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A Symmetry-Aware Shape Descriptor Framework for Automated Defect Detection in Chocolate Images using Geometric Feature Engineering

Ruth Moly Benjamin[1], Abraham Chandy D.[2], Hepzibah Christinal A.[3]

[1,2]Department of Electronics and Communication Engineering, Karunya Institute of Technology and Sciences, Coimbatore, India.
[3]Department of Computer Science and Engineering, Karunya Institute of Technology and Sciences, Coimbatore, India.

E-mail: [1]mbruth17@gmail.com, [2]abrahamdchandy@gmail.com, [3]christyhep@gmail.com

Orcid ID: [1]0000-0002-2272-4304, [2]0000-0002-0655-4544, [3]0000-0003-3965-3183

Abstract

In recent years, developments in food quality and safety regulations have placed greater importance on high-quality food production. Foods that are inspected for quality defects include chocolates that are susceptible to defects during their manufacturing process. Currently, there are various techniques for detecting defects in chocolates, but most focus on global properties of the shape of chocolates. In this study, a new technique called Symmetry Aware Shape Descriptor (SASD) approach was proposed for automatic defect detection in chocolates. This algorithm is composed of two descriptors; Symmetry Difference Index (SDI), which measures the global symmetry properties of a shape, and Symmetry Residual Descriptor (SRD), which measures the local asymmetry properties of the shape. After the extraction of these two descriptors, they form a feature vector, which is then classified using Support Vector Machine (SVM) Classifier. To perform a comparative analysis, classical shape-based approaches, basic shape features, Hu moments, and convex hull-based approaches were also implemented. The dataset used in this study consists of 225 chocolate images from 14 different chocolate brands. The suggested framework exhibited improved performance when compared to conventional methods, where the classification accuracy and precision achieved by this framework were 77.78% and 78.95%, respectively. These results show that the suggested SASD framework is an effective, transparent, and computationally efficient method for automated defect detection in chocolates.

Keywords: Chocolate Defect Detection, Shape Analysis, Symmetry-Aware Descriptors, Support Vector Machine (SVM), Image Processing, Quality Inspection, Geometric Features.

1. Introduction

Food production industries use an inspection process that helps to check the quality of the product. The conventional methods of food inspection used visual and manual inspection

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for the detection of defects in the food products [1]. Some recent studies have used Hu Moments and Convex Hull based features to improve the defect detection techniques [2]. Though effective, they lack in the detection of minute irregularities present on the surface of the product because of limited changes in its geometrical nature.

This research suggests the design of a Symmetry-Aware Shape Descriptor (SASD) approach to improve the performance of automated inspection of chocolate quality [3]. In the proposed SASD approach, the Symmetry Difference Index (SDI) and Symmetry Residual Descriptor (SRD) were used for analyzing global symmetry as well as localized symmetry deviation. SDI and SRD work together to perform effective defect characterization for chocolates. SVM classifier was utilized to classify the extracted feature vector to perform automated defect detection. The effectiveness of the proposed SASD approach was experimentally analyzed using the dataset consisting of defect-free and defective chocolates. It has been observed from the experimental results that the proposed SASD approach performs better than the traditional shape descriptors (Hu moments and Convex Hull). This SASD approach achieves 77.78% accuracy and 78.95% precision.

2. Related Work

The traditional shape analysis techniques involve the use of fundamental geometric features such as area, perimeter, circularity, aspect ratio, and compactness [4]. These features give a global description of the shape of the object and are computationally fast, thus can be employed in industrial inspection systems with low computational capabilities. These traditional approaches typically segment the object, and the information regarding contours is used to evaluate the geometric features. The area and perimeter give an indication of the size of the object and its boundary length. The circularity and aspect ratio are used to calculate the shape uniformity and shape elongation. However, in practical situations, the defect does not significantly change the whole structure of the shape of the object. Therefore, such techniques that only take into consideration the geometric structure of the object may not be able to detect the defects in the object.

2.1 Basic Shape Features with SVM

Food quality evaluation frameworks generally make use of shape- and contour-related characteristics to evaluate the quality of food. For example, Donati et al. [5] proposed a real-time food quality evaluation framework based on shape features. The results indicated that shape features help achieve better defect detection accuracy when compared to traditional color-based inspection methods. This approach extracted geometric features including contour- and area-related parameters such as area, length, width, and anisotropy for efficient classification during food manufacturing. Jiang et al. [6] provided an integrated framework where deep learning-based segmentation is combined with geometric features to evaluate the quality of strawberries. Shape features were utilized to evaluate fruit deformities, and the morphological symmetry was calculated using IoU and ADR indexes.

In this work, Sarkar et al. [7] presented a methodology using geometric shape analysis for automated classification of the freshness of Indian gooseberry (Phyllanthus emblica). This methodology calculated the distance of the periphery from the centroid and utilized them as input features for the SVM and ANN classifiers to classify fresh and deteriorated samples. Edge information was obtained through Canny edge detection, while ConvexImage contour analysis was performed for the purpose of analyzing the irregularity and deformation on the surface due to aging process.

2.2 Extracting Shape Features with Hu Moments

Hu Moments have been widely used to represent the object shape through the extraction of invariant geometric features. This process involves identifying the defects through the use of invariant contour descriptors. Ji et al. [8] proposed a wavelet moment based feature extraction method to detect defects like cracks and holes in the wood. This method takes care of the scale dependency issues associated with traditional Hu Moments. The experimental results suggested that the method was superior to the conventional Hu Moment methods in terms of higher accuracy due to invariance. Negrete et al. [9] designed an automatic image analysis system which incorporates interpretable texture and shape descriptors for the detection and classification of spotted lanternfly egg masses. The system incorporated the use of Hu Moments, Zernike Moments, and texture features with an SVM classifier for image-based detection of egg masses. The results showed that Hu Moment descriptors were capable of representing the invariant shape information and hence visual inspection was possible.

2.3 Convex Hull-Based Shape Analysis

Convex Hull is another geometric shape descriptor that constructs the outer boundary of an object by defining the minimal convex polygon surrounding all the contour points of the object. The algorithm is popularly used in defect detection based on images due to its ability to detect boundaries' discontinuity and irregularities. Yi Shen et al. [10] have applied a combined watershed and Convex Hull algorithms with the help of an SVM classifier for the detection and segmentation of damaged corn kernels, providing 94.3% accuracy. Despite having a small amount of data for training, the Convex Hull-based approach successfully segmented overlapping kernels and detected the presence of their irregularities. Lv et al. [11] presented an automatic framework for fork point and trimming path detection for forked carrots using contour analysis and machine learning techniques together. The proposed framework has applied Convex Hull-based geometrical descriptors using SVMs for detecting fork points and trimming path. The findings have proved the efficiency of the method of Convex Hull-based shape analysis to represent contours and determine defects in geometry. The following researches prove the efficiency of Convex Hull-based extraction of geometrical features to model shape patterns and to carry out image segmentation.

2.4 Limitations of Existing Methods

The traditional techniques discussed above enable effective representation of shape features. However, although very effective, these techniques have been proven to be inefficient in recognizing structural changes, particularly in chocolate products. The Convex Hull and Hu Moments-based techniques allow effective shape recognition, but they have been shown to be inefficient in detecting minor defects and abnormalities in chocolate products. While efficient in shape recognition, Convex Hull based techniques can easily be affected by noise and segmentation problems, making it difficult to identify internal defects and abnormalities [12]. Moment-based techniques tend to have ineffective segmentation and illumination sensitivity [13]. These techniques are mainly concerned with global shape features rather than local defects such as cracks, discolored spots, and damaged edges.

The proposed Symmetry-Aware Shape Descriptor (SASD) system compensates for the limitations associated with existing systems by taking localized residual asymmetries into account. The proposed system involves two descriptors: Symmetry Difference Index (SDI) and Symmetry Residual Descriptor (SRD), which provide a complete shape characterization from the distortion perspective of both global and local aspects of chocolate defect shapes.

Table 1 presents a comparison between conventional shape descriptors and the proposed symmetry-based shape descriptor, showing the rationale behind the proposed Symmetry-Aware Shape Descriptor (SASD) framework.

Table 1. Comparison of conventional and proposed shape descriptors

Method	Shape information captured	Limitation for chocolate defect detection
Basic Shape Features	Global geometric properties (area, perimeter, circularity)	Insensitive to localized contour defects and symmetry violations
Hu Moments	Global invariant shape representation	Limited ability to localize small structural abnormalities
Convex Hull	Outer contour geometry	Does not characterize the spatial distribution of asymmetry
Proposed SASD	Global symmetry deviation and localized residual asymmetry	Simultaneously measures defect magnitude and spatial distribution

3. Proposed Methodology

3.1 System Overview

The proposed Symmetry-Aware Shape Descriptor (SASD) framework integrates multiple image processing and analysis pipelines for automated chocolate quality assessment and defect detection. Figure 1 shows the overall processing pipeline of the proposed SASD framework.

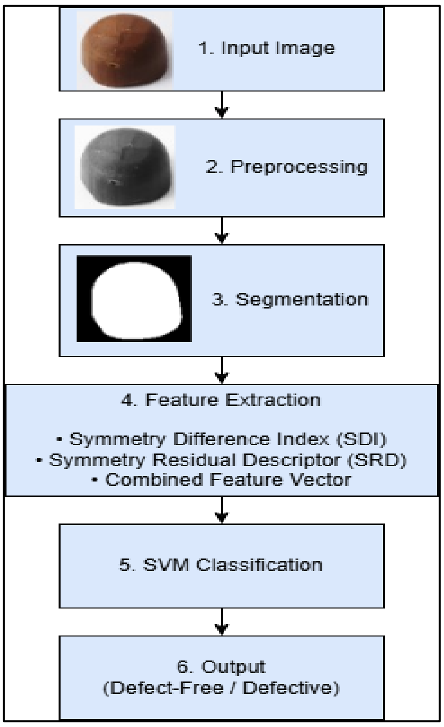

Figure 1. Flowchart of the proposed SASD framework

The framework includes four major stages: preprocessing, segmentation, feature extraction, and classification. Initially, the input images are preprocessed to suppress noise and enhance image quality. The chocolate region is then extracted from the background through segmentation. The segmented chocolate region is subjected to feature extraction utilizing two complementary descriptors: the Symmetry Difference Index (SDI) for measuring global symmetry deviations and the Symmetry Residual Descriptor (SRD) for characterizing localized residual asymmetry through residual region analysis. By capturing both global and local shape distortions, the complementary descriptors enable accurate defect characterization. The extracted features are subsequently classified using a Support Vector Machine (SVM) classifier to discriminate between defective and defect-free chocolates.

To analyze multiple techniques for extracting features, three baseline approaches: Basic Shape Features with SVM, Shape Features with Hu Moments, and Convex Hull-Based Shape Analysis are first implemented. In parallel the proposed methodology is implemented to enable a systematic assessment of traditional and proposed methods for efficient detection of defects.

3.2 Dataset Preparation and Training–Validation–Test Protocol

The dataset used in this study consists of 14 different chocolate brands, including both defect-free and defective samples. Due to the limited availability of naturally defective chocolate samples, the defective chocolate samples were generated using controlled manual deformation and scratching methods such as corner chipping, edge breakage, contour distortion, localized material loss, surface scratches, and symmetry irregularities to simulate common physical defects. All chocolate images were captured on a flat white background using a high-resolution mobile camera under controlled indoor lighting conditions to minimize variations in illumination and background appearance.

A total of 225 original chocolate images were included in the study including 154 non-defective and 71 defective samples. The dataset was separated into training and testing partitions, with 144 original images included in the training set (102 defect-free and 42 defective) and 81 testing images (52 defect-free and 29 defective). The independent test set was reserved exclusively for the final performance evaluation and was not used during model training. Hyperparameter optimization was performed using five-fold cross-validation within the training dataset. Data augmentation was restricted to the training set to enhance data diversity and support improved model generalization. Augmentation techniques comprise geometric transformations, including rotation (±15°), horizontal flipping, scaling (0.8× and 1.2×), and translation. Photometric enhancement techniques, including brightness adjustment, contrast enhancement, saturation modification, and hue variation, were performed on the training images. Also texture-related augmentations, namely Gaussian noise injection, Gaussian blurring, sharpening, and emboss filtering were applied to the training images. Through data augmentation, 1,428 defect-free and 504 defective training images were generated, yielding 1,932 samples overall. To ensure a balanced class distribution during training, 504 augmented defect-free images and 504 augmented defective images were used for the training process. After incorporating the selected augmented samples with the original training images, the resultant training dataset contained 1,152 images, of which 606 were defect-free and 546 were defective. Figure 2 provides examples of both original and augmented defect-free and defective chocolate samples.

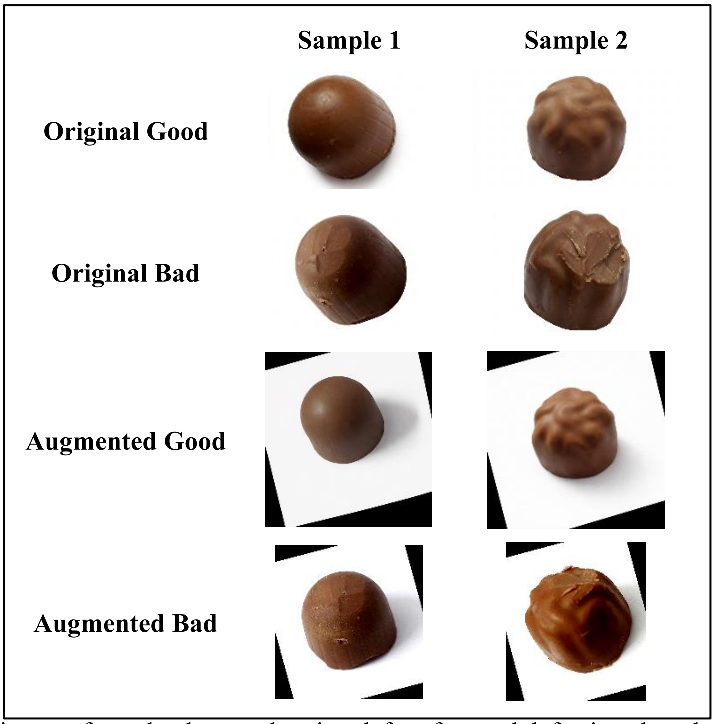

Figure 2. Sample images from the dataset showing defect-free and defective chocolates along with the generated augmented variants

Table 2 represents the distribution of chocolate images which includes the original defect-free, defective and augmented defect-free and defective images.

Table 2. Dataset description

Category	Good	Defective	Total
Original Training Images	102	42	144
Original Test Images	52	29	81
Augmented Images Used for Training	504	504	1008
Final Training Images	606	546	1152

3.3 Segmentation Validation

The quality of segmentation was validated by visual inspection of representative defect-free and defective chocolate samples. The combination of contrast enhancement, thresholding, and morphological operations isolated the chocolate region while suppressing background artifacts. The binary representation of the chocolate shape was used as the basis for symmetry analysis and feature extraction.

3.4 Feature Extraction

Feature extraction is carried out to characterize symmetry deviations and localized structural irregularities associated with chocolate defects. Each segmented chocolate image undergoes grayscale conversion followed by Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve image contrast. A Gaussian filter is applied to suppress noise followed by Otsu thresholding to segment the chocolate shape into a binary image. Morphological closing is applied to improve shape continuity. In the proposed Symmetry-Aware Shape Descriptor (SASD) framework, feature extraction is achieved by conducting a comparative analysis of the left and right halves of the binary chocolate image. The chocolate shape is first divided along a vertical axis of symmetry. The right half is then horizontally flipped and compared with the left half. The Symmetry Difference Index (SDI) measures overall shape asymmetry by quantifying the proportion of non-overlapping pixels between the mirrored left and right halves. To capture localized asymmetry, the Symmetry Residual Descriptor (SRD) is derived from the residual regions obtained during symmetry comparison. Three complementary features are incorporated into the Symmetry Residual Descriptor (SRD): the residual area ratio, the largest residual region area, and the number of residual connected components. Together, the descriptors characterize the degree and spatial localization of defect-induced symmetry violations.

Figure 3 shows that defect-free chocolates exhibit uniform and symmetric shapes, leading to smaller residual regions and lower descriptor values. Defective samples are characterized by larger, fragmented residual regions that are indicative of defect-induced shape distortions and structural abnormalities. SDI and SRD jointly characterize global and local shape distortions caused by defects, and their combined features are used for classification.

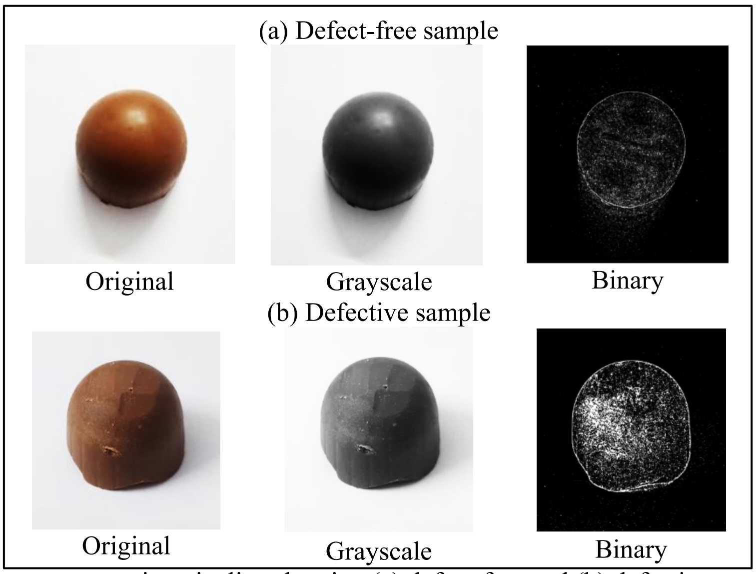

Figure 3. Feature extraction pipeline showing (a) defect-free and (b) defective sample

For SDI computation, the binary chocolate shape is partitioned into two halves using the vertical axis of symmetry [14]. The mirrored right half is subsequently aligned and compared with the left half. A difference map is generated by calculating the absolute difference map between the mirrored halves. Let L(x,y) denote the left half of the binary chocolate image and Rf (x,y) denote the horizontally mirrored right half. A symmetry difference map D (x,y) is computed by performing pixel-wise absolute difference between the two halves as given in Equation 1:

$$D(x, y) = |L(x, y) - R_f(x, y)| \tag{1}$$

where D(x,y) = 0 represents symmetric pixels and D(x,y) >0 represents asymmetric pixels. The total number of asymmetric pixels obtained from the symmetry difference map is denoted by N_{diff} , which forms the basis for computing the Symmetry Difference Index.

The SDI is defined as given below in Equation 2,

$$SDI = \frac{N_{diff}}{N_{total}} \tag{2}$$

where N_{diff} indicates the number of pixels identified in the symmetry difference map and Ntotal indicates the total number of pixels used for comparison.

Since $N_{diff} \leq$ Ntotal, the descriptor satisfies

$$0 \leq \text{SDI} \leq 1$$

An SDI value near zero indicates a highly symmetric chocolate shape, while increasing asymmetry results in progressively larger values. By normalizing with respect to Ntotal, the influence of overall chocolate size on the Symmetry Difference Index (SDI) is eliminated, allowing consistent comparison across chocolates of varying dimensions. In addition to SDI, three Symmetry Residual Descriptors (SRDs)—SRD Ratio, SRD Largest Component, and SRD Component Count—are extracted from the residual asymmetry map.

In contrast to conventional shape descriptors that primarily capture global geometric characteristics, the proposed framework explicitly assesses bilateral symmetry by comparing the left half of the chocolate with the mirrored right half. The generated symmetry difference map highlights regions of geometric symmetry violation, associated with defects such as corner chipping, edge deformation, and contour irregularities. Instead of relying exclusively on the overall asymmetry magnitude, the proposed framework extends beyond overall asymmetry quantification using connected-component analysis. Consequently, the combination of SDI and SRD provides complementary information by simultaneously representing the magnitude and spatial distribution of defect-induced asymmetry.

A summary of the extracted features used in the proposed approach is provided in Table 3.

Table 3. Summary of extracted features used in SASD framework

Feature Category	Feature	Description
Symmetry Descriptor	SDI (Symmetry Deviation Index)	Determines the degree of asymmetry through comparison between the chocolate shape and its horizontally flipped version
Symmetry Residual Descriptors	SRD Ratio	Ratio of residual asymmetry pixels to the total comparison area, quantifying the overall extent of symmetry violation
	SRD Largest Component	Area of the largest connected residual asymmetry region, representing the dominant localized shape distortion
	SRD Component Count	Number of disconnected residual asymmetry regions, indicating the spatial distribution of localized defects

Figure 4 illustrates the computation of the Symmetry Difference Index (SDI) for defect-free and defective chocolate samples by comparing the binary chocolate shape with its mirrored right half and generating the corresponding difference map. The features extracted during the symmetry analysis stage are integrated to generate a compact feature vector.

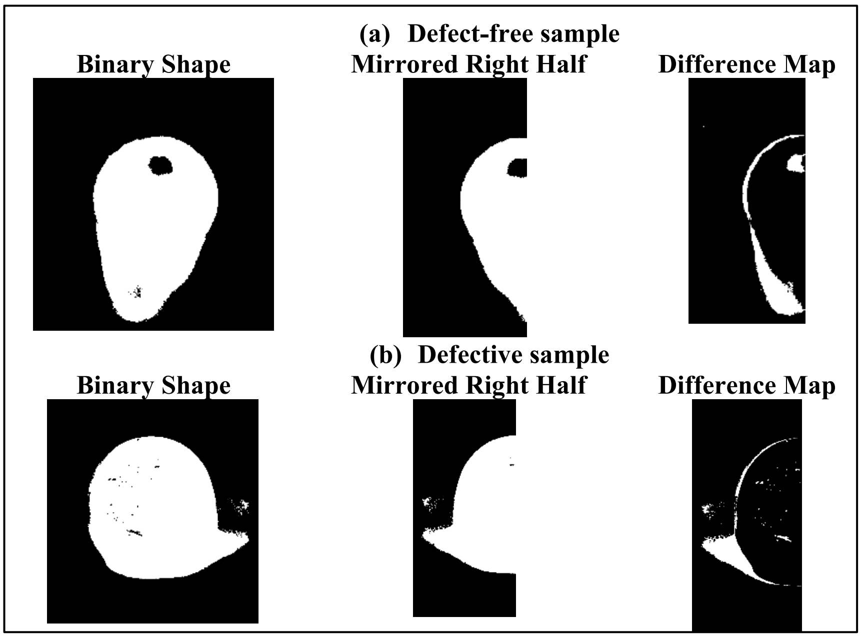

Figure 4. Computation of the symmetry difference index (SDI) for defect-free and defective chocolate samples

3.5 Classification Using Support Vector Machine (SVM)

The symmetry-derived feature vector was used to train a Support Vector Machine (SVM) classifier on chocolate samples. To model the nonlinear characteristics of the classification task, a Radial Basis Function (RBF) kernel was adopted [15]. The RBF kernel transforms the extracted descriptors into a higher-dimensional feature space, thereby enhancing class separability and representation of complex defect-related patterns. Before model training, z-score normalization was performed on all features to ensure balanced feature contributions during classification. Hyperparameter optimization was determined using a five-fold GridSearchCV approach. The search space included $C \in \{0.1, 1, 10, 100\}$ and $\gamma \in \{0.001, 0.01, 0.1, 1\}$. Based on GridSearchCV optimization, the optimal SVM configuration was achieved using an RBF kernel with $C=100$ and $\gamma=0.01$. Class imbalance was handled using balanced class weights, thereby enhancing the robustness of the classification model. The final optimized classifier was retrained using the entire training dataset, and its performance was assessed on an independent test set.

4. Results and Discussion

4.1 Evaluation Metrics

The performance of the proposed framework was assessed against traditional approaches using standard performance metrics, including accuracy, precision, recall, and F1-score.

- **Accuracy:** Accuracy measures the percentage of correctly classified samples and the overall correctness of the model for defect-free and defective samples.
- **Recall:** Recall represents the proportion of actual defective samples that are correctly detected, which leads to a lower occurrence of missed defects.

- **Precision:** Precision evaluates the proportion of predicted defective samples that are truly efective which helps reduce false defect detection.
- **F1-score:** The F1-score is the harmonic mean of precision and recall, thereby generating a reliable performance evaluation.

Recall serves as the primary evaluation metric for defect detection, as it measures the model's ability to correctly identify defective samples [16].

4.2 Performance of Proposed Method

In the proposed Symmetry-Aware Shape Descriptor (SASD) framework, a classification accuracy of 77.78%, a precision of 78.95%, a defect recall of 51.72% and an F1-score of 62.00% were obtained. The experimental results confirmed that the proposed framework had achieved the highest accuracy, precision and F1-score, hence it was effective in the classification of chocolate defects.

Although Hu moment and Convex Hull features performed slightly better in defect recall, they performed poorly in terms of accuracy and precision compared to those of the proposed framework. Out of all the techniques compared, the proposed Symmetry-Aware Shape Descriptor (SASD) framework had a balanced performance on classification reliability and defect detection. It is also noted from the qualitative analysis of the incorrectly classified samples of chocolates that most of the classification errors occurred as a result of minor distortions in the contours and barely visible shape defects.

4.2.1 ROC Analysis

The effectiveness of the proposed Symmetry-Aware Shape Descriptor (SASD) model to discriminate between defective and non-defective chocolate samples was further investigated using the Receiver Operating Characteristic (ROC) curve. Figure 5 shows the ROC curve of the proposed SASD classification model. Based on the ROC analysis, the area under the curve (AUC) is 0.821, which indicates that the proposed model can effectively distinguish between defective and non-defective chocolate samples. Although the overall accuracy rate is 77.78%, the value of the AUC of 0.821 clearly indicates the high discriminative power of the proposed shape descriptors for defect detection.

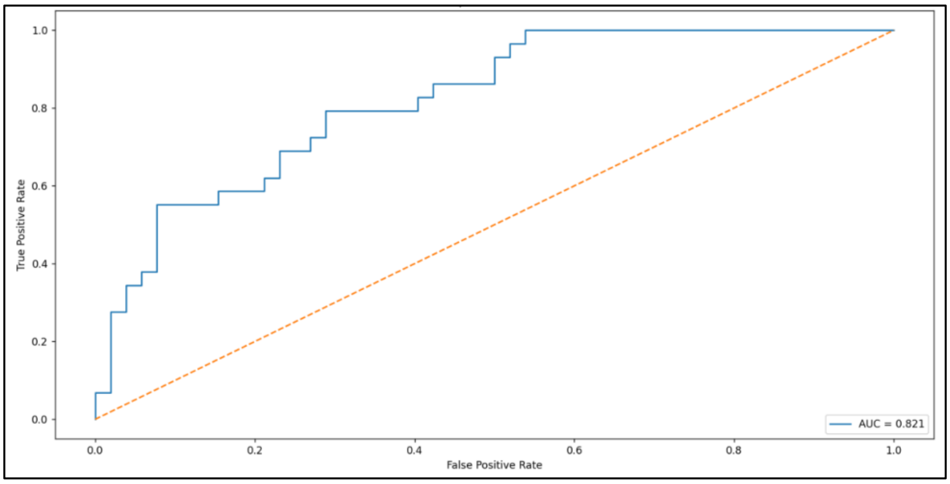

Figure 5. Receiver operating characteristic (ROC) curve of the proposed SASD framework

4.2.2 Qualitative Failure-Case Analysis

Figure 6 shows instances of defective chocolates that have been incorrectly classified as non-defective using the proposed methodology. The chocolates have minor defects in their structure, including chipping of corners, wear and tear at the edges, and deformation of the contours. Although the chocolates have minor structural flaws, the structure as well as symmetry of the chocolates is maintained in most parts. Consequently, the extracted SDI and SRD values are similar to those of the non-defective chocolates.

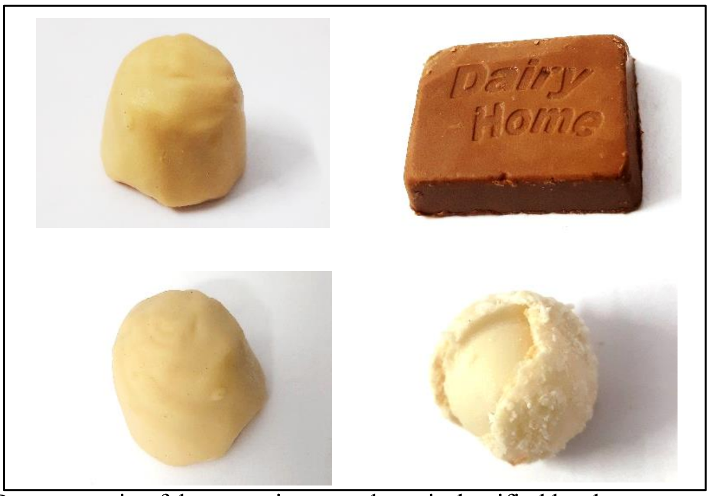

Figure 6. Representative false-negative samples misclassified by the proposed SASD framework.

4.2.3 Computational Complexity Analysis

To evaluate computational efficiency of the proposed SASD framework the average runtime of each processing stage on the independent test dataset was determined. The obtained results are summarized in Table 4.

Table 4. Average computational runtime of the proposed SASD framework

Processing Stage	Average Runtime (ms/image)
Preprocessing	55.76
Feature Extraction (SDI + SRD)	13.98
SVM Classification	0.05
Total Inference Time	69.79

As presented in Table 4, the preprocessing stage consumed an average of 55.76 ms per image, whereas the extraction of SDI and SRD features required 13.98 ms per image. The SVM classifier performed prediction in only 0.05 ms per image, resulting in an overall inference time of 69.79 ms per image. These findings demonstrate that the majority of the computational cost is attributed to the preprocessing stage, whereas feature extraction and classification require relatively low computational overhead. The combination of a compact four-dimensional feature vector and a lightweight SVM classifier provides computationally efficient defect detection for automated chocolate inspection applications.

4.3 Comparison with Traditional Methods

Comparative analysis is carried out between the proposed SASD framework and the three implemented traditional approaches.

Table 5. Performance comparison of the implemented traditional methods and the proposed SASD framework evaluated on the experimental dataset

Method	Accuracy (%)	Precision (%)	Defect Recall (%)	F1-Score (%)
Basic Shape Features	66.67	54.17	44.83	49.00
Shape + Hu Moments	54.32	40.91	62.07	49.00
Convex Hull-Based	58.02	43.90	62.07	51.00
Proposed SASD	77.78	78.95	51.72	62.00

Table 5 provides a comparative evaluation of conventional shape-based methods and the proposed SASD framework. With an accuracy of 77.78%, precision of 78.95%, and F1-score of 62.00%, the proposed SASD framework achieved the highest classification performance. Figure 7 presents a graphical comparison of the evaluated methods.

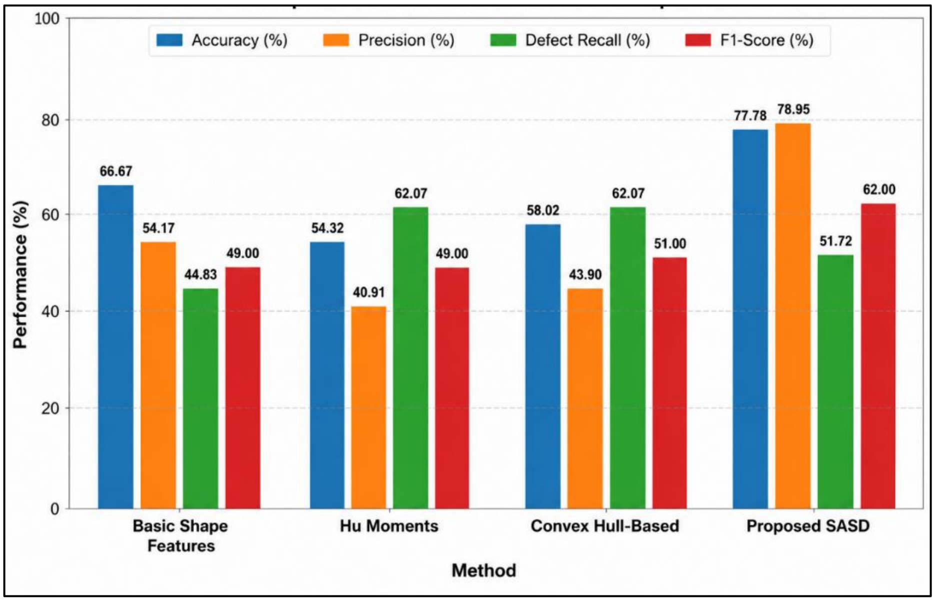

Figure 7. Graphical analysis of performance analysis of different methods

4.4 Comparison with Deep Learning-Based Defect Detection

A MobileNetV2 transfer learning model was implemented as a modern deep learning benchmark to compare with the proposed SASD framework. For consistent performance assessment, both approaches were trained and tested using identical dataset partitions. Experimental results indicate that MobileNetV2 demonstrated superior classification capability compared with the proposed SASD framework, with an accuracy of 88.89%, precision of 95.45%, recall of 72.41%, F1-score of 82.35%, and AUC of 0.9649. MobileNetV2 achieves superior classification performance due to its ability to learn complex and discriminative feature representations directly from image data.

Although MobileNetV2 demonstrated stronger classification performance, the proposed SASD framework provides several practical advantages. The proposed framework utilizes a compact four-dimensional feature vector extracted from interpretable symmetry-aware descriptors. As a result, SASD achieves lower computational complexity and improved interpretability relative to deep-learning approaches. Owing to its computational efficiency and interpretability, the proposed framework offers practical advantages for lightweight industrial inspection systems.

Table 6 shows the comparative performance of the proposed SASD framework and the MobileNetV2 benchmark model.

Table 6. Comparative performance evaluation of the proposed SASD framework and MobileNetV2 transfer learning approach

Method	Accuracy	Precision	Recall	F1
Proposed SASD	77.78	78.95	51.72	62.00
MobileNetV2	88.89	95.45	72.41	82.35

4.5 Ablation Study

An ablation study was performed to assess the individual impact of SDI and SRD on chocolate defect detection performance [17][18]. Table 7 presents the results of experiments. The results of applying SDI alone led to a defect recall of 72.41%, thus proving the potential of SDI for the characterization of defect-related global symmetry variation. While obtaining good results in terms of the sensitivity of defect detection, the low value of precision (53.85%) showed that there were many false positive classifications. Using the SRD-only feature set obtained 72.22% of precision and 74.07% of accuracy. This means that SRD is a good tool for obtaining a meaningful representation of local asymmetry variation. However, due to the low value of recall (44.83%), SRD alone is not enough to represent all possible variations of defects.

By applying both global and local symmetry descriptors in the SASD scheme, we obtained an accuracy of 77.78% and a precision of 78.95%.

Table 7. Ablation study results

Configuration	Accuracy (%)	Recall (%)	Precision (%)
SDI Only	67.90	72.41	53.85
SRD Only	74.07	44.83	72.22
Proposed SASD	77.78	51.72	78.95

4.6 Feature Importance Analysis

To evaluate the significance of the proposed features, a feature importance analysis using Random Forest has been performed for the classification of chocolate defects [19]. Figure 8 demonstrates the outcome of the feature importance analysis. Although an SVM has been used as the main classifier, a Random Forest classifier has been used exclusively for the feature importance analysis due to its high level of interpretation.

According to the feature importance analysis, SRD Largest Component showed the highest feature importance of 0.3339, SRD Components 0.2443, SDI 0.2118, and SRD Ratio 0.2100. This result stresses the fact that characteristics of localized residual asymmetry are very useful and provide discriminative information between defect and defect-free chocolate pieces. The area of the largest residual region is considered a very informative feature for representing structural deformation. The feature importance analysis demonstrated balanced contributions from all four features, which means that each of the features provides complementary information.

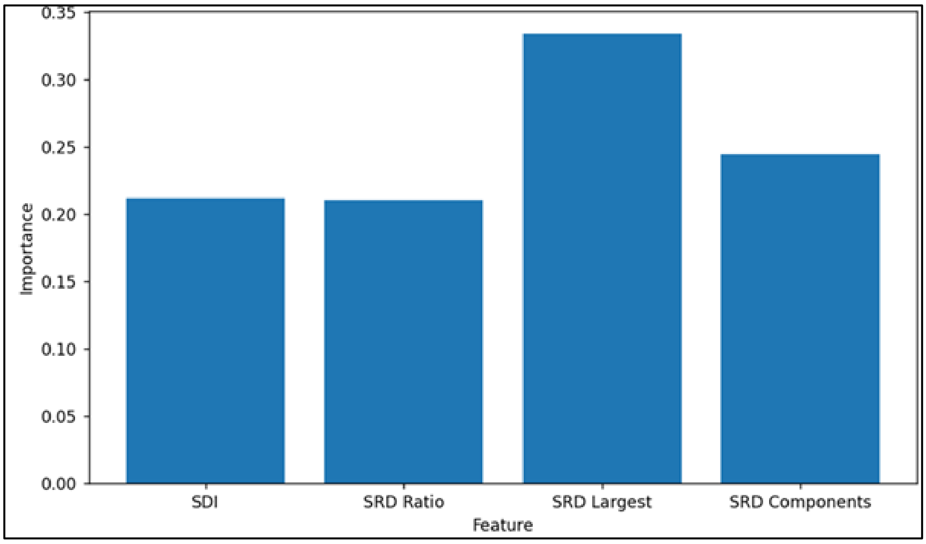

Figure 8. Feature importance analysis of the extracted descriptors using random forest

4.7 Discussion

The results generated have clearly shown that the SASD framework developed performs better than traditional techniques in terms of defect classification. From the experimental results, it has been determined that the SASD framework was measured with an accuracy of 77.78%, precision of 78.95% and defect recall of 51.72%. The ablation test has shown that the integration of SDI and SRD provides complementary information to improve defect representation. SDI gives the measure of global symmetry deviations while SRD describes the local asymmetry patterns associated with the defects in the structure. The SDI-SRD framework has performed better than other frameworks with either SDI or SRD.

The comparison with MobileNetV2 showed that using deep learning algorithms provides better results for classification on the used dataset. Yet, the proposed SASD framework possesses practical benefits in interpretability, computational speed, and less dependency on pretrained big models. First of all, the proposed descriptors describe deviations in symmetry and local structures, while deep learning methods usually work as black box classifiers. Due to the fact that the proposed algorithm uses handcrafted symmetry descriptors, the classification result is based on the way the features reflect the properties of defects.

However, it is essential to mention some limitations associated with the proposed approach despite its positive outcomes. Namely, the experiment was performed using a dataset containing 225 images of original chocolates provided by 14 different chocolate manufacturers. It means that the variety of defects' patterns used in the research is rather limited and cannot be found in practical implementation. Although the researchers have utilized data augmentation only on the training dataset and an independent test set was used for model testing, the lack of original images can lead to overfitting. Consequently, the obtained results may not reveal the true performance of the suggested framework when working with new samples of chocolates. Additionally, the manually manipulated samples can hardly reflect the diversity and complexity of defects occurring in practical industrial settings. Moreover, the effectiveness of the suggested framework for industrial applications involving high throughput needs further investigation. Future directions include applying the proposed framework to large industrial datasets that include naturally occurring defects while developing new symmetry-aware descriptors to improve defect detection performance. Also, even though the framework outperforms existing approaches, its classification accuracy was lower compared to the MobileNetV2 model. The future work includes integration of the symmetry-aware descriptors with deep learning algorithms to improve the accuracy and interpretability of results [20][21][22].

5. Conclusion

The current research has introduced a new method of Shape-Based Defect Detection Framework (SASD) for the detection of defects in chocolates using shape symmetry. In the proposed framework, the use of Symmetry Difference Index (SDI) and Symmetry Residual Descriptor (SRD) has been done to analyze the shape asymmetry as well as the structural defects within the shape. The results of the current study have proved the effectiveness of the proposed framework for the detection of defects in chocolates.

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