Detection and Classification of Philippines Rice Diseases Using YOLO

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CSC173 - Intelligent Systems

October 21, 2024

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Abstract

The Philippines, a country highly reliant on rice as a staple food, faces significant challenges in its agricultural sector due to various rice diseases. These diseases, caused by fungi, bacteria, and viruses, pose a threat to crop yield, quality, and ultimately, food security. This project proposes a plan to leverage advanced machine learning techniques, specifically the YOLO (You Only Look Once) object detection framework, to enhance the detection and classification of rice diseases in the Philippines. The dataset, sourced from Kaggle, comprises 13 classes of rice diseases under fungi, bacterial, and viral categories, as well as one healthy leaf class. The implementation will focus on accurately identifying and classifying these diseases in real-time, aiming to provide a tool that can assist farmers and agricultural experts in managing rice health more effectively. Through this project, we will contribute to improving agricultural practices and outcomes by enabling quicker and more accurate disease detection.

1 Introduction

Rice is an integral part of Filipino cuisine and culture, serving as a staple food consumed at every meal, from breakfast to dinner. It accompanies nearly every dish, including meats, seafood, vegetables, and soups, playing a crucial role in the diet of millions of Filipinos. Beyond its nutritional value, rice holds cultural significance, being deeply embedded in Filipino celebrations, rituals, and traditions as a symbol of community and shared identity.

However, the rice industry in the Philippines faces significant challenges, particularly with the prevalence of various rice diseases. These diseases, caused by fungi, bacteria, and viruses, threaten crop yields and can have severe economic consequences for farmers and the agricultural sector. A variety of fungal, bacterial, and viral diseases can infect rice plants, leading to reduced yield, lower quality, and even total crop loss. These diseases can be devastating to farmers, especially those with limited resources who cannot afford the cost of chemical treatments or disease-resistant seeds. The high humidity and frequent rain in the Philippines create favorable conditions for the growth and spread of rice diseases.

The early detection and accurate classification of rice diseases are critical for implementing timely and effective interventions, ensuring food security, and protecting the livelihood of farmers. Despite advancements in machine learning and computer vision for agricultural applications, current approaches, such as those using MobileNet, ResNet50, and EfficientNet, still face limitations in terms of accuracy and efficiency. There is a pressing need to explore more advanced models to enhance disease detection and classification.

1.1 Background of the Study

The primary aim of this study is to address the pressing challenges posed by rice diseases in the Philippines, which threaten food security and the livelihoods of millions of farmers. By leveraging advanced machine learning techniques, specifically the YOLO object detection framework, this research seeks to enhance the early detection and classification of rice diseases. The objectives outlined below will guide the development of a robust system that not only improves detection accuracy and efficiency but also contributes valuable insights for agricultural practices in the region.

1.1.1 General Objectives

To develop an efficient and accurate system for detecting and classifying rice diseases in the Philippines using the YOLO object detection framework. The system aims to improve the precision and speed of identifying fungal, bacterial, and viral rice diseases, thereby supporting timely interventions to enhance crop yield and protect farmers' livelihoods.

1.1.2 Specific Objectives

- To implement the YOLO model for detecting and classifying 13 rice disease classes and one healthy leaf class using a dataset of Philippine rice diseases.
- To evaluate the performance of YOLO in terms of detection accuracy, classification precision, and processing speed.

1.2 Scope and Limitation

This study focuses on the detection and classification of rice diseases affecting rice crops in the Philippines, specifically targeting 13 classes of diseases caused by fungi, bacteria, and viruses, along with one healthy leaf class. The research will utilize the YOLO object detection framework, employing a dataset that reflects the common rice diseases found in the region.

The scope of the study includes data collection, model training, and performance evaluation, aiming to provide insights into the effectiveness of YOLO model. However, several limitations must be acknowledged:

- The dataset used for training and evaluation may not cover all possible variations of rice diseases, potentially limiting the generalizability of the findings.
- Environmental factors such as varying agricultural practices, soil conditions, and regional differences in rice cultivation are beyond the control of this study and may affect the accuracy of disease detection in real-world applications.
- The study will focus solely on the technical aspects of model implementation and evaluation, and it will not address broader socio-economic factors impacting the rice industry or farmers' access to technology.
- The model's performance may vary based on the quality and quantity of the dataset used, as well as the computational resources available for training.

2 Review of Literature

2.1 Rice Disease

Rice is a staple food in the Philippines, and its cultivation is significantly threatened by various diseases that can severely impact yield and quality. Among the most critical diseases affecting rice in the country are rice blast (caused by Magnaporthe oryzae), bacterial leaf blight (caused by Xanthomonas oryzae pv. oryzae), and tungro virus, which collectively contribute to substantial agricultural losses. Rice blast is particularly notorious for its ability to cause yield losses ranging from 50% to 85% under favorable conditions, making it one of the most destructive diseases globally. Bacterial leaf blight, while historically devastating, has seen reduced impact due to the introduction of resistant rice varieties, yet it remains a concern during wet seasons when conditions favor its spread. Tungro virus, transmitted by leafhoppers, leads to stunted growth and yellowing of leaves, further complicating disease management strategies in rice production systems [2, 4, 6].

The increasing prevalence of these diseases is exacerbated by environmental factors and agricultural practices, such as excessive nitrogen fertilization, which can enhance susceptibility to infections. The interconnectedness of these diseases with pest populations highlights the need for integrated disease management approaches that combine resistant varieties with effective pest control

measures. Recent advancements in machine learning models, like YOLO (You Only Look Once), present promising avenues for real-time detection and classification of these diseases, enabling farmers to respond swiftly and mitigate losses. By leveraging technology to monitor and manage rice diseases effectively, the agricultural sector can enhance food security and sustainability in the Philippines [3, 5].

2.2 Machine Learning for Disease Detection

In recent years, the application of machine learning techniques for disease detection in crops, particularly rice, has gained significant attention due to its potential to enhance agricultural productivity and sustainability. Various models have been employed to identify and classify rice diseases, leveraging deep learning algorithms such as Convolutional Neural Networks (CNNs). Notably, models like ResNet-50, DenseNet121, VGG16, and MobileNetV2 have demonstrated remarkable effectiveness in accurately diagnosing rice diseases. For instance, MobileNetV2 achieved an impressive accuracy of 95.83%, while DenseNet121 reached 90% accuracy, showcasing the capability of these models to discern subtle features and complex patterns in rice leaf images. The integration of these advanced algorithms into user-friendly applications allows farmers to make timely decisions, thereby improving crop management and yield [1].

2.3 YOLO Model

The YOLO (You Only Look Once) model is a prominent deep learning approach known for its real-time object detection capabilities. YOLO transformed the field of object detection by formulating it as a single regression problem, allowing the model to predict bounding boxes and class probabilities directly from full images in a single evaluation [7]. This method significantly improves detection speed compared to traditional approaches that involve region proposal networks or sliding windows. The model's architecture has evolved through various versions, including YOLOv3 and YOLOv4, each improving the balance between accuracy and speed to handle complex scenarios more efficiently [8].

The versatility of YOLO has enabled its application across different fields, including agriculture, healthcare, and autonomous driving. In agriculture, YOLO is employed for detecting plant diseases, identifying pests, and moni-

toring crop conditions, thereby optimizing farming practices [9]. Its real-time performance also extends to medical imaging for identifying abnormalities and in autonomous vehicles for detecting objects such as pedestrians and other vehicles. These diverse applications demonstrate YOLO's utility in real-world scenarios where rapid and accurate object detection is essential.

3 Methodology

In this section, in order to satisfy the objectives of this study, there will be a need of systematic methods or steps for implementation. The following will be;

I **Data Collection and Preparation:** To collect the dataset of Philippine rice diseases, including the 13 disease classes and one healthy leaf class. The dataset will be sourced from Kaggle, specifically from the dataset titled "Philippines Rice Diseases".

II **Model Selection and Configuration:** To utilize the YOLO object detection framework and be configured for the study. This involves setting up the training environment, selecting appropriate hyperparameters, and preparing the model architecture for the specific task of detecting and classifying rice diseases. Transfer learning may be employed to leverage pre-trained weights and improve model performance, particularly if computational resources are limited.

III **Model Training and Evaluation:** The prepared dataset will be used to train the YOLO model, with the training process monitored for convergence and overfitting. Various metrics, such as precision, recall, and mean Average Precision (mAP), will be utilized to evaluate the model's performance.

3.1 Materials

3.1.1 Dataset

The dataset used for this research is sourced from Kaggle, it was collected as part of Omdena's Local Chapter project titled "Creating a Rice Disease Classifier using Open Source Data and Computer Vision."

About the Dataset:

- The dataset consists of images stored in 224 x 224 pixels resolution to facilitate the training of deep learning models.
- It includes data on rice diseases affecting plants in the Philippines, which is a crucial agricultural crop in the region. The country's humid climate and frequent rainfall create favorable conditions for various rice diseases.
- The dataset contains images categorized into 13 different rice diseases, which are grouped under three types:
  - **Fungal**: Includes diseases such as Rice Blast, Sheath Blight, Brown Spot, Narrow Brown Spot, Sheath Rot, Stem Rot, Bakanae, and Rice False Smut.
  - **Bacterial**: Includes Bacterial Leaf Blight and Bacterial Leaf Streak.
  - **Viral**: Includes Tungro Virus, Ragged Stunt Virus, and Grassy Stunt Virus.

3.1.2 Hardware and Software

The research will be conducted using the following hardware and software components:

Hardware:

- **Operating System**: Ubuntu 22.04.5 LTS x86_64
- **Host Machine**: ZenBook UX325UA_UM325UA 1.0
- **Kernel**: 6.8.0-45-generic
- **Desktop Environment**: GNOME 42.9
- **Processor**: AMD Ryzen 7 5700U with Radeon Graphics, 16 cores @ 4.372GHz
- **Graphics Processing Unit**: AMD ATI 04:00.0 Lucienne
- **Memory**: 8 GB RAM

Software:

- **Object Detection Framework**: YOLO (You Only Look Once) - A state-of-the-art object detection model used for identifying and classifying rice diseases.
- **Programming Language**: Python - The primary language used for implementing deep learning models, data preprocessing, and evaluation.
- **Deep Learning Libraries**:
  - **PyTorch** - A widely-used deep learning framework that facilitates model training and evaluation.
- **Development Tools**:
  - **Jupyter Notebook** - For interactive coding, visualization, and documentation.
  - **VSCode** - A code editor used for Python development and debugging.

The combination of these tools and technologies enables efficient model training and evaluation to build a rice disease classifier with high accuracy.

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