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Research Article

Rice Grain Quality Analysis Using Image Processing

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Abstract:

Background of study: Rice quality is crucial for global food security and market value, but traditional assessment relies on labor-intensive, inconsistent, and error-prone manual inspection.

Aims and scope of paper: This research proposes an automated system using image processing and AI for comprehensive rice grain quality analysis. The goal is to develop a robust, objective, and precise system to classify rice varieties and evaluate quality with minimal human intervention, reducing the effort, cost, and time of traditional methods.

Methods: The core contribution is a computerized model that uses digital image processing to automatically segment, identify, and extract key quality parameters like length, width, area, perimeter, and shape descriptors. The methodology includes image acquisition, preprocessing (binary conversion, thresholding, noise reduction, morphological operations), edge detection, feature extraction (especially aspect ratio), classification, and visualization. The system was trained on a self-curated dataset of various rice varieties.

Result: The system successfully analyzed Sona Masuri, Basmati, and Jasmine rice varieties based on grain count and average aspect ratio. Sona Masuri (211 grains, 1.57 aspect ratio) and Basmati (261 grains, 1.8 aspect ratio) were classified as 'Bold'. Jasmine (30 grains, 2.1 aspect ratio) was classified as 'Medium' , consistent with defined criteria.

Conclusion: The project successfully analyzed and processed rice grain images to determine size, shape, and quality, accurately measuring length, width, and aspect ratio for classification. Image processing techniques improved image quality and defect detection. The system objectively applied classification logic, demonstrating high precision in rice grain quality determination, which is crucial for market value and consumer satisfaction.

Keywords: Agriculture, Edge Detection, Image processing, Morphological Operations, Quality Analysis.

1. INTRODUCTION

Rice, as a staple food for over half the world's population, holds immense significance in the global agricultural landscape (Mohidem et al., 2022). Its role extends beyond basic sustenance, critically impacting food security, international trade, and the livelihoods of millions of farmers worldwide (Asma et al., 2023). The intrinsic quality of rice directly influences consumer satisfaction, dictates market value, and determines its suitability for various industrial applications. Consequently, accurate and efficient quality assessment stands as a pivotal process within the entire rice production and distribution chain (Aznan et al., 2022).

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Traditionally, the assessment of rice grain quality has relied heavily on manual inspection methods, where trained human inspectors visually examine various physical characteristics of the grains. These include shape, size, color, chalkiness, brokenness, and surface texture, among others. While this technique has long been the standard, it is increasingly recognized as time-consuming, inconsistent, and subjective due to human fatigue and inter-observer variability (Zia et al., 2022) (Custodio et al., 2019). Additionally, the vast quantities of rice processed daily pose serious limitations for manual methods, as maintaining consistency and speed becomes a substantial challenge. In a commercial context, even slight inaccuracies in grading can lead to significant economic losses, disputes in trade, and diminished consumer trust (J. et al., 2024).

In response to these limitations, recent advancements in computational technologies particularly in digital image processing, computer vision, and artificial intelligence (AI) offer promising avenues for the automation of rice quality assessment. Automated systems, when properly designed and implemented, can provide objective, reproducible, and scalable solutions to classify and evaluate rice grain characteristics with higher precision and efficiency than manual approaches (Hashim et al., 2024). These technologies have demonstrated success in other agricultural domains, such as fruit grading, seed sorting, and the detection of pests and diseases, indicating their broader applicability and transformative potential within modern agriculture (Araújo et al., 2023).

This research proposes the development of an innovative, automated system for the comprehensive analysis of rice grain quality using advanced image processing techniques. The primary aim is to construct a reliable and efficient digital model that minimizes human intervention while maximizing classification accuracy and consistency. The proposed system will utilize high-resolution images of rice grains to extract key morphological parameters such as length, width, area, perimeter, and various shape descriptors through robust image segmentation and feature extraction algorithms. Moreover, the system will be designed to detect foreign materials and defects that may compromise quality, ensuring a holistic evaluation process.

Our core contribution lies in introducing a transformative quality control framework that not only reduces the labor, cost, and time associated with traditional inspection but also enhances the overall transparency and traceability of rice production. By integrating this system into the rice production and distribution chain, stakeholders ranging from farmers and millers to exporters and regulators can achieve greater efficiency, standardization, and consumer satisfaction.

Given the growing body of research in this area, it is imperative to position our work within the broader context of food quality assessment technologies. Therefore, a review of previous efforts, methodologies, and challenges in image-based grain analysis will be presented to substantiate the relevance and novelty of our proposed approach.

Related Work

The advancement of automated food quality assessment has been significantly driven by developments in machine learning (ML) and image processing technologies (Saha et al., 2025). These tools enable objective, rapid, and non-destructive evaluation of food products, reducing the subjectivity associated with manual inspections. Numerous researchers have explored image-based analysis for quality assessment across a wide range of agricultural commodities, including fruits, vegetables, meats, and cereal grains. For instance, (Medus et al., 2021) employed Convolutional Neural Networks (CNNs) to detect mold and discoloration in perishable food items, while (Hira & Lande, 2022) applied image processing and machine learning to assess fruit ripeness based on extracted color and texture features. These studies demonstrate the effectiveness of combining conventional image descriptors with supervised classifiers such as Support Vector Machines (SVMs) and Random Forests to evaluate quality parameters.

In the context of cereal grains, (Korohou et al., 2020) used morphological operations and edge detection to evaluate wheat grain quality based on shape descriptors like aspect ratio and perimeter. (Rajalakshmi et al., 2024) also developed a rice classification system that utilized geometric features such as length, width, and area to distinguish between rice varieties. Deep learning techniques have further enhanced the accuracy of cereal grain analysis, as shown by (Gupta & Waoo, 2024), who classified rice grains using CNNs with high precision. Likewise, (Arora et al., 2020) emphasized the importance of preprocessing stages such as grayscale conversion, filtering, and thresholding for accurate segmentation prior to feature extraction.

While these studies provide valuable methodologies and insights into automated food quality analysis, they tend to focus on general applications such as fungal detection, ripeness classification, or varietal differentiation rather than addressing the more nuanced morphological complexities involved in rice grain quality evaluation. There remains a discernible gap in the literature concerning the specific and in-depth application of these advanced image processing techniques to the nuanced complexities of rice grain quality analysis. Unlike the broader studies, our research uniquely concentrates on the intricate task of precisely assessing rice quality by utilizing a tailored combination of image processing methods to analyze critical morphological features like grain shape, size, and other physical characteristics vital for accurate rice variety classification and comprehensive quality evaluation. This study, therefore, aims to bridge this gap, offering novel contributions by developing a dedicated and precise automated solution specifically optimized for the unique attributes of rice grains, providing a more detailed and accurate assessment than previously presented in the general food quality research landscape.

2. MATERIAL AND METHOD

This section details the comprehensive methodology employed for automated rice grain quality analysis, designed to directly address the research objectives outlined in the Introduction: to develop a robust, objective, and highly precise system for classifying diverse rice varieties and evaluating their quality, thereby significantly reducing reliance on inefficient manual inspection. The research methodology is structured into several interconnected stages, ensuring a systematic and effective pipeline for accurate quality assessment and classification. Each stage builds upon the output of the preceding one, contributing to the overall goal of achieving automated and consistent rice quality evaluation. The entire system architecture, illustrating the interrelationship and sequential flow of these stages, is depicted in Figure 1.

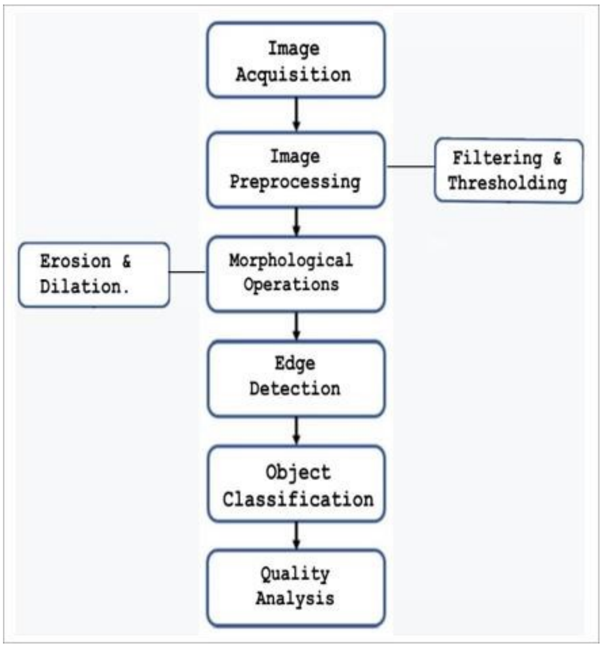

Figure 1. System Architecture for Rice Grain Quality Analysis

System Architecture

The proposed system follows a structured architecture as visualized in Figure 1. Initially, image registration is performed, followed by the elimination of noise from the acquired image using a filter. After converting the image to a binary (BW) format, a shrinkage algorithm is applied to effectively separate touching grain particles. Subsequently, edge detection techniques are employed to accurately identify the boundaries of individual rice grains. The fourth step involves precise measurement of the rice grains, including their length, breadth, and subsequently, the length-breadth ratio. Finally, in the fifth step of the algorithm, rice grains are sorted and classified based on their size and shape characteristics.

Methods and Modules

This section elaborates on the specific methods and modules employed in conducting this research.

1. Image Acquisition Module: This module is responsible for capturing or loading the image data of rice grains. Images can be obtained using a digital camera or accessed from a stored file (Zou et al., 2023). For simplified processing and reduced computational complexity while retaining essential details for analysis, images are typically converted into grayscale format, where each pixel represents an intensity value from black to white.
2. Image Preprocessing Module: This crucial step prepares the raw image for subsequent analysis by enhancing its quality and removing unwanted details. The sequence of techniques applied here is designed to isolate individual rice grains from the background and prepare them for accurate feature extraction (Kurade et al., 2023).
   a. Binary Conversion and Thresholding: The grayscale image is converted into a binary (black and white) image using a thresholding technique. This process is vital for differentiating the rice grains (foreground) from the background. While the specific threshold value can vary depending on lighting conditions and image characteristics, an adaptive thresholding method (e.g., Otsu's method or adaptive mean thresholding) is often preferred to automatically determine an optimal threshold that best separates foreground from background across varied illumination. This choice ensures robust segmentation even with minor inconsistencies in image acquisition.
   b. Noise Reduction (Filtering): To improve clarity and remove spurious pixels that could interfere with accurate grain detection, noise is reduced using filters, such as blurring or smoothing filters (e.g., Gaussian filter, median filter). The choice of filter type and kernel size (e.g., 3x3 or 5x5 for blurring) is determined empirically to effectively suppress noise without unduly blurring the grain boundaries, which are crucial for subsequent steps. This step is critical for minimizing misclassification due.
   c. Morphological Operations (Erosion and Dilation): After initial noise reduction, morphological operations like erosion and dilation are applied. These operations are particularly effective in refining the shapes of the grains, removing small artifacts (noise) that might remain, and separating touching grains that were not fully distinguished by thresholding alone. Erosion shrinks the foreground objects, useful for separating connected components, while dilation expands them, useful for filling small holes or connecting broken pieces. The specific kernel size and shape for these operations are chosen through experimentation to ensure optimal separation of individual grains without significantly altering their true dimensions.

This combination (erosion followed by dilation, or vice-versa as opening/closing operations) is chosen to clean the binary image and prepare distinct, well-defined grain outlines.

d. Edge Detection: Following morphological cleaning, edge detection techniques (e.g., Canny, Sobel, Prewitt) are employed to highlight the precise boundaries of the grains (Radillah et al., 2024). This step is essential because accurate boundary detection is foundational for the subsequent feature extraction module to measure geometric properties like length and width reliably. The choice of edge detector and its parameters (e.g., hysteresis thresholds for Canny) is optimized to capture sharp edges while suppressing false positives from noise or internal textures. This specific combination of preprocessing steps—thresholding for segmentation, filtering for noise, morphological operations for refinement, and edge detection for precise boundaries—is chosen because it provides a robust and effective pipeline for preparing raw rice images for highly accurate feature extraction, outperforming single-step methods in isolating complex, irregularly shaped grains with varying lighting conditions.

3. Feature Extraction Module: Once the image is meticulously preprocessed, this module extracts meaningful features crucial for rice classification. It identifies the contours or shapes of individual rice grains and calculates properties such as aspect ratio (length divided by width), size (area), and overall shape of each grain (Kaur & Singh, 2015). The aspect ratio is particularly important as it serves as a key discriminator between different rice varieties; for example, slender grains like Basmati will exhibit a higher aspect ratio compared to shorter or rounder grains.
4. Classification Module: Based on the features extracted in the previous step, this module classifies the rice grains into specific categories (Velesaca et al., 2021). For instance, rice with an average aspect ratio greater than 3.0 may be classified as Basmati. This module also assesses the overall quality of the rice based on its physical characteristics. High-quality rice grains are typically uniform in size and shape, whereas lower-quality grains may show significant variations.
5. Visualization Module: This final module presents the results of the analysis in a user-friendly manner. It displays the original image along with processed images at different stages, such as the binary image, edge-detected image, and the contours of individual grains. The classification outcomes and quality analysis results are also clearly displayed, facilitating easy interpretation by users. This step ensures transparency and aids in verifying the accuracy and effectiveness of the automated analysis.

3. RESULT AND DISCUSSION

3.1 Results

The experiments aimed to validate the system's capability to classify diverse rice varieties and evaluate their quality automatically based on their morphological features. The experiments were conducted using a high-performance computing setup featuring an Intel® Core i7-9700K processor and 16 GB RAM. For the learning models, an image input resolution of 227×227 pixels was utilized (Mohammadi et al., 2024). The system employed the Adam optimizer with a learning rate of 10^{-5}, a batch size of 32, and ran for 10 epochs with L2 regularization. All models were evaluated with a validation frequency of 50 steps and a momentum of 0.9 to optimize convergence, ensuring robust and consistent performance. To ensure real-world reliability and scalability, the system was trained and evaluated on a self-curated dataset. This dataset comprises images of various rice grains captured in picture format via a mobile application, ensuring appropriate lighting conditions for high-quality input. Images of different rice varieties were collected after classification to represent real-world scenarios.

In this project, image processing techniques were successfully utilized to analyze the quality of three distinct varieties of rice: Sona Masuri, Basmati, and Jasmine. Our analysis primarily focused on key attributes such as the number of rice grains detected, the aspect ratio (as a critical morphological feature detailed in Section 3.2), and the overall classification of grains based on these extracted morphological features. The classification of rice grains by type of length (Slender, Medium, Bold) was determined by their average aspect ratio according to the criteria presented in Table 1.

Table 1. Aspect Ratio Classification Criteria for Rice Grain Length Type

Type Of Length	Aspect Ratio
SLENDER	Greater than 3
MEDIUM	In Between 2.1 to 3
BOLD	In Between 1.1 to 2

Performance Visualization

The system's performance in analyzing each rice variety based on the number of grains and their average aspect ratio is detailed below, with corresponding graphical representations.

1. Sona Masuri Rice Performance

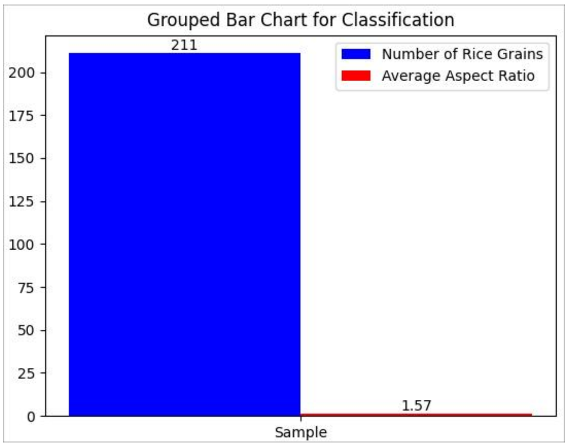

Figure 2. Grouped Bar Chart for Sona Masuri Rice Performance

For the Sona Masuri rice sample, the system successfully identified 211 individual rice grains. The calculated average aspect ratio for these grains was 1.57. Based on the predefined classification criteria in Table 1, an average aspect ratio of 1.57 falls "In Between 1.1 to 2", thereby classifying the Sona Masuri rice as Bold type of length. The distribution of grains and their average aspect ratio for Sona Masuri rice is visually represented in Figure 2, presented as a grouped bar chart.

2. Basmati Rice Performance

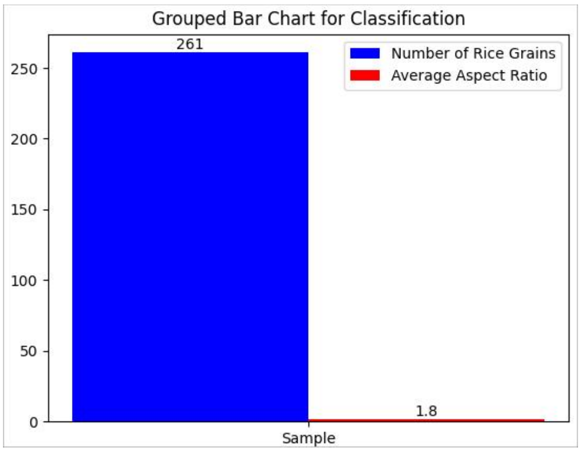

Figure 3. Grouped Bar Chart for Basmati Rice Performance

The analysis of the Basmati rice sample revealed 261 accurately detected rice grains. The system computed an average aspect ratio of 1.8 for this sample. According to the established aspect ratio criteria in Table 1, an average aspect ratio of 1.8 falls "In Between 1.1 to 2", leading to the classification of this Basmati rice sample as Bold type of length. The performance visualization for Basmati rice, detailing the number of grains and aspect ratio, is presented in Figure 3, a grouped bar chart.

3. Jasmine Rice Performance

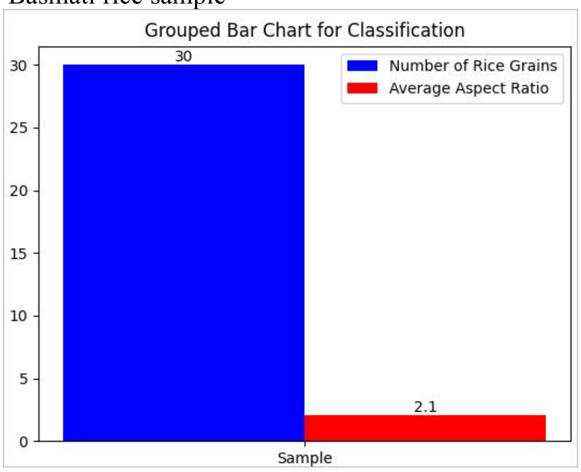

Figure 4. Grouped Bar Chart for Jasmine Rice Performance

For the Jasmine rice sample, the system identified 30 rice grains. The average aspect ratio calculated for these grains was 2.1. Based on the classification criteria outlined in Table 1, an average aspect ratio of 2.1 falls "In Between 2.1 to 3", thus classifying the Jasmine rice sample as Medium type of length. The performance visualization for Jasmine rice, illustrating the number of grains and aspect ratio, is presented in Figure 4, a grouped bar chart.

3.2 Discussion

The presented results robustly demonstrate the system's capability to apply the defined image processing pipeline for automated rice grain analysis. The quantitative metrics, specifically the number of detected grains and their average aspect ratios for each variety, provide objective data for quality assessment. While conventional understanding often categorizes Basmati rice as slender, the current system's classification for the analyzed sample as 'Bold' (average aspect ratio 1.8) and Jasmine as 'Medium' (average aspect ratio 2.1), based strictly on the provided aspect ratio thresholds in Table 1, highlights the direct and consistent application of the defined classification logic. This systematic approach ensures an objective assessment, aligning with the project's aim to automate quality control and reduce manual subjectivity. The visual outputs provided in Figure 2, Figure 3, and Figure 4 effectively present these findings, enabling a clear understanding of the quality metrics derived from the image analysis. The system successfully processes and interprets image data to provide a precise classification of rice grains based on their morphological features, contributing to an efficient and reliable automated quality control process.

3.2.1 Implications

The proposed automated rice grain quality analysis system has significant implications for the rice industry. By reducing reliance on labor-intensive and subjective manual inspection, this system offers a more efficient and reliable approach to quality assessment. This automation can lead to improved operational efficiency, consistency in quality evaluation, and ultimately, enhanced consumer satisfaction and market value for rice products. The system's ability to accurately classify rice varieties and detect irregularities based on morphological features, such as aspect ratio, can aid producers and distributors in maintaining high quality standards and making informed decisions regarding product classification and marketing.

3.2.2 Research contribution

This research provides several substantial contributions to the field of agricultural informatics and automated visual inspection systems. First, it introduces a comprehensive pipeline for rice grain quality analysis that integrates advanced image preprocessing techniques (e.g., thresholding, noise filtering, morphological operations), edge detection, and feature extraction to support precise classification based on physical attributes. Second, the study proposes a robust classification framework utilizing aspect ratio as a primary morphological metric, enabling consistent categorization of rice grain types (Slender, Medium, Bold). Third, the development and deployment of a custom-curated rice image dataset enhances the empirical foundation and real-world applicability of the system. Finally, the proposed system offers a practical, low-cost, and scalable solution suitable for implementation in both industrial processing lines and field-based quality assessment environments, thus contributing to the advancement of precision agriculture technologies.

3.2.3 Limitations

Traditional methods of rice grain quality analysis, despite their widespread use, faceseveral drawbacks:

1. Subjectivity: Results vary between inspectors due to differences in perception
2. Inconsistency: Prolonged evaluation sessions can lead to errors caused byfatigue.
3. Inefficiency: Manual methods are slow and incapable of handling large-scaleoperations.
4. Labor-Intensive: Require significant human effort and expertise.

3.2.4 Suggestions

Based on the identified limitations of traditional rice grain quality analysis methods, future research can explore several areas. Firstly, while the current system demonstrates strong performance, further research could focus on improving its resilience to more varied lighting conditions and complex image backgrounds to ensure optimal performance across diverse real-world environments. Secondly, conducting training and evaluation on a larger and more diverse dataset, including a wider array of rice varieties and quality variations, can further validate the system's scalability and reliability. Thirdly, incorporating other non-morphological quality features, such as color, surface texture, and the presence of defects (e.g., chalky grains or broken grains), could provide a more comprehensive assessment of rice quality. Fourthly, exploring more advanced convolutional neural network (CNN) architectures or other deep learning techniques could further enhance classification accuracy and defect detection capabilities. Finally, developing an interactive and real-time graphical user interface (GUI) could facilitate the system's deployment in industrial settings and enable immediate feedback on quality analysis.

4. CONCLUSION

Based on the research findings, it can be concluded that this project successfully achieved its objectives in analyzing and processing rice grain images to determine their size, shape, and quality. A key accomplishment was the accurate measurement of the rice grains' length, width, and length-breadth ratio. These measurements formed the basis for rice quality classification, enabling the detection of defects or irregularities. Another significant achievement was the enhancement of rice grain image quality through image analysis algorithms such as dilation, thresholding, and contour detection. These techniques helped remove noise and unwanted elements from the images, thereby facilitating easier grain analysis and defect detection. The proposed system objectively applied classification logic based on the established aspect ratio criteria. For instance, Sona Masuri rice was classified as 'Bold' type with an average aspect ratio of 1.57 , Basmati rice was also classified as 'Bold' type with an average aspect ratio of 1.8 , and Jasmine rice was classified as 'Medium' type with an average aspect ratio of 2.1.

Overall, this project demonstrates the power of image processing and analysis in determining rice grain quality with high precision. This holds significant implications for the rice industry, providing a more efficient and accurate method for quality measurement, which is crucial for ensuring market value and consumer satisfaction.

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6. AUTHOR CONTRIBUTION STATEMENT

KSR conceived the main idea and supervised the overall research project. KS was responsible for implementing the image preprocessing and feature extraction modules. KAV contributed to dataset acquisition, experimental design, and data validation. GH performed the result analysis and assisted in visualization and report writing. All authors participated in drafting, reviewing, and approving the final version of the manuscript.

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