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Developing a Multi-Level Nitrogen Malnutrition Detection on Paddy Leaf Using YOLOv11

Muhammad Syahmi Said Omar[1], Nik Shahidah Afifi Md Taujuddin[1]*, Suhaila Sari[1]

[1] *Department of Electronic Engineering, Faculty of Electrical and Electronic Engineering Universiti Tun Hussein Onn Malaysia, Batu Pahat, 86400, MALAYSIA*

*Corresponding Author: shahidah@uthm.edu.my
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Abstract

This project focuses on developing a YOLOv11 deep learning model to classify leaf nitrogen levels to support efficient crop health monitoring in precision agriculture. A dataset of 6,000 annotated images, representing nitrogen levels 2 to 5 based on the Leaf Colour Chart (LCC), was split into training (80%), validation (10%), and testing (10%) sets. The model achieved peak stability and accuracy at Epoch 130. For practical field use, the model was deployed into an Android mobile application via TensorFlow Lite. Real-time testing showed detection accuracy of 86% for Level 5 and 74% for Level 2, while intermediate levels 3 and 4 achieved lower rates of 56% and 46% due to visual color similarities. These findings demonstrate that YOLOv11 is a reliable tool for automated nutrient monitoring.

1. Introduction

Paddy cultivation plays a crucial role in ensuring food security, particularly in Asian countries such as Malaysia. The productivity and quality of paddy crops are highly dependent on proper nutrient management. Among essential nutrients, nitrogen significantly influences leaf colour, chlorophyll content, and overall plant growth. In practice, nitrogen application is often carried out without scientific assessment, leading to over-fertilization or nutrient deficiency.

Conventional approaches for detecting nitrogen malnutrition include laboratory soil analysis and manual observation using the Leaf Colour Chart (LCC) as shown in Fig 1. Although effective, these methods are labour-intensive, time-consuming, and unsuitable for continuous monitoring in large paddy fields. Recent advancements in computer vision and deep learning have enabled automated plant health assessment using image-based techniques [1].

This paper presents the development of a multi-level nitrogen malnutrition detection system using the YOLOv11 object detection model. The proposed system is designed to classify nitrogen levels in paddy leaves and provide real-time feedback through a mobile application, supporting precision agriculture practices.

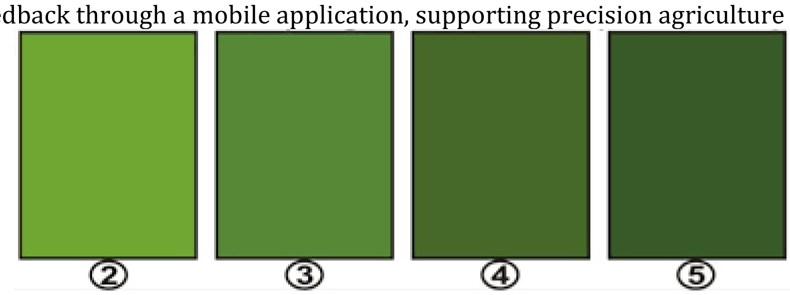

Fig. 1 *Nitrogen Parameter Leaf Colour Chart (LCC) [1]*

Table 1 provides a comparative analysis of various methodologies used to detect malnutrition and diseases in paddy plants.

Table 1 *Summary of Previous Research on Paddy Malnutrition and Detection Techniques*

Author(s) & Year	Model/ Technique	Focus/Application	Key Findings/ Performance	Ref.
Wenhui Wang et al. (2021)	UAV Multispectral Imaging	Estimating Nitrogen concentration across growth stages.	Used AIRPHEN camera with 6 spectral channels; combined UAV data with physical sampling for ground-truth.	[2]
Syamsul Rizal et al. (2023)	CNN (ResNet50 & ResNet152)	Classifying N, P, and K deficiencies using Kaggle & Mendeley data.	ResNet50 performed best with 97% test accuracy and 98% validation value.	[3]
Rusiri Illesinghe et al. (2021)	LCC-based Dataset	Creating a public dataset for Nitrogen levels (L2–L5).	Established a standardized dataset of 20 healthy plants compared to the Leaf Colour Chart (LCC).	[4]
Saifizi et al. (2013)	RGB Image Processing	Colour-based segmentation and thresholding.	Converted images to grey-scale; provided area percentages for nitrogen based on leaf color.	[5]
Jayakrishnan et al. (2024)	Tiny-YOLOv9	Lightweight paddy rice disease detection for UAVs.	Reduced parameters from 60M to 9M while maintaining high mAP and F1-scores.	[6]

2. Methodology

Fig 2 illustrates the overall workflow of the proposed nitrogen malnutrition detection system for paddy leaves, starting from data preparation to real-time mobile application deployment. The process begins with image acquisition, where paddy leaf images are captured under various conditions to represent different nitrogen levels. The acquired images then undergo image pre-processing to improve quality and consistency, such as resizing and normalization, ensuring suitability for model training. After pre-processing, the dataset is divided into training, validation, and testing sets in an 80:10:10 ratio to enable effective learning, tuning, and unbiased performance evaluation. The trained YOLOv11 model was converted into TensorFlow Lite (TFLite) format to ensure compatibility and efficient inference on mobile devices with limited computational resources. Once an image is captured, the application processes the input image and performs object detection to classify the nitrogen level based on the Leaf Colour Chart (LCC) levels. The detection result is displayed on the screen, highlighting the identified nitrogen level to assist users in decision-making related to fertilizer application.

2.1 Data Acquisition

The dataset for this project consists of high-quality paddy leaf images sourced from Kaggle. These images are categorized based on nitrogen content levels using the Leaf Colour Chart (LCC) as in Fig 3, which serves as a visual standard.

In Fig 3, level 2 exhibits a pale yellow-green colour, which clearly indicates severe nitrogen deficiency in the paddy leaf, while Level 3 corresponds to a light green colour, representing a moderate level of nitrogen deficiency. Level 4 shows a green leaf colour, suggesting that the nitrogen content in the plant is sufficient for normal growth. In contrast, Level 5 displays a dark green colour, which typically signifies excessive nitrogen presence in the plant.

2.2 Image Pre-processing and Model Training

The rice leaf images were annotated using Label Studio, where manual annotation was performed by drawing bounding boxes around specific regions. The dataset was divided into training, validation, and testing sets in an 8:1:1 ratio as shown in Table 2. Training was executed in Google Colab using the YOLOv11 architecture for up to 150 epochs.

2.3 Mobile Application Development

To enable deployment on Android devices, the trained YOLOv11 model was converted into TensorFlow Lite (TFLite) format. The mobile application was developed using Android Studio to provide a user-friendly and portable interface for real-time detection.

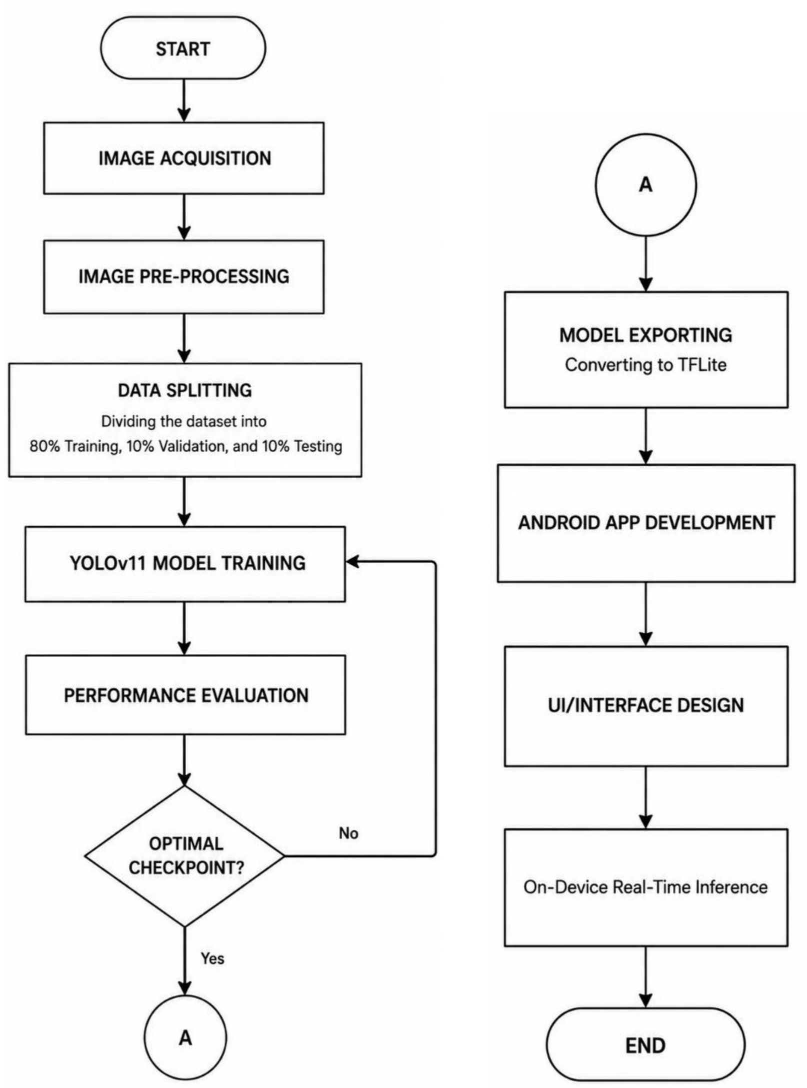

Fig 2 *Flowchart of the Project*

(a) **(b)** **(c)** **(d)**

Fig. 3 *Paddy Leaf with Nitrogen Deficiency (a) Level 2; (b) Level 3; (c) Level 4; (d) Level 5*

Table 2 *Dataset Distribution for Nitrogen Level Classification*

Nitrogen Levels	Training (80%)	Testing (10%)	Validation (10%)	Total
Level 2	1200	150	150	1500
Level 3	1200	150	150	1500
Level 4	1192	150	150	1492
Level 5	1200	150	150	1500
Total	4792	600	600	5992

3. Results and Analysis

3.1 Model Training Performance

Tables 3 and 4 shows training results across multiple epochs to show that model performance improved with additional cycles, though training was limited by Google Colab's runtime.

Table 3 *YOLOv11 Training Duration Across Different Epochs.*

Epoch	Time (Hours)
50	1.535
100	3.004
130	3.884
150	4.471

Table 4 *Performance Comparison of YOLOv11 at Different Epochs*

Epoch	Types	F1	P	PR	R	Training Time
100	Level 2	0.96	0.98	0.99	0.98	3.004 hours
	Level 3	0.92	0.95	0.97	0.96	
	Level 4	0.96	0.98	0.99	0.98	
	Level 5	0.99	0.99	0.99	0.99	
130	Level 2	0.96	0.99	0.94	0.99	3.884 hours
	Level 3	0.94	0.96	0.97	0.98	
	Level 4	0.96	0.99	0.99	0.99	
	Level 5	0.99	1.00	0.99	1.00	
150	Level 2	0.98	0.99	0.99	0.99	4.471 hours
	Level 3	0.95	0.96	0.98	0.98	
	Level 4	0.98	0.99	0.99	0.99	
	Level 5	0.99	1.00	0.99	1.00	

3.2 Real-time Detection Accuracy

The application captures live images and evaluates dominant visual features across the entire image rather than performing leaf-by-leaf detection as shown in Table 5.

Table 5 *Detection accuracy for each Nitrogen Levels*

Nitrogen Levels	Correct Detection	Wrong Detection	No Detection
Level 2	74%	18%	8%
Level 3	56%	22%	22%
Level 4	46%	28%	26%
Level 5	86%	4%	10%

3.3 Paddy Leaftrogen Application

The Paddy LeafTogen application was developed as a mobile-based platform to enable real-time nitrogen level detection in paddy leaves using the trained YOLOv11 model. The application was implemented on the Android operating system using Android Studio, providing a user-friendly interface for field-level usage by farmers and agricultural practitioners. The primary function of the application is to capture images of paddy fields or paddy leaves using a smartphone camera and to analyse the images directly on the device. The trained YOLOv11 model was converted into TensorFlow Lite (TFLite) format to ensure compatibility and efficient inference on mobile devices with limited computational resources. Once an image is captured, the application processes the input image and performs object detection to classify the nitrogen level based on the Leaf Colour Chart (LCC) levels. The detection result is displayed on the screen, highlighting the identified nitrogen level to assist users in decision-making related to fertilizer application.

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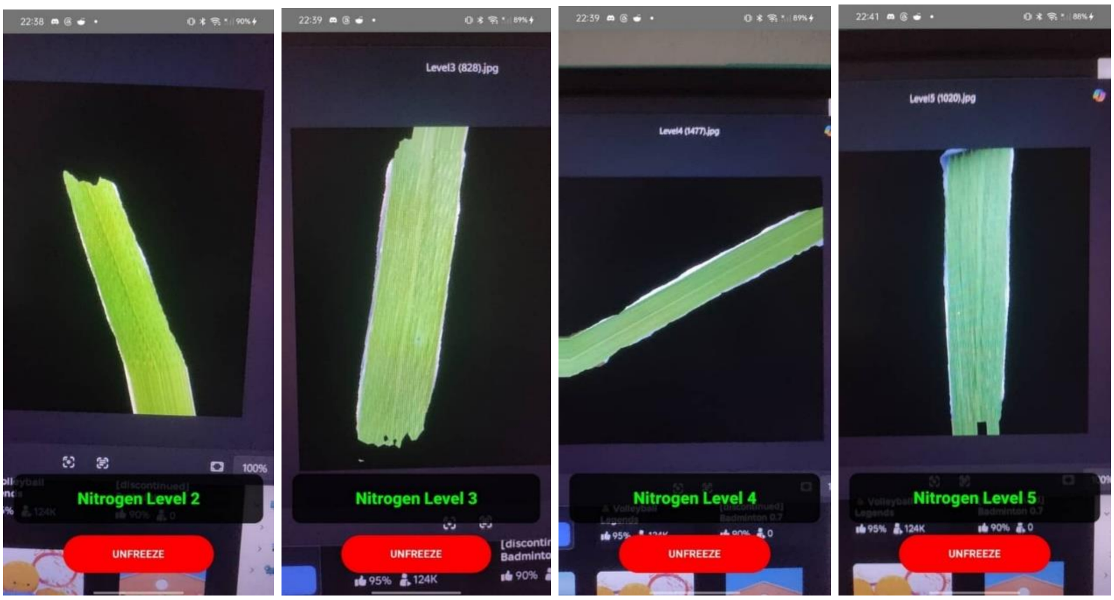
(a) (b)

Fig 4 *Interfaces (a) Logo of Paddy Leaftrogen (b) Home Screen of Paddy Leaftrogen*

Fig 4 illustrates the user interface design of the Paddy LeafTrogen application. Referring to Fig 4, (a) shows the official logo of the Paddy LeafTrogen application, which was designed to represent the integration of agriculture and intelligent detection technology. The logo serves as the visual identity of the application and helps users easily recognize the system during installation and usage. Fig 4 (b) presents the home screen of the Paddy LeafTrogen application. The home screen provides a simple and intuitive layout, allowing users to quickly access the main functionality of the system. From this interface, users can initiate image capture for nitrogen level detection, view detection results, and navigate through the application features with minimal interaction. The design prioritizes usability and clarity to ensure effective operation in real field conditions.

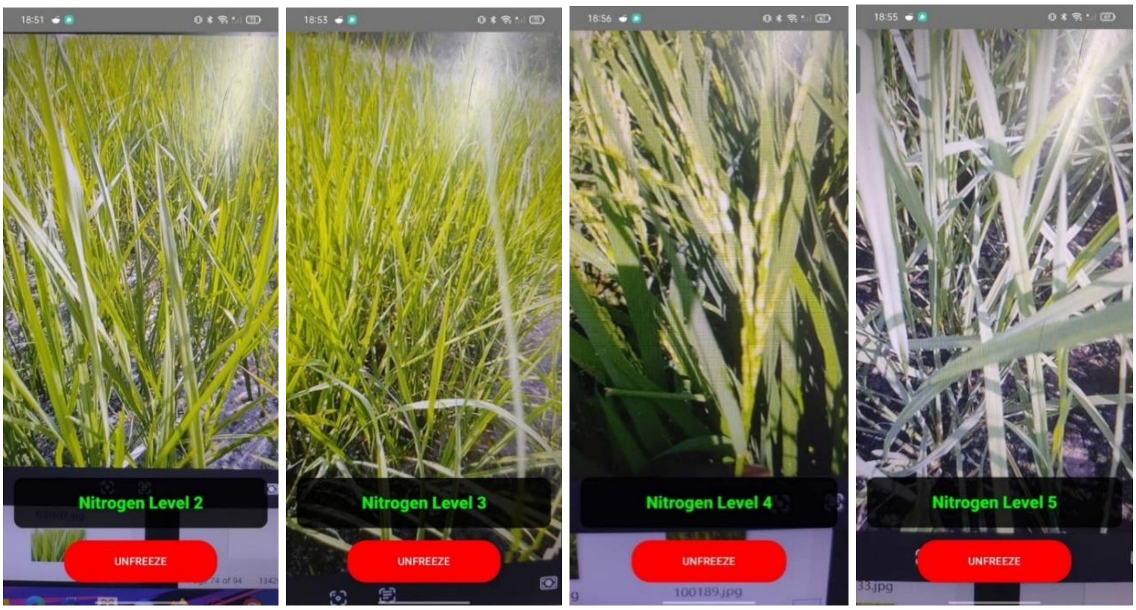
Reffering to Fig 5, the apps show the detection results for different paddy nitrogen levels using the Paddy Leaftrogen. Fig. 5(a) illustrates Level 2 detection, where the leaves appear pale yellow-green, indicating severe nitrogen deficiency. Fig. 5(b) shows Level 3 detection with light green leaves, representing moderate nitrogen deficiency. Fig. 5(c) presents Level 4 detection, where the leaves are green, indicating sufficient nitrogen content. Fig. 5(d) shows Level 5 detection with dark green leaves, which signifies excessive nitrogen in the plant.



(a) **(b)** **(c)** **(d)**

Fig 5 *Detection for each Paddy Nitrogen Levels (a) Level 2 (b) Level 3 (c) Level 4 (d) Level 5*

Fig 6 illustrates the detection results of occluded paddy leaves for different nitrogen levels using the developed mobile application. As observed, the application does not perform leaf-by-leaf detection, instead it classifies the overall nitrogen condition of the paddy plant within the captured image. This occurs because the implemented system is designed for image-level classification rather than object-level localization, and no bounding box mechanism is used to isolate individual leaves.



(a) **(b)** **(c)** **(d)**

Fig 6 *Detection on Occluded Paddy Leaf for each Nitrogen Levels (a) Level 2 (b) Level 3 (c) Level 4 (d) Level 5*

4. Conclusion

This project successfully achieved its primary objective of identifying different nitrogen malnutrition levels in paddy leaves using the YOLOv11 deep learning model. The proposed system can classify multiple nitrogen levels based on leaf colour characteristics and demonstrates reliable performance in detecting extreme nitrogen conditions. However, intermediate nitrogen levels, particularly Levels 3 and 4, remain challenging due to the visual similarity between leaf colours and varying environmental conditions during image capture. The integration of the trained YOLOv11 model into a mobile application provides a practical and efficient tool for real-time nitrogen assessment in paddy cultivation. By enabling on-site detection, the system has the potential to reduce reliance on subjective visual inspection and support more informed fertilizer management practices. Overall, the developed system shows strong potential for application in precision agriculture and contributes toward sustainable and optimized nitrogen usage in paddy farming.

5. Recommendation

To further improve the effectiveness and applicability of the proposed paddy nitrogen malnutrition detection system, several improvements are recommended for future work. Increasing the size and diversity of the dataset, particularly by incorporating more real field images captured under different lighting, weather, and growth conditions, would help improve detection accuracy, especially for intermediate nitrogen levels where visual similarity remains a challenge. The use of advanced image preprocessing techniques, data augmentation, and adaptive colour normalization methods may also reduce the influence of environmental variations on detection performance. In addition, extending the system to support the detection of multiple nutrient deficiencies, such as phosphorus and potassium, would provide a more comprehensive assessment of paddy crop health. The integration of the application with unmanned aerial vehicles (UAVs), Internet of Things (IoT) sensors, or cloud-based analytics platforms is also recommended to enable large-scale monitoring and data-driven fertilizer management. These improvements would enhance the practicality of the system and strengthen its potential contribution to precision agriculture and sustainable paddy farming practices.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The author, Muhammad Syahmi Bin Said Omar, affirms only taking responsibility of the following: conception and design of the study, collection of the dataset, annotation of the images, training and evaluation of the models, development of the application, analysis and interpretation of the results, as well as preparation of the manuscript. The supervisor, Dr. Nik Shahidah Afifi Binti Md Taujuddin, has offered academic advice and suggested appropriate literature as well as useful comments to enhance the system and research direction.

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