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Thai Hom Mali rice grading using machine learning and deep learning approaches

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ABSTRACT

Thai Jasmine rice or Thai Hom Mali rice is a well-known rice type that originated in Thailand. Rice grain qualities are important in determining market pricing and are used in grading systems. The purpose of this research is to use machine learning and deep learning to improve the grading of Thai Hom Mali rice following standardized grading criteria. The appearance of grains and foreign items will determine the grade of rice. The experiment has two parts: grain categorization and rice grading. Multi-class support vector machine (SVM) and convolutional neural network (CNN) are proposed. There are 15 features used as input for multi-class SVM, including morphology and color features. With ImageNet pre-trained weights, CNN with DenseNet201 architecture is implemented. The experiment also tested into how CNN worked with both original and preprocessed images. The results are then compared to a neural network (NN) baseline approach. The CNN approach, which identified each rice variety using preprocessed images, archieved the greatest accuracy rate of 98.25%, with an average accuracy of 94.52% across six categories of rice grading.

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1. INTRODUCTION

Rice has been a staple food of the world for thousands of years. In Asia, there are numerous rice varieties. Jasmine rice is regarded the greatest rice in Thailand, and it is growing increasingly popular among rice consumers all over the world. Thai jasmine rice or Thai Hom Mali rice [1], [2] is valued on the market based on a variety of factors. Some of these properties include texture, shape, color, and fracture rate. Manually evaluating or categorizing grains by human visual inspection is time-consuming, inconsistent, and restricted to the evaluator's experience due to the human factor. Computer-based with image processing techniques are being used to grading seeds automatically, which helps to speed up and improve the accuracy of the process. Rice quality grading is an important aspect of the processes used in the rice-producing businesses to evaluate rice quality and to define rice pricing in the commercial market [3], [4].

Several researches have addressed machine learning algorithms for evaluating rice grains [5]–[10], but none have discussed rice grading for exporting. For export, Thai Hom Mali rice is separated into two categories [1]: white rice and white broken rice. White rice is divided into four grades: 100% white rice, 5% white rice, 10% white rice, and 15% white rice. White broken rice is divided into two grades: A1 extra super white broken rice and A1 super white broken rice. Each rice grade is identified by the presence of whole kernels, broken kernels, red kernels, yellow kernels, chalky kernels, damaged kernels and undeveloped and immature kernels. Each grade of rice has different properties depending on what is contained in the rice. The present of whole kernels, broken kernels, yellow kernels, chalky kernels, damaged kernel and undeveloped and immature kernels are used to grade the white rice. While the present of small while broken c1 is used to grade the white broken rice. Tables 1 and 2 represent the white rice standard and white broken rice standard, respectively. The definition of each composition is described in Table 3.

Table 1. The standards of Thai Hom Mali white rice

Grade	Grain composition (%)						
	Whole kernel	Broken kernel	Red kernel	Yellow kernel	Chalky kernel	Damaged kernels	Undeveloped and immature kernels
White rice 100%	≥60	≤0.50	≤0.50	≤0.20	≤3.00	≤0.25	≤0.20
White rice 5%	≥60	≤0.50	≤2.00	≤0.50	≤6.00	≤0.25	≤0.30
White rice 10%	≥55	≤0.70	≤2.00	≤1.00	≤7.00	≤0.50	≤0.40
White rice 15%	≥55	≥2.00	≤5.00	≤1.00	≤1.00	≤1.00	≤0.40

Table 2. The standards of Thai Hom Mali white broken rice

Grade	Grain composition (%)	
	Whole kernels	Small broken c1
A1 extra super	≤15	≤1
A1 super	-	≤5

Table 3. Definition of kernel's types

Term	Definition
Whole kernel	Rice kernels that have no broken portion
Broken kernel	Kernel fragments that remain less than 80% of the total area
Red kernel	rice kernels that are completely or partly covered in reddish colour
Yellow kernel	rice kernels with a yellow colour
Chalky kernel	Rice kernels that have area of opaque greater than 50%
Damaged kernels	Damaged rice kernel that are clearly visible to the eyes due to insect or other factors
Undeveloped and immature kernels	Rice kernel that has not fully developed and are flat
Small broken c1	small pieces of rice that pass-through sieve no. 7

There were a number of researches about rice classification using image processing [11], [12]. Many techniques were used such as k-nearest neighbors (KNN) classifier [13], [14], support vector machines (SVMs) [15], [16], neural network (NN) [17]–[21] and convolutional neural network (CNN) [22]–[24]. The most of the research based on grain separation features such as morphology, shape, color, and texture. Koklu *et al*. [18] used NN and CNN to classify fours variety of rice. The artificial neural networks technique was used to define the rice seed germination evaluation system by Lurstwut and Pornpanomchai [19]. The system used 18 features of shape, textural and color. The false positive rate was 7.66%. Mavaddati [21] proposed rice grain quality detection using principal component analysis and model learning. Jiang *et al*. [22] used deep learning and SVM to recognize rice leaf diseases. The accuracy was 96.8%. Lin *et al*. [23] proposed three rice species classification using CNN. The accuracy rate was 95.5%. Kuo *et al*. [25] implemented sparse representation-based classification to identify 30 varieties of rice grain. The images are captures by microscopy. Shape texture and color properties are used with 89.1% accuracy. SVM [16], [26] was used to classify rice with 86% and 92.22% accuracy rate corresponding. The RiceNet: CNN based [27] was used to classified Pakistani rice types. Region proposals-based CNN [28] was used to localized and classified rice types. In the literatures, CNN has demonstrated superior performance and benefits over other machine learning algorithms. High accuracy comes at the expense of a number of machine resources and a large data set.

The rice seed quality is one of the most major determinants in the rice trade. Rice grain sample is performed to determine the rice's quality. It's a technique for getting a random sample of grains that is representative of all grains in order to assess the overall quality of a pie. After that, the quality of each grain of rice will be evaluated. According to the literature review, there have been researches to determine the types of rice, but no research focused on rice quality grading for export have been performed. The objective of the study is to enhance the classification of rice grain and grading evaluation for export from Thai Hom Mali rice images based on multi-class SVM and CNN techniques. Multi-class SVM with library for SVM (libSVM) uses morphology and color features as inputs. The CNN architecture employd is DenseNet201. In addition, we performed experiments on CNN using both pre-processed and non-preprocessed images to compare the performance.

2. METHOD

In this paper, we suggested an autonomous rice grading system using machine learning and deep learning techniques. A sampling multiple grain image is used to identify a rice grade categorization. Firstly, Multi-class SVM and CNN are proposed for single rice grain categories. Then, six rice grades are classified from grain sampling image. The accuracy, time, and resource allocation of the two approaches were evaluated in terms of operational outcomes. Baseline NN approach is also tested and compared. The proposed methods are comprised of pre-processing step, rice segmentation using watershed algorithm, feature extraction, rice classification and rice adulteration detection. The system's flowchart is shown in Figure 1.

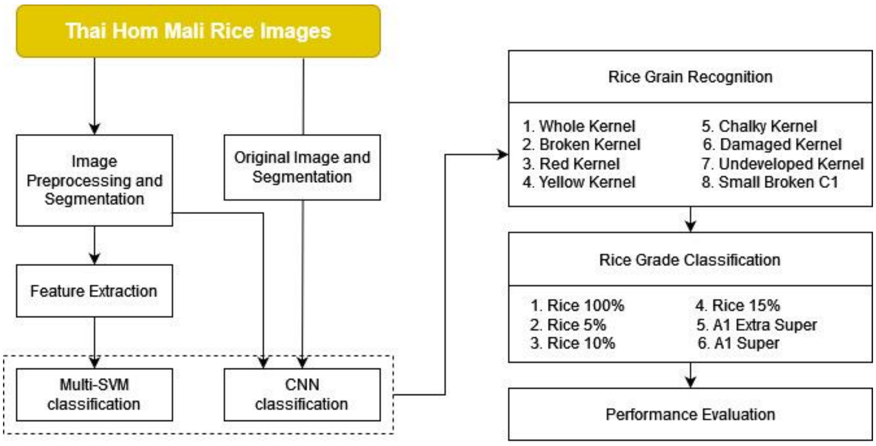


Figure 1. The proposed system's flowchart

2.1. Datasets

The dataset of Thai Hom Mali rice species 105 images used in this paper are taken by rice expert. A total of 8,000 single rice grain photos have been used, with 1,000 of each type. There are 3,000 images of rice grains in total, with 500 images for each grade. Single grain rice image resolution is 140×140 pixels. The images are captured using an ordinary mobile phone camera. The camera was placed 10 inches above the rice plate. Multiple grains image resolution is 2,500×2,000 pixels. The sample grains, which range from 100 to 130 grains of rice, are scattered out in a random manner. The image of rice grain is shown in Figure 2. The image of a single rice grain with complete kernel, fractured kernel, red kernel, yellow kernel, chalky kernel, damaged kernel, undeveloped and immature kernels, and little broken c1 are shown in Figures 2(a) to 2(h), respectively. The image of multiple rice sampling is shown in Figure 2(i).

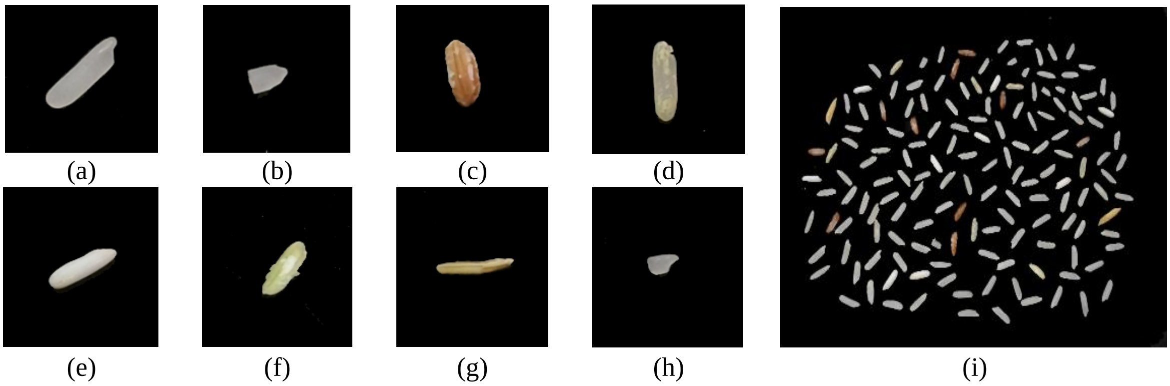


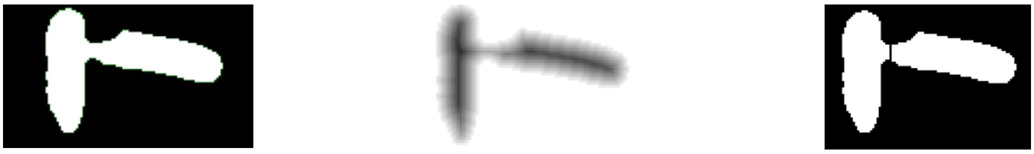
Figure 2. Rice grain (a) whole kernel, (b) broken kernel, (c) red kernel, (d) yellow kernel, (e) chalky kernel, (f) damaged kernel, (g) undeveloped and immature kernels, (h) small broken c1, and (i) multiple rices sampling

2.2. Image preprocessing

Image preprocessing step comprises of image enhancement and image segmentation. To increase the image's quality, median filtering method with mask size 3×3 is used to remove noise and histogram stretch is used to enhance the contrast. Then the image is binarized using Otsu method. Canny edge detection is then applied.

2.3. Rice segmentation using watershed algorithm

In the multiple rice kernel sampling image, some adjacent kernels can be seen. The adjacent kernel must be calculated independently for purpose of detection. The watershed transform [29] is used to separate two connected rice kernels. The watershed algorithm is based on mathematical morphology, which is concerned with an image's topographic representation. The image is addressed as a topographical layer in which the greyish value of each pixel in the input image is indicated by the elevation at each position of the surface. A reduced elevation on the surface is represented by a darkened pixel. The divisions' borders are defined by the watersheds. Two overlapping rice grains are to be separated along a watershed line. The result of segmentation is shown in Figure 3. Figure 3(a) shows two connected rice. Figure 3(b) showns the watershed applied and the disconnect rices's result is shown in Figure 3(c).



(a) (b) (c)

Figure 3. Watershed segmentation (a) two connected rice, (b) watershed, and (c) disconnect rices

2.4. Feature extraction

The images after preprocessed and segmented are used to extract the features. Morphology and color features are used. There are 15 features in the feature extraction step: 9 morphology features and 6 color features. Rice morphology feature can be used to distinguish whole grain, broken grain, damage grain and undeveloped grain. While color feature can be used to distinguish red grain, yellow grain, and chalky grain. The feature used are displayed in Table 4.

Table 4. Feature's description

Features	Description
Morphology	
1. Area	The number of the pixel in rice grain area
2. Perimeter	The perimeter of rice grain
3. Roundness	The circularity of rice grain as shown in (1)
4. Eccentricity	The distance between the ellipse's foci divided by the length of main axis
5. Major axis's length	The rice grain length
6. Minor axis's length	The rice grain width
7. Aspect ratio	The ratio of the major axis to minor axis as shown in (2)
8. Equivalent diameter	The diameter of a sphere with properties equivalent to the object as shown in (3)
9. Convex area	The area of the convex hull on the kernel
Color	
1. Average of red color	The percentage of red color
2. Average of green color	The percentage of green color
3. Average of blue color	The percentage of blue color
4. Average of hue color	The percentage of hue color
5. Average of saturation color	The percentage of saturation color
6. Average of intensity color	The percentage of intensity color

$$Roundness = \frac{perimeter^2}{4 \times \pi \times area} \quad (1)$$

$$Aspect\ ratio = \frac{length\ of\ major\ axis}{length\ of\ minor\ axis} \quad (2)$$

$$Equivalence\ diameter = \frac{2 \times area}{\pi} \quad (3)$$

2.5. Rice classification

To classify single rice grain, a total of 8,000 images are used in the experiment, including 1,000 images of each type of grain. Images are employed for training and testing in percentages of 80% and 20%, respectively. The CNN and the multi-class SVM are employed.

A SVM [30] classifies data through projecting input vectors into a higher-dimensional space and constructing a hyperplane that separates data in that space properly. libSVM [31] is used. SVM employs all of the features as input. The radial basis function is the kernel function of the SVM employed in this work. By varying the penalty value C and the kernel function parameter γ, the accuracy is examined. The optimal SVM parameter is determined using grid search. As SVM is a binary classification, multi-class SVM classifiers are created by combining several single SVM classifiers to categorize all rice types.

CNN [13], [31]–[34] is a deep learning approach that performs feature extraction, pattern identification, and classification using multiple layers of non-linear information processing. The multi-layer perceptron (MLP) is used to classify the image. DenseNet201 architecture with ImageNet pre-trained weight is used in CNN. In the training of algorithms, a 10-fold cross validation value was applied. Input layer, convolutional layer, pooling layer, flatten layer, and fully connected layer compensate a CNN. The feature will be selected automatically by the CNN as an input layer. The convolutional layer generates a feature map or kernel that can be scanned throughout the image and applied to the input image. The pooling layer lowers the size of the output from the preceding layer while preserving as many data attributes as feasible. To prepare data for entry to a fully connected layer, the flatten layer transforms multidimensional output data to one dimension. Data from every input is connected to every output node, each connection is multiplied by a different weight, and every output node can assign an appropriate activation. The CNN architecture is shown in Figure 4.

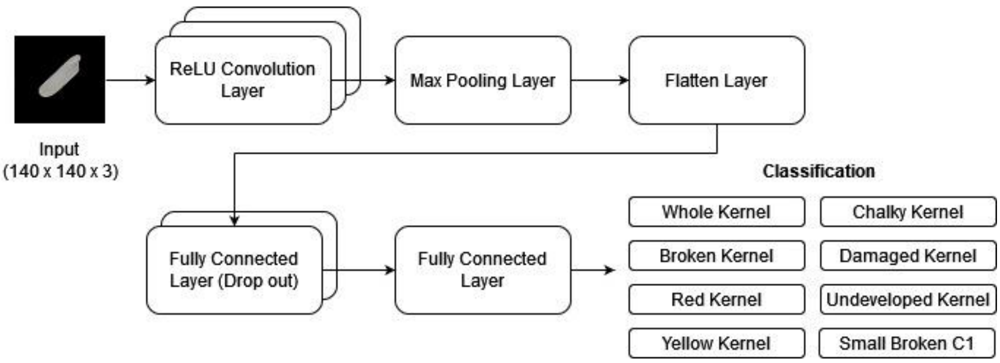


Figure 4. The proposed CNN architecture

2.6. Rice grading

To determine the rice's quality, a multi-grain image is employed. Each grain is extracted into a single grain using watershed segmentation. Each grain is then tested using a classification model to determine which class it belongs to. The proportion of grains detected is statistically computed using component standard table to determine the grade of rice.

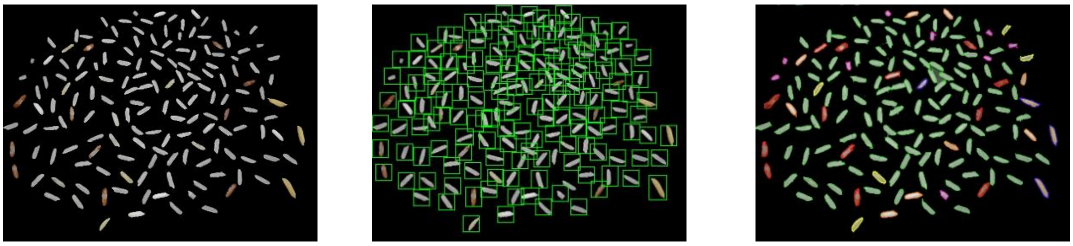
3. RESULTS AND DISCUSSION

The experiment is separated into two parts: single grain classification and rice grading. The accuracy is calculated, as in (4). The accuracy is calculated by dividing the total amount of data by the number of correct classifications. True positive (TP) and true negative (TN) data is a positive and negative data hat has been correctly classified. False positive (FP) and false negative (FN) data is positive and negative data that has been misclassified.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

Three classification result included multi-class SVM, NN and CNN are compared. CNN's performance with both original and preprocessed images was also investigated in the experiment. The CNN technique used preprocessed images has the greatest accuracy rate of 98.25%. The result from CNN is then used in the next grading experiment. The result image of rice grading was shown in Figure 5.

The multiple grains image is shown in Figure 5(a). The detected grains and classified grains are shown in Figure 5(b) and Figure 5(c), respectively. Tables 5 and 6 illustrate the accuracy rate of single grain categorization and rice grading, respectively. Average accuracy of rice grading is 94.52%.



(a) (b) (c)

Figure 5. Rice grading result (a) multiple grains, (b) detected grains, and (c) classified grains

Table 5. The result of single grain categorization

Method	Whole kernel	Broken kernel	Red kernel	Yellow kernel	Chalky kernel	Damaged kernels	Undeveloped and immature kernels	Small broken c1	Average
CNN +preprocessed image	95.12	96.68	96.87	95.23	96.67	96.58	95.55	97.31	98.25
CNN +original image	94.25	92.77	91.24	90.25	91.55	92.87	93.54	95.27	92.72
Multi-class SVM	91.52	90.12	90.11	90.50	90.11	91.54	90.25	91.27	90.68
NN	82.11	81.24	83.24	85.21	84.36	81.58	89.21	80.24	83.40

Table 6. The result of rice grading

Type	Rice 100%	Rice 5%	Rice 10%	Rice 15%	A1 extra super	A1 super
Rice 100%	92.50	2.50	3.00	2.00	0	0
Rice 5%	2.00	93.25	2.12	2.38	0	0
Rice 10%	1.75	3.25	93.75	1.25	0	0
Rice 15%	1.21	2.31	1.91	94.57	0	0
A1 extra super	0	0	0	0	97.50	2.50
A1 super	0	0	0	0	4.43	95.57

There are detection mistakes, as can be observed from the results. The major issue occurs as a result of the seeds' comparable sizes. The size of several grains is misrepresented due to the light and shadows. For example, damage kernel and underdeveloped kernel are essentially identical, resulting in an inaccurate detection. These issues can be solved by increasing the amount of training data sets in varying photography condition. The result shown that deep learning technique with CNN outperforms machine learning with multi-class SVM, but it's crucial to note that increased accuracy comes at a cost of more computing power. Another consideration is that whereas multi-class SVM requires a high number of computational features, CNN can work with image itself. When comparing time complexity, NN is the least complex with O (1), multi-class SVM is the next order with $O(n^3)$, and CNN is the most complexity. Trade-off between accuracy rate and computing power is a preference based on the performance of the available devices.

4. CONCLUSION

Single rice grain classification is an important part of rice grading for determining milling quality and rice export. The multi-class SVM and CNN is used in this experiment. A total of 15 features are provided as input for multi-class SVM, while CNN extracting features automatically. According to the results, using CNN with preprocessed images showed better results than using the originals. Rice grading will be improved by increasing grain categories. Although CNN is more accurate than multi-class SVM and NN in terms of accuracy, it takes longer to process and uses a significant amount of system resources. Machine learning works well with small to medium datasets, whereas deep learning required a large dataset. In image recognition, deep learning is particularly effective for automatic feature extraction across several layers of the network. The proposed approach might be applied in smart phones, allowing local producers to verify rice quality and then improve the quality of their own output to increase sales prices and improve quality of life. In the future work, large-scale datasets are still required for an efficient deep learning system. The combination of deep learning and feature extraction should be investigated. Other deep learning architecture like 3CNNs, MobileNet, or InceptionResNetV2 should be experimented further.

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