Paddy Disease Identification and Impact Calculation Using Machine Learning

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Abstract *- Rice is a crucial staple crop globally, providing over half of humanity's caloric intake. It supports the livelihoods of small-scale farmers and landless laborers worldwide. With the growing population, there is a high demand for rice production. Sri Lanka is renowned for its high- quality rice and has a long history of paddy cultivation. However, not all the country's 708,000 hectares of land dedicated to paddy cultivation are utilized due to water scarcity and unstable terrain. The objective of this paper is to explore the ways of enhancing the quality of the paddy crop during its vegetative phase by early identification of diseases through the utilization of emerging technologies. The vegetative phase constitutes a critical stage in the growth of paddy, exerting significant influence on the overall yield, resistance to pests and diseases, nutrient assimilation, and the environmental implications of agricultural practices. The primary emphasis of this paper is to identify diseases to which paddy crops are susceptible during the vegetative phase and subsequently present avisual representation of their locations on a map, serving as the output for end-users. Early identification of paddy diseases is crucial for effective crop management and high yields. These diseases, caused by different pathogens, can significantly hinder plant growth and productivity if not detected and treated promptly. Identifying them early allows farmers and experts to take timely and targeted actions, like applying suitable fungicides or implementing cultural practices, to control their spread and minimize crop damage.*

Keywords: Diseases, Machine Learning, Object Detection, Paddy Cultivation**,** Web Development and YOLO v8.

I. INTRODUCTION

The paddy crop undergoes a comprehensive lifecycle encompassing seven distinct stages, as illustrated in (Figure 1). These stages include the Pre- planting stage, Planting stage, Vegetative stage, Reproductive stage, ripening stage, Harvesting stage, and post-harvest stage. The initial phase, known as the Pre-planting stage, involves meticulous land preparation and the careful selection of suitable seed varieties. It encompasses tasks such as land ploughing, leveling, and irrigation. Subsequently, the second stage entails either direct seeding or transplanting of the chosen seeds. The ensuing Vegetative stage marks the commencement of the paddy plant's growth. During this phase, leaves emerge from the shoot apex, and the root system undergoes development. Notably, the Vegetative stage is crucial for the successful growth and development of paddy plants as it facilitates photosynthesis and stem elongation. It lays the groundwork for the subsequent stages of the plant's lifecycle. In this study, the researchers have specifically chosen to focus on the pivotal Vegetative phase and have selected the 'Broadcasting method' for planting, as depicted in (Figure 2), to set the project's scope. Object detection plays a crucial role in identifying diseases in paddy crops. By employing advanced computer vision techniques and machine learning algorithms, object detection systems can analyze images or video footage of paddy fields and accurately detect signs of diseases or infections. The system can identify specific symptoms such as discoloration, lesions, or unusual growth patterns

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on the leaves or stems of paddy plants. With the help of object detection, farmers and agricultural experts can quickly and efficiently assess the health status of paddy crops over large areas, enabling them to take timely actions to prevent the spread of diseases.

This project proposes a way to recognize diseased crops using an object detection technique. The pre- identified diseased crops or the clusters of crops with symptoms will be displayed using a map to the end user. Additionally, a high-level overview of the spread of the diseases inside a chunk of land will be provided to the end user. During the vegetative phase, rice plants are vulnerable to a range of diseases, including 'Blast', 'Tungro', 'Sheath Blight', 'Bacterial Leaf Blight', and 'Brown Spot'. These diseases can cause significant damage to the plants, reducing their ability to photosynthesize and produce healthy grains. In severe cases, they can even lead to plant death. Therefore, pre-identification of diseases in a paddy field during the vegetative phase is important to prevent or control disease, improve crop yields and quality, and make informed decisions about inputs and management practices.

The researchers delved into the realm of diagnosing paddy diseases using machine learning, critically reviewing existing methodologies. Developed an advanced plant disease recognition model using YOLOv5 with 'Involution Bottleneck,' SE module, and modified loss function, achieving 70% mean average precision, surpassing original YOLOv5 by 5.4%. Model showcased 86.5% and 86.8% precision in identifying powdery mildew and anthracnose, serving as a technical reference for plant disease prevention.

Introduced DAC-YOLOv4 for real-time strawberry powdery mildew detection with 72.7% mean average precision, demonstrating effectiveness on embedded platforms. Implemented Candy algorithm for rice diseases, using ICAI-V4 with coordinate attention mechanism for 95.57% average classification accuracy, contributing to real-life feasibility in rice disease classification. Proposed leaf disease detection system using YOLO v7 and GPT-3, showing potential for early detection and correction, reducing crop losses. Introduced novel YOLO algorithm for automated rice kernel defect detection, offering an efficient solution for quality assessment. Highlighted accuracy of ResNet 50 and hybrid models in paddy plant disease detection, contributing to the evolving landscape of machine learning in agriculture. Explored machine learning techniques, including Tensor Flow Inception v3, for high-accuracy detection of rice diseases like Brown Spot and Leaf Blast, emphasizing technology's role in crop protection. Utilized modified VGG19 with transfer learning for paddy plant disease, achieving an impressive 96.08% average accuracy, showcasing transfer learning's potential. Discussed diverse approaches, including Bayes hypothesis and SVMs, for automated disease identification and classification in rice crops, contributing to automation in agriculture.

The primary driving force behind this research is the absence of a web application with the ability to effectively visualize and communicate comprehensive data on the prevalence of various diseases within a specific agricultural field. In the proposed method distribution of diseases of the crops will be depicted in a logical map embedded into a web application. Therefore, the end user gets the chance to come up with strategic decisions while identifying the risks to his cultivation.

Figure 1. Seven stages of paddy plant

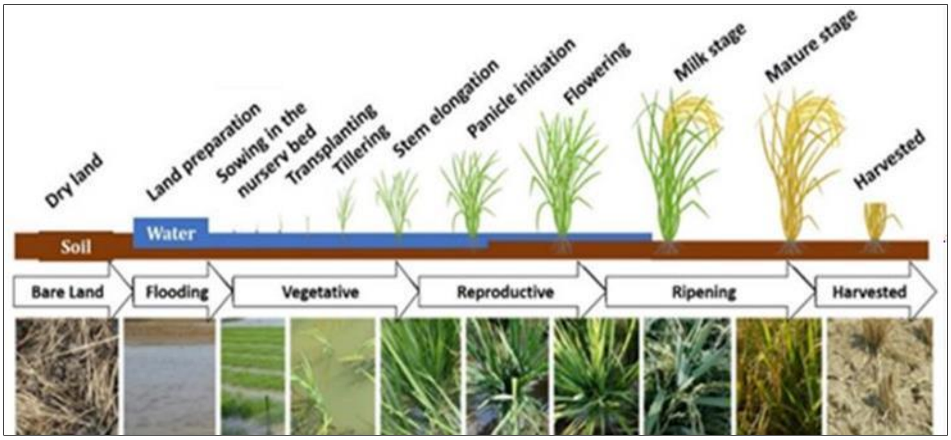


Figure 2. Broadcasting method

II. METHODOLOGY

Crop diseases pose a significant threat to agricultural productivity and food security worldwide. Timely identification and management of these diseases are crucial to mitigate losses. In this research, we focus on disease identification in paddy crops, utilizing the Osmo V3 device for image collection and the YOLO v8 algorithm for automated disease detection. The objective is to develop an accurate, efficient, and scalable solution to aid farmers in early disease detection and effective crop management.

A. Dataset Collection

To build a robust disease identification system, a diverse and representative dataset is essential. We collected an image dataset comprising around 5000 high-resolution images of paddy crops, captured using the DJI Osmo V3 device (Figure 3) and a smart mobile phone (Figure 4) considering the stages in the paddy cultivation (Figure 1 and 2). The gimbal stabilization system of the device helps reduce camera shake, allowing for smoother and more professional-looking shots. The device is particularly useful when capturing footage from moving vehicles or when walking through uneven terrain. Although drone is a matching solution for the given scope, the wind generated by the drone's propellers potentially affects the quality of photographs taken while flying overa paddy field. This movement results in blurry or distorted images, especially if the exposuretime of the camera is relatively long. To get the expected output from the system, the images are recommended to capture in row wise. In brief, the capturing process should be done according to a pattern. The images were acquired from various geographical locations and encompassed different stages of disease progression.

Figure 3. DJI Osmo V3

Figure 4. Samsung A32

B. Labelling the Dataset

The labelling process involved annotating or marking objects of interest within the images with bounding boxes and corresponding class labels. In this case, the exact places infected by diseases were bounded using a box (Figure 5).

Figure 5. Data labeling

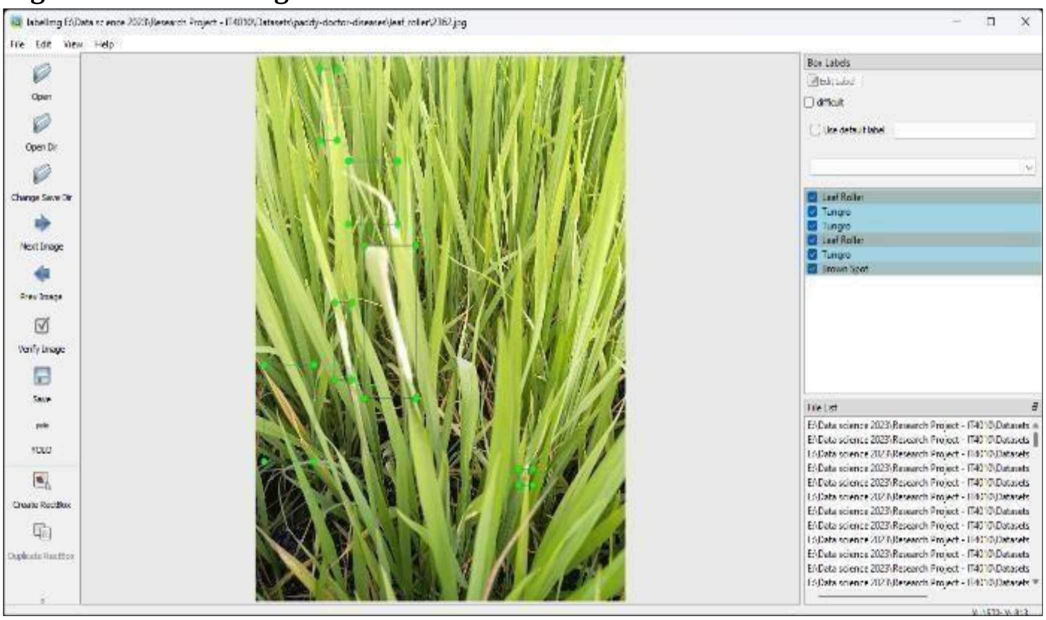
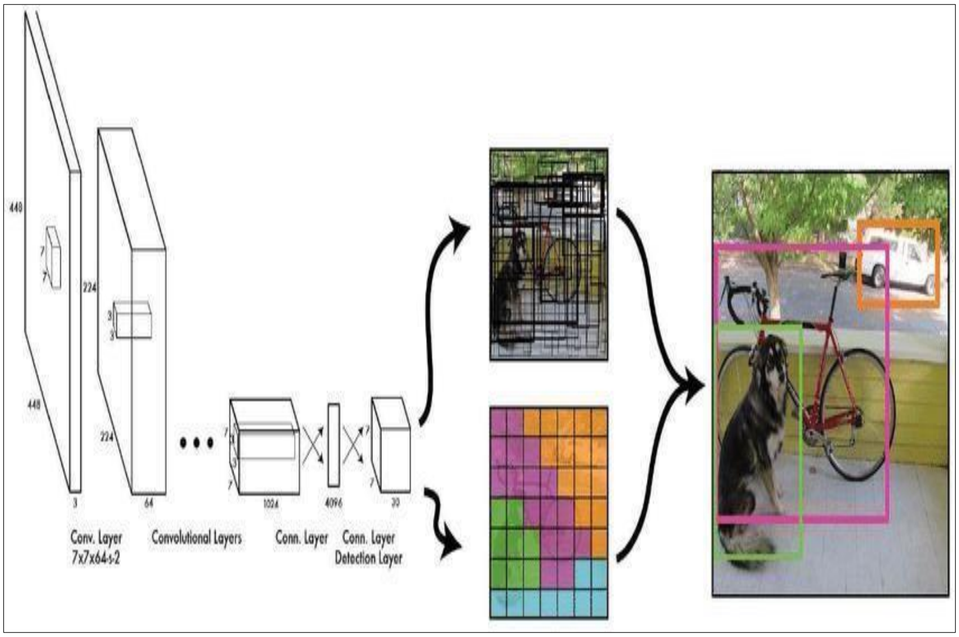


Figure 6. YOLO v8 model arch



After bounding the affected areas, the disease type related to the bounded box should be chosen using a drop-down list. For the labelling process, researchers have chosen an inbuilt labelling software specialized for YOLO algorithm (Figure 6).

C. Preprocessing and Augmentation

To enhance the quality of the dataset and to improve the generalization ability of the model, preprocessing and augmentation techniques were applied. Noise reduction techniques, such as image denoising and contrast enhancement, were employed to improve image clarity. Data augmentation techniques, including random rotations, flips, and translations, were applied to increase the dataset's diversity and robustness.

D. Selecting Suitable Model

The pre-processed data is then divided into three major categories known as ‘Train’, ‘Test’ and ‘Valid’ to be deployed in the YOLO v8 (You Only Look Once Version 8) model. The training dataset is used to train the YOLO v8 model. It consisted of many labeled images, where each image is annotated with bounding box coordinates and class labels for the diseases present. The test dataset is used to evaluate the performance other trained YOLO v8 model. It contained a separate set of images that are not seen during the training process. The validation dataset is used to fine-tune the hyperparameters and monitor the training progress.

The reason for choosing YOLO V8 is due to its state-of -art performance and real-time processing capabilities. YOLO v8 utilizes a single deep neural network to simultaneously predict bounding boxes and class probabilities in a single pass (Figure 6). This architecture enables fast and accurate detection, making it suitable for large-scale disease identification in agricultural settings.

E. Training and Model Development

First installed the necessary libraries and dependencies such as 'OpenCV', 'NumPy' and 'Matplotlib'. Then cloned the Yolo V8 repository existing in GitHub to a local folder in the machine. Defined the YOLOv8 configuration and downloaded the pre-trained weights. Then, loaded the YOLOv8 model and labels while providing the number of epochs. The Yolo V8 model is compatible with arbitrary sized images as long as both sides of the images are multiple of 32. Therefore, in this case image resizing techniques were not applied as shown in Figure 7 and Figure 8.

Figure 7. Model training

Figure 8. Identified diseases using YOLO v8

F. Performance Evaluation

To assess the performance of the developed model, a separate code was written based on the testing image set. A set of testing image data set affected by diseases, bounded by a frame with an accuracy score of identifying the disease was get as the output of the code (Figure 9). Additionally, visual inspection of the detected bounding boxes and class predictions was conducted to analyze the model's performance qualitatively. A performance test with few parameters was carried out to test the accuracy of the model.

Figure 9. Diseases bounded by bounding boxes

As the first parameter, ‘precision’ (1) was considered as a measure of the accuracy of positive predictions. In the context of object detection, it represents the proportion of predicted bounding boxes that contain objects of interest (true positives) out of all predicted bounding boxes (Table 1).

$$Precision = TP / (TP + FP) \quad (1)$$

The second parameter was ‘recall’ (2) and used to measure the proportion of actual positive objects that are correctly identified by the model (Table. 1)

$$Recall = TP / (TP + FN) \quad (2)$$

Third parameter is metrics/mAP50(B): Mean Average Precision and calculates the average precision at a detection threshold of 0.5 (Table 1).
metrics/mAP50-95(B): mAP50-95 calculates the average precision over different confidence thresholds ranging from 0.5 to 0.95 (Table 1).

1) val/box_loss: Box loss measures the discrepancy between the predicted bounding box coordinates and the ground truth box coordinates. Further, it quantifies the localization accuracy of the model (Table 2).

2) val/cls_loss: Class loss represents the error in predicting the object class labels. It captures the accuracy of object classification (Table 2).

3) val/dfl_loss: DFL (Dynamic Feature Learning) loss is specific to YOLO models and is used to optimize the feature learning process. It helps in adapting the network to better represent the features of objects of different scales and aspect ratios (Table 2).

Table 1. Model validation parameters set 1

Metrics/ Precision (B)	Metrics/ Recall (B)	Metrics/ Map50 (B)	Metrics/ Map50-95 (B)
0.07697	0.11361	0.04084	0.01462
0.08058	0.07372	0.0443	0.0133
0.06924	0.121	0.03306	0.01135
0.08478	0.10746	0.02731	0.00884
0.15414	0.13464	0.06067	0.01815
0.1368	0.1264	0.06717	0.02198
0.20784	0.11725	0.08405	0.03786
0.20251	0.15282	0.08612	0.03362
0.21186	0.09919	0.0967	0.02722

Source: Authors'compilation.

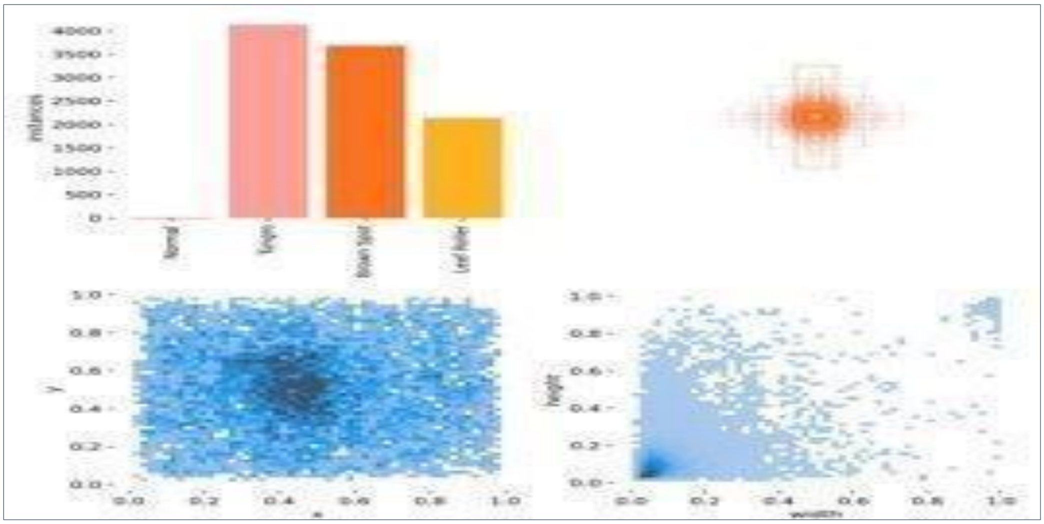
Table 2. Model validation parameters set 2

Val /box_loss	Val /cls_loss	Val /dfl_loss
2.4456	3.6537	2.0365
2.608	3.5708	2.1174
2.5094	3.8878	2.0698
2.606	3.8265	2.2848
2.4844	3.5594	2.1708
2.3708	3.0507	2.0595
2.3703	3.2134	2.0631
2.2689	2.9988	1.9588
2.2958	2.9934	1.9492

Source: Authors'compilation.

Automatically generated graphs depict (Graph of correlogram and graph of Dispersion) the distribution of various diseases among the given images of the dataset (Figure 10). Moving beyond static images, our system incorporates real-time video analysis for dynamic disease monitoring. The Osmo V3's versatility shines in capturing real-time footage, ensuring a seamless transition from static to dynamic disease identification. The logical mapping process unfolds as the algorithm sifts through video frames, providing a comprehensive view of disease progression.

Figure 10. Auto generated graphs

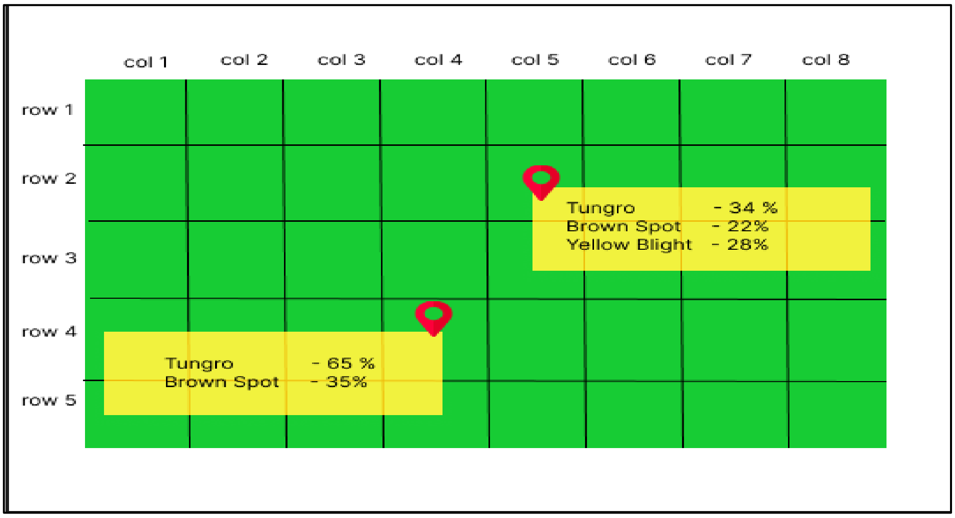


Source: Authors'compilation.

Upon successfully developing the disease detection model, a computation is incorporated to determine the prevalence rate of each disease within a designated land area. For each selected disease in a specific plot of land, a corresponding percentage value of the infection is generated. The ultimate outcome is then visually represented on a map that is integrated into a web application (Figure 11).

$$\text{Percentage-wise existence of each disease} = \frac{\text{Count of each disease type}}{\text{Total count of diseases in a selected plot of land}}$$

Figure 11. Percentage-wise disease existence in a plot of land



Source: Authors'compilation.

III. RESULTS AND DISCUSSION

In the proposed research, YOLO V8 model was trained for 16 epochs. In most of the images, the diseases on the leaf blade are visually imperceptible. Although the symptoms of the diseases are in micro level, YOLO V8 algorithm was able to distinguish them approximately. Additionally, the proposed model was able to work fine with multi scaled images (Figure 12).

Figure 12. Disease identification in multi-scaled images

Source: Authors'compilation.

To increase the precision and recall values generated by the model, the model architecture and parameters were further adjusted. Additionally, the model training process will be optimized by applying techniques like gradient clipping and weight decay to prevent overfitting.

While the YOLO v8 algorithm demonstrated promising results in disease detection and classification, it is essential to acknowledge its limitations. The algorithm's performance might be affected by variations in lighting conditions, image quality, and the presence of occlusions. Additionally, the dataset used in this study focused on a limited number of common diseases, and further research is needed to expand its applicability to a broader range of diseases in paddy cultivation. Future work should also explore the integration of remote sensing techniques and other advanced machine learning algorithms to enhance disease detection accuracy and scalability.

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