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Smart Agriculture: Real-time Pest Detection in Rice Crops with YOLOv8 and ESP-32 Camera Technology

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***Abstract* - Rice is a vital crop globally, serving as a primary food source for a significant portion of the world's population. The cultivation of rice, particularly during the vegetative phase, plays a pivotal role in determining overall crop quality, pest resistance, nutrient uptake, and sustainable agricultural practices. In regions like Sri Lanka, where paddy cultivation holds historical significance, safeguarding paddy fields from various pests becomes paramount to ensuring optimal yields and sustaining the livelihoods of local farmers. This research project aims to address the pressing need for effective pest management in the vegetative phase of paddy growth by leveraging emerging technologies. By utilizing state-of-the-art methodologies, the project seeks to enhance the early identification and control of pests that pose significant threats to paddy fields. By focusing on this critical growth stage, the research aims to minimize potential crop damage and optimize agricultural practices, ultimately improving overall productivity and mitigating economic losses for farmers.**

Through the utilization of advanced pest identification techniques and innovative control measures, this project aspires to provide farmers with timely and accurate information about the pests affecting their paddy fields. By promptly identifying these pests, farmers can take appropriate measures to protect their crops, optimize resource utilization, and minimize the use of harmful chemicals. This research endeavors to contribute to the sustainable management of paddy fields, foster resilient agricultural practices, and ensure the availability of high-quality rice production. By empowering farmers with efficient pest identification and control strategies during the vegetative phase, this project aims to safeguard paddy fields, enhance yields, and promote sustainable agriculture in the face of evolving pest challenges.

Keywords: paddy fields, pest management, vegetative phase, emerging technologies, pest identification, sustainable agriculture.

I. INTRODUCTION

Rice cultivation is characterized by distinct growth stages, namely the vegetative period, reproductive period, and ripening period. Among these, the vegetative phase holds paramount importance as it lays the foundation for the plant's growth and productivity. During this stage, rice plants undergo rapid development, establishing the necessary structure and leaf area for efficient photosynthesis and nutrient assimilation. However, this critical phase also renders the plants susceptible to various pests that can impede their growth and overall health.

Protecting crops from pests during the vegetative period is crucial to ensure optimal growth and maximize yields. Pests such as Moths, Slugs, Weevils, Snails, and Caterpillars pose significant threats to rice plants during this stage. These pests can feed on the leaves, stems, and roots of the plants, compromising their ability to carry out essential photosynthetic processes and nutrient absorption. As a result, the plants may exhibit stunted growth, reduced grain production, and increased vulnerability to diseases.

To address these challenges, advanced computer vision techniques and machine learning algorithms can be employed to develop object detection systems. These systems analyze images captured from paddy fields and accurately identify signs of pest presence. By leveraging such technology, farmers and agricultural experts can promptly assess the pest situation in their fields and take necessary actions to control and mitigate the damage caused.

The first phase was creating customized equipment for data collection using an ESP32-CAM module. This apparatus was a 150 cm tall tripod stand with a rod attached that was stretched horizontally. A strong machine learning model was developed to identify a range of insect kinds in the field by utilizing the YOLO V8 method. For optimum performance, this model underwent 100 epochs of training.

Then, using footage of pests obtained with the aforementioned instrument, thorough model testing was carried out. Frame extraction and stream manipulation were

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made easier by the implementation of OpenCV's video capture functionalities. A dedicated backend server was set up to support video frame receipt, YOLO V8-based pest identification, and result transfer, enhancing the process. Notably, the Flask web framework was used to build this server, which required careful endpoint delineation for frame receiving, processing, and result dissemination.

In addition to timely pest identification, receiving real-time notifications about the detection of new pests in paddy fields is of immense value. The early detection of emerging pests enables farmers to swiftly respond and implement appropriate pest management strategies. Real-time notifications serve as a proactive warning system, empowering farmers to take preventive measures, apply targeted treatments, and minimize the potential impact on crop health and yield.

Furthermore, providing farmers with comprehensive weekly reports detailing the types and abundance of pests in their paddy fields offers valuable insights. These reports enable farmers to gain a holistic understanding of the pest dynamics within their fields over time. Armed with this knowledge, farmers can make informed decisions about pest control measures, adjust management practices, and optimize resource allocation. Moreover, the weekly reports facilitate proactive planning, allowing farmers to implement long-term pest management strategies and minimize the risk of crop losses.

By integrating real-time notifications and weekly reports into pest detection systems, farmers can effectively protect their paddy fields, optimize pest control measures, and enhance overall crop management practices. This holistic approach contributes to sustainable agriculture, improved yields, and the economic well-being of farmers.

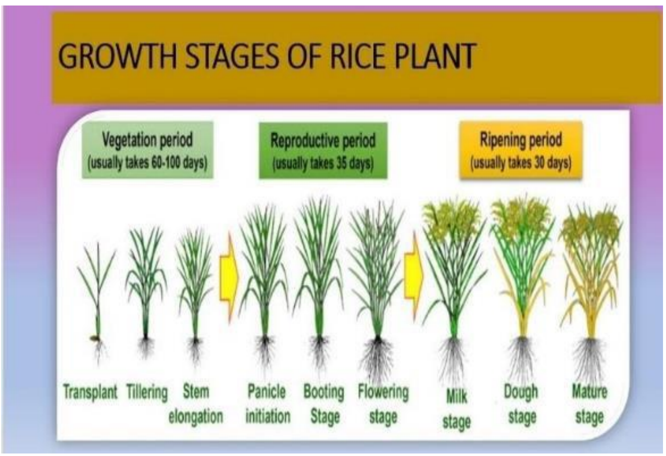

Figure 1: Growth stages of rice plant

Figure 1: Detection

II. METHODOLOGY

Crop pests pose a formidable challenge to global agricultural productivity and the security of food supplies. Swift and accurate identification, as well as effective management of these pests, are imperative in order to minimize detrimental impacts and safeguard crop yields. The early detection and implementation of appropriate pest control measures play a vital role in reducing crop damage, optimizing resource allocation, and promoting sustainable agricultural practices. Failing to address pest infestations promptly can lead to substantial economic losses and compromised food production systems. In this research, we focus on pests' identification in paddy crops, utilizing the IOT (Internet of Things) device for image collection and the YOLOv8 algorithm for automated pest detection. YOLOv8, like its predecessors, YOLOv5 and other YOLO (You Only Look Once) models, employs a Convolutional Neural Network (CNN) backbone to extract features from input images. These extracted features are then processed through a model neck, which combines and refines these features. Finally, the combined features are passed to the model head, where they are interpreted to predict the class of objects in the image and their corresponding bounding boxes. The primary objective of YOLOv8 is to create an accurate, efficient, and scalable solution that can be applied to various applications, including aiding farmers in early pest detection and effective crop management. By using YOLOv8, farmers can harness the power of computer vision to detect and monitor pests and other important aspects of crop health, enabling more timely and precise decision-making for crop management.

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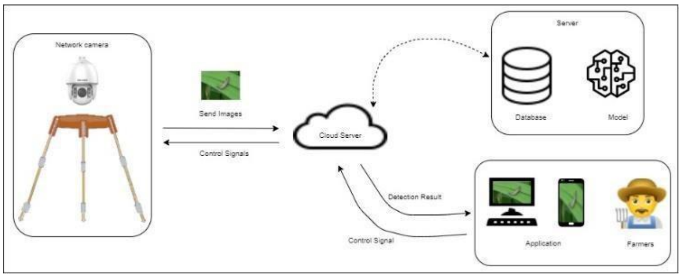

Figure 3: Pest Identification System Diagram

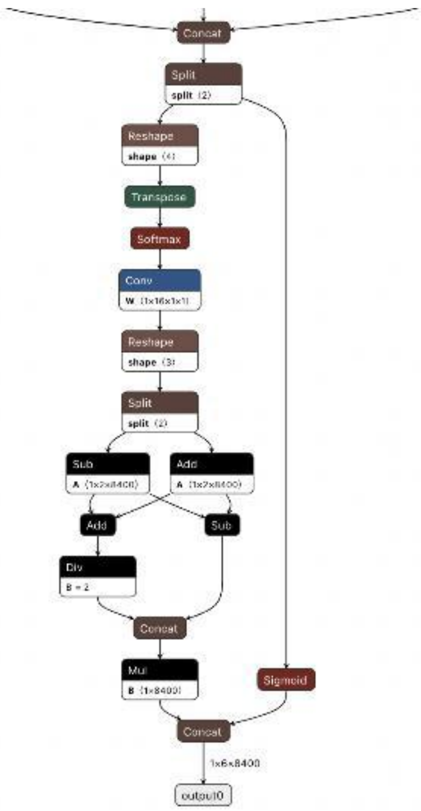

Figure 1: The detection head of YOLO V8

A) Dataset Collection

Creating a high-quality system for pest detection in paddy fields relies on a well-curated dataset. To achieve this, ESP32-CAM modules are deployed in the fields to capture a comprehensive range of images and videos throughout the rice crop's vegetative phase. This dataset is carefully diversified, encompassing imagery of healthy crops at various growth stages and samples showcasing different types of pests and pest-related issues. Furthermore, it incorporates diverse lighting and weather conditions, various camera angles, and different distances from the crops. Thorough annotation of the dataset, marking regions of interest where pests are present, is imperative for training a robust computer vision model. Regular quality checks are performed to ensure data integrity, and the dataset is meticulously stored for future use in developing an effective pest detection system.

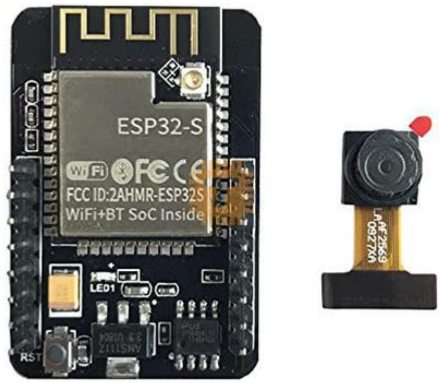

Figure 5: ESP32-Cam

Figure 6: Image Capturing Device

B) Labeling the Dataset

The labeling process we mainly label pest to 12 kinds of pests. Some of them are slugs, snails, moths, wasps, earwigs, caterpillars and weevils.

C) Preprocessing and Augmentation

To enrich the dataset and enhance the model's adaptability, we employed preprocessing and augmentation techniques. Initially, we standardized image resolution for consistency. Enhancing clarity, we utilized image denoising and contrast enhancement methods. To augment dataset diversity and robustness, we employed creative techniques such as random rotations, flips, and rescaling. These steps ensured the model's improved generalization ability, empowering it to recognize pests accurately. The combination of these preprocessing and augmentation techniques strengthened the dataset, facilitating more effective training and yielding a more versatile and reliable model.

D) Selecting suitable model

The preprocessed data is then divided into three major categories known as 'Train', 'Test' and 'Validation' to be deployed in the YOLOv8 model. The training dataset is used to train the model. It consisted of a large number of labeled images, where each image is annotated with bounding box coordinates and class labels for the pests present. The test dataset is used to evaluate the performance of the trained

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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 hyper parameters and monitor the training progress.

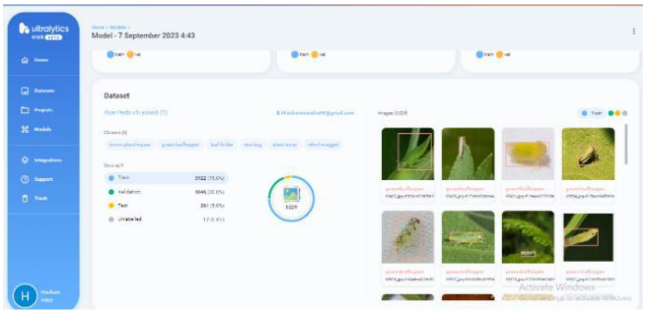

Figure 7: Model Development 1

The reason for choosing YOLOv8 is due to its performance, efficiency, scalability and real-time processing capabilities. The utilization of the YOLOv8 model is essential in accurately identifying pests in paddy fields, which, in turn, enables effective pest management and supports sustainable agriculture practices. By leveraging its superior accuracy and efficiency, the model empowers farmers and agricultural experts to precisely detect and distinguish pest species, facilitating targeted and timely interventions. This capability is crucial in minimizing crop damage, optimizing resource allocation, and reducing the reliance on broad-spectrum pesticides. Ultimately, the use of the YOLOv8 model enhances pest control strategies, promotes environmentally friendly approaches, and contributes to the long-term sustainability of paddy field cultivation.

E) Training and Model Development

First installed the necessary libraries and dependencies such as 'Pandas', 'Numpy', 'Seaborn' and 'Matplotlib'. Then seed everything to reproduce results for future use cases. After that cloned the tensflow-deep-learning repository existing in the Github repository.

Then, loaded the model and labels while providing the number of epochs.

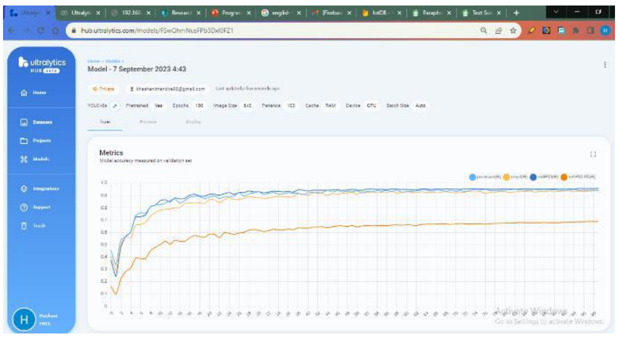

Figure 8: Model Development 2

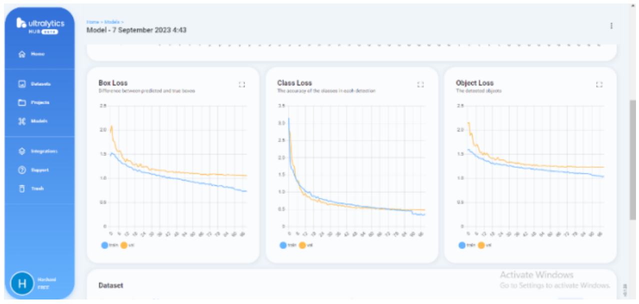

Figure 9: Model Development 3

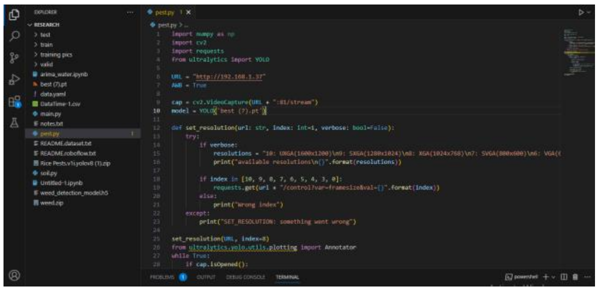

Figure 10: Code 1

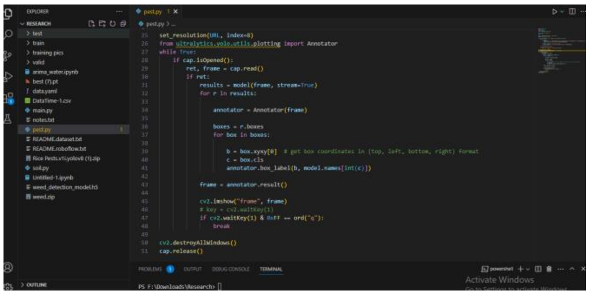

Figure 11: Code 2

F) Performance Evaluation

To assess the performance of the developed model, a separate code was written based on the testing image set. I was able to acquire a set of testing images depicting pests in paddy fields, enclosed within bounding boxes. The code effectively identified the pest species with a high accuracy score, providing pest detection as the output.

Upon successfully developing the pest detection model, a computation is incorporated to determine what pests are in the paddy fields and what actions farmers should take to control them. When there is a new pest appear in the paddy field farmer will get a real-time notification. Not only those things, but farmers also got a weekly report regarding the pests in their paddy fields.

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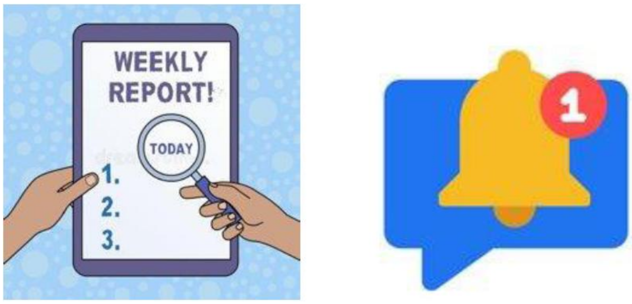

Figure 12: Weekly reports and notifications

III. RESULTS AND DISCUSSION

In the proposed research, the YOLOv8 model was trained for 100 epochs. Although the cameras can focus on a small range of plants (few plants), YOLOv8 was able to detect the pests in those focused plants successfully. Additionally, the proposed model was able to work fine with multi scaled images.

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