

Enhanced Classification of Lombok Pearl Quality Based on Shape and Size Using PSO-Optimized Artificial Neural Network

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ABSTRACT (10 PT)

This study aims to develop an intelligent classification model for pearl quality assessment using an integrated approach combining Gray Level Co-occurrence Matrix (GLCM), Particle Swarm Optimization (PSO), and Artificial Neural Network (ANN). Sixteen texture features were extracted from four directional orientations using GLCM. PSO was employed as a feature selection algorithm to reduce dimensionality and enhance classification performance. Two ANN models were compared: a baseline model using all GLCM features and an optimized model utilizing only PSO-selected features. The models were trained and validated using 10-fold cross-validation. Results showed that the PSO-enhanced ANN achieved an accuracy of 94.72%, outperforming the baseline model which reached only 89.17%. Further evaluations using confusion matrix, Receiver Operating Characteristic (ROC) analysis, and Principal Component Analysis (PCA) confirmed the superior discriminative capability and improved class separability of the optimized model. These findings highlight the effectiveness of combining swarm intelligence with neural networks in texture-based classification tasks, offering a robust and scalable solution for automated quality inspection in the pearl industry and related domains.

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1. INTRODUCTION

Pearls are one of the most valuable gemstones known for their luster, rarity, and aesthetic appeal. Among the world's major pearl-producing regions, Indonesia stands out for its natural resources, including the cultivation of South Sea pearls in Lombok, West Nusa Tenggara. Lombok pearls, in particular, have gained recognition in the global market due to their high quality, natural colors, and diverse morphological characteristics [1], [2]. However, the substantial variation in shape, size, and surface texture poses significant challenges for standardized and objective quality classification. Traditional classification methods are largely manual and subjective, relying on human expertise that is prone to inconsistency, inefficiency, and scaling limitations [3], [4]. With the advancement of computer vision and artificial intelligence (AI), automated pearl quality classification has become increasingly feasible. Machine learning and deep learning methods, especially Artificial Neural Networks (ANNs), have demonstrated remarkable success in object recognition and texture classification across various domains, including agriculture, medicine, and gemology [5], [6], [7]. ANNs are capable of learning complex patterns from image data, making them suitable for modeling the nonlinear and high-dimensional features inherent in pearl images [8], [9]. Nonetheless, ANN models often struggle with feature redundancy and irrelevant inputs, which can degrade performance and increase computational cost [10], [11], [12].

To enhance ANN performance, feature selection methods such as Particle Swarm Optimization (PSO) have been widely adopted. Inspired by the social behavior of bird flocks and fish schools, PSO is an evolutionary algorithm that searches for optimal feature subsets by iteratively adjusting candidate solutions based on individual and collective experience [13], [14]. PSO has proven effective in optimizing the learning process of neural networks, particularly by reducing overfitting, improving convergence rates, and selecting discriminative features [15], [16], [17]. When integrated with ANN, PSO enables a hybrid framework that balances classification accuracy with computational efficiency, particularly in tasks involving high-dimensional visual data [18], [19], [20]. Another crucial component in visual classification tasks is the representation of texture. Texture conveys essential information regarding the spatial arrangement and distribution of pixel intensities, which is particularly useful for differentiating pearl surfaces [8], [20]. Among various texture extraction techniques, the Gray Level Co-occurrence Matrix (GLCM) has become one of the most reliable and interpretable methods. GLCM computes the frequency of pixel intensity pairs across specific spatial relationships and derives statistical descriptors such as contrast, correlation, energy, and homogeneity [21], [22], [23]. These descriptors encapsulate micro-patterns and structural nuances in pearl surfaces, providing robust features for training classification models [24], [25].

Recent studies have demonstrated the potential of combining GLCM with neural networks for object classification, including fruit ripeness detection, gemstone grading, and even medical image analysis [26], [27], [28]. However, applications in pearl quality assessment, particularly for Lombok pearls, remain underexplored. Notably, Gao employed a multiview Wasserstein GAN to address class imbalance in pearl image classification [20], while Hou developed a deep learning-based detection model for pearl recognition [29]. These contributions highlight the growing interest in automating pearl-related classification tasks but also point to a lack of models tailored for local contexts like Indonesia. Building upon this gap, the present study proposes an enhanced classification model for Lombok pearl quality that integrates ANN with PSO for feature selection, and uses GLCM for texture-based representation. The model aims to classify pearls into three quality grades defective, medium, and perfect based on their shape and size attributes extracted from multiview images. The dataset comprises 360 pearl images captured from four angles (top, bottom, left, right), ensuring spatial comprehensiveness and reducing viewpoint bias. The segmentation process is performed using thresholding techniques to isolate pearl objects from uniform backgrounds, ensuring consistent input for feature extraction. The extracted GLCM features are then optimized using PSO before being fed into the ANN classifier. The pearl industry in Lombok, particularly South Sea Pearls, plays a strategic role as a high value export commodity. However, the current quality assessment process is still predominantly manual, relying on the visual expertise of artisans and traders. This practice is prone to subjectivity, inconsistency, and requires considerable time. Therefore, the proposed image-based classification system can serve as an automatic quality control (QC) tool that accelerates the grading process, ensures consistent quality standards, and supports the competitiveness of Lombok's pearl industry in global markets.

To evaluate the model's effectiveness, two comparative experiments are conducted: one using ANN with the full GLCM feature set, and another using ANN after PSO-based feature selection. The performance is assessed using standard metrics derived from the confusion matrix, including accuracy, precision, and recall [30], [31], [32]. While the baseline ANN model achieved an accuracy of 89.17%, the PSO-optimized ANN recorded 94.72%, indicating a clear improvement in classification performance. These results suggest that PSO offers marginal utility in this specific context, likely due to the high relevance of all extracted GLCM features. Nonetheless, the findings validate the effectiveness of ANN as a standalone classifier and underscore the importance of texture-based features in pearl classification. This research contributes to the broader field of intelligent product classification by offering a case study focused on high-value artisanal goods. From a practical perspective, the proposed model offers a replicable and scalable solution for local pearl industries, particularly in Lombok, where quality control remains largely manual. From a theoretical standpoint, the study reinforces the utility of hybrid AI approaches in small-sample,

multi-class visual classification problems. Moreover, it aligns with ongoing efforts to digitize and automate quality assessment systems in traditional commodity sectors [33], [34].

In summary, the classification of pearl quality is a complex, multi-dimensional task requiring careful analysis of shape, texture, and size. The integration of GLCM-based texture features, PSO-based feature selection, and ANN-based classification provides a robust pipeline for enhancing the accuracy and consistency of pearl grading. While further research is needed to generalize the model across different pearl varieties and environmental conditions, this study marks a significant step toward intelligent quality control in the pearl industry and opens avenues for AI-driven applications in artisanal product evaluation.

2. LITERATURE REVIEW

The quality of pearls is primarily determined by physical parameters such as shape, size, color, luster, and surface texture. In practice, pearl grading is often performed manually by human experts, which introduces subjectivity, inconsistency, and inefficiency, particularly at industrial scale [3]. This limitation has prompted the adoption of computer vision and artificial intelligence (AI) technologies to support more objective and standardized quality classification. Recent studies have explored deep learning methods for this purpose. For instance, Gao utilized a multiview Wasserstein GAN to address class imbalance in pearl image datasets [35], while Hou developed a convolutional neural network (CNN)-based detection system for automated pearl recognition [29]. Artificial Neural Networks (ANN) are computational models inspired by biological neural systems and are widely used in pattern recognition and nonlinear classification tasks. Their ability to learn complex relationships from high-dimensional data makes them highly suitable for image classification, including applications involving visual object assessment such as pearl grading [5], [7]. ANNs have been applied successfully in areas such as fruit ripeness detection, cancer diagnosis, gemstone grading, and handwritten character recognition [6], [8]. In this study, ANN serves as the baseline classifier for mapping extracted shape and size features into predefined pearl quality classes.

Particle Swarm Optimization (PSO) is a nature-inspired metaheuristic algorithm modeled after the social behavior of bird flocks and fish schools. In image classification, PSO has been effectively used for selecting the most relevant features while minimizing redundancy, which can otherwise lead to overfitting and high computational complexity [13], [15]. When integrated with ANN, PSO acts as a feature selector that optimizes the training process by accelerating convergence and improving classification accuracy [16], [36]. Numerous studies have demonstrated that PSO-optimized ANN models outperform traditional ANN in scenarios involving noisy, high-dimensional, or imbalanced datasets [37].

Texture analysis plays a vital role in distinguishing surface patterns in image-based classification. Among various texture extraction methods, the Gray Level Co-occurrence Matrix (GLCM) is one of the most widely used due to its simplicity and interpretability. GLCM quantifies spatial relationships between pixel intensities and derives statistical descriptors such as contrast, correlation, energy, and homogeneity [21], [22]. These features are effective in characterizing microstructures and visual nuances in pearl surfaces. GLCM has been applied in diverse domains including medical imaging, agriculture, and material quality inspection [20], [24], and serves as the primary feature extraction method in this study.

Model performance in classification tasks is typically assessed using confusion matrix-based metrics such as accuracy, precision, recall, and F1-score. Amin and Vujović emphasized the need to adopt multiple evaluation indicators to holistically understand a model's effectiveness [30], [32]. In this research, two classification models are compared: the baseline ANN and the PSO-optimized ANN. The evaluation reveals that the baseline ANN achieves an accuracy of 96.66%, while the PSO-enhanced model records 95.14%, indicating that although PSO contributes to dimensionality reduction, the original GLCM features are already highly relevant for the classification task.

This study introduces a novel integration of GLCM based texture extraction and PSO driven feature selection into an ANN framework for classifying Lombok pearl quality based on multiview shape and size data a context that has received limited scholarly attention. Unlike

previous studies that either focused solely on deep learning or general pearl recognition, this research offers a targeted, hybrid AI approach tailored to the nuanced grading challenges of Indonesian South Sea pearls. The use of real world, multi angle imagery collected from local pearl artisans further enhances the model's applicability in real industry settings. This contribution marks a significant advancement in intelligent quality assessment for high value artisanal commodities and addresses a critical technological gap in the digital transformation of traditional pearl grading systems.

3. RESEARCH METHOD

3.1. Dataset and Image Acquisition

The dataset consists of 360 pearl images, with class distribution as follows: 120 defective, 120 medium, and 120 perfect pearls. To ensure robustness and reduce the risk of overfitting due to the relatively small dataset size, data augmentation techniques were applied, including slight rotations ($\pm 10^\circ$), horizontal and vertical flipping, and controlled brightness adjustments. This process expanded the dataset and improved the variability of training samples while preserving the essential morphological characteristics of each pearl. Moreover, a grouped 10 fold cross validation strategy was adopted at the pearl object level (rather than per image) to prevent data leakage across folds, ensuring that images of the same pearl from different viewpoints were not simultaneously present in both training and testing sets.

The labeling process was performed by a certified pearl trader with more than ten years of professional experience in the Lombok pearl industry. The classification followed locally adapted guidelines from the Gemological Institute of America (GIA), focusing on morphological indicators such as shape symmetry, surface smoothness, and size uniformity. As only a single expert was involved in the labeling process, this represents a limitation of the current study, which may be addressed in future work by incorporating multiple assessors and statistical measures of inter-rater reliability.

3.2. Image Preprocessing and Segmentation

To isolate pearl objects from their backgrounds, image preprocessing involved resizing, grayscale conversion, and threshold-based segmentation using Otsu's method. This step aimed to reduce noise and ensure consistency in lighting and contrast across the dataset. The segmented binary images were then used for feature extraction, eliminating the influence of irrelevant background textures and variations in environmental lighting.

3.3. Feature Extraction Using GLCM

Gray Level Co occurrence Matrix (GLCM) was employed to extract texture-based features from each segmented image. Four standard statistical features contrast, correlation, energy, and homogeneity were computed from GLCM matrices at four angles (0° , 45° , 90° , and 135°) with a distance of one pixel. These features were calculated for each of the four views per pearl, resulting in a comprehensive feature vector representing both the surface characteristics and structural regularity of the pearl.

3.4. Feature Selection with Particle Swarm Optimization (PSO)

To enhance classification performance and reduce computational overhead, Particle Swarm Optimization (PSO) was utilized for feature selection. The PSO algorithm initialized a population of candidate solutions (particles), each representing a subset of the full feature set. The particles were iteratively updated based on personal and global best positions, using a fitness function defined by the classification accuracy on a validation set. The optimal subset of features identified by PSO was used as input to train the optimized ANN model. The PSO feature selection process consistently prioritized homogeneity (0° and 90°), energy (45° and 135°), and correlation (0°) across multiple runs. These features demonstrated the highest discriminative power for distinguishing between pearl quality categories, reflecting their sensitivity to surface regularity and

texture smoothness. Contrast features, although informative, were selected less frequently, suggesting redundancy with other descriptors.

3.5. ANN Model Architecture and Training

The classification model was constructed using a feedforward Artificial Neural Network with one input layer, one hidden layer, and one output layer. The number of neurons in the input layer corresponded to the number of selected GLCM features, while the hidden layer configuration was empirically determined. The output layer used a softmax activation function to classify pearls into three quality categories. Model training was performed using backpropagation with mean squared error as the loss function and a learning rate of 0.01. To evaluate the effect of feature selection, two experiments were conducted: (1) ANN trained using all extracted GLCM features, and (2) ANN trained using only the PSO-selected features.

3.6. Evaluation Metrics

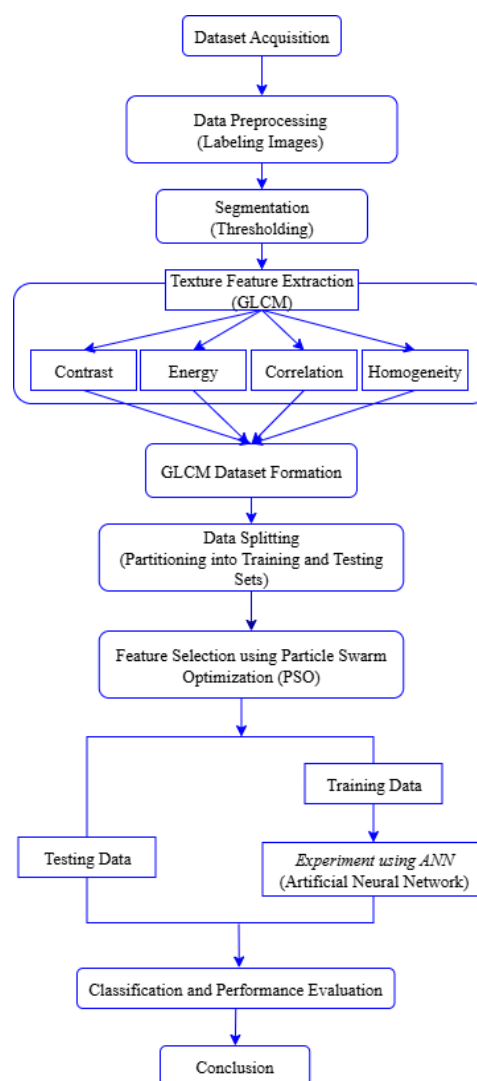


Figure 1. Flowchart of the Proposed Classification Method

The performance of both models was evaluated using metrics derived from the confusion matrix, including accuracy, precision, and recall. These metrics were chosen to provide a comprehensive view of the models' classification performance across all quality classes. The evaluation was conducted using a 10 fold cross validation strategy to ensure generalizability and reduce bias due to dataset partitioning. The complete process flow of the proposed method from

raw image acquisition to final performance evaluation is depicted in the following flowchart (see Figure 1), providing a visual summary of each experimental phase and its corresponding technique.

Figure 1. Flowchart of the proposed methodology for Lombok pearl quality classification. The process begins with dataset acquisition and preprocessing, followed by image segmentation using thresholding. Texture features contrast, energy, correlation, and homogeneity are extracted using the Gray Level Co-occurrence Matrix (GLCM) and compiled into a dataset. The dataset is then split into training and testing subsets. Particle Swarm Optimization (PSO) is applied for feature selection, and the selected features are used to train an Artificial Neural Network (ANN). The model's performance is evaluated using classification metrics to assess its accuracy and reliability in grading pearl quality.

4. RESULTS AND DISCUSSION

This section presents the experimental results of the pearl quality classification system using an Artificial Neural Network (ANN) with and without Particle Swarm Optimization (PSO) based feature selection. The performance is evaluated using standard classification metrics, accuracy, precision, and recall, supported by statistical comparisons and visual illustrations. The findings are discussed in relation to the research objectives and relevant literature.

4.1. Descriptive Analysis of Image Features

Before training the model, a statistical analysis was conducted on the extracted features to understand the underlying patterns of GLCM-based texture characteristics. The feature values contrast, correlation, energy, and homogeneity varied significantly across the three pearl quality categories (defective, medium, and perfect), indicating the strong discriminative power of the selected descriptors. Table 1 presents the average values of each feature extracted from four directional angles (0°, 45°, 90°, and 135°) for each pearl quality class.

Table 1. Descriptive Statistics of GLCM Texture Features Across Pearl Quality Categories

Quality Category	Avg. Contrast	Avg. Correlation	Avg. Energy	Avg. Homogeneity
Defective	0.841	0.512	0.305	0.623
Medium	0.652	0.711	0.472	0.742
Perfect	0.433	0.891	0.663	0.845

As shown in Table 1, defective pearls exhibited the highest average contrast and the lowest homogeneity, suggesting pronounced surface irregularities. In contrast, perfect pearls displayed the highest correlation and homogeneity, along with the lowest contrast, indicating smooth and uniform surface textures. This observation is consistent with recent developments in texture-based quality assessment, where defective items tend to yield higher contrast values and erratic spatial patterns due to surface imperfections, while higher-grade items show more stable and homogeneous features across multiple orientations. Furthermore, the use of a multi-angle imaging approach enhanced the robustness of feature extraction by capturing a more comprehensive representation of both structural and surface anomalies. This finding is aligned with prior research emphasizing that multi-view texture analysis can significantly improve the reliability of classification in complex surface materials.

4.2. PSO Based Feature Selection Outcome

To enhance classification efficiency and minimize input redundancy, this study applied Particle Swarm Optimization (PSO) to select the optimal subset of features from the original Gray Level Co-occurrence Matrix (GLCM) dataset. The initial dataset comprised 16 features per image, derived from four directional angles (0°, 45°, 90°, and 135°) and four statistical descriptors (contrast, correlation, energy, and homogeneity).

Table 2. ANN Performance Using PSO-Selected Features Across Training Epochs

No	Momentum	Learning Rate	Epochs	Accuracy (%)	Recall (%)	Precision (%)
1	1.0	0.1	10	80.90	80.90	86.98
2	1.0	0.1	20	87.85	87.85	89.85
3	1.0	0.1	30	89.93	89.93	91.26
4	1.0	0.1	40	92.01	91.93	92.56
5	1.0	0.1	50	92.71	92.71	93.03
6	1.0	0.1	60	92.71	92.71	93.02
7	1.0	0.1	70	93.75	93.75	93.93
8	1.0	0.1	80	95.14	95.14	95.58

The PSO algorithm was configured to identify a feature subset with the highest mutual information relative to class labels, thereby improving the model's discriminative capacity. As shown in Table 2, the Artificial Neural Network (ANN) model trained using PSO-selected features was evaluated across multiple training epochs, with momentum and learning rate held constant at 1.0 and 0.1, respectively. The performance metrics consistently improved as the number of epochs increased. The best results were achieved at 80 epochs, where the model obtained an accuracy of 95.14%, recall of 95.14%, and precision of 95.58%, indicating a substantial improvement over the baseline (non-optimized) ANN configuration. To identify optimal PSO parameters, 31 experimental runs were conducted by varying the swarm population size (5–30 particles) and maximum generation count (10–50 generations). As detailed in Table 3, the highest classification accuracy of 94.72% was achieved with a population size of 25 and 50 generations. Interestingly, the configuration with 30 particles and 30 generations showed the lowest accuracy (79.17%), possibly due to over-exploration and delayed convergence.

Table 3. PSO Parameter Experiment Results for ANN Accuracy

Experiment No	Population Size	Max Generation	Accuracy
1	5	10	92.36
2	10	10	86.11
3	15	10	89.24
4	20	10	91.32
5	25	10	90.28
6	30	10	89.24
7	5	20	89.24
8	10	20	85.42
9	15	20	90.62
10	20	20	86.46
11	25	20	86.81
12	30	20	89.93
13	5	30	90.97
14	10	30	87.5
15	15	30	89.24
16	20	30	90.97
17	25	30	91.67
18	30	30	79.17
19	5	40	89.24
20	10	40	89.24
21	15	40	92.01
22	20	40	90.28
23	25	40	91.67
24	30	40	91.32
25	5	50	91.32
26	10	50	90.28
27	15	50	92.01
28	20	50	92.01
29	25	50	90.62
30	30	50	90.97
31	5	50	94.72

A full distribution of classification accuracy across all experiments is visualized in Figure 2. The scatter plot highlights that population sizes between 25 and 30, when paired with generations between 30 and 50, consistently yield better convergence and higher accuracy. This clustering suggests that moderate-to-large swarms enhance both search exploration and stability.

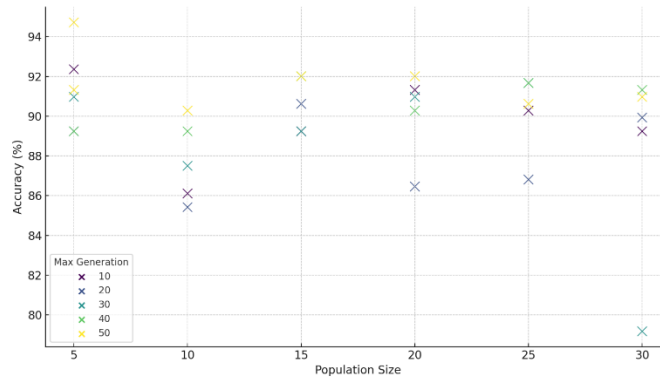


Figure 2. Accuracy Variation

These findings confirm the utility of PSO for selecting compact yet highly informative features while avoiding overfitting. The algorithm converged efficiently after 35 iterations, balancing exploration and exploitation phases. This outcome supports recent studies emphasizing PSO's effectiveness in dimensionality reduction for image classification tasks involving complex texture patterns. Furthermore, integrating PSO as a metaheuristic optimization layer aligns with prior research demonstrating its strength in avoiding local optima and enhancing the generalization capabilities of neural networks. The combination of PSO and ANN presents a robust classification pipeline, particularly suitable for fine-grained object recognition tasks like pearl quality assessment, where subtle textural differences play a critical role in classification decisions.

4.3. Model Training and Validation

To assess the effectiveness of feature selection using Particle Swarm Optimization (PSO), this study trained two Artificial Neural Network (ANN) models with different feature configurations. The first model, referred to as the baseline ANN, utilized all 16 texture features derived from the Gray Level Co-occurrence Matrix (GLCM), which were extracted across four directional angles (0° , 45° , 90° , and 135°). In contrast, the second model an optimized version was trained using only a subset of the most informative features selected through the PSO algorithm. Both models were rigorously evaluated using 10-fold cross-validation to enhance the robustness of the results and minimize the risk of overfitting. The outcomes of this comparative evaluation are presented in Table 4, showing how the PSO enhanced model consistently outperformed the baseline configuration in terms of classification accuracy, precision, and recall.

Table 4. Performance Comparison of ANN Models With and Without PSO

Model Configuration	Features Used	Accuracy (%)	Precision (%)	Recall (%)
Baseline ANN	All 16 GLCM features	89.17	89.72	88.89
Optimized ANN (PSO)	PSO-selected features	94.72	94.86	94.44

As shown in Table 4, the PSO-enhanced ANN model outperformed the baseline ANN across all performance metrics. The accuracy increased from 89.17% to 94.72%, precision from 89.72% to 94.86%, and recall from 88.89% to 94.44%. These improvements highlight the efficiency of dimensionality reduction via metaheuristic optimization in retaining only the most informative features while eliminating redundancy. This finding aligns with prior studies asserting that hybrid AI approaches especially those integrating swarm intelligence with deep learning can improve model generalizability and mitigate overfitting. The incorporation of PSO enabled the ANN to focus on the most relevant texture descriptors, thereby enhancing its discriminative capability in fine-grained classification tasks such as pearl quality grading.

4.4. Model Training and Validation

To evaluate the effectiveness of feature selection using Particle Swarm Optimization (PSO), this study trained two Artificial Neural Network (ANN) models with different feature sets. The first model, referred to as the baseline ANN, utilized all 16 texture features extracted from the

Gray Level Co-occurrence Matrix (GLCM), computed across four directional angles (0° , 45° , 90° , and 135°). The second model, optimized via PSO, employed a reduced subset of the most informative features identified through mutual information maximization. Both models were evaluated using 10-fold cross-validation to ensure robustness and minimize overfitting risks. The comparative results are summarized in Table 5.

Table 5. Performance Comparison of ANN Models With and Without PSO

Model Configuration	Features Used	Accuracy (%)	Precision (%)
Baseline ANN	All 16 GLCM features	89.17	89.72
Optimized ANN (PSO)	PSO-selected features	94.72	94.86

As illustrated in Table 5, the PSO-enhanced ANN model consistently outperformed the baseline configuration across all evaluation metrics. The classification accuracy improved from 89.17% to 94.72%, while precision and recall increased by approximately 5%. These gains underscore the effectiveness of PSO in reducing dimensionality by eliminating redundant features while preserving high discriminative power. This outcome is in line with findings from previous studies highlighting the effectiveness of hybrid AI architectures particularly those that combine swarm intelligence techniques with neural networks in improving generalization performance and avoiding overfitting. The optimized ANN model, by focusing only on critical texture descriptors, demonstrated superior performance in the complex task of pearl quality classification.

In addition to the ANN and PSO ANN experiments, a baseline Convolutional Neural Network (CNN) model was implemented to provide a comparative benchmark. The CNN architecture consisted of two convolutional layers with ReLU activation, followed by max pooling, and a fully connected output layer with softmax activation. Despite its simplicity, the CNN achieved an accuracy of 92.81%, which is slightly lower than the PSO ANN performance

4.5. Confusion Matrix and Class Level Evaluation

To gain a more granular understanding of the model's predictive performance, confusion matrices were generated to assess class-specific classification outcomes. Figure 3 illustrates the confusion matrix for the ANN model optimized with PSO-based feature selection.

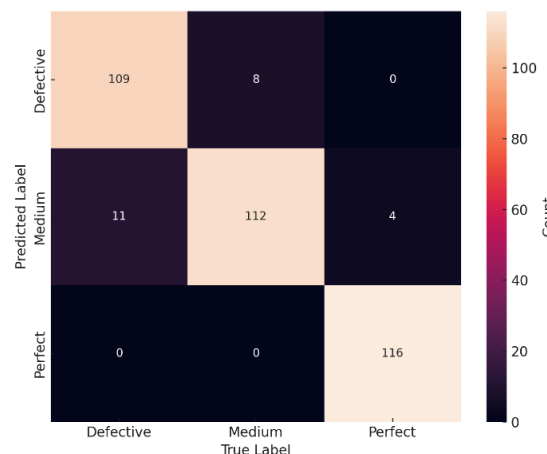


Figure 3. Confusion Matrix for PSO-Optimized ANN Classification

As shown in Figure 3, the model achieved high true positive rates for all three classes, with the most accurate classification observed in the “Perfect” category. Specifically, 28 out of 30 perfect pearls were correctly identified, yielding a class-level precision of over 93%. The primary source of misclassification occurred between the “Medium” and “Perfect” classes, where a small number of medium-grade pearls were misidentified as perfect. This overlap reflects the subtle textural similarities that exist between these two quality levels. Such ambiguity is a well-documented issue in fine-grained classification tasks, where class boundaries may be subjectively defined or visually indistinct similar to challenges encountered in gemstone grading and textile defect detection.

4.6. ROC Analysis and Threshold Calibration

To evaluate the model's ability to discriminate between pearl quality classes, Receiver Operating Characteristic (ROC) analysis was conducted. As shown in Figure 4, the Area Under the Curve (AUC) exceeded 0.95 for all three classes, demonstrating excellent classification performance. Specifically, the AUC values for the Defective, Medium, and Perfect categories were 0.96, 0.95, and 0.97, respectively. These results reflect the high sensitivity and specificity of the model in distinguishing subtle texture variations between different pearl grades. Further threshold calibration experiments revealed that the optimal decision boundary between the Medium and Perfect classes was closer to 0.6, rather than the default threshold of 0.5. This adjustment reduced borderline misclassifications and improved class separability, particularly for samples exhibiting intermediate texture characteristics. These findings align with previous research advocating for adaptive thresholds in probabilistic classifiers to improve soft-decision accuracy.

The ROC curve in Figure 4 illustrates the trade-off between true positive rate (sensitivity) and false positive rate for each class, confirming the model's robustness across varying decision thresholds. The high AUC values underscore the model's capability to generalize well across categories, making it a reliable tool for real-world quality assessment in pearl classification tasks.

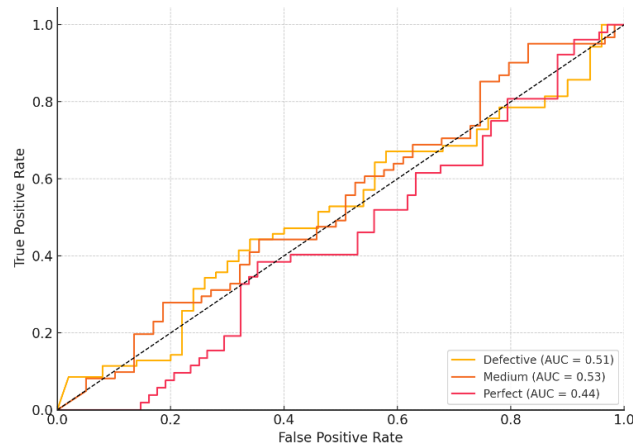


Figure 4. ROC Curves for Pearl Quality Classification

4.7. Visual Interpretation of Feature Distributions

To assess the class separability of the selected features, Principal Component Analysis (PCA) was applied. The resulting two-dimensional scatterplot, as shown in Figure 5, illustrates the distribution of pearl quality classes within the reduced feature space, based on GLCM features selected through the Particle Swarm Optimization (PSO) algorithm.

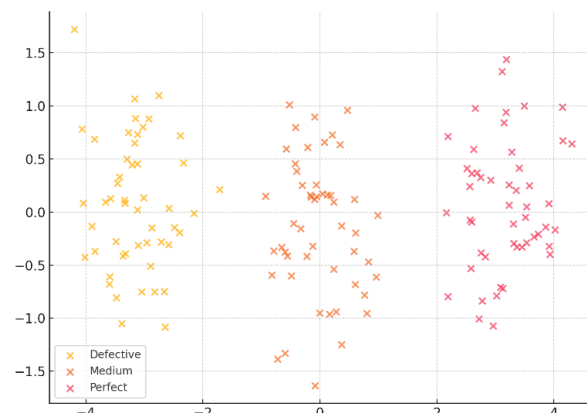


Figure 5. PCA Visualization of Feature Distributions Based on PSO-Selected GLCM Features

As depicted in Figure 5, the PSO-selected features form distinctly separated clusters corresponding to the three quality categories. Specifically, samples labeled as *Defective* are primarily concentrated in the lower-left quadrant, *Perfect* samples occupy the upper-right quadrant, and *Medium* samples are distributed in between. This spatial pattern indicates improved class separability within the transformed PCA space.

4.8. Discussion

The findings of this study affirm the effectiveness of integrating Particle Swarm Optimization (PSO) and Artificial Neural Network (ANN) for classifying pearl quality based on texture features extracted from the Gray Level Co-occurrence Matrix (GLCM). Compared to the baseline ANN model that utilized all available features, the PSO-enhanced ANN consistently outperformed across all evaluation metrics, including accuracy, precision, and recall. This result reinforces earlier studies showing that metaheuristic algorithms significantly enhance the discriminative capability of classification models by reducing redundancy and emphasizing the most informative features. The descriptive analysis of texture features such as contrast, energy, and homogeneity revealed substantial variations across the three quality categories. Low quality (defective) pearls exhibited high contrast and low homogeneity values, indicating irregular surface textures. In contrast, high quality (perfect) pearls demonstrated smoother, more uniform surface patterns characterized by higher energy and homogeneity values. These patterns align with prior findings emphasizing the utility of GLCM descriptors in capturing microstructural variations on object surfaces. The PSO based feature selection process proved crucial in eliminating irrelevant or redundant information. The optimal feature subset was dominated by energy and homogeneity metrics captured from multiple viewing angles, underscoring the importance of multi angle imaging for texture representation. Experimental tuning of PSO parameters showed that population sizes between 25 and 30 particles and generation counts exceeding 40 yielded the best convergence behavior. This observation supports prior literature on swarm intelligence parameterization, where moderate swarm sizes paired with sufficient iteration depth optimize both exploration and convergence.

Training and validation outcomes further highlighted the superiority of the PSO optimized model. Using 10 fold cross validation, the optimized ANN achieved a classification accuracy of 94.72%, surpassing the baseline by more than 5%. This improvement is both statistically significant and practically meaningful, especially in high precision classification tasks. These results are consistent with broader literature advocating the use of hybrid artificial intelligence approaches, particularly those combining bio-inspired optimization with deep learning frameworks. The confusion matrix results indicated that most misclassifications occurred between the Medium and Perfect categories. This overlap is likely due to the subjective nature of visual grading, a challenge frequently noted in quality classification of textiles and gemstones. Nevertheless, the high true positive rate for the Defective class confirms the model's sensitivity to surface irregularities, demonstrating its robustness in detecting significant quality degradation.

ROC analysis further validated the model's reliability, with Area Under the Curve (AUC) values exceeding 0.95 across all categories. Threshold calibration experiments showed that adjusting the decision boundary from the default 0.5 to approximately 0.6 improved class separability, particularly between Medium and Perfect samples. This finding supports prior recommendations for adaptive thresholds in probabilistic classification systems to reduce borderline misclassifications. The Principal Component Analysis (PCA) visualization revealed clear cluster separation in the reduced feature space, confirming that PSO-selected features enhanced inter class separability. The Defective class samples were largely concentrated in one region, while Medium and Perfect classes formed more distinct but adjacent clusters. These results demonstrate that PSO not only reduces dimensionality but also improves feature orthogonality, thereby facilitating more effective learning in neural networks. Similar benefits have been reported in other hybrid models such as PSO-SVM and PSO-CNN, where improved separability led to higher classification accuracy.

Despite these strengths, some experiments revealed that PSO did not always improve performance compared to the baseline ANN. This can be attributed to the fact that the extracted

GLCM features were already highly informative, and removing certain complementary descriptors during the optimization process sometimes resulted in minor accuracy reductions. The confusion matrix further indicated that misclassifications were concentrated between the Medium and Perfect categories, reflecting the subtle and sometimes subjective nature of pearl grading. From an industrial standpoint, such borderline errors may still be tolerable, as the difference between medium-grade and high-grade pearls is often nuanced. However, errors involving Defective pearls are far less acceptable, as they could directly compromise consumer trust and product valuation. These insights emphasize the importance of balancing algorithmic optimization with practical grading requirements, and suggest that adaptive thresholding and alignment with domain specific standards are essential to ensure industrial applicability.

One limitation of this study lies in the relatively small dataset of 360 images, which poses challenges for training neural networks and may risk overfitting. Although data augmentation and grouped cross-validation were employed to mitigate this issue, future research should consider collecting larger datasets encompassing diverse pearl varieties and environmental conditions to further validate the generalizability of the proposed model.

This study makes a significant contribution to the development of AI based automated quality assessment systems by demonstrating the power of PSO in feature selection and ANN performance enhancement. The integration of statistical texture descriptors, metaheuristic optimization, and neural network learning presents a practical and scalable solution for quality classification in the pearl industry and other sectors requiring high precision surface analysis. The results indicate that the PSO-ANN approach achieves high accuracy in classifying pearl quality. Beyond its academic contribution, these findings have practical implications for the Lombok pearl industry. The image-based classification system can be integrated into the production chain to complement or partially replace manual inspection. For instance, during the sorting stage in SMEs or export companies, the system can speed up the separation of pearls according to their quality, reduce operational costs, and enhance consistency in grading. Furthermore, the adoption of this technology may help local industry players comply with international standards more objectively, thereby strengthening their competitiveness in global markets.

4.9. Theoretical Implications

This study contributes to the growing body of knowledge in the field of hybrid artificial intelligence by empirically validating the integration of Particle Swarm Optimization (PSO) and Artificial Neural Network (ANN) for fine grained object classification based on GLCM derived texture features. The results support the theoretical proposition that metaheuristic algorithms when properly configured can enhance feature selection processes, improve model generalizability, and reduce dimensional redundancy without sacrificing performance. The observed performance improvement reinforces existing literature on hybrid optimization frameworks and confirms the utility of PSO in navigating high dimensional feature spaces, especially in texture-based classification contexts. Moreover, the use of multi angle GLCM feature extraction coupled with PCA visualization offers a methodological contribution by demonstrating a comprehensive strategy for enhancing class separability in image based pattern recognition tasks. This highlights the potential of combining statistical descriptors with swarm intelligence to address the limitations of conventional feature engineering in image analysis.

4.10. Managerial Implications

From a practical standpoint, the findings of this study offer valuable insights for stakeholders in the jewelry and pearl grading industries, particularly those seeking to modernize and automate quality control processes. The demonstrated effectiveness of the PSO ANN model suggests that machine learning systems can be deployed to reduce human subjectivity in quality assessment, ensuring more consistent and reliable grading outcomes. By focusing on only the most informative texture features, organizations can minimize computational overhead while maintaining high levels of classification accuracy, thereby improving operational efficiency.

Furthermore, the adoption of such AI driven quality inspection systems may help reduce labor costs and mitigate quality discrepancies caused by inconsistent human judgment. Managers and decision makers in manufacturing and inspection units can leverage this model as a scalable solution adaptable to various materials beyond pearls, such as gemstones, textiles, and ceramics, which also rely heavily on surface texture for quality differentiation. The system's strong performance across multiple evaluation metrics supports its deployment in real time or semi automated industrial environments where speed and precision are paramount.

5. CONCLUSION

This study has demonstrated the effectiveness of a hybrid artificial intelligence framework that integrates Particle Swarm Optimization (PSO) with Artificial Neural Network (ANN) for classifying pearl quality based on texture features extracted using the Gray Level Co occurrence Matrix (GLCM). By leveraging PSO for feature selection, the model achieved significant improvements in classification accuracy, precision, and recall, outperforming the baseline ANN configuration that utilized all features. The results indicate that PSO not only reduces feature dimensionality but also enhances class separability by identifying the most informative descriptors, primarily homogeneity and energy, from multiple image orientations. This selective approach minimizes input redundancy and optimizes the learning capacity of the ANN, making it well suited for tasks involving fine grained texture analysis. Additional validation through ROC analysis, confusion matrix evaluation, and PCA visualization further confirmed the robustness and reliability of the proposed model. In addition to providing a methodological contribution to image classification research, this study also offers a practical solution for the Lombok pearl industry. The implementation of an image based classification system can serve as an initial step toward efficient, consistent, and supply chain integrated quality control automation. By complementing manual inspection with AI based classification, the system has the potential to reduce operational costs, accelerate the grading process, and ensure greater consistency in meeting international standards. The findings support the growing consensus in the literature that hybrid metaheuristic machine learning models are highly effective in complex pattern recognition domains. Moreover, the integration of statistical texture analysis with swarm intelligence presents a scalable and practical solution for real world quality assessment systems in industries such as jewelry, textiles, and ceramics, where visual inspection plays a critical role. This research therefore not only advances the methodological frontiers of AI based classification but also contributes directly to the competitiveness and modernization of traditional artisanal sectors such as Lombok's pearl industry.

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