

GrapeNet: An Explainable, Custom Deep Learning Architecture for Early Detection of Grape Leaf Disease

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Abstract

Speedy, reliable identification of grape leaf diseases is crucial to minimize crop losses and ensure sustainable production. Agronomic manual investigations are sometimes labor-intensive, subjective, and difficult to scale in large-scale vineyards. In this study, we categorize grape leaf diseases using two architectures: GrapeNet, a lightweight CNN designed specifically for grape leaf disease, and a Custom ResNet-50 trained via transfer learning. We use data augmentation throughout to enhance robustness in real-world imaging. The Custom ResNet-50 model achieves an incredibly high test-set accuracy of 99%, whereas GrapeNet achieves 95% accuracy and performs best on most precision, recall, and F1-score metrics. This demonstrates how deep residual networks can be useful for disease detection in precision ag environments for grapevines.

Keywords. Grapevine disease identification, CNN, Deep learning, ResNet50, Transfer learning.

1. INTRODUCTION

Viticulture is a main contributor to global agricultural production, farmers' livelihoods, and sustainable land use. Grapevines are susceptible to several foliar diseases; however, these can delay development, cause poor fruit quality, and affect yields. Early detection of disease is important. Traditional diagnosis methods rely on visual observations by expert agronomists and can be subjective and time-consuming, particularly on a large scale [1], [3]. In recent years, with the development of artificial intelligence and computer vision technology, subtle variations in leaf color have been used to recognize diseases automatically and rapidly. Visual features can be learned from raw images effectively using convolutional neural networks (CNNs). Using pretrained models, such as ResNet, EfficientNet or DenseNet, that have been trained on a large, unbalanced dataset, they can also help in improving the results even when the number of labeled data is small, thereby making real-time monitoring feasible in precision agriculture for scalability and cost-effectiveness [2, 9, 12, 14]. However, difficulties remain, including the risk of overfitting and small validation sets of real-world data [7, 8, 10]. To address these problems, this paper proposes a custom CNN for diagnosing grapevine leaf diseases, GrapeNet. It compares the performance of GrapeNet with that of the transfer-learning-based Custom ResNet-50 and provides an understanding of and validation of the results of both models using explainable AI (XAI).

2. RELATED WORK

Early attempts at computer vision recognition of grapevine diseases used conventional machine learning techniques based on handcrafted features such as color and texture. Classifiers such as Support Vector Machines (SVMs) and Random Forests performed well in controlled settings, but their performance in real-world settings was limited. In recent years, Convolutional Neural Networks (CNNs) have become the preferred way as they learn directly from images. Ji et al. created a Unified Model to classify grape leaf diseases using

multiple CNNs [4]. Liu et al. and Math & Dharwadkar proposed deep CNN architectures to detect earlier and with higher accuracy [5] and [7].

New techniques such as capsule networks and attention mechanisms have further improved the reliability of distinguishing similar symptoms by vision. Andrushia et al. integrated a convolutional capsule network (CNN) [6], and Tang et al. combined a lightweight CNN with channel-wise attention to improve efficiency. When labels are limited, transfer learning has been useful using pretrained models such as VGG and ResNet. Noteworthy examples include VGG-based methods for downy and powdery mildew detection [9], improved ResNet-50 using batch normalization [2], and benchmarking different ResNet variants [14]. Some researchers have created synthetic data using Generative Adversarial Networks (GANs) [11] and used deep learning and Particle swarm optimization to classify limited and imbalanced training data [15]. Research applications have been mainly on automatic detection of downy mildew and powdery mildew in the vineyard [13], damage-aware leaf disease classification [3], and grape leaf diagnosis [1]. Despite these developments, data limitations and variability remain, requiring a bespoke CNN-versus-ResNet-50 comparison in addition to explainable AI.

3. METHODOLOGY

This study used 6,189 grape leaf images across six disease categories, split into 75%, 10%, and 15% training, validation, and test sets, respectively, from Mendeley Data. The images were resized, normalized, denoised, and rotated and flipped to improve robustness to variation and better match the models. Two models: a custom CNN and a transfer learning model (Custom ResNet-50) were trained separately, and their outputs were compared using SoftMax.

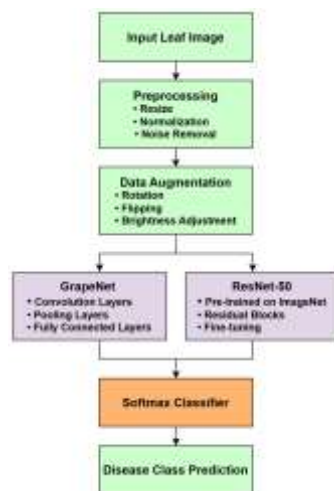


Fig 3.1. Overall architecture of the customized deep-learning-based grapevine leaf disease detection pipeline.

3.1. GrapeNet Custom CNN Architecture

GrapeNet (Fig. 2) comprises four convolutional blocks, each using 3×3 kernels, ReLU activation, and max pooling, with the number of feature maps increasing from 16 to 64 across these blocks, allowing the network to capture progressively more abstract features while remaining lightweight. The resulting feature maps are flattened and passed into a fully connected layer with 128 neurons before the classification head. The whole model is optimized with Adam at a learning rate of 0.001.

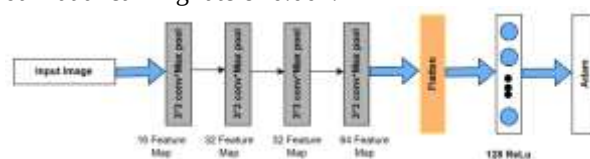


Fig 3.2. Layer-wise architecture of the GrapeNet custom CNN.

3.2. Custom ResNet-50 Architecture

The Custom ResNet-50 pipeline (Fig. 3) accepts $224 \times 224 \times 3$ input images. First, it passes them through an initial 7×7 convolution and max-pooling stage, followed by residual blocks stacked in a 3-4-6-3 arrangement that use a mix of 1×1 and 3×3 convolutions together with skip connections to counter vanishing gradients [2], [9]. Global average pooling then condenses the feature maps before a fully connected classification layer, with Adam used for optimization; together, these improve training stability and overall classification accuracy.

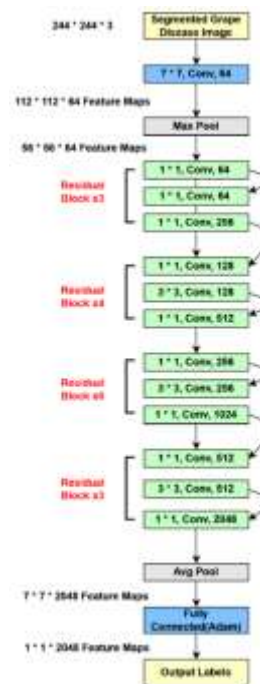


Fig 3.3. Layer-wise architecture of the Custom ResNet-50 model.

3.3. Explainability Using SHAP

To interpret model predictions, we used Shapley Additive Explanations (SHAP) and computed pixel-level attribution scores for both CNN models. The summary plots illustrated the feature importance across the dataset, and the force plots gave instance-by-instance explanations of predictions.

4. RESULTS AND DISCUSSION

GrapeNet and the Custom ResNet-50 were both trained on Google Colab using a Tesla T4 GPU (16 GB) with a batch size of 16 over 10 epochs. To prevent overfitting, we monitored validation performance during training, and we used the held-out test set to assess accuracy, precision, recall, and F1-score after training.

4.1. Confusion Matrix Analysis

Tables II and III share the characteristic of diagonal dominance, indicating that most of the samples were classified correctly for each disease class in both models. GrapeNet has fewer recall points than CPE, but there is little overlap in the classes used for training. GrapeNet has fewer recall points than CPE, but a significant lack of overlap in terms of the classes that are used for training. The Custom ResNet-50, on the other hand, maintains 99% overall accuracy and shows more consistent performance across classes.

Table 1

Performance of grapenet
custom cnn model

Class	Precision	Recall	F1-Score	Support
Bacterial Leaf Spot	0.85	0.73	0.79	15
Black Rot	0.96	1.00	0.98	284
Downy Mildew	0.98	0.82	0.89	146
ESCA	1.00	0.97	0.98	288
Healthy Leaves	0.85	0.99	0.91	189
Leaf Blight	1.00	0.99	1.00	259
Powdery Mildew	0.91	0.82	0.86	62
Accuracy		0.95		1243

Table 2

Performance of custom
resnet50 model

Class	Precision	Recall	F1-Score	Support
Bacterial Leaf Spot	0.71	1.00	0.83	15
Black Rot	1.00	1.00	1.00	284
Downy Mildew	0.99	0.98	0.98	146
ESCA	1.00	1.00	1.00	288
Healthy Leaves	1.00	0.98	0.99	189
Leaf Blight	1.00	1.00	1.00	259
Powdery Mildew	0.95	0.95	0.93	62
Accuracy		0.99		1243

4.2. Significance Analysis

As shown in Figs. 4 & 5, Custom ResNet-50 always outperforms GrapeNet in terms of precision, recall, and F1-score. That 4% increase in accuracy (99% compared to 95%) is significant enough to suggest it is not due to chance. This validates that deeper residual networks with skip connections can be more discriminative for leaf features under the same experimental settings.

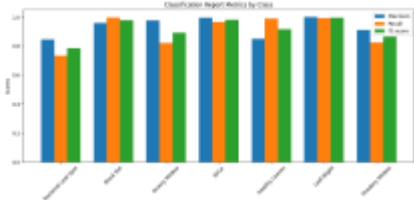


Fig 4. Per-class classification performance of the GrapeNet CNN.

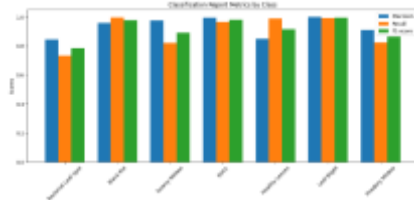


Fig 5. Per-class classification performance of the Custom ResNet-50 model.

5. CONCLUSION

In this work, we have developed a lightweight custom-designed CNN (GrapeNet) and a transfer-learning-based Custom ResNet-50 pipeline to detect grape leaf diseases. GrapeNet was outperformed by the Custom ResNet-50 with a 99% accuracy, due to its deeper residual structure. The precision, recall, and F1-scores were high, though, and GrapeNet was competitive, resilient to a small number of errors between classes that share similar visual features. SHAP-based explainability was used to gain a dataset-wide and case-specific view of the models' predictions. All in all, this pipeline provides a valid, interpretable, scalable, and accurate solution for both precision agriculture and automated monitoring of vineyards and cultivation in the real world.

6. REFERENCES

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Biographies



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