

A Deep Learning-Based Intelligent Approach for Automated Olive Leaf Disease Detection Using the Optimized VGG16

Issam Trrad

Department of Computer & Communications Engineering, Faculty of Engineering, Jadara University, Jordan
itrrad@jadara.edu.jo

Issa Alsmadi

Department of Data Science and Artificial Intelligence, Faculty of Information Technology, Ajloun National University P.O.43, Ajloun-26810, Jordan
i.alsmadi@anu.edu.jo

Mohamed S. Sawah

Department of Data Science and Artificial Intelligence, Faculty of Information Technology, Ajloun National University P.O.43, Ajloun-26810, Jordan | Department of Information Systems, Al-Alson Higher Institute, Cairo, Egypt
m.elsawah@anu.edu.jo (corresponding author)

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ABSTRACT

Olive leaf diseases significantly impact crop yield and quality, posing a threat to agricultural productivity and economic stability. Traditional disease detection methods are often time-consuming and costly. This study presents an automated deep learning approach for olive leaf disease classification, utilizing the VGG16 architecture with optimized fine-tuning. A dataset of 954 olive leaf images (382 infected, 572 healthy) collected from agricultural fields in Turkey was augmented via rotation, cropping, and flipping to enhance model robustness. The pre-trained VGG16 model was fine-tuned for feature extraction, followed by classification layers incorporating dropout and Softmax activation. Experimental results demonstrated a state-of-the-art classification accuracy of 99.47%, outperforming existing methods. The results confirm the effectiveness of deep learning for agricultural automation, providing a rapid, low-cost solution for early disease detection and management.

Keywords-olive leaf diseases; image classification; machine learning; agricultural automation; transfer learning

I. INTRODUCTION

Crop cultivation necessitates the meticulous management of each activity to achieve enhanced yields across the growing seasons. It entails a meticulous analysis of the crop, the specific varieties of seeds utilized, the essential minerals necessary for growth, as well as various other pertinent factors. The yields from the crops, along with other resources, are utilized to meet the daily necessities of the producers and the broader community [1]. Numerous plant diseases contribute to diminished harvest yields, adversely affecting both crop quantity and quality. Any alteration that inhibits a plant's ability to carry out its standard functions is referred to as a plant disease. Such maladies may considerably impact crop productivity, thereby diminishing both the overall yield and

quality [2]. Agricultural activities represent predominant economic sectors in numerous nations, as demonstrated by various studies. Agricultural commodities are exchanged on a substantial scale. Olives represent one of the products that is in high demand across numerous countries [3].

The olive tree represents a significant agricultural asset, serving multiple economic and functional purposes. Primarily cultivated for olive oil production (approximately 80%) and table olive consumption (roughly 20%), this versatile tree provides a diverse range of products and applications. Beyond its culinary significance, olive tree derivatives find extensive utilization in nutritional, dermatological, cosmetic, and medicinal domains. In the dermo-cosmetic sector, olive products are employed for hygiene and hair care treatments.

Additionally, olive-derived compounds demonstrate potential therapeutic applications, including blood pressure regulation and diabetes management. The tree's utility extends to agricultural and environmental sectors; with olive leaves and pomace being utilized for biomass production and livestock feed [4].

The trade of olive oil is considered one of the most important sources of income within many countries, and many citizens work in this sector, making it a vital sector for the country's economy. Indeed, significant endeavors have been undertaken globally to achieve comprehensive modernization of olive production, with the objective of enhancing the quality of olive oil and increasing the area of cultivated land. Recently, olive producers have been contending with numerous significant diseases, including olive leaf spot, which is attributable to fungal pathogens. Symptoms may manifest as purple or brown rings encircling a green or yellow center, or they may present as solid purple or brown circles. Olive leaf spot disease adversely impacts the vitality of the olive tree by inflicting damage upon the leaves, resulting in their premature abscission. This phenomenon leads to a substantial decline in productivity. Consequently, it is imperative to establish connections with specialists in order to advance the process of disease detection. This procedure may prove to be both time-consuming and financially burdensome. Human errors are also possible. Indeed, there exists a necessity for an automated, cost-effective, precise, and particularly rapid method for the detection of this olive disease.

Artificial Intelligence (AI) technologies, particularly Artificial Neural Networks (ANNs), have demonstrated widespread applicability as classification instruments across numerous fields [5]. As a crucial subset of AI, deep learning utilizes neuron-like mathematical operations to accomplish learning objectives. Neural Networks (NNs) have recently emerged as integral components in decision-making frameworks. Notably, Deep Neural Networks (DNNs), especially Convolutional Neural Networks (CNNs), have received considerable research focus, primarily due to their extensive implementation in identifying various diseases. Deep CNNs represent a sophisticated deep learning paradigm that has demonstrated significant success in comparison to traditional methodologies across various levels of image complexity. Deep learning has recently addressed numerous intricate challenges and has demonstrated exceptional efficacy in various computer vision and machine learning applications, including image classification. Deep CNN architectures have been specifically deployed for identifying plant diseases, aiming to supersede conventional disease detection methodologies.

In this study, we investigated the feasibility of using DNN models to detect olive leaf diseases. The dataset comprises images sourced from actual agricultural fields. Deep learning methodologies were employed to identify diseases affecting olive leaves. The proposed solution in this work consists of a deep learning model that employs VGG16 to detect olive leaf diseases. Unlike previous works using standard VGG16 [6, 7], our model applies an optimized fine-tuning process and tuned

dropout layers to prevent overfitting and enhance performance on the datasets.

II. RELATED WORKS

Contemporary research has witnessed a significant surge in the development of computer-aided systems for plant disease detection. The scholarly literature encompasses a broad spectrum of investigations addressing diverse plant pathologies. Specifically, in the domain of olive leaf disease detection, multiple studies have implemented various analytical approaches for classification purposes. These research endeavors have integrated an array of deep learning and machine learning algorithms architectures to achieve classification objectives. The following review examines key studies in the literature concerning olive leaf disease detection.

In [8], a pioneering machine learning and hybrid deep learning model was proposed, successfully achieving 96.14% accuracy in olive leaf disease classification. Authors in [9] introduced the MobiRes-Net hybrid deep learning model, which integrates ResNet50 and MobileNet architectures to detect and categorize three olive leaf disease types, utilizing drone-captured images from a Saudi Arabian olive grove. Authors in [10] developed a deep learning framework employing the Inception V3 architecture for olive leaf disease identification, demonstrating an accuracy of 96.66%. Authors in [11] proposed an innovative approach utilizing VGG16 with fine-tuning for olive leaf disease classification, achieving a remarkable 98% testing accuracy. Authors in [6] presented an optimal deep learning diagnostic model based on an adaptive genetic algorithm, which demonstrated superior performance in both multiclass and binary classification scenarios compared to alternative machine learning methodologies.

Authors in [12] introduced an innovative deep ensemble learning approach that integrates CNNs with vision transformer models to classify and detect olive leaf diseases, demonstrating exceptional performance in both binary and multiclass classification scenarios. The research presented in [13] developed a comprehensive diagnostic model for olive diseases, which combines image enhancement methodologies, clustering techniques, and deep learning-based classification to ensure precise and dependable diagnostic outcomes.

Authors in [14] proposed an innovative methodology integrating deep learning techniques, encompassing CNNs and vision transformers with cloud computing-based models, successfully detecting and classifying olive tree diseases with a remarkable multiclass classification accuracy of approximately 99.6%. Authors in [15] leveraged Unmanned Aerial Vehicles (UAVs) and deep learning, specifically employing transfer learning techniques, to achieve precise olive tree disease classification with an outstanding 99% precision accuracy. Authors in [16] developed a deep learning model utilizing the AlexNet architecture to detect and classify olive disease, demonstrating superior performance compared to existing state-of-the-art methodologies across accuracy, precision, recall, and F1-measure metrics. Additionally, author in [17] conducted an extensive comparative analysis of various CNN models with different optimization algorithms for olive disease detection, ultimately recommending the MobileNet architecture

with RMSProp optimization as the most effective model for constructing a robust disease detection system.

Authors in [18] used Decision Tree and Naive Bayes machine learning models to predict olive diseases with 97% and 80% accuracy, respectively, based on image processing of olive leaves. A deep CNN was proposed in [19] to detect anthracnose, a primary disease affecting olive production, in olives using hyperspectral images. Authors in [20] used deep CNNs to classify the condition of olive trees from aerial images captured by a drone, with the goal of distinguishing between healthy, high-density healthy, diseased, and dead olive trees, and found that the ResNet50 model achieves the highest classification accuracy of 97.2%.

A deep learning approach using the pre-trained Xception model was introduced in [21] to detect olive leaf diseases, achieving 93% accuracy on a validation set. A deep Recurrent Neural Network (RNN) model was introduced in [22] to detect and classify diseases affecting olive leaves, using image leaf collections from various sources. A novel lightweight incremental deep learning model was presented in [23] for classifying olive diseases in images, which is deployed on resource-limited mobile devices and can be continuously updated through new data collection and retraining. Authors in [24] introduced a deep learning model that achieves exceptional accuracy in classifying olive leaf diseases, particularly for imbalanced datasets, and outperforms existing models.

The study in [25] explored the application of CNNs for detecting diverse diseases and pests in olive tree leaves through image analysis using RGB and multispectral cameras, subsequently integrating classifier and detector mechanisms to assess the comprehensive disease level of an entire olive tree canopy, with results documented alongside temporal and geographical metadata. Authors in [26] employed image processing methodologies to categorize and identify two specific olive leaf diseases, namely, Neofabra leaf spot disease and Peacock leaf spot disease, by conducting a detailed analysis of infected leaf texture characteristics. Authors in [27] demonstrated the utilization of deep learning techniques, specifically CNNs, to precisely determine the onset of the olive tree flowering phenophase, a critical parameter for Integrated Pest Management (IPM). Authors in [28] introduced an optimized RNN model to detect olive leaf disease, employing wavelet transform and Ant Colony Optimization (ACO) for feature extraction, thereby developing a sophisticated deep learning model capable of comprehensive olive leaf disease classification.

Despite these significant contributions, most existing approaches exhibit limitations such as overfitting or limited generalization to diverse environmental conditions. To address these gaps, the proposed optimized VGG16 model integrates data augmentation and dropout-based regularization to enhance generalization while maintaining computational efficiency.

III. DATASET

This study employed the publicly available Olive Leaf Disease dataset, originally introduced in [29]. The dataset comprises 954 olive leaf images collected from agricultural

fields in Edincik, Bandırma Balıkesir province, Turkey, during the spring months. The collection includes 382 images of infected olive leaves and 572 images of healthy leaves, providing a balanced representation for binary classification. All images were acquired under natural field conditions and subsequently segmented for analysis. The dataset was randomly split into 80% for training and 20% for testing, ensuring a stratified balance of healthy and infected leaf images in both subsets to maintain the original class distribution.

IV. PROPOSED MODEL

A. Methodology

The proposed methodology employs an optimized VGG16 architecture organized into four distinct phases (Figure 1): Phase 1 transforms input images through preprocessing and augmentation; Phase 2 implements selective fine-tuning of the VGG16 backbone; Phase 3 fuses hierarchical features via Global Average Pooling (GAP); and Phase 4 performs classification with multi-layer regularization. This systematic pipeline ensures robust feature extraction from olive leaf images while maintaining generalization through comprehensive regularization strategies. Complete training specifications, including optimizer settings, learning rates, and hardware configuration, are detailed in Table I to ensure full reproducibility. The model's performance was evaluated using accuracy, precision, recall, and Area Under the Curve (AUC) metrics, achieving state-of-the-art classification results [30, 31].

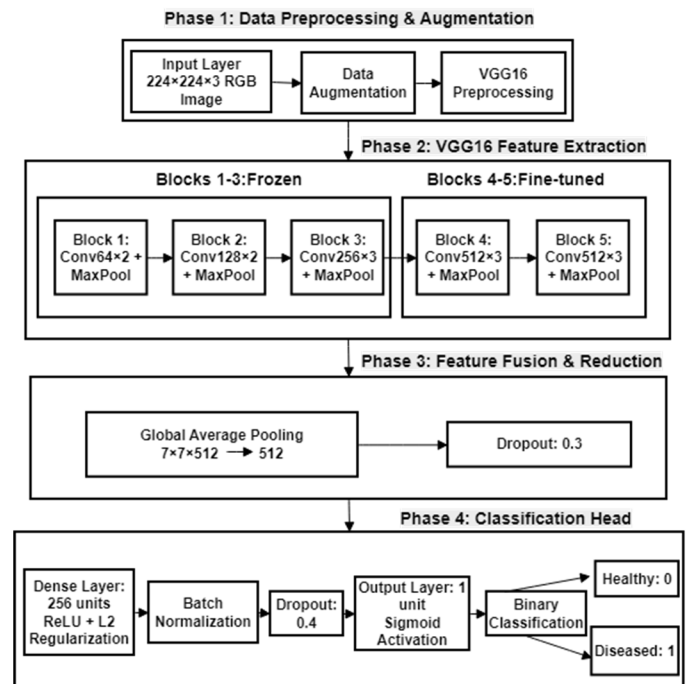


Fig. 1. Architecture of the proposed optimized VGG16 model.

1) Data Preprocessing and Augmentation

This initial phase transforms raw olive leaf images into optimized inputs suitable for deep learning. First, all images are resized to $224 \times 224 \times 3$ dimensions to comply with VGG16 input requirements, ensuring uniformity across the dataset. This

is followed by VGG16-specific preprocessing, which normalizes pixel values without the conventional $1/255$ scaling. To further enhance the model's ability to generalize, we implement extensive data augmentation techniques, including random rotations (12°), width/height shifts (12%), zoom variations (12%), shear transformations (8°), and horizontal flipping. These augmentation operations artificially expand the diversity of the dataset, effectively simulating various field conditions and enhancing model robustness against real-world variations in leaf orientation, lighting, and background interference.

2) VGG16 Feature Extraction with Selective Fine-Tuning

The core feature extraction process employs a transfer learning strategy using the VGG16 backbone pre-trained on the ImageNet dataset. We implement a two-stage optimization approach: initially freezing all VGG16 convolutional layers (Blocks 1-3) while training only the custom classification head for 10 epochs to stabilize feature adaptation. Subsequently, we unfreeze and fine-tune the last 8 convolutional layers (Blocks 4-5) with a reduced learning rate ($1e-5$) for 30 epochs. This selective fine-tuning allows the higher-level feature detectors to adapt to specifically to olive leaf disease patterns while preserving general-purpose edge and texture detectors from earlier layers. Overall, this strategy effectively balances domain adaptation with the retention of pre-trained knowledge.

3) Feature Fusion and Dimensionality Reduction

Feature fusion transforms the hierarchical VGG16 output through GAP, which reduces the final $7 \times 7 \times 512$ feature maps to a compact 512-dimensional vector by computing spatial averages across each channel. This fusion approach provides significant advantages over traditional flattening: it dramatically reduces the parameter count (preventing overfitting), enhances translation invariance, and generates more interpretable feature representations. The fused feature vector then passes through a 30% dropout layer for additional regularization before progressing to classification.

4) Classification with Progressive Regularization

The classification head processes the fused features through a carefully designed sequence: a 256-unit dense layer with ReLU activation and L2 weight regularization ($\lambda=1e-4$), batch normalization for stable gradient flow, progressive 40% dropout for enhanced regularization, and final sigmoid activation for binary classification. This multi-layered regularization strategy, combining L2 constraints, batch normalization, and progressive dropout ensures robust generalization while maintaining the model's discriminative power for distinguishing between healthy and diseased olive leaves with 99.47% accuracy.

B. Implementation Details and Training Configuration

The model was implemented using the comprehensive hyperparameter configuration detailed in Table I, ensuring complete reproducibility. All experiments were conducted using TensorFlow/Keras framework on NVIDIA Tesla P100 GPU hardware with fixed random seeds (SEED = 42) for deterministic results.

TABLE I. COMPREHENSIVE TRAINING CONFIGURATION

Hyperparameter	Value
Base model	VGG16 (pre-trained on ImageNet)
Optimizer	Adam
Initial learning rate (head training)	$1e-4$
Learning rate (fine-tuning)	$1e-5$
Epochs (head training)	10
Epochs (fine-tuning)	30
Batch size	32
Image size	224×224
Data augmentation	Rotation, shifting, zooming, shearing, horizontal flip
Dropout rates	0.3 (after GAP), 0.4 (after dense layer)
Dense layer units	256
Activation	ReLU (dense), Sigmoid (output)
Hardware	NVIDIA Tesla P100 (Kaggle)

V. RESULTS AND DISCUSSION

The proposed model demonstrates robust performance in olive leaf disease classification, accurately identifying various disease manifestations. Smooth convergence in training and validation curves indicates effective discriminative feature learning while mitigating overfitting. These findings confirm the model's potential as a reliable tool for early detection and classification of olive leaf diseases, aiding in agricultural disease management. The model's performance is demonstrated in the following figures.

Figure 2 presents the loss evolution of the proposed VGG16 model over 50 training epochs. Both training and validation loss decrease steadily, indicating effective learning and smooth convergence. The close alignment of the two curves demonstrates the model's strong generalization capability and minimal overfitting. Occasional fluctuations in validation loss around mid-epochs were quickly corrected, reflecting the stabilizing effect of dropout regularization. These results confirm that the optimized architecture and augmentation strategies successfully minimized the classification error during training.

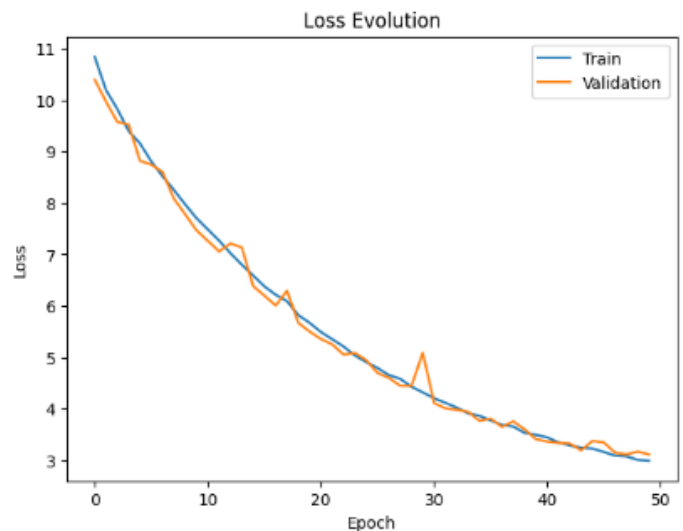


Fig. 2. Loss evolution of the proposed VGG16 model.

Figure 3 illustrates the training and validation accuracy curves for the olive leaf disease classification task. The model achieves rapid improvement in accuracy within the early epochs, surpassing 95% after only ten iterations. Both curves later stabilize near the final accuracy of 99.47%, confirming consistent learning and strong discriminative performance. Although minor oscillations are observed in validation accuracy, the overall trend shows that the fine-tuned VGG16 network effectively captures robust features, maintaining high generalization across unseen samples.

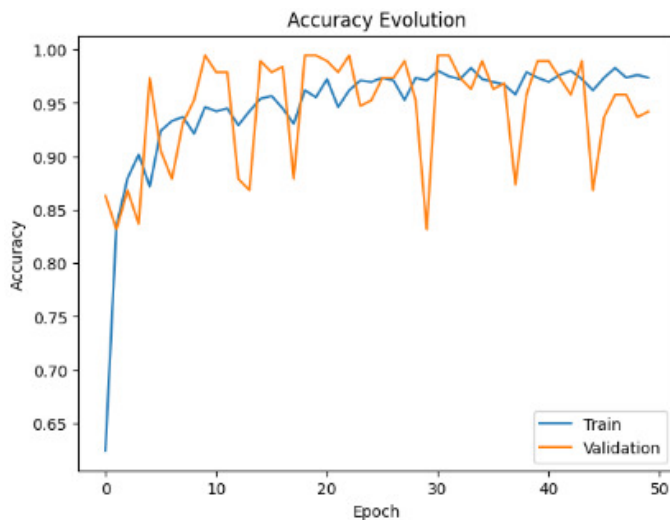


Fig. 3. Training and validation accuracy of the proposed VGG16 model.

Figure 4 demonstrates exceptional classification performance with only one misclassification among 190 samples. The model correctly identified 75 diseased leaves (true positives) and 114 healthy leaves (true negatives), with a single false negative where one diseased leaf was incorrectly classified as healthy. The absence of false positives confirms the model's reliability in avoiding incorrect disease diagnoses, which is crucial for effective agricultural intervention.

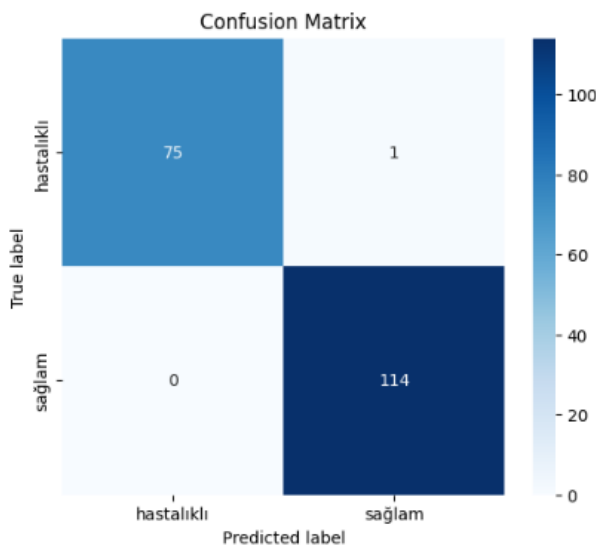


Fig. 4. Confusion matrix of the proposed VGG16 model.

Figure 5 demonstrates exceptional model discrimination with an AUC of 0.9999, approaching perfect classification capability. This near-perfect score indicates the model's outstanding ability to distinguish between healthy and diseased olive leaves, maintaining high true positive rates while minimizing false positives across all classification thresholds. The steep curve hugging the top-left corner reflects optimal diagnostic performance essential for reliable agricultural disease detection systems.

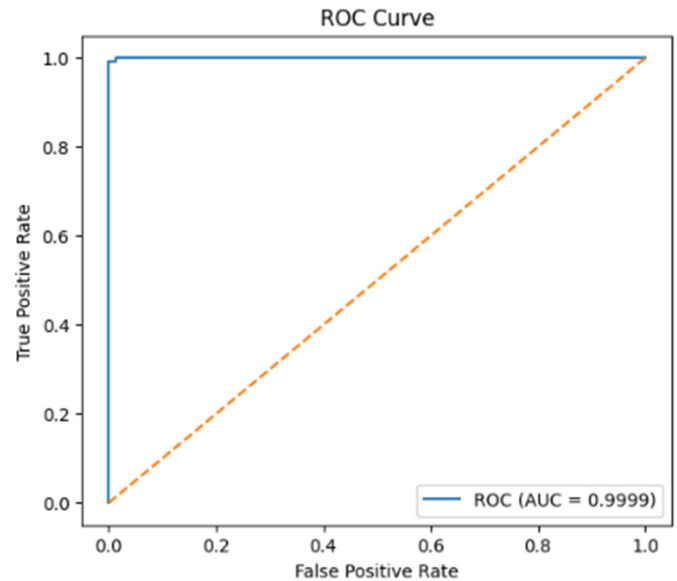


Fig. 5. Receiver Operating Characteristic (ROC) curve of the proposed VGG16 model.

Table II shows that the model demonstrates near-perfect performance with balanced metrics across both classes. Diseased leaves achieve flawless precision (1.0000) whereas healthy leaves show perfect recall (1.0000), indicating robust classification capability with minimal errors in practical application.

TABLE II. CLASSIFICATION PERFORMANCE METRICS FOR OLIVE LEAF DISEASE DETECTION

Class	Precision	Recall	F1-score
Diseased	1.0000	0.9868	0.9934
Healthy	0.9913	1.0000	0.9956

Table III presents a comparative analysis between the proposed optimized VGG16 model and several state-of-the-art approaches for olive leaf disease classification. The reported accuracies confirm that deeper and hybrid architectures, including ResNet101 + MobileNet [29] and CNN-ViT models [13], achieve strong performance. However, the proposed VGG16 framework attains the highest accuracy of 99.47%, exceeding the best previously reported value of 98.63%. This improvement results from the integrated optimization strategy that combines fine-tuning, dropout regularization, and data augmentation to enhance feature learning and generalization. Unlike complex hybrid networks that incur high computational costs, the optimized VGG16 offers an efficient balance

between accuracy and efficiency, enabling practical deployment for real-time agricultural disease monitoring.

TABLE III. COMPARISON RESULTS OF OLIVE LEAF DISEASE CLASSIFICATION METHODS

Study	Method	Features	Accuracy (%)
[32]	Single shot detector	Detector	96.0
[33]	VGG16, VGG19, and modified custom CNN	CNN	95.0
[9]	MobiResNet: MobileNet and ResNet50	CNN	97.08
[17]	AlexNet, VGG, GoogleNet and ResNet	CNN	92.59
[13]	Vision Transformers + CNN hybrid model	ViT + CNN	97.0
[4]	Mask RCNN, Fast RCNN, and Inception V3	RGB + multispectral	89.9
[29]	ResNet101 + MobileNet	CNN	98.63
This study	VGG16	CNN	99.47

VI. CONCLUSION AND FUTURE WORK

This study successfully developed a deep learning model for the classification of olive leaf diseases using the VGG16 architecture. By augmenting a dataset of olive leaf images and fine-tuning the pre-trained VGG16 model, the proposed model achieved an exceptional accuracy of 99.47%, surpassing previous methods documented in the literature. The model's performance underscores the effectiveness of transfer learning and data augmentation in addressing challenges related to limited agricultural datasets. The integration of rotation, cropping, and flipping during preprocessing significantly improved model generalization. VGG16's hierarchical feature extraction capability enabled precise discrimination between healthy and diseased leaves.

However, limitations include the dataset's geographic specificity (limited to olive leaves from Turkey). Future work could expand the dataset to include diverse olive varieties and disease types, and integrate Unmanned Aerial Vehicle (UAV)-based imaging for large-scale field monitoring. Additionally, combining hyperspectral imaging with deep learning may further enhance diagnostic accuracy. This research contributes to advancing precision agriculture, offering a scalable tool for mitigating crop losses caused by olive leaf diseases. The model's robustness highlights its potential for real-time agricultural deployment, particularly on low-cost mobile and UAV-based systems for early disease detection and control.

DATA AVAILABILITY

This study used the Olive Leaf Disease dataset, available at: <https://www.kaggle.com/datasets/serhathoca/zeytin>.

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