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RICE GRAIN TRAIT ESTIMATION USING COLOR SPACE CONVERSION AND DEEP LEARNING-BASED IMAGE SEGMENTATION

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ABSTRACT

Accurately extracting traits from rice grains is of importance for effective crop management and yield estimation, providing valuable understanding for improving agricultural practices. However, manual intervention in these tasks is labor-intensive, time-consuming, and error-prone. This research proposes a new approach that leverages low-cost digital cameras and deep learning technology for counting and extracting rice grain traits. Our study introduces a preprocessing step to separate rice grain regions from the input image background using color space conversion. After that, a deep learning image segmentation model based on YOLOv8 is utilized for the extraction of both the number and morphological traits of the grains. The accuracy of the proposed method was experimented on 88 different rice varieties provided by the Plant Resource Center in Hanoi. The experimental results show that the proposed approach is high-accurate and high-throughput for low-cost extraction of rice grain traits from color digital images, which is potentially helpful in facilitating effective evaluation in rice breeding programs and functional gene identification of rice varieties.

ƯỚC LƯỢNG KIỂU HÌNH HẠT LÚA BẰNG PHƯƠNG PHÁP ĐỔI HỆ MÀU VÀ PHÂN ĐOẠN ẢNH DỰA TRÊN HỌC SÂU

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YOLOv8

TÓM TẮT

Việc trích chọn đặc điểm kiểu hình của hạt lúa một cách chính xác là việc rất quan trọng trong việc quản lý và ước lượng năng suất trồng lúa một cách hiệu quả, đồng thời mang lại những hiểu biết quý giá để cải tiến các phương pháp nông nghiệp. Tuy nhiên, thực hiện thủ công các công việc này là rất tốn công sức, tốn thời gian và dễ gây sai sót. Nghiên cứu này đề xuất một phương pháp mới sử dụng máy ảnh kỹ thuật số giá rẻ và công nghệ học sâu để đếm và trích chọn các đặc điểm kiểu hình của hạt lúa. Nghiên cứu của chúng tôi giới thiệu một bước tiền xử lý để phân tách các vùng hạt lúa từ nền ảnh đầu vào bằng cách chuyển đổi không gian màu. Sau đó, một mô hình phân đoạn ảnh dựa trên học sâu dùng YOLOv8 được sử dụng để đếm số lượng và trích chọn các đặc điểm kiểu hình của hạt lúa. Độ chính xác của phương pháp đề xuất được thử nghiệm trên 88 giống lúa khác nhau được cung cấp bởi Trung tâm Tài nguyên Thực vật tại Hà Nội. Kết quả thực nghiệm cho thấy phương pháp đề xuất có độ chính xác cao và có khả năng xử lý lượng lớn ảnh màu với chi phí thấp để trích chọn đặc điểm kiểu hình của hạt lúa. Kết quả này có tiềm năng trong việc hỗ trợ các chương trình lai tạo giống lúa và xác định các gene chức năng của các giống lúa.

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1. Introduction

Rice (Oryza Sativa), as a fundamental cereal crop on a global scale, holds the utmost importance. Enhancing rice yield and quality is essential to meet the rising demand for food worldwide [1]. Accurate data regarding rice yield plays a critical role in effectively managing rice production. It guides agricultural practices, such as planting strategies, and assists in making informed decisions about breeding [2]. These practices and decisions are linked to the grain phenotype of rice. Therefore, accurately counting and measuring morphological-related traits in rice varieties is crucial for rice breeding and functional gene identification.

(a) Rice variety G1 *(b) Rice variety G20* *(c) Rice variety G7*

Figure 1. *Samples of rice grain images*

Over the last few decades, scientists have traditionally used manual techniques to measure rice grain traits [3]. These methods, which involve threshing and manual measurements, are usually time-consuming, labor-intensive, and prone to human error [4], [5]. Furthermore, the process of threshing can also impact the accuracy of the results due to its destructive nature [6], [7]. In recent years, image processing and computer vision technologies have emerged as cost-effective and easily implementable methods for crop recognition and counting [8], [9]. These approaches perform the segmentation and counting of the crops by extracting visible characteristics of crops such as color, size, shape, and texture through image processing and analysis [10], [11].

Regarding phenotyping methods for crops, many methods are proposed to extract important phenotypic traits of the rice grains using image processing and machine vision algorithms [12]. For instance, researchers in [13] proposed to minimize shielding effects in the analysis of rice grain traits by separating multiple branches of a single rice panicle. Others [14]-[16] employed X-ray imaging systems to compute panicle traits in rice. These methods, however, are still high-cost due to the use of X-ray images. This limitation prevented the widespread adoption and advancement of such phenotyping methods. To address these challenges, this study proposes a new method that leverages low-cost digital cameras and deep learning technology for accurately counting and extracting rice grain traits from color digital images (Figure 1). The main points of our method are as follows:

- The proposal of a preprocessing step using color space conversion (RGB-HSV) to separate rice grain regions from the input image background;
- The utilization of a deep learning image segmentation model based on YOLOv8 for accurate extraction of both the number and morphological traits of the rice grains.

The organization of this paper is structured as follows. Section 2 presents the image dataset of rice grains and the methods used for color space conversion and image segmentation. The experiments and results of the proposed method are presented in Section 3. Section 4 demonstrates the conclusion and some future directions of this work.

2. Materials and Methods

2.1. Materials

The dataset used in this project contains 224 pictures of 224 rice varieties. The rice seeds were provided by the Plant Resource Center (located in An Khanh, Ha Noi, Vietnam). A core collection included 224 rice landraces collected from different provinces in Vietnam. The rice seed image database was provided by the International joint laboratory LMI-RICE (USTH/AGI/IRD/UM) in which rice seeds were captured right after receiving from the Plant Resource Center (PRC). The images in the dataset were captured using Canon digital cameras, ensuring uniformity in terms of distance from the rice grains, lens type, lighting conditions, and aperture settings. Each image includes a label that provides the rice grain's variety name and a 13.5 cm long ruler, facilitating the estimation of measurement parameters in subsequent analysis (Figure 1). An Excel file provided by the PRC, which comprises the length and the width of 88 rice varieties out of 224 rice varieties from the pictures, is used to verify the accuracy of the proposed method in this work. These width and length values are measured by the biologists using a specialized ruler and considered the ground truth values of the rice grain traits.

2.2. Methods

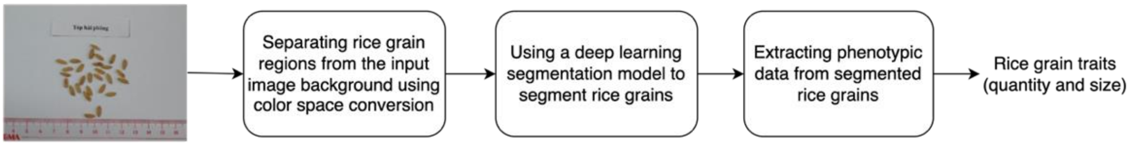


Figure 2. *Illustration of the proposed method*

The proposed method contains three main steps (Figure 2). The first step is to separate rice grain regions from the input image background using RGB-HSV color space conversion. After that, a deep learning segmentation model (YOLOv8) is utilized to segment the rice grains. Finally, the phenotypic data (the width and height) of the rice grains are extracted from the segmented rice grains using the fit Ellipse technique of the OpenCV library.

2.2.1. Separating rice grain regions from the image background

The input images are provided in the RGB color space. To separate rice grains from the input image background, the images are first converted from RGB to HSV color space (Figure 3). We chose HSV color space since it has an intuitive representation of colors and better control over color information compared to other models like RGB or CMYK. HSV is often the preferred choice for segmenting objects based on color, particularly when color is the most distinctive feature of the object. Its ability to separate color information from brightness information makes it advantageous, especially in scenarios with varying lighting conditions or shadows. By focusing on the hue and saturation channels, HSV allows for consistent color-based segmentation, as changes in brightness have less impact on these channels. This is particularly useful when segmenting rice grains based on their color, as variations in lighting or shadows primarily affect brightness, while the hue and saturation values remain more stable. By setting appropriate thresholds in the hue and saturation channels, the rice grains can be effectively isolated based on their color, irrespective of brightness variations. In HSV color space, the image is then thresholded in Hue and Saturation channels to obtain the rice mask (the black image in Figure 3).

Since the natural color range of the rice grains is within the orange and yellow, the range of the Hue value approximately between 10 to 40 should be chosen to perform color thresholding. In this work, to ensure more accurate thresholding, the blue and red color ranges are also included, resulting in a broader range from 0 to 80 for the Hue values to perform color thresholding in HSV color space. For Saturation, the analysis of data shows that the highly saturated areas extend beyond the yellow range in which the saturation intensity is significantly higher in the background compared to the desired foreground (represented by the yellow region). Based on the analysis, a Saturation value of 60 and above is selected to perform Saturation thresholding in HSV color space.

By applying the Hue ranges from 0 to 80 and Saturation values of 60 and above, the rice mask (the black image in Figure 3) effectively captures the desired foreground (the rice grain regions) while excluding the background. This set of rice masks is then used to perform rice grain segmentation in the next step of the proposed method.

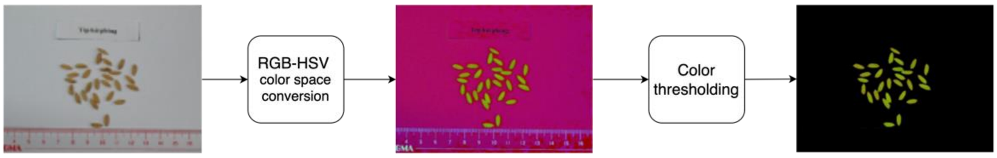


Figure 3. *Workflow to separate rice grains from the input image background*

2.2.2. Rice grain segmentation based on YOLOv8

YOLOv8 is a state-of-the-art object detection model developed by the Ultralytics team [17]. It is widely used in computer vision applications. YOLOv8 has the same architecture as YOLOv5 with major improvements such as the addition of anchor-free detection or the introduction of new neural network architecture using both Feature Pyramid Network (FPN) and Path Aggregation Network (PAN), etc. In this work, YOLOv8 is utilized to perform image segmentation of rice grains (Figure 4). From the figure, the CNN backbone (CSPDarknet53) is applied to extract the rice grain features. After that, the image objects of different sizes and shapes are detected using the FPN and PAN of YOLOv8. Finally, each detected bounding box is passed through the YOLO segmentation head to obtain the rice masks (the output of Figure 4). A visualization of the feature maps extracted by the CSPDarknet53 backbone is presented in Figure 5.

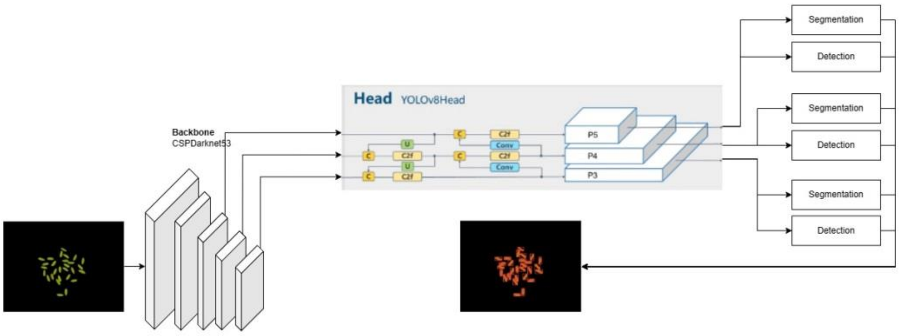


Figure 4. *Rice grain segmentation model based on YOLOv8* [18]

Figure 5. *Illustration of feature maps extracted by CSPDarknet53 backbone*

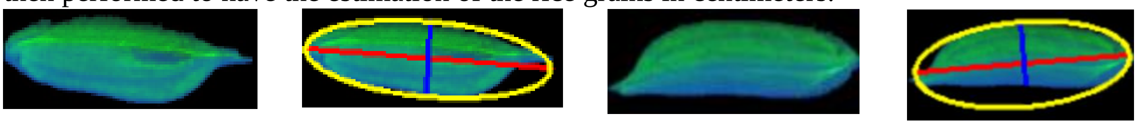
The main hyperparameter settings of YOLOv8 for rice grain segmentation are presented in Table 1. To train and infer the YOLOv8 segmentation model, a total of 224 input images of rice grains were provided. After manual labeling, these images were divided into training, validation, and test sets containing 140, 40, and 44 images, respectively. After 120 epoch number of model training and validation, the YOLOv8 model was selected for testing on 44 images of the test set. After the testing phase, the model obtains an Average Precision (AP) value of 99.5% with a default threshold IoU of 0.5. Hence, it is utilized to perform rice grain segmentation in this work.

Table 1. *Hyperparameter settings of YOLOv8 for rice grain segmentation*

Hyperparameter	Setting
Image size	1834x1376 pixels
Batch size	1
Optimizer	AdamW
Learning rate	0.002
Momentum	0.9
Maximum epoch number	200

2.2.3. Rice grain trait extraction

The contours and the “fitEllipse()” function from the OpenCV library are employed to extract the major and minor axes of each rice grain. The major axis represents the length and the minor axis represents the width of the grain (the cases (a) and (b) of Figure 6). In some cases, the rice grains may be bent (the cases (c) and (d) of Figure 6). To account for this, the minimum distance from the center of the ellipse to the contour and half of the minor axis length is calculated and added. This provides an estimate of the grain width. By averaging the length and width across all contours, the estimated length and width of the rice grains are obtained in pixels. A conversion is then performed to have the estimation of the rice grains in centimeters.



(a) HSV image of normal grain *(b) Morphological traits of normal grain* *(c) HSV image of bent grain* *(d) Morphological traits of bent grain*

Figure 6. *Rice grain trait extraction*

3. Experimental Results

3.1. Evaluation metrics

The evaluation metrics used to evaluate the proposed method are R^2 coefficient, mean absolute percentage error (MAPE), root mean square error (RMSE) and the difference between the mean of the estimated size traits and the mean of the actual size traits measured by the biologists (DIFF) [19]. In this paper, we did not use object detection and segmentation metrics (such as Jaccard Index) since we evaluate the correctness of the major and minor axes from the estimated ellipse-like shape, which is in our dataset provided by the biologists. Additionally, it is important to note that not all grains are assumed to have an elliptical shape, and therefore, the shape area is not evaluated in this context. The following equations calculate these metrics mentioned above:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \qquad MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\%$$

$$DIFF = \left|\frac{\bar{\bar{m}} - \bar{m}}{\bar{m}}\right| \times 100\% \qquad RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

where $\hat{y}_i$ is the predicted value, y_i is the real value, $\bar{y}_i$ represents the average of real values in the samples; $\bar{\bar{m}}$ is the mean of the estimated values; $\bar{m}$ is the mean of the actual values; n is the number of samples.

3.2. Experimental setup

This experiment was run on a server equipped with 2 Intel(R) Xeon(R) Gold 5222 CPUs @ 3.80GHz, 512 GB system memory and 4 NVIDIA GeForce RTX 3090 GPUs (24 GB graphic memory each). The software environment uses Python language under an Ubuntu operation system with Pytorch deep-learning framework.

3.3. Results

Table 2. *Difference between the mean of the estimated size traits and the mean of the actual size traits. The smaller the values are the better.*

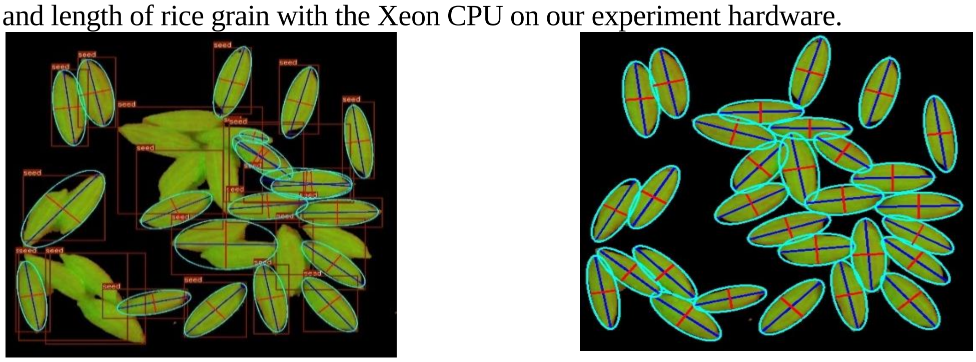
Type	Trait	DIFF (%)			
		Our method	Smartgrain [19]	YOLO-NAS + SAM + fitEllipse	SAM + fitEllipse
Quantity trait	Grain number	0.089%	32.13%	8.56%	33.75%
Size trait	Mean value of grain length	0.14%	17.56%	0.31%	1.06%
	Mean value of grain width	0.24%	22.50%	5.64%	5.06%

From Table 2, our method obtains more accurate estimation of quantity and size traits of the rice grains from the color digital images than the compared methods (Smartgrain [19], YOLO-NAS with SAM, and SAM only).

Table 3. *Performance comparison of the proposed method and the latest ones*

Model	Number of varieties	R^2		RMSE (mm)		MAPE (%)		Time spend (each image)
		Width	Length	Width	Length	Width	Length	
Pix2Pix + findContour [20]	08	0.96	0.83	0.68	0.18	7.15	5.76	10s
YOLOv8 + fitEllipse	88	0.70	0.80	0.23	0.33	5.85	2.85	0.47s
YOLO-NAS + SAM + fitEllipse	88	0.56	0.78	0.29	0.35	8.02	3.08	0.59s
SAM + fitEllipse	88	0.54	0.52	0.3	0.52	8.07	3.75	37.78s

Table 3 shows that our method outperforms the state-of-the-art methods in automatic rice trait estimation in terms of the MAPE metric and the time processing and trait calculation for each rice grain image. For RMSE, our method gains better results than others for width trait but lower ones for length trait (0.33 mm vs. 0.18 mm). Regarding R^2 metric, although our method obtains lower outputs than in [20] (0.70 vs. 0.96 for width and 0.80 vs. 0.83 for length), it can be explained that our method is performed on 88 varieties of rice while the method in [20] only experimented in 08 varieties of rice. In terms of inference speed, our proposed method takes 1.283 seconds to estimate width and length of rice grain with the Xeon CPU on our experiment hardware.



YOLO-NAS + SAM + fitEllipse *YOLOv8 + fitEllipse*

Figure 7. *Visualization of detection and segmentation results on dense rice grain images*

From Figure 7, in the cases of image with densely-packed rice grains, YOLO-NAS encompasses them together inside a bounding box. Consequently, the predicted masks generated by SAM become less accurate (left). In contrast, YOLOv8 works better in those cases (right).

4. Conclusions and Future Works

In this study, a new deep learning-based method was proposed for low-cost counting and extracting phenotyping traits of rice grains from the color digital images. Firstly, the method applies a color space conversion and analysis (RGB-HSV) to separate rice grains from the image background. After that, a deep learning segmentation model based on YOLOv8 is employed to segment the rice grains. Finally, the fitEllipse technique of the OpenCV library is utilized to count and estimate the rice grain traits. The accuracy of the proposed method was verified on 88 different rice varieties provided by the PRC. The evaluation shows that our method is high-accurate and high-throughput for low-cost extraction of rice grain traits from color digital images.

In the future, there are several potential directions to continue this work. Firstly, the development of visible-light scanning devices could provide images of rice grains with more consistent lighting conditions and potentially eliminate shadows. Next, more robust image processing techniques could be developed to overcome reliance on color space, as certain rice varieties with darker colors may yield suboptimal images after preprocessing. Last but not least, the study on more rice varieties and more rice grain traits can also be a potential direction to continue this work.

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