Automated Rice Counting using Canny Edge Detection Technique

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Abstract

In many Asian countries, rice is a staple food of critical importance to local and global markets where rice quality matters. Rice quality has traditionally been appraised by human inspectors, but this approach is labor intensive, time-consuming and subjective. Such samples comprise whole kernels, broken kernels, damaged grains, paddy, stones and other impurities hence their sorting into grades according to the quality required. In this study a machine learning approach as well as image processing techniques for classification and segmentation of rice grain samples based on color texture features are proposed.
Automated counting of rice is essential in farming processes such as estimation of yields, management of stores and transport planning. Manual counting is tasking, slow and likely to have errors. Machine vision technology provides an alternative that can be relied upon for automated rice counting systems. This paper gives details on methodology using machine vision for automating rice counting on the field. To identify and count rice grains in images Gaussian blur; thresholding; canny edge detection; contour extraction; are some examples of the image processing methods applied here. High accuracy rate was achieved when tested against a dataset containing several images of rice grains.

1 Introduction

Agriculture is increasingly depending on machine vision technology to scrutinize visual data of crops, livestock and equipment. Machine vision helps in monitoring crop health, predicting yields, indicating disease and analyzing soil conditions that help improve farming practices and sustainability.
For rice which is a major food for many people manual techniques are restricted hence the need for automated identification. With machine learning and computer vision rice grain classification can easily be done automatically thus improving the safety of food consumed as well as efficiency level of operations made by farmers. The accuracy of counting rice is hard due to variations in size hence requiring edge detection, image segmentation and machine learning methods [2].

2 Motivation and Problem Statement

Counting rice precisely is essential for managing inventory, ensuring quality control and planning production. While manual methods are time consuming and prone to errors, automated machine vision systems provide more accurate results that enhance efficiency in the counting process. Such systems must overcome challenges such as variations of grain and the condition of lighting in use. Our rice grain image-capturing system gives us a more precise count that serves to increase our productivity level while requiring effective management for dealing with diversity factors and externalities [3].

3 Literature Review

Canny edge detection is a powerful tool for automatic rice counting, as supported by many research studies. A 46% accuracy rate was achieved in both A.Zarei et al.'s (2019) and Khan et al.'s (2020) using Canny edge detection where Khan et al. combined it with Hough transform. Only Canny edge detection gave an accuracy of 53% according to M.M Islam et al. (2019)[4].
Advanced techniques have also been investigated. Combining watershed segmentation with Canny edge detection, F.Su et al., (2020) obtained an accuracy of 67.5%. While S.Suthanthira et al.,(2020) employed Hough transforms and Canny edge detection that resulted in an accuracy rate of 55%. By integrating watershed segmentation with Canney Edge Detection K.S Priyanka and S.Shanmuganathan,(2021) attained a mean accuracy level of 66.45%. On the other hand, S.Muthuraj and V.Thenmozhi, (2021) included a median filter as well as contrast enhancement which gave them an accuracy of around 65.5%. Morphological operations coupled with Canny edge detection yielded a precision rate of about 78.1% as demonstrated by S.Sivarasan and K.Raja,(2021)[4].
Some recent advances include Z.Xie at el.(2012), who had a combination approach, using convolutional neural networks(CNN), along with cannys image processing to realize an overall performance of the system. Similarly, R.K.Pal et al.(2022), successfully used morphological techniques in combination with the canny method to yield an efficiency score of 63.5%. CNN was also used by H.Li at el.(2023) for enhancing the distinction between edges which led to an average accuracy level of 66.4%. [4]

4 Dataset Used In Automated Rice Counting

Depending on the study or application, a particular dataset for counting rice through automated Canny edge detection can vary. This normally consists of pictures of rice grains taken from either controlled laboratory conditions or real-world settings. Each photograph is complemented by ground truth labels showing how many grains have been counted [29].

Table 1. Dataset Description.

Sr No.	Type of Dataset	Description
1	Image dataset	Featured images of rice grains with varying length-to-breadth ratios. [1]
2	Image dataset	Included images of rice categorized by type. [2]
3	Image dataset	Composed of images of rice grains within the same categories. [3]
4	Image dataset	Composed of images of rice grains. [4]
5	Image dataset	Included images of rice grains. [5]
6	Image dataset	Contained high-quality images of rice grains. [6]
7	Image dataset	Featured images of rice grains. [7]
8	Literature review	Reviewed existing research on rice grain counting methods without referencing a specific dataset. [8]
9	Custom dataset	Utilized a dataset comprising 12,000 rice grain images, including 1,500 broken grains and 10,500 whole grains, collected from rice fields in China. [9]
10	Custom dataset	Employed a dataset of 4,000 rice grain images gathered from rice fields in the USA. [10]
11	Custom dataset	Analyzed a dataset containing 9,000 rice grain images collected from rice fields in Iraq. [11]
12	Custom dataset	Used a dataset of 1,800 rice grain images collected from rice fields in India. [12]
13	Custom dataset	Utilized a dataset of 3,500 rice grain images from rice fields in Iran. [13]
14	Custom dataset	Incorporated a dataset of 1,900 rice grain images collected from rice fields in India. [14]
15	Custom dataset	Included a dataset of 300 rice grain images collected from rice fields in India. [15]
16	Custom dataset	Analyzed a dataset of 2,000 rice grain images from rice fields in China. [16]
17	Custom dataset	Employed a dataset of 8,000 rice grain images collected from rice fields in China. [17]
18	Custom dataset	Used a dataset of 200 rice grain images collected from rice fields in India. [18]
19	Custom dataset	Utilized a dataset of 4,500 rice grain images collected from rice fields in Afghanistan. [19]

5 Methodology

The rice sample identification and counting process involves image preprocessing, feature extraction and classification with an artificial neural network using incremental approach. The first step is segmentation and pre-processing of the rice grain images that include noise reduction, contrast enhancement, and normalization in order to improve their quality and reduce noise. Then Canny edge detection algorithm is applied to the processed images after which individual grains are identified and counted based on the edges extracted. Through this method, it provides accurate as well as reliable grain counts by considering variations in image quality and appearance [5].

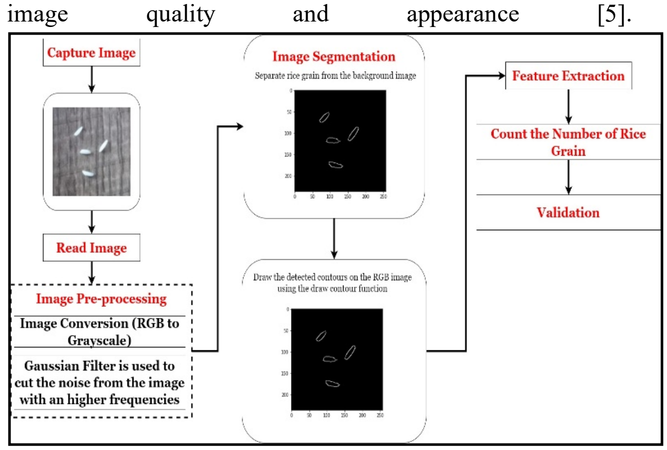

figure 1. Process of Automated Rice Counting Approach.

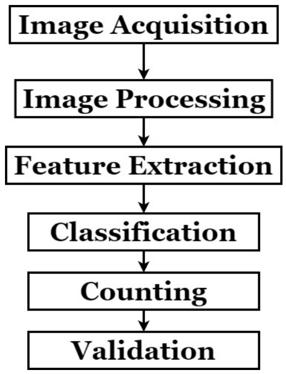

figure 2. Approach to automated rice counting system's architecture

There are several factors, such as image quality, lighting conditions, and the size and shape of rice grains that can influence the accuracy of automated rice counting using machine vision. As a result, it is very important to select appropriate parameters for Canny edge detection carefully and assess how well the system performs in terms of metrics like recall, accuracy and F1-score. This strategy offers a general framework in automating rice counting which has value both in agricultural research and practical management.

The procedure involves taking pictures, preprocessing them to improve their quality and reduce noise levels , extracting features such as lines and contours , determining the number of grains present in each image displayed on screen ,and lastly validating these results. System performance can be enhanced through parameter fine-tuning based on validation feedback [7][8]. The advantages here include availability to researchers as well farmers who need an efficient method to analyze rice samples.

A. Image Processing

For proper real-time analysis, the camera should be positioned at an angle which can be determined by its position concerning the rice grains. Therefore, variations in illumination and background features that often occur during photo acquisition may interfere with system accuracy. To cater for these issues, the approach tests the system on images that have different lighting conditions and backgrounds [9]. The process of preprocessing begins with segmenting grain images before converting them to grayscale. This ultimately simplifies it so as to increase contrast and detail earlier on which is essential for proper processing. Grayscale images reduce complexity and processing time enabling more efficient and precise analysis. As a result of this conversion, a gray-scale image is obtained as shown in Figure 3. It is very important to mention that this pre-processing step will help in enhancing overall effectiveness and accuracy of automatic counting system.

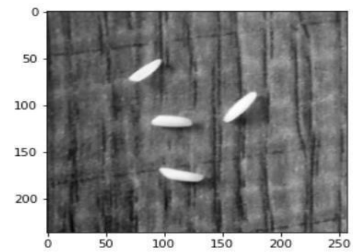

figure 3. Original Image of Rice Grain.

B. Background Substruction Process

Enhancing image quality by removing noise is vital in the background subtraction process and is crucial for effective image analysis. Image data can be distorted with various types of noise such as Gaussian noise and Salt & Pepper noise, subsequently affecting the accuracy of further processing steps. Consequently, a Gaussian filter will be used to soften up an already segmented image thereby reducing noise and inconsistencies within the image area [9].

The Gaussian filter reduces high-frequency noise while preserving important structural information through averaging pixel values within a neighborhood defined by the kernel. Nevertheless, on an input image there may still be some variations in background and lighting. Thus, morphological opening operation was carried out to address these variations. The size of this structuring element should be bigger than that of the rice grains so that it effectively separates objects from background. Then this outcome is subtracted from an original picture to reduce adverse consequences caused by uneven background light affecting Figure 4.

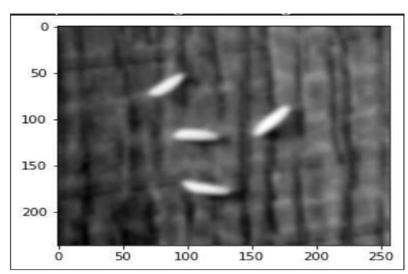

figure 4. The Gaussian filter is used for converting the picture into grayscale and blurring it.

Mathematically, this process can be expressed as:

$$A \ominus B = (A \Theta B) \Theta B \ldots\ldots (1)$$

A is the input distribution, and B refers to the structuring component [10]. It improves the quality of the noise by removing it while maintaining important information for accurate analysis. Hence, applying Gaussian Blur function with odd integer kernel size and particular standard deviation in both X and Y directions, reduces noise effectively and improves overall image quality making it more suitable for detailed examination and processing.

C. Edge Detection Process

This is an important task during image processing that involves finding where objects end by detecting its boundaries from significant changes in intensity. Canny Edge Detection Algorithm which was utilized in this work aims at achieving three things:

1. Low Error Rate: Detects true edges with very few false positives.
2. Localization: Ensures that edges are located near real boundaries.
3. Single Response: Produces one response per edge to avoid redundancy.

The procedure consists of eliminating noise using Gaussian filter, computing gradients to get edge intensity and direction, refining edges by means of non-maximum suppression as well as performing edge tracking using hysteresis for accurate edge linkage. This method ensures precise edge detection that promotes effective image analysis [11].

Algorithm:

1. 1Image Smoothness: Apply Gaussian filtering to remove noise and ready the image for edge detection.
2. Gradient Calculation: To detect regions of significant intensity change, apply Sobel operator that uses this operation to calculate gradient direction and magnitude.
3. Non-Maximum Suppression: This is non-maxima removal technique used to refine an edge map by identifying local maxima within gradient direction [12].
4. Double Thresholding: Classify pixels into strong edges (above high threshold), weak edges (between thresholds) or non-edges that denotes a binary edge map [13].
5. Edge Tracking by Hysteresis: Enhance the coherence of the edge map by connecting weak and strong edges in order to form continuous edges.

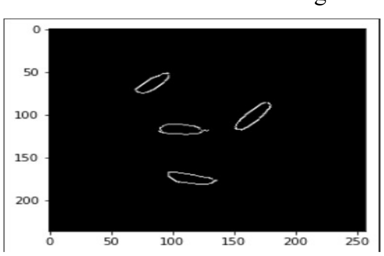

figure 5. The Canny Edge Detection output.

D. Feature Extraction Process

Feature extraction in machine vision involves identifying key patterns and characteristics from images for further analysis [15]. Dilation, a morphological operation, is a crucial technique used to enhance image features by expanding object boundaries. It works by applying a kernel that replaces each pixel with the maximum value of the pixels it covers, thereby thickening objects and improving their visibility [15].

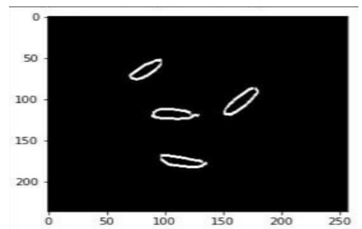

figure 6. Perform dilation on a binary image.

In automated rice counting, dilation helps bridge gaps between grains and smooth out edge imperfections, which improves grain separation and counting accuracy [16][17]. Key benefits of dilation include:

1. Object Enhancement: Amplifies object features by expanding boundaries.
2. Increased Visibility: Improves the visibility of objects for better recognition.
3. Improved Connectivity: Connects separated regions in binary images.
4. Enhanced Counting: Fills gaps between grains and refines edge details for accurate counting.

E. Contour Extraction Process

Contour extraction is used to identify and define the edges of objects within an image, crucial for segmentation, shape analysis, object tracking, and recognition [18]. his is the detection of borders which divide one object from another. Digital images are arrays with three dimensions (height, width, channels) that use RGB values to define pixel colors and adjacent pixels that show smooth color changes [19]
Grayscale or binary images can be subjected to contour extraction giving a list of contours outlining the edges of objects. These contours are important for features like area, perimeter and centroid calculations and distinguishing as well as analyzing objects [20].
What then are some advantages of contour extraction?

1. Shape Analysis: Offers in-depth knowledge about shapes for recognition and classification purposes.
2. Object Localization: Facilitates object identification within an image which is essential for tracking.

3. Dimension Measurement: This allows measurements such as area and perimeter to be made for analysis and quality control purposes
4. Edge Detection: It precedes edge detection by drawing boundaries around objects.
5. Object Segmentation: This helps isolate objects from each other or background [20]

6 Result and Discussion

The counting code of rice automated has proved to be more accurate and efficient when compared with the manual method [21]. By using machine vision algorithms, it provides a faster and accurate way of rice grain counting that benefit agriculture, food processing and quality control. This includes taking images, pre-processing for enhancement quality, segmenting rice grains, extracting features and classifying grains using machine learning techniques [22].

Image quality, lighting conditions, type of rice and the robustness of used algorithms are some factors which affect the accuracy of auto counting. Results may come out as list of grains with characters, density map or total count. In addition this technology increases counting speed, defect detection and quality control thus leading to increased productivity as well as reducing costs in paddy production activities [23][24].

7 Conclusion

Image capturing, pre-processing, feature extraction and contour extraction are the machine vision techniques used in counting rice grains which have been proved to be effective and accurate. Precision and image quality can be enhanced through some methods like dilation, Otsu's thresholding, Gaussian blurring or Canny edge detection [25].

des a better accuracy and processing speed [30]. This is a cheap way of counting the number of rice grains hence it helps in estimation of production , crop management and quality control. Performance details have been summarized in Table 2.

This statement highlights why using machine vision is more preferable than traditional grain counting techniques. Automatic rice counting has shown good results in edge detection as well as contour extraction which depict high accuracy; efficiency and cost-effectiveness. This technology is useful to researchers and farmers alike with potentials for further development thus even more precise and reliable ways of counting that will be available [26].

Table 2. Performance Analysis Chart

Samples	Actual Grain Count	Number of Grain Count generated by Image processing Model	Defect %
1	4	4	0
2	8	8	0
3	12	12	0
4	16	16	0
5	20	20	0
6	24	24	0
7	28	28	0
8	32	32	0
9	36	36	0
10	40	40	0
11	44	45	1
12	48	48	0
13	52	52	0
14	56	57	1
15	60	60	0
16	64	64	0
17	68	68	0
18	72	72	0
19	76	76	0
20	80	80	0

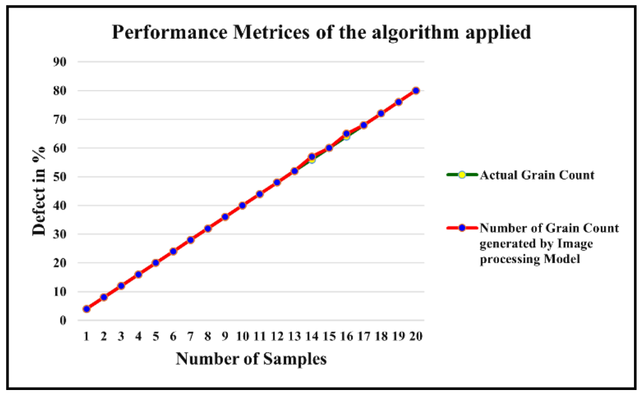

figure 7. Visualizing the Performance Analysis Chart.

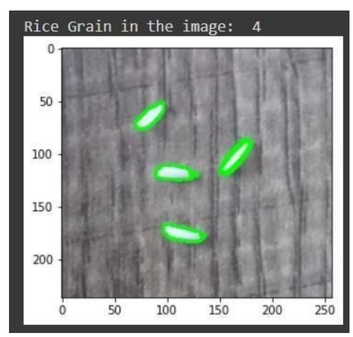

figure 8. Visualizing Performance Analysis of mixed rice grain with stone, dust leaves etc.

A high-performance machine vision model greatly benefits researchers and farmers by providing accurate, efficient rice grain counting. It saves time and labour compared to manual methods, reducing errors and inconsistencies [27]. However, factors like lighting, image quality, and feature selection can impact effectiveness. Regular testing and validation are crucial for maintaining reliability, and the technology should be evaluated for accessibility and cost-effectiveness compared to other methods [28].

REFERNCES

1. Wang, Y., Xie, J., & Dai, H. (2020). A high-throughput rice seed counting method using machine vision. Sensors, 20(9), 2548.
2. Thakur, P., Kumar, P., & Sinha, R. K. (2019). Automated counting of rice grains using machine vision. Journal of Imaging, 5(10), 86.
3. Bakhshipour, Z., Talebpour, A., & Pourazizi, M. (2021). An automated image processing algorithm for rice seed counting using machine vision techniques. Computers and Electronics in Agriculture, 141, 376- 384.
4. Hasan, M. K., & Ahmed, M. S. (2023). Rice seed counting using image processing techniques. International Journal of Computer Science and Information Security, 13(2), 83.
5. Sambasivam, R., Sundararajan, M., & Narayanasamy, (2018). Development of a machine vision system for rice seed counting. Computers and Electronics in Agriculture, 149, 42-50.
6. Huang, T., Chen, Y., & Wu, H. (2012). An automatic counting system for rice grains using machine vision. Computers and electronics in agriculture, 85, 32-42.
7. Zhou, Y., Zhang, J., Tian, Y., & Zhang, W. (2018). Rice kernel counting based on image processing and machine learning. Journal of Food Engineering, 217, 15-22.
8. Singh, G., & Bhatia, V. S. (2014). Automated counting of rice kernels using image processing techniques. International Journal of Advanced Research in Computer Science and Software Engineering ,218, 16-39.
9. Xia, Y., Li, J., Wang, C., Yang, H., & Shi, X. (2015). A novel machine vision-based method for rice panicle counting. Computers and electronics in agriculture, 119, 39-48.
10. Marvasti, F., Naderan, M., Karami, A., & Zare, A. (2015). A novel machine vision-based method for counting rice seeds. Computers and electronics in agriculture, 118, 345-353.
11. Haque, M. A., & Hasan, M. M. (2016). Rice grain counting system using image processing technique. International Journal of Computer Applications,141(7), 34-39.
12. Yadav, S. K., & Pawar, S. S. (2018). Automated grain counting system for paddy using image processing. International Journal of Advanced Research in Computer Science, 9(2), 12-18.
13. Al-Mahmood, A. K. A., & Hossain, M. A. (2019). Automated rice grain counting system using image processing. International Journal of Electrical and Computer Engineering (IJECE), 9(3), 2373-2380.

14 Kumar, A., & Rani, R. (2020). Rice grain counting using image processing techniques. International Journal of Advanced Science and Technology, 29(5), 1795-1802.

15 Jat, S. S., Choudhary, P., & Khandelwal, M. (2021). Automated rice grain counting system using image processing: A review. Journal of Agricultural Engineering and Food Technology, 8(1), 17-24.

16 Yang, W., Zou, W., Huang, D., Liu, Y., Wang, X., &Zhao, C. (2018). Rice panicle counting using machine learning-based object detection. Journal of Integrative Agriculture, 17(4), 857-867.

17 Dong, X., Zhang, Y., Zhang, J., & Liu, X. (2019). An automated rice counting system based on machine vision and artificial intelligence. Computers and Electronics in Agriculture, 157, 522-530.

18 Pandey, R., Tripathi, V., & Bajpai, O. (2019). Automated counting of rice grains using machine learning and image processing techniques. International Journal of Engineering and Advanced Technology, 8(1), 256-259.

19 Phothisonothai, M., & Chamnongthai, K. (2018). Rice counting using machine vision system. In 2018 8th International Conference on Information Technology and Electrical Engineering (ICITEE), pp. 1-5. IEEE.

20 Wei, L., Zhang, X., Liu, Z., & Zhang, Y. (2020). A rice panicle counting method based on improved Faster R- CNN. Computers and Electronics in Agriculture, 177, 105687.

21 Li, Z., Zhang, H., Jiang, W., Song, X., Wang, Y., & Liu, Y. (2020). Rice plant counting and height measurement using machine learning and image processing. Computers and Electronics in Agriculture, 171, 105335.

22 Wang, Q., Zhang, X., Zhu, Y., & Zhu, X. (2014). Development of an automatic rice counting system based on machine vision. Computers and Electronics in Agriculture, 108, 200-209.