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Development of an Integrated Artificial Intelligence Model for Bottle Inspection Using Geometric Feature Extraction and ROI-Based Statistical Analysis

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ABSTRACT

In the era of Industry 4.0, the demand for manufacturing systems that are fast, precise, and efficient has become increasingly urgent. This drives the adoption of artificial intelligence (AI) technologies as a promising solution, including in the field of automatic bottle sorting. However, many industries still use manual bottle sorting systems, which often have significant drawbacks. This study presents an integrated AI-based inspection model for automated bottle inspection in the context of smart manufacturing. The proposed approach integrates geometric feature extraction with region-of-interest (ROI)-based statistical image analysis to improve classification accuracy and robustness. Geometric features extracted from bottle contours are combined with optimized ROI selection to enhance feature relevance prior to classification using a Random Forest algorithm. The dataset consists of four bottle types: plastic, glass, cans, and cardboard, captured under controlled imaging conditions. Experimental results show that the proposed integrated method achieves classification accuracy ranging from 96% to 97.72%. The findings confirm that ROI optimization significantly influences statistical feature characteristics and improves overall model performance. This integrated framework is suitable for implementation in automated visual inspection systems supporting Industry 4.0 applications.

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I. INTRODUCTION

The rapid development of Industry 4.0 has intensified the need for measurement and inspection systems that are not only fast and accurate but also reliable from a physical and instrumentation perspective. In industrial physics and applied instrumentation, automated visual inspection systems function as optical measurement systems, where image sensors, illumination conditions, and feature extraction methods determine the quality of the measured information. The rapid development of Industry 4.0 has intensified the need for manufacturing systems that are fast, precise, and efficient. Automated visual inspection systems have become a critical component in modern manufacturing, particularly in quality control and sorting processes. Traditional manual inspection methods are labor-intensive, time-consuming, and prone to human error, making them unsuitable for large-scale industrial applications. the demand for accurate and efficient automatic bottle sorting systems has risen significantly (B. Fang et al*,* 2023). Traditionally, many industries still use manual bottle sorting systems. These manual systems often require substantial labor and are prone to errors, reducing the effectiveness and efficiency of the process (J. Lee et al, 2018). The application of AI technology also aligns with the smart factory concept in Industry 4.0, where automation and data analytics are key to optimizing production processes (S. Wang et al, 2016).

Artificial intelligence (AI) and computer vision technologies offer promising solutions for automated inspection by enabling machines to interpret visual data with high accuracy. In bottle inspection and sorting applications, AI-based systems can be utilized to identify bottle types, detect defects, and ensure product quality consistency.

Most existing studies on automated bottle inspection rely on geometric feature extraction as a standalone technique, using global shape descriptors such as area, perimeter, aspect ratio, and circularity(L. Phalawan et al, 2023) (Kaur, S et al, 2015) (Bhamre, H et al, 2023). While these features provide basic shape representation, prior works largely overlook the influence of spatial image context and implicitly assume that geometric features are unaffected by region selection. This assumption limits the robustness of the extracted features, particularly in practical inspection scenarios where background, printing regions, and object boundaries vary.

Furthermore, geometric feature extraction can be effectively used in various other applications. Research conducted by Yang et al. demonstrates that this method can be used for object recognition, pose estimation, and shape recovery (B. Yang et al, 2015) (K. Thushara et al, 2017). Additionally, this method can provide accurate descriptions of object shapes and sizes. These advantages make it a promising approach for developing AI-based automatic bottle sorting systems using geometric feature extraction. The geometric feature extraction method is used to obtain unique characteristics from geometric elements such as points, lines, curves, and surfaces of the objects (K. Thushara et al, 2017) (Kaur, S et al, 2015). Based on these geometric elements, various features such as area, perimeter, aspect ratio, major axis length, and minor axis length will be extracted for AI model training. These features enable the AI model to recognize patterns and differentiate between various types of bottles with high accuracy.

Separately, ROI-based statistical image analysis has been applied to improve classification performance by focusing on localized image information. However, previous studies typically apply ROI-based analysis in isolation, without explicitly integrating it with geometric feature extraction or analyzing how ROI selection alters geometric feature distributions. As a result, the relationship between global shape descriptors and localized statistical information remains unclear and underexplored.

The present study directly addresses these shortcomings by introducing an explicitly integrated framework that combines geometric feature extraction with optimized ROI-based statistical analysis. Unlike earlier approaches that merely apply multiple methods independently, this work systematically evaluates different ROI configurations and demonstrates that ROI optimization directly enhances the discriminative power of geometric features. This clear methodological integration constitutes the main distinction from previous studies and results in improved classification accuracy and robustness for automated bottle inspection systems.

II. METHOD

2.1 Materials

The dataset used in this study consists of images from four types of bottles: plastic bottles, glass bottles, cans, and cardboard bottles. Images were captured using an ELP IMX179 camera against a black background to minimize noise and background interference. Each bottle type was photographed from multiple angles to ensure sufficient data variability. The image resolution was set to 2448 × 3264 pixels.

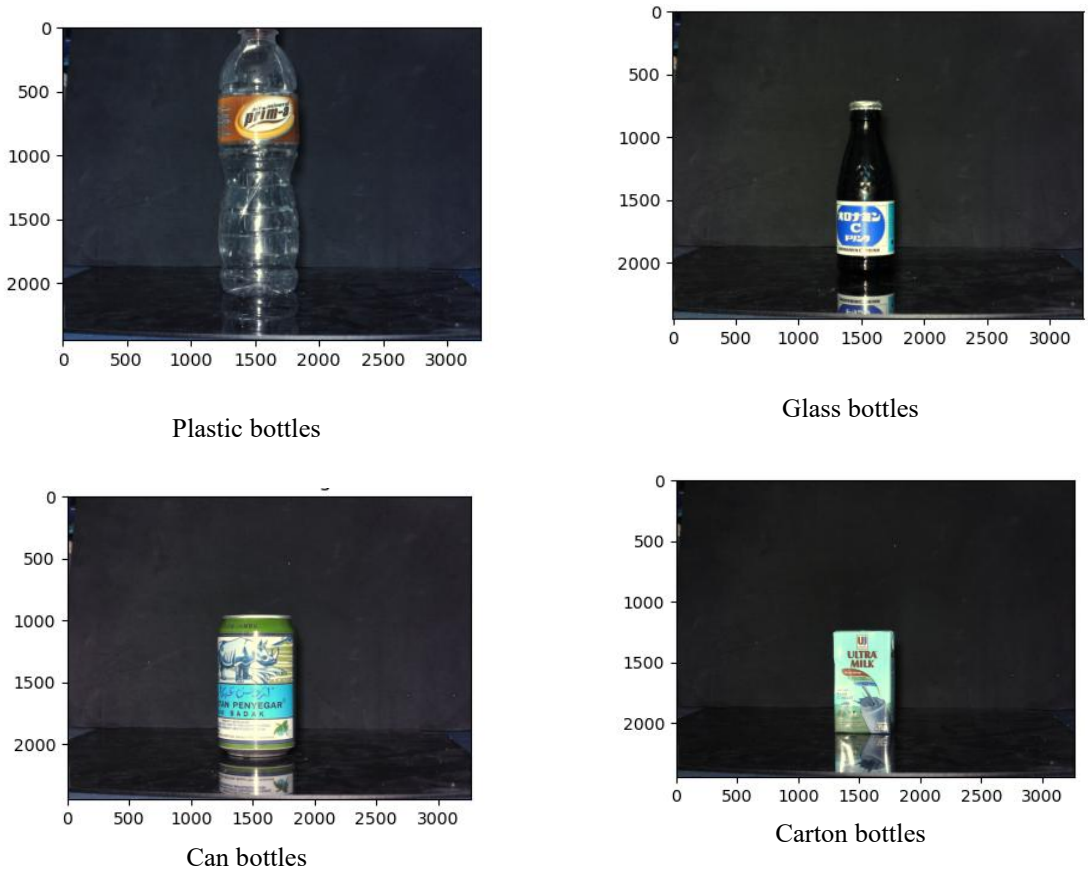


Figure 1 Bottle Image Data

2.2 Processes

The proposed system integrates geometric feature extraction and ROI-based statistical analysis within a single inspection pipeline. The framework consists of image acquisition, preprocessing, ROI determination, feature extraction, classification, and evaluation.

Figure 2 illustrates the methodology implemented in this research, which encompasses two primary steps: model training and model validation. The model training phase focuses on developing the model using the Random Forest Classifier algorithm and geometric feature extraction methods. Conversely, the model validation phase is conducted to assess the performance of the trained model. The key processes involved include preprocessing, feature extraction, classification, and evaluation metrics.

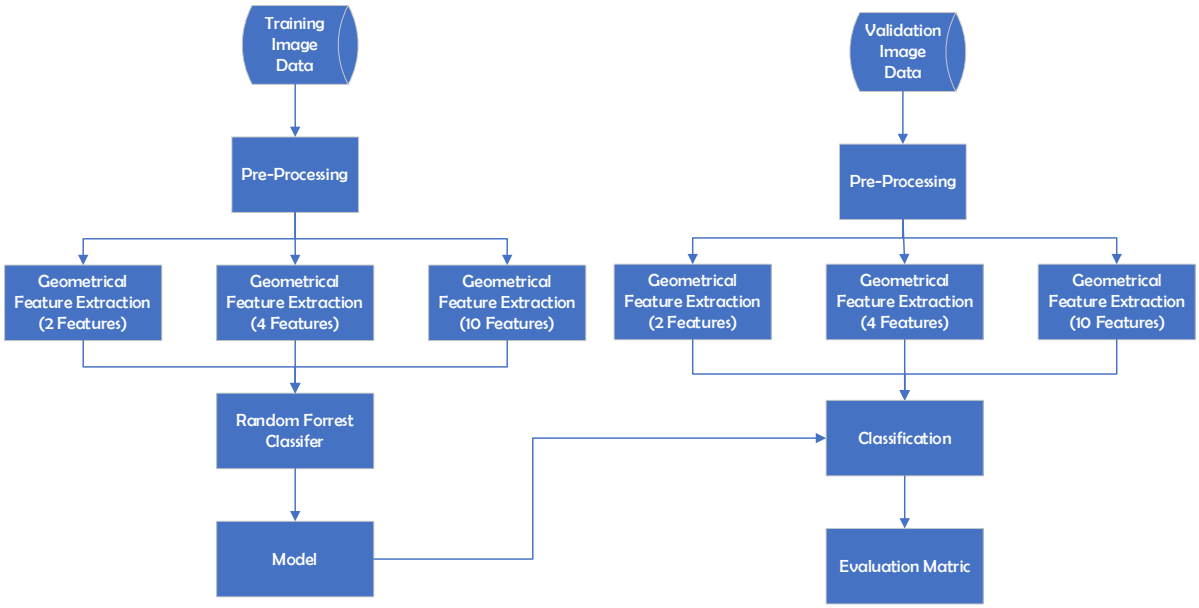


Figure 2 Training and Validation Methodology Flowchart

2.2.1 Preprocessing

Prior to feature extraction, preprocessing is an essential preliminary step to prepare images for the feature extraction algorithm. This stage also aims to ensure data quality by eliminating noise or unwanted pixels. The preprocessing procedures include cropping, morphological filtering, and contour detection. Cropping involves removing unnecessary areas from the images. Morphological filtering, including operations such as erosion and dilation, is applied to enhance the clarity of the bottle shape by adjusting small gaps around the object. Contour detection is employed to obtain the shape representation of the bottle.

2.2.2 Region of Interest (ROI) Selection

Three ROI configurations are evaluated: full image ROI, bottle-only ROI, and printing-only ROI. Statistical image features are analyzed within each ROI to assess their influence on classification accuracy. The ROI selection is integrated into the feature extraction stage to ensure that only the most relevant image regions contribute to the model.

Region of Interest (ROI) selection is a critical factor in automated visual inspection, as it determines which image information contributes to feature extraction and classification. Many previous studies implicitly use the full image or fixed ROIs without evaluating their impact on feature quality, potentially introducing irrelevant background information and reducing classification robustness.

In this study, ROI selection is treated as an optimizable parameter rather than a fixed preprocessing step. Three ROI configurations, full image, bottle-only, and printing-only are systematically evaluated to analyze their influence on feature distributions and classification performance. This approach enables a direct assessment of how spatial localization enhances feature discriminability and reduces misclassification between geometrically similar objects.

2.2.3 Feature Extraction

The primary objective of geometric feature extraction in this research is to obtain the geometric characteristics of each bottle as classification parameters. This process involves calculating geometric features to gain information about the object, including its shape, size, orientation, and other characteristics. These calculations are based on the contours detected during the preprocessing stage.

In this research, three variations of geometric features are utilized: 2 features (area, perimeter), 4 features (area, perimeter, circularity, aspect ratio), and 10 features (area, perimeter, circularity, aspect ratio, major axis, minor axis, bounding box area, convex area, solidity, eccentricity). The variations in the number of features are intended to analyze the impact of feature quantity on model performance.

Geometric feature extraction was conducted using three feature configurations to analyze the influence of feature quantity on classification performance. The two-feature configuration includes area

and perimeter, representing object size and boundary complexity. The four-feature configuration extends this set by incorporating aspect ratio and circularity to capture shape proportionality and roundness. The ten-feature configuration further adds major axis length, minor axis length, bounding box area, convex area, solidity, and eccentricity to describe object dimensions, spatial extent, compactness, and elongation.

2.2.4 Classification

The Random Forest Classifier algorithm is chosen for its capability to handle diverse classification scenarios, such as complex data, non-linear data, and high-dimensional data (D. Yuan et al, 2020) (Dugalam, R et al, 2024). This algorithm functions by constructing multiple decision trees and aggregating the results using majority voting. The geometric feature extraction results serve as input for training the model, enabling it to accurately classify each type of bottle.

2.2.5 Evaluation Metrics

The evaluation metrics employed in this research include the classification report and confusion matrix. The classification report provides detailed information on the model's performance by presenting evaluation metrics such as accuracy, precision, recall, and F1-score. The confusion matrix displays the number of correct and incorrect predictions for each class, thereby aiding in identifying tendencies of the model's misclassifications.

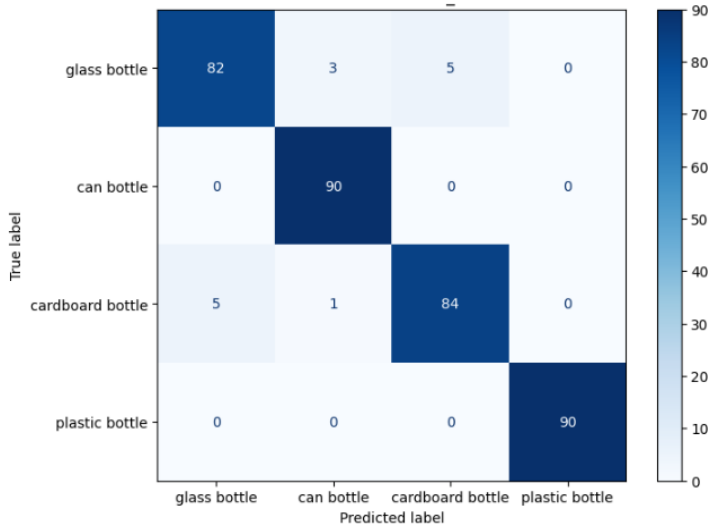
III. RESULT AND DISCUSSION

After training the model, validation was performed by testing it with new data outside the training set. The validation results indicate that the model's performance improved with the addition of geometric features. Tables 1, 2, and 3 present the model performance for each feature set (2 features, 4 features, and 10 features). Using 2 features resulted in a model accuracy of up to 96%. When the number of features increased to 4, the model accuracy improved to 97%. However, with the addition of up to 10 features, the model accuracy remained at 97%, indicating that there was no significant improvement. This suggests that adding features does not always enhance model accuracy and may increase model complexity.

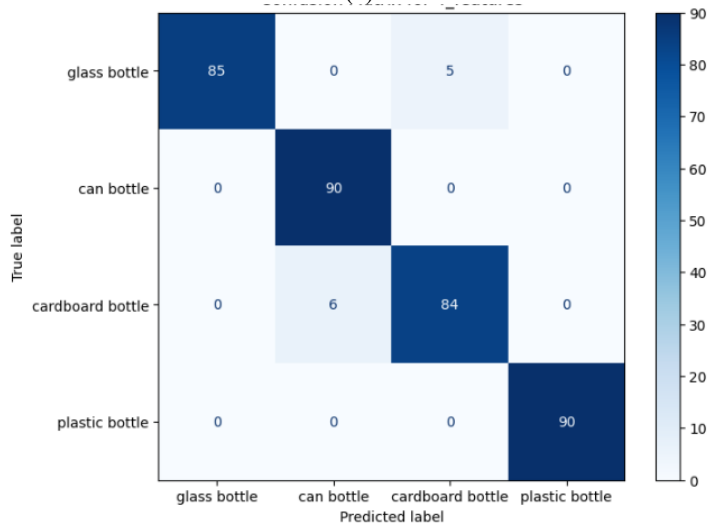
Table 1. Classification Report for 2, 4, and 10 Features

Class	Precision (2F)	Recall (2F)	F1-Score (2F)	Precision (4F)	Recall (4F)	F1-Score (4F)	Precision (10F)	Recall (10F)	F1-Score (10F)
Glass Bottle	0.94	0.91	0.93	1.00	0.94	0.97	1.00	0.92	0.96
Can Bottle	0.96	1.00	0.98	0.94	1.00	0.97	0.96	1.00	0.98
Cardboard Bottle	0.94	0.93	0.94	0.94	0.93	0.94	0.95	0.98	0.96
Plastic Bottle	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Accuracy			0.96			0.97			0.97

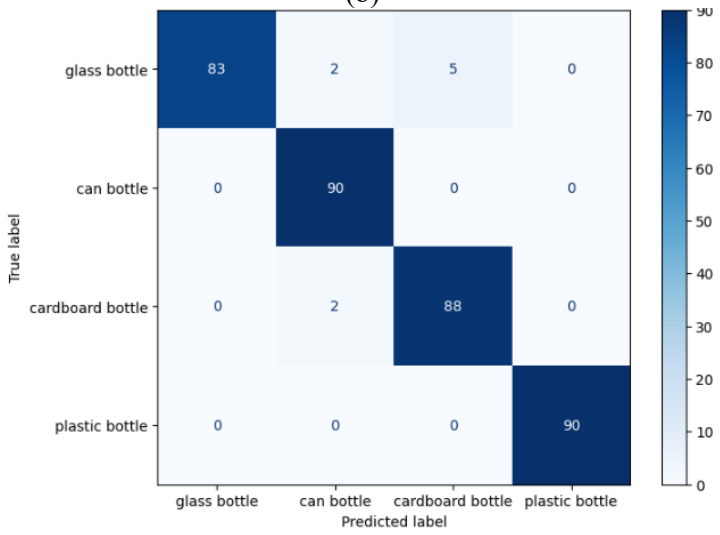
Figure 3 shows the number of instances of each bottle type that were correctly and incorrectly classified for each feature set. From this matrix, it is evident that the model performs accurately in detecting plastic bottles and cans, with all instances correctly classified for each feature set. Detection errors are most frequent with glass and carton bottles, particularly when using 2 features. However, detection errors begin to decrease with an increasing number of features. This information helps identify areas where the model can be further improved. The detection errors are attributed to the similarity in the calculated feature values, which leads to the model's failure in accurately classifying the bottle types.



(a)



(b)



(c)

Figure 3 Confusion Matrix for a) 2 Features b) 4 Features c) 10 Features

The experimental results demonstrate that the integration of geometric feature extraction and ROI-based statistical analysis yields high classification performance. Using geometric features alone, the Random Forest classifier achieved accuracy values between 96% and 97%. When ROI optimization

was incorporated, the accuracy improved further, reaching up to 97.72% for the printing-only ROI configuration.

The results indicate that increasing the number of geometric features from 2 to 4 improves classification accuracy; however, adding up to 10 features does not produce a significant improvement and may increase model complexity. Additionally, ROI size and position significantly affect statistical feature distributions, influencing classifier performance.

Misclassification analysis shows that errors primarily occur between glass and cardboard bottles due to similarities in geometric characteristics. Optimized ROI selection reduces these errors by enhancing feature discriminability. These findings confirm that integrating ROI-based analysis with geometric feature extraction enhances model robustness and reliability.

IV. CONCLUSION

This study demonstrates that classification performance in automated bottle inspection is strongly influenced by both feature selection and feature variation. Among the evaluated geometric features, area and perimeter serve as the most fundamental descriptors, while the addition of aspect ratio and circularity provides significant improvement by capturing shape proportionality and roundness differences between bottle types. These four features consistently show strong discriminative capability across all classes, particularly in reducing misclassification between geometrically similar objects.

Comparative evaluation reveals that the four-feature configuration achieves the best overall performance, yielding higher accuracy, precision, recall, and F1-score than the two-feature configuration, while maintaining lower model complexity than the ten-feature configuration. Although the ten-feature variation produces comparable accuracy, it does not offer a meaningful improvement in precision or recall and introduces redundant geometric information. Therefore, increasing the number of features beyond four does not significantly enhance classification performance.

Furthermore, the integration of optimized ROI selection strengthens the reliability of these geometric features, leading to the highest observed accuracy of 97.72%. These findings confirm that a compact and well-selected set of geometric features, combined with optimized ROI-based analysis, provides the most effective and robust solution for automated bottle inspection systems.

Overall, the optimal configuration is achieved using four geometric features (area, perimeter, aspect ratio, and circularity) combined with optimized ROI selection, resulting in the highest performance with an accuracy of 97.72%, along with consistently high precision, recall, and F1-score across all bottle classes.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECNOLOGIES IN THE WRITING PROCESS

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