Atish Dipankar University of
Science and Technology (ADUST)

Presentation on :–
Potato Leaf Disease Detection Using Machine Learning

B.Sc. DEFENSE, Summer 2025

Department of Computer Science & Engineering(CSE)

Introduction to the Student & Supervisor

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Objective

- To acquire and preprocess a public dataset of potato leaf images for disease classification.
- To build and train three distinct deep learning models (EfficientNetB3, DenseNet121, ResNet152V2) using a transfer learning approach.
- To implement a two-phase training strategy (feature extraction and fine-tuning) to optimize model performance.
- To systematically evaluate and compare the models to identify the best-performing one based on accuracy, precision, and recall.
- To deploy the best model as an interactive web application using Gradio for real-time prediction.

Motivation

- Global Food Security: The potato is a critical global food crop, but its yield is severely threatened by fungal diseases like Early Blight and Late Blight.
- Limitations of Manual Detection: Traditional disease identification by farmers is labor-intensive, time-consuming, and prone to error, leading to crop loss and overuse of pesticides.
- Power of AI: Advancements in computer vision and deep learning offer a way to automate disease detection with high accuracy.
- Need for Accessible Tools: There is an urgent need for accessible and scalable solutions to help farmers make timely, informed decisions for crop management.

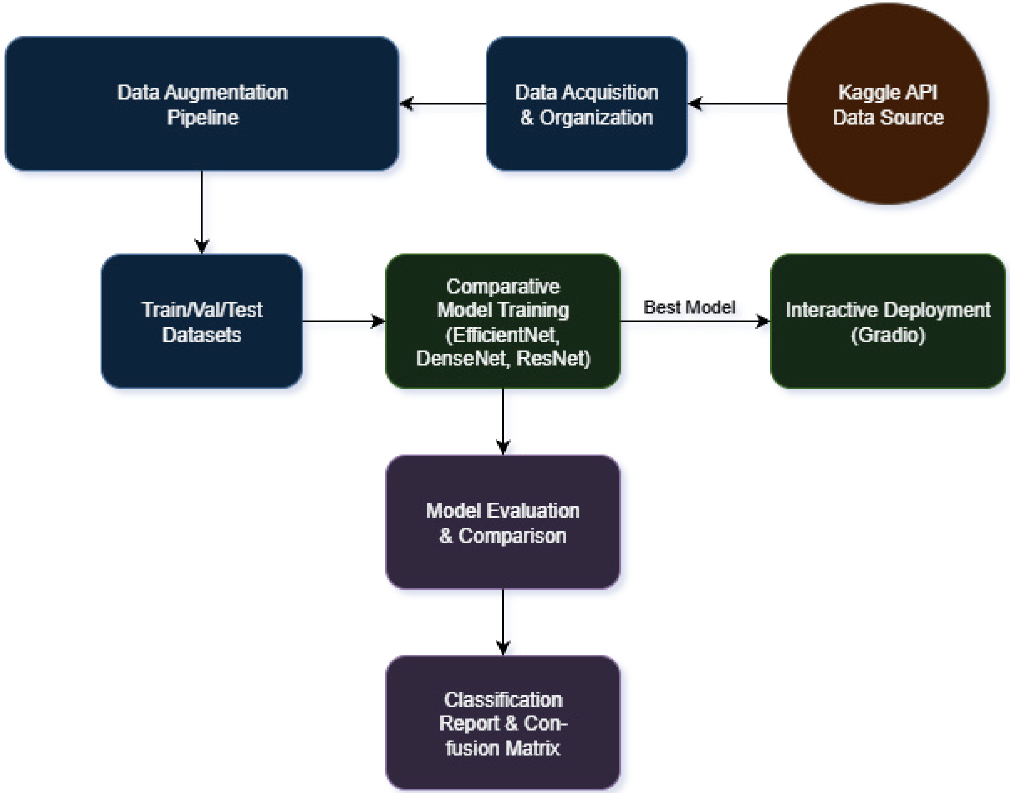
Proposed Solution & Components

- Programming Language: Python 3
- Core ML Libraries:

  1.TensorFlow/Keras: For building, training, and evaluating the deep learning models.

  2.Scikit-learn: For generating detailed classification reports and confusion matrices.
- Data Manipulation: NumPy, Pillow (PIL)
- Data Acquisition: Kaggle API
- Visualization: Matplotlib, Seaborn
- Deployment & UI: Gradio
- Models: EfficientNetB3, DenseNet121, ResNet152V2

Design and Implementation (Architecture)



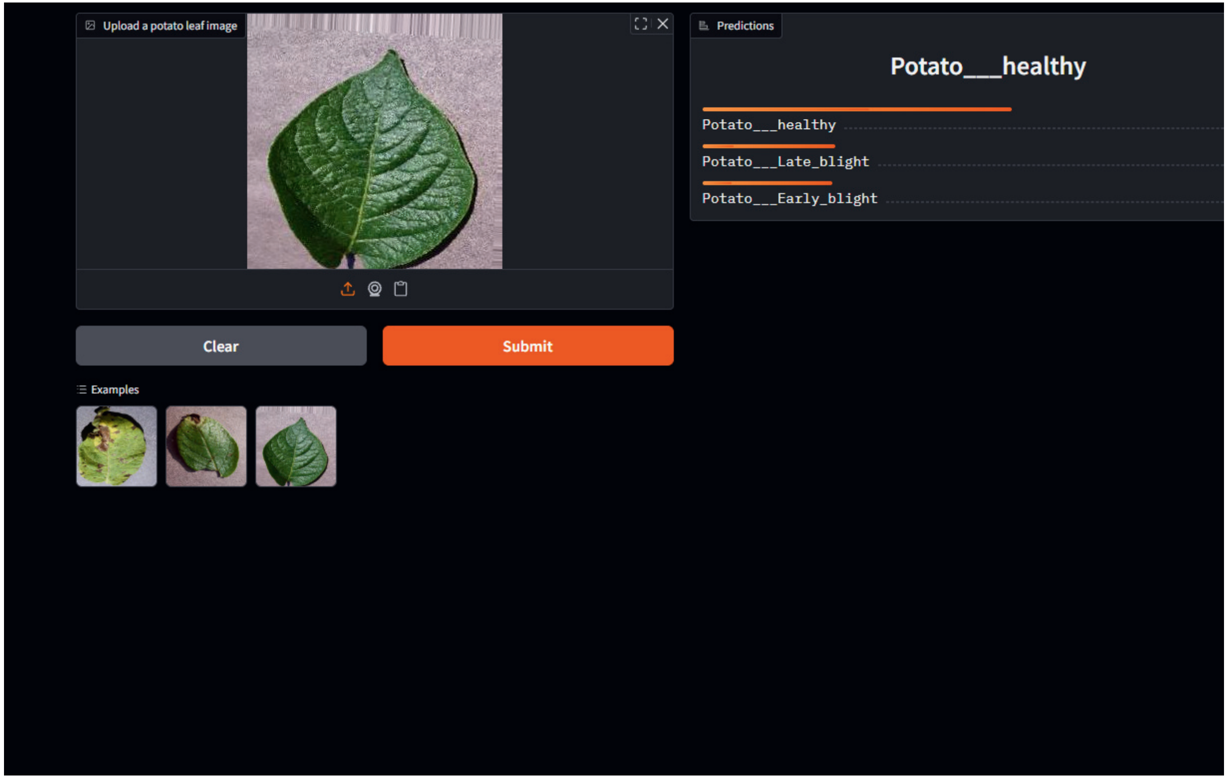
Design and Implementation (Workflow)

- Data Acquisition: The "Potato Leaf Disease" dataset (1500 images) was downloaded from Kaggle.
- Preprocessing: Images were resized to 224x224 pixels and normalized. The dataset was split into training (900), validation (300), and test (300) sets.
- Augmentation: The training data was augmented with random flips, rotations, zooms, and contrast adjustments to prevent overfitting.
- Training: A two-phase transfer learning strategy was used.
  - Phase 1 (Feature Extraction): Trained only the new classification head for 25 epochs.
  - Phase 2 (Fine-Tuning): Unfroze the top 40% of layers and trained the entire model with a lower learning rate for another 25 epochs.
- Evaluation: The trained models were evaluated on the held-out test set.
- Deployment: The best-performing model (DenseNet121) was deployed as a web application using Gradio.

Design and Implementation (Data)

- Dataset:
  "Potato Leaf Disease" dataset from Kaggle.
- Content:
  1500 pre-labeled images of potato leaves.
- Classes (3):
  1. Potato Early Blight
  2. Potato Late Blight
  3. Potato Healthy
- Data Split:
  1. Training Set: 900 images
  2. Validation Set: 300 images
  3. Test Set: 300 images
- Distribution:
  The validation and
  test sets have a balanced distribution of 100 images per class.

Implementation of the Project



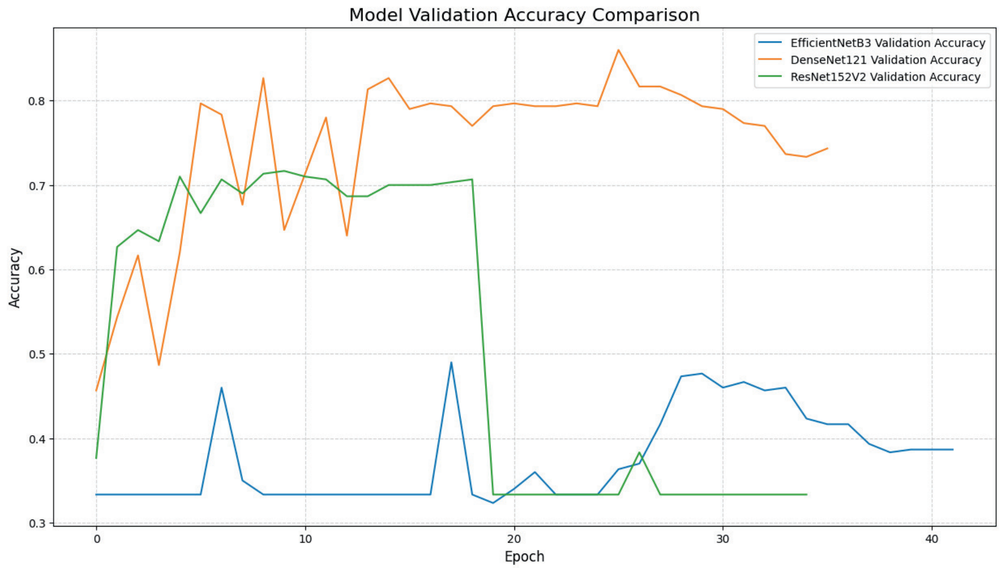
The fine-tuned DenseNet121 model was deployed using Gradio to create a simple, interactive web interface. This allows non-technical users to:

- Upload an image of a potato leaf.
- Receive an instant prediction of the leaf's health status (Healthy, Early Blight, or Late Blight).
- View the confidence scores for the top predictions.

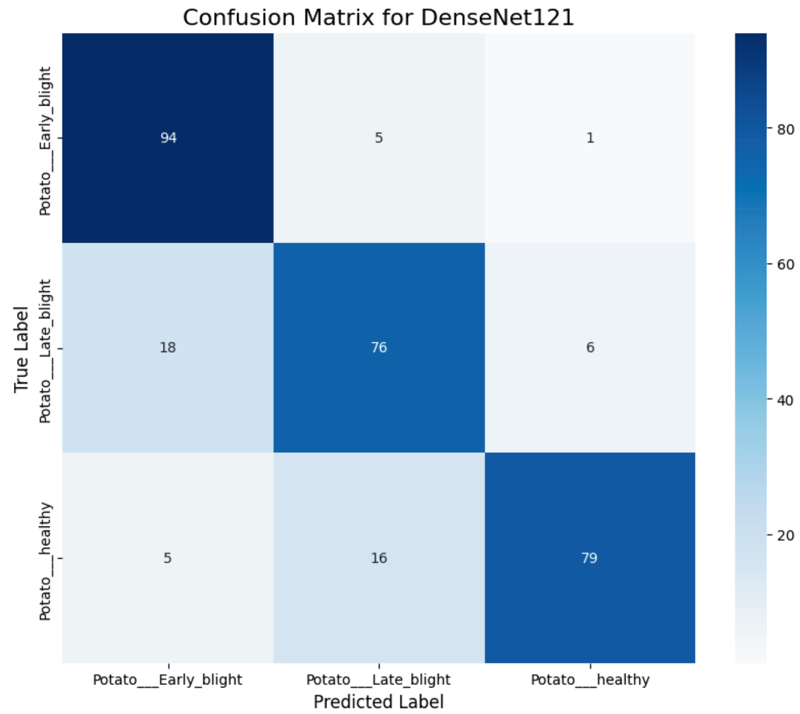
This deployment serves as a proof-of-concept for a real-world agricultural decision support tool.

Results (Training Performance)

- <u>Strong Performers:</u> DenseNet121 and ResNet152V2 showed strong, consistent learning, with validation accuracies steadily increasing to over 80%.
- <u>Struggling Model:</u> EfficientNetB3 struggled during the initial phase and never reached the performance levels of the other two models.
- <u>Best Model Selection:</u>The use of ModelCheckpoint ensured that the best version of each model was saved based on validation loss for final evaluation.



Results (Evaluation)



Final Test Accuracy:

- DenseNet121: 83.00% (Best Model)
- ResNet152V2: 68.67%
- EfficientNetB3: 37.33%

DenseNet121 Performance Metrics:

- Overall Accuracy: 83%
- Early Blight: High recall (0.94), meaning it correctly identified 94% of all Early Blight cases.
- Healthy: High precision (0.92), meaning its "healthy" predictions are very reliable.
- Late Blight: The most challenging class, with more misclassifications

Conclusion

- Successfully engineered an end-to-end system for automated potato leaf disease detection.
- The DenseNet121 model achieved the highest performance with a test accuracy of 83.00%.
- Demonstrated a complete and effective workflow, from data acquisition and augmentation to model training and deployment.
- The project delivers a functional, user-friendly web interface (via Gradio) for real-time predictions, serving as a valuable proof-of-concept.

Future Scope

- Dataset Expansion: Improve performance by training on a larger, more diverse dataset with varied lighting, backgrounds, and potato cultivars.
- Advanced Architectures: Experiment with newer models like Vision Transformers (ViT) to potentially capture different features.
- Explainable AI (XAI): Integrate techniques like Grad-CAM to highlight the leaf regions influencing the model's decision, increasing user trust.
- Mobile and Edge Deployment: Optimize the model for deployment on smartphones using TensorFlow Lite for practical, offline field use.
- Multi-Disease & Severity Classification: Expand the system to identify a wider range of diseases and classify the severity of an infection.

Thank You!
Questions?