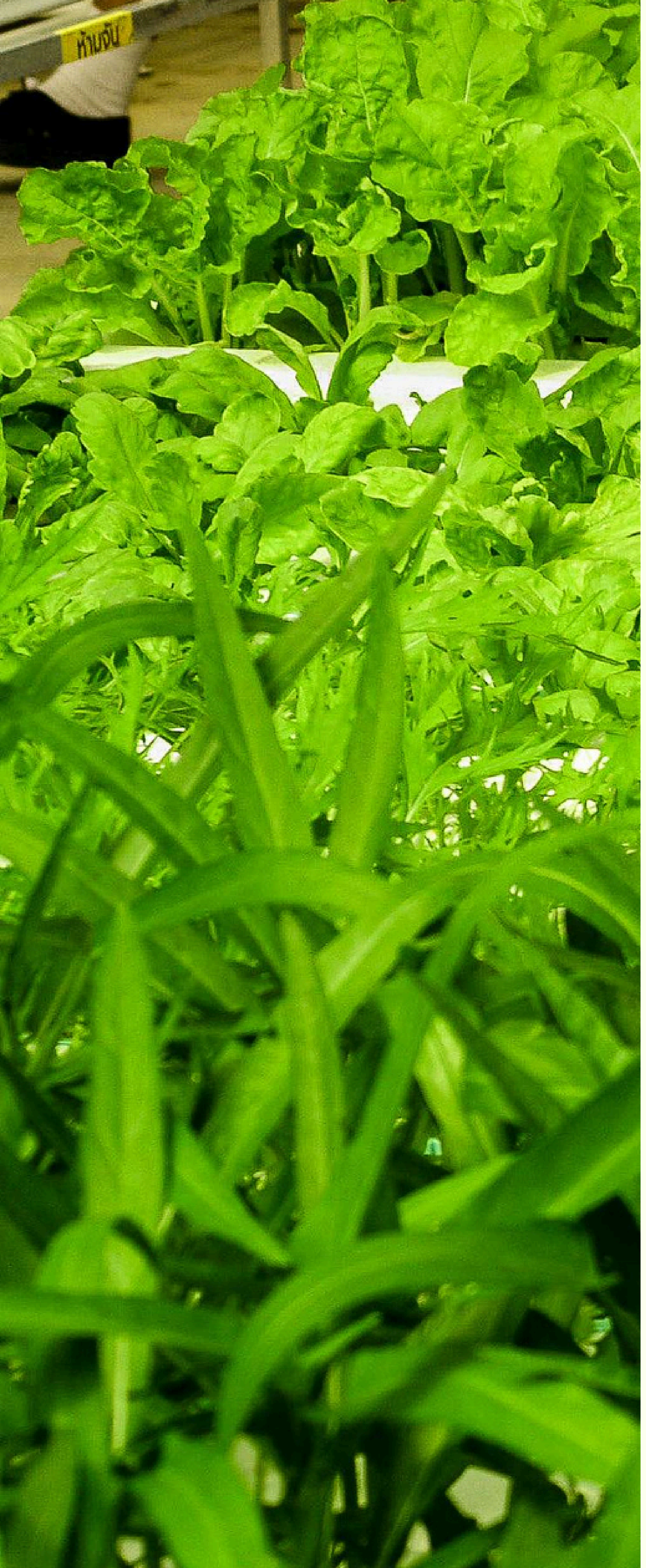
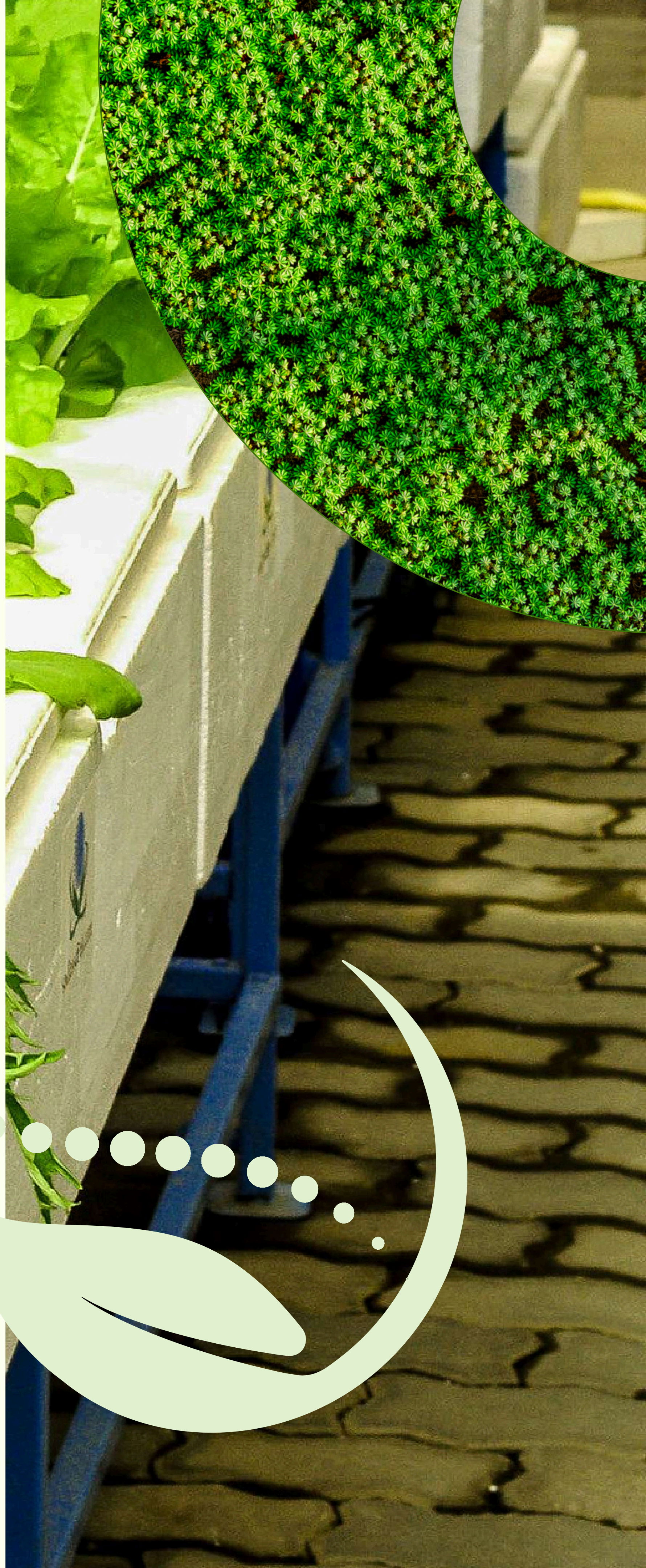


AgriScan

Smart Leaf Disease Detection System



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PROBLEM STATEMENT :

LACK OF EARLY DISEASE DETECTION:

Plant diseases often remain unnoticed in the early symptomatic stages, leading to delayed intervention and severe crop yield loss.

LIMITED ACCESS TO EXPERT SUPPORT:

Farmers in rural and remote agricultural communities generally lack access to agronomists, plant pathologists, and extension services, preventing timely diagnosis.

RAPID DISEASE PROPAGATION:

Undetected diseases can spread quickly through airborne pathogens, soil-borne infections, or vector transmission, affecting entire farms or neighboring fields.

ECONOMIC IMPACT:

Delayed detection results in large-scale crop failure, reduced productivity, and financial instability, pushing farmers toward unsustainable or costly treatment methods.

PROPOSED SOLUTION:

ML-Driven Disease Diagnosis:

A mobile application powered by Machine Learning (ML) / Deep Learning (DL)—specifically Convolutional Neural Networks (CNNs)—to identify diseases from leaf images with high accuracy.

Bilingual, Accessible Interface:

A user-friendly, bilingual UI designed for low-literacy and multilingual farming communities, ensuring inclusivity and ease of use.

Real-Time Analysis:

On-device or cloud-based real-time image processing for rapid disease detection, even in areas with limited connectivity.

Actionable Agronomic Insights:

The app provides evidence-based recommendations, including preventive measures, targeted treatments, pesticide/fungicide suggestions, and best agricultural practices.

OBJECTIVES:

1. Develop a high-accuracy machine learning pipeline using Convolutional Neural Networks (CNNs) and image preprocessing techniques trained on large-scale, annotated plant leaf disease datasets.

2. Design and implement a bilingual, user-centric mobile interface (UI/UX) optimized for accessibility, low digital literacy, and offline functionality, using modern cross-platform frameworks.

3. Generate actionable agronomic insights through model-based disease classification, severity estimation, and recommendation algorithms that deliver precise treatment and prevention solutions.

4. Enhance agricultural decision-making by reducing dependence on manual visual inspection through automated disease detection, real-time diagnostics, and knowledge dissemination modules.

METHODOLOGY:

Data Acquisition & Preprocessing:

Collect leaf images from Kaggle, then apply normalization, augmentation, and dataset splitting.

Economic Foundation

Train a CNN-based classifier (ResNet/MobileNet) using transfer learning and hyperparameter tuning.

Model Optimization & Integration:

Convert the model to TensorFlow Lite for mobile deployment and integrate it for on-device inference.

App Development & Evaluation:

Build a bilingual UI using Flutter, then perform field testing and iterative refinement based on user feedback.

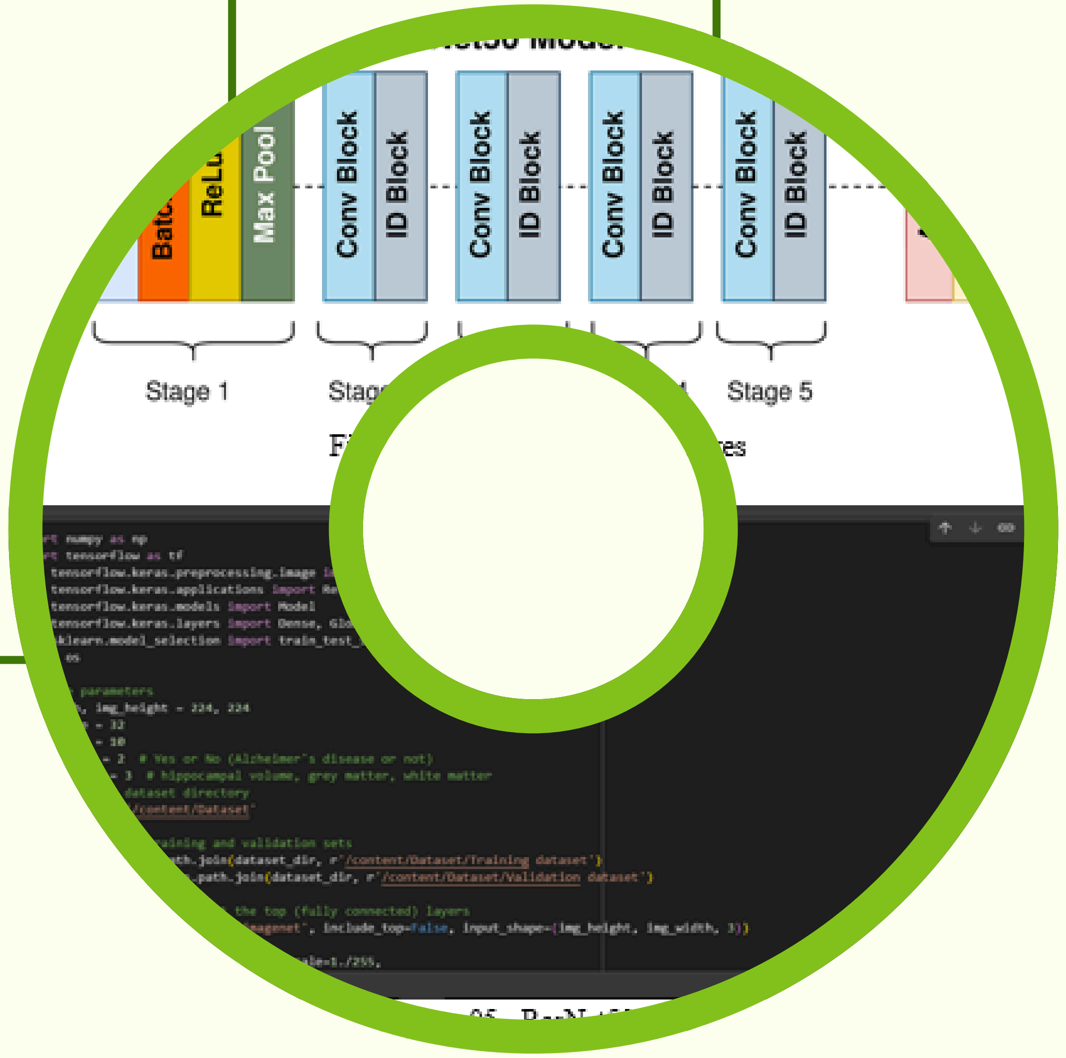
ResNet50 : Detailed Explanation

Why ResNet50?

ResNet-50 is a computer vision model based on a type of neural network called a Convolutional Neural Network (CNN). CNNs are designed to help computers understand visual information by learning patterns in images, such as edges, colors, or shapes, and using those patterns to recognize and classify objects.

Elements of ResNet50

Input Layer
Convolutional Layers
Skip Connections
Pooling Layers
Fully Connected Layer
Softmax Activation Function
Batch Normalization & ReLU



How ResNet50 works?

Problem: Vanishing Gradient

In traditional CNNs, as data passes through many layers, the signal (gradient) used to update the weights gets smaller and smaller until it effectively vanishes.

Solution: Residual Learning

Instead of trying to learn a completely new representation at every layer, a ResNet block tries to learn the "residual" (the difference) between the input and the desired output.

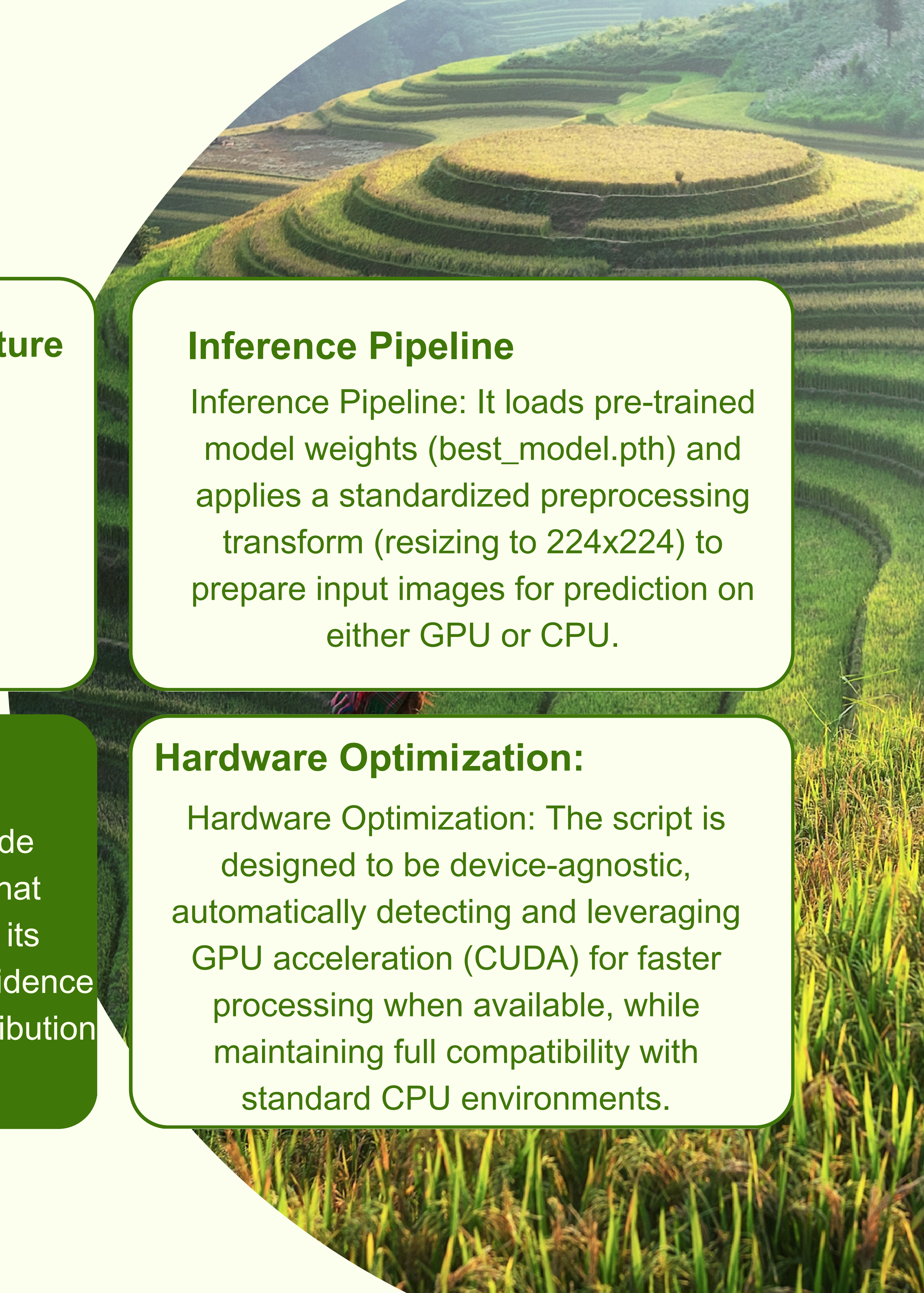
Output=F(x)+x

Where:

- x is the input.
- F(x) is the learned change (residual) processed by the layers.
- F(x)+x is the final output.

The Bottleneck Block

ResNet50 specifically uses a "Bottleneck" design to save computational resources. Instead of two large 3x3 convolutions, it uses a stack of three layers: 1x1 Conv: Reduces dimensions (squeezes the data), 3x3 Conv: Processes the data and 1x1 Conv: Restores dimensions (expands the data).



Predictive Analysis

We are using transfer learning with ResNet50. We replaced the final layer to match our specific dataset, which consists of 11 different classes like 'Early Blight' and 'Healthy'.

This snippet handles the 'testing' phase. It takes raw images, formats them mathematically, and feeds them into our trained neural network.

Customized ResNet50 Architecture

Customized ResNet50 Architecture: The script utilizes a ResNet50 backbone modified with a custom fully connected layer (including ReLU, BatchNorm, and Dropout) to classify images into 11 specific tomato disease categories.

Inference Pipeline

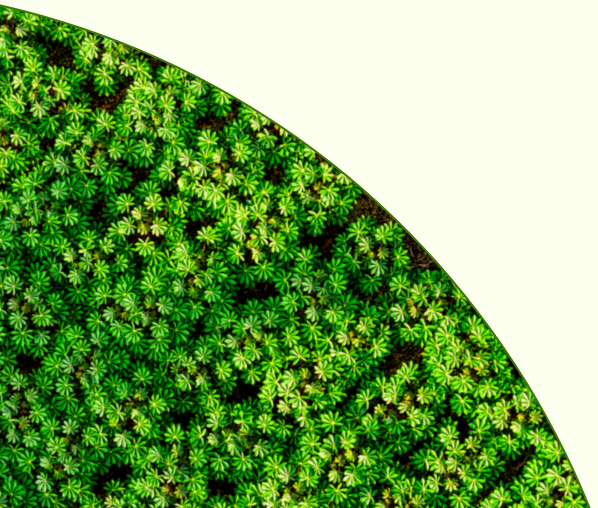
Inference Pipeline: It loads pre-trained model weights (best_model.pth) and applies a standardized preprocessing transform (resizing to 224x224) to prepare input images for prediction on either GPU or CPU.

Visualization & Analytics:

Visualization & Analytics: The code includes a visualization function that displays the analyzed image with its predicted label and generates a confidence bar chart to show the probability distribution across all disease classes.

Hardware Optimization:

Hardware Optimization: The script is designed to be device-agnostic, automatically detecting and leveraging GPU acceleration (CUDA) for faster processing when available, while maintaining full compatibility with standard CPU environments.



Technology in Agriculture

Drones & Aerial Imaging

Drones help farmers monitor crop health, detect pests, and map large fields with precision saving time and improving decision-making.

Smart Sensors & IoT Devices

Soil and weather sensors collect real-time data, allowing farmers to know exactly when and how much to water or fertilize reducing waste and maximizing yield.

Automated Machinery

Tractors, harvesters, and irrigation systems are now automated, making farming less labor-intensive and more consistent.

Thank You!