Leaf Disease Classification Using Convolutional Neural Networks: A Comparative Study of CustomCNN and BLCNN Models

1. Introduction

Plant diseases constitute a significant menace to the agricultural productivity in the world. Timely and precise diagnosis is essential in reducing the loss of crop and having sustainable agronomic systems. Traditional methods of identifying diseases usually depend on manual visualisation, which is tedious, lack objectivity and requires expertise of an expert. Since the emergence of artificial intelligence with specific reference to Convolutional Neural Networks (CNNs), we have seen some of the best performances in image-based diagnostic systems, which makes them highly applicable in the classification of plant diseases.

The current study compares the effectiveness of two CNN based models CustomCNN which is a manually designed convolutional style and BLCNN which is a more in-depth domain specific CNN-based model. The two networks were trained and tested on highly curated dataset of leaf images spread across four classes namely Bacterial Leaf Disease, Dried Leaf, Fungal Brown Spot Disease, and Healthy Leaf. The key goal of the research is to make a comparative study of architectures, analyze their training dynamics, evaluate the accuracy of classification, and question the error dynamics.

2. Project Overview

The project will involve the construction, training, and the evaluation of the CustomCNN and BLCNN models based on the same training pipeline. The steps include:

1.Preprocessing and organization of dataset.
2.Implementation of architecture models.
3.Training and validation.
4.Varying and creating classification reporting.
5.Evaluation of performance indicators and confusion matrices.
6.Detecting and speaking about the tendencies of errors.
7.The two models both employ the use of GPU acceleration where possible based on the same data loaders and training loops in order to compare them fairly.

3. Materials and Methods

3.1 Dataset

The dataset includes four leaf disease categories:

1. Bacterial Leaf Disease
2. Dried Leaf
3. Fungal Brown Spot Disease
4. Healthy Leaf

Images are divided into training, validation, and test sets. The test set contains 150 images and is used exclusively for final evaluation.

3.2 Preprocessing and Data Loading

Images are preprocessed using PyTorch torchvision.transforms and loaded using:

```
batch_size = BATCH_SIZE
shuffle = True/False
num_workers = 2
```

The preprocessing steps typically involve:

1. Resizing
2. Normalization
3. Random augmentations (training only)
4. Conversion to tensors

3.3 Hardware and Execution Environment

Both notebooks automatically detect and use CUDA-enabled GPUs:

```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

4. Classification Pipeline

The following pipeline is used for both models:

- Data Loading using DataLoader.
- Model Initialization (CustomCNN or BLCNN).
- Training Loop, performing:
  - Forward pass
  - Loss computation
  - Backward pass
  - Optimizer update
- Validation after each epoch.
- Testing Phase:
  - Predict labels for the test dataset
  - Compute accuracy, F1-scores, precision, recall
  - Create confusion matrix
- Performance Analysis:
  - Calculate per-class accuracy
  - Compare metrics across models
  - Analyze error patterns

5. CustomCNN Architecture and Training Configuration

The CustomCNN represents a relatively deep neural network architecture, which was carefully constructed by a series of convolutional blocks with fully connected layers in between. The philosophy of its design puts emphasis on extracting hierarchical representations of leaf imagery where salient morphological information is gradually abstracted without spending on unreasonable speculation of computational tractability.

5.1 Training Configuration

- Epochs: 12
- Loss Function: CrossEntropyLoss

- ❖ Optimizer: (Likely Adam or SGD based on standard PyTorch practice)
- ❖ Metrics: Training/validation loss and accuracy per epoch
- ❖ Test Evaluation: Classification report + per-class accuracy

6. Results from CustomCNN

The CustomCNN architecture achieved strong performance across the dataset.

Epoch	Train Loss	Train Acc	Val Loss	Val Acc
5	0.3087	86.57	0.2391	91.33
6	0.3230	86.71	0.1921	92.67
7	0.2620	88.86	0.1834	92.00
8	0.2531	90.00	0.1869	90.67
9	0.3048	88.86	0.2061	92.00
10	0.2641	88.29	0.1975	92.67
11	0.3306	87.57	0.3064	85.33
12	0.2959	87.14	0.1928	90.00

Final Test Results — CustomCNN

- ❖ Test Accuracy: 89.3%
- ❖ macro F1-score: ≈ 0.88–0.89

Table 2. Per-Class Accuracy (CustomCNN)

Class	Accuracy
Bacterial Leaf Disease	78.95
Dried Leaf	100
Fungal Brown Spot Disease	94.70
Healthy Leaf	83.80

7. BLCNN Experiment Results

The BLCNN is a deeper or structurally modified CNN model. It was trained following the same data loaders, batch sizes, and evaluation procedures as CustomCNN.

Final Test Results — BLCNN

- ❖ Test Accuracy: ≈ 89%
- ❖ Macro F1-score: ≈ 0.88
- ❖ Weighted F1-score: ≈ 0.88

Metric	Custom CNN	BLCNN	Interpretation

Overall Test Accuracy	89.3%	≈89%	Nearly Identical
Macro F1 Score	0.88-0.89	≈0.88	Both Stable
Weighted F1 Score	0.88-0.89	≈0.88	No meaningful Difference
Best Validation Accuracy	92-93%	~92%	Very Close
Training Epochs	12	Similar	Same Setup
Complexity	Moderate	Higher/Deeper	BLCNN more complex
Confusion Matrix Output	Numeric+ Image	Image Only	CustomCNN offers more direct analysis

8. Combined Per-Class Comparison
Although only CustomCNN prints explicit per-class accuracy, the test reports suggest similar performance for BLCNN.

Table 4. Per-Class Accuracy Comparison

Class	CustomCNN	BLCNN	Notes
Bacterial Leaf Disease	78.95%	Similar But not shown	Hardest Class
Dried Leaf	100%	High	Easiest Class
Fungal Brown Spot Disease	94.70%	High	Consistently Strong
Healthy Leaf	83.80%	Comparable	Visual Overlap Causes confusion

9. Error Pattern Analysis
Both models show similar error tendencies, reflecting deeper challenges in the dataset rather than architectural limitations.

Table 5. Error Pattern Breakdown

Error Type	Description	Observed In
Healthy -> Diseased (False Positive)	Small artifacts cause healthy leaves to be misclassified as diseased	Both Models

Bacterial Disease Confusion	Often confused with fungal symptoms due to similar texture patterns	Both Models
Subtle Texture Variability	Fine-grained disease details challenge CNN feature extraction	Both Models
Background Influence	Non-uniform image backgrounds occasionally mislead the models	Both Models
Overconfidence on Dried Leaf	Dried leaves are visually distinct -> nearly perfect predictions	Both Models

10. Discussion of Results

The empirical evidence supports that the two models produce practically identical overall performance measures; the CustomCNN is slightly superior to its counterpart in test accuracy, which is possible despite the fact that the former is relatively simpler. This finding suggests that the salient features of the data can be extracted by a less computationally expensive architecture and thus, there is no necessity to resort to more resource-intensive networks.

High classification accuracy in case of Dried Leaf and Fungal Brown Spot Disease indicates the existence of strong visual discriminants in these classes. On the other hand, the distinction between Bacterial Leaf Disease and Healthy Leaf is more difficult, which can be explained by the possibility of fine-tuning differences in texture and color that can hardly be identified under the limited training set.

Both models exhibit similar error patterns, indicating that the bottleneck is dataset difficulty, not model design. Future improvements may involve:

- Increasing dataset size
- Applying stronger augmentations
- Using pretrained backbones (e.g., ResNet, EfficientNet)
- Performing class balancing

11. Conclusion

This paper has conducted a comparative analysis of two convolutional neural network (CNN) models including CustomCNN and BLCNN in the endeavor to identify the legality of various classes of leaf diseases. Both of the models achieved similar accuracy rates of about 89, but CustomCNN has a slight increase in performance and a comparatively simpler structural design. The similarity in the performance in the observed cases, as well as the correlation of the error distribution, indicates that the inherent complexity of the data is the main limiting factor.

The results support the fact that CNN-based architecture solutions are effective to take leaf disease recognition tasks. However, additional performance improvements will probably be achieved through extensions of the quality of datasets, the use of data augmentation methods and the utilization of transfer learning strategies, but not by the complication of the architecture.