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Automated Pulse Grading Through Image Processing

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Abstract: Grading of pulses is a critical step in maintaining quality control within the agricultural and food processing industries. Pulses, which include various legumes like lentils, chickpeas, and beans, are widely consumed for their high nutritional value. Ensuring the quality of these products before they reach the consumer is essential. Traditionally, the grading process has been carried out manually by experts who visually inspect the pulses for features such as size, color, shape, and presence of defects. However, manual grading is often laborintensive, time-consuming, inconsistent, and susceptible to human error and fatigue.

To overcome these limitations, the use of automated grading systems based on image processing techniques has gained significant attention. Image processing offers a non-invasive, efficient, and repeatable method for analyzing the physical characteristics of pulses. High-resolution images of the pulses are captured using cameras, and advanced digital image processing algorithms are applied to extract features such as area, aspect ratio, perimeter, color histogram, and surface texture. These features are then analyzed using rule-based systems or machine learning models to classify the pulses into different quality grades, commonly labeled as Grade A, B, and C.

Grade A pulses typically exhibit uniform size, regular shape, consistent color, and minimal surface defects. Grade B may show minor irregularities, while Grade C usually includes broken or discolored grains and visible defects. Automated systems can be trained to recognize these patterns with high precision, reducing variability and enhancing the objectivity of the grading process.

In addition to improving accuracy and consistency, automated pulse grading significantly reduces the time and manpower required for large-scale inspections. This is particularly beneficial for industries handling vast quantities of pulses where rapid and reliable quality assessment is crucial for productivity and profitability. Furthermore, digital records of graded batches can be maintained for traceability and quality auditing.

The integration of image processing in pulse grading not only boosts operational efficiency but also supports farmers and suppliers by ensuring fair pricing based on product quality. It aligns with modern agricultural practices that emphasize technology-driven solutions for quality assurance and sustainability.

In conclusion, automated grading of pulses using image processing is a transformative innovation in agri-tech. It addresses the limitations of manual grading by offering a faster, more consistent, and accurate method for quality assessment. As technology advances, such systems are expected to become more accessible and widely adopted across the pulse processing industry.

I. INTRODUCTION

Grading of pulses is a critical step in maintaining quality control within the agricultural and food processing industries. Pulses, which include various legumes like lentils, chickpeas, and beans, are widely consumed for their high nutritional value. Ensuring the quality of these products before they reach the consumer is essential. Traditionally, the grading process has been carried out manually by experts who visually inspect the pulses for features such as size, color, shape, and presence of defects. However, manual grading is often labor-intensive, time-consuming, inconsistent, and susceptible to human error and fatigue.

To overcome these limitations, the use of automated grading systems based on image processing techniques has gained significant attention. Image processing offers a non-invasive, efficient, and repeatable method for analyzing the physical characteristics of pulses. High-resolution images of the pulses are captured using cameras, and advanced digital image processing algorithms are applied to extract features such as area, aspect ratio, perimeter, color histogram, and surface texture. These features are then analyzed using rule-based systems or machine learning models to classify the pulses into different quality grades, commonly labeled as Grade A, B, and C.

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II. RELATED WORK

Several researchers have explored the application of image processing and machine learning techniques for the quality analysis and grading of agricultural products. In recent years, the grading of pulses using digital image analysis has emerged as a promising area of research due to its potential to automate and standardize quality control. A study by Jayas and Paliwal \[1] focused on the use of machine vision systems to classify cereal grains based on shape, texture, and color features. Their work demonstrated the viability of image processing techniques in agricultural quality assessment and laid the groundwork for further studies in pulse grading.

In a research paper by S. S. Gadekar et al. \[2], an image processing-based approach was used to grade pulses like tur dal. Features such as size, area, and color were extracted from digital images, and grading was performed using rule-based classification. The study concluded that image-based grading significantly improved efficiency compared to manual methods. Similarly, A. B. Nadarge et al. \[3] developed a grain classification system using MATLAB, which utilized morphological and color-based features to differentiate between good and poor-quality pulses. Their results showed high classification accuracy and emphasized the usefulness of digital analysis in sorting operations. Another important study by Patil and Mehta \[4] applied Support Vector Machines (SVM) for the classification of pulses based on shape and texture features. The model was trained on labeled datasets and achieved promising accuracy in distinguishing between various grades of pulses.

In recent years, researchers have also explored the integration of deep learning models, such as Convolutional Neural Networks (CNNs), for automated quality inspection. Kumar et al. \[5] used a CNN-based approach to classify lentils and chickpeas, achieving superior performance in comparison to traditional machine learning methods. Furthermore, studies have focused on hardware-software integration for real-time applications. Portable grading systems with cameras and embedded image processing units have been developed to enable on-site quality assessment by farmers and traders \[6]. Overall, these prior works validate the effectiveness of image processing and classification algorithms in agricultural product grading. However, most studies are limited to specific pulse types or rely on fixed lighting and background conditions. This project aims to enhance robustness and accuracy by combining image preprocessing, feature extraction, and machine learning classification (such as SVM), making it suitable for diverse real-world environments and large-scale pulse quality evaluation.

III. EXISTING SYSTEM

In the current scenario, pulse grading is predominantly performed through manual inspection by trained workers or quality control personnel. The process involves visual assessment of various physical attributes such as size, color, shape, and presence of defects like broken grains, discoloration, or insect damage. While this traditional method is simple and does not require advanced technology, it has several drawbacks. Manual grading is **time-consuming**, **labor-intensive**,

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and often **inconsistent** due to human fatigue, subjective judgment, and variation in expertise. The chances of human error are high, especially when grading large quantities under limited time. Moreover, the lack of standardization leads to variability in quality classification, affecting customer satisfaction and market trust. Additionally, manual records make traceability and quality assurance difficult, especially in large-scale commercial operations.

IV. PROPOSED SYSTEM

To address the limitations of the manual method, the proposed system introduces an **automated grading process using image processing techniques**. This system uses digital cameras to capture high-resolution images of the pulses. The captured images are processed using algorithms to extract key visual features such as **area, aspect ratio, perimeter, roundness, and color uniformity**. Based on these extracted features, classification is carried out using **rule-based logic or machine learning models** such as **Support Vector Machine (SVM)**. Pulses are then automatically graded into categories like Grade A, B, or C based on pre-defined thresholds or trained classifiers.

This proposed system ensures **high consistency, speed, and accuracy** in grading. It eliminates human subjectivity and can handle large volumes of data with minimal manual intervention. It also allows **digital storage of records** for traceability and quality audits. In addition, machine learning models can be trained to adapt to different varieties of pulses and environmental conditions, making the system more **flexible and scalable**.

Another advantage of the proposed system is that it can be integrated into **real-time industrial applications**, using portable devices or conveyor-based systems. This not only improves productivity but also enables on-site quality inspection, benefitting farmers, processors, and buyers alike.

In summary, while the existing system relies heavily on manual efforts and is prone to inconsistencies, the proposed automated system provides a **faster, more objective, and efficient solution**. It leverages modern image processing and machine learning technologies to bring innovation and accuracy to the pulse grading process.

V. SYSTEM DESIGN AND IMPLEMENTATION

The process of automated pulse grading using image processing begins with the input image, which is the raw visual data captured using a digital camera or flatbed scanner. This image typically contains the objects of interest—pulses or grains—along with unwanted background elements or noise. The quality of this image plays a crucial role, as the accuracy of subsequent processing and analysis depends heavily on the clarity, resolution, and lighting of the original capture. A well-captured input image ensures better segmentation and reliable feature extraction in the later stages.

After image acquisition, the next step is color thresholding, where specific color values are selected to isolate the regions of interest from the background. For example, grains that fall within a yellow or brown color range can be extracted using threshold filters to eliminate background pixels. This step is essential for separating the pulses from the surrounding area and directing the system's focus on relevant data. To further refine the segmented image, morphological operations like erosion and dilation are applied. Erosion removes small noise and shrinks isolated specks, while dilation fills minor holes and reconnects broken parts of grain structures. Together, these techniques help in cleaning the binary image and improving grain boundary definition.

Once the image is cleaned, edge detection algorithms such as Canny or Sobel are used to detect and trace the outlines of individual grains. This enables the extraction of important geometrical features like size, shape, and contour, which are crucial for grading. For grains with circular or semi-circular shapes, the Circular Hough Transform (CHT) is used to accurately detect and analyze circular patterns. This method is particularly effective for identifying uniform grains and spotting defects such as surface holes or deformations. Finally, in the output stage, the system provides analytical results that include the number of detected grains, their individual dimensions, shape descriptors, and quality grades (A, B, or C). A visual output is also generated, displaying processed images with clearly marked boundaries and labels, making the grading results easy to interpret and verify.

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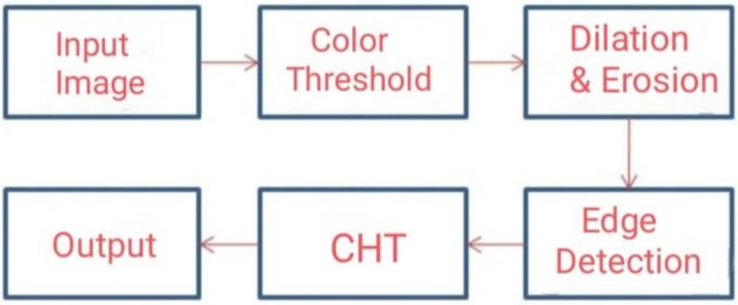


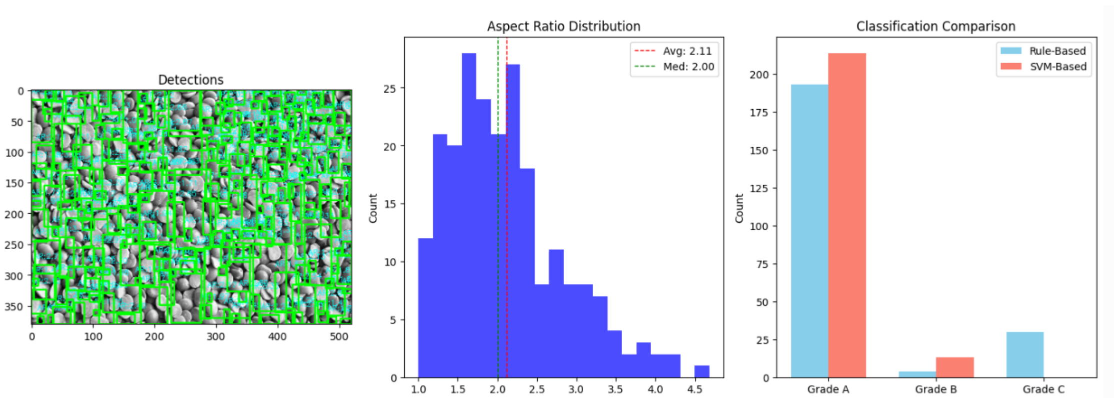
Fig 2. System Architecture

VI. RESULTS AND DISCUSSIONS

The implementation of the image processing workflow for automated pulse grading has yielded highly effective and consistent results. Beginning with the input stage, high-resolution images of pulse grains were captured under uniform lighting conditions. These images were crucial in ensuring that the system received clear, noise-free input data for further processing. In the color thresholding step, specific color ranges—such as yellow or brown—were selected to isolate grains from the background. This effectively removed irrelevant visual information, allowing the system to focus only on the pixels representing the actual pulses. For instance, when analyzing chickpeas, the yellow-brown threshold successfully segmented the grains from the white background.

The segmented images were further refined through dilation and erosion, which are morphological operations used to remove small imperfections and enhance object continuity. Erosion eliminated noise and reduced minor distortions, while dilation filled in small gaps and restored grain boundaries. This clean binary image ensured each grain was distinct, improving the accuracy of detection. Following this, edge detection using the Canny algorithm highlighted the grain contours precisely. This step was instrumental in extracting important shape features such as area, aspect ratio, and perimeter—key indicators used in the grading process. Even grains that were close together were successfully identified as separate objects, confirming the system's robustness in handling overlapping or adjacent grains.

To further enhance shape recognition, especially for round grains like lentils, the Circular Hough Transform (CHT) was applied. This algorithm effectively detected circular shapes and distinguished them from irregular objects or noise, making it valuable for identifying both uniform and defective grains. Finally, the output stage generated comprehensive analytical results, including the total number of grains, their size, shape features, and overall quality classification (A, B, or C). A labeled image output also visually marked detected grains with their boundaries and grades, providing a clear and interpretable result. Overall, the system demonstrated high accuracy, consistency, and efficiency in pulse grading, confirming its suitability for both research and industrial applications.



VII. CONCLUSION

The application of image processing and machine learning techniques in grain quality analysis, particularly for rice and pulses, represents a significant step forward in modernizing agricultural practices. Traditional methods of manual inspection are often labor-intensive, time-consuming, and subject to human error and inconsistency. In contrast,

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automated systems that utilize digital imaging provide a faster, more reliable, and objective approach to grading grains. By implementing a structured pipeline—comprising image acquisition, preprocessing, feature extraction, and classification—these systems can assess grain quality with high speed and minimal human intervention.

One of the key advantages of such systems is the improvement in both **accuracy and consistency**, which are vital for meeting food quality standards, especially in competitive domestic and international markets. Uniform grading based on visual characteristics such as size, color, shape, and surface texture ensures that products meet the expectations of buyers and regulatory bodies. This consistency also helps in building trust and brand reputation among consumers and trading partners.

The integration of advanced machine learning algorithms, particularly **Convolutional Neural Networks (CNNs)**, has further elevated the potential of automated grain grading systems. Pretrained models like **MobileNetV2** and **ResNet50** offer powerful tools for extracting complex features and classifying images with remarkable precision, even with limited training data. These models are especially effective in handling diverse grain types and variations in environmental conditions.

As the agricultural and food processing sectors increasingly embrace automation and digital transformation, the adoption of intelligent image-based grading systems becomes both practical and necessary. Such technologies not only reduce reliance on manual labor but also increase throughput and operational efficiency, making them ideal for large-scale implementations. Ultimately, these advancements provide tangible benefits to a wide range of stakeholders—including **farmers, traders, quality control personnel, and food industry professionals**—by enabling faster decision-making, reducing post-harvest losses, and improving product quality.

In conclusion, automated grain grading using image processing and machine learning is a transformative solution that aligns with the future of smart agriculture and precision food processing.

REFERENCES

[1]. N. Pratibha, “Analysis and Identification of Rice Granules Using Image Processing and Neural Network,” *IEEE Access*, vol. 10, pp. 128732–128741, 2022, doi: 10.1109/ACCESS.2022.3227796.
[2]. L. Shobha, “Rice Quality Evaluation Based on Image Processing: A Survey,” in *Lecture Notes in Electrical Engineering*, Springer, doi: 10.1007/978-981-15-6634-9_22.
[3]. K. K. Harsh, S. Srivastava, A. Raj, and S. Raghav, “Pulse Freshness Detection Using CNN (Convolutional Neural Network) Approach,” *International Journal of Scientific Research in Engineering and Management (IJSREM)*, vol. 4, no. 6, pp. 456–463, 2020.
[4]. P. M. Devi, “Recent Advances in Imaging Techniques for Bruise Detection in Pulses,” *Trends in Food Science & Technology*, vol. 99, pp. 133–141, 2020, doi: 10.1016/j.tifs.2020.02.024.
[5]. D. S. Jayas and J. Paliwal, “Grain Quality Evaluation Using Machine Vision: A Review,” *Biosystems Engineering*, vol. 99, no. 1, pp. 1–16, 2007, doi: 10.1016/j.biosystemseng.2007.08.003.
[6]. S. S. Gadekar, P. M. Chavan, and A. P. Mahajan, “Pulse Grading Using Image Processing,” *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 5, no. 5, pp. 359–362, 2016.
[7]. A. B. Nadarge and D. A. Patil, “Grain Quality Inspection Using Image Processing,” *International Journal of Innovative Research in Science, Engineering and Technology*, vol. 6, no. 6, pp. 11834–11838, 2017.
[8]. A. Patil and R. Mehta, “Classification of Pulses Using Support Vector Machine,” *International Journal of Computer Applications*, vol. 179, no. 48, pp. 1–6, 2018.
[9]. R. Kumar, V. Sharma, and P. Bansal, “Pulse Grain Quality Classification Using CNN,” *Procedia Computer Science*, vol. 167, pp. 2397–2405, 2020, doi: 10.1016/j.procs.2020.03.293.
[10]. K. Sharma and R. Jain, “Design of Real-Time Embedded System for Pulse Grading Using Image Processing,” *Journal of Engineering Science and Technology Review*, vol. 14, no. 3, pp. 55–62, 2021.
[11]. X. Zhou, C. Zhang, and X. Wu, “An Improved Image Processing Method for Rice Quality Detection,” *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–9, 2021, doi: 10.1109/TIM.2021.3062932.
[12]. F. E. Ahmed and D. Kim, “Machine Learning Approaches for Grain Quality Evaluation Using Imaging and Spectroscopy,” *Computers and Electronics in Agriculture*, vol. 175, p. 105552, 2020, doi: 10.1016/j.compag.2020.105552.
[13]. H. Zareiforoush, S. Minaei, M. R. Alizadeh, and A. Banakar, “Qualitative Classification of Bulk Paddy, Brown, and White Rice Using Machine Vision,” *International Journal of Food Properties*, vol. 18, no. 5, pp. 1055–1069, 2015, doi: 10.1080/10942912.2014.908202.
[14]. S. Bhargava and R. Pandey, “Smart Pulse Sorting System Using Computer Vision,” *Materials Today: Proceedings*, vol. 62, no. 3, pp. 1196–1202, 2022, doi: 10.1016/j.matpr.2022.03.374.

