# Automatic Rice Seed Varietal Purity Testing Machine Using Artificial Intelligence and Automation

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# Automatic Rice Seed Varietal Purity Testing Machine Using Artificial Intelligence and Automation

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**Abstract:** *Ensuring varietal purity in rice production is vital, but currently relies on labor-intensive, subjective, and hard-to-scale methods. This study introduces an AI-based Rice Seed Varietal Purity Testing Machine that classifies NSIC Rc160, Rc216, and Rc222 seeds using a 48MP CMOS camera paired with a custom-trained YOLOv11s-seg deep learning model featuring segmentation. The system achieved a mean Average Precision (mAP@0.5) of 96.9% and an F1 score of 93%, with classification accuracies of 96.94% for Rc160, 96.38% for Rc216, and 95.83% for Rc222. Its processing speed is on par with manual testing while meeting accuracy thresholds for reliable use. Real-time seed sorting is managed by an ESP32-driven electromechanical system. Despite Rc222's morphological complexity, this solution offers a scalable, intelligent, and efficient approach for varietal certification, addressing key challenges in Philippine rice agriculture.*

**Keywords:** Rice seed varietal purity; Automated seed sorting; Computer vision in agriculture; Precision agriculture; AI-based seed classification

## 1. INTRODUCTION

Rice is a staple food for over 116 million Filipinos, yet the purity of rice seeds—critical to ensuring high yields and grain quality—is often compromised by outdated inspection methods. Manual seed classification is labor-intensive, error-prone, and inefficient for the demands of modern agriculture [1]. Impure seeds can lead to reduced productivity, unstable supply chains, and decreased market value, all of which threaten national food security.

As global rice demand is projected to increase by 40% by 2030 [2], ensuring varietal purity has become urgent. Current inspection methods cannot scale to meet this demand. This study responds to the challenge by introducing an AI-powered Automatic Rice Seed Varietal Purity Testing Machine, designed to improve speed, accuracy, and scalability in varietal classification. Utilizing deep learning and computer vision, the system uses a 48MP CMOS camera and the YOLOv11s-seg object detection algorithm, developed and trained through Roboflow and Google Colab, to classify morphologically similar rice varieties: NSIC Rc160, Rc216, and Rc222. YOLO enables real-time detection based on seed shape, size, and color, while Roboflow simplifies model training and deployment. This solution aligns with the UN Sustainable Development Goals [3], particularly:

SDG 2: Zero Hunger – by improving rice productivity,

SDG 9: Industry, Innovation, and Infrastructure – through AI adoption in agriculture,

SDG 12: Responsible Consumption and Production – by enhancing seed classification efficiency.

Through innovation in AI and automation, this system provides a pathway to more resilient and sustainable rice production in the Philippines.

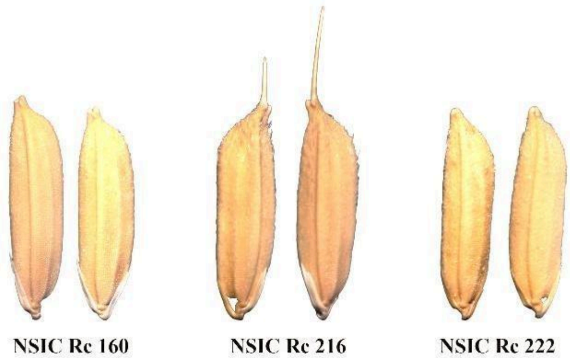


Figure 1. Sample images of the three rice seed varieties: NSIC Rc160, NSIC Rc216, and NSIC Rc222

## 2. METHODOLOGY

This chapter presents the research design and methodology used to develop an AI- and automation-based system for rice seed varietal purity testing. Building on the gaps identified in the Review of Related

Literature, this study focuses on classifying three morphologically similar rice seed varieties using machine vision, image processing, and deep learning techniques.

### 2.1 Rice Varieties for Classification

The rice seeds used for this study include three varieties: NSIC Rc160, NSIC Rc216, and NSIC Rc222. This addresses the first objective of the study: to develop and train an AI model capable of identifying the three rice seed varieties—NSIC Rc160, NSIC Rc216, and NSIC Rc222—with a target classification accuracy of at least 96%, as illustrated in Figure 1.

### 2.2 Sampling Using 48MP CMOS Camera

To build a high-quality dataset for training the AI model, high-resolution images of rice seeds were captured using a 48MP Panasonic CMOS camera sensor. The goal of this sampling process was to obtain clear, detailed, and consistent images that emphasize the morphological features of each seed. A total of 3,850 images were collected and distributed across the three rice seed varieties: 1,333 images for NSIC Rc160, 1,257 images for NSIC Rc216, and 1,260 images for NSIC Rc222. These images collectively formed the complete dataset used to train the AI model.

### 2.3 Dataset of Rice Seed Classification

The collected dataset was uploaded to Roboflow, an online platform for computer vision tasks such as object detection and image classification. Using Roboflow, each image containing multiple rice seeds was carefully annotated by drawing bounding boxes around individual seeds and labeling them according to their respective variety. The dataset includes labeled images of rice seed varieties NSIC Rc160, NSIC Rc216, and NSIC Rc222. Users could manually select each rice seed and assign its correct label, or utilize the AI Label Assist tool to accelerate and improve the accuracy of the annotation process.

### 2.4 Annotating the NSIC Rc160, NSIC Rc216, and NSIC Rc222 in Roboflow

The annotation process for the NSIC Rc160 rice seed variety was conducted using Roboflow's AI Label Assist feature. This tool automatically detected seed objects and suggested bounding boxes, which could be manually adjusted or removed if inaccurate, significantly streamlining the labeling process. During annotation, the number of seeds per image was carefully verified. Any missing or incorrect labels were corrected manually to ensure a clean and reliable dataset for AI training, a critical step in achieving the study's target classification accuracy. The same annotation method was subsequently applied to the NSIC Rc216 and NSIC Rc222 seed varieties. NSIC Rc216 seeds typically feature an awn—a tail-like extension—that serves as a distinguishing characteristic. Conversely, NSIC Rc216 seeds without an awn, allowing the model to learn these variations during training. For NSIC Rc222 seeds, the annotation process similarly involved outlining and labeling individual seeds to guide the AI model's recognition and classification.

### 2.5 Pre-processing and Augmentation

To further optimize the dataset for training the YOLO-based classification system, a series of pre processing and augmentation techniques were applied to enhance image consistency, clarity, and diversity. First, the rice seed images were resized to 640 × 640 pixels using a stretch-to-fit method. This resizing ensured compatibility with YOLO's input size requirements. While minor distortions were inevitable, the resizing process significantly improved training speed, memory efficiency, and batch processing capability without notably compromising critical visual features. To introduce further variability, geometric augmentations such as flipping and rotation were employed. It shows how vertical and horizontal flipping was used to expose the model to inverted and mirrored orientations of the seeds.

### 2.6 Using YOLO-v11 Model Variants and Capabilities

YOLOv11s-seg was selected for this study as it offers an optimal balance of speed and accuracy, making it suitable for the hardware constraints of the system and in identifying individual seeds—even when overlapping without inference speed. This balance ensures smooth integration into the automated and time-sensitive classification pipeline.

### 2.7 Model Training Epochs

The YOLOv11s-seg model was trained for 100 epochs, which provided sufficient convergence based on early experiments. This training duration allowed the model to effectively learn distinguishing features of rice seeds without overfitting. The loss functions used were Complete IoU (CIoU) loss for localization accuracy and cross-entropy loss for classification, with Stochastic Gradient Descent (SGD) as the optimizer.

### 2.8 Model Training Using Google Colab

The YOLOv11s-seg model was trained using Google Colab, applying a Tesla T4 GPU as the hardware accelerator to expedite the training process. The Ultralytics YOLO version 8.3.40 framework was used for its simplicity and robust object detection capabilities. The NVIDIA-SMI command verified the availability of the GPU (15,360 MiB memory), ensuring optimal training conditions with full resource allocation.

### 2.9 Model Deployment on Laptop

The trained model was deployed on a MacBook Air with an M3 chip, which was selected for its availability and capable performance. The device efficiently handled the rice seed varietal classification tasks during the testing phase.

### 2.10 Accuracy Test

This section involves the Accuracy Test of the machine in different ratios of TRUE-TO-TYPE or OFF-TYPE rice seed samples. The accuracy test will be carried out to determine the accuracy of the sorter. Each Test is composed of three trials. The sets of rice seeds samples that will be used for the accuracy tests will be the following: Test 1 (T1) – 120 true-to-type rice seed samples (NSIC Rc160, NSIC Rc216, NSIC Rc222) Test 2 (T2) – 100 true-to-types rice seeds samples and 20 off-types Test 3 (T3) – 60 true-to-type and 60 off-types rice seeds samples

### 2.11 Speed Test

A speed test will be conducted to compare the machine's performance against the traditional method of varietal purity testing. The time taken to sort a 500g rice seed sample will be measured based on the maximum number of seeds the machine can process. Similarly, the time required for the traditional testing of a 500g sample will also be recorded. The speed test will consist of 10 repetitions.

### 2.12 Statistical Tools

The Bayes Factor compares the prediction effectiveness of two different hypotheses (H0 and H1) where, H0 is the Null Hypothesis representing the status quo or no significant advantage (i.e., the machine performs no better than manual testing). On the other hand H1 is the Alternative Hypothesis representing the experimental condition (i.e., the machine performs better than the manual testing). The following interpretation of the strength of the evidence against the Null Hypothesis (H0):

•A Bayes factor between 0 and 2 indicates that the null hypothesis is not strongly refuted and is only worthy of passing notice.

•A Bayes factor between 2 and 6 means that there is positive evidence against the null hypothesis.

•A Bayes factor between 6 and 10 means there is strong evidence against the null hypothesis.

•A Bayes factor that is greater than 10 means there is very strong evidence against the null hypothesis. The Alternative Hypothesis (H1) is the speed of the Automated Rice Varietal Purity Testing Machine is significantly faster than the manual testing.

### 2.13 System Overview


Figure 2. General Framework of the Study

In the automated rice seed varietal testing machine, illustrated in Figure 2, the Input-Process Output (IPO) framework ensures efficient seed testing. The system is designed to separate off-type rice seeds from true-to-type varieties. During the input phase, a 500g sample of rice seeds is fed into the machine, and the user selects the variety for comparison. These inputs are critical to the machine's performance and effectiveness. The process phase involves the sorting mechanism, where the machine uses a conveyor belt, powered by a stepper motor, to regulate the movement of the seeds. This controlled flow leads the sample to the AI detection stage, where a CMOS camera analyzes each seed to determine if it matches the chosen variety based on its morphological features, such as length, width, shape, and color. If any irregularities or mismatches are detected, the system activates an ejector mechanism to divert the off type seeds. In the output phase, the machine delivers two sorted categories: true-to-type and off-type rice seeds.

### 2.14 Block Diagram Figure

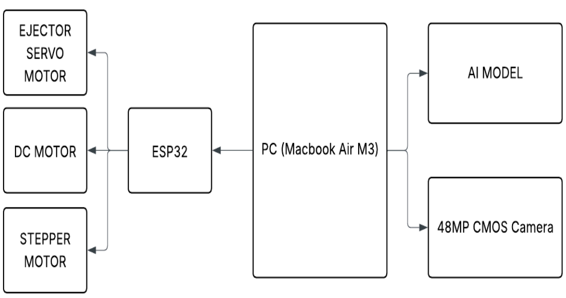


Figure 3. Block Diagram of the System

The system architecture illustrates a PC (MacBook Air M3) at the core, managing motor controls and image processing. A high-resolution 48MP CMOS camera captures visual data, which is processed by an AI model running on the PC for decision-making tasks. The PC communicates with an ESP32 microcontroller to control various actuators: a stepper motor for precise movement, a DC motor for continuous rotation, and an ejector servo motor for selective actuation. This setup enables efficient automation guided by real-time image analysis and intelligent control.

### 2.15 Overall System

Once the user selects the variety for testing, the rice seed samples are first directed to the feeder as the process starts. The seeds are then transferred onto a conveyor belt, which moves them to the imaging system. The camera examines the seeds to determine if they match the selected variety (true-to-type) or not (off-type). If a seed is off-type, the system uses an ejector to redirect it into a designated cylindrical bin for rejected seeds. After that, a lamp is turned on to check further if it is a different variety. On the other hand, if the seed matches the selected variety's characteristics, it is automatically deposited into a separate bin labeled for true-to-type seeds.

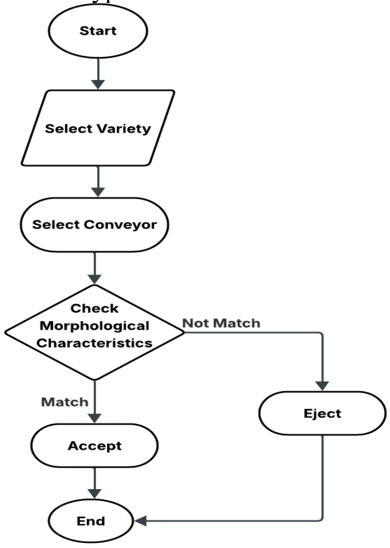


Figure 4. System Flowchart

### 2.16 Motor Control System

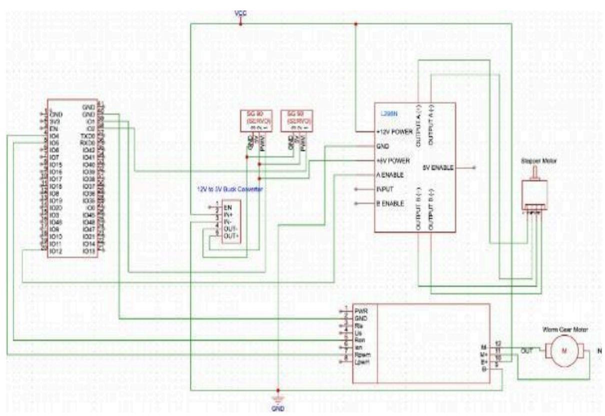

Figure 5 illustrates the integration of an ESP32 microcontroller with various motor drivers and actuators for the automated seed varietal purity testing system. The diagram shows the connection of SG90 servo motors, an L298N stepper motor driver, and a worm gear motor, all powered and regulated through a 12V to 5V buck converter. This configuration enables precise coordination of mechanical movement and reliable communication, which are essential for the system's automated operation.

### 2.17 Overall Design Construction

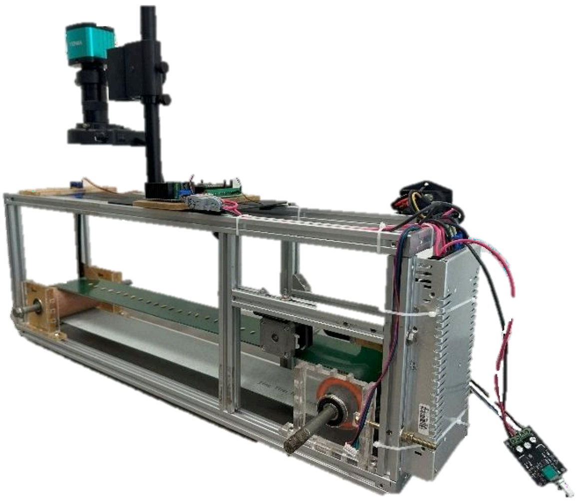

Figure 6. Hardware Overview

The Figure 6 comprises a rigid aluminum extrusion frame that carries a belt-driven seed conveyor, an CMOS camera with integrated LED illumination, and a compact control-electronics enclosure—together forming the complete hardware foundation of the automatic rice-seed varietal-purity testing.

## 3. RESULTS AND DISCUSSION

This chapter presents the results of testing the Automatic Rice Seed Varietal Purity Testing Machine Using Artificial Intelligence and Automation. It analyzes the system's performance in sorting rice seeds into true to-type and off-type categories, highlighting machine accuracy, speed under different test conditions, and comparisons to traditional manual methods.

### 3.1 Confusion Matrix

Figure 7 shows the confusion matrix for six classes, including background. NSIC Rc160 and NSIC Rc216_w/o_awn achieved the highest correct classifications with 867 and 506 instances, respectively. However, background misclassification was the most common error, notably affecting NSIC Rc160 (90 instances) and NSIC Rc216 (54 instances). Some confusion also occurred between morphologically similar varieties, such as NSIC Rc216 and NSIC Rc216_w/o_awn, and between NSIC Rc222 and NSIC Rc222_w_o_stain. The system demonstrated strong classification accuracy but requires improved background filtering and finer feature discrimination to enhance robustness in varietal purity assessment. background filtering and finer feature discrimination to enhance robustness in varietal purity assessment.

### 3.2 Training and Validation Loss Curves

Figure 8 illustrates the model's training and validation performance over 100 epochs, showing consistent declines in both training and validation losses across all tasks—bounding box regression, segmentation, classification, and objectness—indicating effective learning and minimal overfitting. Precision and recall for both bounding boxes and masks steadily increased, while mAP50 and mAP50-95 scores also improved, nearing optimal values. These trends confirm the model's strong accuracy, stability, and generalization, demonstrating its reliability for automated rice varietal purity assessment.

### 3.3 Classification Performance Metrics

Figure 9 shows the F1-Confidence Curve for all classes, with an overall F1 score of 0.93 at a confidence threshold of 0.616. Most classes maintained high F1 scores across confidence levels, except for NSIC Rc222 without stain, which showed consistently lower performance—likely due to reduced visual features after stain removal—indicating difficulty for this variant.

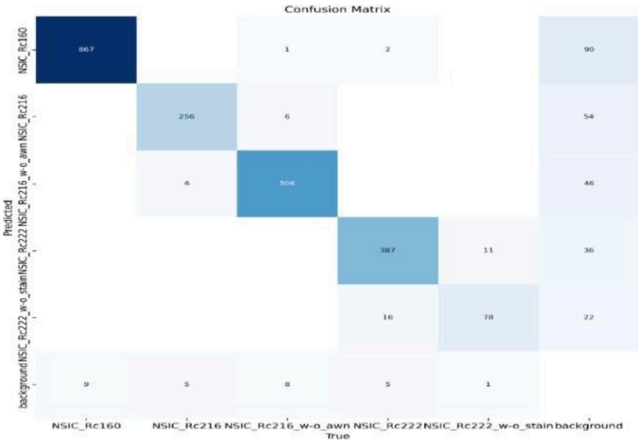


Figure 7. Confusion Matrix of the Rice Variety

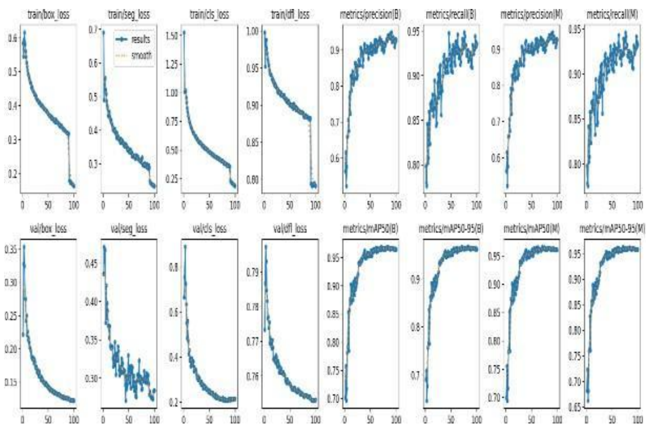


Figure 8. Training and Validation Loss Curves and Evaluation Metrics Across 100 Epochs

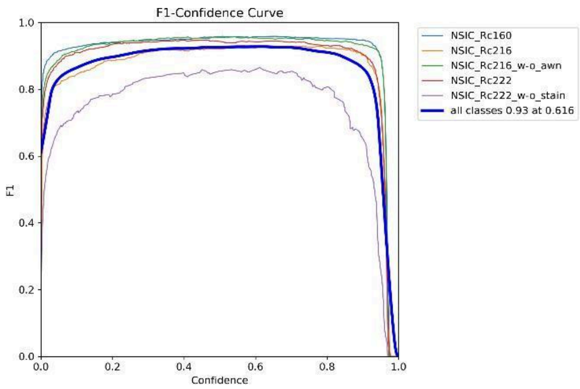


Figure 9. Precision-Confidence Curve of the Classification Model

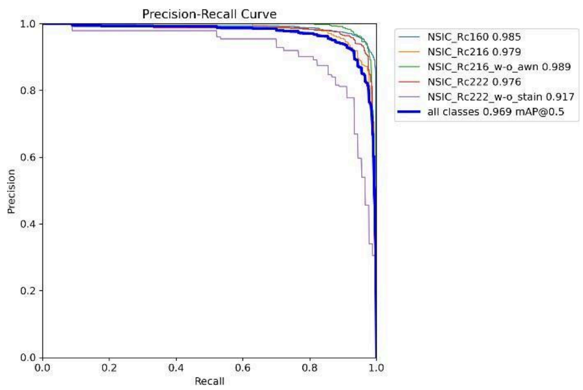


**Figure 10.** Precision-Recall Curve of the Classification Model

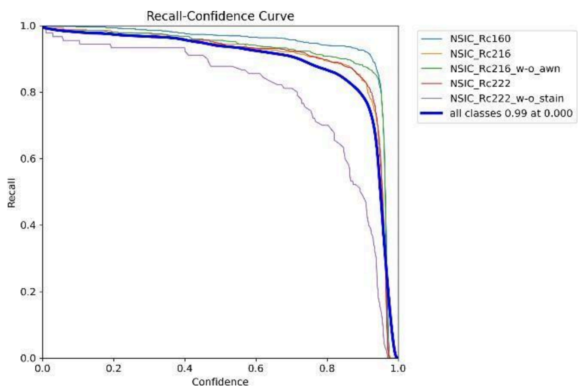


**Figure 11.** Recall-Confidence Curve of the Classification Model

Figure 10 presents the Precision-Recall Curve, with an overall mAP@0.5 of 0.969, reflecting strong model performance. NSIC Rc160 achieved the highest AP (0.985), while NSIC Rc222 without stain had the lowest (0.917), highlighting classification challenges for this variant. Most classes showed tightly clustered curves, indicating consistent precision and recall.
Figure 11 shows the Recall-Confidence Curve, where NSIC Rc222 achieved the highest recall, followed by NSIC Rc216 and Rc160. Models without stain or awn processing—NSIC Rc216_w-o_awn and NSIC Rc222_w-o_stain—performed worse, especially at lower confidence levels. The sharp drop in recall for NSIC Rc222_w-o_stain highlights the impact of removing stain pre-processing. The averaged curve (all classes) confirms strong overall recall, emphasizing the value of complete data preparation for reliable classification.

### 3.4 Detection and Classification Results for NSIC Rc160, NSIC Rc216, NSIC Rc222

The detection and classification results for NSIC Rc160, NSIC Rc216, and NSIC Rc222 were evaluated through three tests. Each test assessed the system's capability to accurately detect true-to-type seeds, identify off-types, and analyze misclassifications. The results for NSIC Rc160 are summarized in Table 1.
The system achieved high detection accuracy for NSIC Rc160 in pure samples. However, the presence of off-types in Tests 2 and 3 slightly reduced the detection rate, mainly due to misclassification with NSIC Rc216 and NSIC Rc222. The classification performance for NSIC Rc216 is presented in Table 2.

**Table 1.** Analysis for NSIC Rc160

| **NSIC Rc160** | **True -to-Type** | **Off-type** | **No-detection** | **Mis detection** | **Misdetected as (True/Predicted)** |
|---|---|---|---|---|---|
| **TEST 1** | 119 | 0 | 0 | 1 | NSIC **Rc222** |
| **TEST 2** | 100 | 8-Rc216<br>9-Rc222 | 0 | 3 | 1-**Rc222**/Rc160<br>2-**Rc216**/Rc160 |
| **TEST 3** | 58 | 28-Rc216<br>27-Rc222 | 0 | 7 | 2-**Rc160**/Rc216<br>2-**Rc222**/Rc160<br>1-**Rc222**/Rc216<br>2-**Rc216/160** |

**Table 2.** Analysis for NSIC Rc216

| **NSIC Rc216** | **True -to-Type** | **Off-type** | **No-detection** | **Mis detection** | **Misdetected as (True/Predicted)** |
|---|---|---|---|---|---|
| **TEST 1** | 119 | 0 | 0 | 1 | NSIC **Rc160** |
| **TEST 2** | 99 | 8-Rc222<br>9-Rc160 | 0 | 4 | 1-**Rc216**/Rc160<br>1-**Rc160**/Rc216<br>1-**Rc222**/Rc216<br>1-**Rc222**/Rc160 |
| **TEST 3** | 59 | 26-Rc222<br>27-Rc160 | 0 | 8 | 2-**Rc222**/Rc160<br>1-**Rc216**/Rc160<br>3-**Rc160**/Rc216<br>2-**Rc222**/Rc216 |

NSIC Rc216 also showed a high detection rate, particularly in Test 1. Misclassification primarily occurred when off-types were present, often involving confusion with NSIC Rc160 and NSIC Rc222 seeds. The detection performance for NSIC Rc222 is shown in Table 3.

**Table 3.** Analysis for NSIC Rc222

| NSIC Rc222 | True-to-Type | Off-type | No-detection | Mis detection | Misdetected as (True/Predicted) |
|---|---|---|---|---|---|
| **TEST 1** | 118 | 0 | 0 | 2 | 1-NSIC **Rc160** 1-NSIC **Rc216** |
| **TEST 2** | 97 | 9-Rc160, 10-Rc216 | 0 | 4 | 2-**Rc222**/Rc160 1-**Rc222**/Rc216 1-Rc160/Rc222 |
| **TEST 3** | 56 | 27-Rc216 28-Rc160 | 0 | 9 | 4-**Rc222**/Rc216 3-**Rc216**/Rc160 2-**Rc160**/Rc222 |

NSIC Rc222 exhibited significantly lower detection accuracy across all tests. A large number of seeds were misclassified, mostly as NSIC Rc160. This result suggests that distinguishing NSIC Rc222 remains a challenge for the developed system, likely due to its close morphological similarities with the other varieties.

**Table 4.** Overall Percentage of the three rice seed varieties

| | |
|---|---|
| NSIC Rc160 | 96.94% |
| NSIC Rc216 | 96.38% |
| NSIC Rc222 | 95.83% |

The system achieved high accuracy in identifying NSIC Rc160 and NSIC Rc216, with overall classification percentages of 96.94% and 96.38% respectively, indicating reliable performance for these varieties. In contrast, NSIC Rc222 showed a significantly lower accuracy at 95.83%, suggesting challenges in distinguishing its features, which may be due to similarities with other varieties or limited image data quality. This highlights the need for further optimization to improve the detection of NSIC Rc222.

### 3.5 Comparison of Automated and Traditional Manual Testing Accuracy: Bayesian Analysis

**Table 5.** Accuracy Comparison via Bayesian Analysis

$H_0$: Accuracy of Automated Varietal Purity Testing Machine < Accuracy of Traditional Manual testing
$H_1$: Accuracy of Automated Varietal Purity Testing Machine = Accuracy of Traditional Manual testing

| | NSIC Rc160 | NSIC Rc216 | NSIC Rc222 |
|---|---|---|---|
| **Prior Odds** | 95% | 95% | 95% |
| **Posterior Odds** | 96.94% | 96.38% | 95.83% |
| **Bayes Factor** | 1.67 | 1.21 | 1.40 |
| **Kass and Raftery's Scale** | 1-3 | 1-3 | 1-3 |
| **Interpretation** | Weak evidence in favor of the model | Weak evidence in favor of the model | Weak evidence in favor of the model |

The Bayesian analysis shows that all three rice varieties—Rc160, Rc216, and Rc222—have Bayes Factors close to 1, indicating minimal evidence favoring the automated system over manual testing. Despite this, the posterior odds remain slightly higher than the prior, supporting the system's aim of achieving functional equivalence with traditional methods in terms of accuracy.

**Table 6.** Speed Test

| Replicates | Speed grains/minute |
|---|---|
| **1** | 555 |
| **2** | 569 |
| **3** | 570 |
| **4** | 559 |
| **5** | 561 |
| **6** | 568 |
| **7** | 560 |
| **8** | 566 |
| **9** | 564 |
| **10** | 570 |
| **Average:** | **564.2** |

The speed test was conducted across 10 replicates, measuring the number of grains processed per minute. Results ranged from 555 to 570 grains/minute, with an average speed of 564.2 grains/minute. This indicates that the automated machine operates at a consistent and efficient rate, supporting its potential for practical use in high-throughput seed testing applications.

## 4. CONCLUSION

An Automatic Rice Seed Varietal Purity Testing Machine using AI and automation was successfully developed to classify NSIC Rc160, Rc216, and Rc222. The system achieved classification accuracies of 96.94%, 96.38%, and 95.83%, meeting the target benchmark of 96%. A Bayes Factor of 1.002 indicates weak evidence favoring the machine's performance as comparable to manual testing. Although the difference is not statistically significant, the results support the objective of achieving functional parity with traditional methods. The system's processing speed is on par with manual testing while meeting accuracy thresholds, confirming its reliability and potential for real-world agricultural application. 5. Recommendations To enhance the system's applicability, the AI model should be trained to recognize a broader range of rice varieties beyond the currently supported NSIC Rc160, Rc216, and Rc222. This includes commonly encountered varieties such as pigmented rice (e.g., black and red rice) and purple-tipped rice. A more balanced dataset—both in terms of class distribution and sample quantity—is essential to improve model generalization. Furthermore, improved imaging conditions and consistent data acquisition practices are recommended to enhance the overall quality and stability of the dataset. Although exporting the model to various formats (e.g., TensorRT, ONNX, CoreML) is critical for optimizing performance across different hardware architectures, this step was constrained by resource limitations. Specifically, exporting to these formats often requires distinct computing environments, which were not readily accessible during the development phase. Benchmarking tests conducted on a cloud-based system utilizing an NVIDIA RTX 4090 GPU demonstrated that the TensorRT format achieved the highest inference speed, reaching up to 456 FPS. Based on these results, the researchers recommend future studies explore deployment using TensorRT, ONNX, and CoreML formats to optimize performance across diverse computing platforms.

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