Potato Leaf Disease Classification Using CNN

Course: Artificial Intelligence (CO401)

Problem Statement:

- Potato crops frequently suffer from Early Blight and Late Blight fungal infections.
- Manual disease detection is:
  → Time-consuming
  → Requires expert knowledge
  → Prone to human subjectively
- Need for **automated**, **scalable**, and **accurate** detection.

Why Deep Learning?

- Classical image processing approaches relied on:
  - Color thresholding
  - Texture features
  - Morphological analysis
- Limitations: sensitive to lighting, background, and noise.
- CNNs learn hierarchical features directly from pixel data.
- Proven high accuracy in PlantVillage datasets.

Project Objectives

1. Build a CNN model to classify potato leaf diseases.
2. Apply preprocessing + augmentation to prevent overfitting.
3. Train a multi-layer deep CNN from scratch.
4. Evaluate accuracy/loss across epochs.
5. Test on unseen images for real-world validation.

Dataset Overview

- Classes:
  - Potato_Early_Blight
  - Potato_Late_Blight
  - Potato_Healthy
- Characteristics:
  - RGB images, varying resolution
  - Resized to 256x256
- Data split: Training / Validation / Testing
- Augmentation applied to enhance dataset size.

Data Augmentation Techniques

- Random shear transformations
- Random zoom
- Horizontal flip
- Normalization
- Rescaling to 0–1
- Purpose:
- Reduce overfitting
- Improve robustness to orientation, lighting, texture variations

Convolution Layer Mechanics (Technical)

- A filter/kernel slides over the image:
  - Performs convolution: element-wise multiplication + summation
- Creates feature maps representing:
  - Edges
  - Spots
  - Texture variations (common in diseased leaves)
- Uses same padding to preserve spatial dimensions.
- Potato_Disease_CNN_Full_Report

Pooling Layer Mechanics

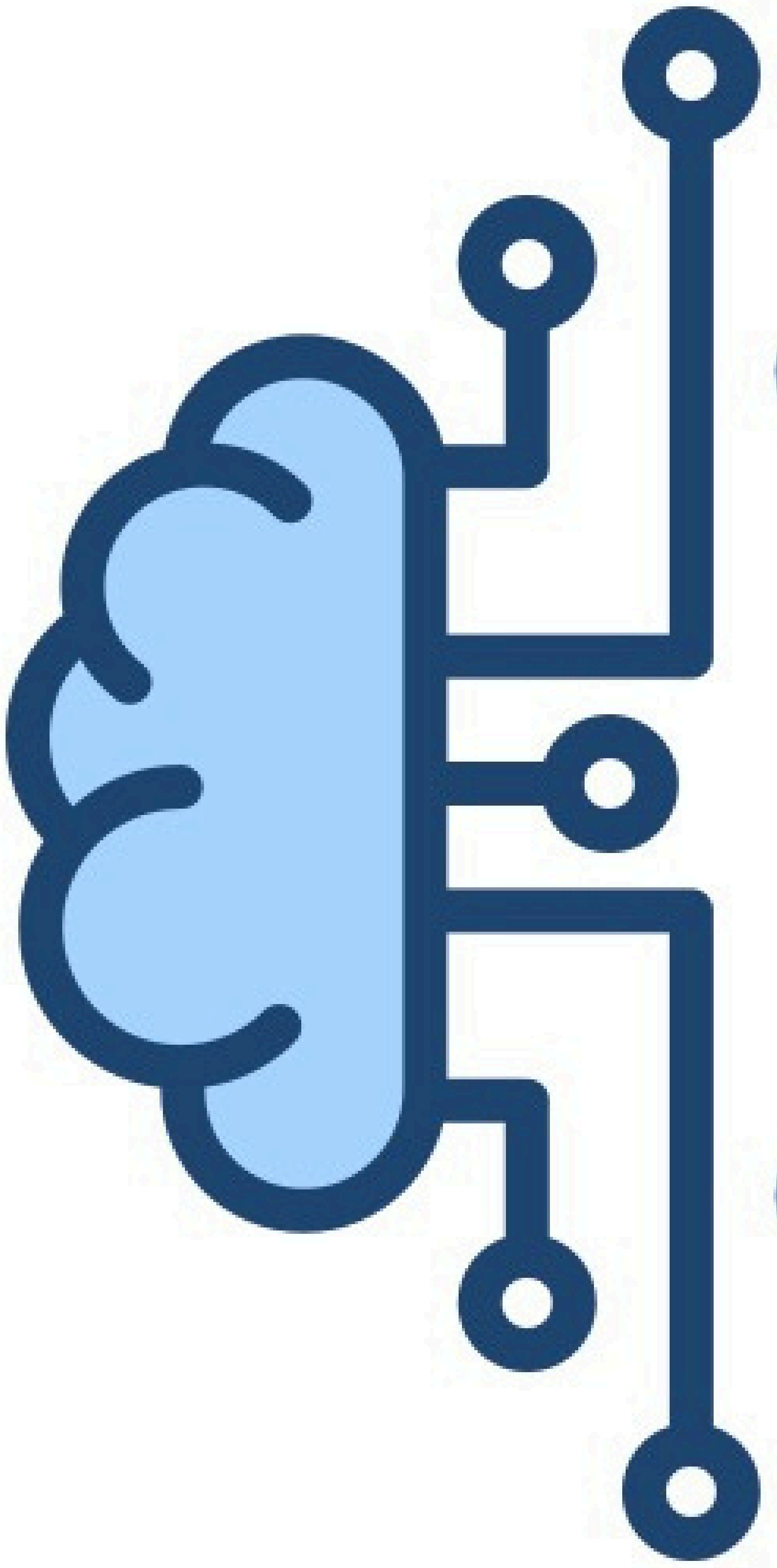
- Max Pooling extracts dominant activations.
- Reduces spatial size
- Benefits:
  - Lower computation
  - Translation invariance
  - Focus on important spatial patterns
- Helps model generalize to real-world plant images.

Model Compilation & Hyperparameters

- Frameworks: TensorFlow + Keras
- Optimizer: Adam
- Loss: Categorical Cross-Entropy
- Batch Size: 32
- Epochs: 20
- Learning rate tuning built into Adam
- GPU used for faster training

Training Process

- Training pipeline:
  - Load dataset from folders
  - Augment on the fly using ImageDataGenerator
  - Forward pass → compute predictions
  - Backpropagation → update weights
- Loss decreases steadily
- Accuracy improves consistently



Results: Accuracy & Loss

- Accuracy curve rises smoothly → indicates stable learning
- Loss curve decreases without sudden spikes
- No noticeable overfitting due to augmentation
- Final training accuracy: high (exact % depends on your output)

Sample Predictions

Example:

- Input: Potato leaf image
- Model Output:
    - Class → Early Blight
    - Confidence → 95%

Shows ability to generalize to unseen images.

Technical Strengths of the Model

- Lightweight CNN (small # of parameters)
- Fast inference
- Low computational requirements → deployable on mobile/IoT
- High accuracy even with limited dataset due to augmentation
- Model can be exported as SavedModel / TFLite

Limitations of the Approach

- Training dataset from controlled environment (PlantVillage style)
- Performance may drop with:
- Natural farm backgrounds
- Variable lighting
- Occluded or partially damaged leaves
- Only 3 disease classes included

Future Scope (Technical Enhancements)

- Use Transfer Learning:
  - ResNet50
  - EfficientNet
  - MobileNetV2 (for mobile app deployment)
- Add segmentation (Mask-RCNN, U-Net) for leaf isolation
- Expand to multi-crop and multi-disease datasets
- Integrate with IoT smart farming systems
- Deploy on cloud or mobile (TensorFlow Lite)

Conclusion

- CNN effectively identifies Early Blight, Late Blight, and Healthy leaves.
- Achieves strong accuracy and robustness.
- Demonstrates AI's potential in automated agriculture disease monitoring.
- Can be extended to large-scale farm deployment.

Thankyou