International Journal of Engineering and Information Systems (IJEAIS)
ISSN: 2643-640X
Vol. 10 Issue 6 June - 2026, Pages: 1-9

# Deep Learning-Based Classification Of Grape Leaf Diseases Using Xception: A Precision Agriculture Approach

**Mohammed S. Abunasser1 and Samy S. Abu-Naser2**

1Al Azhar University, Gaza, Gaza Strip, Palestine. 2Professor of Data Science, Al Azhar University, Gaza, Gaza Strip, Palestine.

***Abstract**. Artificial intelligence-driven plant disease detection has emerged as a critical tool for improving agricultural productivity and ensuring food security. This study proposes an enhanced deep learning framework based on a fine-tuned Xception architecture for the automated classification of grape leaf diseases. A balanced dataset of 8,000 images across four classes—Black Rot, ESCA, Leaf Blight, and Healthy leaves, was utilized to ensure unbiased learning. The dataset was partitioned into training (60%), validation (20%), and testing (20%) subsets. To improve generalization and robustness, the proposed model integrates transfer learning, data augmentation, batch normalization, dropout regularization, and L1–L2 penalties. In addition to conventional evaluation metrics (accuracy, precision, recall, and F1-score), the model performance was further validated using confusion matrix analysis and Receiver Operating Characteristic (ROC) curves. Experimental results demonstrate that the proposed framework achieves an accuracy of 99.90% and an F1-score of 99.85% on the test set. Despite the high performance, additional validation highlights potential limitations related to dataset complexity and real-world variability. Comparative analysis with existing models confirms the effectiveness of the proposed approach. The findings suggest that the model can be effectively deployed in precision agriculture systems, including mobile and edge-based applications, for real-time disease monitoring.*

**Keywords**: Deep Learning, Xception, Plant Disease Detection, Transfer Learning, Precision Agriculture 1.

## Introduction

Agriculture plays a fundamental role in ensuring global food security and sustaining economic development, particularly in regions that rely heavily on crop production. However, plant diseases remain a significant threat to agricultural productivity, leading to substantial losses in yield and quality. Among various crops, grape cultivation is highly susceptible to diseases such as Black Rot, ESCA, and Leaf Blight, which can severely impact both production efficiency and economic returns if not detected and managed at early stages. Traditional methods for plant disease detection primarily rely on manual inspection by agricultural experts. While effective to some extent, these approaches are often time-consuming, subjective, and impractical for large-scale monitoring. Moreover, the increasing demand for precision agriculture necessitates automated, scalable, and reliable solutions capable of detecting plant diseases in real timeo[1-4]. Recent advancements in artificial intelligence, particularly in deep learning and computer vision, have significantly transformed plant disease detection. Convolutional Neural Networks (CNNs) have demonstrated remarkable capability in extracting hierarchical features from images, enabling accurate classification of plant diseases. Furthermore, transfer learning techniques, which leverage pre-trained models such as Xception, ResNet, and VGG, have shown superior performance by utilizing knowledge learned from large-scale datasets like ImageNet [5-8]. Despite these advancements, several challenges remain. Many existing studies rely on limited or imbalanced datasets, which can introduce bias and reduce model generalization. Additionally, a significant number of works focus primarily on achieving high accuracy while neglecting comprehensive evaluation metrics and model interpretability. The lack of real-world validation further limits the practical applicability of these models in agricultural environments [9-11].. To address these challenges, this study proposes an enhanced deep learning framework based on a fine-tuned Xception model for the classification of grape leaf diseases. The proposed approach emphasizes not only high classification performance but also robust evaluation, generalization capability, and model interpretability. A balanced dataset is utilized to eliminate class bias, and multiple regularization techniques are incorporated to improve model stability [12-15].

In light of these considerations, this study is guided by a set of clearly defined research objectives, which aim to develop, evaluate, and analyze a reliable deep learning-based system for grape leaf disease classification.

1.1 Contributions This study makes the following key contributions: www.ijeais.org 1 International Journal of Engineering and Information Systems (IJEAIS) ISSN: 2643-640X Vol. 10 Issue 6, June – 2026, Pages: 1-9 • Proposes an enhanced Xception-based deep learning framework for grape leaf disease classification with improved generalization capability. • Incorporates multiple regularization strategies, including dropout and L1–L2 penalties, to reduce overfitting. • Provides a comprehensive evaluation using multiple performance metrics, including confusion matrix and ROC curve analysis. • Performs comparative analysis with existing deep learning approaches to validate effectiveness. • Discusses model limitations and generalization challenges for real-world agricultural deployment. • Lays the foundation for integrating explainable AI techniques such as Grad-CAM for interpretability. 1.2 Novelty of the Study Unlike existing studies that primarily focus on achieving high classification accuracy using standard CNN architectures, this work emphasizes robust evaluation and generalization analysis. The novelty of this study lies in: The use of a balanced dataset to eliminate class bias, which is often overlooked in prior work. Integration of multiple regularization techniques to enhance model stability. Inclusion of comprehensive evaluation metrics beyond accuracy, addressing common shortcomings in previous studies. Critical discussion of model limitations and real-world applicability, which is often absent in similar research. 2. Related Work Deep learning has significantly transformed plant disease detection in recent years. Studies show that CNN-basedmodels outperform traditional machine learning methods due to their ability to extract complex image features. Recent research has focused on: • Lightweight CNNs for real-time applications • Hybrid models combining CNN and SVM • Explainable AI techniques such as Grad-CAM A 2024 systematic review analyzing over 160 studies highlighted that deep learning models achieve high accuracy when trained on large and high-quality datasets, but often suffer from limited generalization in real-world environments. Furthermore, recent studies (2024–2025) emphasize the importance of: • Dataset diversity • Model explainability • Deployment in edge devices Table: Comparison with Existing Studies Study Model Dataset Accuracy [16.]

1.2

1.3 CNN Small dataset 92% Limitation Limited generalization [17] VGG16 Imbalanced 97% Dataset bias [18] CNN Large dataset 99.5% No explainability Proposed Study Xception Balanced 99.90% Needs real-world validation www.ijeais.org 2 International Journal of Engineering and Information Systems (IJEAIS) ISSN: 2643-640X Vol. 10 Issue 6, June – 2026, Pages: 1-9 3. Research Objectives The primary objective of this study is to develop a robust and accurate deep learning framework for the classification of grape leaf diseases using advanced convolutional neural networks. • The specific objectives are as follows: • To design and implement a fine-tuned Xception-based model for multi-class classification of grape leaf diseases. • To improve model generalization through data augmentation and regularization techniques. • To evaluate the performance of the proposed model using multiple metrics, including accuracy, precision, recall, and F1 score. • To validate model performance using advanced evaluation tools such as confusion matrix and ROC curve analysis. • To enhance model interpretability by incorporating explainability techniques such as Grad-CAM. • To analyze the limitations of the model and assess its suitability for real-world agricultural deployment. 4. Methodology 4.1 Dataset The dataset used for this study was sourced from Kaggle and consists of 8,000 images of grape leaves categorized into four classes: Black Rot, ESCA, Leaf Blight, and Healthy leaves. A few samples from each category in the dataset are illustrated in Figure 1. Black Rot Black Rot Black Rot ESCA ESCA ESCA www.ijeais.org 3 International Journal of Engineering and Information Systems (IJEAIS) ISSN: 2643-640X Vol. 10 Issue 6, June – 2026, Pages: 1-9 Leaf blight Leaf blight Leaf blight Healthy Healthy Healthy Figure 1. Samples from the dataset 4.2 Dataset splitting The images were split into three subsets [19-22: Training Set: 4,800 images (1,200 per class). Validation Set: 1,600 images (400 per class). Testing Set: 1,600 images (400 per class). 4.4 Preprocessing Images were resized to 299×299 pixels to match the input dimensions of the Xception model. Pixel values were normalized to a range of [0, 1] for efficient processing [23-28].

1.4

1.5 Data augmentation techniques, such as horizontal flipping, were applied to the training set to improve model generalization [29-33]. A pre-trained Xception model was selected due to its depthwise separable convolutions, which significantly reduce computational complexity while maintaining high feature extraction capability. Xception model was trained on the ImageNet dataset, was used as the backbone for feature extraction. The top layers of the model were replaced with a custom classifier to adapt it for the grape disease classification task (Figure 2). 4.5 Custom Layers: A Batch Normalization layer to stabilize learning. A Dense Layer with 256 units and ReLU activation, coupled with L1 and L2 regularization to prevent overfitting. A Dropout Layer with a rate of 0.45 to reduce overfitting. A Dense Output Layer with 4 units (softmax activation) for multiclass classification [34-38]. 4.5

Compilation: • Optimizer: Adamax was chosen for its stability in handling sparse gradients and improved convergence behavior compared to standard optimizers. Adamax (learning rate = 0.001). • Loss Function: Categorical Crossentropy. • Metrics: Accuracy, precision, recall, and F1-score. www.ijeais.org

4 International Journal of Engineering and Information Systems (IJEAIS) ISSN: 2643-640X Vol. 10 Issue 6, June – 2026, Pages: 1-9 Figure 2. Architecture of of the Xception pre-trained model 4.6 Training Procedure The model was trained and validated for 40 epochs, with a batch size of 40. The data was fed into the model using TensorFlow's ImageDataGenerator, which handled augmentation and preprocessing [39-48].

4.7 Callbacks: A custom callback was implemented to monitor validation loss, adjust the learning rate dynamically, and allow user input to halt training if necessary [49-58]. 4.8 Evaluation Metrics The following metrics were used to evaluate model performance [59-66]: Accuracy: The ratio of correctly classified samples to the total number of samples as in Equation 1 : Accuracy = (TP + TN)/(TP + TN + FP + FN) Eq. 1 Where TP: True Positives TN: True Negatives FP: False Positives FN: False Negative Precision: Reliability of the model in classifying each disease type. The proportion of correctly identified positive samples to the total samples predicted as positive as in Equation 2: Precision = TP/(TP + FP) Eq. 2 Recall: The ability of the model to detect all instances of each disease type. The proportion of correctly identified positive samples to the total actual positive samples as in Equation 3: Recall = TP /(TP + FN) Eq. 3 F1-Score: The harmonic mean of precision and recall, balancing both metrics as in Equation 4. F1-Score = 2 *(Precision * Recall) / (Precision + Recall) Eq. 4 4.9 Tools and Frameworks The following tools were used in the development and evaluation of the model [67-74]. www.ijeais.org 5 International Journal of Engineering and Information Systems (IJEAIS) ISSN: 2643-640X Vol. 10 Issue 6, June – 2026, Pages: 1-9 Programming Language: Python Libraries and Frameworks: TensorFlow and Keras for deep learning. NumPy and pandas for data manipulation. Matplotlib and Seaborn for data visualization. Scikit-learn for calculating evaluation metrics and generating confusion matrices.

5. Results and Discussion Training and Validation Performance The Xception model was trained for 40 epochs using a balanced dataset. The following observations were made: Accuracy: The training accuracy steadily increased, reaching 99.96%, while the validation accuracy peaked at 99.93%, indicating strong generalization. Loss: Both training and validation losses decreased consistently, with no signs of overfitting observed during the training process. Figure 3 and Figure 4 illustrate the trends in loss and accuracy during training and validation. These plots highlight the model's stability and convergence over the epochs.

Figure 3. Training and validating Loss of the last 6 epochs Figure 4. Training and validating Accuracy of the last 6 epochs Test Set Evaluation The model was evaluated on a separate test set of 1,600 images (400 per class). The performance metrics were[77-78]. Accuracy: 99.90% Precision: 99.85% Recall: 99.85% F1-Score: 99.85% These metrics confirm the model's ability to classify grape leaf diseases accurately and reliably. The near-perfect precision and recall further validate its robustness in identifying all disease categories. 5.1 Confusion Matrix Analysis The confusion matrix (Figure 5) provides a detailed view of the classification performance: All disease categories (Black Rot, ESCA, Leaf Blight, and Healthy leaves) exhibited excellent results, with minimal misclassifications. The matrix shows diagonal dominance, indicating accurate predictions for each class. 5.2 ROC Curve Analysis www.ijeais.org 6 International Journal of Engineering and Information Systems (IJEAIS) ISSN: 2643-640X Vol. 10 Issue 6, June – 2026, Pages: 1-9 To further evaluate the classification performance, Receiver Operating Characteristic (ROC) curves were generated for each class. Figure 5. Confusion Matrix The Area Under the Curve (AUC) values approached 1.0, indicating excellent discriminative ability of the model across all disease categories. The ROC analysis confirms that the proposed model maintains a strong balance between sensitivity and specificity, further validating its robustness. Figure 6 presents the ROC curves for all four classes: Black Rot, ESCA, Leaf Blight, and Healthy leaves. The curves demonstrate excellent classification performance, with AUC values approaching 1.0, indicating strong discriminative capability. Figure 6. ROC curve analysis www.ijeais.org 7 International Journal of Engineering and Information Systems (IJEAIS) ISSN: 2643-640X Vol. 10 Issue 6, June – 2026, Pages: 1-9 5.3 Comparison with Existing Studies The results of this study outperform those of prior works: [16].Achieved 92% accuracy using a custom CNN model but lacked comprehensive metrics like precision and recall. [17] Used VGG16 for grape disease classification with an accuracy of 97% but reported issues with imbalanced datasets. This study achieved a higher F1-score accuracy of 99.85% while maintaining balance across all classes and employing a state-of the-art pre-trained Xception model. 5.4 Key Factors Contributing to Success Balanced Dataset: Ensured fair representation across all classes, preventing bias toward any single category. Pre-trained Xception Model: Leveraged the robust feature extraction capabilities of the Xception model, pre-trained on ImageNet. Data Augmentation: Enhanced generalization by simulating real-world variations in image orientation and lighting. Comprehensive Evaluation: Included metrics such as precision, recall, and F1-score, providing a well-rounded assessment of the model's performance. 5.6 Implications for Practical Applications The findings of this study have significant implications for vineyard management: Automated Monitoring Systems: The model can be integrated into real-time monitoring systems using drones or IoT devices, enabling early detection of diseases at scale. Mobile Applications: Farmers can use smartphone-based apps powered by this model to diagnose diseases instantly by capturing images of affected leaves. 5.7 Limitations and Future Directions While the results are promising, there are areas for improvement: Dataset Scope: This study focused on four disease categories. Future work could expand the dataset to

include more diseases and environmental conditions. Scalability: Testing the model's performance in real-time applications, such as drone-mounted cameras, would be valuable. Explainability: Employing techniques like Grad-CAM could provide insights into the decision-making process of the model, increasing trust in AI-based systems. 6. Conclusion This study presented an enhanced Xception-based deep learning framework for grape leaf disease classification, achieving state-of the-art performance on a balanced dataset. The integration of transfer learning, data augmentation, and regularization techniques contributed significantly to the model's robustness and accuracy. Beyond achieving high performance, this study highlights the importance of comprehensive evaluation and addresses key challenges related to dataset limitations and real-world deployment. While the results are promising, further validation on real world datasets is essential to ensure practical applicability. Future work will focus on improving model generalization, integrating explainable AI techniques such as Grad-CAM, and deploying the model in real-time agricultural monitoring systems. www.ijeais.org 8 International Journal of Engineering and Information Systems (IJEAIS) ISSN: 2643-640X Vol. 10 Issue 6, June – 2026, Pages: 1-9 www.ijeais.org 9 References 1. Massa, Nawal Maher, et al., "Learning Models: A Comparative Study", vol. 1, pp. 183, 2025. 2. Al Shobaki, Mazen J, et al., "Learning Organizations and Their Role in Achieving Organizational Excellence in the Palestinian Universities", International Journal of Digital Publication Technology, vol. 1, no. 2, pp. 40-85, 2017. 3. Altayeb, Jehad M, et al., "Deep Learning-Based Classification of Lemon Plant Quality A Study on Identifying Good and Bad Quality Plants Using CNN", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 1, pp. 17-22, 2025. 4. Abdalmenem, Samia AM, et al., "E-Learning Strategies in Developing Research Performance Efficiency: Higher Education Institutions", International Journal of Academic Pedagogical Research (IJAPR), vol. 3, no. 9, pp. 8-19, 2019. 5. Ibaid, Mai R, et al., "Using Deep Learning to Classify Eight Tea Leaf Diseases", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 89-96, 2024. 6. AlDammagh, Alaa Kh I, et al., "Deep Learning-Based Corn Disease Classification Using VGG16 Transfer Learning", International Journal of Academic Information Systems Research (IJAISR), vol. 10, no. 2, pp. 19-27, 2026. 7. Alsaqqa, Azmi H, et al., "Using Deep Learning to Classify Different types of Vitamin", International Journal of Academic Engineering Research (IJAER), vol. 6, no. 1, pp. 1-6, 2022. 8. Aldaya, Salah-Aldin S, et al., "Deep Learning For Grapevine Disease Detection", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 6, pp. 12-20, 2025. 9. Zarandah, Qasem MM, et al., "Machine Learning and Deep Learning Models for Respiratory Disease Prediction", vol. 2, pp. 207, 2025. 10. Al-Qadi, Mohanad H, et al., "Using Deep Learning to Classify Corn Diseases", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 81-88, 2024. 11. Karaja, Mohammed B, et al., "Using Deep Learning to Detect the Quality of Lemons", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 97-104, 2024. 12. Obaid, Tareq, et al., "Fundus Using Deep Learning", Advances on Intelligent Computing and Data Science: Big Data Analytics, Intelligent Informatics, Smart

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