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A Hybrid Model for Dry Waste Classification using Transfer Learning and Dimensionality Reduction

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***Abstract*— The categorization of waste plays a crucial role in efficient waste management, facilitating the recognition and segregation of various waste types to ensure appropriate disposal, recycling, or repurposing. With the growing concern for environmental sustainability, accurate waste classification systems are in high demand. Traditional waste classification methods often rely on manual sorting, which is time-consuming, labor-intensive, and prone to errors. Hence, there is a need for automated and efficient waste classification systems that can accurately categorize waste materials. This research introduces an innovative waste classification system that merges feature extraction from a pre-trained EfficientNet model with Principal Component Analysis (PCA) to reduce dimensionality. The methodology involves two main stages: (1) transfer learning using the EfficientNet-CNN architecture for feature extraction and (2) dimensionality reduction using PCA to reduce the feature vector dimensionality. The features extracted from both the average pooling and convolutional layers are combined by concatenation, and subsequently, classification is performed using a fully connected layer. Extensive experiments were conducted on a waste dataset, and the proposed system achieved a remarkable accuracy of 99.07%. This outperformed state-of-the-art waste classification systems, demonstrating the effectiveness of the combined approach. Further research can explore the application of the proposed waste classification system on more extensive and more diverse datasets, optimize the dimensionality reduction technique, consider real-time implementation, investigate advanced techniques like ensemble learning and deep learning, and assess its effectiveness in industrial waste management systems.**

***Keywords*— Waste classification; feature extraction; EfficientNet; transfer learning; PCA; dimensionality reduction.**

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I. INTRODUCTION

Effective and sustainable waste management has become a pressing global issue, given the staggering volume of waste generated daily by consumers worldwide [1]. In Indonesia, this concern is enshrined in Law No. 18 of 2008 on Waste Management [2], establishing a comprehensive legal framework for waste control, management, and oversight throughout the nation. The significance of proper waste management becomes evident when one considers the substantial waste production within Indonesia.

As reported by the National Waste Management Information System (SIPSN), maintained by the Ministry of Environment and Forestry (KLHK), Indonesia generated 19.45 million tons of waste in 2022. This represents a remarkable 37.52% reduction compared to the previous year's production of 31.13 million tons [3]. These figures underscore the formidable challenges associated with waste management in the country.

The repercussions of inadequate waste management are far-reaching, encompassing adverse environmental impacts [4], public health concerns [5], and inefficient use of natural resources [6]. These issues are not unique to Indonesia; similar challenges are encountered in other nations, including India and the United States [7]. High waste production coupled with limited awareness of waste categorization and processing contribute to the accumulation and misclassification of waste [8].

In recent years, various studies have explored dry waste classification using Convolutional Neural Network (CNN) algorithms [9], [10]. For instance, one study utilized a pre-trained ResNet model to classify waste like cardboard, metal, plastic, paper, glass, and achieved an accuracy of 91% [11]. The GECM-EfficientNet experiment achieved even higher accuracy, with 94.54% on a household waste dataset and 94.23% on the TrashNet dataset [1].

EfficientNet-B3 demonstrated exceptional performance, reaching 98.4% accuracy on the TrashNet dataset and 92.87% in classifying plastic sub-categories [12], highlighting its potential in waste classification. Previous research also successfully applied transfer learning techniques with MobileNetV2, ResNet34, and Densenet121, achieving high accuracies of 96.42%, 96.27%, and 96.273%, respectively [7].

Our study introduces an innovative approach to dry waste classification by combining Transfer Learning, PCA-based Dimensionality Reduction, and CNN integration. Our primary aim is to enhance the accuracy of dry waste classification compared to previous methods. We detail our approach in the upcoming sections.

We begin with Transfer Learning, where we modify the architecture by adding a new CNN layer on top of EfficientNet, leveraging pre-trained weights for knowledge transfer from ImageNet to our task. Following Transfer Learning, we perform Feature Extraction, gathering information from the avg_pool layer of transfer learning and the convolutional layer of the CNN model. These features are merged to create a comprehensive representation of each waste sample.

To refine the model further, we employ Feature Reduction through Principal Component Analysis (PCA) to simplify the feature representation without losing vital information [13]. After Feature Reduction, we proceed to Feature Fusion, combining the reduced PCA features with those from the avg_pool layer. This fusion creates a single feature vector for each waste sample.

In the forthcoming sections, we delve into the intricacies of our model, elucidating how we have tailored the architecture to our specific task. We commence with Transfer Learning, removing the last output layer of EfficientNet and introducing a new Convolutional Neural Network (CNN) layer on top. By initializing this layer with pre-trained weights from EfficientNet, we leverage knowledge transfer from ImageNet to our dry waste classification task.

Combining Transfer Learning, PCA-based Dimensionality Reduction, and CNN integration, our research can potentially revolutionize dry waste classification. We anticipate that our study will significantly contribute to more effective waste management practices locally and globally in Indonesia.

II. Materials and Method

This section provides a comprehensive overview of the materials and methods employed in this study. We discuss the datasets utilized, the preprocessing steps, and the implementation of Transfer Learning using EfficientNet and CNN architectures explicitly tailored to the TrashNet dataset. We include Figure 1, outlining the general workflow, to visually represent our proposed method and its various phases.

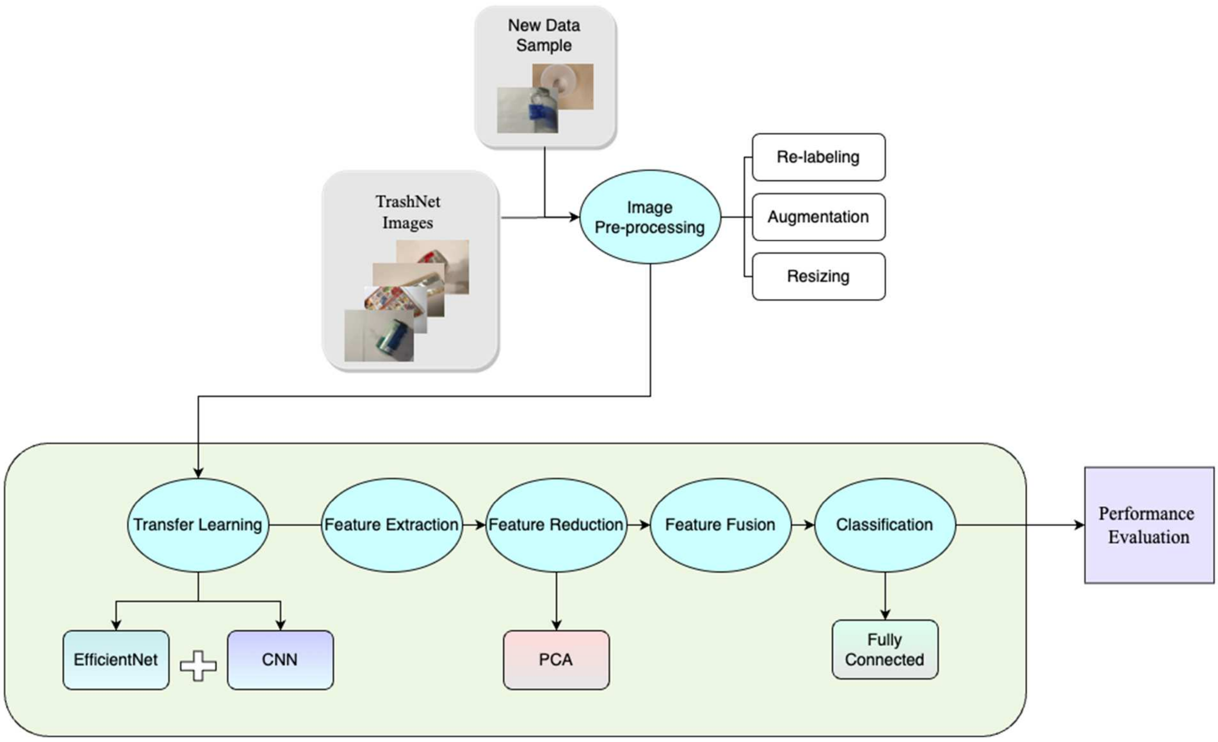

Fig. 1 Workflow of the proposed method

A. CNN Architectures

Convolutional Neural Networks (CNN) stand at the forefront of deep learning, particularly in image classification tasks [15]. Their significance lies in their robust feature extraction capabilities, which make them an ideal choice for the classification of waste materials. Developed initially in the 1980s and 1990s [16], CNN has proven its mettle in various pattern recognition fields, particularly relevant to waste classification.

CNN is designed explicitly for image analysis, utilizing convolutional operations to extract features [17]. This approach significantly reduces the number of model parameters while preserving the ability to express crucial image features effectively. Over the years, CNN has revolutionized large-scale image classification tasks, consistently improving the quality of image recognition structures [18]. While many new architectures have emerged, only a handful have proven suitable for waste classification tasks [1].

In dry waste classification, CNN is not just suitable but pivotal. Its extensive application in image processing and classification tasks has reshaped the landscape of waste categorization. By harnessing CNN's power, we can analyze critical features within waste images, leading to more accurate pattern recognition. Figure 2 illustrates the architecture of the proposed CNN model, highlighting its role in our methodology.

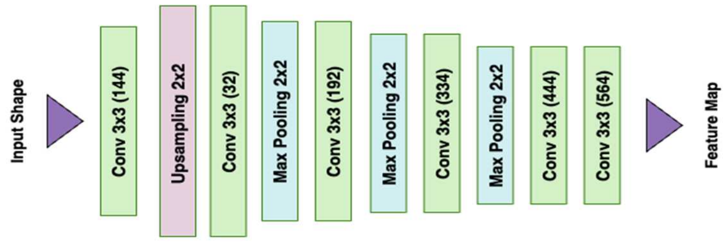

Fig. 2 The Architecture of the Proposed CNN Model

B. *EfficientNet*

EfficientNet is a highly effective Convolutional Neural Network (CNN) architecture for achieving an optimal balance between accuracy and computational efficiency in image recognition tasks [19]. It boasts scalability and compressibility, enabling adaptation to varying computational resource requirements [20]. Furthermore, EfficientNet has consistently demonstrated superior accuracy while consuming fewer computational resources and achieving faster computation speeds [21]. Given its performance advantages, EfficientNet is the foundational architecture for our waste classification task, contributing to enhanced accuracy, efficiency, and model adaptability [22]. Figure 3 provides an overview of the EfficientNet architecture.

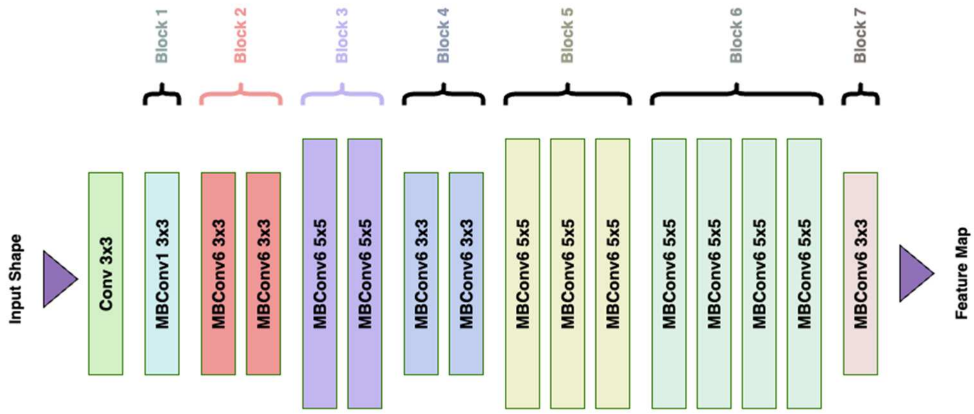

Fig. 3 The architecture of EfficientNet

C. *Transfer Learning*

Transfer learning is a pivotal component of our methodology. It leverages the capabilities of pre-trained models, specifically EfficientNet and CNN, by fine-tuning their architectures to suit our waste classification task. Transfer learning involves minor adjustments to these architectures to adapt them to our specific context. By capitalizing on the knowledge acquired during pre-training on extensive datasets, we harness relevant features crucial for our task [23]. This approach has demonstrated its effectiveness in waste classification and enables us to explore its potential in improving classification accuracy and convergence speed.

D. *Feature Extraction*

Feature extraction plays a central role in our methodology, capturing the unique characteristics of waste materials. We employ two feature extraction techniques to represent waste images comprehensively. Firstly, we extract features from the average pooling layers of the pre-trained EfficientNet architecture, offering a high-level representation capturing overall information and global patterns. Secondly, features are directly extracted from the convolutional layers of the CNN model without leveraging transfer learning. These features capture detailed local patterns and specific image structures relevant to waste classification. This dual-feature extraction approach enhances our model's ability to learn discriminative representations and improves the accuracy of dry waste classification.

E. *Dimensionality Reduction*

Recognizing the substantial dimension difference between features extracted from the average pooling layers and those from the convolutional layers, our goal was to achieve an equitable contribution of both feature types to the classification process. However, we aimed to prevent the convolutional layer features from dominating the process due to their higher vector dimensionality. To address this, we employed Principal Component Analysis (PCA) to reduce the dimensionality of the convolutional layer features. This approach allowed us to merge features from both layers, ensuring a balanced influence while mitigating dimensionality-related challenges.

PCA, short for Principal Component Analysis, is a dimensionality reduction technique designed to identify a new set of data dimensions [24], referred to as principal components. These components represent the data in a lower-dimensional space while preserving most of its variance [25]. These dimensions are orthogonal and independent, ranked according to the variance they capture, with the first principal component retaining the highest variance. The PCA process can be summarized as follows:

1) Collect feature vectors from the convolutional layers, organizing them into a matrix, X, where each row (x_i) represents a feature vector from one data sample, totaling n samples and featuring dimension d:

$$X = [x_1, x_2, \dots, x_n](n \times d) \quad (1)$$

2) Standardize the feature vectors in matrix X by subtracting the mean and dividing by the standard deviation to ensure uniform scaling:

$$X_{std} = \big(X - mean(X)\big)/std(X) \quad (2)$$

3) Calculate the covariance matrix (C) by taking the matrix product of the standardized matrix (X_std) and its transpose:

$$C = \left(\frac{1}{n}\right) \times X_{std}^{t} \times X_{std} \quad (3)$$

4) Perform eigen decomposition on the covariance matrix C, where v represents the eigenvector and λ is the corresponding eigenvalue:

$$C \times v = \lambda \times v \quad (4)$$

5) Select the top eigenvalues and eigenvectors that explain at least 95% variance:

$$V = [v_1, v_2, \dots, v_k](d \times k) \quad (5)$$

In this formula, "V" represents the matrix of selected eigenvectors, where "k" is the number of eigenvectors chosen to capture at least 95% of the variance in the data. These eigenvectors will be used in the subsequent step (Step 6) to project standardized feature vectors.

6) Project the standardized feature vectors (X_std) onto the selected eigenvectors (V) to obtain the principal component scores:

$$X_{reduced} = X_{std} \times V \quad (6)$$

By applying PCA to retain at least 95% of the variance, we ensure that the selected principal components capture a substantial portion of the data's information while reducing its dimensionality. This approach facilitates the integration of features from both the average pooling layers and the dimensionality-reduced convolutional layers in the ensuing classification process.

F. Datasets

The dataset utilized in this study, known as "TrashNet" and obtained from Kaggle (Figure 4), consists of 2,567 data samples categorized into six primary classes: paper, cardboard, glass, plastic, metal, and trash waste. These classes represent the most common types of dry waste encountered in daily life. To maintain consistency, we resized all images in the dataset to a uniform dimension of 512x384 pixels. The TrashNet dataset serves as a robust foundation for both training and evaluating our waste classification model. In addition to the existing classes, we have introduced two new classes, "Plastic Glass" and "Plastic Bottle," to enhance the dataset's ability to distinguish between different plastic waste types. This diversification of the dataset enables us to comprehensively assess the accuracy and adaptability of our waste classification model.

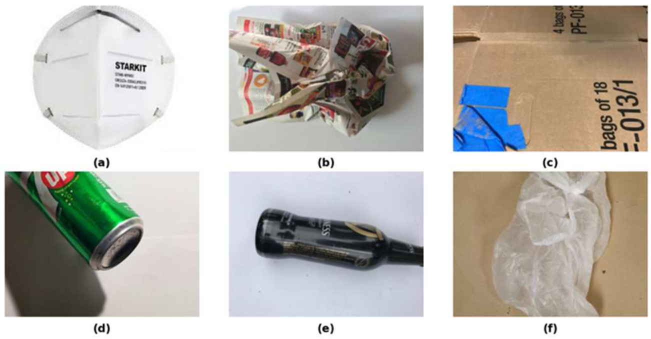

Fig. 4 Image classes in TrashNet dataset: (a) trash; (b) paper; (c) cardboard; (d) metal; (f) glass; (g) plastic.

G. Pre-processing

Image preprocessing plays a pivotal role in our methodology for extracting essential information from images. Its primary objective is to enhance image quality by mitigating undesirable distortions and accentuating specific visual features relevant for subsequent analysis. Within this framework, our initial preprocessing step involves resizing images to a standardized dimension of 224 × 224 pixels.

The preprocessing stage encompasses integrating new data from field samples to enrich the dataset. This process involves incorporating additional images or samples not initially part of the dataset. We carefully curate and select this new data to ensure its relevance to dry waste classification. Adding these samples during preprocessing expands the dataset's size and augments the model's capacity to generalize and accurately classify various types of dry waste. Furthermore, we apply data augmentation techniques to bolster the dataset's robustness and diversity. Various augmentation parameters are employed, as detailed in Table I:

TABLE I
IMAGE DATA GENERATOR PARAMETERS

No	Parameter	Value
1	Rotation Range	90
2	Width Shift Range	0.1
3	Height Shift Range	0.1
4	Shear Range	0.2
5	Zoom Range	0.2
6	Horizontal Flip	True
7	Vertical Flip	True
8	Fill Mode	Nearest

These augmentation techniques introduce controlled variations, including rotation, shifting, shearing, zooming, and image flipping. By applying these transformations, we enrich the dataset with diverse instances, reducing the risk of overfitting and enhancing the model's generalization to unseen data. Additionally, we conduct manual relabeling to categorize specific images in the dataset accurately. This process involves meticulously examining images and adjustments to their labels based on specific dry waste categories. Manual relabeling ensures the dataset's accuracy and correctness, establishing a robust foundation for subsequent training and evaluation processes. Figure 5 illustrates the new class labels after relabeling.

In our new dataset, we have categorized waste images into several distinct classes, each representing specific types of waste items. Here is a summary of the classes present in our dataset:

1) *Paper Class:* This class includes images of paper-based waste items, such as magazine pages, writing paper, and other paper materials.

2) *Cardboard Class:* Images in this class depict waste items made of cardboard, including cardboard boxes, containers, and similar cardboard-based items.

3) *Glass Class:* This class consists of images featuring various glass items, including glass bottles, glass shards, and other glass containers.

4) *Plastic Class:* Images in this class represent plastic waste, including plastic packaging, plastic bags, and other plastic items.

5) *Metal Class:* This class comprises images of metallic waste items, such as beverage cans, metal scraps, and other metal pieces.

6) *Trash Class:* The miscellaneous class includes images of items that cannot be categorized explicitly into the above classes. It encompasses items like masks, tissues, fabrics, or unidentified objects.

7) *Plastic Glass Class (Added):* This additional class includes images of plastic glasses, such as disposable plastic cups.

8) *Plastic Bottle Class (Added):* Another added class, "Plastic Bottle," contains images of various types of plastic bottles.

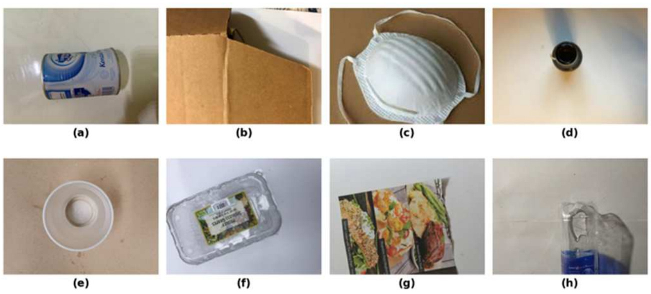

Fig. 5 Image classes after relabeling dataset: (a) metal; (b) cardboard; (c) trash; (d) glass; (e) plastic cup; (f) plastic; (g) paper; (h) plastic bottle.

H. Experimental Setup

The simulations were conducted on different hardware setups to ensure robustness and versatility. The hardware configurations included a MacBook Pro M2 Pro with 16 GB of RAM and Colab Pro, which employed the GPU T4 with 12.5 GB of RAM. The simulations were executed efficiently using the TensorFlow library.

Our experimental setup was designed to encompass critical steps in alignment with the specified methodology. Initially, all input images were uniformly resized to a dimension of 224x224 pixels, accounting for the RGB channels. Subsequently, the dataset was partitioned into a training set (70%) and a testing set (30%) to facilitate feature extraction and evaluation. As outlined in the previous survey study, a series of preprocessing techniques were meticulously applied to prepare the data for analysis. The experimental setup unfolded in two distinct phases to investigate dry waste classification comprehensively:

1) *Phase 1 - Transfer Learning:* We employed transfer learning techniques using the EfficientNet and CNN models in the initial phase. Specifically, we leveraged a pre-trained EfficientNet-CNN model, retaining the deep architecture's parameters to extract features from the average pooling layer. Simultaneously, feature extraction was executed on the CNN model, focusing exclusively on the convolutional layers. The extracted features from both sources were thoughtfully concatenated and subsequently subjected to classification using a fully connected layer.

2) *Phase 2 - Feature Extraction and PCA Reduction:* The second phase of our survey study aimed to enhance classification performance through feature extraction and dimensionality reduction via Principal Component Analysis (PCA). For feature extraction, we harnessed two distinct layers from the EfficientNet-CNN model. One layer consistently represented the average pooling layer, while the other layer corresponded to the convolutional layer within the EfficientNet-CNN model. The selection of these specific layers and networks was informed by insights gained from the initial simulations.

To facilitate the seamless integration of features, we applied PCA transformation to the features extracted from the convolutional layer. This transformation reduced their dimensionality while preserving critical information. Subsequently, we normalized the average pooling and PCA-derived features to ensure fair comparison and compatibility. These normalized features were then effectively concatenated into a unified representation. Classification was performed using a fully connected layer to ascertain the class labels.

This comprehensive experimental framework encompassed a spectrum of essential steps for dry waste classification. These steps included image resizing, dataset partitioning, transfer learning, feature extraction from different layers, dimensionality reduction via PCA, and fine-tuning hyperparameters. This rigorous approach ensured the robustness and effectiveness of our classification model.

I. Performance Parameter

True positive (TP) refers to the number of images correctly classified in a specific class in the evaluation parameter. False positive (FP) indicates the number of images incorrectly classified as belonging to a particular class when they are not. False negative (FN) represents the number of images that are mistakenly recognized as belonging to another class when they should have been assigned to the specified class. True negative (TN) signifies the number of images that do not belong to a class and were correctly not assigned to that class.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (7)$$

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

$$Recall = \frac{TP}{TP+FN} \quad (9)$$

$$F1-Score = 2 \times \frac{1}{\frac{1}{precision}+\frac{1}{recall}} \quad (10)$$

III. Results and Discussion

A. *Classification based on Extracted Features from Transfer Learning EfficientNetB3-CNN*

As described in the experimental setup, the first scenario focuses on classification using features extracted from the transfer learning model, EfficientNetB3-CNN. We anticipated that features extracted from this architecture would yield high accuracy. The evaluation results of this scenario are depicted in Figure 6 (training and validation visualization of EfficientNetB3 avg_pool layer) and Figure 7 (training and validation visualization of EfficientNetB3-CNN last conv layer). Further insights into performance are provided in Table II, summarizing classification accuracy.

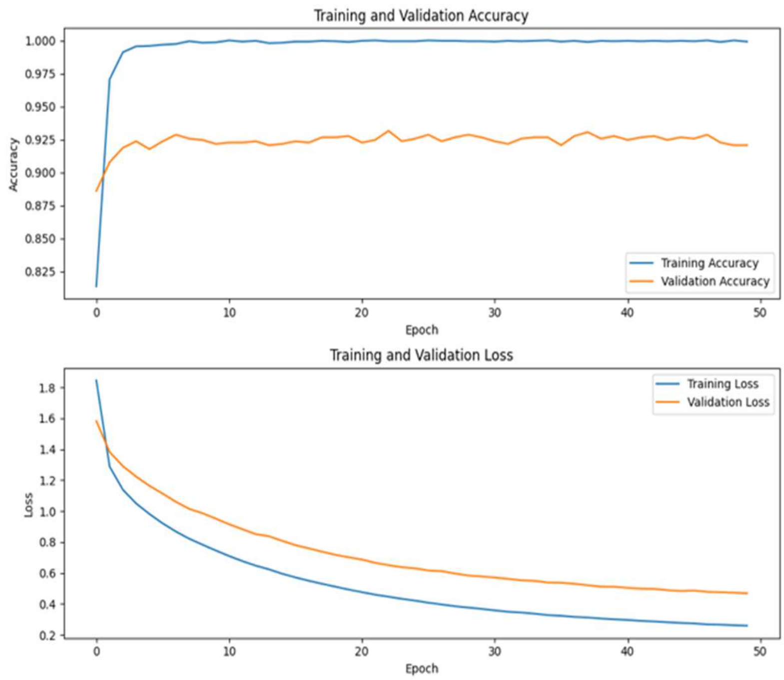

Fig. 6 Training and Validation Visualization of EfficientNetB3 (avg_pool layer extraction)

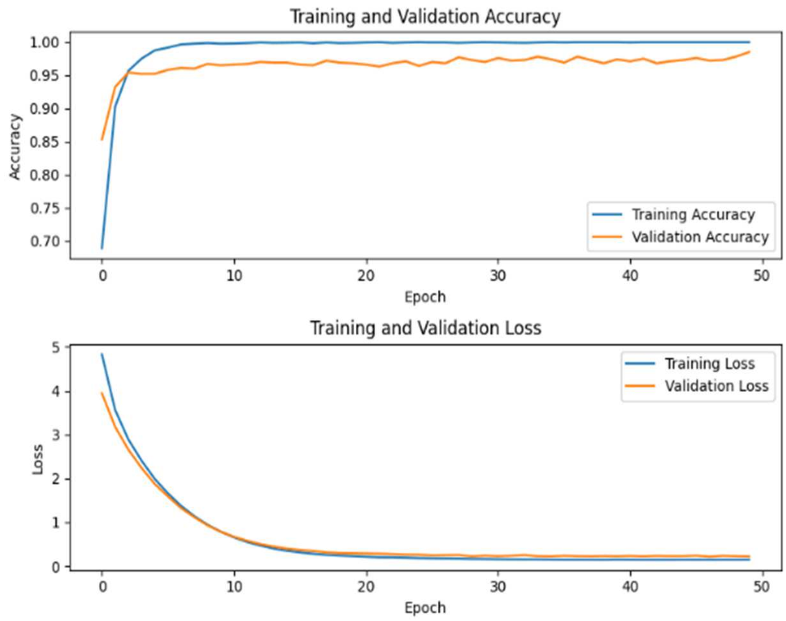

Fig. 7 Training and Validation Visualization of EfficientNetB3-CNN (last conv layer extraction)

TABLE II
MODEL PERFORMANCE COMPARISON OF SCENARIO 1

Method	Accuracy
EfficientNetB3 (avg_pool layer)	92.59%
EfficientNetB3-CNN (last conv layer)	98.15%

Accompanying these results are confusion matrices, providing visual representations of classification outcomes for both methods. The confusion matrix for feature extraction using EfficientNetB3 (avg_pool layer) is shown in Figure 8, while the confusion matrix for EfficientNetB3-CNN (last conv layer) is presented in Figure 9. These matrices enable an in-depth assessment of classification accuracy across different waste categories.

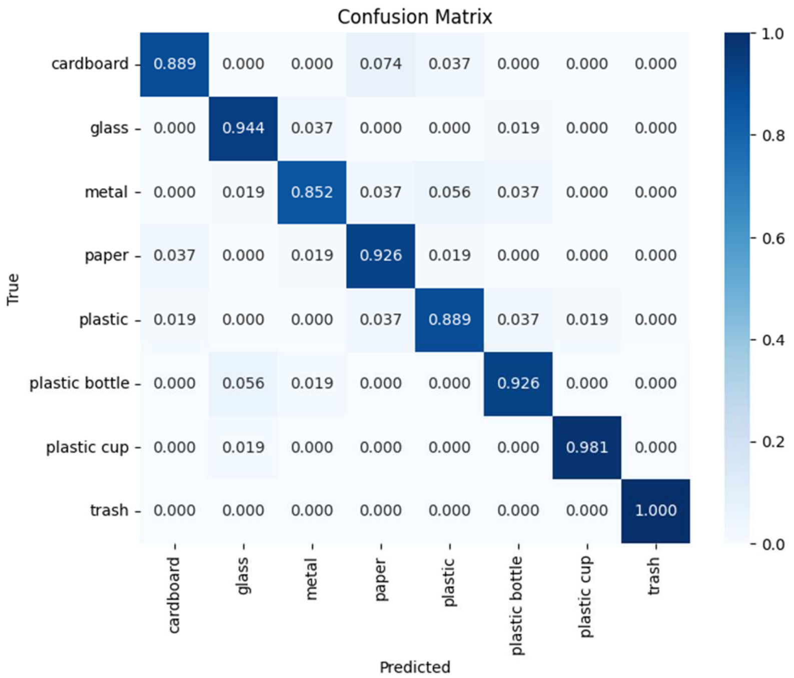

Fig. 8 Confusion Matrix for Feature Extraction using EfficientNetB3 (avg_pool layer)

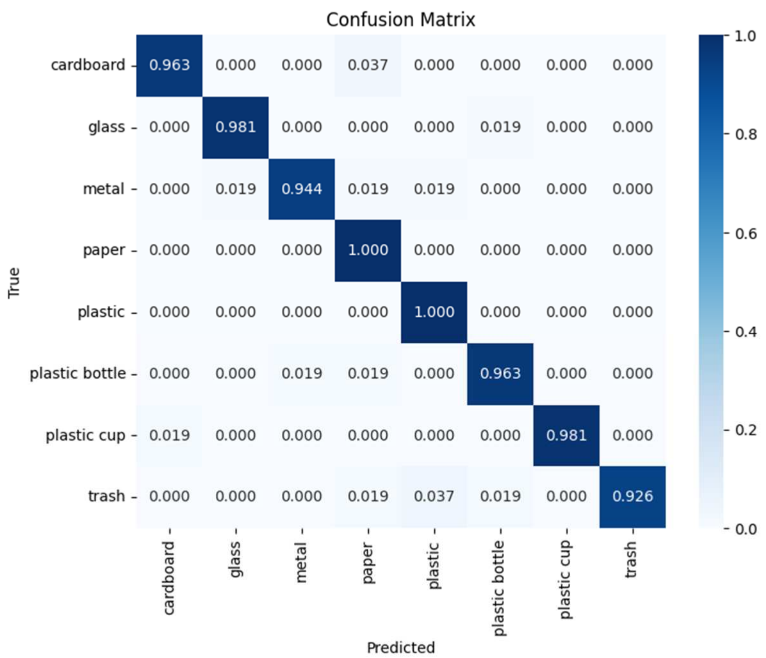

Fig. 9 Confusion Matrix for EfficientNet-CNN (last conv layer)

Upon careful analysis of this scenario, it is evident that feature extraction using the EfficientNetB3-CNN architecture has performed remarkably well. However, this approach relies more heavily on features extracted from the CNN's convolutional layers than those from the average pooling layers. These findings have provided insights for our second scenario. In scenario 2, we will still extract features as in the first scenario. However, considering the significant impact of the convolutional layers on accuracy, we will perform feature transformation or reduction using PCA on the convolutional layers of the EfficientNetB3-CNN. Additionally, we will combine the reduced features obtained through PCA with the average pooling layers from the pre-trained EfficientNetB3-CNN. By adopting this approach in the second scenario, we aim to improve the classification performance.

B. Classification based on Concatenated Features with PCA Transformation

In the second scenario, we present the outcomes of a technique that involves the classification of features obtained by combining the average pooling layer features with the convolutional layer features reduced by PCA, similar to the approach used in the first scenario. During the PCA decomposition, we retained the components that account for 95% of the variance. The objective of attaining 95% variance is to balance the available features. To assess the classification accuracy of this technique, we compare it with the classification accuracy achieved in our experiments.

Figure 10 illustrates the training and validation visualization for combining the EfficientNetB3-CNN average pooling layer with the last convolutional layer. The obtained classification accuracy for this approach is 98.84%. Additionally, Figure 11 showcases the training and validation visualization for the combination of EfficientNetB3-CNN average pooling layer with the last convolutional layer after applying PCA for dimensionality reduction.

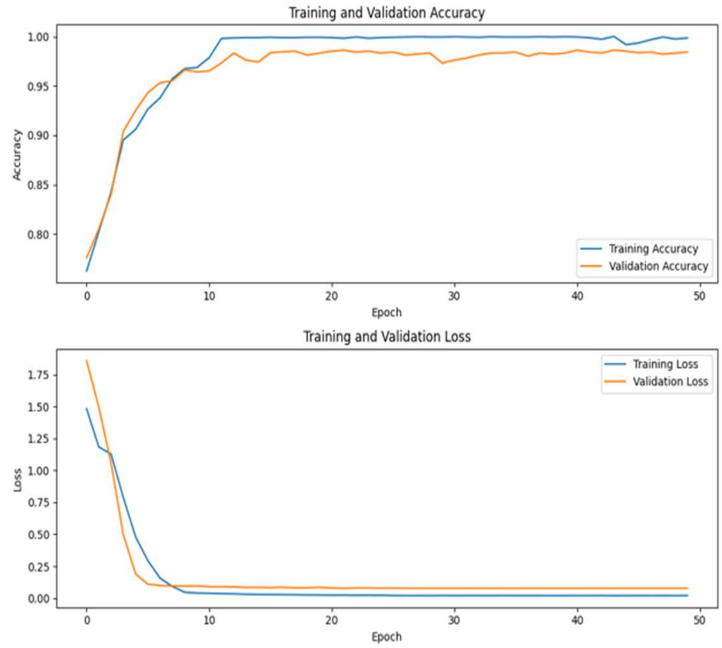

Fig. 10 Training and validation visualization for EfficientNetB3-CNN average pooling layer concatenated with the last convolutional layer

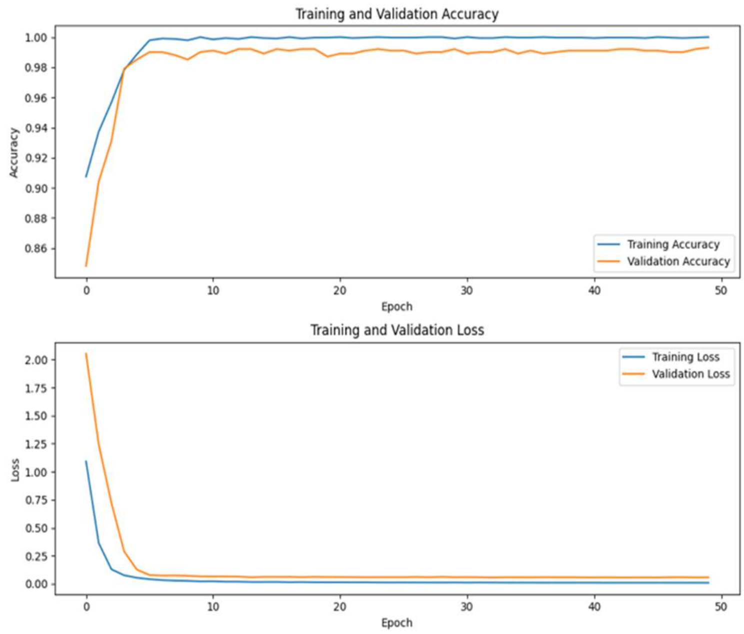

Fig. 11 Training and validation visualization for EfficientNetB3-CNN average pooling layer concatenated with the last convolutional layer after applying PCA for dimensionality reduction

The classification accuracy achieved with this approach is 99.54%. The comparison between these two approaches allows us to assess the effectiveness of incorporating PCA in improving the classification accuracy of dry waste categories. The performance of different techniques is showcased in Table III, which represents the performance of the feature concatenation technique. The confusion matrix corresponding to the classification results obtained from the concatenated features is presented in Figure 12 and Figure 13.

TABLE III
MODEL PERFORMANCE COMPARISON OF SCENARIO 2

Method	Accuracy
EffecientNetB3 project_conv layer (PCA) + EfficientNetB3-CNN avg_pool layer	98.84%
EffecientNetB3 avg_pool layer + EfficientNetB3-CNN last_conv layer (PCA)	99.07%

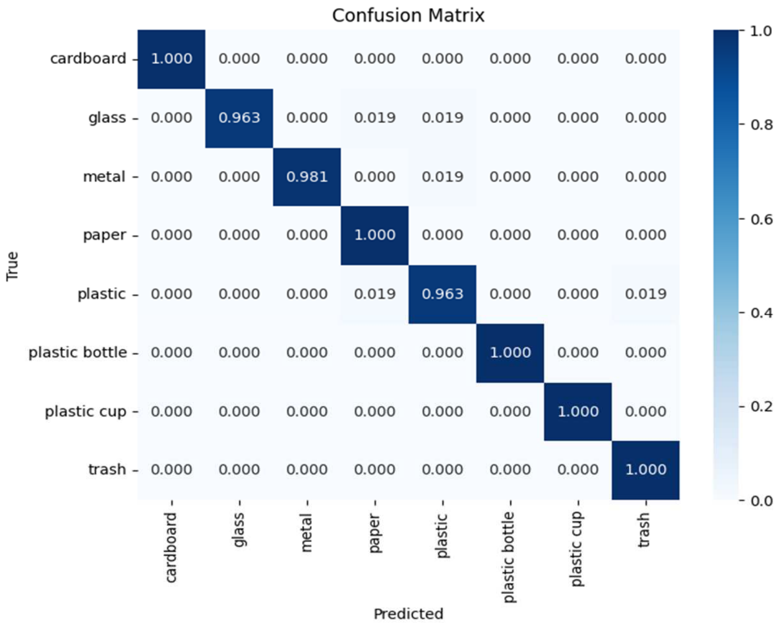

Fig. 12 Confusion matrix from the concatenated features of EfficientNetB3 project_conv (PCA) and avg_pool EfficientNetB3-CNN

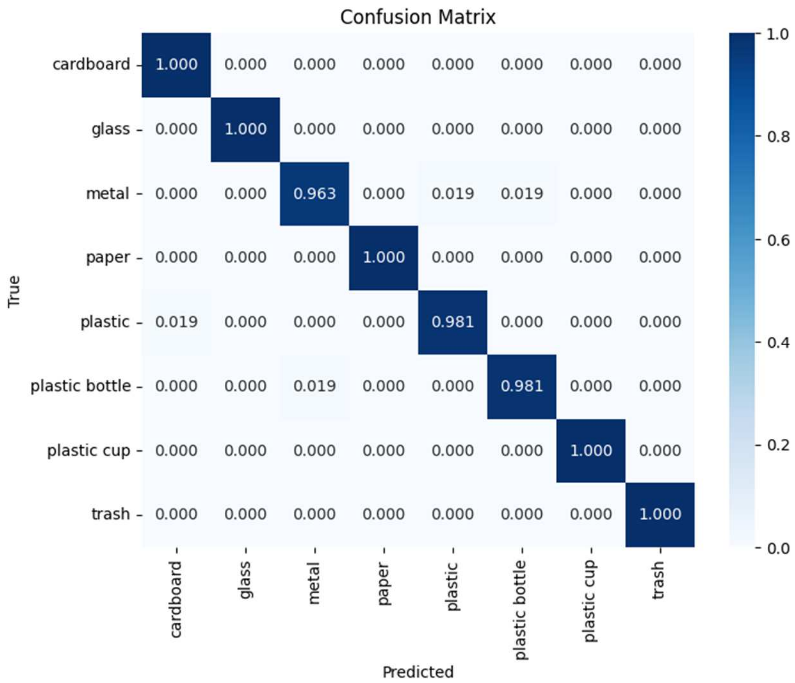

Fig. 13 Confusion matrix from the concatenated features of EfficientNetB3 avg_pool and last_conv of EfficientNetB3-CNN (PCA)

These evaluations provide insights into the technique's effectiveness that combines the average pooling layer with the features reduced by PCA. The second scenario presents a comprehensive analysis of the technique that combines the average pooling layer with PCA-reduced features from the convolutional layers. Through this approach, we aim to exploit the unique characteristics of both the average pooling layer and the PCA-reduced features to improve the classification accuracy of the proposed method for dry waste classification.

The evaluation results provide valuable insights into the effectiveness of this technique and offer a detailed comparison with the achieved classification accuracy. The confusion matrix, along with the accompanying visualizations, presents a comprehensive overview of the classification performance, showcasing the ability of the technique to accurately classify different types of dry waste. The confusion matrix allows us to analyze the true positive, true negative, false positive, and false negative predictions, enabling a deeper understanding of the model's performance.

By leveraging the strengths of the average pooling layer, which captures global information, and the PCA-reduced features, which represent the most informative aspects of convolutional layers, our approach demonstrates significant improvements in the classification accuracy. The combination of these features allows for a more robust and comprehensive representation of the dry waste images, enabling the model to capture both local and global patterns effectively.

Furthermore, the utilization of dimensionality reduction through PCA helps to overcome the curse of dimensionality by reducing the feature space while retaining most of the important variance in the data. This reduction not only improves the efficiency of the classification process but also helps to mitigate the risk of overfitting, resulting in a more generalized and reliable model.

Overall, the findings from the second scenario highlight the effectiveness of combining the average pooling layer and PCA-reduced features in enhancing the classification accuracy for dry waste classification. This approach demonstrates the potential of leveraging advanced techniques in feature extraction and dimensionality reduction to optimize the performance of classification models in challenging tasks. The confusion matrix and visualizations provide a comprehensive understanding of the effectiveness of this approach in enhancing classification accuracy in our proposed method.

C. *Result Comparison*

The evaluation and comparison of the proposed model system, which combines PCA dimensionality reduction and feature extraction from pre-trained EfficientNetB3-CNN, against the state-of-the-art waste classification system are presented in Table III. The table showcases the performance accuracy of both systems. The results demonstrate that the proposed model system outperforms the state-of-the-art system, achieving higher accuracy and overall performance. This highlights the effectiveness of the combined approach of PCA and feature extraction from pre-trained EfficientNetB3-CNN in improving the classification accuracy and performance of the waste classification system. The comparison in Table III emphasizes the superior performance of the proposed model system, validating its potential as an advanced solution in waste classification.

TABLE IV

EVALUATION COMPARISON RESULTS OF THE PROPOSED MODEL SYSTEM AND STATE-OF-THE-ART WASTE CLASSIFICATION SYSTEM

No	Reference	Feature Extraction Approach	Classifier	Dataset	Accuracy (%)
1	[26]	Classification of Waste using BoF and PCA for feature extraction	LR KNN SVM	TrashNet	78% 67% 77% 72% 81% 84%
2	[27]	Classification of Waste using SIFT and PCA for feature extraction	SVM	TrashNet	62%
3	[28]	Deep features extraction of MLH-CNN	CNN	TrashNet	92%
4	[29]	CNN LeNet-5 VGG16	CNN LeNet-5 VGG16	Huawei Garbage Classification Data	90.12% 90.39% 92.56%
5	[30]	Image Segmentation using PSPNet and GLCM for feature extraction	SVM	TrashNet	76.49%
6	[8]	MobileNetV2	MobileNetV2	Trash Classification	82.92%
7	[31]	The feature was extracted by PCA in MobileNetV2 Architectures	N/A	Huawei Garbage Classification Data	90.7%
8	[23]	Deep feature extraction using MobileNetV2	SVM	TrashNet	98.4%
9	[32]	Deep feature extraction using ResNext and DCA for feature fusion	N/A	TrashNet	97.81%
10	[33]	ResNet-50 VGG-19 XBoost	ResNet-50 VGG-19 XBoost	Taco Dataset	86% 86.4% 69%
11	[34]	Deep feature extraction using pre-trained model	ELM	TrashNet	93.97%
12	**Proposed Model**	**Feature extraction from EfficientNetB3-CNN and PCA for dimensional reduction**	**CNN**	**TrashNet**	**99.07%**

D. *Discussion*

Our research introduces innovative approaches to waste classification that set it apart in the field. Notably, we combine feature extraction from convolutional layers with Principal Component Analysis (PCA) dimensionality reduction, resulting in improved accuracy in waste classification. Our model surpasses existing methods, including a state-of-the-art system, in terms of accuracy, making a substantial contribution to resolving the current challenge of accurate waste classification. The utilization of PCA for dimensionality reduction not only enhances accuracy but also addresses the challenge of handling high-dimensional data often encountered in image classification tasks. Furthermore, our research ensures balanced feature utilization by harnessing the strengths of both the average pooling layer and PCA-reduced features, capturing both local and global patterns in waste images. This approach not only improves efficiency but also generalizes the model, making it applicable to a broader range of waste classification scenarios. The potential impact of our research extends to waste management and recycling efforts, as improved accuracy in waste classification can lead to better waste sorting practices, reduced contamination, and more effective recycling processes. Looking ahead, our work opens up avenues for applying our model to larger and more diverse waste datasets and exploring various hyperparameter settings to further optimize performance.

IV. Conclusion

In this study, we introduced an innovative approach to waste classification by combining feature extraction from convolutional layers with Principal Component Analysis (PCA) dimensionality reduction. Our model, integrating PCA and feature extraction from pre-trained EfficientNet-CNN, exhibited superior performance with an accuracy of 99.54% on the TrashNet dataset. This surpasses contemporary waste classification models, highlighting the efficacy of our combined approach.

Discrepancies in accuracy among studies may stem from variations in feature extraction techniques and model architectures. Prior research often relied solely on PCA for feature extraction, utilizing a single layer that might be less effective in capturing intricate patterns in waste images.

Acknowledging our study's limitations, particularly its generalization to different waste types and settings, is crucial. Results should be interpreted considering these limitations. Therefore, testing the model's performance in real-world situations and identifying practical implementation challenges is essential.

Our research offers substantial potential for future exploration by encouraging performance evaluations on more extensive, diverse waste datasets and assessing adaptability across various waste categories. Research recommendations involve exploring different hyperparameter settings to refine the model's performance.

Our model system holds promise for extension to other related tasks, including sorting and identifying specific waste materials. Exploration of advanced techniques, such as deep reinforcement learning and attention mechanisms, is desired further to enhance the model's capabilities in waste classification.

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