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PEARLVISION AI: AN AUTOMATED PEARL QUALITY GRADING SYSTEM BASED ON MORPHOLOGICAL FEATURES AND ENSEMBLE LEARNING

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Abstract

Conventional pearl quality assessment remains heavily reliant on manual visual inspection, which is subjective and inconsistent. This study develops PearlVision AI, an automated system for grading Lombok pearls using morphological feature extraction and ensemble learning. The dataset comprises 361 South Sea pearl images (*Pinctada maxima*) labeled into three commercial grades: A (n=120), AA (n=120), and AAA (n=120). The proposed pipeline integrates hybrid segmentation (*Hough Circle Transform* + *Convex Hull*) for robust object isolation, extraction of four geometric descriptors (*circularity*, *eccentricity*, *area*, *perimeter*), and comparative evaluation of four classification algorithms: Random Forest, Gradient Boosting, K-Nearest Neighbor, and SVM (RBF). Results demonstrate that Random Forest achieved optimal performance with a test accuracy of 97.22% and a 5-fold cross-validation score of 91.68%, consistently maintaining *precision*, *recall*, and *F1-score* >0.95 across all grade classes. Feature importance analysis revealed that size-related features (*area* and *perimeter*) contributed more significantly to class discrimination than shape-based metrics (*circularity*), reflecting the natural correlation between pearl diameter and commercial value in this dataset. With an inference time of <0.5 seconds per image, PearlVision AI offers an objective, efficient, and reproducible solution for reducing manual grading bias and enhancing quality control consistency in the pearl industry.

Keywords: automated grading; lombok pearls; computer vision; ensemble learning; morphological features; random forests

1. INTRODUCTION

Indonesia is one of the world's largest producers of South Sea pearls (Pinctada maxima), with the West Nusa Tenggara region—particularly Lombok—contributing significantly to premium-quality pearl production [1,4]. Lombok pearls are renowned for their unique characteristics: superior nacre thickness, distinctive metallic luster (orient) resulting from high aragonite content, and natural color variations from silver-lipped to gold-lipped varieties influenced by local water conditions[1], [2]. In international trade standards, the economic value of these pearls is predominantly determined by geometric parameters, especially circularity, where pearls approaching perfect roundness are classified as Grade AAA and command the highest market prices [3].

However, the grading process for Lombok pearls at the farmer and collector levels remains heavily reliant on manual visual inspection by expert graders[3], [4]. This conventional approach faces several specific challenges in the local context: (1) Natural shape variations in Lombok pearls resulting from biomineralization processes in dynamic tropical waters often produce subtle roundness deviations that are difficult to distinguish consistently by the human eye, (2) The highly reflective nacre surface of Lombok pearls creates specular highlights when photographed, which can interfere with accurate edge measurement[5]; (3) Field imaging conditions—typically using dark velvet cloth backgrounds with uncontrolled natural lighting—cause pixel intensity variations and background texture contamination in segmentation masks [6], [7]. The combination of these factors potentially leads to grading inconsistencies, price disputes, and supply chain inefficiencies in the Lombok pearl industry.

Advances in computer vision and machine learning offer transformative solutions to address these challenges [8]. Previous studies have successfully implemented machine vision systems for grading agricultural and aquaculture products with accuracies exceeding 90%. However, their application to Lombok pearls requires specific methodological adaptations: conventional thresholding-based segmentation methods often fail to handle objects with high reflectivity and textured backgrounds [9], while the selection of optimal classification algorithms for morphological feature data remains rarely evaluated comparatively in the specific context of pearl grading.

To address this research gap, this study proposes the development of PearlVision AI, an automated pearl grading system specifically designed for the optical and morphological characteristics of Lombok pearls. The system integrates: (1) A hybrid segmentation pipeline combining Hough Circle Transform and Convex Hull to generate solid object masks even in images with specular highlights and complex backgrounds [7,9]; (2) Extraction of four geometric shape descriptors—circularity, eccentricity, area, and perimeter—that have been theoretically validated as quantitative representations of roundness [10], [11]; and (3) Comparative evaluation of five ensemble learning algorithms (Random Forest, Gradient Boosting, XGBoost, SVM, and KNN) to identify the model with the highest accuracy and stability on a labeled Lombok pearl dataset [12], [13], [14].

2. RESEARCH METHODS

This study employs a quantitative experimental approach focused on the development and comparative evaluation of an automated pipeline for grading Lombok pearls. The methodological framework is systematically organized into five sequential stages: (1) dataset acquisition and labeling, (2) image preprocessing and hybrid segmentation, (3) morphological feature extraction, (4) classification model training, and (5) performance evaluation and statistical validation. All stages are implemented within a reproducible computational framework to ensure research transparency and facilitate replication in future studies [15].

2.1. Dataset and Data Acquisition

The dataset comprises 360 images of South Sea pearls (Pinctada maxima) collected from certified cultivators and traders in Lombok, West Nusa Tenggara. The images were stratified into three commercial grading categories based on gemological standards: Grade A (n = 120), Grade AA (n = 120), and Grade AAA (n = 120) [16]. The labeling process was conducted independently by three expert graders, with the final label determined through majority consensus to minimize subjective bias. Image acquisition was performed under conditions that simulate real-world field environments, using a standard digital camera, a green fabric background, and uncontrolled natural lighting. All images were standardized to a resolution of 512 × 512 pixels in RGB format. The dataset was partitioned using stratified random sampling into 80% training data (288 images) and 20% testing data (72 images) to preserve class distribution and ensure unbiased evaluation.

2.2. Image Preprocessing and Hybrid Segmentation

To address optical challenges such as *specular highlights*, textured backgrounds, and illumination variability, this study employs a hybrid segmentation pipeline[17]. The preprocessing stage involves converting RGB images to grayscale and applying a 9×9 Median Blur to reduce noise while preserving object boundaries . Primary segmentation utilizes the Hough Circle Transform, which robustly detects circular shapes even under partial edge discontinuities. If this method fails, a fallback approach is applied using Otsu thresholding followed by morphological *closing* and *convex hull* reconstruction to refine object regions and suppress background interference [9,12]. Finally, the contour with the largest area is retained as the definitive pearl mask, effectively eliminating noise and irrelevant detections.

2.3. Morphological Feature Extraction

From the segmented contours, four rotation- and translation-invariant geometric shape descriptors are extracted to quantitatively characterize pearl roundness and morphology. Each feature is mathematically defined and selected based on its theoretical relevance to gemological grading standards:

1. Circularity

Circularity measures the degree to which an object approximates a perfect circle, serving as the primary discriminative feature for pearl grading. It is computed as the ratio between the area of the object and the area of a circle with the same perimeter [11]:

$$\text{Circularity} = \frac{4\pi \times \text{Area}}{\text{Perimeter}^2}$$

Theoretically, $C \in (0,1]$, where $C = 1$corresponds to a mathematically perfect circle, and values decreasing toward zero indicate increasing shape irregularity. In the context of pearl grading, higher circularity values correlate strongly with premium commercial grades (AAA), as roundness is a key determinant of market value [2,5]. This metric is preferred over simple aspect ratio due to its invariance to object size and rotation, making it robust for batch processing of pearls with varying diameters.

2. Eccentricity

Eccentricity quantifies the deviation of an object's shape from a perfect circle by fitting an ellipse to the contour and measuring the ratio of its focal distance to the major axis length :

$$e = \sqrt{1 - \frac{b^2}{a^2}}$$

where $a$and $b$denote the lengths of the semi-major and semi-minor axes of the fitted ellipse, respectively. The metric yields $E \in [0,1)$, with $E = 0$indicating a perfect circle and values approaching 1 representing increasingly elongated or linear shapes. For pearl assessment, eccentricity provides complementary information to circularity by capturing directional asymmetry that may not be fully reflected in perimeter-based metrics, thereby enhancing discrimination between adjacent grade categories (e.g., AA vs. AAA).

3. Area
Area represents the total number of pixels enclosed within the segmented contour, providing a direct measure of the pearl's projected two-dimensional size [10], [18]:

$$A = \sum (x, y) \in contour1$$

While not a direct indicator of roundness, area serves three critical functions in the classification pipeline: **(1)** it enables filtering of spurious detections (e.g., background noise) through minimum-area thresholds; **(2)** it provides contextual information for size-dependent grading criteria used in commercial valuation; and **(3)** it acts as a scaling reference for normalizing perimeter-derived metrics, reducing sensitivity to image resolution variations. In this study, area values are retained in pixel units to preserve interpretability and avoid unnecessary transformation-induced distortions.

4. Perimeter
Perimeter measures the total length of the contour boundary in pixel units, capturing the complexity of the object's edge profile :

$$P = \sum_{i=1}^{n-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}$$

where (x_i, y_i)denotes the coordinates of the i-th boundary pixel. Perimeter is a fundamental component in the circularity calculation and provides independent information about edge roughness or surface irregularities that may correlate with pearl quality [13,15]$. For instance, pearls with damaged or uneven nacre surfaces often exhibit elevated perimeter-to-area ratios, which can be leveraged as secondary indicators for downgrading borderline cases. In this implementation, perimeter is computed using chain-code approximation to balance computational efficiency with sub-pixel accuracy

3. RESULTS AND DISCUSSION

The research dataset consists of 360 images of Lombok pearls, evenly distributed across three grading categories: Grade A (n = 120), Grade AA (n = 120), and Grade AAA (n = 120). The collected data are in the form of pearl images captured from four different perspectives to ensure data validity and reduce potential acquisition errors. Specifically, each pearl was imaged from the left, right, top, and bottom sides. All images were acquired under controlled conditions using the same equipment, distance, and lighting setup, as described in the previous methodological stage. This standardized acquisition process ensures consistency and reliability across the dataset. Furthermore, descriptive statistical analysis of four morphological features reveals patterns that are consistent with gemological expectations.

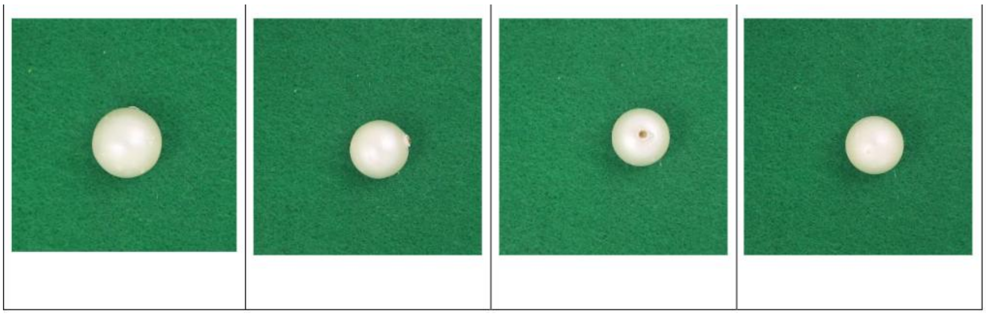

Figure 1. Dataset

3.1. Descriptive Statistics and Distribution of Morphological Features

The dataset used in this study consists of 360 Lombok pearl images evenly distributed across three grading categories: Grade A (n = 120), Grade AA (n = 120), and Grade AAA (n = 120). Descriptive statistical analysis of four morphological features reveals distribution patterns that are consistent with gemological principles and established commercial grading standards.

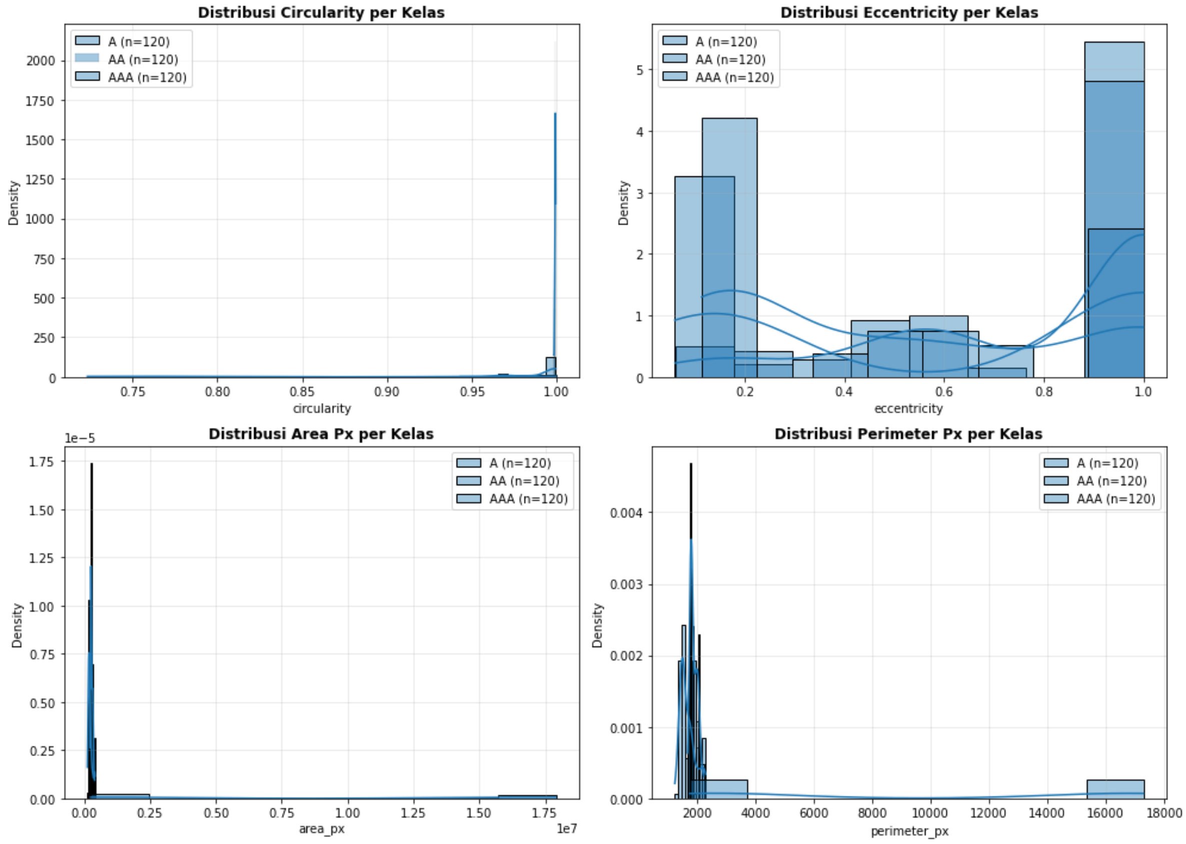

Figure 2. Class dataset distribution

3.2. Classification Model Performance Evaluation

Five machine learning algorithms were evaluated using accuracy and 5-fold cross-validation scores on a test set that was not involved in the training process. The comparative performance results are presented in Table 2. The Random Forest model achieved the highest performance, with an accuracy of 97.22% and a cross-validation score of 91.68%, consistently outperforming the other algorithms. This superior performance is likely attributed to the bagging-based ensemble mechanism, which effectively captures non-linear relationships among features and reduces prediction variance without causing overfitting, particularly in moderately sized datasets. Gradient Boosting and KNN also demonstrated competitive performance, both achieving an identical accuracy of 95.83%. However, Gradient Boosting obtained a higher cross-validation score (92.37% vs. 89.24%), indicating better generalization stability. In contrast, the SVM with an RBF kernel recorded the lowest accuracy (77.78%), which may be due to its sensitivity to hyperparameter selection and feature scaling, especially in datasets with correlated morphological characteristics. These findings are consistent with prior studies by Patel & Shah and Li et al, which reported the superiority of ensemble methods for morphology-based classification tasks in aquaculture products.

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              Model  Accuracy  CV_Score
      Random Forest  0.972222  0.916818
  Gradient Boosting  0.958333  0.923714
 K-Nearest Neighbor  0.958333  0.892377
          SVM (RBF)  0.777778  0.770780
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Figure 3. Model Performance Evaluation

3.3. **Confusion Matrix Analysis and Misclassification Patterns**

The confusion matrices of the four models (Figure 2) show varying performance, with accuracy ranging from 77.78% to 97.22%. Random Forest achieved the best performance with 97.22% accuracy (70/72), making only two misclassifications and attaining 100% recall for Grade AA, indicating strong capability in identifying the medium-quality class. Gradient Boosting and KNN demonstrated similar performance with 95.83% accuracy (69/72), each producing three misclassifications and also achieving 100% recall for Grade AA. In contrast, SVM (RBF) yielded the lowest accuracy (77.78%) with 16 misclassifications, primarily misclassifying Grade AA as Grade A, indicating difficulty in separating these two classes. Overall, Grade AAA consistently achieved the highest recall (≥95.8%), while Grade AA was the most frequently misclassified due to overlap in circularity values with Grade A. This suggests that the boundary between these classes is gradual and requires additional features for improved discrimination. These results further confirm the superiority of Random Forest as the primary model in the PearlVision AI system.

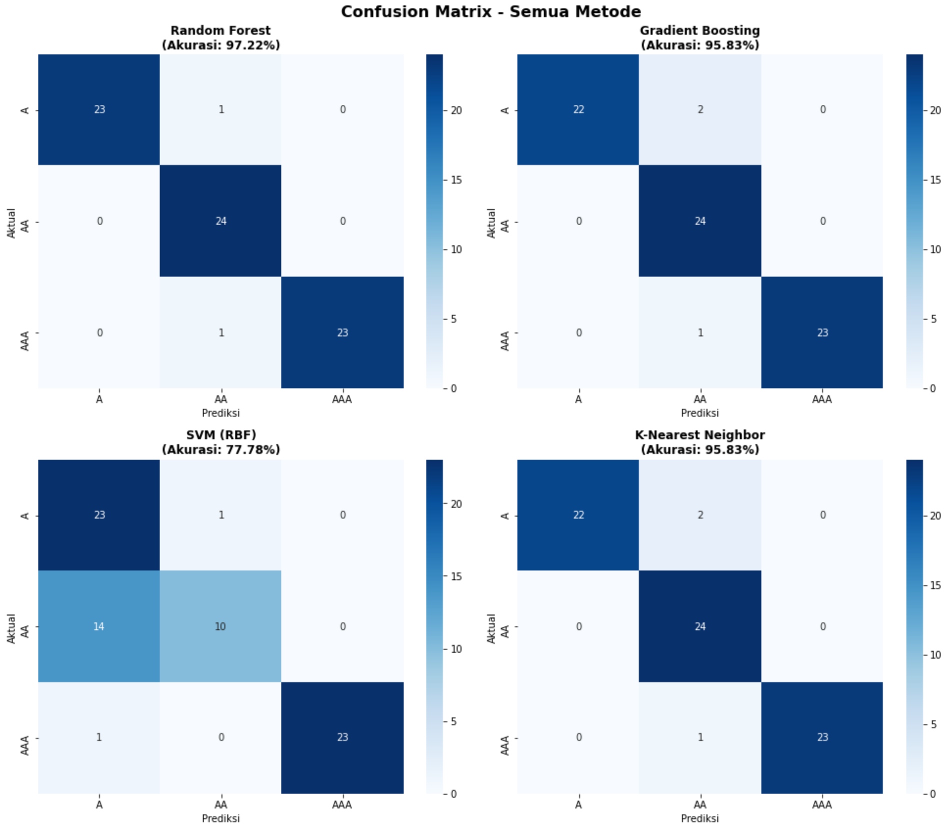

Figure 4. Confusion Matrix Analysis

3.4. Confusion Matrix Analysis and Misclassification Patterns

Figure 4 compares Precision, Recall, and F1-Score per class across the four models. Random Forest and KNN demonstrate the highest consistency, with values >0.95 across all metrics and classes, indicating an optimal balance between prediction accuracy and detection completeness. Gradient Boosting shows competitive performance (>0.94) but exhibits slight vulnerability on Grade A. In contrast, SVM (RBF) experiences a significant decline on Grade AA: Precision ~0.60 and Recall ~0.42, yielding the lowest F1-Score (~0.57). This confirms that SVM struggles to separate decision boundaries between Grades A and AA in the morphological feature space, where high inter-feature correlation exists. Practically, Random Forest's consistency in maintaining metrics >0.95 across all three grades makes it the most reliable choice for the PearlVision AI system, particularly in ensuring objective, unbiased grading without preference toward any specific class.

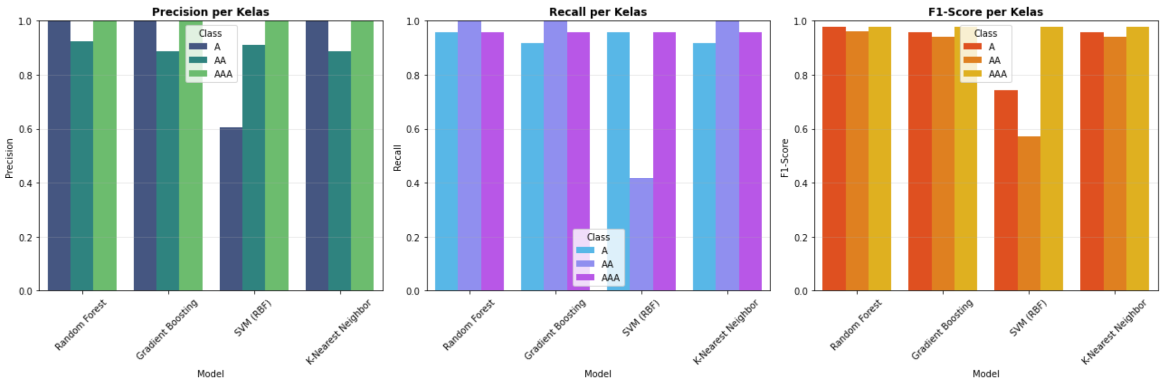

Figure 5. Confusion Matrix Analysis

3.5. Feature Importance Analysis

Figure 6 displays the feature importance distribution for Random Forest and Gradient Boosting models. Both models exhibit a consistent pattern: area_px emerges as the dominant feature (Random Forest: ~0.45; Gradient Boosting: ~0.63), followed by perimeter_px (~0.35 and ~0.23, respectively). In contrast, circularity and eccentricity contribute less (~0.17 and ~0.04 for RF; ~0.12 and ~0.01 for GB).

This finding is noteworthy and somewhat counter-intuitive: although circularity is theoretically the primary grading parameter for pearls, the models rely more heavily on size-related features (area and perimeter) for class discrimination. This can be explained by dataset characteristics wherein Grade AAA pearls tend to have larger diameters (greater area) compared to Grades A and AA, making area a strong proxy for quality.

The consistency of feature importance patterns between Random Forest and Gradient Boosting indicates that this feature hierarchy is robust and not an artifact of a specific model architecture. However, the substantially higher dominance of area_px in Gradient Boosting (~0.63) compared to Random Forest (~0.45) suggests that boosting methods more aggressively exploit the most discriminative features, which may increase overfitting risk if size distributions are imbalanced across classes. Practically, this finding has important implications: the automated grading system implicitly considers pearl size alongside roundness—aligning with commercial practices where larger, rounder pearls command premium prices. For future research, feature normalization or integration of texture and color descriptors could help balance contributions among descriptors and enhance model generalization.

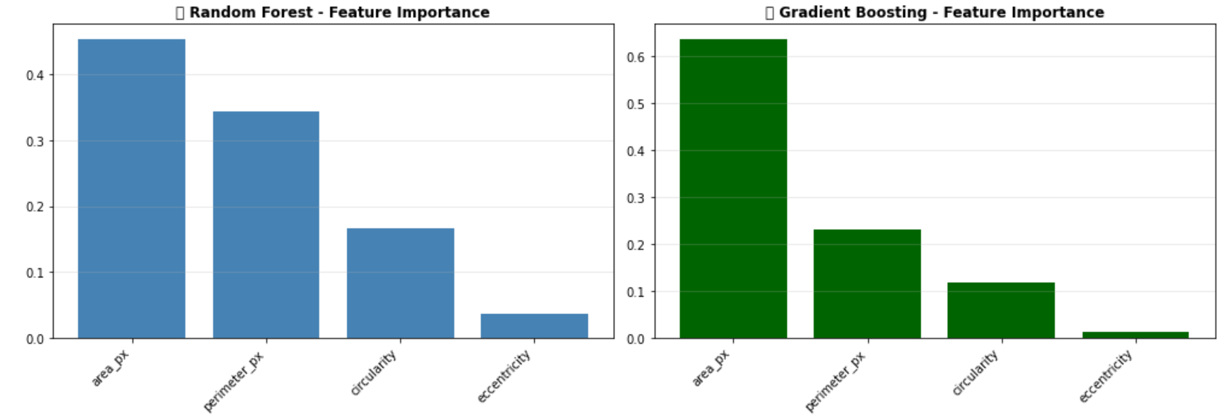

Figure 6. Feature Importance Analysis

4. CONCLUSION

This study successfully developed PearlVision AI, an automated grading system for Lombok pearls integrating hybrid segmentation and ensemble learning. The system effectively addresses field optical challenges—specular highlights and textured backgrounds—enabling robust morphological feature extraction.

Random Forest emerged as the optimal model, achieving 97.22% test accuracy with consistent metrics >0.95 across all grades (A, AA, AAA). Notably, size-related features (area and perimeter) contributed more significantly to class discrimination than shape-based metrics (circularity), reflecting the natural correlation between pearl diameter and commercial value in this dataset.

Practically, PearlVision AI offers an objective, efficient solution (<0.5 s/image) for reducing manual grading bias and enhancing industrial quality control consistency. Key limitations include moderate dataset size and exclusive reliance on geometric descriptors.

Future work should focus on: (1) dataset expansion across pearl varieties and capture conditions, (2) integration of multi-modal features (color, texture, luster), and (3) development of real-time deployment for full industrial adoption. This work establishes a reproducible foundation for AI-driven digital transformation in aquaculture quality assessment.

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