A Comparative Study of Lightweight CNN Architectures for Real-Time Plant Disease Diagnosis on Mobile Devices

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Abstract

Rapid and accurate plant disease detection is critical for reducing agricultural losses, particularly in resource-limited regions lacking expert diagnostics and reliable internet. This study evaluates state-of-the-art lightweight CNNs—GhostNet, ShuffleNetV2, EfficientNet-B0, MobileNetV2, MNASNet, MobileNetV3, and SqueezeNet—for real-time disease classification on mobile devices, optimizing the trade-off between accuracy, computational efficiency, model size, and inference latency.

Benchmarking results highlight EfficientNet-B0 as the top performer in accuracy (97.40% test accuracy), attributed to its compound scaling method that balances network depth, width, and resolution. ShuffleNetV2 excels in efficiency, achieving 96.54% accuracy with the smallest model size (5.10 MB) and fastest inference time (0.0091 seconds). MNASNet provides the best speed-accuracy balance (96.04% accuracy, 0.0068 seconds inference), leveraging its platform-aware neural architecture search. GhostNet demonstrates competitive performance (95.25% accuracy, 15.34 MB model, 0.0132 seconds inference) but is surpassed by EfficientNet-B0 and MNASNet in both accuracy and speed. MobileNetV2 offers moderate accuracy (95.12%) but suffers from higher latency (0.0474 seconds) and larger size (16.90 MB). MobileNetV3 variants and SqueezeNet exhibit significant limitations, revealing challenges in excessive model compression.

For practical deployment, EfficientNet-B0 is optimal for maximum accuracy, ShuffleNetV2 for speed and resource efficiency, and MNASNet for balanced performance. All models maintain robustness when ported to mobile hardware, validating their suitability for real-time disease diagnosis in connectivity-scarce environments.

This research advances mobile-compatible deep learning solutions for precision agriculture, addressing infrastructural gaps in underserved regions. Integrating these models into smartphone applications enables timely, on-site disease detection, supporting data-driven crop management and food security.

In conclusion, EfficientNet-B0, ShuffleNetV2, and MNASNet emerge as the most effective lightweight CNNs for mobile-based plant disease classification, offering scalable solutions to enhance agricultural resilience in resource-constrained settings. Their deployment aligns with smart agriculture objectives, bridging technological disparities and promoting sustainable farming practices.

Keywords

Lightweight CNN, plant disease classification, mobile deep learning, real-time diagnosis, precision agriculture.