

DETECTION AND CLASSIFICATION OF GRAPE LEAF DISEASES USING CNN-BASED DEEP LEARNING MODELS¹

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Abstract: Nutrition is a fundamental requirement for all living organisms and is defined as one of the most basic physiological needs in Maslow's hierarchy of needs. Among the food products consumed by humans, grapes attract attention with their high nutritional value and strong antioxidant components. Similar to other plants, grapevines are susceptible to various diseases caused by environmental and biological factors. Therefore, the early detection of such diseases is of great importance, as it enables timely interventions and helps preserve plant health. In this study, the early-stage identification of diseases was targeted by analyzing images of grape leaves. The aim was not only to detect existing diseases but also to distinguish between different disease types through the learning ability of the model. In this context, deep learning-based Convolutional Neural Network (CNN) architectures were employed. A dataset consisting of grape leaf images was processed in the Python-based Google Colab environment, and disease detection and classification were carried out using the AlexNet, DenseNet121, EfficientNetB3, MobileNetV2, and ResNet50 architectures. All models were trained for 20 epochs, and performance metrics such as accuracy, precision, recall, and F1-score were calculated. According to the findings, the accuracy rates of the AlexNet, DenseNet121, EfficientNetB3, MobileNetV2, and ResNet50 models were 56%, 98%, 43%, 97%, and 51%, respectively. Based on these results, it was concluded that the DenseNet121 and MobileNetV2 architectures achieved the most successful performance in detecting and classifying grape leaf diseases.

Keywords: Grape leaf disease, Deep learning, Convolutional Neural Networks (CNN), DenseNet121, MobileNetV2, AlexNet, EfficientNetB3, ResNet50, Image Classification

INTRODUCTION

Agriculture is regarded as a transformative turning point in human history—a fundamental revolution that enabled the survival, development, cognitive expansion, and productivity of humankind. Historical analyses show that early humans adopted a hunter-gatherer lifestyle, which required continual migration. The extensive amount of time spent searching for food made this activity the central focus of their life cycle. With the advent of agriculture, humans transitioned to a sedentary lifestyle, and regular cultivation practices necessitated the monitoring of seasonal changes and precipitation patterns. This requirement contributed to the emergence of planning, strategic thinking, and organized production. Moreover, the development of agricultural tools and the use of animal power supported human cognitive advancement and laid the groundwork for new inventions.

Agriculture is a sector that depends directly on soil, water, and climatic conditions and requires patience (Topal, 2010). In its broadest definition, agriculture refers to the economic activity of obtaining plant-based and animal-based products through the utilization of soil and seeds, and transforming these products into high value-added goods (Tokatlıoğlu et al., 2018).

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Among agricultural crops, grapes hold a particularly significant place and possess a historical background as old as humanity itself. The grapevine is believed to have originated in the southern region of the Caspian Sea, Northeastern Anatolia, and the Caucasus. Archaeological findings indicate that grapes have been cultivated across various regions of the world for millions of years. Historically, grapes were intensively used in the production of wine and vinegar. During the Hittite period in Anatolia, viticulture had a prominent role, and even specific laws were enacted to protect vineyards. Although the importance of winemaking decreased with the spread of Islam in the region, grapes continued to be used in the production of vinegar, molasses, and other grape-based products (Sağlam, 2018).

Despite its robust structure, the grapevine is vulnerable to various diseases. Although it is relatively tolerant to cold, it is particularly susceptible to fungal and rust diseases. However, when these diseases are detected at an early stage, their spread can be rapidly controlled, and appropriate interventions can facilitate the recovery of affected plants.

Technological advancements in the modern era have increased productivity in agricultural Production, and mechanization has reduced the need for human labor. With the integration of artificial intelligence technologies into agriculture, disease detection and intervention processes have become faster and more effective. In particular, image processing and deep learning techniques play a crucial role in the identification of plant diseases. By processing leaf images, the health status of the plant can be analyzed, and deep learning models can accurately determine the type of disease.

Image processing is a discipline concerned with modifying an image from its original form, enhancing specific features, and analyzing it using statistical methods. It fundamentally consists of optical devices that capture images, analog-digital converters, and software systems that analyze the processed images (Aytan et al., 1993). Beyond agriculture, it is widely applied in fields such as industry, healthcare, and defense.

Deep learning, on the other hand, is a machine learning approach inspired by the functioning of the human brain. It involves training multilayered artificial neural networks with large datasets. Each layer processes the output of the preceding layer, enabling the extraction of increasingly abstract and meaningful features (Deng & Yu, 2014). Common architectures used in deep learning include convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, deep belief networks, and autoencoders (Şeker et al., 2017).

In this study, the effectiveness of Convolutional Neural Network (CNN)-based deep learning methods in the detection and classification of diseases observed in grape leaves is examined.

MATERIALS AND METHODS

Dataset

This study aims to investigate the detection and classification of diseases observed in grape leaves using CNN-based deep learning methods. The dataset used in the research consists of grape leaf images included in the PlantifyDr Dataset available on the Kaggle platform. The dataset comprises four distinct classes, each containing approximately three thousand images. This comprehensive and well-balanced data structure provides a suitable foundation for the training and evaluation processes of deep learning models (Kaggle, 2024).

The images belonging to the dataset are presented in Figure 1. The dataset consists of the following classes:

- Grape Black Measles
- Grape Black Rot
- Grape Isariopsis Leaf Spot
- Grape Healthy

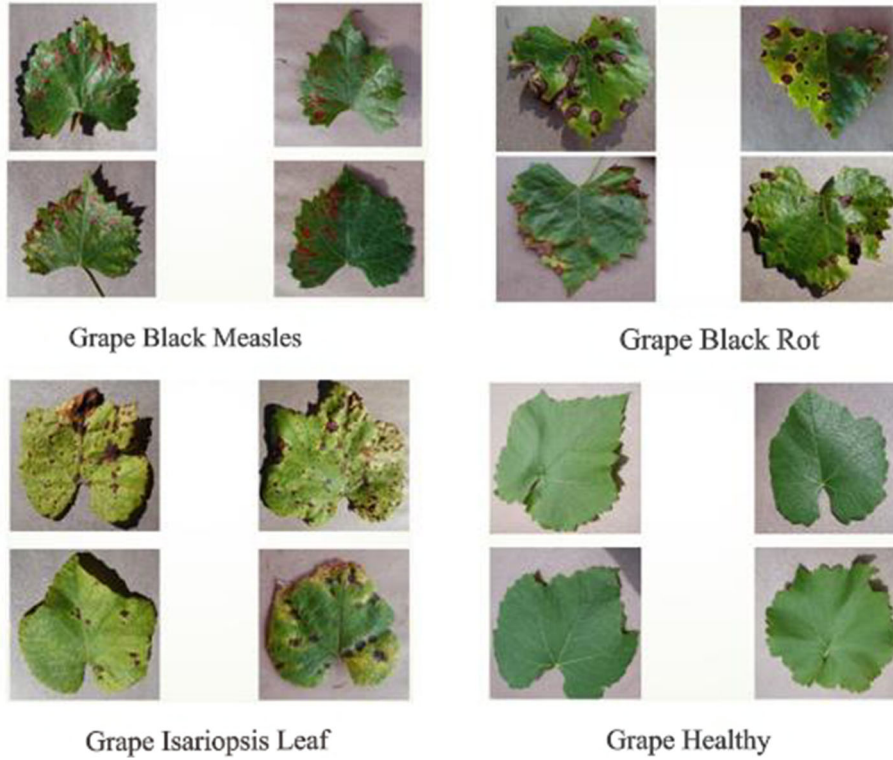


Figure 1. Grape Leaf Dataset

Google Colab

Google Colab (Google Colaboratory) is a cloud-based Python development environment provided by Google. It is designed for applications that require high computational power, such as machine learning, deep learning, data analysis, and scientific computing. Colab allows users to access a pre-configured Jupyter Notebook environment directly through a web browser, without the need to install any additional software.

Through this platform, users can leverage Google's powerful computational resources, including GPUs and TPUs, regardless of their personal computer's hardware capabilities. This enables the efficient training of complex models, execution of large-scale data analyses, and running of AI projects that demand high computational power.

CNN Architectures

Convolutional Neural Networks (CNNs) are a type of artificial neural network architecture that enables the application of deep learning algorithms to various types of data, including images, videos, audio, and text. CNNs are particularly popular in image processing and image classification tasks due to their high performance in these domains.

The primary function of CNN algorithms is to automatically extract meaningful features from the input images and perform accurate classification based on these features. This process involves hierarchical learning of both local and global image features through layers such as convolution, activation, and pooling.

In this study, the following CNN architectures were utilized: AlexNet, DenseNet121, EfficientNetB3, MobileNetV2, and ResNet50.

- **AlexNet:** Developed by Alex Krizhevsky and colleagues in 2012, AlexNet revolutionized image classification using deep learning. It consists of 8 layers, including 5 convolutional layers and 3 fully connected layers (Krizhevsky et al., 2012).

- **DenseNet121:** Introduced by Gao Huang and colleagues in 2017, the DenseNet architecture connects each layer to all preceding layers. DenseNet121 is a version of this architecture with 121 layers (Huang et al., 2017).
- **EfficientNetB3:** Part of the EfficientNet family proposed by Tan and Le in 2019, this model balances depth, width, and resolution using a compound scaling method (Tan & Le, 2019).
- **MobileNetV2:** Developed by Google in 2018, MobileNetV2 is a CNN architecture optimized for mobile and embedded devices (Sandler et al., 2018).
- **ResNet50:** The 50-layer version of the Residual Network (ResNet) architecture developed by He and colleagues in 2015, ResNet50 introduced residual connections to facilitate the training of very deep networks (He et al., 2016).

RESULTS

In this study, AlexNet, DenseNet121, EfficientNetB3, MobileNetV2, and ResNet50 Convolutional Neural Network (CNN) architectures were employed for the detection and classification of diseases in grape leaves. The dataset used in the study was uploaded to the MyDrive folder on Google Drive as `uzum_dataset`. The dataset was divided into two parts: 80% for training and 20% for testing. The training data were defined as `train_dir`, while the testing data were defined as `test_dir`. This structure allowed the dataset to be automatically recognized within the Google Colab environment.

For all CNN architectures, the number of epochs was set to 20. An epoch represents one complete pass of the training dataset through the model. Increasing the number of epochs can improve the model's learning process but also increases computational time. After training, the obtained results are presented in detail in Figure 2 and Table 1 to evaluate the performance of the models.

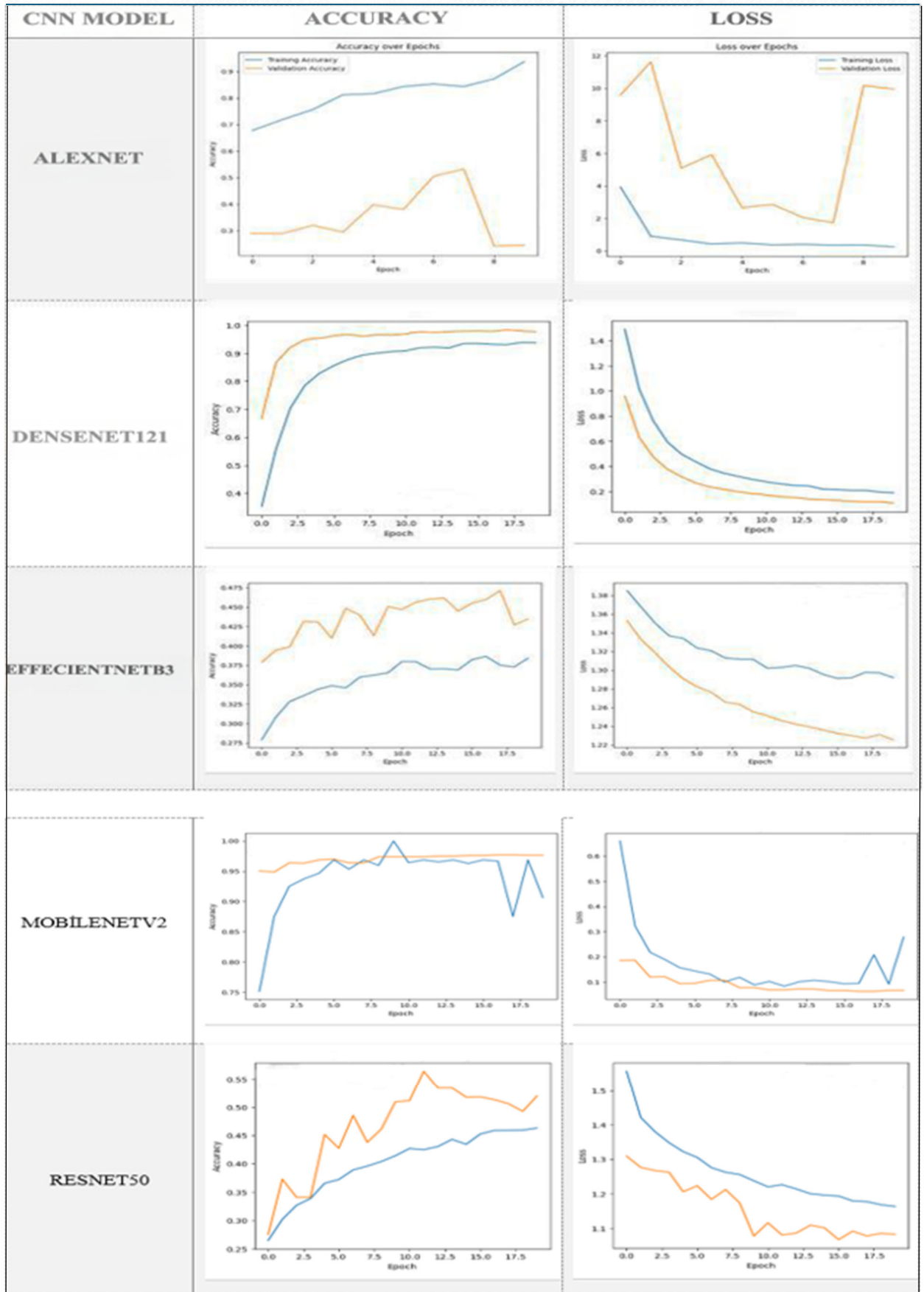


Figure 2. Accuracy and Loss Curves of CNN Architectures

Table 1. Accuracy rates of CNN architectures used for grape leaf disease classification

CNN Models	AlexNet	DenseNet121	EffecienNetB3	MobileNetV2	ResNet50
Accuracy	0.56	0.98	0.43	0.97	0.51

To compare the performance of the different deep learning algorithms used in this study, various evaluation metrics were calculated. These metrics include accuracy, recall, and precision, which are further used to derive composite measures such as the F1-score. Performance metrics in artificial intelligence are particularly important for assessing the success of machine learning and deep learning models in terms of accuracy, sensitivity, recall, F1-score, and ROC curves.

In this context, five different CNN architectures were trained, and the resulting accuracy values were analyzed comparatively. Classification performed on the dataset of grape leaf images yielded the following accuracy values: 0.56 for AlexNet, 0.98 for DenseNet121, 0.43 for EfficientNetB3, 0.97 for MobileNetV2, and 0.51 for ResNet50.

When converted to percentages, the highest accuracy was achieved by DenseNet121 at 98%. MobileNetV2 exhibited a comparable performance with an accuracy of 97%, closely approaching that of DenseNet121. The remaining models demonstrated lower accuracy values in comparison. These results indicate that DenseNet121 and MobileNetV2 architectures provide more effective and stable classification performance on this dataset.

CONCLUSION

In this study, the effectiveness of Convolutional Neural Network (CNN)-based deep learning methods for the detection and classification of diseases in grape leaves was comprehensively evaluated. Multiple CNN architectures were employed to compare performance, and the models' accuracy, generalization ability, and stability were analyzed. The findings indicate that DenseNet121 and MobileNetV2 architectures produced more consistent results compared to other models. This is clearly reflected in the accuracy curves (Ferentinos, 2018). Both models achieved accuracy rates close to 98%, with DenseNet121 slightly outperforming MobileNetV2.

As highlighted in the literature, CNN-based deep learning models offer significantly higher accuracy and stronger generalization capacity compared to traditional machine learning methods, due to their ability to automatically extract features from visual data. This observation aligns with the results obtained in this study, reaffirming that CNN architectures provide an effective and reliable approach for image classification problems (Mohanty, 2016).

Data augmentation techniques play an important role in the success of deep learning models. Operations such as image rotation, brightness adjustment, zooming, and horizontal flipping enhance the model's generalization ability while reducing the risk of overfitting (Brahimi, 2017). Furthermore, transfer learning applications significantly improve accuracy. Using pre-trained models such as ResNet, MobileNet, or EfficientNet on large-scale datasets reduces training time and enhances classification performance (Kamilaris & Prenafeta-Boldú, 2018).

The trained CNN models have high potential for integration into agricultural production processes. Combined with mobile applications or drone systems, these models enable real-time disease detection in vineyards (Ferentinos, 2018), allowing early diagnosis and rapid intervention by farmers.

With the rapid advancement of technology, artificial intelligence has emerged as one of the most important innovations, offering superior analysis and decision-making capabilities. AI should be utilized not only for human health but also for plant health and agricultural productivity. The primary aim of this study is to identify an effective CNN model capable of early detection of grape leaf diseases and to provide a foundation for future developments in this field. Integration of these models with camera systems in the future will enable automatic scanning of grape leaves and instant identification of diseases.

In conclusion, artificial intelligence has become an indispensable technology, and its integration into mobile devices has expanded its scope of application. Agricultural early warning systems developed using this technology can provide significant benefits to both society and future generations.

REFERENCES

- Aksoy, B., Halis, H. D., & Salman, O. K. M. (2020). Detection of diseases in apple plants using artificial intelligence methods and comparison of AI performance. *International Journal of Engineering and Innovative Research*, 2(3), 194–210.
- Altaş, Z., Özgüven, M. M., & Dilmaç, M. (2021). Detection of grape leaf mite damage using image processing techniques. *GBAD*, 10(3), 77–87.
- Arı, A., & Berberler, M. E. (2017). Interface design for solving prediction and classification problems using artificial neural networks. *ACTA INFOLOGICA*, 1(2).
- Brahimi, M., Boukhalfa, K., & Moussaoui, A. (2017). Deep learning for tomato diseases: classification and symptoms visualization. *Applied Artificial Intelligence*, 31(4), 299–315.
- Bütüner, R., Şimşek, M., Akgöz, G., & Şan, S. (2023). Detection of diseases in corn leaves using artificial neural networks. *Bilişim Sistemleri ve Yönetim Araştırmaları Dergisi*, 5(2), 21–31.
- Çetiner, H. (2021). Pre-trained deep network model for classifying leaf diseases. *ADYU Mühendislik Bilimleri Dergisi*, 15, 442–456.
- Demir, Ü., Kula, N., & Uğurlu, B. (2021). A decision support model for AI applications in agriculture: A case study on tomato pest detection. *ÇOMÜ LJAR*, 2(4), 91–108.
- Deng, L., & Yu, D. (2014). *Deep Learning: Methods and Applications*. *Found. Trends® Signal Process.*, 7(3–4), 197–387.
- Fawcett, T. (2006). *An introduction to ROC analysis*. *Pattern Recognition Letters*.
- Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, 145, 311–318.
- Han, J., Kamber, M., & Pei, J. (2012). *Data Mining: Concepts and Techniques*. Morgan Kaufmann.
- He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778.
- Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 4700–4708.
- Kaggle. (2024). *PlantifyDr dataset*. <https://www.kaggle.com/datasets/lavaman151/plantifydr-dataset> (Accessed: 04.02.2024)
- Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90.
- Kohavi, R., & Provost, F. (1998). *Glossary of terms for evaluating machine learning classification models*. Technical Report.
- Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems (NeurIPS)*, 25, 1097–1105.
- Powers, D. M. W. (2011). *Evaluation: From Precision, Recall and F-Measure to ROC, Informedness, Markedness and Correlation*.

- Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. C. (2018). MobileNetV2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 4510–4520.
- Şeker, D., Diri, B., & Balık, Ö. (2017). *Gazi Mühendislik Bilimleri Dergisi*, 3(3), 47–64.
- Sokolova, M., & Lapalme, G. (2009). *Information Processing & Management*.
- Tan, M., & Le, Q. V. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. In *Proceedings of the 36th International Conference on Machine Learning (ICML)*, 6105–6114.