International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Rice Field Health Detection

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A B S T R A C T :

Timely identification of crop diseases is essential for maintaining agricultural productivity and minimizing economic losses. This project presents a comprehensive system for detecting unhealthy regions in rice fields using multispectral imaging and deep learning techniques. A pretrained UNet model is used to segment disease-affected areas from drone-captured images. The processed image is analyzed using the Normalized Difference Vegetation Index (NDVI), which quantifies plant health based on red and near-infrared reflectance. The system divides the segmented image into a 6×4 grid to localize and highlight unhealthy zones with NDVI values below a set threshold. A FastAPI-powered backend handles image processing, while a PyQt-based frontend provides an intuitive graphical interface for image selection, processing, and NDVI-based visualization. This lightweight and user-friendly approach supports real-time, on-field assessment of crop health, making it suitable for precision farming applications. It enhances decision-making for timely intervention, reduces dependency on manual inspection, and can be deployed in resource-limited environments.

Keywords: Rice field disease, multispectral imaging, deep learning, convolutional neural networks, transfer learning, image classification, precision agriculture, crop disease detection, smart farming.

Introduction

In modern agriculture, early detection of crop diseases is critical for ensuring high yield and reducing economic losses. Traditional methods of visual inspection are time-consuming, subjective, and impractical for large-scale monitoring. With advancements in remote sensing and deep learning, automated field detection systems have become a viable alternative. This project presents a solution for detecting unhealthy regions in rice fields using multispectral images captured by drones. By leveraging a pretrained UNet model for image segmentation and applying NDVI (Normalized Difference Vegetation Index) analysis, the system accurately highlights diseased areas. A FastAPI backend processes the images, while a PyQt-based frontend provides a simple and intuitive interface for real-time field evaluation.

Related Work

Several studies have explored the use of image processing and deep learning techniques for plant disease detection. Ronneberger et al. introduced the UNet architecture, which has been widely used for semantic segmentation tasks in agriculture due to its effectiveness on limited datasets. NDVI, a widely adopted vegetation index, has been used for assessing plant health based on reflectance in the red and near-infrared spectrum. Recent advancements have combined deep learning models with spectral data to detect diseases in crops like maize, wheat, and rice. Researchers have also developed drone-based monitoring systems to collect real-time data, enabling large-scale surveillance. However, many of these methods either lack grid-level disease localization or require high computational resources. Our approach addresses these limitations by integrating UNet segmentation with NDVI analysis and a lightweight, user-friendly desktop application for field-level detection

Methodology

Datasets

Rice field disease dataset (custom dataset): The dataset contains images captured from rice fields using near-infrared (NIR) drone cameras. Images represent different disease types affecting rice crops, such as leaf blight, sheath rot, and nutrient deficiency. Each image is resized to 512×512, normalized to [0,1], and processed for segmentation using NDVI-based analysis. Dataset split: 70% training, 15% validation, and 15% testing.

1.1. **UNet-Based Segmentation Architecture**

- Pretrained UNet: Utilizes an encoder-decoder structure trained on segmentation datasets, adapted for rice disease localization.

  The model segments unhealthy regions in the NIR image input..

- Input Preprocessing: Each image is resized to 512×512 pixels, converted to array format, and normalized before being fed into the model.
- Segmentation Output: A single-channel grayscale mask is generated, where lighter regions indicate high probability of unhealthy leaf areas.
- Postprocessing with NDVI: NDVI is computed using the red and NIR bands of the segmented output. Image is divided into a 6×4 grid, and regions with NDVI ≤ 0.3 are flagged as abnormal.
- Backend and GUI Integration: FastAPI handles model inference requests, while the PyQt-based GUI allows image upload, visualization of segmented results, and display of NDVI metrics.

Training

The UNet model is pretrained and fine-tuned on custom rice field images. Inference is handled on the backend without requiring retraining during deployment. The model weights are loaded on server startup to ensure fast response.

Evaluation Metrics

- Primary: Segmentation accuracy, mean NDVI, identification of low-NDVI zones.
- Secondary Visual inspection of output masks and NDVI region heatmaps

System Performance

- Backend response time: ~1–2 seconds per image
- NDVI accuracy for unhealthy region marking: ~90% agreement with manual labels
- Lightweight frontend: Deployed on standard desktop environments using PyQt5

Results

The proposed system successfully identified unhealthy regions in rice fields using multispectral image segmentation and NDVI-based analysis. The results are evaluated based on visual inspection and NDVI metrics.

Segmentation Output:

The backend, powered by a pretrained UNet model, produces segmented images that highlight affected leaf areas. These regions are extracted and passed to the NDVI calculator for further analysis.

NDVI Grid Analysis:

Each image is divided into a 6×4 grid, and NDVI is calculated for each segment:

- Healthy region: NDVI > 0.3
- Unhealthy region: NDVI ≤ 0.3
- Unhealthy grid segments are overlaid with red rectangles, providing a clear visual cue for infected or stressed regions

Performance:

- The system processes an image and returns results in under 5 seconds on a standard CPU.
- Visual comparison with known disease-affected images shows high accuracy in flagging problem zones.
- Grid-based reporting (e.g., "Image (2, 3) Unhealthy") allows localized disease tracking.

4.5 Observations:

- Average NDVI values across healthy fields ranged from 0.5–0.8, while unhealthy segments dropped below 0.3.
- False positives were minimal due to the combined segmentation + NDVI pipeline.
- The system is robust across varying light conditions due to normalization.

Discussions

The proposed system integrates multispectral imaging, deep learning-based segmentation, and NDVI analysis to detect unhealthy rice plant regions efficiently. By combining these approaches, we address several limitations seen in traditional disease detection methods, such as manual inspection, subjective diagnosis, and slow feedback cycles.

Model Efficiency and Practicality:

The use of a pretrained UNet model for segmentation enables high-quality feature extraction without the need for extensive retraining. The model processes input images in real time and generates precise disease masks, demonstrating that deep learning models can be efficiently deployed in lightweight environments such as a local server or edge devices.

NDVI-Based Interpretation:

NDVI remains a reliable vegetation index for assessing plant health based on spectral reflectance. The project successfully employs the red and NIR channels from segmented images to compute NDVI values, identifying regions with chlorophyll loss or stress. The grid -based strategy allows spatial localization of affected zones, which is valuable for targeted field interventions.

Frontend Interaction:

The PyQt interface is intuitive, allowing farmers, agronomists, or field technicians to:

- Upload drone-captured images,
- Visually assess the segmented and analyzed result,
- Interpret NDVI overlays without deep technical expertise.
- This accessibility supports real-world deployment in agriculture.

Limitations:

- The system assumes clear, high-resolution input images. Poor image quality or excessive noise can reduce segmentation accuracy.
- NDVI thresholding is currently static (0.3); dynamic thresholds based on crop growth stage or seasonal conditions could further improve performance.
- The pretrained model may need retraining to generalize across different crop types or geographic regions.

Comparison with Conventional Methods:

Compared to manual leaf inspection or traditional image classification:

- Our method is faster (under 5 seconds per image).
- More consistent, avoiding human bias.
- And supports large-scale analysis through grid-based breakdown.

Conclusion

This project presents an effective method for detecting unhealthy rice plant regions using multispectral imaging, UNet-based segmentation, and NDVI analysis. The system accurately identifies stressed areas and provides visual feedback through a user-friendly interface. It is fast, lightweight, and suitable for real-world agricultural applications, paving the way for smarter crop monitoring solutions.

Acknowledgements

We would like to express our sincere gratitude to the faculty and staff of Sri Shakthi Institute of Engineering and Technology for their guidance and support throughout this project. Special thanks to our mentor for valuable insights and encouragement, which were instrumental in the successful completion of this work.

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