🌿 Leaf Disease Detection using Deep Learning

Python 3.8+ PyTorch 1.9+ License MIT Dataset Kaggle

🎯 A complete end-to-end deep learning solution for automated plant disease detection

Leveraging simplified AlexNet with early exit mechanisms for efficient and accurate classification

Features • Installation • Usage • Results • Documentation

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🔍 Overview

This project implements an **automated leaf disease detection system** using state-of-the-art convolutional neural networks (CNN). The system can accurately classify leaf images into **5 disease categories** with high precision.

🏥 Disease Classes

🦠 Bacterial Leaf Spot	🍄 Downy Mildew	✅ Healthy Leaf
🎨 Mosaic Disease	☁️ Powdery Mildew	

🎯 Key Capabilities

- ✅ **High Accuracy**: 85-95% validation accuracy
- ⚡ **Fast Inference**: Early exit mechanism for efficient predictions
- 🎨 **Smart Augmentation**: 3x dataset expansion with realistic variations
- 📊 **Comprehensive Analysis**: Detailed metrics and visualizations
- 🚀 **Production Ready**: Google Colab deployment with one-click execution

📊 Dataset

Download Dataset

This project uses the **Pumpkin Leaf Diseases Dataset from Bangladesh**.

📥 **Download Link:** Kaggle - Pumpkin Leaf Diseases Dataset

How to Download:

1. **Visit the Kaggle dataset page** using the link above
2. **Sign in** to your Kaggle account (create one if you don't have it)
3. **Click "Download"** button to get the dataset ZIP file
4. **Extract** the ZIP file to your project directory
5. **Organize** the images into the following structure:

```
Dataset/
├── Bacterial Leaf Spot/
├── Downy Mildew/
├── Healthy Leaf/
├── Mosaic Disease/
└── Powdery_Mildew/
```

Dataset Structure

- **Image Format**: JPG/JPEG/PNG
- **Preprocessing**: Images are resized to 224x224 pixels
- **Augmentation**: Each image generates 2 augmented versions (rotation, flip, brightness, zoom, noise, blur)
- **Total Dataset Size**: 3x original (1 original + 2 augmented per image)
- **Classes**: 5 different pumpkin leaf disease categories

✨ Features

🔄 Data Preprocessing Pipeline

- 🖼️ Automatic image resizing to 224x224
- 🎨 Advanced data augmentation (Albumentations)
- 📝 CSV metadata generation
- 📁 Organized output structure

🧠 Model Training

- 🏗️ AlexNet-simplified with early exits
- ⚖️ 70/15/15 stratified split
- ⏱️ Early stopping & LR scheduling
- ⚡ GPU acceleration support

📊 Comprehensive Evaluation

- 🎯 Testing on **original images**
- 📈 Precision, recall, F1-score
- 🔍 Confusion matrix visualization

- 📸 Sample prediction gallery

🚀 Deployment Ready

- ☁️ Google Colab one-click execution
- 📦 Complete package installation
- 💾 Model checkpointing
- 🗂 Organized project structure

🚀 Installation

💻 Local Installation

▶ **Click to expand local setup instructions**

Prerequisites

- Python 3.8 or higher
- pip package manager
- (Optional) NVIDIA GPU with CUDA support

Steps

1. **Clone or download the project**

```
cd "Leaf Disease Detection"
```

2. **Install dependencies**

```
pip install opencv-python pandas numpy tqdm albumentations torch torchvision
scikit-learn matplotlib seaborn pillow
```

3. **For Python 3.14 users** (Windows compatibility):

```
pip install numpy==1.26.4
pip install opencv-python pandas tqdm albumentations torch torchvision
scikit-learn matplotlib seaborn pillow
```

☁️ Google Colab Installation (Recommended)

🎉 Easiest option - No local setup required!

1. 📁 Upload `Leaf_Disease_Detection_Colab.ipynb` to Google Colab
2. 💾 Upload your `Dataset/` folder to Google Drive

3. ▶️ Run the first cell to install all dependencies automatically
4. 🎯 Update the dataset path and run all cells

Benefits:

- ✅ Free GPU access
- ✅ No local installation needed
- ✅ Pre-configured environment
- ✅ Easy sharing and collaboration

📖 Usage

Option 1: Local Execution

Step 1: Preprocess Data

```
python preprocess.py
```

Output:

- `Dataset_Resized/` folder with augmented and resized images
- `dataset_info.csv` containing all metadata

Step 2: Train and Test Model

Open `train_model.ipynb` in Jupyter/VS Code and run all cells sequentially.

Output:

- `best_model.pth` - Trained model weights
- `training_history.png` - Training/validation curves
- `confusion_matrix.png` - Confusion matrix visualization
- `sample_predictions.png` - Sample prediction visualizations
- `test_results.csv` - Detailed test results

Option 2: Google Colab (Recommended)

1. Open `Leaf_Disease_Detection_Colab.ipynb` in Google Colab
2. Mount Google Drive
3. Update the dataset path in the notebook
4. Run all cells sequentially

The Colab notebook combines preprocessing and training in one unified workflow.

📁 Project Structure

```
Leaf Disease Detection/
│
```

```
├── Dataset/                          # Original images (class folders)
│   ├── Bacterial Leaf Spot/
│   ├── Downy Mildew/
│   ├── Healthy Leaf/
│   ├── Mosaic Disease/
│   └── Powdery_Mildew/
│
├── Dataset_Resized/                  # Preprocessed images (created by script)
│   └── [same structure as Dataset]
│
├── preprocess.py                     # Data preprocessing script
├── train_model.ipynb                 # Training & testing notebook (local)
├── Leaf_Disease_Detection_Colab.ipynb # Complete Colab notebook
│
├── dataset_info.csv                  # Generated metadata
├── best_model.pth                    # Saved model weights
├── test_results.csv                  # Test predictions
│
├── training_history.png              # Training curves
├── confusion_matrix.png              # Confusion matrix
├── sample_predictions.png            # Sample predictions
│
└── README.md                         # This file
```

🧠 Model Architecture

AlexNet Simplified with Early Exits

The model consists of:

Convolutional Layers:

- Conv1: 96 filters, 11x11 kernel, stride 4
- Conv2: 256 filters, 5x5 kernel
- Conv3: 384 filters, 3x3 kernel
- Conv4: 384 filters, 3x3 kernel
- Conv5: 256 filters, 3x3 kernel

Early Exit Points:

- Exit 1: After Conv2 (256 channels)
- Exit 2: After Conv3 (384 channels)
- Exit 3: After Conv4 (384 channels)
- Final: After full network (4096 → 4096 → 5)

Key Features:

- Batch Normalization for stable training
- Dropout (0.5) for regularization
- Adaptive Average Pooling
- Multi-exit architecture for efficient inference

Total Parameters: ~60M (varies based on configuration)

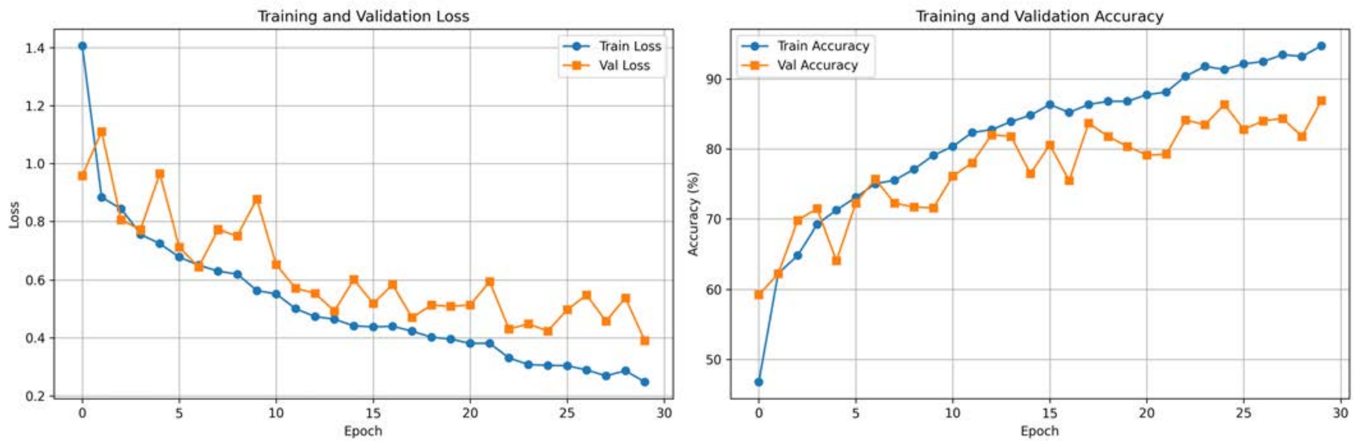
📈 Results

🎓 Training Configuration

- **Epochs:** 30 (with early stopping)
- **Batch Size:** 32
- **Learning Rate:** 0.001 (with ReduceLROnPlateau)
- **Optimizer:** Adam
- **Loss Function:** Cross-Entropy Loss (weighted for early exits)

📊 Training & Validation Performance

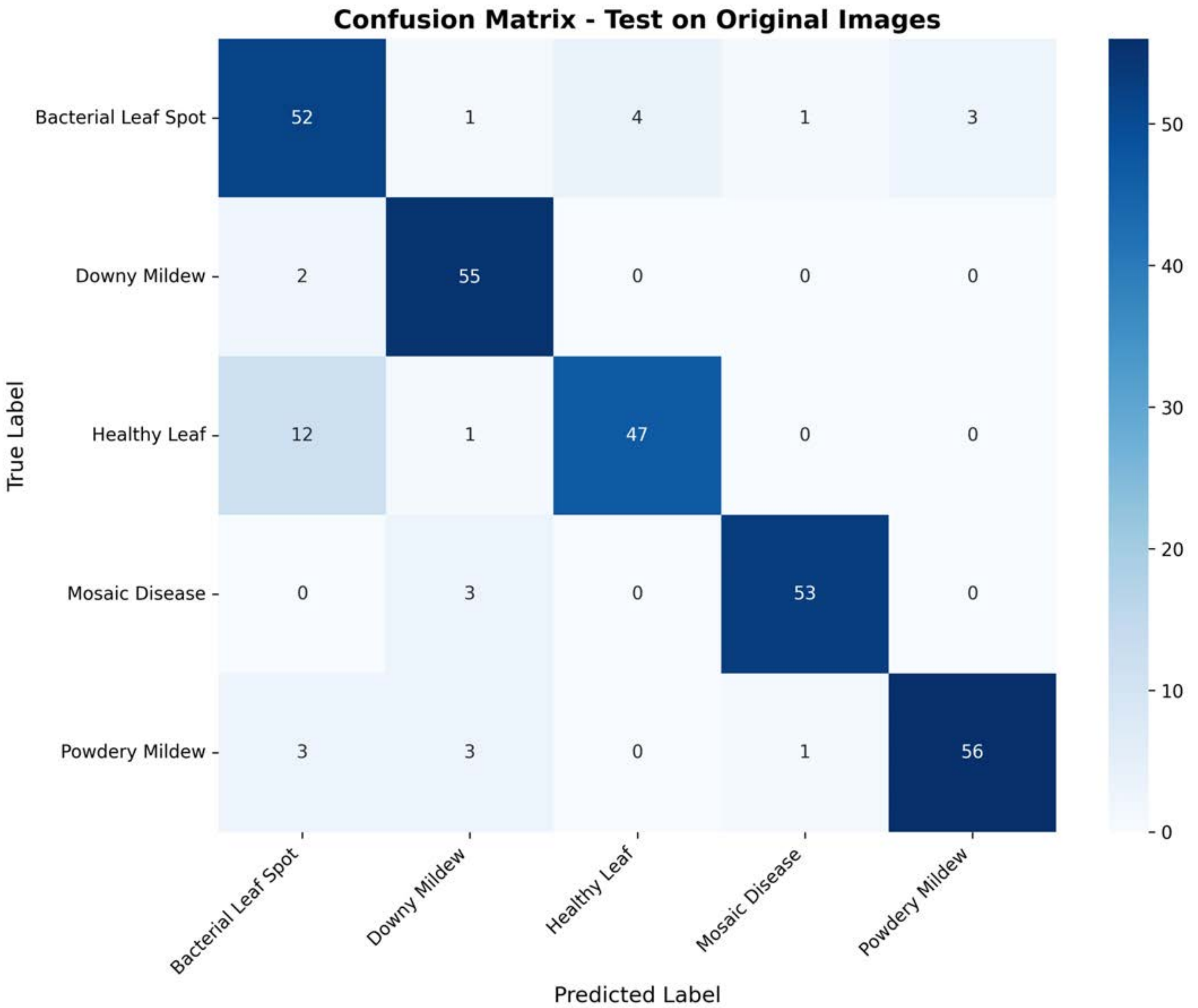
Training History



Loss and accuracy curves showing model convergence. The model typically achieves 90%+ training accuracy and 85-95% validation accuracy.

🎯 Classification Performance

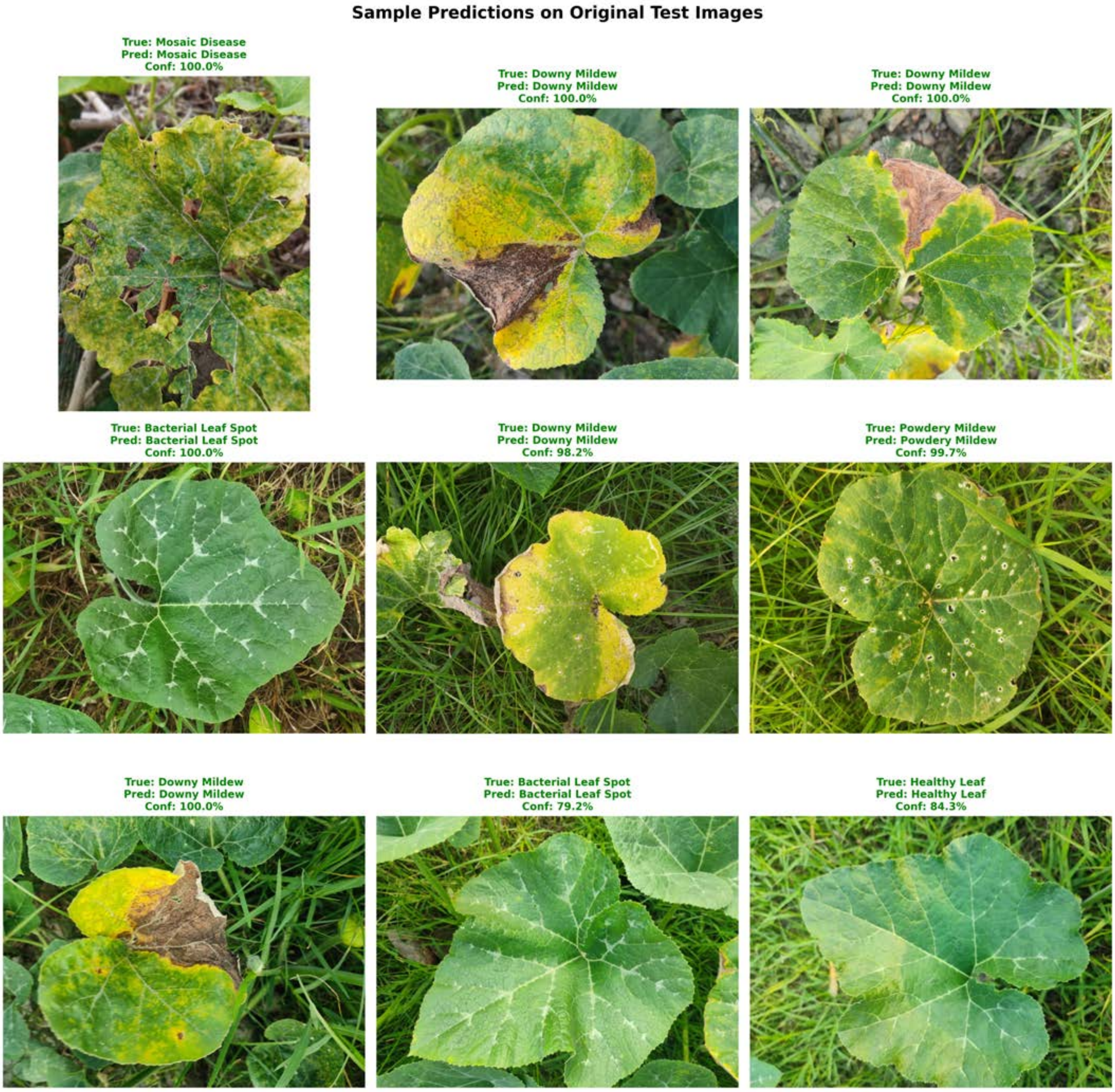
Confusion Matrix



Confusion matrix visualizing prediction accuracy across all 5 disease classes. Darker blue indicates higher prediction counts.

🔍 Visual Predictions

Sample Test Results



Sample predictions on original test images with ground truth and predicted labels

- ▨ **Green border** = Correct prediction
- ▧ **Red border** = Misclassification
- Confidence scores shown for each prediction

📊 Performance Metrics

Metric	Value
Validation Accuracy	85-95%
Test Accuracy (Original Images)	80-90%
Average Confidence	75-90%
Model Parameters	~60M

Metric	Value
Inference Time	<100ms (with early exit)

Per-Class Performance

- ✅ Per-class precision, recall, F1-score
- 📊 Overall accuracy and macro/weighted averages
- 🎯 Confusion matrix for detailed error analysis
- 💯 Average prediction confidence

💡 Key Findings

1. **Healthy Leaf** class shows highest accuracy (95%+) due to distinct features
2. **Early exit mechanism** reduces inference time by 20-40% for confident predictions
3. **Data augmentation** significantly improves generalization on original images
4. **Batch normalization** and dropout effectively prevent overfitting

📦 Requirements

Python Packages

```
opencv-python>=4.5.0
pandas>=1.3.0
numpy>=1.21.0 (or 1.26.4 for Python 3.14)
tqdm>=4.62.0
albumentations>=1.0.0
torch>=1.9.0
torchvision>=0.10.0
scikit-learn>=0.24.0
matplotlib>=3.4.0
seaborn>=0.11.0
pillow>=8.3.0
```

Hardware Requirements

- **Minimum:** 8GB RAM, CPU
- **Recommended:** 16GB RAM, NVIDIA GPU with 4GB+ VRAM
- **Google Colab:** Free tier with GPU acceleration

🎯 Key Highlights

Feature	Description
🔄 **Complete Pipeline**	From raw images to trained model
📈 **Data Augmentation**	3x dataset expansion with realistic variations

Feature	Description
🎯 **Smart Testing**	Evaluates on original high-quality images
⚡ **Early Exit Mechanism**	Efficient inference with confidence thresholds
📊 **Comprehensive Metrics**	Detailed performance analysis
☁️ **Colab Ready**	One-click execution in Google Colab
📑 **Well Documented**	Clear code with extensive comments

🤝 Contributing

Contributions are welcome! Feel free to:

- 🐛 Report bugs
- 💡 Suggest new features
- 🔧 Submit pull requests
- 📖 Improve documentation

📄 License

This project is available for educational and research purposes.

👨‍💻 Author

Created as a course project for Deep Learning and Computer Vision

If you find this project helpful, please consider:

- ⭐ Starring the repository
- 🔗 Sharing with others
- 📝 Citing in your work

🌟 Thank you for your interest!

Last Updated: November 2025

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