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Title: FusionNet-GLD: A Dual-Backbone CNN Model Combining Xception and Inception for Grape Leaf Disease Recognition

Id: 196

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Objective

Problem to solve / motivation:

- Grapevine leaf diseases (e.g., Black Rot, Esca) significantly reduce crop yield and fruit quality.
- Traditional manual inspection of vineyards is slow, costly, labor-intensive, and often unreliable.
- There is a need for an automated, accurate, and efficient detection system.

Research scope/goal:

- To design and validate a novel dual-backbone deep learning model, FusionNet-GLD.
- The goal is to accurately classify four conditions of grape leaves (Black Rot, Esca, Leaf Blight,
- and Healthy) by combining the strengths of Xception and InceptionV3 models.

Expected outcomes:

- A highly accurate classification model that outperforms existing single-backbone models.
- A lightweight architecture with the potential for deployment on real-time field devices (smartphones, drones).

Introduction

Background Context:

- Grapevine is a vital commercial crop globally for wine and table grapes.
- AI and Deep Learning (DL) are increasingly being adopted for precision farming and automated disease detection.

Importance of the Problem:

- Early and precise disease detection is critical for timely intervention and effective vineyard management.
- Automation can save time, reduce labor costs, increase the consistency of disease identification.

Basic Overview of Technology Involved:

- **Convolutional Neural Networks (CNNs):** The core technology for image pattern recognition.
- **Xception:** A CNN architecture that uses Depthwise separable convolutions to extract fine-grained, detailed patterns.
- **InceptionV3:** A CNN architecture that uses multi-scale filters to capture features at different sizes

Key Challenges:

Existing single-backbone CNNs often face a trade-off between high accuracy and computational efficiency. Achieving high performance requires capturing both subtle, fine-grained disease textures and broader, multi-scale patterns simultaneously.

Related Work

Short Review of Similar Technologies/Research:

- **Lightweight Models:** YOLOv8-ACCW and GCS-YOLO focus on real-time detection on edge devices.
- **Dual-Path Models:** GrapeLeafNet (Inception-ResNet + Transformer) achieved 99.56% accuracy.
- **Other CNNs:** EfficientNet and MobileNetV3 have shown high accuracy in similar tasks.
- **Transformers:** Vision Transformers have also been used, reaching 100% validity in some studies.

Existing Solutions & Approaches:

- **Deep Learning:** Standard CNNs (VGG16, MobileNetV2, EfficientNetB0).
- **Machine Learning:** Traditional classifiers like Random Forest (RF) and SVM.

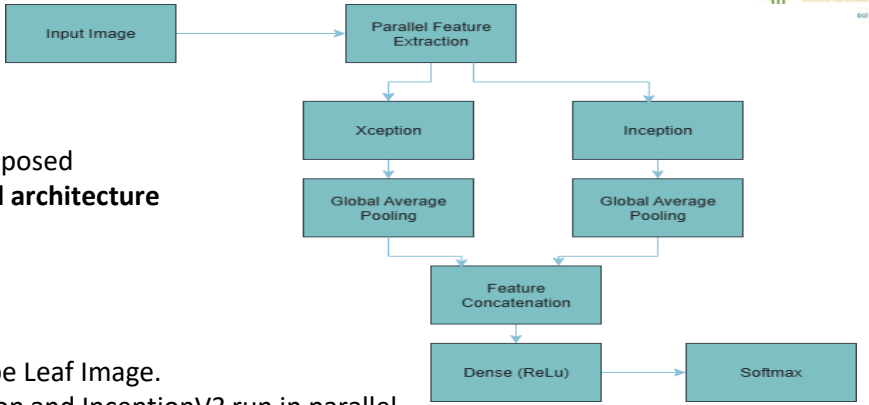
Limitations of Current Works:

- Traditional ML models (like RF) are less accurate (87.65% in this study).
- Single-backbone CNNs may not capture the complex combination of features needed for robust detection.

Novelty of Your Approach:

- **Dual-Backbone Fusion:** This model is *not* a single CNN. It proposes a novel hybrid architecture.
- **Complementary Strengths:** It fuses Xception (for Depthwise features) and InceptionV3 (for multi-scale features) in parallel.

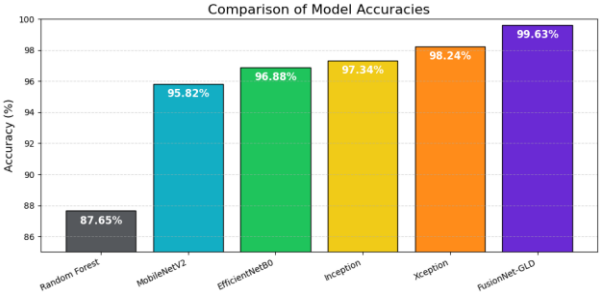
Flow Charts/Images/ working prototype

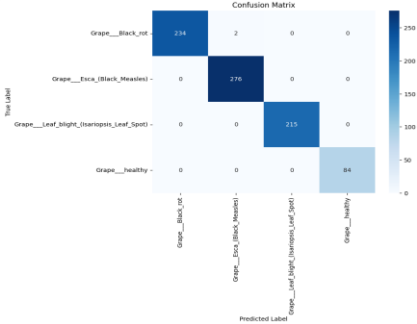


A flowchart of the proposed **FusionNet-GLD model architecture**

- **Input:** 224x224 Grape Leaf Image.
- **Dual-Branch:** Xception and InceptionV3 run in parallel.
- **Concatenate:** Features from both models are combined.
- **Output:** Disease Class (Black rot, Esca, Leaf blight, or Healthy).

Simulation Result





Brief Observations & Insights

- **FusionNet-GLD** significantly outperformed all five baseline models across all metrics.
- The fusion model (99.63%) was more accurate than its individual components, Xception (98.24%) and InceptionV3 (97.34%).
- The confusion matrix shows near-perfect classification, correctly identifying 100% of Esca, Leaf blight, and Healthy samples in the validation set.
- The model achieves higher accuracy (99.63%) than the complex GrapeLeafNet (99.56%) reported in the literature review.

Conclusion

Main Findings:

The dual-backbone FusionNet-GLD model is highly effective for grape leaf disease classification, achieving **99.63% accuracy.** Combining Xception's Depthwise feature extraction with InceptionV3's multi-scale feature capture provides a robust and superior result.

Advantages of our Solution:

- **Superior Performance:** Highest accuracy, precision, recall, and F1-score.
- **Scalable:** Demonstrates a viable path for an efficient, accurate AI tool.

Key Contributions:

- Proposed a novel hybrid CNN architecture (FusionNet-GLD).
- Validated the model's effectiveness on an augmented benchmark dataset, proving its potential for smart agriculture.

Limitations: Model performance is validated on a public dataset, not yet on diverse, real-world vineyard conditions. The model is not yet optimized for low-resource (e.g., non-GPU) devices.

Future Scope: The proposed model can be deployed on smartphones or edge devices and integrated with drones or IoT systems for large-scale monitoring. Future work includes optimizing through model compression and extending it to other crops or multimodal data for improved diagnostics.

Reference

Standard references in IEEE format:

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