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A contour-based pixel distribution for segmenting unpolished and broken rice grain

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Abstract

Rice quality grading is a critical step in ensuring the market value and consumer acceptance of rice. It involves assessing various physical attributes such as grain integrity, polish level and shape to determine its suitability for consumption, processing, or export. Traditional methods of identifying unpolished and broken rice grains rely on manual inspection, which is time-consuming and prone to human error. This article suggests an automatic segmentation of unpolished and broken rice grains using contour-based pixel distribution approach. The method leverages image processing techniques such as greyscale conversion, adaptive thresholding and morphological operations to extract individual grains from a sample. Contours are detected using the Canny edge detection algorithm, followed by connected component analysis to segment grains based on their shape and size. To differentiate the unpolished grains, pixel intensity distributions are analysed, as unpolished rice exhibits higher roughness and uneven textures. Similarly, broken grains are identified based on contour perimeter, aspect ratio and area thresholds. The proposed system was tested on rice samples collected from the VIT School of Agricultural Innovations and Advanced Learning (VAIAL), Vellore and NK Rice Mill, Redhills, Chennai, achieving high accuracy in distinguishing whole, broken and unpolished grains. This approach provides a cost-effective, non-destructive and efficient solution for automated rice quality grading, reducing dependency on manual inspection.

Keywords: broken grains; contour segmentation; edge detection; rice grain; unpolished grain

Introduction

Rice (*Oryza sativa*) is the world's most important staple cereal crop. More than half of the world's population relies on rice and in the 2023-2024 crop year, the globe produced approximately 523.9 million tonnes of it (milled) (1, 2). Paddy is processed in many stages including harvesting, threshing, drying, cleaning, de-husking to produce brown rice, separating un-hulled paddy, polishing to obtain white rice, grading and sorting by size and quality and finally packaging and storage to fit for consumption. The two steps in the milling process are dehulling paddy using rubber roll, mechanical or friction huskers, to produce brown rice and exfoliating the outermost layer (bran) by employing abrasive or friction polishing methods to obtain milled rice. Milling greatly influences the grain quality, which depends on the duration and temperature of milling, methods, etc. Higher milling temperature results in higher breakage of grains and lowers the head rice yield (3). Breakage of the rice kernel is associated with the moisture content of 12-14 % results in lesser breakage (4).

Post-harvest and processing of rice cause considerable loss, especially during milling. Post-harvest loss in rice accounts for around 16 %. The rough or parboiled rice can be dehulled following hand pounding or mechanical methods. Around 60 % of rice in India is parboiled rice (5). Anatomically, rice grains are enclosed in layers of unpalatable bran and husk. It must undergo a series of milling operations to completely remove these fibrous components and render them fit for human consumption. Therefore, rice milling aims to create white rice by removing the bran and hull. The aim of the milling process is to achieve quality whole grain with a total rice recovery. Milling of grains leads to the loss of nutrients that are present on the outer surface layer of the rice. To prevent the loss of nutrients and breakage of the rice, a parboiling technique has been recommended to preserve the vitamins and minerals in the polished rice. Parboiling which entails soaking, steaming and drying the paddy before milling strengthens the grain, lessens brittleness and encourages water-soluble nutrients to migrate into the endosperm (6, 7). The milling fractions of rice are the hull, bran, brown rice and milled rice. Milling yield varies depending on the variety (72 % milled rice) and degree of milling (12 % bran and 20 % husk) (8). The degree of milling is an excellent metric to assess head rice productivity, insect infestation, sensory quality and beginning gelatinization. The increase in milling time ultimately decreases the head rice yield (9).

Numerous smart post-harvest techniques have been created to minimise product loss, including as data-driven systems that optimise processing and storage conditions, automated sorting and grading by machine vision or artificial intelligence, sensor-based monitoring and precisely regulated milling and drying. The major problem with rice during milling is the breakage of the grains. Consumers highly prefer rice with minimal broken grains. The assessment of rice quality is an important criterion in rice mills to identify damaged, broken and chalky seeds. The quality of the grains can be estimated by following computational machine learning algorithm programmes (10 - 12). Machine vision was used in rice for variety classification based on morphology, color and texture. One of the most crucial objectives in the rice processing sector is to check the quality of the rice kernels during the parboiling process (13). Image analysis enables grading and monitoring of rice grains to meet market and consumer standards, achieving up to 90 % accuracy (14).

In rice mills, skilled operators visually check the product's quality grade at 1-2 hr intervals because continuous online assessment technologies are not readily available. This means that by simply looking at the machine output and making the necessary modifications, the operator determines the product's quality grade based on his expertise and skill with the processing machinery. Most of the time, this operation is not completed quickly enough or accurately enough. In this sense, creating automated systems that can function according to the experience of the operators could be a useful way to quickly and accurately grade the product's quality (15, 16). Computer vision has proven effective method to segregate the milled rice into broken and unbroken grains. The logistic regression method is used in rice quality analysis, but the study on rice grains during the process of milling is limited. Machine vision has been used in various agricultural products, including fruits, vegetables, grains, fish, meat and other products. The use of AI tools in agriculture for grain quality evaluation provides an accuracy range of 80 - 98 % (17). Digital image processing and analysis techniques must be employed to extract enough appropriate features used for process control and monitoring or rice quality assessment. Pattern classification and recognition techniques are used to comprehend the underlying content of rice photographs (18).

In the literature, there are separate models for detecting broken rice grains and for grading the rice quality but still there is a scope to improve the performance of the models. The main objective of the model is to develop a single image processing-based model to detect the broken, unpolished rice grains and the insects if any.

In this study, we present an image statistical modelling-based rice quality inspection method by employing a suitable algorithm to address the challenges of effectively classifying rice quality in complex grainy images with many local homogeneous particles or fragmentations that lack a clear distinction between the image foreground and background. The main objective of the research is to evaluate the broken and unbroken grains, counting the number of grains and broken grains during polishing. To assess the percentage of broken kernels and polished grains using hand-pounded and parboiled rice varieties during milling by using digital image processing systems. The methodology was developed to identify the amount of parboiled rice grains broken and unbroken during polishing and to find the polished and unpolished grains. The goal of the research is to identify the impact of the milling of parboiled rice grains. The purpose of this study is to use several milled rice grains with distinctive characteristics to develop a recognition technique that can be used for various rice types. The rice quality affected by the milling process can be further reduced by using machine vision algorithms. The research aims to identify the polished and unpolished grains, broken and unbroken grains and to count the number of grains.

Materials and Methods

Sample collection

The rice samples developed by the International Rice Research Institute (IRRI) are collected from various places like VAIAL, Vellore and NK Rice Mill, Redhills, Chennai. Polished and unpolished samples were collected from the storage areas for use in the proposed image processing system. Other foreign items like stones, weeds, paddy husks and rice straw are present along with the rice samples.

Image acquiring and preprocessing

FLIR E8 XT thermal camera is used to collect both the thermal and RGB images of the rice samples. The camera was positioned 20 cm above the rice samples, which were arranged in various orientations during image capture. The RGB samples are predominantly used for analysing the rice quality by differentiating the whole and broken, polished and unpolished rice samples. During the process of image acquisition, 10 g of rice is used for capturing each sample.

Methodology

The flowchart of the method for rice quality using image processing is shown in Fig. 1. Edge detection for rice samples is used for quality assessment, counting and classification of rice grains. Canny edge detection is a multi-stage process to emphasize the edges when intensity changes significantly. Gaussian filtering is applied to suppress noise in the grayscale images. Non-maximum suppression is used to identify the thin edges and remove the weak edges using hysteresis thresholding. An effective contour method is used for detecting, segmenting and analyzing the individual grains. Using cv2.findContours function the grain boundaries are extracted and drawn as the contours on the original image. Using the pixel distribution for each contour region of the rice sample, identify the polished and unpolished grains and insects in the grain samples. Additionally, the percentage of broken and unbroken rice grains is identified using the grain parameters such as area, perimeter and shape.

Results and Discussion

The quality of the rice grains is that they should be free from broken grains during the polishing process. The image processing technique was introduced to regulate the degree of whiteness (degree of milling). To draw in customers and ultimately generate financial gain for the millers, the proportion of broken rice kernels in milled rice must be decreased (19, 20). The number of broken grains and unbroken parboiled rice grains is estimated more efficiently by machine vision image analysis by incorporating an algorithm.

As shown in Fig. 2, broken grains are highlighted with thin blue contours, while unbroken grains are marked with thick green contours. A technique for determining the size distribution of rice as well as the quantity of broken rice grain, was created by utilizing image analysis and flatbed scanning (21). The quality of milled rice was determined by classifying the grains into head rice and broken rice in five different rice varieties (22). Visualizing broken and unbroken grains with unique colours during the milling process can help assess their condition. Assessing the percentage of broken and

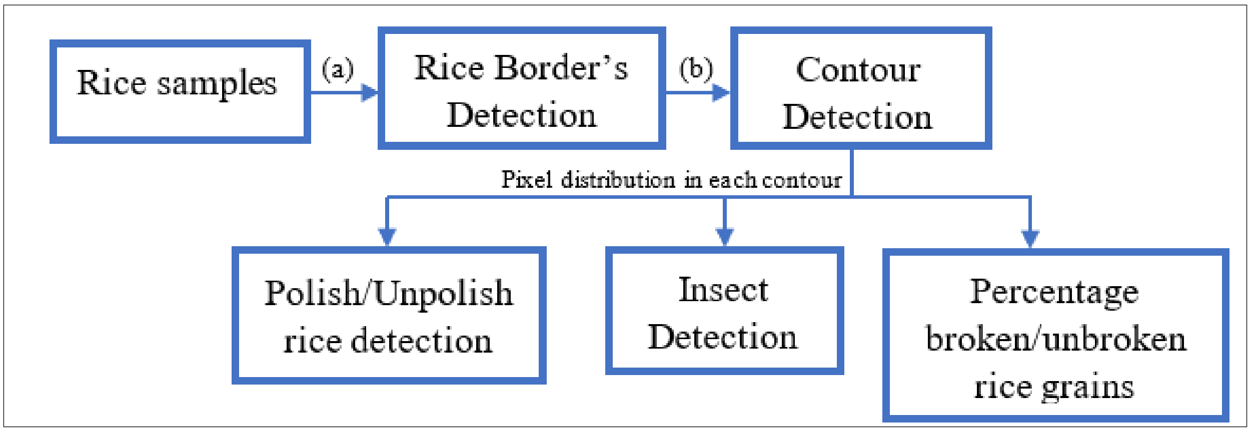
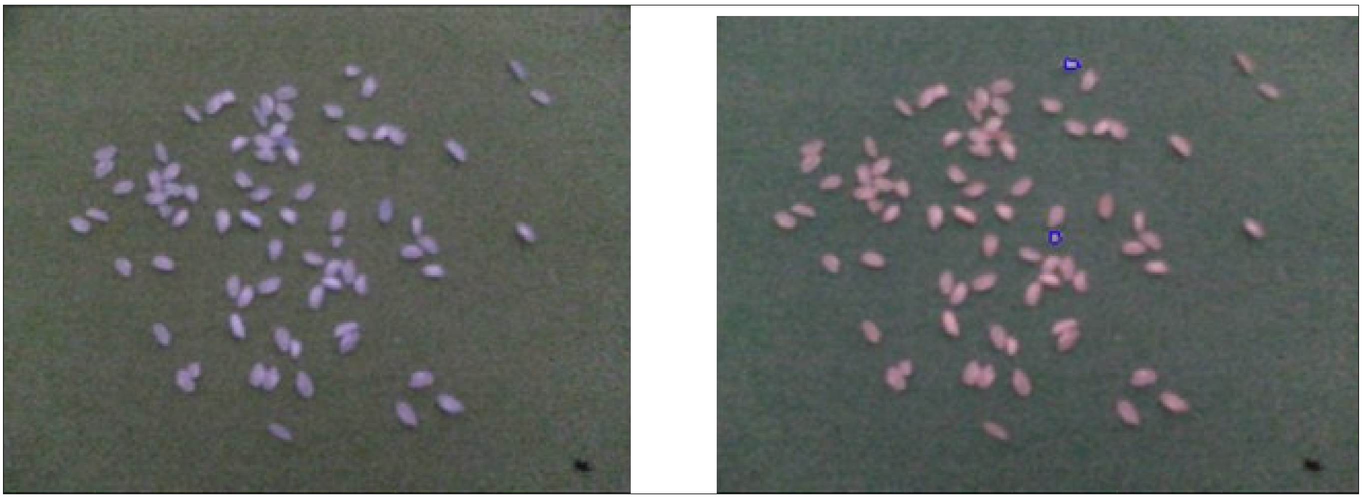


Fig. 1. Flowchart of the method used for rice quality grading.

a) RGB to grey conversion b) Finding and drawing contour



A B

Fig. 2. Detection of broken rice grains. 2a) Raw rice grain sample. 2b) Broken rice with blue- coloured polygon.

unbroken grains further helps reduce grain loss during the milling process.

As the manual process of counting the seeds are tedious and often associated with errors, algorithm based studies provide higher accuracy. Similar machine learning based counting methods have been applied to maize and soybean (23). The cracks and breakage of parboiled rice grains were detected and counted by using an algorithm, but it does not classify and separate the fissures in the seeds (24). Fig. 3 indicates the density image of counting grains by employing the proposed algorithm. Out of 54 rice grains in the test image, all the grains were successfully detected and highlighted with thick green contours.

An algorithm that used PCA and the Wilks distribution approach was used to identify and categorize rough rice hybrids and inbreds. The electronic nose is used to classify and recognize the four varieties of polished rice. According to their study, rice could be recognized using an electronic nose. However, they noted that while applying principal component analysis (PCA), the classification and recognition impact could not achieve the optimal state since parboiled rice was combined with three other kinds of rice that are not classed with each other. Clear recognition without overlap was achieved for polished rice and cooked rice, unlike brown and rough rice (25, 26). Fig. 4 depicts the image of unpolished rice grains before the milling process. Fig. 4b represents the unpolished rice.

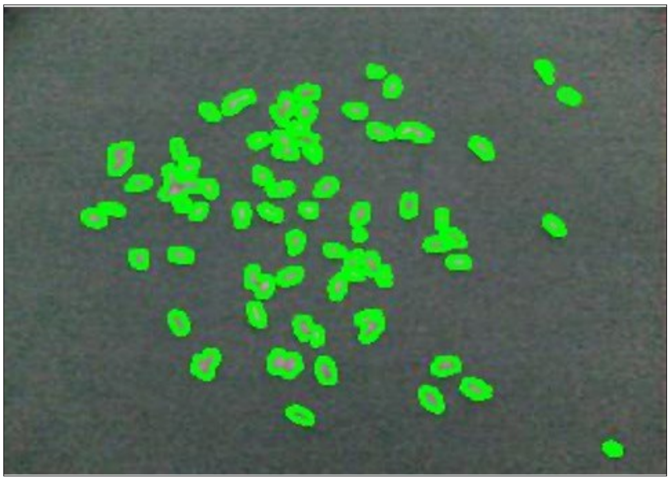


Fig. 3. Counting of rice grains.

Fig. 5 shows the polished and unpolished rice grains of milled seeds. The polished rice grains appear white, whereas the unpolished rice grains remain coloured. The percentage of the number of rice grains polished and unpolished during the milling process can be interpreted. Additionally, an insect located in the bottom right corner of the image was detected and outlined with a black polygon.

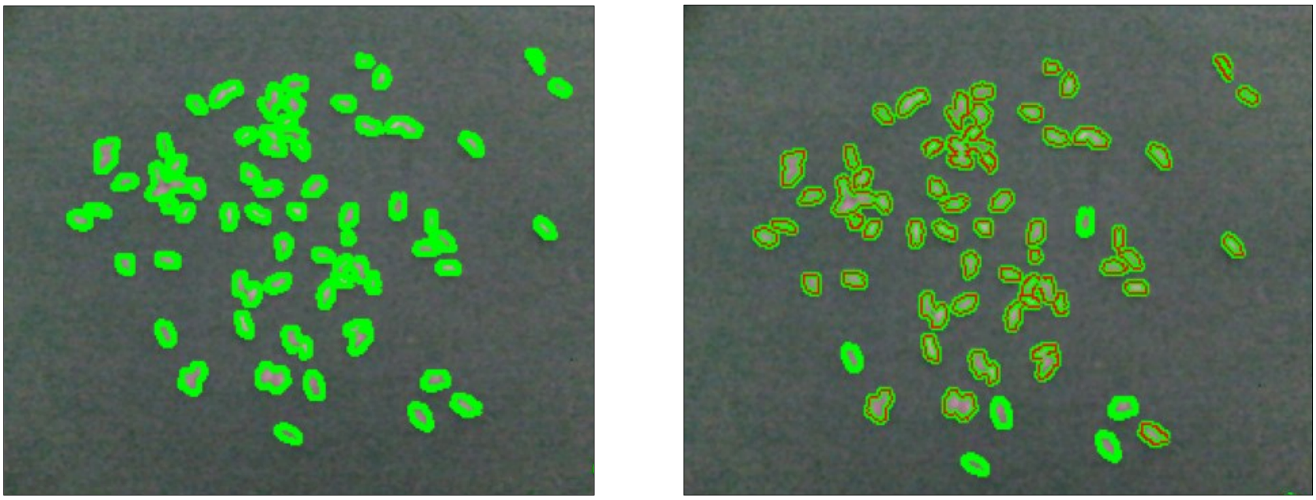


Fig. 4. Detecting unpolished rice grains. a) Green-coloured polygon approximation for the grains presents in the sample image. b) Contour representation for polished and unpolished rice.

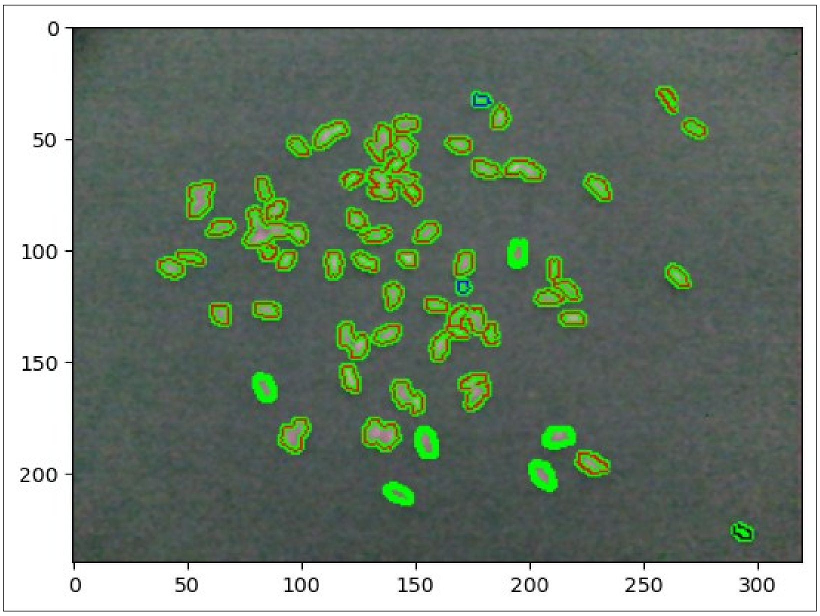


Fig. 5. Sample labelling of polished and unpolished rice grains.

Conclusion

The loss of rice grain quality is significant during the milling process. To mitigate this, an efficient and reliable method must be developed. In this work, we proposed a novel contour-based pixel distribution approach for segmenting unpolished and broken rice grains. The method effectively distinguishes whole and broken grains by analysing contour characteristics and pixel distributions, allowing for precise segmentation. Experimental results demonstrate that contour-based segmentation provides a reliable means of differentiating broken grains from whole ones, particularly in unpolished rice, where texture variations can pose challenges. Research was conducted for the detection of broken and unbroken rice grains, counting the number of grains and differentiating the polished and unpolished rice grains during the milling process. By estimating the loss of grains, factors that are responsible for the loss of grains can also be minimized, which is also computationally efficient and can be integrated into automated rice quality assessment systems. Future work can focus on advanced automatic rice grain classification systems by enhancing the robustness of the method by incorporating machine learning techniques and refined contour extraction for the overlapped grains.

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Authors' contributions

SK identified the problem and design the overall proposed system and JJA contributed in the sequential alignment of the methodology and validation. KRR participated in overall designing and coordination. DN supported in the manuscript drafting and formatting. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare.

Ethical issues: None

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