024-04493-0

Zhang S, Zhang S, Zhang C, Wang X, Shi Y (2019). Cucumber leaf disease identification with global pooling dilated convolutional neural network. *Computers and Electronics in Agriculture 162*: 422-430.

Zhang X, Zhou X, Lin M, Sun J (2018). Shufflenet: An extremely efficient convolutional neural network for mobile devices. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.*

Zhong Y, Zhao M (2020). Research on deep learning in apple leaf disease recognition. *Computers and Electronics in Agriculture 168*: 105146.