Paper ID:216

Enhancing Crop Quality of Paddy using Object Detection Techniques

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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 of 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 project is to enhance 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 project is to identify diseases to which paddy crops are susceptible during the vegetative phase and subsequently present a visual 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—machine learning, object detection, web development, YOLO v8, diseases, paddy cultivation

I. INTRODUCTION

The paddy crop undergoes a comprehensive lifecycle encompassing seven distinct stages, as illustrated in (Fig. 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 plowing, 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 (Fig. 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 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.

This Researchers examined existing machine learning approaches in diagnosing paddy diseases, highlighting two key studies: one utilizing diverse paddy plant images for a 96.25% accurate disease classification, and another introducing a specialized Convolutional Neural Network (CNN) model achieving 97.3% accuracy in identifying six rice diseases. However, this proposed research distinguishes itself by presenting a machine learning model capable of accurately processing images with varying sizes (multi-scalable images), yielding enhanced accuracy compared to prior systems. The addition of a web interface depicting disease distribution across land plots provides further substantiation of the research's efficacy. This adaptability addresses real-world image diversity, potentially advancing the reliability of paddy disease diagnosis.

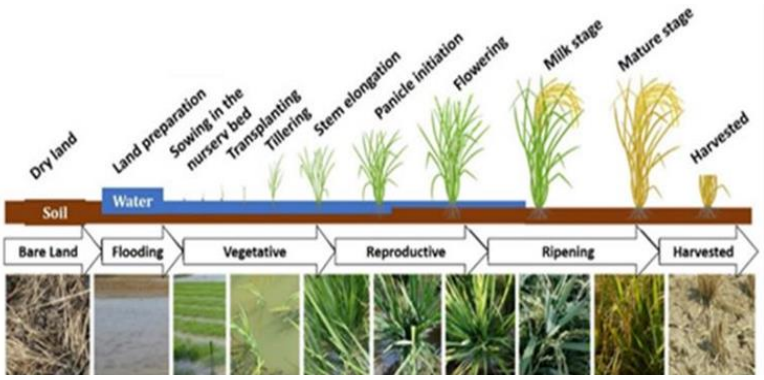

Figure. 1: Seven stages of paddy plant

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. The researchers collected an image dataset comprising around 5000 high-resolution images of paddy crops, captured using the DJI Osmo V3 device. (Fig. 3) and a smart mobile phone (Fig. 4). 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 over a paddy field. This movement results in blurry or distorted images, especially if the exposure time of the camera is relatively long. In order 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. *Labeling the Dataset:*

The labeling 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.

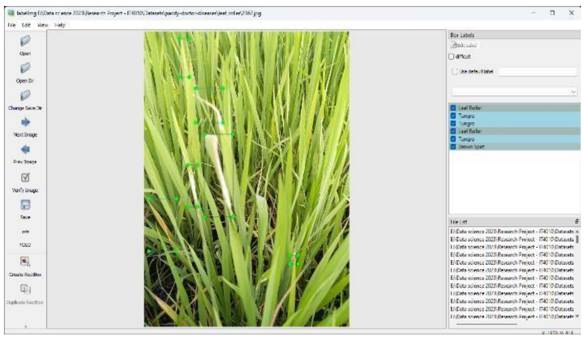

Figure. 5: Data Labeling

After bounding the affected areas, the disease type related to the bounded box should be chosen using a drop-down list. (Fig. 5) For the labeling process, an inbuilt labeling software specialized for YOLO algorithm was selected.

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 preprocessed 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 of the 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. (Fig. 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. (Fig. 7) (Fig. 8)

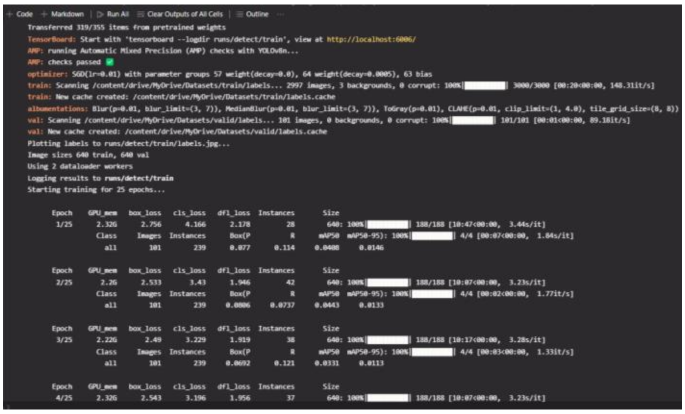

Figure. 7: Model Training

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,

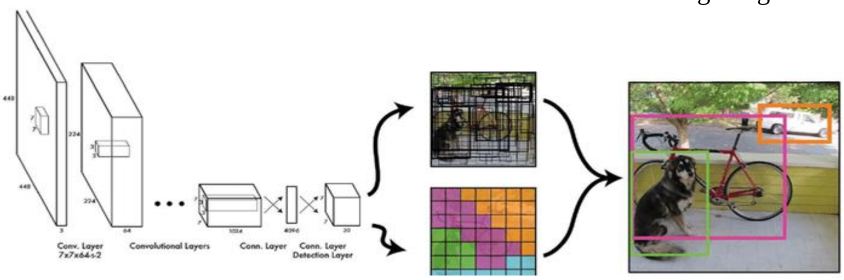

Figure. 6: YOLO V8 Architecture

bounded by a frame with an accuracy score of identifying the disease was get as the output of the code. (Fig. 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 is carried out to test the accuracy of the model.

Figure. 9: Diseases bounded by bounding boxes.

As the first parameter, ‘precision’ 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)

$$\text{Precision} = TP / (TP + FP) \qquad (1)$$

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

$$\text{Recall} = TP / (TP + FN) \qquad (2)$$

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

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
0.19197	0.14091	0.10572	0.04275
0.17098	0.18506	0.11714	0.04758
0.14329	0.17159	0.12019	0.04525
0.18309	0.18859	0.11884	0.05068
0.19719	0.19101	0.12378	0.0514
0.24553	0.18695	0.14085	0.05447
0.25636	0.19787	0.13603	0.05182
0.23214	0.21118	0.14517	0.05413

TABLE 2: Metrics used to measure the accuracy of the model.

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
2.2347	2.9024	1.8963
2.2277	2.7167	1.8707
2.2057	2.7407	1.8256
2.1921	2.6651	1.8444
2.1557	2.6462	1.8755
2.1716	2.6713	1.8591
2.132	2.8167	1.8165
2.112	2.7526	1.792

Automatically generated graphs depict (Graph of correlogram and graph of Dispersion) the distribution of various diseases among the given images of the dataset. (Fig. 10)

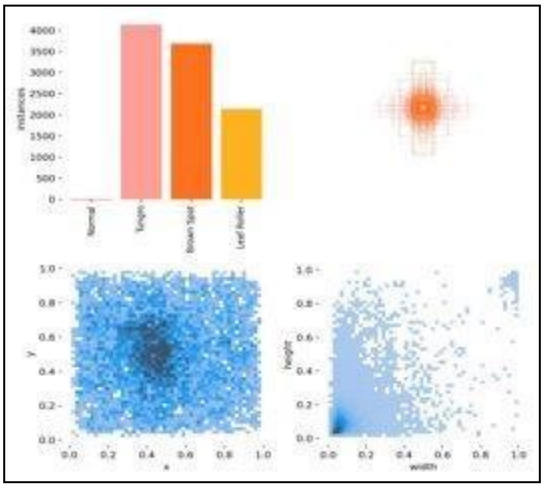

Figure. 10: Auto generated graphs

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. (Fig. 11)

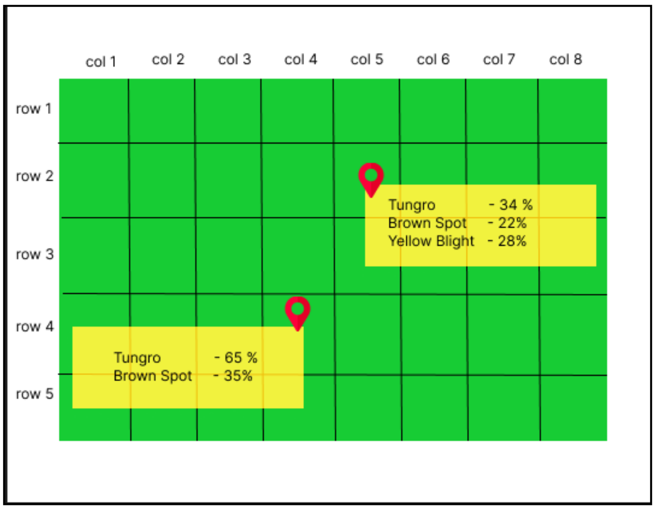

Figure.11: Percentage wise disease existence in a plot of land

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. (Fig. 12)

Figure. 12: Disease identification in multi scaled images.

To increase the precision and recall values generated by the model, the researchers wish to adjust the model architecture and parameters further. 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.

IV. ACKNOWLEDGMENT

I express my sincere gratitude to the following individuals and institutions for their valuable support and contributions to our research project.

Firstly, I thank the Yakkala Govijana Sewa Center, Bathlegoda Rice Research Institute, and Pelwehera CIC Agro Business Farm for providing resources and facilities for our research. Their cooperation and assistance were crucial for our experiments.

I'm deeply grateful to Mr. Samadhi Rathnayake for his guidance, expertise, and constant encouragement. His insights and feedback significantly shaped our research.

Mrs. Amali Gunasinghe deserves my appreciation for her valuable input and support in refining my research methodology and addressing challenges.

I also acknowledge the staff members and colleagues who provided assistance and support throughout the project. Their collaboration and expertise greatly contributed to my success.

Lastly, I extend my gratitude to the research participants who volunteered their time and provided valuable data.

I'm humbled by everyone's efforts and remain indebted to each and every one of them for their contributions.

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6. AUTHOR BIOGRAPHY

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