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UNMANNED AERIAL VEHICLE-BASED LARGE AREA DISEASE DETECTION OF PADDY FIELDS USING MACHINE LEARNING

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ABSTRACT

Early disease detection in agriculture is critical to ensuring sustainable agricultural practices and maintaining high yields. Diseases cause significant economic losses and food insecurity. Delayed detection often leads to the extensive spread of pathogens, making recovery challenging and resource-intensive. Although current practices, such as hyperspectral and multispectral imaging systems, provide precise disease detection through advanced spectral analysis, their high costs, complex data requirements, and limited accessibility restrict their adoption by small to medium-scale farmers. Addressing these challenges, this research develops a cost-effective UAV-based remote sensing system leveraging a low-cost method with RGB cameras and machine learning techniques for early disease detection in large paddy fields. To enhance detection accuracy, the study has utilized vegetative indices such as VARI, GLI, ExG, and VIgreen. Random Forest machine learning algorithm outperforms Support Vector Machine, K-Nearest Neighbour, and Logistic Regression. Random Forest processes these vegetative indices to classify diseased areas with 68% of accuracy and 73% of precision. Field testing validated the system's performance, demonstrating its ability to deliver reliable results. This scalable, low-cost approach bridges the gap between advanced imaging technologies and practical agricultural needs, offering an accessible solution for efficient crop health monitoring.

KEYWORDS: UAV, RGB Imagery, Machine Learning, Vegetation Indices, Paddy Disease Detection

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1 INTRODUCTION

The vast expanse of paddy fields adds complexity to disease monitoring. Inspecting each plant for signs of disease in large-scale fields is labour-intensive, time-consuming, and prone to human error. This approach often results in undetected disease patches, which spread unnoticed until symptoms become severe. Furthermore, detecting disease at the individual plant level within a large area is particularly challenging without advanced technological support. Traditional monitoring methods are not scalable for large farms, making automated solutions necessary to improve efficiency and accuracy.

Current practices for disease detection frequently rely on multispectral, hyperspectral, or thermal imaging systems. While these technologies provide valuable insights into plant health and stress indicators, they are often prohibitively expensive for small to medium-scale farmers. The high cost of specialized sensors and processing equipment restricts their widespread adoption. Additionally, the complex data analysis required for hyperspectral and thermal imaging systems demands technical expertise and computational resources, further limiting their practicality in resource-constrained settings. These challenges highlight the need for an alternative solution that balances cost-effectiveness with accuracy.

This research addresses these limitations by using low-cost RGB imaging, vegetative indices, and ML techniques. RGB cameras attached to a drone offer an affordable yet effective solution for capturing imagery of paddy fields, which can be processed using advanced ML algorithms to detect early signs of disease. By leveraging UAVs for data acquisition, this approach ensures timely and comprehensive monitoring of large fields, enabling large-scale disease detection and promoting sustainable crop management practices.

1.1. Literature Survey

Rice (*Oryza sativa* L.) is a staple food for more than half of the world's population. To meet the ever-increasing demand for food due to population growth and improved living standards, world rice production needs to double by 2030. Considerable increases in rice yields have been attributed primarily to genetic improvement, innovations in crop management, and increases in resource input. Rice cultivation is impacted by several diseases that can severely reduce yield and quality. The Rice Research and Development Institute, Bathalagoda, Sri Lanka, identifies some of the major diseases affecting paddy fields, such as Rice Blast, Bacterial Leaf Blight, Sheath Blight, and Brown Spot (Ahmed et al., 2023).

In agriculture, remote sensing serves as a cornerstone of precision farming by enabling the monitoring of crop health, soil conditions, and water usage. It employs a range of technologies, including satellite imagery, UAV-based systems, and ground-based sensors, to gather high-resolution spatial, spectral, and temporal data. These non-invasive methods are invaluable for studying agricultural, ecological, and climatic processes across vast areas (Elhamdouni et al., 2026) (Zhang & Zhu, 2023). Using UAVs for disease identification in paddy fields aligns with sustainable agriculture practices by reducing chemical usage and minimizing crop losses (Thapa et al., 2021).

UAVs are used to detect and manage diseases in paddy fields, particularly those causing leaf discoloration. Equipped with multispectral and hyperspectral sensors, UAVs can capture detailed imagery of crop canopies, identifying early signs of diseases like rice blast, bacterial blight, and sheath blight. The high spatial resolution of UAV imagery allows for precise mapping of affected areas, enabling targeted interventions (Mohsan et al., 2023) (Delavarpour et al., 2021) (Cuaran et al., 2021).

Current research on large area disease detection in agriculture mainly focuses on advanced imaging technologies such as multispectral, hyperspectral, and thermal imaging. However, these methods are often expensive, restricting their adoption to large-scale commercial paddy farms with significant financial resources (Anthonys et al., 2009). RGB imaging has emerged as a potential low-cost alternative for paddy disease monitoring. Studies have demonstrated that RGB imaging can identify broader crop health issues, such as areas of significant discoloration or canopy loss. However, its inability to capture detailed spectral signatures limits its effectiveness in detecting specific diseases or early-stage symptoms in paddy fields. As a result, RGB imaging is primarily used for general crop monitoring rather than detailed disease analysis, and its adoption for precision paddy farming remains limited (Sethy et al., 2020).

Machine learning (ML) has the capability to classify and diagnose crop health with high accuracy. Algorithms like support vector machine (SVM), and Random Forest are widely applied in analysing images to distinguish between healthy and diseased plants (Zhang, 2022; Thapa, Garcia Millan, & Eklundh, 2021). Convolutional neural networks (CNN) are useful for complex pattern recognition, automatically learning hierarchical features from images, starting with simple features like edges and progressing to more complex features like shapes and textures (Mohsan, Othman, Alsharif, & Khan, 2023) (Andrade, Hott, de Magalhães Junior, & DOLIVEIRA, 2019). In some cases, hybrid models combining multiple machine learning methods, such as combining SVM with CNN or using Random Forests for feature selection before applying CNN, have shown enhanced accuracy.

Vegetation indices are mathematical combinations of spectral reflectance values designed to highlight vegetation properties such as chlorophyll content, plant health, and canopy structure. They are critical tools in agriculture for monitoring crop growth, assessing stress factors, and guiding precision farming practices. Integrating hyperspectral, multispectral, thermal, and infrared sensors in UAV platforms has significantly improved the accuracy and usability of vegetation indices for agricultural applications. There are several vegetative indices such as the normalized difference vegetation Index (NDVI), visible atmospherically resistant index (VARI), vegetation index green (VIgreen), excess green (ExG), green leaf index (GLI) (L. S. Eng, 2019) (Kazemi & Parmehr, 2023). Furthermore, researchers have emphasized the importance of utilizing specific vegetation indices that heavily weight the green reflectance channel to mitigate variable outdoor lighting conditions. Investigations into UAV-based canopy extraction have found that the ExG and GLI are particularly robust for segmenting healthy vegetation from diseased patches in field environments (Peticilă et al., 2025). To overcome the limitations of standard RGB imaging, recent advancements in precision agriculture have increasingly explored the integration of ML classifiers with visible-spectrum data. Studies utilizing models such as SVM and Random Forest have demonstrated that applying ML algorithms to RGB-derived vegetation indices can effectively categorize crop stress levels without the need for infrared bands (Sharma et al., 2022).

While Machine Learning ML has shown immense potential in agricultural disease detection, existing studies predominantly rely on data acquired from expensive hyperspectral or multispectral sensors. This creates a significant limitation, as high-cost, computationally heavy ML solutions remain largely out of reach for small to medium-scale farmers. There is a critical need for an automated, ML-driven approach that relies strictly on affordable, easily deployable technologies. Specifically, there remains a critical gap in leveraging RGB for fine-scale pathological classification using accessible, lightweight ML models, which this study aims to address. Therefore, the main objective of this research is to evaluate vegetation indices and texture features acquired from UAV-based low-cost RGB imagery for the identification of diseases of large area paddy fields using lightweight ML models. The proposed approach offers a scalable and affordable solution, bridging the gap between high-cost imaging technologies and the practical needs of small to medium-scale paddy farmers.

2 METHODOLOGIES

A vital aspect of this research is developing an ML model specifically tailored to analyse the captured aerial images and identify disease-affected areas. The model utilizes vegetation indices such as VARI, GLI, VIgreen, and ExG to quantify leaf greenness, while local binary pattern analysis enhances the model's ability to detect early signs of crop diseases. Data acquired during multiple test flights demonstrated the drone's capability to provide RGB imagery of large area paddy fields.

2.1 UAV

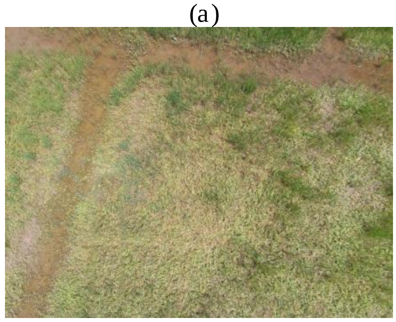
The UAV used in this research, as shown in Figure 01, is a custom-made quadcopter parallel to this research with a flight controller that consists of TM32F411CEU6 (Madanayaka et al., 2026). Sensors such as MPU6050 for real-time angular velocity and linear acceleration measurements, BMP280 for altitude measurements based on barometric pressure, GY-271 for the measurements of the Earth's magnetic field, and Neo6M GPS module for positioning. The FlySky FS-i6 Transmitter is used for manual control of the UAV, which utilizes the i-BUS protocol to communicate between the transmitter and the flight controller. The four 850 kV brushless motors were used to generate the thrust required for flight. The drone is powered by a 3300 mAh LiPo (Lithium Polymer) 3S Battery. The Rev 1.3 camera features a 5-megapixel Omni-vision OV5647 sensor. It can capture still images up to 2592 x 1944 pixels, sufficient for most entry-level image capture needs. The Raspberry Pi 3B+ was integrated into the drone as the central processing unit for camera operations.

Figure 01: Quadcopter developed in the research used for image acquisition

2.2 Image Acquisition and Dataset Preparation

Through collaboration with the Labuduwa rice research station, specific paddy fields in the Galle area were selected based on known disease prevalence and field accessibility. This selection process ensured that the data set covered a range of conditions, including areas with visible signs of disease and healthy sections, providing a well-rounded foundation for training the ML model. The images were collected from various paddy fields of healthy and unhealthy fields with a range of disease symptoms to keep the diversity, which helps the model to generalize better. The study planned to capture images six weeks post-planting, during the vegetative stage, before the reproductive phase begins, allowing for effective disease monitoring. At this stage, paddy plants are mature enough to exhibit visible disease symptoms, such as colour changes and leaf texture anomalies. Images were acquired early in the morning since, based on preliminary research and field trials, the best time for image capture was stated as early morning, shortly after sunrise. During this period, sunlight is evenly distributed, providing natural lighting in midday without harsh shadows and glare. This timing minimized the risk of shadow-related distortions and helped maintain uniform lighting across images.

(a)



(b)

Figure 02: Categorizing images (a) healthy (b)unhealthy.

The primary equipment for image acquisition was a UAV equipped with a Raspberry Pi camera. It was selected due to its adaptability, ease of integration, and adequate resolution for capturing colour and texture variations that may indicate plant health or disease. Further, the camera was focused on ensuring clarity at an altitude of 20- 25 feet, allowing for precise capture of broader sections of the paddy field.

A total of 130 images of diseased areas and 130 images of healthy areas were obtained from 41 separate paddy fields across the Galle district to maintain a strict class balance within the dataset, as shown in Figure 02. Maintained the uniformity in image quality (resolution, focus) and capture settings (consistent height, RGB colour format), which was necessary to standardize the dataset and minimize variations that could complicate model training. The camera's exposure and white balance were manually set and locked since vegetation indices like ExG and GLI rely on accurate color values; locking these settings ensured that fluctuating lighting conditions would not skew color data used for disease detection. *Dataset Labelling and Organization* - After the image acquisition phase, the collected images were systematically labelled and organized to facilitate efficient use in ML model development. The dataset was organized in a way that supported broad-area disease detection.

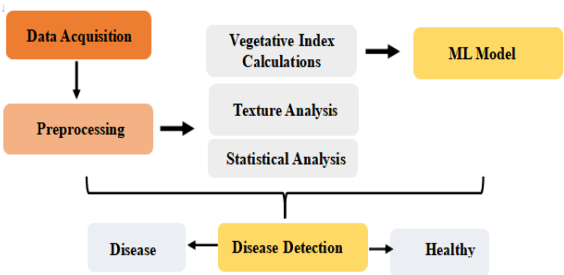


Figure 03: Workflow of the large area disease detection model

2.3 Large Area Disease Detection Model Development

Categorizing Images as "Healthy" or "Diseased" - Images were initially categorized into two primary groups based on field observations and visual assessment: "healthy" and "diseased," as shown in Figure 02. This categorization was based on field inspection records and analysis of visual cues in the images, such as colour consistency and visible symptoms like spotting and discoloration. Diseased images were further examined to confirm that they contained clear indicators of plant health issues.
The workflow of the large area disease detection model is shown in Figure 03.

Data Preprocessing Techniques - The data preprocessing phase involved several crucial steps to prepare image data for ML analysis. This process aimed to ensure consistent input quality, minimize noise, and enhance the performance of the disease detection models. The blurring occurred in the images due to the movement of the UAV, which was identified during the pilot testing, and was reduced by using a gimbal to mount the camera to the drone. Further, deblurring operations applied to the images remove the noise.

Image Loading and Colour Conversion - In this research, images were initially loaded in BGR format, the default colour scheme for images read using OpenCV. To ensure compatibility with the selected vegetation indices, each image was converted from BGR to RGB.

Grayscale Conversion for Texture Analysis - Each image was converted to grayscale for texture-based analysis, eliminating color information to focus solely on intensity variations.
Feature Scaling for Model Stability - Scaling each feature with a mean of zero and a standard deviation of one ensured that all features contributed equally to model training and avoided bias toward features with larger numerical ranges.

Data Splitting (Train Test Split) - The pre-processed dataset was split into training and validation sets using an 80:20 ratio for model evaluation. To address practical issues such as limited dataset size and potential data imbalance, stratified splitting was employed to maintain class proportions across the training and validation sets. Furthermore, k-fold cross-validation was utilized to mitigate overfitting and ensure the model's interpretability and reliability when deployed in unpredictable field environments.

Feature Extraction -Two main feature types were extracted: 1. Vegetation indices, 2. texture feature called Local Binary Pattern (LBP) analysis. Vegetation indices such as VARI in Eq. 01, GLI in Eq. 02, ExG in Eq. 03, and VIgreen in Eq. 04 were extracted.

$$VARI = \frac{Green - Red}{Green + Red - Blue} \text{.......................... Eq. 01}$$

$$\text{GLI} = \frac{2\times Green - Red - Blue}{2\times Green + Red + Blue} \text{..........................Eq. 02}$$

$$\text{ExG} = 2 \times Green - (Red + Blue) \text{.........Eq. 03}$$

$$VIgreen = \frac{Green - Red}{Green + Red} \text{..........................Eq.}$$

Table 01: Statistical comparison of vegetative indices VARI and VIGreen

	GLI		ExG	
Metric	**Health**	**Diseased**	**Health**	**Diseased**
Mean	45639.41	40433.77	123.74	100.48
Median	44960.41	41800.53	124.17	105.26
Stand. Devi.	10631.25	15449.91	24.19	32.70
Minimum	24894.11	11782.27	68.40	30.91
Maximum	70731.86	76419.51	173.82	151.23

04

Texture Analysis - Texture analysis, such as Gray-level Co-occurrence matrix (GLCM), Gabor Filters, and HOG, was applied to grayscale versions of each image to capture texture variations indicative of disease symptoms. LBP is a method for extracting micro-textures by analysing local pixel intensity variations. The grayscale image is processed by comparing each pixel to its surrounding neighbours, resulting in a binary pattern that quantifies texture information. An LBP histogram was generated for each image, capturing the distribution of textures across healthy and diseased leaves.

Finally, all these features were fed into the ML models for disease detection, significantly improving model accuracy and robustness in distinguishing between healthy and diseased plants.

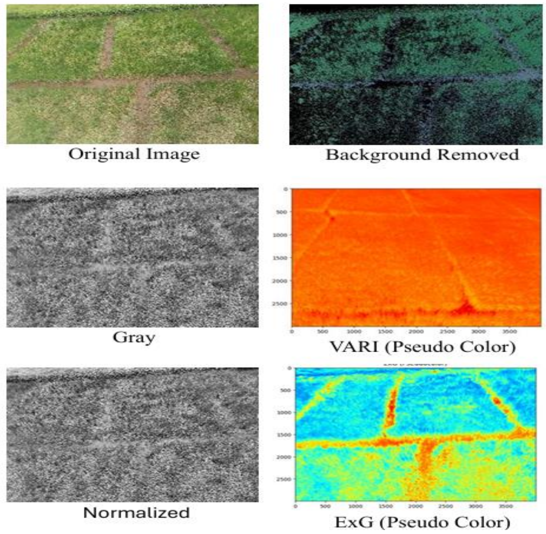


Figure 04: Visual representation of healthy and disease areas after applying vegetative indices

2.4. Web Application Development

To facilitate real-world implementation, the proposed system architecture includes a prototype web application named 'PaddyGuard'. This is a chatbot designed to assist users with paddy disease detection and field management. Using an API, PaddyBot guides users through the image upload process, explains disease analysis results, and provides tailored advice on paddy cultivation. This interactive feature enhances user experience by offering real-time support specific to the application's functionalities.

Figure 05: Web application development

3 RESULTS AND DISCUSSION

3.1 Image processing-based visual identification of healthy and diseased paddy areas

Figure 04 shows the outputs of healthy and diseased images after application of different vegetative indices. ExG has shown visually distinct results when compared with the other vegetative indices.

3.2 Statistical Comparison of Vegetation Indices

Statistical comparison of vegetation indices is shown in Table 01 and Table 02.

Table 02: Statistical comparison of vegetative indices GLI and ExG

	VARI		VI Green	
Metric	**Health**	**Diseased**	**Health**	**Diseased**
Mean	180.16	707.40	50438.08	45508.82
Median	29.60	129.33	46508.61	43697.55
Stand. Devi.	351.38	1406.86	21215.54	19173.39
Minimum	-246.28	0.45	9037.87	8493.44
Maximum	1825.64	7314.20	102259.82	95039.38

Healthy images have significantly lower VARI values (mean: 180.16) than diseased images (mean: 707.40), with a notable difference in their median and range. This indicates VARI's strong ability to distinguish between healthy and diseased plants based on significant variability. VIgreen values for healthy images (mean: 50,438) are slightly higher than those for diseased images (mean: 45,508). The overlap in medians and standard deviations suggests moderate differentiation, making it a complementary index for plant health analysis. GLI values show a clear distinction, with healthy images having a higher mean (45,639) and lower variability than diseased images. The consistent difference highlights its utility in health classification, but there is some overlap in ranges. ExG shows relatively small differences between healthy (mean: 123.75) and diseased (mean: 100.48) images, with minimal overlap. Its stability makes it useful for subtle health variation detection. Figure 05 shows the graphical representation of the statistical comparison of vegetative indices for the purpose of differentiating health and disease areas in paddy fields.

The boxplots in Figure 06 demonstrate the ability to classify healthy and diseased paddy plots using four vegetation indices (VARI, VIgreen, GLI, and ExG).

Boxplot for Each Index Between Healthy and Diseased

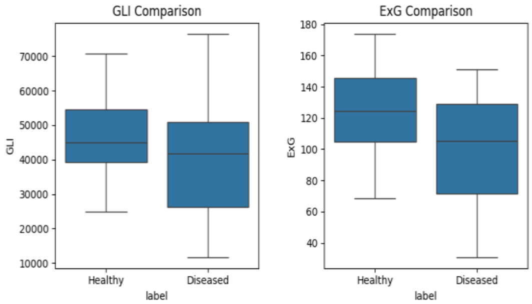


Figure 06: Boxplot comparison between healthy and diseased images

VARI shows the highest distinction, making it particularly suitable for health and disease detection. VIgreen, GLI, and ExG also contribute valuable insights, supporting their applicability in the model for accurate plant health classification.

3.3 Texture-Based Analysis to Differentiate Healthy and Diseased Paddy Areas

Results obtained when different texture features, used in GLCM, Gabor filters, and HOG, were used in identifying healthy and diseased images.

Table 04: Results obtained by applying the texture features

Texture Model	Accuracy (%)	Precision	Recall	F1 Score	AUC
GLCM	57	0.57	0.57	0.57	0.64
Gabor Filters	61	0.62	0.57	0.59	0.68
HOG	58	0.59	0.56	0.57	0.65

The results highlight the performance of different texture features (GLCM, Gabor filters, and HOG) when used individually in the model. Among these, Gabor Filters achieve the highest accuracy (61%) and outperform others in precision, recall, F1 score, and AUC. Its performance demonstrates its ability to capture meaningful texture patterns for distinguishing healthy and diseased plants.

Table 06: Random Forest model across distinct vegetation indices algorithms

Texture Model	Accuracy (%)	Precision	Recall	F1 Score	AUC
GLCM	57	0.57	0.57	0.57	0.64
Gabor Filters	61	0.62	0.57	0.59	0.68
HOG	58	0.59	0.56	0.57	0.65

3.4 ML Algorithm Results

Table 05: Testing results with different ML algorithms

Algorithm Name	Accuracy (%)	Precision	Recall	F1 Score
SVM	43	0.43	0.13	0.20
Logistic Regression	48	0.45	0.43	0.48
KNN	52	0.51	0.52	0.50
Random Forest	57	0.59	0.58	0.57

The results from testing various machine learning algorithms reveal significant performance differences. SVM shows the lowest accuracy (43%) and poor recall, making it unsuitable for the task. KNN achieves moderate performance with 52% accuracy but falls short in recall and F1 score. Logistic Regression performs well with 48% accuracy and balanced metrics, demonstrating its potential. However, the Random Forest algorithm outperforms all others with 58% accuracy. These results establish Random Forest as the better-performing algorithm, providing robust and reliable predictions for detecting plant health and diseases.

3.5 Performance of Random Forest

The individual performances of the four indices (VARI, VIgreen, GLI, and ExG) demonstrate their ability to distinguish between healthy and diseased plants effectively when combined with the Random Forest ML algorithm, as shown in Table 06. ExG and GLI provide the most distinct results, while VIgreen and VARI also show considerable classification capabilities.

The proposed approach uses a low-cost RGB camera mounted on a UAV and applies Random Forest machine learning along with vegetation indices such as GLI and ExG. The results show that this approach effectively isolates healthy canopy areas and is capable of capturing subtle disease textures in paddy fields. In comparison, the study by Anthonys utilizes standard RGB cameras combined with basic image processing techniques and traditional machine learning methods. (Anthonys et al., 2009). While their approach is effective for broad crop monitoring, it often struggles with detecting detailed or early-stage diseases. Similarly, Thapa et al.employ high-cost multispectral and thermal sensors, using NDVI and advanced spectral analysis techniques (Thapa et al., 2021). Their method achieves highly precise stress detection, often exceeding 90% accuracy, but depends on infrared bands that are not visible and require more expensive equipment.

4. CONCLUSION

This research developed image processing and machine learning algorithms for large area paddy disease detection, focusing on the plot-wise analysis of UAV-acquired imagery to identify early signs of disease spread. Machine learning-based disease identification outperforms both statistical analysis and texture-based analysis of vegetative indices. Moreover, the Random Forest machine learning model outperforms other machine learning algorithms such as KNN, SVM, and Logistic Regression. Further, implementation of a Random Forest machine learning model combined with the existing vegetative indices for identifying large area paddy diseases shows promising results, other than using them alone.

Building upon the promising results of this study, several avenues for further research and development are identified to enhance the system's performance and scalability. Future improvements will focus on expanding the dataset size, incorporating data augmentation techniques, and deploying advanced deep learning models to further enhance classification effectiveness and competitiveness.

Moreover, combining several vegetative indices for better performance by incorporating additional datasets to classify a broader range of paddy diseases, including rare and complex conditions, would increase the system's utility and adaptability to various farming contexts. Collaboration with agricultural stakeholders to adapt the system for other crops and farming conditions can extend its applicability, supporting precision agriculture on a larger scale. The proposed future directions aim to refine and expand the system's capabilities, ensuring its continued relevance and impact in promoting sustainable and efficient crop management.

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