Identifying Nutritional Deficiencies in Plants Using Leaf Pattern Analysis🌱

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INTRODUCTION

Agriculture is vital to the Indian economy, employing much of the rural population and ensuring food security. As the need for sustainable, high-yield farming grows, maintaining crop health is increasingly critical. Nutrient deficiencies—visible on plant leaves—pose a major threat to productivity. However, farmers in remote areas often lack expert agronomic support. Manual diagnosis is time-consuming, error-prone, and can lead to poor decisions and economic loss.

To address this challenge, our research focuses on developing an AI-powered, image-based system that automatically detects nutrient deficiencies in plant leaves using deep learning and image processing techniques. The solution is currently tailored for three major crops: banana, groundnut, and rice. It leverages lightweight, optimized models that ensure fast inference and low computational load, and is deployed through Hugging Face-hosted APIs. Through this system, we aim to empower farmers with a fast, reliable, and easy-to-use diagnostic tool that enables early intervention, reduces dependency on experts, and ultimately improves crop yield and economic outcomes.

OBJECTIVE

The primary objective of this project is to design and implement an intelligent, image-based system that can automatically detect nutrient deficiencies in plant leaves through deep learning techniques. By analyzing visual symptoms captured in images, the system provides early, accurate, and interpretable diagnosis, empowering farmers to take timely corrective action. Our approach involves building crop-specific models for banana, groundnut, and rice leaves, trained on publicly available datasets. These models are optimized for efficient inference, ensuring minimal latency and resource usage.

Impact and Relevance

- Applies Deep Learning to Agricultural Challenges.
- Implements Lightweight Models for Practical Use Cases.
- Explores Multi-Crop Generalization.
- Demonstrates Feasibility of AI-Driven Diagnosis.
- Lays Groundwork for Scalable Future Applications

PROBLEM STATEMENT

Many farmers, especially those in villages and remote areas, do not have access to expert help when it comes to keeping their crops healthy. When plants don't get the right nutrients, their leaves show warning signs like color changes or spots. But most farmers rely only on their eyes and experience to notice these changes. This method can be slow, confusing, and sometimes wrong. If the problem is not spotted early, it can damage the crop badly, reduce the harvest, and cause big financial losses.

Although modern technologies like AI and sensors exist, most of these tools are either too expensive or are too complicated for everyday use on farms. Many early farmers also don’t know how to identify nutrient problems, and getting expert advice takes time and money. As a result, help comes too late—and by then, the crop may already be damaged.

There is a clear need for a simple, affordable, and reliable tool that can help farmers easily identify nutrient deficiencies in crops by simply taking a photo of a leaf. Such a solution should work in real farming conditions, be easy to use, and not require any technical knowledge. This would allow farmers to catch problems early, take the right steps in time, and protect their crop yield and income.

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Identification of Nutrient Deficiency Based on Leaf Image Data Using Machine Learning

- Problem Addressed:

Automated identification of nitrogen, phosphorus, and potassium deficiencies in rice crops through leaf image analysis for Indian agriculture

- Methodology:

Image preprocessing, FCTH and CEDD feature extraction, and Random Forest classification

- Datasets Used:

1,156 rice leaf images from Kaggle with N, P, K deficiency samples from India (2024)

- Results:

Achieved 94.66%, 89.63%, and 89.71% accuracy for N, P, K deficiency detection respectively

- Drawbacks:

Limited to 3 nutrients with small dataset and no real-field validation

- Future Scope:

Expand to more nutrients, apply deep learning, and develop mobile app for farmers

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Multi-Nutrient Deficiency Identification via Improved LinkNet-SqueezeNet Model and Improved BIRCH based Segmentation

- Problem Addressed:

Multi-nutrient deficiency identification in paddy plants using hybrid deep learning approach

- Methodology:

I-BIRCH clustering with adaptive thresholds, Improved MRE-LBP for noise reduction, and hybrid ILink-SqueezeNet with enhanced RELU activation

- Datasets Used:

Same Kaggle rice leaf dataset with Gaussian filtering for image quality enhancement

- Results:

Achieved 86.5% to 96.6% accuracy across different training percentages with 94.1% sensitivity and 92.5% specificity

- Drawbacks:

Complex multi-stage preprocessing pipeline, computational overhead from hybrid architecture, and limited real-world deployment validation

- Future Scope:

Real-time mobile implementation, extension to other crop types, and integration with IoT sensors for comprehensive plant health monitoring

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Green Insight: A Novel Approach to Detecting and Classifying Macro Nutrient Deficiencies in Paddy Leaves

- Problem Addressed:

Automated detection and classification of N, P, K deficiencies in paddy crops using HSV color pattern analysis

- Methodology:

HSV color space conversion with background removal, horizontal leaf partitioning, and pixel ratio calculation using predefined color thresholds

- Datasets Used:

Kaggle dataset with 426 paddy leaf images split 7:3 for training/ testing with 300x3000 resolution resizing

- Results:

Achieved 96% accuracy for nitrogen, 90% for phosphorus, and 92% for potassium deficiency detection

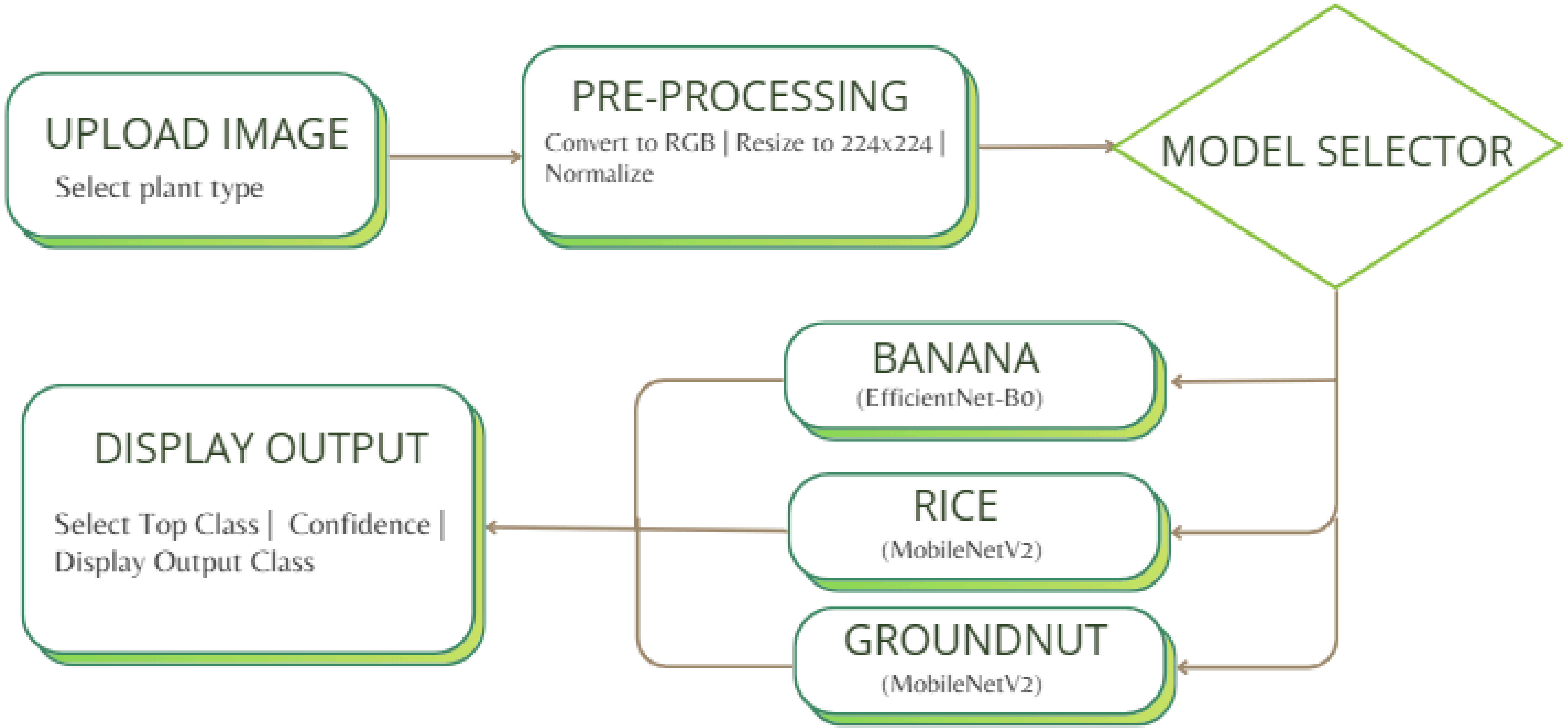
- Drawbacks:

Limited to moderate growth stage detection, single deficiency per image, and requires manual background removal

- Future Scope:

Multi-deficiency detection capability, automated background segmentation, and extension to all plant growth stages

PROPOSED SOLUTION



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MODEL EVALUATION AND COMPARISON

Model	Accuracy	Pros	Cons	Suitability
Advanced UNet Segmentation Classifier (Banana)	51.93	Handles pixel-wise segmentation, useful when symptoms are spatially distinct	Low accuracy, overkill for simple classification tasks	When precise segmentation is required, not ideal for basic classification
Histogram Equalization with SVM Classifier (Banana)	73.56	Simple, interpretable, improves contrast	Not robust to complex patterns, feature engineering required	Basic traditional CV pipeline, suitable for low-resource settings
EfficientNet B0 (Banana)	83.10	Balanced in size and performance, pretrained, efficient	May underperform compared to deeper variants	Good choice for edge devices and banana disease classification
MobileNet V2 (GroundNut)	96.13	Very high accuracy, lightweight, mobile-friendly	May miss complex patterns compared to larger models	Ideal for on-device classification in field conditions
MobileNet V2 (Rice)	88	Fast inference, good performance on moderate datasets	Less accurate than EfficientNet in some tasks	Suitable for real-time crop diagnosis in mobile apps

MODEL EVALUATION AND COMPARISON

ADVANCED UNET SEGMENTATION CLASSIFIER (BANANA)

- UNet adapted for image classification
- Uses residual and group conv blocks in encoder
- Attention gates in decoder to refine skip connections
- Global Average Pooling at multiple levels
- Final dense layers for multi-class classification

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COMPREHENSIVE ADVANCED UNET EVALUATION
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94/94 ━━━━━━━━━━━━━━━━━━━━ 12s 89ms/step
Overall Accuracy: 0.5193
Weighted Precision: 0.5643
Weighted Recall: 0.5193
Weighted F1-Score: 0.5086
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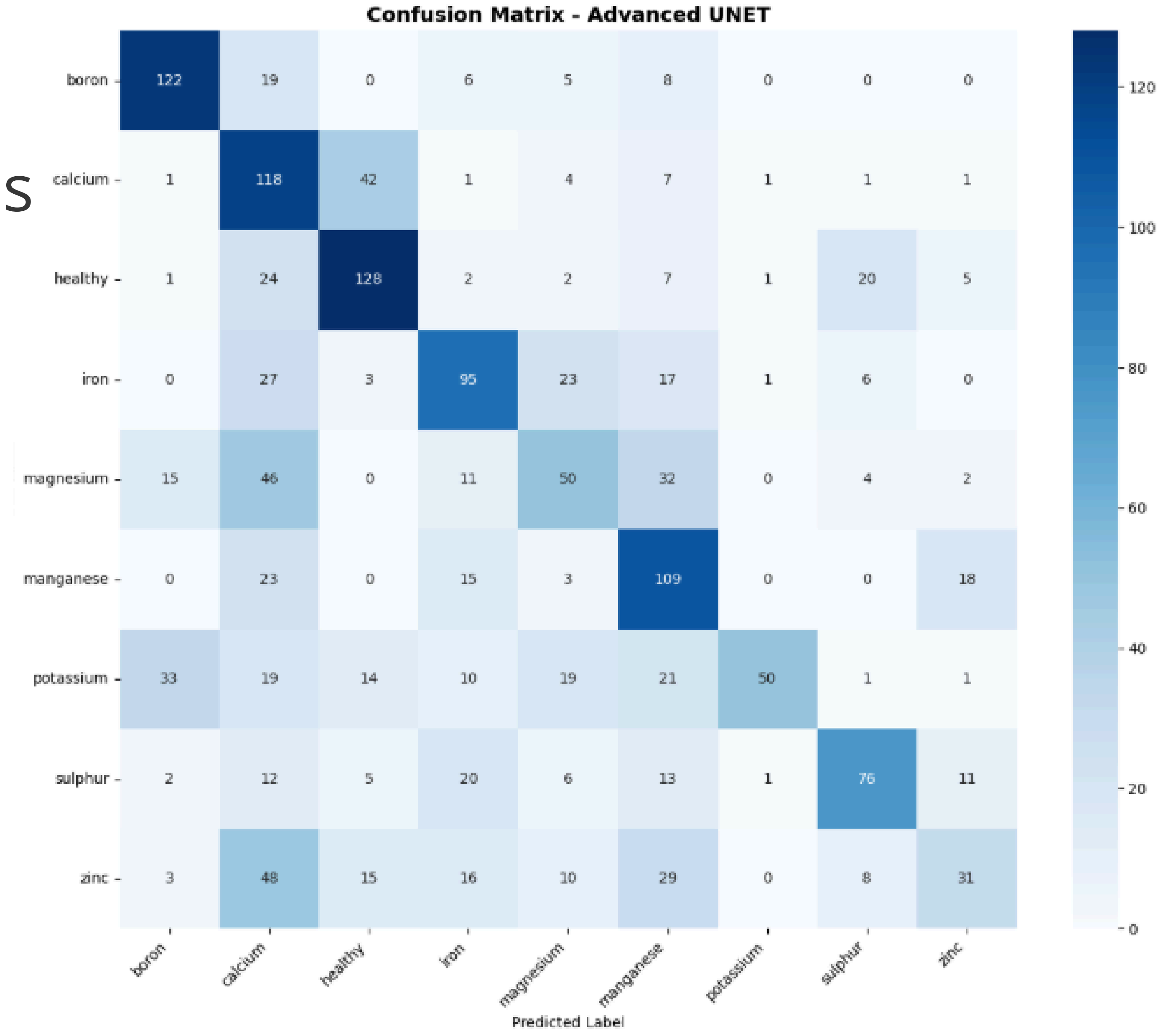

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MODEL EVALUATION AND COMPARISON

HISTOGRAM EQUALIZATION WITH SVM CLASSIFIER (BANANA)

- Used EfficientNet-B0 for GPU-based feature extraction.
- Applied advanced histogram equalization for preprocessing.
- Selected features using variance filtering, SelectKBest, and PCA.
- Trained SVM classifier with hyperparameter tuning (GridSearchCV).
- Achieved high accuracy on banana nutrient deficiency classification.

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FINAL MODEL EVALUATION RESULTS
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Test Accuracy: 0.7356
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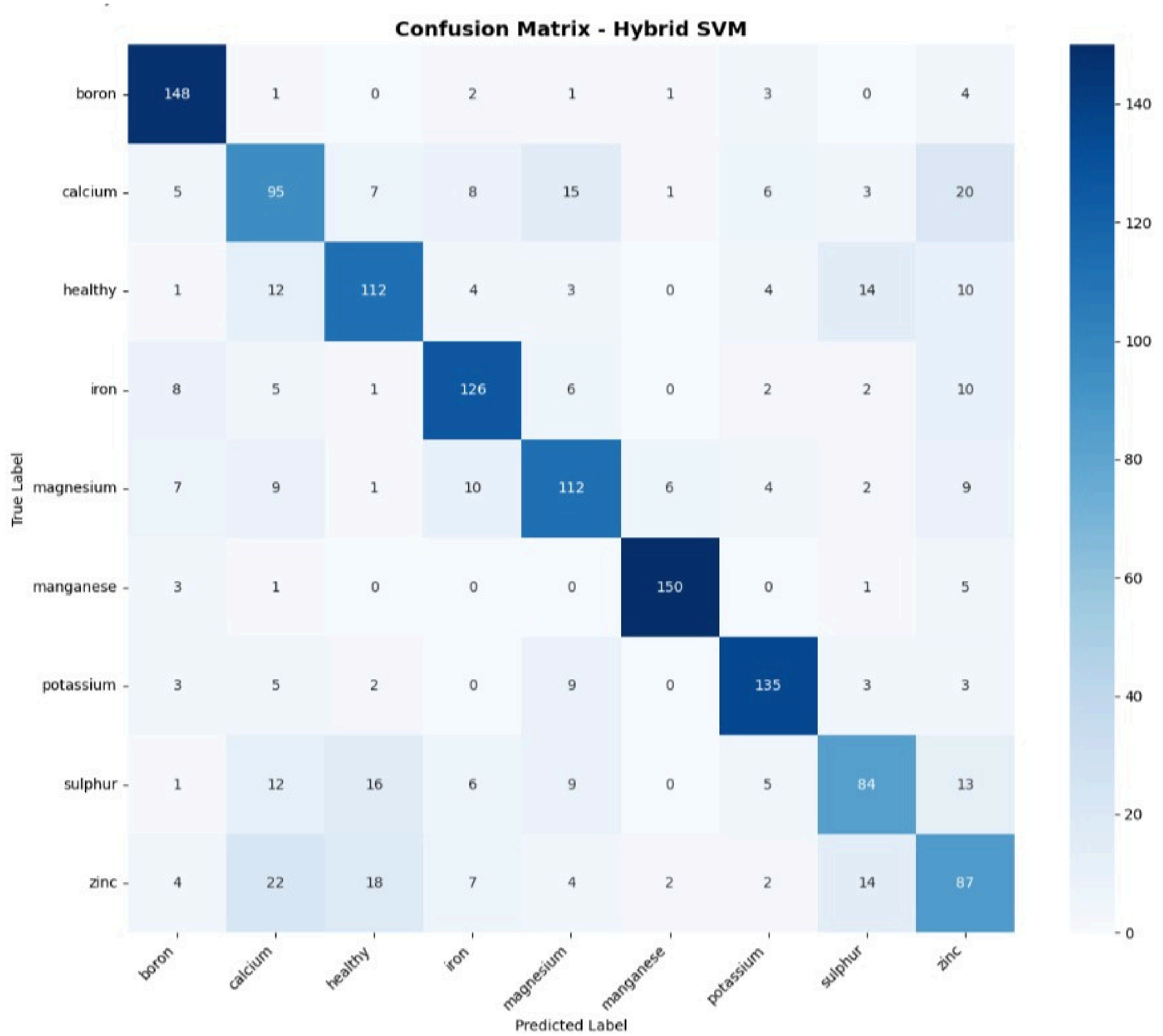

MODEL EVALUATION AND COMPARISON

EFFICIENTNET B0 (BANANA)

- Used EfficientNet-B0 for GPU-based fine-tuning on banana leaf images.
- Applied data augmentation and normalization for robust preprocessing.
- Trained with AdamW optimizer and CrossEntropyLoss for classification.
- Achieved strong validation accuracy on nutrient deficiency classes.
- Visualized results using confusion matrix and classification report.

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FINAL MODEL EVALUATION RESULTS (on Validation Set)
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Validation Accuracy: 0.8310
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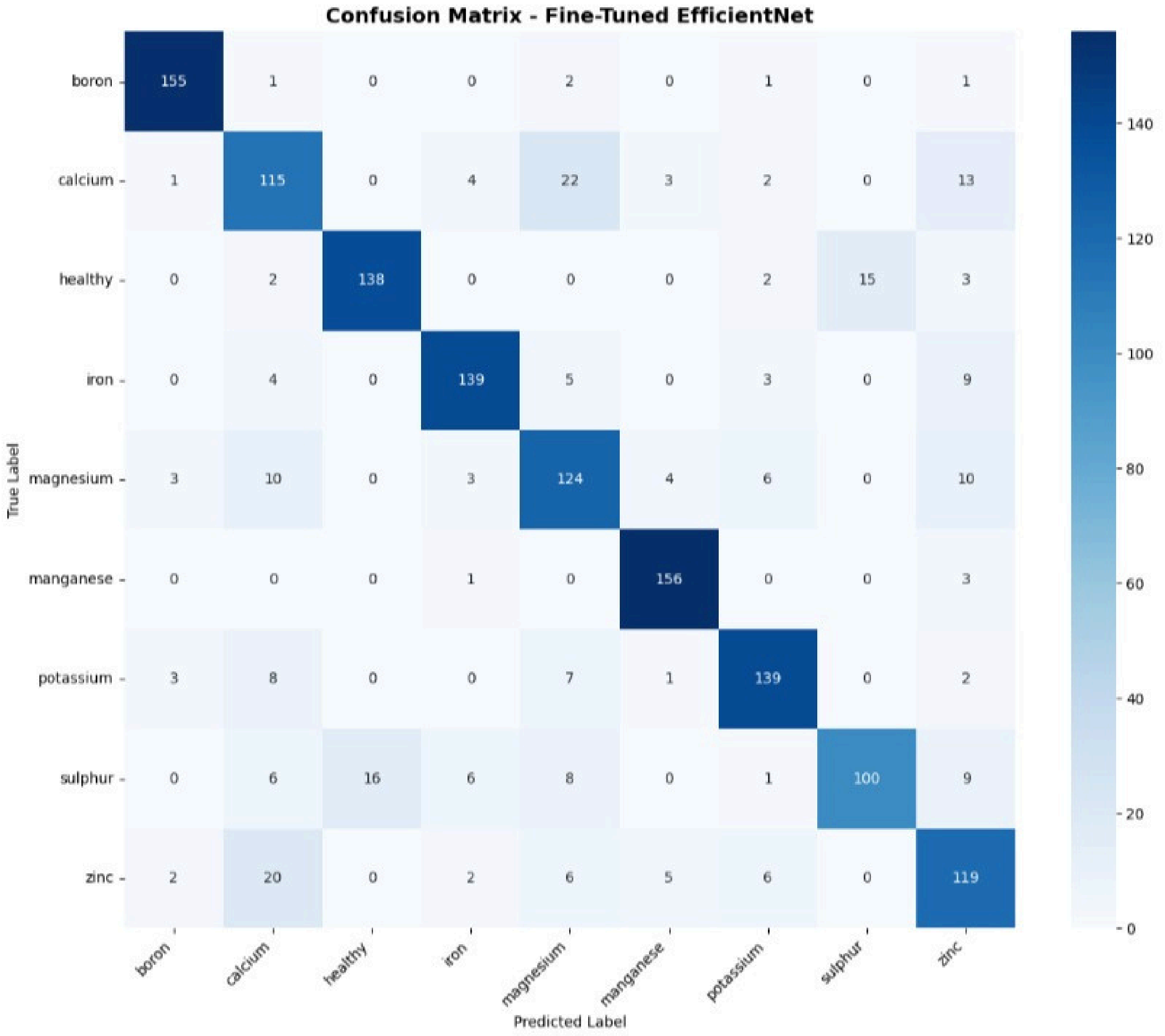

MODEL EVALUATION AND COMPARISON

MOBILENET V2 (RICE)

- Trained a MobileNetV2 model from scratch for rice leaf nutrient deficiency classification.
- Used class-weighted CrossEntropyLoss to address class imbalance.
- Applied Adam optimizer with learning rate scheduling using ReduceLROnPlateau.
- Included early stopping to prevent overfitting based on validation accuracy.
- Saved the best model checkpoint and tracked training/validation metrics across epochs.

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Training complete in 10m 37s
Best val Acc: 0.867052
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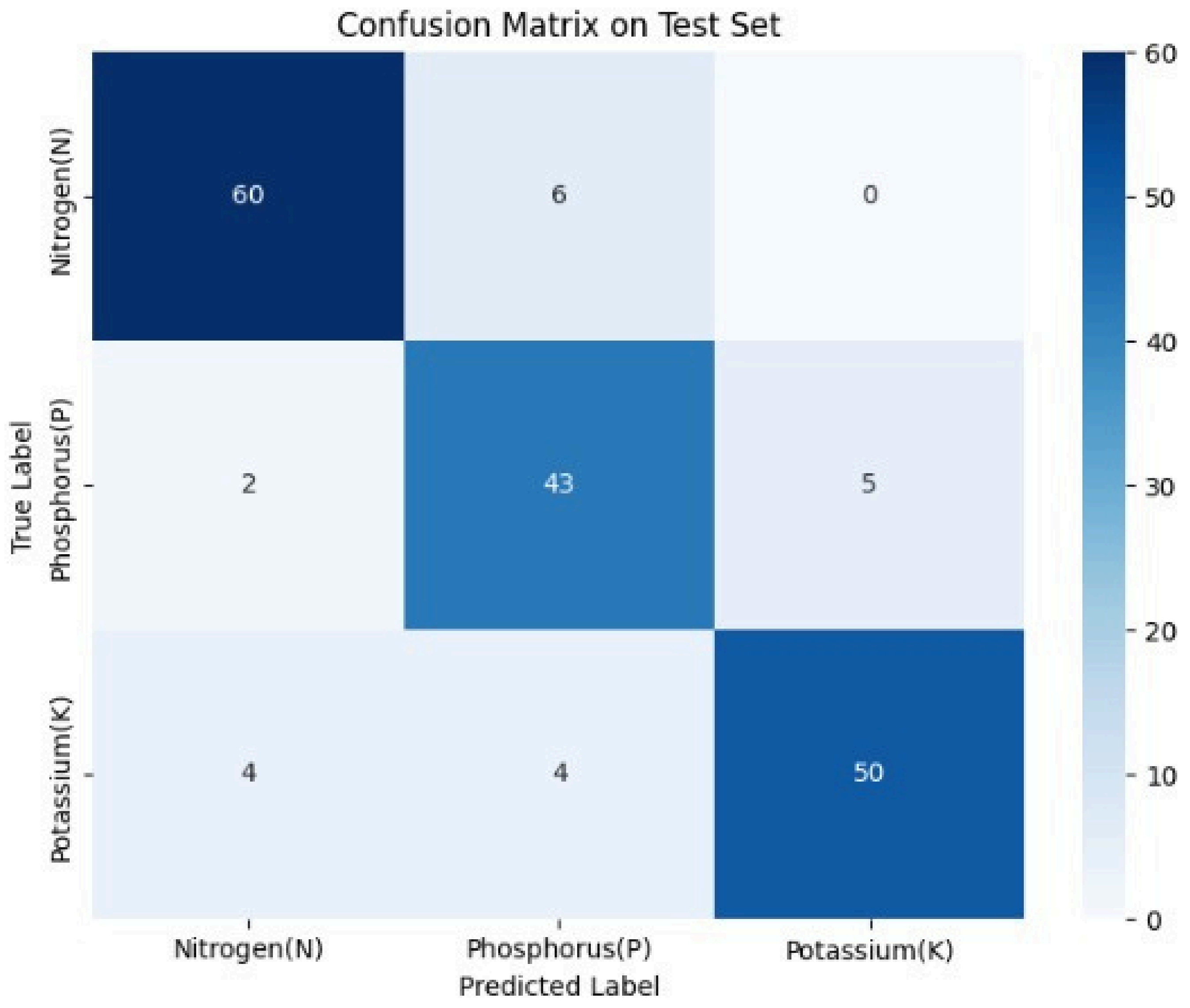

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MODEL EVALUATION AND COMPARISON

MOBILENET V2 (GROUNDNUT)

- Fine-tuned a pretrained MobileNetV2 model for groundnut leaf classification.
- Frozen all base layers and trained only the classifier head.
- Used standard CrossEntropyLoss without class weighting.
- Optimized classifier parameters using Adam optimizer.
- Tracked training loss and accuracy across epochs.

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Test Accuracy: 0.9649
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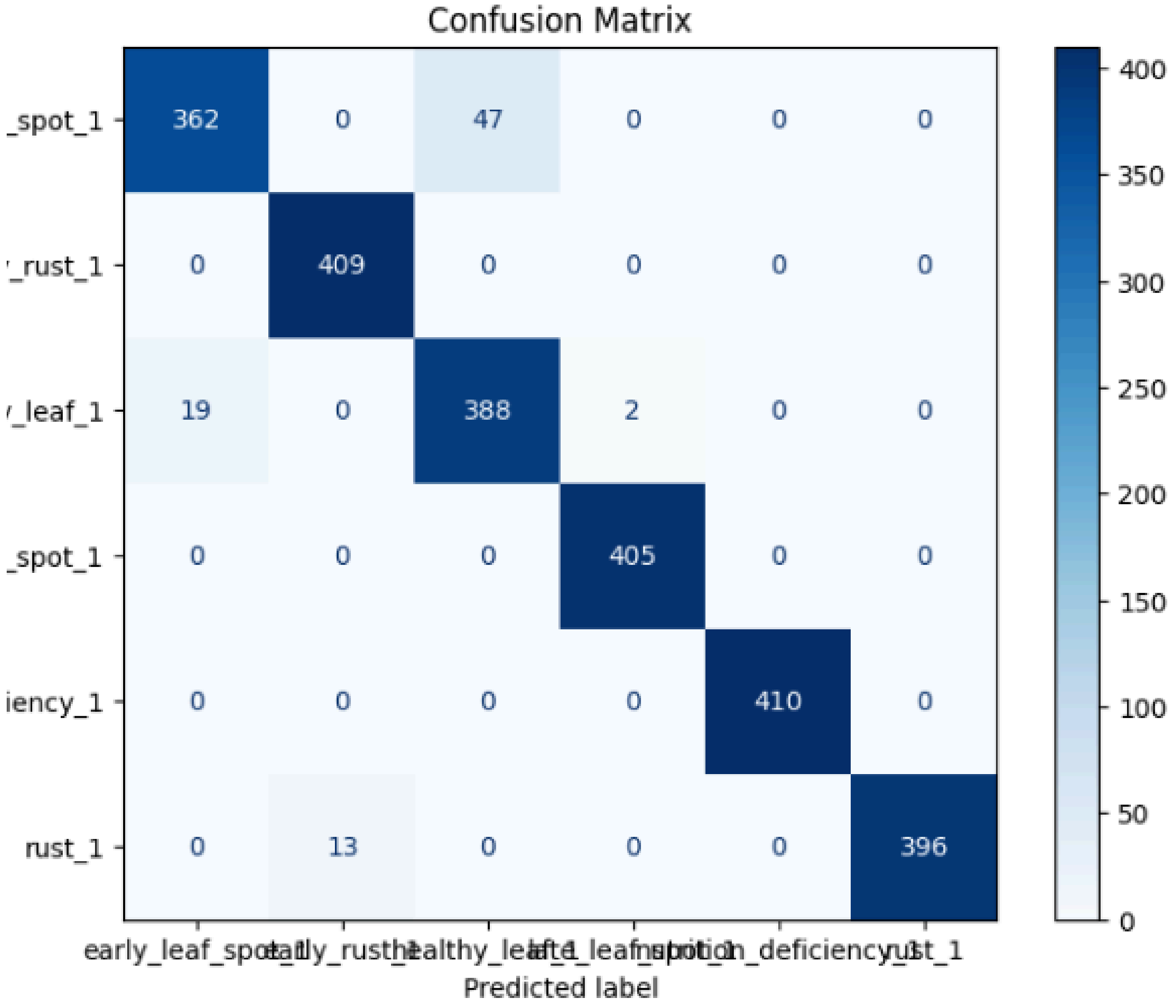

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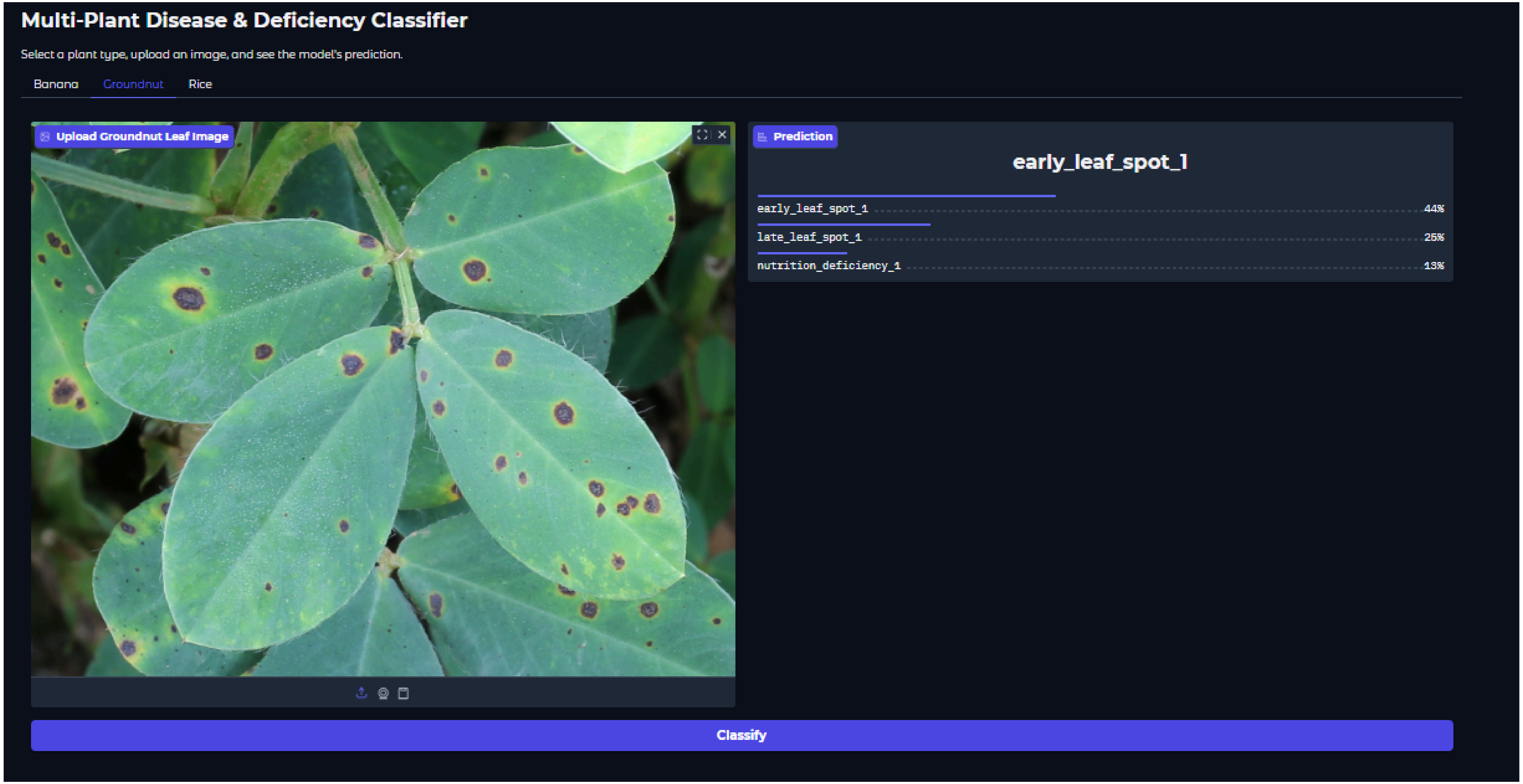
TECH STACK

- Programming Language: Python
- Deep Learning Framework: PyTorch
- Pre-trained CNN Models: MobileNet, EfficientNet
- UI Framework: Gradio
- Model Deployment: Hugging Face
- Visualization & Analysis: Matplotlib, Seaborn, Pandas
- Image Processing: PIL (Python Imaging Library)
- Model Evaluation: scikit-learn
- Others: NumPy, Pickle

IMPLEMENTATION



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FUTURE WORK

- **Broader Crop & Deficiency Coverage**: Expand classification to more crops and nutrient deficiencies, enabling wider agricultural application.
- **Edge & Mobile Deployment:** Further compress EfficientNet/MobileNet models (e.g., via quantization or pruning) for real-time use on mobile and embedded devices.
- **Explainable AI:** Integrate Grad-CAM or similar methods to highlight affected regions and improve model transparency for end-users.
- **Field Data Integration & Active Learning:** Continuously refine models using real-world feedback from farmers to improve robustness and reduce dataset bias.
- **Multilingual & Accessible Design:** Add support for local languages and voice-based interaction to increase accessibility for rural farmers.

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