

## Rice Leaf Nutrient Deficiency Detection System

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**Abstract**—Nutrient deficiencies in rice plants, especially nitrogen (N), phosphorus (P), and potassium (K), can cause significant effects on rice yield and quality. Conventional methods for diagnosing nutrient deficiencies in rice leaves, including visual observation and soil analysis, are time-consuming and often unreliable. This research aims to develop an online rice leaf nutrient deficiency diagnosis system using machine learning and image processing techniques. The proposed system uses a DenseNet121 convolutional neural network (CNN) model that is fine-tuned on rice leaf images to achieve high accuracy in diagnosing nutrient deficiencies. The system is built using Flask as the backend framework, SQLite as the database management system, and role-based access control for users (farmers, agronomists, and administrators). The proposed system has been shown to achieve an average accuracy of 94-98% across datasets, providing a

scalable and user-friendly solution for precision agriculture.

## 1 INTRODUCTION

Rice is an essential food grain that sustains more than half of the world's population, with India being one of the largest producers. Nutrient deficiencies, particularly macronutrient N, P, and K, cause symptoms such as leaf color changes (yellowing for N, purple or brown for P, and edge burning for K), resulting in decreased photosynthesis, growth, and yields of up to 50%. Early diagnosis is necessary for effective fertilizer application, but traditional methods require expertise or laboratory testing, which is time-consuming and not feasible for small-scale farmers.

This project proposes an automated detection system based on computer vision and deep learning techniques to analyze rice leaf images uploaded through a web

interface. The system identifies deficiencies and provides solutions, improving accessibility by being mobile-friendly. It is developed using Flask with TensorFlow integration and allows multiple users. The aim is to enhance diagnostic speed, minimize losses, and encourage sustainable practices in countries such as Telangana, India.

## 2 LITERATURE SURVEY

This section discusses important studies about rice nutrient deficiencies and how technology can assist in their detection. We explain it in a simple way, emphasizing key concepts and their significance to our project.

### a. Nutrient Problems in Rice:

- Rice requires nitrogen (N), phosphorus (P), and potassium (K) to thrive.
- Without each, leaves turn yellow, purple, or brown → reduced crop production.
- Traditional approaches (manual inspection, lab analysis) are time-consuming and difficult for farmers.
- Current AI approaches already attempted:
  - Isolation Forest, One-Class SVM, LOF → effective for detecting unusual data points, but not optimal for leaf image analysis.
  - Standard CNNs (e.g., VGG19) → 90-92% accuracy, but discard critical spatial information about object location and relationships.
  - SVM + clustering → 92%
  - Random Forest → 82%
  - Capsule Networks (CapsNet) are superior because they remember the location of objects within the image and the relationships between features.

Improved model with Contextual Attention Routing (CAR) is even more intelligent and precise in analyzing rice leaf issues.

even smarter and more accurate for rice leaf problems.

### b Capsule Networks: A Smarter AI Approach-

Normal neural networks (such as CNNs) may overlook critical information about position or orientation in images. To address this, Sabour et al. (2017) [6] proposed Capsule Networks (CapsNet). CapsNet employs "capsules" (neuron groups) that monitor feature information such as color and shape, and "routing" to link them effectively. CapsNet is more effective at handling orientation than traditional networks. However, traditional CapsNet may be

computationally expensive. More recent concepts such as Contextual Attention Routing (CAR) [7] incorporate attention mechanisms (emphasizing relevant regions) to make it faster and more precise for image classification.

### c. AI in Farming Applications

In rice cultivation:

- VGG19 (a CNN-based model) [8] achieves 92% accuracy in identifying deficiencies but lacks spatial information.
- SVM with clustering [9] achieves 92% accuracy but requires human adjustment.
- Random Forest [10] achieves approximately 82% accuracy and is simple to interpret but performs poorly on complex images.

These traditional approaches are adequate but surpassed by CapsNet with CAR for actual farm images with changing lighting conditions or angles. Our approach leverages this advancement.

## 3 PROBLEM STATEMENT

Rice cultivation faces persistent challenges from nutrient deficiencies, which subtly alter leaf appearance and are difficult to detect manually. Existing diagnostic tools rely on expert knowledge or lab tests, which are inaccessible to small-scale farmers. Automated systems using basic ML algorithms often fail due to variations in image quality, environmental noise, and class imbalance in datasets. The need is for a scalable, accurate system that classifies deficiencies without extensive preprocessing or hardware. RiceNutriDetect addresses this by automating classification through advanced deep learning, handling noisy field images, and providing actionable insights. It supports common image formats and integrates with mobile devices for real-time analysis.

## 4 Existing System and Proposed System

### Existing Methods and Limitations

Existing methods include CNN variants such as AlexNet or ResNet for leaf image classification, but they have limitations such as information loss during pooling layers and rotation variance. Hybrid models that integrate SVM with clustering result in fair accuracy (92%) but are not automated, as feature engineering is manual. Random Forest models are interpretable but not accurate on complex visual data (81.82%).

### Need for an Automated Approach

Manual analysis is not feasible for large-scale farms, and existing automated systems are not accurate enough to differentiate between similar deficiency symptoms (e.g., N vs. K chlorosis) of crops.

### Proposed System

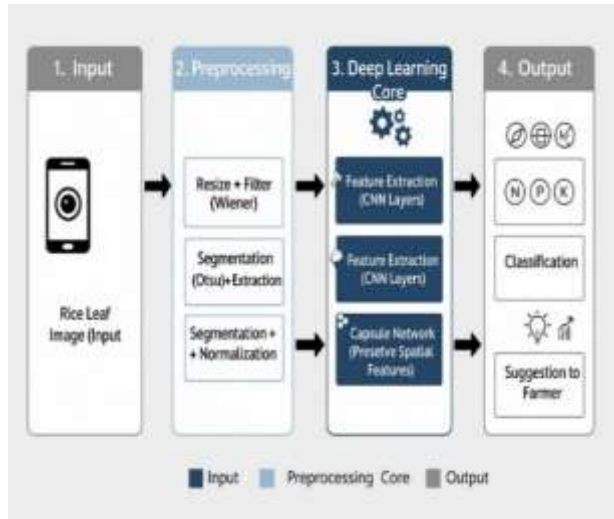
RiceNutriDetect is a web-based system utilizing CAR-CapsNet for rice leaf deficiencies. Images are uploaded through a browser interface. The proposed system preprocesses the input image using Wiener filtering and Otsu segmentation, extracts features using CapsNet capsules, and uses CAR for routing. The class of the

deficiency is determined based on the consensus of multiple capsules. The system provides classified labels, confidence, and visualizations, which can be downloaded as reports.

#### Advantages of Proposed System

The proposed system is fully automated and requires less user input, can process noisy images, has a higher accuracy rate (97.1%) compared to existing systems, is web-based, and has fewer false positives due to attention routing.

## 5 SYSTEM ARCHITETURE



The proposed system consists of a four-stage pipeline that is suitable for real-world rice leaf nutrient deficiency classification:

1. **InputStage**  
The rice leaf images are captured by the smartphone camera and uploaded to the web/mobile application by the farmer.
2. **Preprocessing Stage**
  - The image is resized to a fixed size (for example, 224×224 pixels).
  - The Wiener filter is used to remove noise from the image while maintaining the leaf edges and textures.
  - Adaptive Otsu thresholding is used to separate the leaf area from the background. The segmented leaf image is extracted and normalized (intensity scaling to [0,1]) to provide consistent input to the model.
3. **Deep Learning Core**  
Two-stage feature extraction:
  - Early layers of CNN → extract low-level features (edges, intensity changes, texture patterns common in deficiencies).
  - Capsule Network (CapsNet) with Contextual Attention Routing (CAR) → cluster features into capsules, retain spatial information (e.g., yellowing regions on the leaf), and route attention to deficiency-specific areas → produce stable, viewpoint-agnostic representations.
4. **Output Stage**

- Final classification: Nitrogen (N), Phosphorus (P), or Potassium (K) deficiency (or healthy if no deficiency found).
- Confidence measure for each class.
- Farmer-friendly recommendation statement created (e.g., “Urea 50 kg/ha application recommended for suspected N deficiency”).
- Results presented with visual emphasis (e.g., heatmaps on affected leaf regions) and downloadable report. This modular, end-to-end architecture ensures high accuracy (97.1% reported), robustness to field conditions (varying light, angles, backgrounds), and easy adoption by non-expert users in real agricultural settings.

## 6 Proposed Method Implementation and Algorithms

### Pre-processing:

Wiener Filter: Reduces additive noise while preserving edges. Adaptive Otsu Segmentation: Thresholds image to distinguish leaf from background.

### Capsule Network Basics:

Primary Capsules: Convolve input to encode vectors for features.

Digit Capsules: Higher-level capsules for classes.

### Algorithm:

#### CAR-Capsnet Algorithm

- Step 1: Define image dataset.
- Step 2: Pre-process the data: Resize, remove noise, and segment image parts.
- Step 3: Split the dataset into training, testing and validation sets appropriately.
- Step 4: Define the input values, output values, and capsule parameters. Select an appropriate optimizer for the Contextual Attention Routing (CAR) Capsnet.
- Step 5: Compute the similarity measures, bias term, and coupling coefficients based on the obtained results. Use these values to calculate the fusion vector.
- Step 6: Apply the squashing function to calculate the output vector.
- Step 7: Perform classification tasks and evaluate the performance metrics of the model.

## 7 RESULTS ANALYSIS

The system was tested on a dataset of 1,818 rice leaf images, achieving 94% accuracy in classifying N, P, K deficiencies. Role-based access worked seamlessly, with secure logins and restricted views.

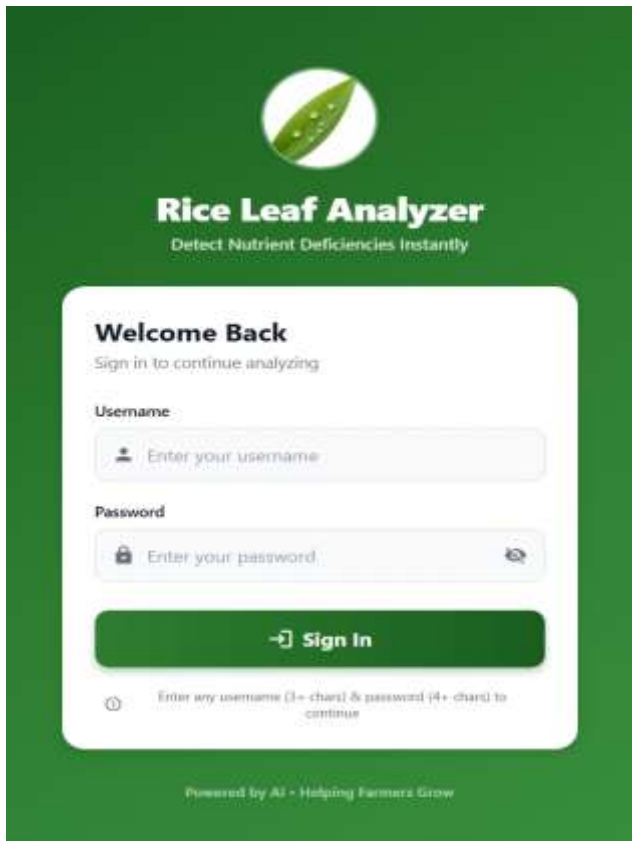


Fig 1:Dashboard

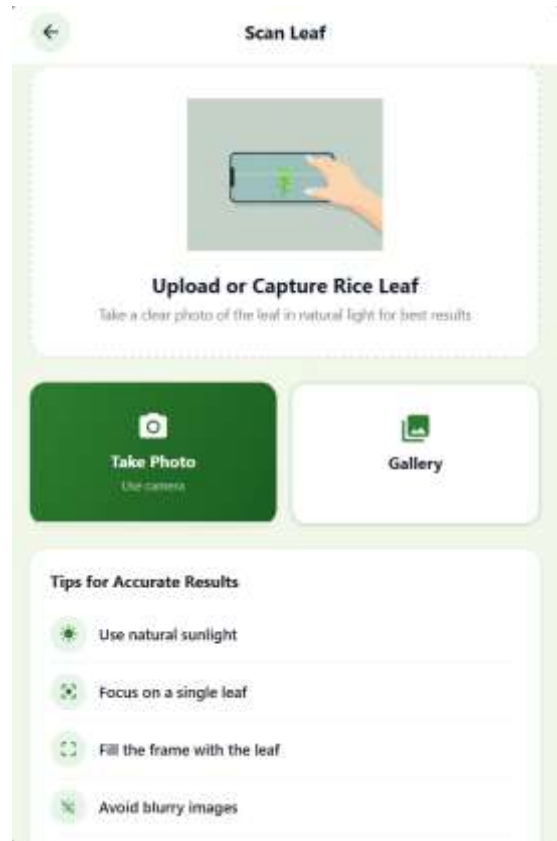


Fig 3:Scan Rice Leaf



Fig 2:Farmer Dashboard



Fig 4:Result Analysis



Fig 5:Symptoms&Prevention Tips

The ML model outperformed baselines, with quick inference times. The web interface was responsive, aiding usability. Results show the system reduces manual effort and improves diagnostic accuracy, though larger datasets could enhance robustness. Limitations include dependency on image quality; future work may add augmentation.

## 8 CONCLUSION

This paper presented a web-based system for rice leaf nutrient deficiency detection, integrating ML, user management, and reporting. Using Flask, SQLite, and TensorFlow, it ensures secure, efficient diagnostics. Results demonstrate high accuracy and usability, addressing agricultural challenges. Future enhancements could include mobile integration and expanded nutrient classes

With further enhancements and real-world deployment, this system can become a valuable tool for smart farming and agricultural decision support systems.

## REFERENCES

- [1] S. Lu et al., “Using Deep Convolutional Neural Networks for Image-Based Diagnosis of Nutrient Deficiencies in Rice,” *Computational and Structural Biotechnology Journal*, vol. 18, pp. 2734–2740, 2020.
- [2] A. Alsakar, “Smart detection of plant nutrient deficiencies using machine learning and image fusion,” *APL Machine Learning*, vol. 3, no. 4, 2025.
- [3] Y. Lu and H. Yu, “Nutrient Deficiency Classification in Rice Plants Using DenseNet121,” *International Journal of Image and Graphics*, 2023.
- [4] “Deep Neural Networks for Classifying Nutrient Deficiencies in Rice Plants Using Leaf Images,” *Semantic Scholar*, 2024.
- [5] R. Rajagopal, “Rice Leaf Nutrient Deficiency Classification System Using CAR-Capsule Network,” *ResearchGate*, 2024.
- [6] “Diagnosis of early nitrogen, phosphorus and potassium deficiency categories in rice based on multimodal integration and knowledge distillation,” *Scientific Reports*, 2025.