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Support Vector Machine and Histogram of Oriented Gradients-Based Classification System for Waste Type Identification

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ABSTRACT
This study examines the effectiveness of classical computer vision methods for modern waste classification by combining Histogram of Oriented Gradients (HOG) for feature extraction with Support Vector Machine (SVM) for classification. The TrashNet dataset, consisting of five categories—cardboard, glass, metal, paper, and plastic—was used as the primary benchmark. To address data limitations and improve generalization, augmentation techniques such as random rotations, horizontal flipping, and brightness adjustments were applied. Hyperparameter optimization was further conducted using GridSearchCV with the RBF kernel to determine the most effective configuration. The optimized model achieved an accuracy of 84.36%, representing a substantial improvement from the 60% baseline. These findings confirm that non-deep learning approaches remain relevant and can serve as computationally efficient alternatives to CNNs, which typically require GPUs and extensive training time. Challenges persist in classifying reflective materials such as glass and metal, where HOG descriptors are less effective. Future work should integrate complementary descriptors, including color and texture-based features, to enhance robustness and scalability. Overall, the study demonstrates that an optimized HOG-SVM pipeline offers a practical, resource-efficient solution for automated waste classification, with strong potential to support sustainable waste management in real-world applications.

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Waste Classification; HOG; SVM; Data Augmentation; Hyperparameter Optimization.

1. Introduction

Effective waste management remains a critical environmental challenge worldwide, including in Indonesia, where the lack of systematic waste separation at the source continues to undermine recycling efficiency and exacerbate ecological degradation. To address this issue, automated image-based classification systems have gained attention as a viable approach. Recent years have seen a strong reliance on deep learning, particularly Convolutional Neural Networks (CNN), which consistently demonstrate high accuracy in waste recognition tasks (Nainggolan *et al* ., 2024; Sutanty *et al* ., 2023; Homepage *et al* ., 2024). For instance, Sunardi *et al* ., (2023) proposed a hybrid SVM-CNN model that achieved 99.34% accuracy for classifying organic and inorganic waste. However, such accuracy often comes at the cost of substantial computational resources, as CNN-based solutions typically require GPUs and extended training times, limiting their practical deployment in resource-

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constrained environments (Ramadhani *et al* ., 2021). These limitations have renewed interest in classical computer vision methods, which offer computationally efficient alternatives.

The combination of Histogram of Oriented Gradients (HOG) for feature extraction and Support Vector Machines (SVM) for classification has been shown to be effective across diverse visual domains. Li *et al* ., (2020) demonstrated a real-time traffic sign detection system with 97.41% accuracy using HOG-SVM, while Xu *et al* ., (2022) applied the same approach for fault detection with promising results. Huda *et al* ., (2022) further reported that in medical image datasets with limited samples, HOG-SVM achieved up to 100% accuracy, surpassing several CNN architectures. Comparable evidence is available from Tanjung and Muhathir (2020), who applied HOG-SVM to facial expression classification, and Adilah and Azizah (2022), who used it for brain tumor detection. In the specific context of waste classification, Shafira and Utaminingrum (2020) successfully designed an automatic waste bin system capable of classifying three types of waste—plastic bottles, cans, and paper—achieving 96.88% accuracy. Yet, this system remains constrained to three categories, whereas urban solid waste streams commonly include a broader set of materials, such as cardboard, glass, and metal, which present additional classification challenges. Studies have also emphasized that feature-based SVM models can perform competitively in tasks involving texture-rich objects such as plastics (Hartono & Rachmat, 2022; Wong, 2022). Despite these promising findings, there has been no systematic attempt to extend HOG-SVM approaches to a more complex five-class waste classification problem, nor to rigorously evaluate the impact of modern techniques such as data augmentation and hyperparameter optimization in this setting. This research addresses that gap by developing and benchmarking an HOG-SVM model optimized through GridSearchCV on the TrashNet dataset, enriched with augmentation techniques, to assess its capacity for balancing computational efficiency and classification accuracy in automated waste sorting applications.

2. Methodology

This study adopts an experimental quantitative design to systematically evaluate the performance of classical image classification methods, focusing on the integration of Histogram of Oriented Gradients (HOG) for feature extraction and Support Vector Machine (SVM) for classification. The dataset employed is the publicly available TrashNet collection, which includes five waste categories: cardboard, glass, metal, paper, and plastic. To overcome the limited size of the dataset and to minimize the risk of overfitting, extensive data augmentation was applied through horizontal flipping, random rotations of up to ±15 degrees, and brightness adjustments, a strategy consistent with previous studies that enriched visual data to improve robustness (Fachrisyam *et al* ., Abdillah *et al* ., 2024). Each augmented image was then validated manually to ensure that the transformations did not distort the class identity. Following augmentation, all images were resized and padded to 128×128 pixels and converted to grayscale prior to feature extraction. HOG was then used to generate gradient-based feature descriptors, with parameters set at pixels_per_cell = (6,6), a configuration reported in earlier works to capture fine structural detail more effectively than the conventional (8,8) cell size (Achyunda Putra *et al* ., 2020; Wang *et al* ., 2020). The resulting feature vectors were stored for subsequent training. The dataset was split into 80% for training and 20% for testing with stratification to maintain class balance. Training involved an SVM framework optimized through GridSearchCV, exploring parameter values of C = [1, 10, 100] and γ = [0.1, 0.01, 0.001] using the RBF kernel, a practice consistent with findings that nonlinear kernels outperform linear separation in complex feature spaces (Luo *et al* ., 2021; Xu *et al* ., 2022). The grid search incorporated three-fold cross-validation for reliable model selection before final evaluation on the hold-out set. To quantify performance, standard classification metrics including Accuracy, Precision, Recall, F1-score, and Confusion Matrix were employed, following evaluation standards recommended in applied SVM-HOG research (Lubis *et al* ., 2021; Yohannes *et al* ., 2021; Al Rivan *et al* ., 2022). To visualize the research flow, the experimental workflow is summarized in figure 1.

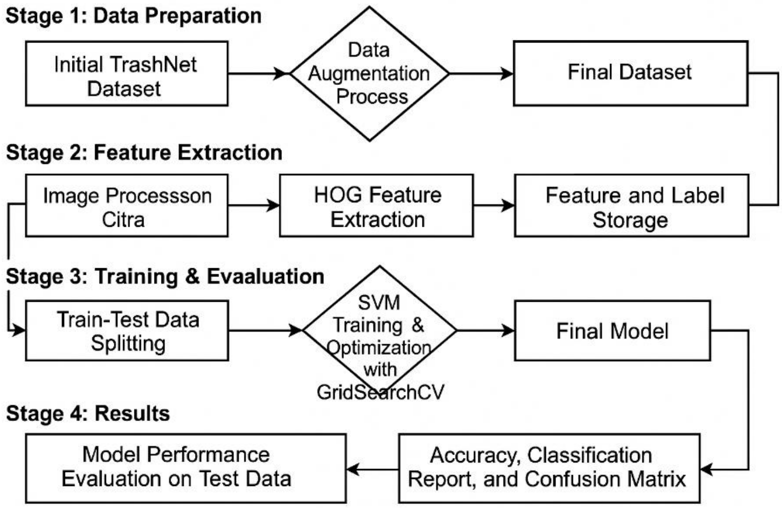

Figure 1. Research Workflow Diagram

3. Results

The experimental results are presented in two stages: quantitative model evaluation and prototype application implementation. Quantitative evaluation reports the baseline and optimized model performance using classification metrics, followed by a comparison of computational efficiency with CNN-based approaches. The second part describes the functionality of the developed prototype as a proof of concept for practical waste classification. The first experiment established a baseline by training a linear-kernel SVM on the original TrashNet dataset without augmentation. The results, summarized in Table 1, indicate a moderate overall accuracy of 60%, with the best performance observed in the paper class (F1-score 0.74) and the lowest in glass (F1-score 0.49). This confirms the necessity of data augmentation and hyperparameter optimization to achieve robust generalization.

Table 1. Baseline Model Performance

Class	Precision	Recall	F1-score	Support
Cardboard	0.66	0.73	0.69	81
Glass	0.47	0.51	0.49	100
Metal	0.53	0.57	0.55	82
Paper	0.78	0.71	0.74	119
Plastic	0.52	0.46	0.49	96
Accuracy			0.60	478
Macro avg	0.59	0.60	0.59	478
Weighted avg	0.60	0.60	0.60	478

Building on this baseline, the second experiment involved an augmented dataset and extensive SVM hyperparameter tuning via GridSearchCV. The optimized model, using an RBF kernel with C=10 and γ=0.01, achieved an overall accuracy of 84.36%. Table 2 details the performance across classes, where cardboard and paper attained the highest F1-scores (0.88 and 0.87, respectively), while glass, plastic, and metal also demonstrated notable improvements compared to the baseline.

Table 2. Final Model Classification Report

Class	Precision	Recall	F1-score	Support
Cardboard	0.90	0.86	0.88	322
Glass	0.80	0.83	0.81	401
Metal	0.88	0.77	0.82	328
Paper	0.84	0.92	0.87	475
Plastic	0.83	0.82	0.82	386
Accuracy			0.84	1912
Macro avg	0.85	0.84	0.84	1912
Weighted avg	0.85	0.84	0.84	1912

To further support the claim of computational efficiency, Table 3 contrasts the resource requirements of the proposed HOG-SVM method with CNN-based solutions reported in prior literature. While CNNs achieve higher accuracy, they generally require specialized hardware such as GPUs and extensive training time. In contrast, the HOG-SVM pipeline in this study successfully operated on a standard CPU with manageable training and prediction times, validating its suitability for low-resource settings.

Table 3. Estimated Computational Efficiency Comparison

Evaluation Aspect	HOG-SVM Method	CNN Method
Hardware	Standard CPU (Intel Core i5-4200U, 8GB RAM)	Typically requires GPU (e.g., Nvidia V100, RTX series) (Nainggolan *et al* ., 2024)
Feature Extraction Time	453.03 s (~7.5 min) for 11,585 images	Integrated within training
Training Time	~41.7 hours (with GridSearchCV)	Ranges from minutes to days, GPU-dependent (Ramadhani *et al* ., 2021)
Prediction Time	~775 ms per image	Tens to hundreds of ms, but requires loading large models

Classification errors were further analyzed using a confusion matrix of the final model (Figure 2). The visual representation shows that the majority of errors occurred between classes with overlapping visual properties, such as glass and plastic, or cardboard and paper.

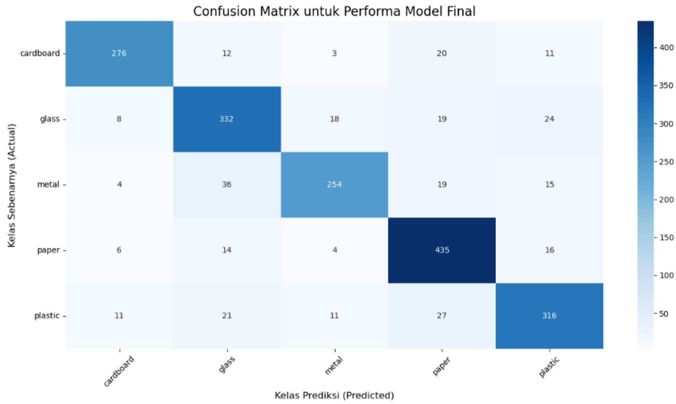

Figure 2. Confusion Matrix of the Final Model

The optimized model was also deployed as a web-based prototype to demonstrate real-world applicability. The system was built with Flask (Python) as the backend, handling model inference, and HTML/CSS/JavaScript for the frontend interface. The application enables users to upload an image of waste, which is then classified by the model. Results are displayed interactively, with prediction confidence represented by dynamic progress bars and color-coded feedback. Figure 3 illustrates the interface of the prototype application.

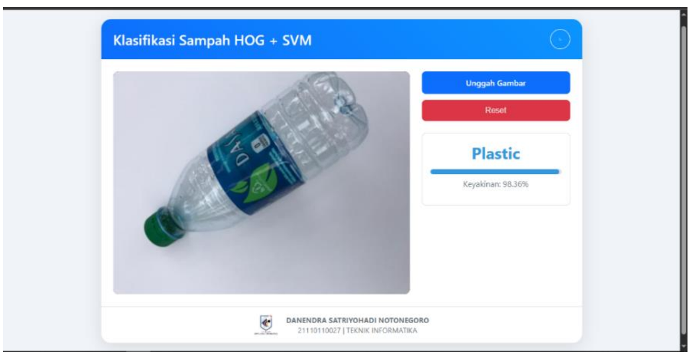

Figure 3. Web Application Prototype Interface

A qualitative test was conducted by uploading sample images from the original TrashNet dataset. Results confirmed that under ideal conditions, the system produced consistently correct predictions, with confidence levels frequently above 95%. While formal usability testing lies outside the scope of this research, the implementation successfully validates the feasibility of deploying the optimized HOG-SVM model into a functional application.

4. Discussion

The results demonstrate a substantial improvement in model performance, with accuracy increasing from a baseline of approximately 60% to 84.36% in the final configuration. This outcome is not incidental but rather the consequence of two deliberate methodological interventions: systematic data augmentation and precise hyperparameter optimization. The baseline experiment highlighted the limitations of relying on the original TrashNet dataset, as the linear SVM exhibited poor generalization, reflecting insufficient variability in the training data. The introduction of augmentation increased the dataset size from 2,390 to 9,560 images, significantly enhancing the diversity of input patterns. Previous studies similarly emphasized that augmentation can reduce overfitting by forcing models to learn generalized representations rather than memorizing training examples (Fachrisyam *et al* ., Abdillah *et al* ., 2024). In this research, random rotations improved orientation invariance, horizontal flips introduced symmetry invariance, and brightness adjustments simulated different illumination conditions—together strengthening the robustness of the model. The second intervention, hyperparameter optimization, played an equally critical role. While the linear kernel in the baseline produced unsatisfactory results, optimization through GridSearchCV identified the RBF kernel with C=10 and γ=0.01 as the best-performing configuration. This kernel's ability to form nonlinear decision boundaries aligns with prior findings that RBF-SVM is highly effective for separating overlapping data distributions (Luo *et al* ., 2021; Xu *et al* ., 2022).

The resulting 24% improvement in accuracy underscores the necessity of careful parameter selection in SVM models, as emphasized in other domains such as facial expression recognition (Tanjung & Muhathir, 2020) and traffic sign detection (Li & Wang, 2020). Performance across individual classes provides further insight. Cardboard and paper achieved the highest F1-scores (0.88 and 0.87, respectively). Both materials are characterized by matte surfaces and consistent textural gradients, which are well-suited to HOG feature extraction. This observation is consistent with reports by Hartono and Rachmat (2022), who demonstrated the effectiveness of SVM in classifying textured plastics, and by Wong (2022), who applied SVM-based models for differentiating organic and inorganic waste. Cardboard also achieved the highest precision (0.90), indicating that predictions for this class were almost always correct, while paper yielded the highest recall (0.92), confirming the model's reliability in detecting nearly all instances of paper waste. Minor confusion between cardboard and paper in the confusion matrix can be attributed to their shared fibrous composition, which produces visually similar gradient patterns. In contrast, glass, plastic, and metal presented greater challenges, with F1-scores of 0.81, 0.82, and 0.82, respectively. Their reflective and, in the case of glass and plastic, sometimes transparent surfaces generated inconsistent gradients, introducing noise into the HOG feature space. This effect has been noted in other computer vision applications, where reflective surfaces distort gradient-based descriptors (Lubis *et al*, 2021; Yohannes *et al* ., 2021). Misclassification between glass and plastic was particularly common, reflecting their overlapping visual properties.

Despite this, the relatively stable cylindrical shapes of bottles and cans may have prevented further degradation of classification accuracy, consistent with prior findings that structural consistency can partially mitigate surface-level variability (Achyunda Putra *et al* ., 2020). Comparison with previous research underscores both the strengths and limitations of the proposed approach. Shafira and Utaminingrum (2020) reported a higher accuracy of 96.88% using HOG-SVM for a three-class waste classification system. However, their dataset involved clearer inter-class distinctions, whereas this study tackled a more complex five-class problem, introducing greater overlap among classes. Thus, while the reported accuracy is lower in absolute terms, it establishes a new benchmark for HOG-SVM in multi-class waste classification. Similar findings of high HOG-SVM performance in simpler tasks, such as mammal recognition (Al Rivan *et al* ., 2022) and tumor classification (Adilah & Azizah, 2022), further support the view that dataset complexity significantly influences achievable accuracy. When compared to CNN-based approaches, the accuracy of 84.36% achieved in this study falls below the state-of-the-art levels, with Nainggolan *et al* . (2024) and Nuariputri *et al* . (2023) reporting accuracies above 98%. This disparity is expected given CNNs' capacity to automatically learn multi-level representations (Szeliski, 2021; Solem, 2025).

Nonetheless, the strength of the HOG-SVM pipeline lies in computational efficiency. While CNNs often require days of training on GPU clusters (Ramadhani *et al* ., 2021), the experiments here were conducted entirely on a standard CPU, demonstrating feasibility for environments with limited resources. Comparable efficiency-driven studies, such as real-time object detection on embedded systems (Mulyana & Rofik, Nandyal & Kattimani, 2021), emphasize that model deployment often depends more on computational constraints than on absolute accuracy. In summary, the 84.36% accuracy achieved through systematic augmentation and optimization confirms the continuing relevance of classical methods in modern waste management applications. Although CNNs remain superior in raw performance, the trade-off between accuracy and computational cost favors HOG-SVM in low-resource contexts. The findings position the optimized HOG-SVM model not as a competitor to CNNs in high-end environments but as a practical, cost-effective alternative for real-world waste classification systems where efficiency and accessibility are paramount.

5. Conclusion

This study demonstrates that classical computer vision techniques, when systematically optimized, remain effective for modern waste classification tasks. By combining Histogram of Oriented Gradients (HOG) with Support Vector Machines (SVM), and applying data augmentation alongside hyperparameter tuning via GridSearchCV, the model achieved an accuracy of 84.36%—a marked improvement from the 60% baseline. These results establish a meaningful benchmark, indicating that non-deep learning methods can provide a computationally efficient and reliable alternative to more resource-intensive deep learning models. Nevertheless, the findings also reveal limitations, particularly in handling reflective and transparent materials such as glass and metal, where gradient-based HOG features are less discriminative. Future research should consider integrating complementary descriptors, such as color or texture-based features, to enhance robustness. Further directions include analyzing feature importance within HOG representations, scaling the approach to larger and more diverse datasets, and testing under varying illumination conditions. For practical deployment, the method is best suited for textured materials such as cardboard and paper, while applications involving reflective objects may require additional preprocessing or hybrid approaches.

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