Inspect Characteristics of Rice via Machine Learning Method

Xin Ma[1*], **Mingliang Li**[1*], **Jinxi Kong**[3], **Siming Zhao**[4], **Wei Li**[2†], **Xiaohui Cui** [2†]
[1]School of Sofware, Tsinghua University
[2]School of Cyber Science and Engineering, Wuhan University
[3]GREE Electric Appliances
[4]College of Food Science and Technology, Huazhong Agricultural University
mx19@mails.tsinghua.edu.cn, lml19@mails.tsinghua.edu.cn, kongjinxi18@gmail.com,
zxmjx@mail.hzau.edu.cn, auto_weili@whu.edu.cn, xcui@whu.edu.cn

***Abstract*-For more than half of humanity rice is life. Therefore, assessing the quality of rice in fast, accurate and objective methods has attracted a lot of attention of rice producers and processors. Unfortunately, the current inspection methods that focusing on the computer vision to inspect the characteristics of rice are either cost expensive (e.g., it needs extra sensors to assist photography) or need to be significantly improved in practice (e.g., framed object incorrectly). In this paper, we make an in-depth study of the characteristics of rice and explore an alternative direction to use machine learning methods to inspect them through photos taken by cell phones. To be exact, we develop a new mathematical variation formula and a new area calculation formula, combining clustering methods, to inspect the main characteristics of rice both statically and dynamically. The effectiveness of our approach is very visible no matter what the type of rice it is, which is shown by comprehensive experiments on four typical types of rice datasets. Moreover, We cooperate with one of the world's largest home appliance manufacturers, applying the rice characteristics extraction approach to produce smart electric rice cookers, thus improving the quality of life for millions of people.**

***Keywords*— characteristics of rice; machine learning; digital image processing; IoT**

1 Introduction

Among the cereals, rice is the most important foodstuff in the world and nearly half the population of the world takes rice as a staple food. Rice is often damaged by the agricultural machinery during past-harvest handling and processing, such damaged could affect the quality and appearance. When consuming or processing rice, people prefer to obtain sound products with less fissure and breakage. Furthermore, people have a higher pursuit of the quality of rice cooking. For rice with different characteristics, we should adopt different strategies to cook to achieve the best taste. With the rapid development of Internet of Things (IoT), smart electric rice cookers are becoming much more popular. If we can identify the characteristics of rice conveniently and accurately and apply it to the rice cooker, we can improve the quality of life for many people by choosing a specific cooking strategy dynamically when cooking rice. In this way, inspecting and understanding the quality of rice is necessary.

In general, the methods of inspecting the characteristics of rice are categorized into two aspects. The first one is to use a special machine, the rice detector, to inspect the characteristics of rice. It scans each rice in a special closed space (the space can shield the natural light and just remains a single light-source to scan the rice like a scanner), and calculates the characteristics with specific machine-borne software. Although it can produce very precise results, the cost is very expensive, the size of such a machine is too huge to be a home appliance. The second one is to develop a computer vision algorithm to inspect the characteristics of rice, and it is a thriving direction currently, because of its potential flexibility and the extra cost is unnecessary. This is because one can use portable devices such as mobile phones[7] to take images and validate their algorithm on such images.

Traditional rice property testing is mainly based on large analytical instruments in laboratories and the result is used in agricultural research. Before the rapid development of Internet of Things (IoT), lightweight rice characteristic analysis was difficult to apply to production or life. However, with the popularity of smart rice cookers and the establishment of IoT, the demand for rice analysis that relies solely on pictures through computer vision and machine learning has increased rapidly. This also puts forward requirements on how we apply machine learning and computer vision technology.

Currently, directly using the traditional computer vision methods to detect the appearance of rice basically focuses on judging whether the rice is intact or broken with edge detection [4]. Such a case always assumes that there is only rice in an image, this is not often the case where the impurities and connected rice usually arise. The traditional computer vision method cannot handle this challenge.

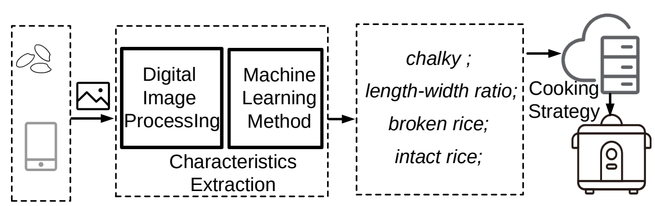

Figure 1: Application of rice characteristics extraction in smart rice cooker

In this study, we, instead, explore an alternative direction, which is to use machine learning to inspect the characteristics of rice. The five characteristics of rice can be grouped into two sets. The first group is chalky, it includes the percentage of chalky (The rice with chalkiness / All rice) and the chalkiness (Amount of chalky pixels / Amount of all pixels). The chalkiness indicates the untransparent region with a grain of rice. Although the chalkiness can measure the quality of the rice, few computer vision studies focus on it. The

*Co-primary authors.
†Co-corresponding authors.
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second group consists of the length-width ratio, the percentage of broken rice (Broken rice / All rice) and intact rice (Intact rice / All rice).

For calculating the chalkiness, we develop a new mathematical variation formula to set a threshold to separate the chalkiness from other components, given that the chalkiness is the untransparent region and other components are transparent. All components within a grain of rice can be grouped into two aspects, the brightness and the darkness. The former one indicates the chalkiness in our study while the last one indicates other components. We can dynamically calculate the difference between the brightness and the darkness with our new formula. More details are shown in Section III.

For the second group of characteristics, we calculate them by using the clustering methods (e.g., K-Means or Spectral-Clustering [10]), which have been widely used in image classification[9]. To make a reasonable calculation, we consider the impurities and the connected rice. we develop a new area calculation formula and make it worked with the clustering method to cluster the four characteristics. We can observe more details in Section III. Our proposed method does not need an extra machine, and there is no need for people to learn professional knowledge.

Our characteristics extraction technology has been adopted by the world 's largest home appliance manufacturer to manufacture smart rice cookers. As shown in Fig.1, when rice pictures taken by mobile phones are uploaded, digital image processing and machine learning methods designed by us are used for characteristics extraction. Upload characteristics to the cloud service to request cooking strategies to achieve the effect of intelligent cooking. By the way, cooking strategies are provided by cooperative agricultural researchers.

In summary, the major innovations and contributions of this paper are as follows:

- This paper casts light on applying machine learning to inspect the rice characteristics. In particular, this paper introduces the clustering method to the impurities, broken rice, intact rice and connected rice.
- To the best of our knowledge, this paper proposes for the first time to develop a new mathematical variation formula to dynamically inspect the chalkiness.
- Through comprehensive experiments on inspecting the characteristics of rice, we demonstrate the effectiveness of the proposed approach. Meanwhile, Our characteristics extraction technology has been adopted by the world 's largest home appliance manufacturer to manufacture smart rice cookers, thus improving the quality of life for millions of people.

This paper is organized as follows. In Section II we discuss some related work. In Section III, We will present our main idea. In Section IV we will show our experiment results, and we conclude in Section V.

2 Related Work

Many image acquisition instruments and image processing algorithms are based on the computer vision method, and a lot of researchers try to use these instruments and algorithms to inspect the characteristics of foodstuff. Typically, we categorize them into two aspects: image acquisition systems and image processing methods.

Image acquisition systems for food. When researchers want to analyze the characteristics of food, the first step is to collect enough available images. In current, although there are many instruments, such as the USB-based camera, scanner, ultrasound, X-ray and near-infrared spectroscopy, to be used to collect images in practice, it still needs to design new machine, given that the food has different shapes and colors. Peter et al. [16] design a line-scan camera to take the photo to obtain precise information (foreign body) when the food products pass through the camera, given that the food products can always mix the foreign body during processing. The camera reaches to 2000 times per minute. Besides, since some food products exist special characteristics (e.g., core or bones), researchers try to use the X-ray radiography to generate available images to analyze. Kim et al. [11] use a two-dimensional (2-D) X-ray radiography to detect whether an apple contains watercore or not, especially in the early stages. Although the machines tremendously facilitate people to improve the efficiency of agriculture product inspecting and handling, those machines belong to professional equipment and the cost is expansive.

Image processing methods for food. Image processing is the principal core for computer vision because the results from image processing are directly related to the goal of a task. Such steps can be categorized into two sub-steps, the pre-processing and processing. In some cases, the pre-pocessing step has been adopted to reduce the noise in the image to improve the quality of the image for inspection, with the method of enhancing the important features of interest [3]. In the process of quality inspection, Dissing et al. [3] use a rapid multispectral imaging device to quantify the degree of spoilage for pork, given different qualities of pork display different chromatic aberrations in spectral. It can classify 76.13% of the meat samples correctly. Since different foods hold different colors, Eddins et al. [8] use the histogram to calculate the threshold value of different foods to classify. Those methods belong to low-level image processing. As for high-level image processing, it involves objection recognition and interpretation, and always requires more complicated models. Ying et al. [17] use the Artificial Neural Network (ANN) [2] to classify the Huanghua pears.

Instead of directly inspecting the characteristics of rice using the computer vision method, we apply machine learning to inspect rice characteristics. In next section, we would introduce the specific technical details of our approach.

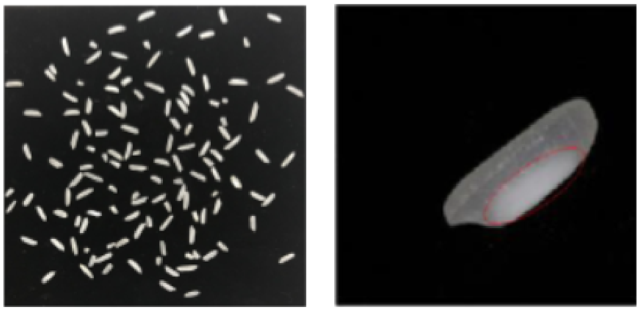
3 The proposed method

In this section, we will introduce how to apply the machine learning method to inspect the characteristics of rice. Specifically, we will discuss two important challenges: a new mathematical variation formula for getting chalkiness of rice, and use the machine learning method to get the quality measurements of rice(the broken rice ratio and the intact rice ratio). Since our focus is on calculating the characteristics of each rice, the first step is to extract rice from the picture.

3.1 Preprocessing

Although we can easily observe the rice in an image with the naked-eyes, it is a non-trivial thing for a computer since there are a lot of observations(e.g., noise, broken rice and overlapping rice) in an image, and we need to filter out what we expect. A picture with a lot of rice is shown in Fig.2.

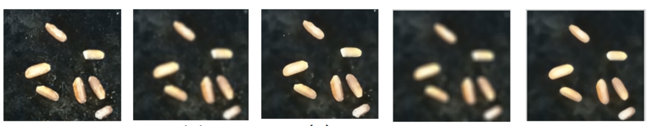
In Fig.2, the rice shown in sub-figure (a) is taken by the cellphone, while that shown in sub-figure (b) is from the camera with high resolution. The red ellipse marks the chalky grain (this rice is from the sub-figure (a). For illustrating the chalkiness we use a specific camera to take the photo). Before framing the rice shown in sub-figure (a) correctly, we need to know the position of each rice. Here we adopt the edge detection method. If we can detect the edge of each rice, we naturally find each rice. The clearer the edge is, the better the inspection is. Since the sub-figure (a) is taken in the natural scene, two major kinds of noise (the dust and the blot) are inevitable. The edge detection method also detects the edge of noise, which would affect the precision of framing rice. More details are shown in Section experiment. In this way, we need to filter out the



(a) (b)

Figure 2: Sub-figure (a) is taken by the cell-phone, while sub-figure (b) is from the camera with high resolution. The untransparent region marked by the red ellipse indicates the chalkiness.

noise within this image before calculating the characteristics of rice. Because we do not want our algorithm mistakes the noise for rice. In our study, we adopt the Bilateral filter method to filter out the noise, because the Bilateral filter can preserve the edge of anobject,which is important for our future calculation. Although other filters can filter out more noise in some cases, they blurry the edge of the expected object. The remaining noise can be separated in the next step by clustering. We would use an example to demonstrate our point. We choose different filters and apply them to the image shown in sub-figure (a) of Fig.2, and the results are shown in Fig.3.



(a) (b) (c) (d) (e)

Figure 3: (a) indicates the original sample. (b) indicates the filtered sample with Gaussian filter [1].(c) indicates the filtered sample with Bilateral filter [15]. The filtered sample in sub-figure (d) is from the Average filter while that in sub-figure (e) is from the Median filter. From the results, we can see that the denoised result from Bilateral filter is better than others.

In Fig.3, we can see that the sub-figures (b), (d) and (e) blurry the edge of the rice even though they have denoised the noise. The blurry edge would cause the edge detection method to detect the wrong edge of rice. If this happened, the rice cannot be framed correctly, and we cannot calculate the true characteristic of rice. Despite the performance of denoise shown in sub-figure (c) is weaker than sub-figures (b), (d) and (e), the bilateral filter still eliminates most of the noise and keeps edges as complete as possible. Given that in most real cases the noise cannot be filtered out completely(even if we use other filters), we must process the remaining noise in future steps. So we choose the bilateral filter as the denoise filter. Besides, some rice may be connected, which also hurts the calculation of the characteristics but still do not get any treatment. Next, we will explore how to process the rice image further.

3.2 Frame the rice

First, we find out each rice edge and box it using the rectangle. We use the Bilateral filter to denoise the noise, and we adopt edge detection with the Canny operator to detect the edge of rice for framing. The results are shown in Fig.4.

From sub-figure (b) of Fig.4, we can see that the outlines of those rice are plotted correctly, even for noise. What we need to do is to track and find the smallest circumscribed rectangle of the individual edges. We continue to frame the contour of rice using the traditional computer vision methods (e.g., topological structural analysis method [6] [12]). This method uses the encoding method to give different integer values for different edges, the input image is a binary image, and it uses a function $f(i,j)$ to indicate each pixel value. The value of $f(i,j)$ would be updated when the method scans the image. We frame each closed edge with the smallest circumscribed rectangle. The results, after applying the topological structural analysis method to the rice, are shown in sub-figure (c) of Fig.4.

Although those rice are framed correctly, there remain several challenges needing to be addressed. 1). The noise has also been framed. 2). Several rice grains overlapped are extracted by one frame, for the framed algorithm thinks that the connection area is integration. These two challenges affect the precision of calculating the characteristics.

Our method is based on the edge-detection (See the sub-figure (b) of Fig.4) because detecting the edge is necessary for understanding the shape of one object. Since the traditional method holds the low performance, we would introduce our model to improve the performance in the next subsection.

3.3 Using clustering method to frame the rice

Although noise hurts the performance of characteristics inspection of rice products, few studies focus on it. Researchers are just interested in how to find out the broken rice in a noise-free environment and try to disperse the rice grains to each other to avoid overlap. Sansomboonsuk et al. [14] use these features such as area, perimeter, circularity and shape compactness as criteria to classify the broken rice and intact rice. They also utilize the Fuzzy logic method to organize and classify the class of each kernel. Comparing with human inspection, the proposed method reaches to 90% accuracy and saves 70% of the time. However, there still exit challenges.

First, the required time may not be suitable for real-time processing operations. Second, the proposed method could not separate the line formed by touching kernels, which indicates that there may exist errors [18].

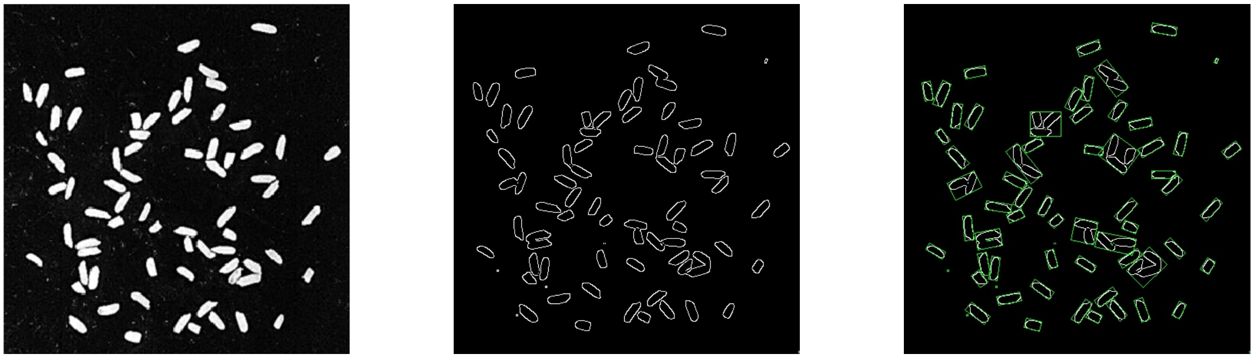
When we use the common cell-phone to take a photo of rice under the nature scene, the noise and the connected rice is inevitable. Since the four characteristics (broken rice, intact rice, dust, and connected rice) are different from each other in appearance, we try to address those issues using the appearance feature. To this end, we combine mathematical calculations with the clustering method to inspect the noise and the rice. Our goal is to categorize the circumscribed rectangles of the individual edges (including noise) into four categories (noise, broken rice, intact rice, and connected rice). We make use of the clustering method (K-Means over the case) to cluster these samples. We expect that a specific sample would be clustered into the corresponding category (e.g., the noise would be clustered around the noise category while the connected rice would be clustered around the connected category). Because the areas of noise are much smaller than that of intact rice, and the areas of connected rice are much larger than that of normal rice, the performance of the cluster can be guaranteed. More details are shown in section experiments.

Next, we would use an example to demonstrate our clustering method. Assuming there is a rice dataset $(X_1, X_2, ..., X_m)$, m indicates the number of rice. The function of X_i is shown as follows.

$$X_i = \begin{bmatrix} H_i \\ W_i \end{bmatrix} \tag{1}$$

In Eq.(1), H_i indicates the length of rice and W_i indicates the width of rice. In the initial step, we randomly initialize four categorical centers, which are marked as $\alpha_1, \alpha_2, \alpha_3, \alpha_4$, respectively. For each X_i, we label it as α_j in which X_i has the shortest distance from α_j. The function is shown in Eq.(2).

$$label_i = \arg_{1\leq j\leq k} min(\sqrt{\sum_{i=1}^{n}(X_i - \alpha_j)^2}) \tag{2}$$



(a) (b) (c)

Figure 4: Sub-figure (a) indicates the original image taken by the cell-phone. In this image, we can see that there are much noise and connected rice. (b) indicates that we adopt edge detection with the Canny operator to plot the outline of rice after using the Bilateral filter. Although the Bilateral filter filters out most noises, there still remains noise. Sub-figure (c) indicates that we adopt the traditional method (e.g., [18]) to frame the outline of the rice.

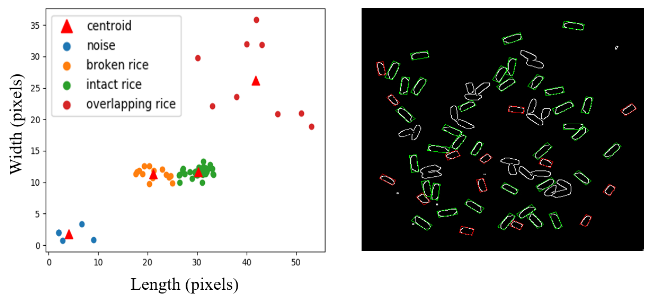


Figure 5: In the left sub-figure, the four red triangles indicate the categorical centers, and the four red eclipses indicate the four clusters (, broken rice, intact rice and overlapping samples). In the right sub-figure, the green rectangle frames the intact rice, while the red rectangle frames the broken rice. The other touched or connected rice is not framed.

In Eq.(2), k indicates the number of cluster (here $k = 4$). We proceed to perform the clustering method, the samples belonging to the categorical center α_j would be updated. The updated function is shown in Eq.(3).

$$\alpha_j = \frac{1}{N(c_j)} \sum_{i \in c_j} X_i \tag{3}$$

In Eq.(3), c_j is such sample that holds the shortest distance from α_j, while $N(c_j)$ indicates the number of c_j. We repeat the Eq.(2) and the Eq.(3) until the change rate of the categorical center is less than 0.0001 (the number can be randomly set. In this study, we found that 0.0001 is enough to categorize all samples. The clustering results are shown in Section experiment. In this way, we can filter out the impurities and the connected rice and just keep the broken rice and intact rice. If we can frame the rice correctly, we can calculate the characteristics of length-width ratio and percentage of broken rice as well as that of intact rice.

3.4 Designing new variation formula to inspect the chalkiness

The chalkiness is an important criterion to measure the quality of rice, because it can affect the quality of appearance and the economy of rice. The chalkiness is caused by the insufficient accumulation of albumen starch and protein granules. The larger region the chalkiness is, the less the nutrition of rice is. The image of chalkiness is shown in sub-figure (b) of Fig.2. Fig.2 implicitly indicates that inspecting the chalkiness of one rice can rely on the color change.

An intact white-rice is actually translucent (the colored rice is not translucent so it has no chalkiness) when we observe it with naked-eyes. The chalky grain is the opaque region (See the marked eclipse of sub-figure (b) of Fig.2) and it stops the light transmission, while other regions allow the transmission of scattered light. Based on these characteristics, Fang et al. [4] hypothesize the chalky grain is brighter than other parts within a grain of rice, and they set a threshold to identify the chalkiness. However, there still exist some issues. 1). The threshold in [4] is fixed, and there are no more details to demonstrate how to find out such threshold. If the threshold is fixed, it is hard to distinguish the chalkiness under different chromatic aberrations which could affect the performance of the computer vision algorithm. 2). Although the threshold is related to the gray-level, the number of levels is hard to define because the fewer levels cannot distinguish the chalkiness and the larger levels could cause the loss of chalkiness. 3) The color of chalkiness also holds differences in practice. Also, the different shooting scenes could cause different color distributions in gray-level(especially shooting scenes by cell-phone). Thus, we propose our idea to inspect the chalkiness.

We use the chromatic aberration strategy to calculate the chalkiness instead of using a fixed threshold. The difference between our idea and traditional method [4] is that we first dynamically divide the rice pixels into two aspects (brightness and darkness), and then find out whether the difference between the two parts is significant, given that the shooting scenes are different. Even though the rice belongs to white rice, the white color is also different (See sub-figure (a) of Fig.2). Therefore, we need to determine the boundary dynamically.

Moreover, when the rice has been divided into two parts (brightness and darkness), the brightness cannot guarantee that it is real chalkiness (because when we divide the rice into two parts, it does not care about whether it exists the chalkiness or not. The brightness is only relative to the darkness, it may just a little lighter than darkness). The method shown in [4] does not care this detail. Here we make use of the maximum inter-cluster variance (the larger the inter-cluster variance, the more the difference) and the minimum intra-cluster variance (the smaller the intra-cluster variance, the closer the color of intra-cluster) to find out the optimal Boundary Value (BV) to distinguish the two parts. The proof of formulation is as follows.

$$u = w_0 \times u_0 + w_1 \times u_1 \tag{4}$$

In Eq.(4), u indicates the number of pixels in an image, w_0 indicates the bright pixels proportion to whole image and w_1 indicates the dark pixels proportion to whole image. u_0 indicates the average of bright pixels while u_1 indicates the average of dark pixels. The variation of two parts is shown in Eq.(5).

$$V = w_0 \times (u - u_0)^2 + w_1 \times (u - u_1)^2 \tag{5}$$

In Eq.(5), u indicates the average gray of rice. We integrate the two equations into a new formula, which is shown in Eq.(6).

$$V = w_0 w_1 (u_0 - u_1)^2 \tag{6}$$

The mean square deviation of bright pixels is shown in Eq.(7) while that of dark pixels is shown in Eq.(8).

$$V_0 = \frac{1}{w_0} \sum_{0 \le i \le BV} (i - u_0)^2 p_i \tag{7}$$

$$V_1 = \frac{1}{w_1} \sum_{BV \le i \le 255} (i - u_1)^2 p_i \tag{8}$$

In Eq.(7) and Eq.(8), the p_i indicates the frequency of ith gray level. Thus, the boundary value can be formulated as follows.

$$BV = \arg \max_{0 \le BV \le 255} \frac{V}{V_0 V_1} \tag{9}$$

According to the boundary value (BV), we can divide the rice into two parts (brightness and darkness) no matter what kind of rice is or scene is. Then, we calculate the average value of gray levels of the two parts. When the value reaches to a certain range (Here we use the term T to indicate this range so T can be viewed as a threshold), we can point out that the color difference between the two parts is significant and the two parts can be distinguished. Note it is feasible to use T as a fixed value here We define the brightness part as the chalkiness (that is to say, $|u_0 - u_1| > T$). We empirically recommend that T ∈ [20, 30] is a good value for distinguishing the chalkiness of the rice, the larger one or the smaller one cannot distinguish the same thing. We can validate our idea in Section experiment.

4 Experiments

To validate our approach, we choose four types of rice, which are GangTeYou37 (red-brown rice), purple glutinous rice, red glutinous rice, and Thai fragrant rice (white rice), respectively. We take the traditional algorithms (e.g., [4], [18], [13]) as the baselines and compare the baselines with our idea.

4.1 Inspecting broken rice and intact rice with K-Means

	length-width ratio	height	width	area
mean	2.2119	30.4385	14.8607	486.4525
std	0.5262	7.8109	6.8117	343.2865
min	1.0104	16.9706	9.8	191.9999
25%	1.7415	26.0325	11.303	286.6873
50%	2.4289	30.0744	11.7041	355.3846
75%	2.6057	32.9344	12.6196	405.2769
max	2.9706	52.6264	35.1187	1498.3458

Table 1: The four features (length-width ratio, height, width, area) indicate the features of rectangle which is used to frame the rice. All framed samples are 60. The mean, std, min, max indicate the mean-value, variation, minimum value and maximum value of those 60 samples, while the 25%, 50% and 75% indicate the quantile [5].

From the visual perspective, we find that the connected rice has been viewed as an intact object to be framed and the framed region is larger than that of single intact rice, while the region of noise is smaller than that of intact rice. To validate our hypothesis, we calculate each framed region and the corresponding height and width. The results are shown in Table.1.

In Table.1, the three quantiles indicate that they have similar values on height, width, and area, while the values of min or max display the abnormally small or large value, which could be noise or connected samples in the original image. Therefore, we think that if we set a categorical center for noise or connected samples, and the small values or larger values are clustered into this center, we can filter out the noise or connected samples. In this way, we adopt the K-Means to cluster these samples. K-Means is one of the simplest clustering strategies. If we can get good performance on K-Means, we can also get good performance on other clustering strategies.

In K-Means, the number of clusters is set to 4 (k=4), which indicates the noise, the broken rice, the intact rice, and the connected rice, respectively. From Table.1, we can see that the minimum value and maximum value are very different from the three quantiles. The center point of each cluster is randomly set. Because the samples within the four clusters hold different region values, K-Means can guarantee that holding the same or similar region value would be grouped into the same cluster after iteration. The parameters of K-Means if default and the clustering processes are as follows.

- We view each frame as an object, and the length and width of this object would be regarded as the features.
- We randomly initialize the central values of k.
- The rice would be grouped into a certain cluster with the shortest distance.
- We use the Eq.(6) to repeat the last step until the change rate of each categorical center is less than 0.0001, given that the four categories have their special features on the shape (e.g., different lengths and widths).

The results are shown in Fig.5. In sub-figure (a) of Fig.5, the left-bottom cluster, and the right-top cluster indicate the noise and the connected samples, respectively. We then abandon the two abnormal clusters using our proposed method, the results are shown in sub-figure (b).

In comparison with sub-figure (c) of Fig.4, Fig.5 shows the excellent effectiveness. We can see that the broken rice and the intact rice are framed correctly with different colors, while the and connected rice are filtered out. Because we abandon them during clustering, they have not framed by the rectangle. In this way, we can calculate the length-width ratio, the percentage of broken rice and intact rice.

4.2 Inspecting the chalkiness

We continue to inspect the chalkiness. In general, the chalky is the opaque part of the rice, and we can observe it with our naked-rice (See Fig.2). For inspecting the chalkiness, we need to pick up each framed rice. Here we use the binarization method to collect the framed rice from an image. After that, we continue to separate the opaque chalky from the transparent region using Eq.(9). Here we set T as 20 (we also test other values (from 21 to 30) of T, the results are similar. Larger T or less T would cause that we cannot distinguish the chalky), and the separated results are shown in Fig.6.

In Fig.6, the sub-figure (a) indicates the original image. We set T to 20 and we use Eq.(9) to separate the chalky from the intact rice, the sub-figure (b) shows the separated result.

4.3 The results of characteristics

After that, We use our methods to calculate the five characteristics (Length-Width Ratio (LWR), percentage of Intact Rice (IR),

Table 2: The traditional algorithms are viewed as baselines, and the results produced by the machine (Automated seeds and grains analyzer) are viewed as the benchmark. The results show that our algorithm approaches the benchmark, which indicates the effectiveness of our approach.

	LWR	IR (%)	BR (%)	Cky (%)	Cki
Thai fragrant rice (machine)	3.41	96.13	3.87	18.32	3.33
Thai fragrant rice (our approach)	3.21	90.32	9.6	15.16	2.11
Thai fragrant rice (traditional approach)	2.84	75	25	10.92	0.5
Purple glutinous rice (machine)	2.632	90.42	9.58	0	0
Purple glutinous rice (our approach)	2.82	89.36	10.63	0	0
Purple glutinous rice (traditional approach)	3.52	96.88	3.12	0	0
Red glutinous rice (machine)	1.88	99.03	0.97	0	0
Red glutinous rice (our approach)	1.86	95.35	4.6	0	0
Red glutinous rice (traditional approach)	2.05	90.3	9.7	0	0
GangTeYou (machine)	2.811	93.89	6.11	0	0
GangTeYou (our approach)	2.79	91.63	8.36	0	0
GangTeYou (traditional approach)	3.06	92.04	7.95	0	0

Figure 6: The left sub-figure shows the original image, while the right sub-figure shows the separated chalky with Eq.(9).

percentage of Broken Rice (BR), percentage of Chalky (Cky) and Chalkiness (Cki)) on four types of rice (red-brown rice, purple glutinous rice, red glutinous rice, and Thai fragrant rice), and the results are shown in Table

In Table.2, the results from the traditional approaches ([4], [18], [13]) are viewed as the baselines, and the results generated by the machine (Automated seeds and grains analyzer) are regarded as the benchmark. The results show that our algorithm approaches to the benchmark and outperforms traditional algorithms, which shows the effectiveness of our approach.

5 Conclusion

In this study, we've created a lightweight and high-precision method to inspect the major characteristics of rice (length-width ratio, chalkiness, the percentage of chalky and the percentage of broken rice and intact rice). We have achieved our goal by using a combination of digital image processing and machine learning algorithms. Our work can effectively extract the characteristics of rice from the photos taken by mobile phones. In the era of the IoT, we cooperate with one of the world's largest home appliance manufacturers to help intelligent rice cookers make more intelligent decisions based on the rice characteristics extraction technology.

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