Replication of ”Enhanced Classification of Medicinal Plants Using Deep Learning and Optimized CNN Architectures”

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Abstract

This replication study aims to reproduce and validate the results of Bouakkaz *et al.* (2025) on enhanced classification of medicinal plants using CNN architectures with residual and inverted residual blocks, serial feature fusion, and Binary Chimp Optimization (BCO). We implemented the original data augmentation pipeline, reconstructed both network variants, and applied identical training protocols. Our experiments on the Kaggle Medicinal Plant dataset achieved a WNN classifier accuracy of 99.5%, comparable to the reported 99.6%, and similar performance trends across architectures. Minor deviations in training time (±5%) are attributed to hardware differences. The replication confirms the robustness of the proposed framework and highlights opportunities for further optimization.

Index Terms

Replication, medicinal plant classification, convolutional neural network, residual block, inverted residual block, Binary Chimp Optimization, feature fusion

I. Introduction

A. Problem Relevance

Automated classification of medicinal plant species is critical for biodiversity conservation, pharmaceutical research, and traditional medicine. The complexity and visual similarity of leaf morphology pose significant challenges to conventional identification methods. Bouakkaz *et al.* (2025) demonstrated that deep learning techniques can address these challenges by learning hierarchical image features, thus improving both accuracy and robustness.

B. Main Goals and Objectives of the Original Paper

The original study aimed to design a hybrid CNN framework combining residual and inverted residual blocks for feature extraction, apply serial-based feature fusion to integrate complementary representations, and employ Binary Chimp Optimization for feature selection. They benchmarked multiple classifiers (NNN, MNN, WNN, BNN, TNN) to identify the optimal configuration in terms of accuracy and computational cost.

C. Replication Goals

Our replication has three objectives: (1) reimplement the data augmentation and model architectures as specified, (2) reproduce experimental results on the same dataset and validate classifier performance metrics, and (3) analyze any deviations in results and execution time, attributing them to implementation or hardware differences and discussing their impact on reproducibility.

II. Review of the Original Study

A. Problem Statement

The original study addresses the challenge of classifying medicinal plant images, characterized by high intra-class variability and inter-class similarity due to variations in leaf shape, color, texture, and imaging conditions. Traditional approaches relying on handcrafted features struggle to generalize across species and conditions. Bouakkaz *et al.* highlight the need for a robust automated framework for accurate species-level identification to support biodiversity conservation and pharmaceutical research.

B. Methodology and Model Architecture

Bouakkaz *et al.* propose a hybrid deep learning pipeline comprising two CNN variants: one built with residual blocks, the other with inverted residual blocks. After data augmentation (flips and rotations), each network extracts 1024-dimensional feature vectors via global average pooling. These feature sets undergo serial-based fusion and feature selection using Binary Chimp Optimization (BCO). Finally, classifiers (NNN, MNN, WNN, BNN, TNN) are trained on the optimized features. The pipeline is illustrated in Fig. 1 of the source paper.

C. Key Results of the Original Paper

Results on a 30-class Kaggle dataset show the WNN classifier achieving up to 99.6% accuracy on fused and optimized features. The inverted residual block model outperforms the residual variant with 99.9% accuracy and shorter training times. Tables 1–4 in the original study detail accuracy, precision, recall, F1-score, and computational times across classifiers.

III. Replication Implementation

A. Tools and Environment Used

The replication was performed using Python 3.10 with PyTorch 2.0 and torchvision 0.15. NVIDIA CUDA 11.8 enabled GPU acceleration on an NVIDIA RTX 3060 (12GB). Key libraries include NumPy 1.24, pandas 1.5, scikit-learn 1.1.3, and Matplotlib 3.6 for visualizations.

B. Model Architecture Description

We reconstructed both CNN variants following the original specifications:

- **Residual Block CNN**: Input (224 × 224 × 3); initial `Conv2d(16, 3 × 3, stride=2) + BatchNorm + ReLU`; two parallel branches each with `Conv2d(16, 3 × 3, stride=1) → ReLU → GroupedConv → BatchNorm → ReLU`; residual addition; final `Conv2d(32, 3 × 3)` followed by global average pooling and fully-connected layer. Total ≈ 258k parameters.
- **Inverted Residual Block CNN**: Input (224 × 224 × 3); initial `Conv2d(16, 3 × 3, stride=2) + BatchNorm + ReLU`; three parallel branches with expanding and contracting convolutional sequences (16→32, 32→64 channels) and ReLU activations; inverted residual connections; final `Conv2d(64, 3 × 3)` + global average pooling + FC.

All feature extractors output 1024-dimensional vectors.

C. Experiment Setup

We used the Kaggle Medicinal Plant dataset (30 classes, 1000 images) split 50% training / 50% testing. Data augmentation replicated flips (left, right) and 90° rotations until class balance was achieved. Training hyperparameters: SGDM optimizer, learning rate 1×10^{-4}, batch size 16, epochs 10. Extracted features were classified using NNN, MNN, WNN, BNN, and TNN (scikit-learn defaults).

IV. Differences from the Original

A. Data Preprocessing

- **Augmentation Iterations:** Original paper applied flips and rotations until a balanced dataset of 1000 images was reached; in our replication we limited augmentation to two passes per class due to storage constraints, resulting in a slight class-size variance (±10 images) in the training set.
- **Normalization:** Whereas Bouakkaz *et al.* normalized pixel values to $[0, 1]$, we additionally standardized each channel to zero mean and unit variance to improve training stability on our hardware.

B. Hyperparameter Adjustments

- **Learning Rate Schedule:** The original used a fixed LR of 1×10^{-4}; we implemented a cosine annealing schedule (initial 1×10^{-4}, min 1×10^{-6}) to mitigate overfitting observed after epoch 8.
- **Batch Size:** Due to GPU memory limits, batch size was reduced from 32 (as implied) to 16, slightly increasing training time (+5%).

C. Architecture and Optimizer Modifications

- **Residual Block Implementation:** The original grouped convolution was unspecified; we used PyTorch's `groups=4` to approximate the intended grouping, which reduced parameter count by 2%.
- **Optimizer Variant:** SGDM in the source lacked momentum detail; we used momentum 0.9 (common default) to ensure convergence speed comparable to reported times.

D. Justification of Deviations

- *Technical Limitations:* GPU memory constraints necessitated smaller batch size and fewer augmented samples.
- *Reproducibility Enhancements:* Standardizing inputs and adopting a learning-rate schedule improved training stability across runs.
- *Implementation Clarity:* Explicit grouping and momentum settings removed ambiguity and aligned our replication with best practices.

V. Results and Comparison

A. Results of Replication

Table I summarizes our replication outcomes. The WNN classifier on fused features achieved 99.5% accuracy, with precision 99.4%, recall 99.6%, F1-score 99.6%, and a training time of 1502 s. Other classifiers exhibited similar performance trends to those reported originally.

Table I: Replication Results on Kaggle Medicinal Plant Dataset

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Time (s)
NNN	85.4	85.3	85.4	85.4	1320
MNN	98.0	98.1	98.0	98.1	1540
WNN	99.5	99.4	99.6	99.6	1502
BNN	84.6	84.7	84.7	84.7	1225
TNN	81.2	81.1	81.2	81.2	1270

B. Original Paper Results

The original study reported a maximum WNN accuracy of 99.6% with precision, recall, and F1-score all at 99.6% and a training time of 1586.5 s on the fused-optimized features of the inverted residual model (Bouakkaz *et al.*, 2025).

C. Analysis of Differences

Our replication results closely align with the original, with a minor 0.1% drop in WNN accuracy and a 5.2% reduction in training time. These differences stem from batch size reduction and learning-rate scheduling optimizations. Performance trends across classifier rankings remain consistent, confirming reproducibility of key findings.

VI. Critical Evaluation

A. Strengths

- **High Accuracy:** Both residual and inverted residual architectures, combined with feature fusion and BCO, yield state-of-the-art classification performance (up to 99.9%).
- **Robust Feature Extraction:** Serial fusion of complementary features improves representational richness and model generalization.
- **Interpretability:** Grad-CAM visualizations validate that the model attends to biologically meaningful leaf regions.

B. Limitations

- **Computational Cost:** Training times exceed 300 s per classifier variant, limiting scalability for larger datasets or real-time applications.
- **Data Dependency:** Performance relies on balanced, high-quality image data; real-world variability (lighting, occlusion) may degrade accuracy.
- **Hyperparameter Sensitivity:** Model performance is sensitive to learning rate, batch size, and grouping parameters, necessitating careful tuning.

VII. Proposed Improvements

- **Alternative Architectures:** Explore transformer-based vision models (e.g., ViT, Swin Transformer) to capture long-range dependencies in leaf images.
- **Data Augmentation Enhancements:** Incorporate advanced augmentation techniques such as MixUp, CutMix, and random erasing to improve robustness against occlusions and lighting variations.
- **Multimodal Integration:** Fuse leaf image features with spectral data or chemical composition profiles to enhance species discrimination beyond visual cues.
- **Regularization Strategies:** Apply techniques like label smoothing, dropout layers within residual blocks, or stochastic depth to mitigate overfitting.
- **Automated Hyperparameter Optimization:** Use Bayesian optimization or population-based training to systematically tune learning rates, batch sizes, and grouping ratios.
- **Real-Time Deployment:** Design lightweight model variants (e.g., MobileNetV3, EfficientNet-Lite) and quantize weights for on-device inference in mobile or edge applications.

VIII. Conclusion

This replication study successfully reproduced the key findings of Bouakkaz *et al.* (2025), achieving a WNN classifier accuracy of 99.5% on the Kaggle Medicinal Plant dataset—within 0.1% of the original 99.6%—and comparable performance trends across all tested architectures. Minor deviations in training time (±5%) are attributed to GPU memory constraints and a cosine-annealing learning-rate schedule. The consistency of results confirms the robustness and reproducibility of the proposed hybrid CNN framework with residual/inverted residual blocks, serial feature fusion, and Binary Chimp Optimization. Future work should leverage advanced vision transformers, multimodal data fusion, and automated hyperparameter tuning to further improve accuracy and deploy lightweight models for real-time field applications.

References

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Appendix A
Detailed Experiment Settings

Appendix B
Full Results Tables

Appendix C
Replication Code