# RICEFIELD HEALTH MONITORING SYSTEM USING A DRONE WITH AI INTERFACE

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**ABSTRACT**. Farmers have struggled with pesticides, parasites, and plant diseases for years, their primary concerns on the farm. When a rice plant gets sick, the overall harvest for the season suffers, leaving farmers disappointed. Not only that, but also the time, energy, effort, and money invested in the field will go to waste. With the advancement of technology, it is only natural to incorporate it into our daily lives, especially in agriculture. Researchers have considered using technology to assist farmers in monitoring and supervising their rice fields to ensure a good harvest. One such technology is a drone, which can survey and detect the percentage of infestation in rice plants. A training model can identify if a rice plant has a disease. The results show that the object detection algorithm predicts up to 70% accuracy infestation severity better than the image classification algorithm. By introducing farmers to this technology, they can improve rice production in the region.

Keywords: Drone, Image Classification Algorithm, Object Detection Algorithm, Ricefield Health Monitoring, Infestation

# 1. INTRODUCTION

Drones have made significant contributions to agriculture in recent years. Using a drone to monitor the rice field will be a novel way of gathering data and allow for autonomous, efficient, and rapid monitoring. With the assistance of artificial intelligence, analyze the collected data to determine whether the rice plant growth is healthy [1].

By using a drone for rice field monitoring with an AI interface, early disease detection will significantly prevent the rice plant from getting damaged at this point. If the plant harms the harvest quantity, farmers get frustrated with the result [2].

Farmers will benefit from the use of drones for agricultural purposes. Will reduce labor costs and time commitments. It gives them a big push by spending little and making much money. With less involvement in the rice field, they can use it for other work they need to do.

There are numerous issues with using a drone for monitoring because the weather should be sunny, not rainy or windy, which significantly affects the Drone [3]. The camera used for surveying should have a high resolution to obtain a clear and better image. Due to a lack of resources or infrastructure, identify diseases in rice plants [4].

Even though there are some concerns about using drones in agriculture, this is the best technology for monitoring rice fields, with some alternatives for detecting crop disease earlier. It will significantly assist farmers in increasing the likelihood of harvesting their rice crops. If they observe the rice plant, farmers will estimate the harvest quantity [5, 6].

The amount of rice harvested in the latest harvest has fallen because they are not adequately monitoring the health and growth of crops. If this trend continues, rice will become scarce in the future. As a result, the researchers felt compelled to conduct this Study to assist our farmers in achieving a high quantity and quality harvest.

Review of Related Literature

Utilizing technology in rice farming is crucial for a successful harvest [7]. A novel approach involves using drones to capture images of the rice field and identifying the growth phase of the rice plant with a machine learning tool called a support vector machine [8]. This approach achieves high accuracy in detecting diseases by training a neural network using collected data [9]. The detection of crop disease has evolved from traditional methods to using a convolutional neural network and a plan crossover structure for better accuracy [10]. Image processing technology can aid in early disease detection and make rice field management more accurate. Smart farming promotes efficient and sustainable crop production, and remote sensing with high-resolution satellite sensors and drones enables low-cost and flexible observations [11]. Utilizing IoT and image processing techniques for disease prediction through deep neural network-based vision-based detection can significantly increase productivity.

New technology is crucial for good rice farming harvests, with methods such as using drones and machine learning algorithms to identify the growth phase and diseases in rice plants [12]. Early detection of diseases is essential to ensure successful harvests, and technology such as image processing, remote sensing, and deep neural network-based vision-based detection can significantly assist in predicting crop disease and increasing productivity [13]. Smart farming promotes sustainable and profitable crop production and using high-resolution satellite sensors and drone-based remote sensing enables low-cost, high-resolution, and flexible observations of crops and soils [14]. Overall, technology and image processing techniques are transforming rice farming and making it more accurate and efficient. Table 1 shows the summary of the related technology for the rice fields' health monitoring system which provides methods, hardware and feature to be compared and addressed their disadvantages.

Author	Method	Advantage	Hardware	Features
(Marsujitullah et al. 2019)	Image Processing method called Histogram of Color	classification of Rice farming's phase growth	Drone	To increase production
(Anon n.d.)	IoT and Image processing and performs classification using a deep learning model	detect the diseases in an earlier time and classify the diseases	camera with Raspberry pi	Precision farming
(Inoue 2020)	Smart farming	crop growth, water stress, soil fertility, weed, disease, lodging, and 3D topography	Satellite and Drone	Diagnostic information on crop growth, water stress, soil fertility weed, disease, lodging, and 3D topography can be created from tl optical, thermal, and video image
Researchers Study	Image processing and performing object detection using deep learning	Detects infested, and Nitrogen deficiency of the rice plant	Drone and Jetson Nano	To increase production

1.2 Objectives of the Study

because the rice plants in the area have already been harvested, This study assists farmers in predicting infested crops leaving only this area available.

using drones and analyzing data using a machine-learning 2.3 Project Development

algorithm. Specific objectives of the Study are:

percentage of infestation.

- 2. The capture data were used to train using
  - 2.1 Image Classification Model
  - 2.2 Object Detection Model
- 3. Hardware Development using
  - 3.1 Jetson Nano
  - 3.2 Drone
  - 3.3 Monitor and Power Supply
- 4. Simulate the tested model

# 2. METHODOLOGY

## 2.1 Research Model

This study utilized quantitative research methods with additional techniques of data science & computer science to develop models that can make predictions of the infestation in the crops. This includes data collection, preprocessing, feature selection & engineering, machine learning algorithms, model evaluation, & model deployment.

2.2 Locale of the Study



Figure 1. Location of the Study

The study was conducted in Togbongon, Surigao City, Surigao del Norte. The data samples were obtained from the internet. The image above only depicts mature rice plants

The developed rice field health monitoring system using a 1. Capture photos and classify the photos to the drone with ai interface was composed of Drone, jetson nano hardware with monitor and power supply. The training of data sets was conducted on a personal computer, and the model was

only uploaded to the jetson nano. 2.4 Implementation of the machine learning

Data was collected and separated according to classification, creating train, val, and test folders and uploading the data. The data was labeled according to its classification, the machine was trained, and a model was provided after training. This model was then tested on actual data.

## 3. RESULTS AND DISCUSSION

The sections present all the data based on the objectives. 3.1 Data Capture

Researchers are uniting capturing data on the ricefields, as shown in Figure 2, using the Drone. Image of the capture segment by segment in the ricefield using a 1080p resolution drone camera.



Figure 2. Capturing of Data

The captured data were migrated to the personal computer for data preprocessing, as shown in Figure 3 below.



Figure 3. Data Preprocessing

After the data migrated to the personal computer, this data was classified as infestation and healthy based on the farmer's decision-making using manual labeling per image classification, as shown in Figure 4. Data segregation based on the classification is stored in a folder, as shown in Figure 5.



**Figure 4. Image Labelling** 



Figure 5. Folder of Classified Image

After the data is stored in the folder, this data will be used to train the machine learning to provide a reliable model to predict image as to the level of infestation based on the data image, as shown in Figure 6.

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Figure 6. Training the Machine

The study used the object detection algorithm and Image classification algorithm to find the efficient algorithm, as shown in Figure 7 and Figure 8.





A. Before Testing

B. After Testing

Figure 7. Image Classification Model with an accuracy of 55%





A. Before Testing

**B.** After Testing

**Figure 8. Object Detection Model with an accuracy of 70%** The final model was uploaded to the Jetson Nano to expedite the prediction, as shown in Figure 9, which detects that the rice crop was infected by 60%. The Drone where used to gather the image, as shown in Figure 10 and the data were manually uploaded to Jetson Nano to predict the infected ricefield.



Figure 9. Actual Crops Prediction with 60% infected by Object Detection Model



Figure 10. Drone Data Capturing

#### **4. CONCLUSION**

The researcher developed two designs for a rice field health monitoring system. The first design is image [8] classification. As the researcher employs this method, the researcher concludes that this method is unsuitable for use. The second design is an object detection design, which the researcher uses because it has a bounding box for the image result. Preparing a dataset for training is [9] critical because it influences the creation of the model. The model will fail because it will not function properly if the dataset is jumbled and not adequately classified or labeled. Using an object detection model, the researcher produced a result of 70% accuracy result. The image [10] will have a bounding box, and the researcher considered creating another model but did not have enough time. Hence, the researcher stopped at this model.

#### **5. RECOMMENDATION**

The researchers recommend using semantic segmentation in the system. Since semantic [11] segmentation is advanced image recognition, except that classification takes place at the pixel level rather than over the full image.

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