

## FEATURE FUSION IN INDONESIAN PLASTIC WASTE CLASSIFICATION FOR ENHANCED RECYCLING PROCESS

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**ABSTRACT.** *Plastic waste classification is crucial for optimizing recycling, particularly when different plastic types appear visually similar, especially in Indonesia. This study introduces a multimodal feature fusion method that integrates deep features from VGG16 with handcrafted texture descriptors using Local Binary Pattern (LBP) and Gray Level Co-occurrence Matrix (GLCM). The extracted features are normalized using Min-Max scaling and concatenated into a unified feature vector. Classification is conducted using Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), and Random Forest (RF). Results show that MLP achieved the highest accuracy of 97%, outperforming other models, especially under image preprocessing via resizing. Further evaluation using random cropping demonstrates that the model maintains robust classification performance, although errors may occur when discriminative visual features are missing. The findings confirm that combining deep and handcrafted features significantly improves classification accuracy and robustness, offering a promising direction for intelligent vision-based plastic waste recognition systems.*

**Keywords:** Plastic waste classification, Feature fusion, Machine learning, Random cropping

**1. Introduction.** The rapid increase in plastic waste poses a significant challenge to environmental sustainability and waste management systems, with countries like Indonesia generating over 65 million tons annually, contributing to landfill accumulation and marine pollution [1,2]. Effective recycling depends on accurate sorting by polymer type; however, visual similarities among plastics make appearance-based classification difficult [3-5]. Despite this need, recycling systems face major challenges, particularly in developing countries where sorting relies on manual labor, leading to inefficiency and health risks [6,7]. Although Near-Infrared (NIR) technologies exist, their high cost and limitations in detecting dark or visually similar plastics restrict their practical adoption [8].

Recent advances in computer vision, particularly Convolutional Neural Networks (CNNs), have enabled scalable solutions for waste classification [9,10]. However, CNNs primarily rely on global shape features, making them less effective when plastic waste is deformed, occluded, or visually similar across classes. Moreover, deep features alone often fail to capture fine-grained texture differences, which are essential for distinguishing

similar plastic types. To address these limitations, hybrid approaches that combine deep and handcrafted features have been proposed to improve robustness [11,12]. Indonesia generates approximately 64 million tons of waste annually, with increasing improper disposal posing serious environmental challenges [13,14]. Automated classification systems offer an effective solution to support waste management, reduce marine pollution, and enhance national waste reduction strategies [15,16]. Recent studies show that integrating deep learning with handcrafted feature extractors improves accuracy and robustness in handling visually similar materials [17-19], leading to superior performance in plastic waste classification tasks [20]. Therefore, feature fusion presents a promising approach for improving classification performance in plastic waste processing.

This study addresses two key challenges in plastic waste classification: physical deformation and intra-class visual similarity. Deformed plastic objects often lose global shape cues, limiting the effectiveness of deep models like VGG16, while handcrafted features such as GLCM and LBP capture fine-grained texture information that is invariant to shape. By fusing these complementary features, the proposed method integrates high-level semantic and detailed texture representations to improve classification robustness. The fused features are evaluated using MLP, SVM, and Random Forest, aiming to enhance accuracy in distinguishing visually similar plastic types and support efficient automated recycling systems.

The contribution offered by this research focuses on proving that the combination of features generated by deep learning and features generated by handcrafted techniques results in an improvement in the classification of plastic waste objects that are visually difficult to distinguish. An efficient and scalable workflow is constructed as an automatic plastic waste sorting system that can be implemented in recycling facilities, which is a practical contribution of this research. This paper is structured by presenting a review of previous studies, explaining the methodological flow, showing experimental results, and providing conclusion regarding the findings and future research directions. This paper is an extended version of the authors' thesis [21].

**2. Related Works.** Image-based waste classification has been extensively studied, with existing methods generally falling into three distinct categories: deep learning-based approaches, handcrafted feature extraction, and hybrid feature fusion strategies.

**2.1. Deep learning approaches.** Deep learning, particularly Convolutional Neural Networks (CNNs), has become the standard approach for image classification due to its ability to learn hierarchical features. Architectures such as VGG16 have shown promising results, achieving up to 89% accuracy [9], although performance varies with dataset complexity, with some studies reporting lower results around 69.77% [22]. More advanced models like ResNet34 and DenseNet201 have further improved accuracy, reaching 95.31% and 95.05%, respectively [10,23], while attention-based models such as improved YOLOv7 highlight the importance of fine-grained feature learning [24]. However, despite these advancements, single-stream CNNs remain limited by their reliance on global spatial features, making them less effective for classifying deformed objects or those with high visual similarity.

**2.2. Handcrafted feature extraction.** Before the rise of deep learning, traditional methods relied on handcrafted features to capture visual properties such as texture and patterns. Techniques like GLCM combined with SVM achieved up to 83% accuracy with lower computational cost [25]. Although lacking semantic representation, these methods are effective in capturing fine-grained surface details, which are crucial for challenging materials such as transparent objects. Advanced texture analysis can reveal subtle features

that are often missed by standard visual models, highlighting the importance of handcrafted descriptors in addressing visual ambiguity in plastic waste [26].

**2.3. Feature fusion strategies.** To address the limitations of single approaches, recent studies emphasize hybrid methods that fuse deep spatial features with handcrafted texture descriptors, showing strong performance in fine-grained classification tasks. For instance, combining deep features with HOG achieved over 97% accuracy [11], while similar improvements were reported in gemstone [27] and autism face recognition [12]. Various strategies, such as triplet loss, attention mechanisms, and intra-class augmentation, have also been proposed to reduce class similarity issues [28-30]. However, most waste classification studies still rely on standalone deep learning models, often overlooking the complementary role of texture features [9,10,23]. To address this gap, this study integrates VGG16 with GLCM and LBP to enhance robustness against deformation and intra-class visual similarity in plastic waste.

**3. Research Methodology.** This study focuses on classifying six types of plastic waste in Indonesia, including visually similar classes that pose classification challenges. To address this, a feature fusion approach is proposed by combining deep features from VGG16 with handcrafted texture features from GLCM and LBP. The fused features are evaluated using multiple classifiers, namely MLP, SVM, and Random Forest, to determine the optimal model and achieve the best classification performance.

**3.1. Research procedure.** This study initiates with the collection of data, where the dataset is derived directly from field observations. As depicted in Figure 1, the acquired image data undergoes preprocessing to ensure consistency and uniformity, facilitating subsequent classification. Following preprocessing, feature extraction is performed to derive numerical representations from the images. These extracted features are then employed for classification tasks. Finally, the classification results are evaluated and tested to assess the performance and accuracy of the model.

**3.2. Data collection.** The dataset was collected from household plastic waste, with each item cleaned and isolated to simulate recycling conditions. Images were captured using a smartphone under natural lighting and include six categories: PETE, HDPE, LDPE, PP, PS, and Other plastics, while PVC was excluded due to safety and availability constraints. To improve diversity and generalization, images were taken from various angles, lighting conditions, and orientations. The characteristics of each plastic type are summarized in Table 1.

**3.3. Data preprocessing.** Preprocessing step is performed to prepare the data for classification. Preprocessing involves resizing all images to  $224 \times 224$  pixels to standardize the input dimensions and ensure consistency throughout the classification process, as well as applying image enhancement techniques to improving feature extraction.

**3.4. Feature extraction.** The preprocessed images were processed using three parallel feature extraction techniques: VGG16, GLCM, and LBP.

As illustrated in Figure 2, extracted features were normalized and fused via horizontal concatenation into a single high-dimensional vector for classification. Each method captures complementary information: VGG16 provides abstract features, GLCM captures statistical textures, and LBP encodes local patterns. The feature details are summarized in Table 2, and the fused representation is well-suited for complex non-linear classification tasks.

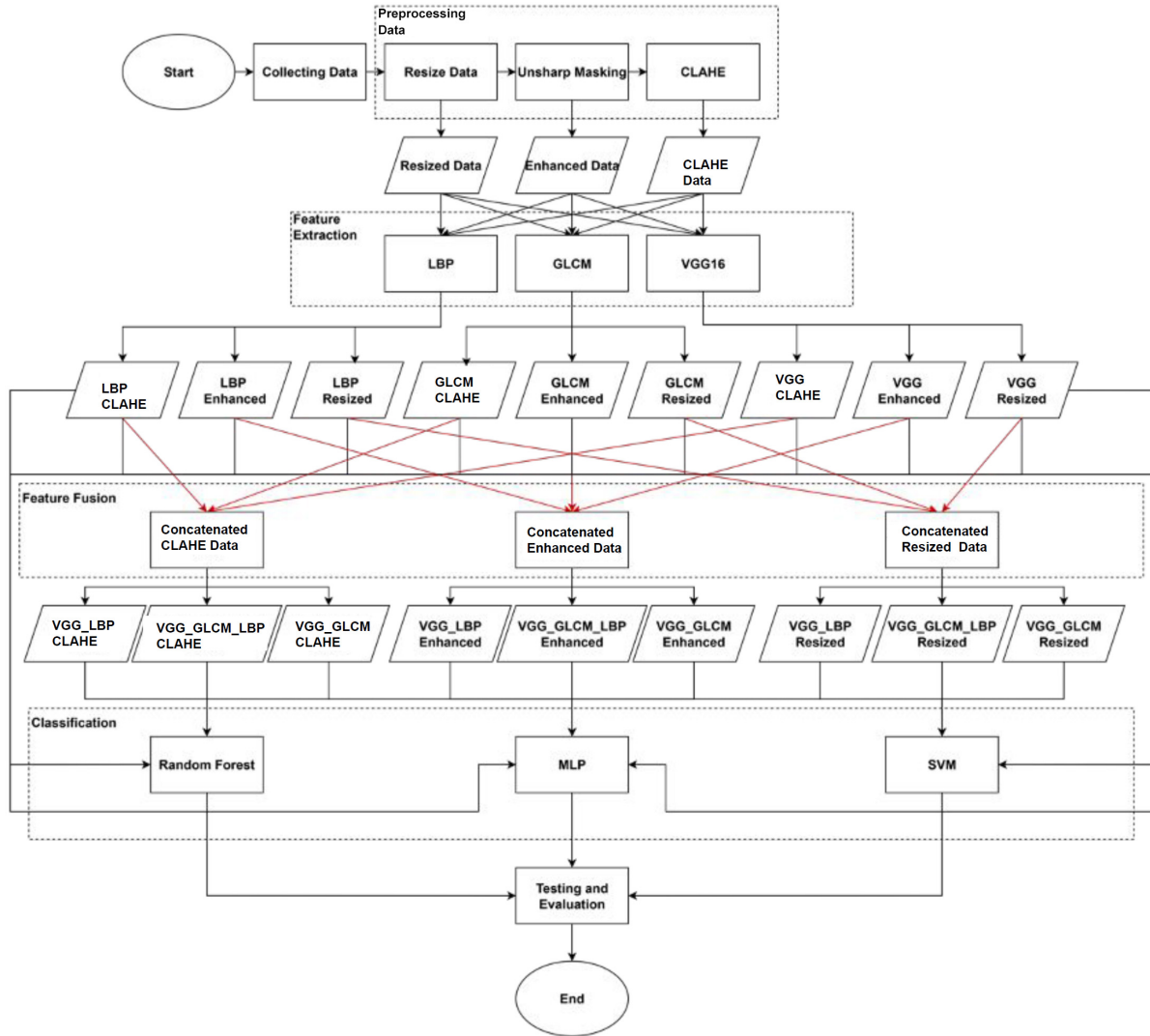
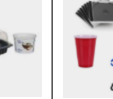


FIGURE 1. Research flow

TABLE 1. Data examples

| Image example |  |  |  |  |  |  |
|---------------|-------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------|
| Label         | PETE                                                                                | HDPE                                                                                | LDPE                                                                                | PP                                                                                  | PS                                                                                    | Other plastic                                                                         |
| Data count    | 100                                                                                 | 100                                                                                 | 100                                                                                 | 100                                                                                 | 100                                                                                   | 100                                                                                   |

3.4.1. *Deep spatial features (VGG16)*. We utilized VGG16 model as the backbone, using 3-channel ( $224 \times 224 \times 3$ ) inputs to maintain compatibility with ImageNet weights. Although texture features were extracted in grayscale, intensity information was replicated across channels for VGG16. The classification head was removed, and features were extracted from the final convolutional layer (block5\_pool), followed by global average pooling to produce a compact 512-dimensional feature vector.

3.4.2. *Statistical texture features (GLCM)*. GLCM was used to capture surface properties such as roughness and sheen. Images were converted to grayscale and quantized into 256

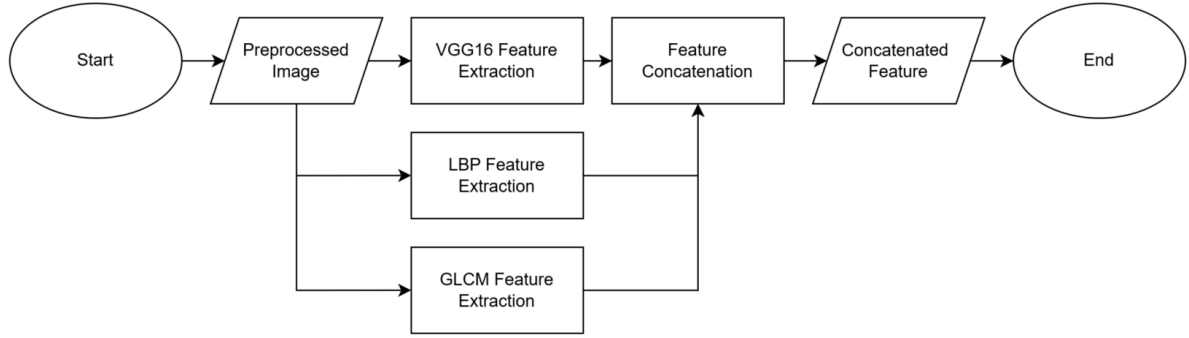


FIGURE 2. Extraction feature flow

TABLE 2. Input and output of each feature

| Method | Input           | Output                                                                                                                    |
|--------|-----------------|---------------------------------------------------------------------------------------------------------------------------|
| LBP    | Grayscale image | The binary code that represents the intensity relationship between the central pixel and its neighboring pixels.          |
| GLCM   |                 | A matrix that represents the frequency of pixel pair occurrences with specific intensities at a given distance and angle. |
| VGG16  |                 | A feature tensor that represents the visual characteristics of an image at a higher level.                                |

levels, with matrices computed at distance  $d = 1$  across four directions ( $0^\circ$ ,  $45^\circ$ ,  $90^\circ$ ,  $135^\circ$ ) for rotational invariance. Six statistical features were extracted and concatenated across all directions, producing a 24-dimensional feature vector per image.

**3.4.3. Local micro-pattern features (LBP).** LBP was employed to capture local edge and corner patterns using the uniform variant for compactness and rotation invariance. A configuration of radius  $R = 3$  and  $P = 24$  sampling points was used to capture coarser textures, producing a histogram that summarizes local surface irregularities.

**3.4.4. Feature fusion.** The features from the three streams were standardized using Min-Max scaling to ensure equal contribution during classification. The final representation is a concatenated vector formed by merging the deep features with the handcrafted texture descriptors, creating a rich multimodal representation for the classification head.

**3.5. Classification.** Classification in this study employs SVM, Random Forest, and MLP to evaluate classification performance, leveraging their respective strengths in handling high-dimensional data, robustness, and non-linear learning. Hyperparameter tuning was conducted using grid search with an 80 : 20 stratified train-validation split, optimizing accuracy as the main metric. For SVM, parameters  $C \in \{0.5, 1, 5\}$  and  $\gamma \in \{\text{scale}, \text{auto}, 0.1\}$  were tested; for Random Forest,  $n\_estimators \in \{70, 150\}$ ,  $max\_depth \in \{\text{None}, 20\}$ , and  $min\_samples\_split \in \{2, 7, 15\}$ ; and for MLP, different architectures (single and two hidden layers), solvers (L-BFGS, SGD), and activation functions (ReLU, Tanh) were explored. Detailed configurations are provided in Table 3.

**3.6. Testing and evaluation.** Testing and evaluation are essential to assess the performance and accuracy of the model. The testing phase will employ preprocessed image data to evaluate the model's accuracy in real-world conditions. Model evaluation will be carried out using a confusion matrix, with metrics such as accuracy, precision, and recall. The use of this matrix allows for a comprehensive analysis of the model's performance, providing valuable insights into its strengths and limitations.

TABLE 3. Hyperparameter tuning for classification model

| Algorithm              | Hyperparameter                                                                                 |
|------------------------|------------------------------------------------------------------------------------------------|
| SVM                    | C = [0.5, 1, 5]; Kernel = [linear, rbf, poly]; Gamma = [scale, auto, 0.1]                      |
| Random Forest          | n_estimator = [70, 150, 200]; max_depth = [None, 10, 20]; min_samples_split = [2, 7, 15]       |
| Multi-Layer Perceptron | hidden_layer_size = [1, 2, 3]; solver = [adam, lbfgs, sgf]; activation = [relu, tanh, sigmoid] |

#### 4. Results and Discussion.

**4.1. Results on data type test.** To identify the optimal image preprocessing strategy for the proposed framework, we evaluated the performance of the complete Feature Fusion + MLP model on three different data representations: raw resized images, Contrast Limited Adaptive Histogram Equalization (CLAHE), and Unsharp Masking (Enhancement). Unlike preliminary tests that often rely on simple classifiers, this experiment utilizes the full multimodal architecture to strictly determine which data type maximizes the synergy between deep features and texture descriptors.

TABLE 4. Comparison of performance based on data processing type

| Type        | Feature        | Classifier | Acc (%)   | Precision (%) | Recall (%) | F1 (%)    |
|-------------|----------------|------------|-----------|---------------|------------|-----------|
| Resize      | Feature fusion | MLP        | <b>97</b> | <b>97</b>     | <b>97</b>  | <b>97</b> |
| Enhanced    |                |            | 91        | 90            | 90         | 90        |
| Enh + CLAHE |                |            | 92        | 91            | 91         | 91        |

The results show that the Resize-only approach achieves the best performance with 97.00% accuracy, outperforming CLAHE (91.06%) and Unsharp Masking (90.24%). Enhancement methods degrade performance by amplifying noise such as reflections and glare, which distort texture features extracted by GLCM and LBP and introduce misleading patterns for VGG16. Thus, preserving the original intensity through simple resizing provides a more robust representation by avoiding artificial artifacts.

**4.2. Results in feature test.** Table 5 evaluates various feature combinations using SVM, RF, and MLP, showing that feature fusion generally improves classification performance. SVM achieved up to a 3% accuracy increase with fused features, while RF performed best using only VGG (95%) but declined with additional features due to redundancy. MLP achieved the highest accuracy (97%) with full feature fusion, demonstrating its effectiveness in handling high-dimensional representations.

**4.3. Comparison with state-of-the-art baselines.** To validate the proposed feature fusion method, a comparative analysis was conducted against baseline models, including VGG16 (single-stream), ResNet-50, and Bilinear CNN (B-CNN), all trained on the same dataset with an 80 : 20 split and ImageNet pre-trained weights. This evaluation aims to assess the capability of standalone deep learning models in handling the complexity of deformed plastic waste, with results summarized in Table 6.

Results in Table 6 show a significant performance gap between pure deep learning models and the proposed fusion approach. Baseline models such as VGG16, ResNet-50, and Bilinear CNN achieved only around 17%-20% accuracy, indicating poor generalization due to limited data (data starvation). In contrast, the proposed method reached 97.00%

TABLE 5. Comparison of performance based on feature scenarios

| SVM (Kernel = rbf, C = 5)                           |                   |           |               |            |           |
|-----------------------------------------------------|-------------------|-----------|---------------|------------|-----------|
| Feature                                             | Gamma             | Acc (%)   | Precision (%) | Recall (%) | F1 (%)    |
| vgg                                                 | scale             | 91        | 91            | 92         | 91        |
| glcm                                                | scale             | 72        | 72            | 73         | 72        |
| lbp                                                 | scale             | 76        | 76            | 75         | 75        |
| vgg_lbp                                             | scale             | 93        | 93            | 93         | 93        |
| vgg_glcm                                            | scale             | 93        | 93            | 94         | 93        |
| vgg_glcm_lbp                                        | scale             | <b>94</b> | <b>94</b>     | <b>95</b>  | <b>94</b> |
| Random Forest (n_estimator = 150, max_depth = none) |                   |           |               |            |           |
| Feature                                             | min_samples_split | Acc (%)   | Precision (%) | Recall (%) | F1 (%)    |
| vgg                                                 | 2                 | <b>95</b> | <b>96</b>     | <b>96</b>  | <b>96</b> |
| glcm                                                | 2                 | 72        | 72            | 72         | 72        |
| lbp                                                 | 2                 | 65        | 65            | 65         | 65        |
| vgg_lbp                                             | 2                 | 89        | 89            | 90         | 89        |
| vgg_glcm                                            | 2                 | 85        | 86            | 85         | 85        |
| vgg_glcm_lbp                                        | 2                 | 86        | 87            | 86         | 86        |
| MLP (HL Size = 50 50 50, Activation = tanh)         |                   |           |               |            |           |
| Feature                                             | Solver            | Acc (%)   | Precision (%) | Recall (%) | F1 (%)    |
| vgg                                                 | lbfgs             | 89        | 90            | 90         | 89        |
| glcm                                                | lbfgs             | 73        | 74            | 75         | 74        |
| lbp                                                 | lbfgs             | 72        | 73            | 73         | 72        |
| vgg_lbp                                             | lbfgs             | 89        | 90            | 90         | 89        |
| vgg_glcm                                            | lbfgs             | 90        | 90            | 91         | 90        |
| vgg_glcm_lbp                                        | lbfgs             | <b>97</b> | <b>97</b>     | <b>97</b>  | <b>97</b> |

TABLE 6. Performance comparison with baseline methods

| Method                                      | Precision (%) | Recall (%)   | F1 (%)       | Acc (%)      |
|---------------------------------------------|---------------|--------------|--------------|--------------|
| VGG16 (single-stream)                       | 16.50         | 17.80        | 17.12        | 17.89        |
| ResNet-50 (fine-tuned)                      | 19.50         | 20.10        | 19.80        | 20.12        |
| Bilinear CNN (FGVC)                         | 20.15         | 20.35        | 20.25        | 20.38        |
| <b>Proposed (Fusion VGG16 + GLCM + LBP)</b> | <b>97.00</b>  | <b>97.00</b> | <b>97.00</b> | <b>97.00</b> |

accuracy, demonstrating that integrating handcrafted texture features effectively compensates for data limitations. This confirms that hybrid approaches are essential for accurate plastic waste classification in resource-constrained scenarios.

**4.4. Quantitative feature space analysis.** To provide measurable evidence for the misclassification cases and strictly validate the qualitative observations, we conducted a quantitative analysis using feature space centroid distance. This method calculates the Euclidean distance between the feature vector of a misclassified sample and the geometric centroid of its true class versus the predicted class. Table 7 presents the distance metrics for representative misclassified samples extracted from the test set.

The results in Table 7 show that misclassifications are driven by feature similarity rather than model instability, as samples are consistently closer to the centroids of incorrect classes than their true classes. For example, Sample 48 (PETE) is closer to the LDPE centroid, while Sample 33 (PS) is closer to the “Other” class, indicating overlap in the

TABLE 7. Euclidean distance analysis for misclassified samples

| Sample index | True label     | Predicted label | Distance to true centroid | Distance to pred. centroid |
|--------------|----------------|-----------------|---------------------------|----------------------------|
| Index 48     | PETE (class 1) | LDPE (class 4)  | 3.4445                    | 3.2323                     |
| Index 10     | LDPE (class 4) | PP (class 6)    | 3.3745                    | 3.3458                     |
| Index 33     | PS (class 5)   | Other (class 7) | 3.0620                    | 2.6364                     |

feature space. This confirms that classification errors arise from high inter-class similarity in the learned representations.

**4.5. Evaluation on visually similar images and misclassification analysis.** In the best-performing model, an accuracy of 97% was achieved. However, four instances were misclassified, highlighting the need for further analysis to understand the system's limitations and identify potential improvements.

Figure 3(a) shows a misclassification where a class 1 sample was predicted as class 6, likely due to transparency and tilted orientation that distorted shape and reduced texture contrast. This weakened GLCM and LBP features and affected VGG16 representations, causing the fused features to align more closely with class 6.

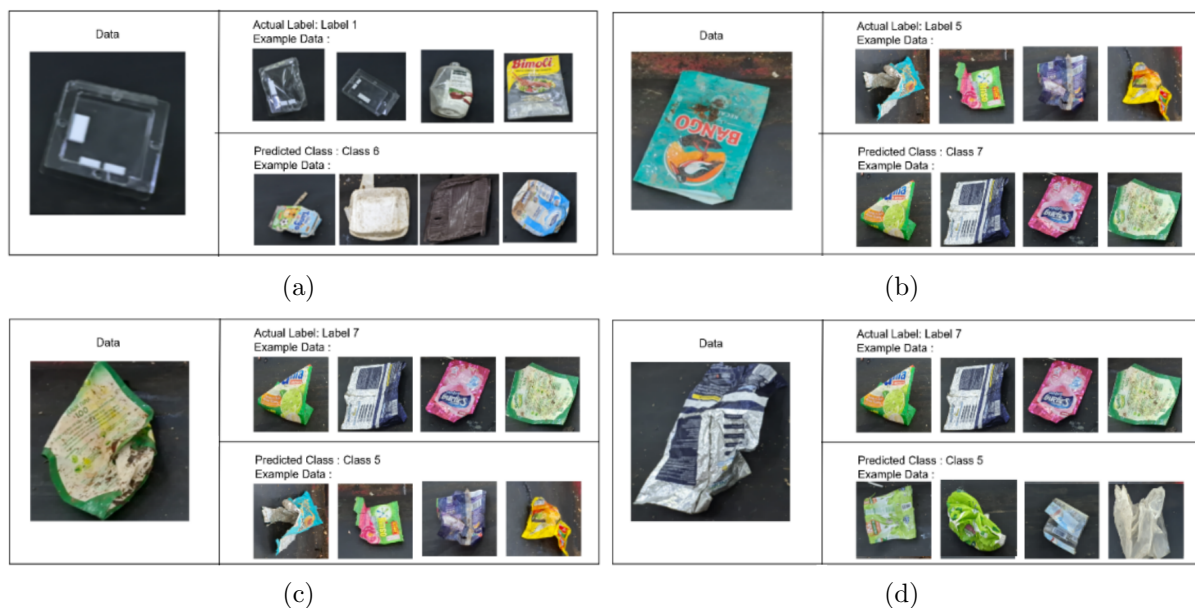


FIGURE 3. The misclassification data

Figure 3(b) shows a misclassification where a class 5 sample was predicted as class 7, while Figure 3(c) shows a misclassification where a class 7 sample was predicted as class 5, due to strong visual similarity in color and surface patterns. This similarity, combined with background noise, reduced the discriminative power of GLCM, LBP, and VGG16 features, resulting in an ambiguous representation that led to incorrect classification.

Figure 3(d) shows a misclassification where a class 7 sample was predicted as class 5 due to similar color and reflective surface characteristics. These similarities reduced the discriminative power of GLCM and LBP, while lighting variations and noise affected VGG16 features, causing the fused representation to align more closely with class 5.

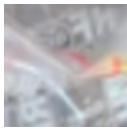
Overall, misclassifications primarily occurred between PP and Other classes due to similar transparent appearance and shape. These errors were more frequent under challenging conditions such as high transparency, reflective surfaces, suboptimal angles, and

low-contrast backgrounds. Nevertheless, feature fusion of VGG16, GLCM, and LBP reduced misclassification by capturing subtle surface differences.

**4.6. Performance evaluation using random cropping.** To evaluate robustness under real-world conditions, random cropping was applied to simulating partial object visibility. This test assesses the model's ability to classify plastic types from incomplete visual information, where consistent predictions indicate strong spatial robustness.

Table 8 shows that the model maintains correct predictions on several classes (4, 5, 6, and 7) under random cropping, indicating that local texture features (GLCM and LBP) remain informative even with partial inputs. However, misclassification occurred for a class 1 (PETE) sample due to the loss of key features, such as shape and transparency, causing confusion with class 6 (PS). This highlights that while the model is robust to partial information, performance degrades when essential spatial features are missing.

TABLE 8. Cropped data testing

|                        |                                                                                    |                                                                                    |                                                                                     |                                                                                      |                                                                                      |
|------------------------|------------------------------------------------------------------------------------|------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------|
| <b>Full image</b>      |   |   |   |   |   |
| <b>Cropped image</b>   |  |  |  |  |  |
| <b>Actual label</b>    | 1                                                                                  | 5                                                                                  | 6                                                                                   | 7                                                                                    | 4                                                                                    |
| <b>Predicted label</b> | 6                                                                                  | 5                                                                                  | 6                                                                                   | 7                                                                                    | 4                                                                                    |

**4.7. Overall evaluation results.** Resizing achieved the best performance, ensuring consistent input for pretrained models. The proposed fusion of VGG16, GLCM, and LBP with MLP yielded the highest results (97% accuracy, precision, recall, and F1-score), while SVM improved to 94% and RF performed best with VGG alone (95%) but declined with fusion due to redundancy. These results highlight the effectiveness of combining spatial and texture features, with MLP outperforming SVM and RF in handling high-dimensional data. Despite strong performance, misclassifications persisted among visually similar classes (e.g., PETE vs. PS, PP vs. Other), and limitations remain due to dataset size and background variability.

**5. Conclusion.** This study shows that feature fusion of VGG16, GLCM, and LBP with MLP achieves superior performance (97% accuracy, precision, recall, and F1-score) in classifying plastic waste, particularly for visually similar classes. Resizing proved more effective than enhancement techniques, which introduced noise. Although some misclassifications remain, the results confirm that combining deep and handcrafted features significantly improves performance over single-feature methods. Future work should explore advanced architectures, stronger data augmentation, and multimodal approaches, as well as real-time deployment in IoT or robotic systems.

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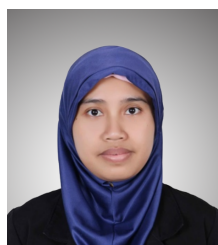
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