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Automatic Inspection System for Red Paddy Seeds

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Paddy rice is one of the most crucial crops worldwide. In Taiwan, 3500 paddy seed cases (4000 grains/case) are manually inspected every year. However, red paddy seeds are abnormal and must be inspected. Because red paddy is covered with paddy hull, it cannot be recognized according to their appearance. In this study, we developed an automatic inspection system with an inlet-outlet mechanism, machine vision, and a control system. The machine vision including the camera, infrared sensor, backlight source, and inspecting software is used to recognize the red paddy with hull. The system can inspect red paddy seeds through machine vision. Our results indicated that the proposed system can inspect the transmittance of paddy seeds and then classify them as either “good” or “red” (not good), with a classification accuracy of 91.0%. The developed system is a sensor for red paddy efficiently.

1. Introduction

Paddy seed inspection is an essential component of paddy seed multiplication and certification systems.[1,2] As shown in Fig. 1, paddy seed inspection can be divided into field and indoor inspections. Field inspection refers to observing the distribution of weeds in a paddy field and the growth pattern of paddy plants within a certain period. Indoor inspection refers to observing plant breeds that have been cultivated by field inspection. In accordance with international seed inspection regulations, samples are packaged and delivered to a laboratory, where their moisture content, volumetric weight, purity, and germination potential are examined. Purity analysis is conducted by evaluating the appearance features of grains, including the tip of the chaff, glume, palea, lemma, carina, length, and width.

During the pollination stage, paddy undergoes hybridization with other *Poaceae* species, leading to reddish-brown coloration on the seed coat. Hybrid varieties have a germination rate of 8.9 to 86.8%,[2] and hybridization will ultimately have impacts on yield reduction of 10 to 50%. Hybrid varieties also exhibit higher tolerance and germination capabilities than their cultivated

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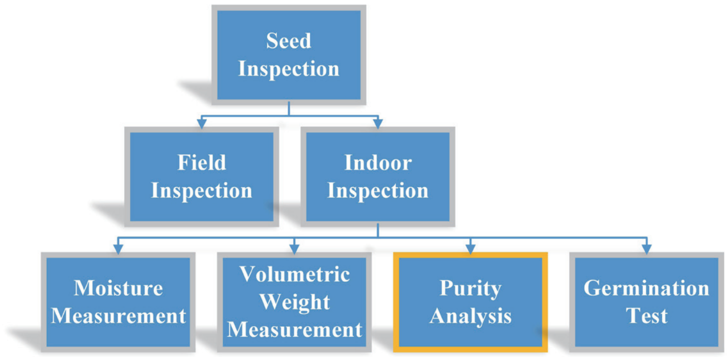


Fig. 1. (Color online) Seed inspection process.

counterparts, and they retain their morphological characteristics after germination. Given the difficulty of identifying and eliminating hybrids, the detrimental effect of hybridization surpasses those of other weed species and may result in a sustained inability to replant in the area. Currently, the primary method used by local inspectors for detecting red paddy seeds involves the direct visual examination of samples placed on a platform, unaided by any optical instruments.

Image processing is an advanced and widely used method for detecting the attributes of agricultural products. Golpour *et al.*(3) trained and established a backward transfer neural network with 9 color features, 44 morphological features, and 31 texture features. They reported that their network achieved an identification rate of 97.6%. Huang and Cheng(4) developed a classifier to identify the quality of Chinese cabbage seeds according to the shape, color, and textural features. Manohar and Gowda(5) used the *k*-nearest neighbor (KNN) algorithm to segment the foreground and extract texture features for paddy leaf disease. Accuracy of the clarification is 89.47% for testing leaf samples. Ansari *et al.*(6) explored the separability of paddy seed varieties by using the PLS-DA, SVM-C, and KNN models with 7 color features, 9 morphological features, and 4 textural features. Their accuracies were 83.8, 93.9, and 87.2%, respectively. Kuo *et al.*(7) classified the rice grains of 30 varieties using image processing and sparse-representation-based classification (SRC). The proposed approach could discriminate rice grain varieties with an accuracy of 89.1%. Durai *et al.*(8) implemented rice seed quality analysis for varietal purity estimation by using image processing techniques for south India rice. Lurstwut and Pornpanomchai(9) developed the Rice Seed Germination Evaluation System (RSGES), which can evaluate a rice seed image for germination prediction by using digital image processing and an artificial neural networks technique. Morphological, color, textural, and wavelet features were extracted from colored images of Canada Western Red Spring (CWRS) wheat, Canada Western Amber Durum (CWAD) wheat, barley, oats, and rye for classification.(10) Tu *et al.*(11) aimed to improve the selection of pepper seeds for separating high-quality seeds from low-quality seeds. The germination percentage in a calibration set of seeds was 79.1%. Maheshwari(12) proposed a quality analysis of Masoori rice seeds via image analysis. Image the recognition software was used to automate recognition of seed feature quality using

400 kernels of pepper cultivar 101. Wiwart *et al.*(13) used principal component analysis (PCA) to recognize 3 wheat varieties, 5 spelt breeding lines, and 24 single hybrids between wheat and spelt. Hong *et al.*(14) focused on analyzing the visual features of rice seed images such as color, shape, texture. The average accuracy of our classification system can reach 90.54% using the random forest method.

Training specialized experts in detection is challenging,(15) and the volume of inspection cases is substantial; approximately 3500 paddy seed cases (4000 grains/case) must be manually inspected every year. Currently, inspections are conducted through visual assessment by well-trained inspectors. However, prolonged inspection may lead to inspectors becoming fatigued, thus potentially affecting both the accuracy and efficiency of the process. Therefore, an automatic inspection system for analyzing the purity of paddy varieties would not only relieve the burden on inspectors but also generate a comprehensive database of paddy seed images and features, thus paving the way for the realization of smart agriculture in the future.

In summary, we develop an inspection system to automatically inspect red paddy seeds. The system includes an inlet-outlet mechanism, machine vision, and a control system.

2. Materials and Methods

As shown in Figs. 2(a) and 2(b), inspecting red paddy seeds that are shown in images with front-on lighting has inherent challenges. Under front-on lighting, the images of various types of paddy seed are all similar, as indicated in Figs. 2(c) and 2(d). In these images, the rate of inspection success for red paddy seeds is relatively low. In this study, we adopted an alternative approach in which a backlit imaging environment is employed; this mirrors the inspector technique used in the manual inspection of red paddy seeds. We captured images under front-on lighting conditions when paddies were detected by an infrared sensor. Figures 3(a) and 3(b) present images of a red paddy seed, whereas Figs. 3(c) and 3(d) present images of normal paddy seeds. These images can be effectively used to classify seeds.

The proposed system comprised an automatic feeding mechanism, a backlight source, an image-capturing system, and an automatic discharge and collection system. In this study, a light-transmitting belt was used for automatic feeding. Light-emitting diodes and halogen bulbs can be used as light sources, but we discovered that the halogen bulb used by inspectors was best for the platform's light source. Various external light conditions were adopted to achieve different image effects in various locations. To achieve the optimal imaging conditions, a light hood was used over the camera employed to obtain images. Figure 4 depicts the system's components.

An automatic mechanical system was developed. As shown in Fig. 4, the system consisted of an automatic feeding turntable (Fig. 5), a collection bucket, a vibration transport track (Fig. 6), a light-transmitting feeding system (Fig. 7), an image-capturing system (Fig. 8), collection cups [Fig. 9(a)], a pneumatic discharge system [Fig. 9(b)], a human–machine interface, and a personal computer. The image-capturing system consisted of a halogen bulb, a light hood, a CCD camera, an adjustment device, and a trigger sensor. The light-transmitting feeding system consisted of a light-transmitting belt, a motor, a motor controller, belt regulators, and a receiving and direction-changing platform.

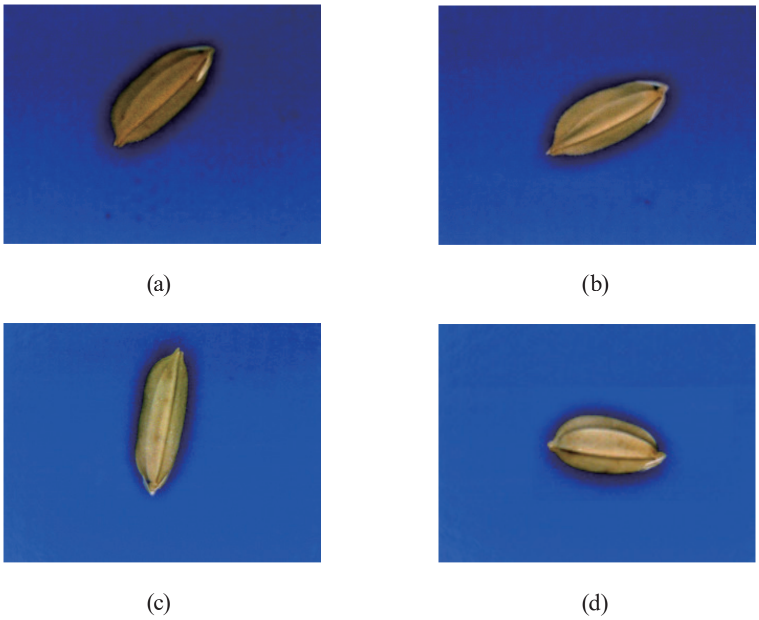


Fig. 2. (Color online) Frontlit images of paddy seeds. (a) Red paddy, (b) Red paddy, (c) Indica, and (d) Japonica.

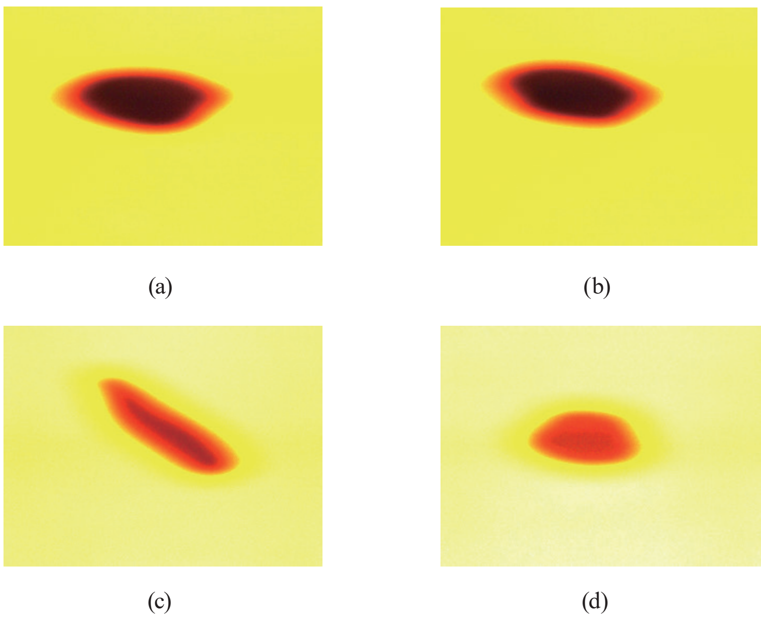
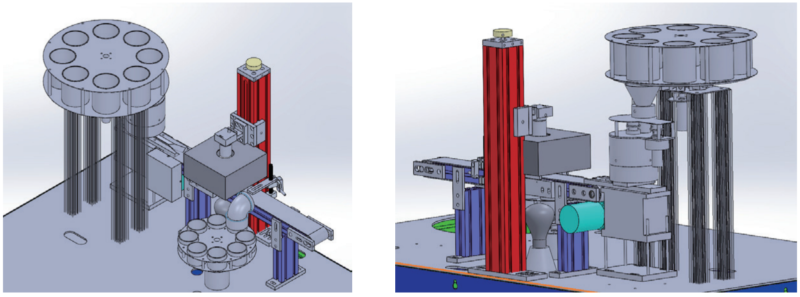
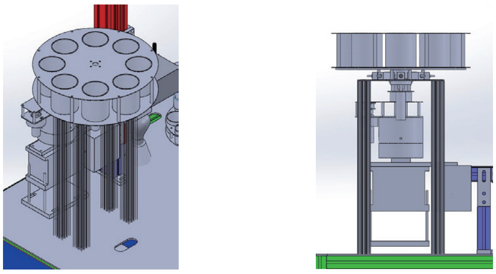


Fig. 3. (Color online) Backlit images of paddy seeds in Fig. 2. (a) Red paddy, (b) Red paddy, (c) Indica, and (d) Japonica.



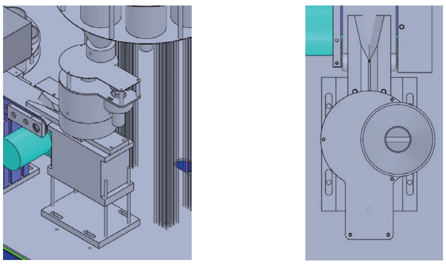
(a) (b)

Fig. 4. (Color online) Automatic mechanical system of design drawings. (a) Top-right front and (b) top-left rear views.



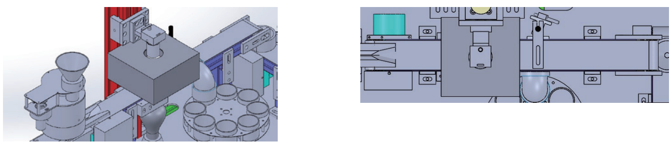
(a) (b)

Fig. 5. (Color online) Automatic feeding turntable. (a) Top-left front and (b) front views.



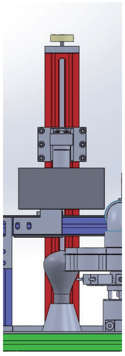
(a) (b)

Fig. 6. (Color online) Collection bucket and vibration transport track. (a) Top-left rear and (b) top views.

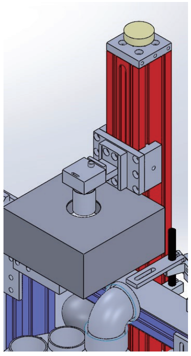


(a) (b)

Fig. 7. (Color online) Light-transmitting feeding system. (a) Top-left front and (b) top views.

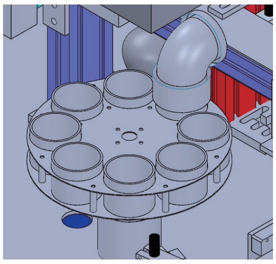


(a)

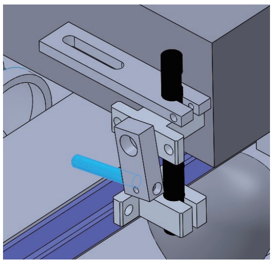


(b)

Fig. 8. (Color online) Image capturing system. (a) Front and (b) top-right front views.



(a)



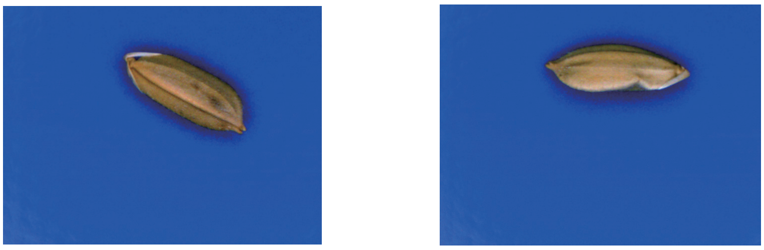
(b)

Fig. 9. (Color online) (a) Top-right front view of collection cups. (b) Top-right rear view of pneumatic discharge systems.

The light-transmitting belt was used to transport the machine and a yellow halogen bulb was used as a source of backlight. The light transmittance and appearance features were used to inspect red and abnormal paddy images.

As a result of the carinas (uneven surfaces) of paddy, seeds stand up on the belt. As shown in Fig. 10, the paddy seed is narrow and long. Because of light diffraction, the average grayscale value for the center of the standing red paddy seed exceeds that for a general red paddy seed. In addition, because of the upright position of the red paddy seed, the ratio of long to short axes is smaller than that for a normal red paddy seed and a normal paddy seed (Fig. 11). This distinction can help differentiate between standing and normal paddy seeds (Fig. 12).

In this study, 200 red paddy seed images, 200 upright red paddy seed images, 200 normal paddy seed images, and 200 upright normal paddy seed images were analyzed[16]. The image's green layer was employed to remove the background from the image and determine the center of the image of the paddy seed. An average grayscale value of 5 × 5 pixels was adopted for the red layer of each image center. The average grayscale value and the ratio of long to short axes on each paddy image were calculated. The results are presented in Figs. 13 and 14.



(a) (b)

Fig. 10. (Color online) Frontlit images. (a) Paddy and (b) upright paddy seeds.

(a) (b)

Fig. 11. (Color online) Backlit images. (a) Red and (b) normal paddy seeds.

(a) (b)

Fig. 12. (Color online) Backlit images of upright paddy seeds. (a) Upright red and (b) upright normal paddy seeds.

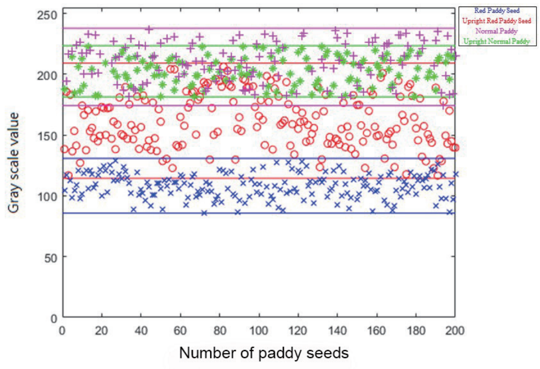


Fig. 13. (Color online) Distribution of grayscale values.

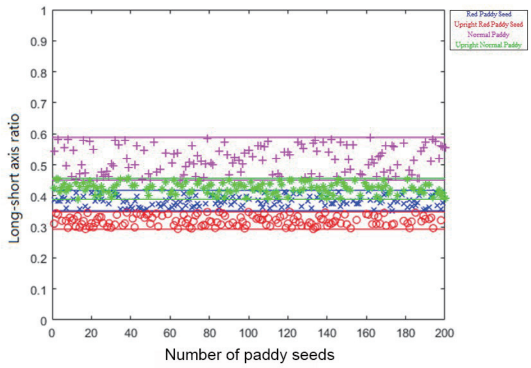


Fig. 14. (Color online) Distribution of ratio of long to short axes.

In this study, the process of red paddy seed inspection comprised four levels: total area, variety, axis ratio K, and dark area at the paddy seed center. In the first level, when the area was larger than 38000 pixels, the system did not transmit a signal to the automatic pneumatic discharge system. By contrast, when the area was smaller than 38000 pixels, the system proceeded to the next level. Figure 15 depicts the remaining inspection conditions.

$$K = \frac{Short\ Axis}{Long\ Axis} \tag{1}$$

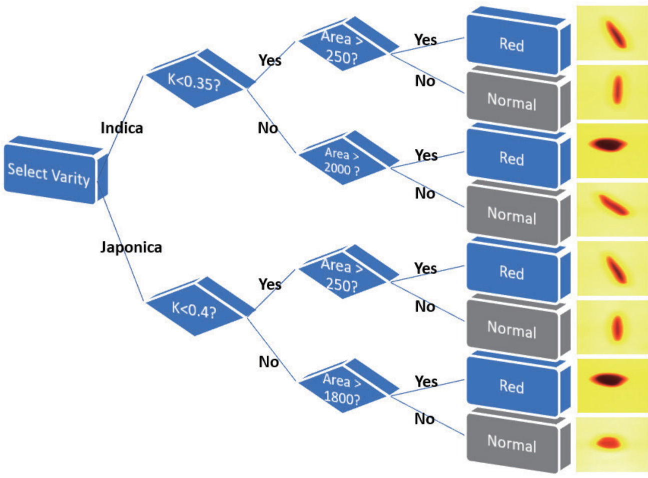


Fig. 15. (Color online) Flowchart of inspection process.

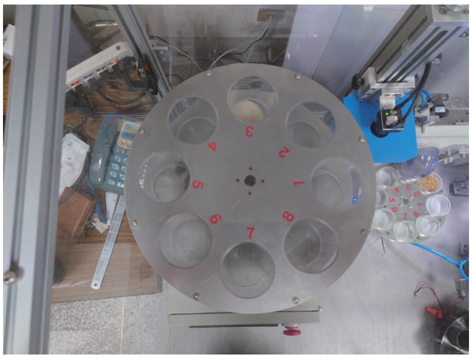
3. Results

The developed system consisted of an automatic feeding turntable (Fig. 16), a collection bucket and a vibration transport track (Fig. 17), a light-transmitting feeding system (Fig. 18), an image-capturing system (Fig. 19), collection cups (Fig. 20), and a pneumatic discharge system (Fig. 21).

Figure 22 shows the flowchart of the program and Fig. 23 shows the flowchart of the machine. Paddy samples were successively placed in collection cups within an automatic feeding turntable. Depending on the serial number of each feeding cup, a variety was set on the operation interface of the computer. Once the variety had been set, the inspection process was initialized. A human–machine interface was used to press the start button. The samples in the first feeding cup were dropped into a collection bucket and sequentially arranged on a vibration transport track in a translucent feeding system. The samples were then successively fed into an image-capturing system at an interval of approximately 30–50 mm. A trigger sensor was used to detect sample movement and to instruct the CCD camera to capture an image. The captured image was then moved to an inspection stage and the output was forwarded to a PLC. To inject red paddy seeds into the red paddy seed collection cups, an automatic pneumatic discharge system was used. A belt was employed to transport the remaining samples to a receiving and direction-changing platform. At this point, the inspection process was deemed complete.

Although the features of red paddy seeds differ between the Indica and Japonica varieties, light transmission effectively identifies both of these varieties. In this study, red paddy seeds of the Japonica (TN11 and TK8) and Indica (TCS10) varieties were evaluated. Table 1 presents the statistical results.

(a)



(b)

Fig. 16. (Color online) Automatic feeding turntable. (a) Front and (b) top views.

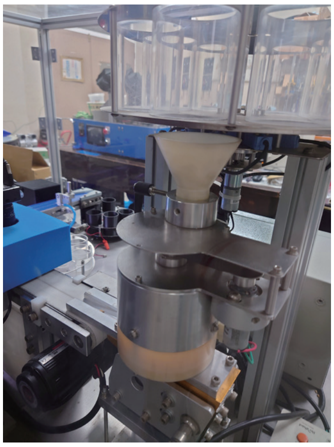


Fig. 17. (Color online) Top-left rear view of collection bucket and vibration transport track.

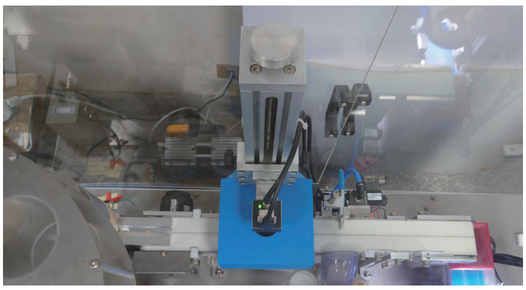
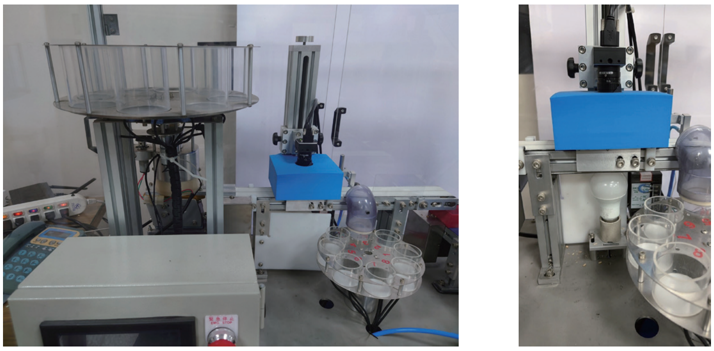


Fig. 18. (Color online) Top view of light-transmitting feeding system.



(a) (b)

Fig. 19. (Color online) Image-capturing system. (a) Top-left rear and (b) top views.

Fig. 20. (Color online) Top view of collection cups.

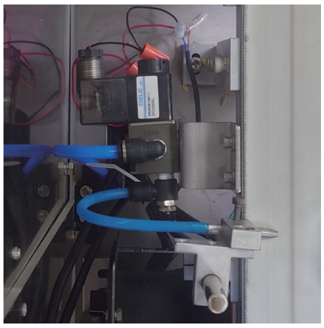


Fig. 21. (Color online) Top view of pneumatic discharge system.

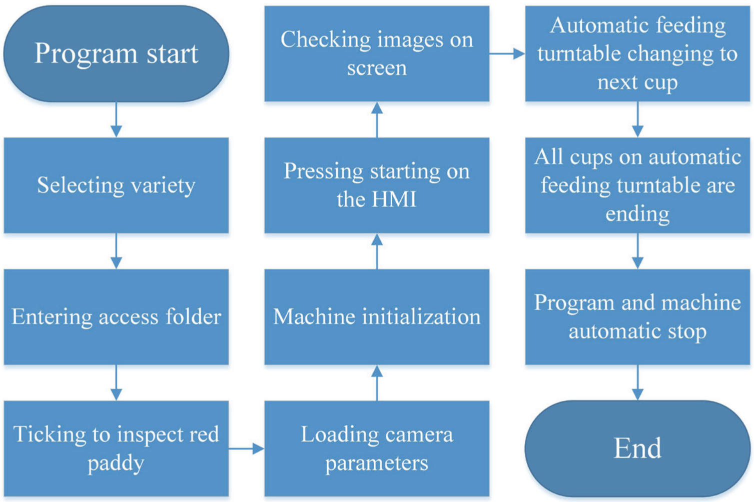


Fig. 22. (Color online) Flowchart of program.

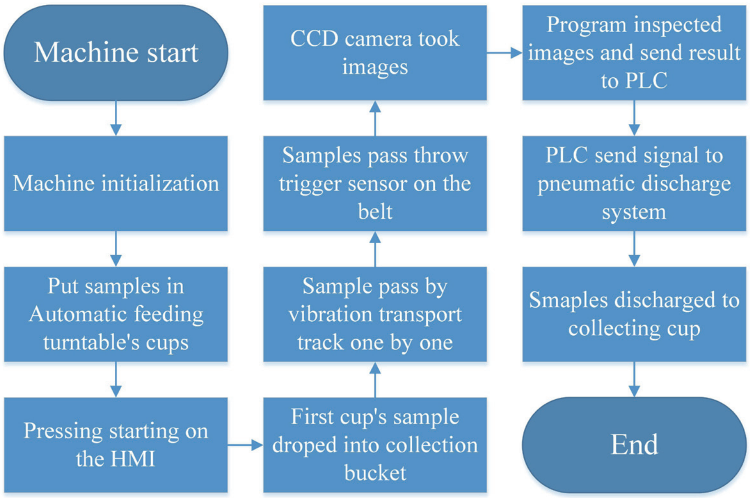


Fig. 23. (Color online) Flowchart of machine.

Table 1
Acceptable ratios.

Variety	Total images	Not good	Acceptable ratio(%)
Red paddy Seed	2573	60	97.7
Japonica (TN11)	4217	554	86.9
Japonica (TK8)	1102	106	90.4
Indica (TCS10)	801	83	89.6
		Total ratio	91.2

4. Discussion

Various automatic feeding and classification systems were developed in accordance with the design concept. Vibration transport tracks cannot separate all samples, in which case the sample was classified as “not good” and was not released into a collection cup.

During paddy growth in fields, wind can injure the plants. These injuries prevent light from passing, resulting in a black brindle appearance of the paddy seeds. These injuries also result in a dark plaque in images, which can cause misjudgment. If a wind injury is detected in a paddy seed, it is classified as problematic.

5. Conclusions

In this study, we developed a system that can identify red paddy seeds. There are 4000 grains/case and the proposed system achieved an image capture success rate of 92%. Identifying red and upright paddy seeds is difficult; thus, we developed an algorithm for this task and achieved an accuracy of 91%. The developed system is an efficient sensor for red paddy seeds.

In this study, we developed a novel automatic inspection system for red paddy seeds with an inlet-outlet mechanism, machine vision, software, and a control system. Red and abnormal paddy seeds were inspected with the light transmittance and appearance features. The test results showed that red paddy seeds can be inspected efficiently with this inspecting system. These findings can be used as a reference to improve the work conditions of inspection personnel and considerably reduce their workload.

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