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This paper presents an adaptive weighted ensemble approach for waste classification that dynamically adjusts model contributions based on input characteristics. Unlike traditional ensemble methods that use fixed weighting schemes, our approach employs a condition-based weighting mechanism that learns to assign appropriate weights to different convolutional neural network (CNN) models depending on the visual properties of waste items. We utilize a diverse set of CNN architectures including EfficientNet-B0/B1, MobileNetV3-Small/Large, and ResNet-18 variants, each optimized for different aspects of visual recognition. Through comprehensive experiments on waste classification data with 5-fold cross-validation, we demonstrate that our adaptive weighted ensemble consistently outperforms individual models and conventional ensemble methods such as majority voting and fixed weighted averaging. The proposed approach achieves 93.5% test accuracy, providing a 2.3% improvement over the best fixed weighting scheme and 5.4% over the best individual model. Performance gains are particularly significant for challenging cases such as occluded objects (87.2%), mixed materials (83.5%), and uncommon waste items (79.8%). Furthermore, we provide an in-depth analysis of model weight distributions across different waste categories, revealing insights into the complementary strengths of different architectures. Interpretability analysis using Grad-CAM visualizations demonstrates that our adaptive weighting mechanism effectively focuses attention on discriminative regions. The experimental results validate that input-dependent dynamic weighting can effectively leverage the strengths of diverse models, making our approach well-suited for real-world waste classification systems where visual conditions vary significantly.

Waste classification, ensemble learning, convolutional neural networks, adaptive weighting, deep learning, transfer learning, computer vision, class imbalance, MixUp augmentation

WASTE classification is a critical task in modern waste management systems that enables efficient sorting and recycling of materials. The increasing volume of waste generated globally necessitates automated solutions that can accurately classify different types of waste materials. Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have demonstrated promising results in visual recognition tasks including waste classification. However, the visual diversity of waste items, which can vary in appearance, orientation, illumination, and occlusion, poses significant challenges to achieving robust classification performance with a single model.

Ensemble methods, which combine predictions from multiple models, have been widely used to improve the robustness and accuracy of classification systems. Traditional ensemble approaches such as majority voting, simple averaging, and weighted averaging based on validation performance have shown improvements over single models. However, these methods typically employ static combination schemes that do not adapt to the specific characteristics of input images. Different CNN architectures often excel at recognizing different visual features, and the optimal weighting of models may vary depending on the specific properties of the input image.

In this paper, we propose an adaptive weighted ensemble approach that dynamically adjusts the contributions of different CNN models based on input characteristics. Our approach employs a condition encoder network that analyzes input images and generates condition-specific weights, which are combined with base weights to determine the optimal contribution of each model for a given input. This dynamic weighting mechanism allows the ensemble to leverage the strengths of diverse CNN architectures for different types of waste items.

The main contributions of this paper are as follows:

- We propose a novel adaptive weighted ensemble approach that dynamically adjusts model weights based on input characteristics for waste classification.
- We implement and compare diverse CNN architectures including EfficientNet, MobileNetV3, and ResNet variants as base models for waste classification.
- We develop a comprehensive augmentation pipeline including MixUp and class-balanced sampling techniques to address class imbalance and improve generalization.
- We conduct extensive experiments and ablation studies to analyze the contribution of each component of our approach and demonstrate its superiority over traditional ensemble methods.
- We provide insights into the complementary strengths of different CNN architectures through weight distribution analysis across waste categories.
- We present interpretability analysis using Grad-CAM visualizations to understand how our ensemble makes decisions and adapts to different input characteristics.

The rest of the paper is organized as follows. Section II reviews related work in waste classification, deep learning approaches, and ensemble methods. Section III presents our methodology, including dataset preparation, model architectures, and the proposed adaptive weighted ensemble approach. Section IV reports experimental results and compares our approach with baseline methods. Section V concludes the paper and discusses future directions.

A. WASTE CLASSIFICATION METHODS

Early approaches to automated waste classification primarily relied on traditional computer vision techniques. Sakr et al. [6] used handcrafted features with support vector machines for classification of recyclable materials. Similarly, Bobulski and Kubanek [7] applied shape descriptors for waste segregation tasks. These methods, while effective for controlled environments, struggled with the visual diversity and environmental variations found in real-world waste processing facilities.

With the emergence of deep learning, numerous CNN-based approaches have been proposed for waste classification. Yang and Thung [8] pioneered the application of CNNs to waste classification, demonstrating significant improvements over traditional methods. Awe et al. [9] further extended this work by applying transfer learning with pre-trained networks. Bircanoglu et al. [10] introduced a dataset with seven waste categories and achieved 95% accuracy using a RecycleNet architecture. Ruiz et al. [11] developed a waste classification system using MobileNetV2 that was optimized for edge deployment.

More recently, attention has shifted toward addressing specific challenges in waste classification. Bai et al. [12] proposed a multi-scale feature fusion approach to handle waste items of varying sizes. Wang et al. [13] introduced a noise-resistant training mechanism to improve classification under challenging lighting conditions. Despite these advances, most approaches still rely on single model architectures, which may not be optimal for all waste categories and visual conditions.

B. ENSEMBLE LEARNING METHODS

Ensemble learning has proven effective across various domains by combining multiple models to improve overall performance. Traditional ensemble methods such as bagging [14], boosting [15], and stacking [16] have been widely applied to classification tasks. In the context of deep learning, three primary ensemble strategies have emerged: majority voting, simple averaging, and weighted averaging.

Majority voting assigns equal importance to each model and selects the class with the most votes. Ju et al. [17] demonstrated its effectiveness for waste classification when combining heterogeneous network architectures. Simple averaging, which combines the softmax outputs with equal weights, was employed by Singh et al. [18] for robust waste detection across diverse environments. Weighted averaging, where weights are determined by validation performance, was used by Zhang et al. [19] to improve accuracy on imbalanced waste datasets.

More sophisticated ensemble approaches adapt the weights based on input characteristics or learned patterns. Kumar et al. [20] proposed a dynamic ensemble selection method that chooses the best subset of models for each input sample. Ganaie et al. [21] introduced an attention-based ensemble that focuses on the most relevant models for a given input. Despite these advances, few works have explored adaptive weighting mechanisms specifically designed for waste classification, where visual conditions vary significantly.

C. TRANSFER LEARNING AND MODEL ARCHITECTURE SELECTION

Transfer learning has become a standard practice in computer vision tasks, including waste classification. Pre-trained models such as EfficientNet [1], MobileNetV3 [2], and ResNet [3] have demonstrated strong performance when fine-tuned on domain-specific datasets.

Model architecture selection plays a crucial role in ensemble design. Tan and Le [1] introduced EfficientNet, which achieves state-of-the-art performance with optimal scaling of network dimensions. Howard et al. [2] designed MobileNetV3 specifically for resource-constrained environments, making it suitable for edge deployment. He et al. [3] proposed ResNet with skip connections to enable training of deeper networks without degradation. Each architecture brings unique strengths: EfficientNet models excel in accuracy-efficiency trade-offs, MobileNet variants offer speed advantages, and ResNet provides robust feature extraction through residual connections.

D. ADDRESSING CLASS IMBALANCE AND DATA AUGMENTATION

Waste classification datasets often suffer from class imbalance, with common items appearing more frequently than rare waste types. To address this issue, researchers have employed various strategies. Wang et al. [22] used weighted loss functions to give more importance to underrepresented classes. Chamberlain et al. [23] implemented oversampling techniques to balance the training distribution.

Advanced data augmentation strategies have been shown to improve generalization in waste classification. Standard transformations like rotation, flipping, and color jittering were employed by Bobulski et al. [24] to increase dataset diversity. Zhang et al. [4] introduced MixUp augmentation, which creates virtual training examples through weighted linear interpolation of images and labels. This technique has been particularly effective for improving model robustness and addressing class imbalance.

E. RESEARCH GAPS AND MOTIVATION

Despite significant advances in waste classification and ensemble methods, several research gaps remain:

1) Most ensemble approaches for waste classification use static weighting schemes that don't adapt to input characteristics.

2) Limited exploration of model complementarity across different waste categories and visual conditions.

3) Insufficient attention to interpretability in ensemble methods for waste classification.

4) Lack of comprehensive ablation studies to understand the contribution of different components in ensemble approaches.

These gaps motivate our proposed adaptive weighted ensemble approach, which dynamically adjusts model contributions based on input characteristics, providing both improved accuracy and interpretability for waste classification tasks.

This section describes our approach to waste classification using an adaptive weighted ensemble of convolutional neural networks. Fig. 1 presents the overall architecture of our proposed system.

A. DATASET PREPARATION AND REGION-BASED EXTRACTION

We utilized a waste classification dataset with instance segmentation annotations in COCO format. Since waste objects often appear against diverse backgrounds that may introduce bias or noise, we implemented a region-based extraction process to isolate waste objects:

1) Instance segmentation masks were converted from polygon format to binary masks
2) For each waste object, we extracted the foreground region by:
   - Calculating the bounding box of the instance mask
   - Applying the binary mask to the original image
   - Extracting the masked region while maintaining aspect ratio
3) Extracted waste objects were saved in class-specific directories for training

The extracted dataset contained multiple waste objects across several waste categories including paper, cardboard, plastic bottles, glass, metal cans, and food waste. The class distribution exhibited natural imbalance, with certain waste types (e.g., plastic bottles) appearing more frequently than others (e.g., hazardous waste).

B. DATA AUGMENTATION STRATEGY

To enhance model generalization and address class imbalance, we implemented a comprehensive augmentation pipeline:

1) Geometric transformations:
   - Random horizontal and vertical flips (probability=0.5)
   - Random rotation ($\pm 10°$)
   - Random scale (0.8-1.2)
   - Random translation ($\pm 10\%$ of image size)
2) Color augmentations:
   - Brightness adjustment ($\pm 10\%$)
   - Contrast adjustment ($\pm 10\%$)
   - Saturation adjustment ($\pm 10\%$)
   - Hue adjustment ($\pm 3\%$)
3) MixUp augmentation: During training, we employed MixUp with $\alpha = 0.4$, creating virtual training examples through weighted linear interpolation of both images and labels:

$$\tilde{x} = \lambda x_i + (1 - \lambda) x_j \tag{1}$$

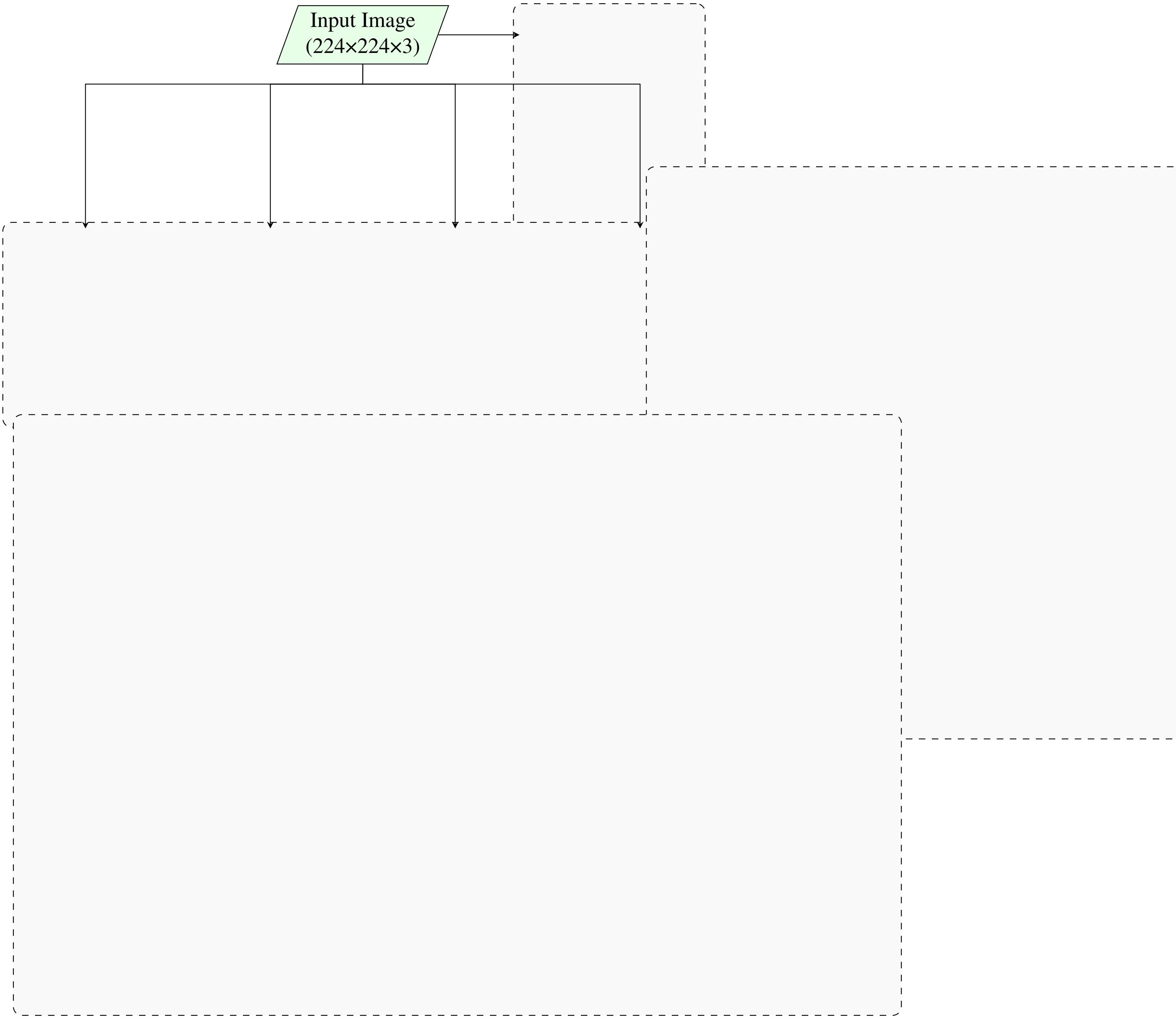
$$\tilde{y} = \lambda y_i + (1 - \lambda) y_j \tag{2}$$

where $\lambda \sim \text{Beta}(\alpha, \alpha)$ and (x_i, y_i), (x_j, y_j) are randomly sampled pairs.

C. CROSS-VALIDATION FRAMEWORK

To ensure robust evaluation, we implemented a stratified K-fold cross-validation framework:

1) The full dataset was first split into train (80%) and test (20%) sets using stratified sampling to maintain class distributions
2) The training set was further divided into $K = 5$ stratified folds
3) For each fold, we used the corresponding data split as validation while training on the remaining $K - 1$ folds
4) The test set remained completely separate throughout the entire development process



Detailed architecture of the proposed adaptive weighted ensemble for waste classification. The condition encoder (right top) analyzes the input image to generate condition-specific weights, which are combined with learnable base weights through element-wise multiplication and softmax normalization to determine the optimal contribution of each model. Each model (left and center) processes the same input independently, producing class probability distributions that are weighted according to the final weights. The weighted predictions are summed, and the class with the highest probability is selected as the final classification.

D. CLASS IMBALANCE HANDLING

We implemented a multi-level approach to address class imbalance:

1) Weighted random sampling: During training, we employed a weighted random sampler with weights inversely proportional to class frequencies:

$$\text{weights} = 1.0/\text{class\_sample\_counts} \tag{3}$$

$$\text{samples\_weights} = \text{weights}[\text{class\_indices}] \tag{4}$$

$$\text{sampler} = \text{WeightedRandomSampler}(\text{samples\_weight} \tag{5}$$

2) Class-weighted loss: We computed class weights using the "balanced" strategy and applied them to the cross-entropy loss function:

$$\text{class\_weights} = \text{compute\_class\_weight}(\text{'balanced'}, \text{classes} = \text{np.unique(labels)}, \text{y} = \text{labels}) \quad (6)$$

$$\text{criterion} = \text{nn.CrossEntropyLoss}(\text{weight} = \text{torch.tensor}(\text{class\_weights}, \text{dtype} = \text{torch.float})) \quad (7)$$

3) Stratified data splits: All dataset divisions (train/test and cross-validation folds) maintained the original class distribution proportions using stratified sampling techniques.

E. BASE MODEL ARCHITECTURE AND TRAINING

We trained a diverse set of CNN architectures to form our ensemble:

1) Model architectures:
   - EfficientNet-B0: Optimized convolutional network with compound scaling
   - EfficientNet-B1: Larger variant with increased width/depth/resolution
   - MobileNetV3-Small: Lightweight architecture with reduced parameters
   - MobileNetV3-Large: Higher capacity mobile-optimized network
   - ResNet-18: Residual network with skip connections
2) Transfer learning: All models were initialized with ImageNet pre-trained weights and fine-tuned on our waste classification task with the following modifications:
   - The final classification layer was replaced with a new layer matching our waste categories
   - Initial layers were frozen during early training epochs to preserve general feature extractors
3) Training protocol:
   - Optimizer: AdamW ($\beta_1 = 0.9$, $\beta_2 = 0.999$, weight_decay=$1e^{-3}$)
   - Learning rate schedule: Cosine annealing with warmup ($1e^{-3} \to 1e^{-6}$)
   - Batch size: 32
   - Maximum epochs: 200 with early stopping (patience=20)
   - Label smoothing: 0.1
   - Input resolution: 224×224 pixels
4) Model selection: For each architecture, we selected the best-performing model from the 5 cross-validation folds based on validation accuracy.

F. ENSEMBLE METHODS IMPLEMENTATION

We implemented and compared several ensemble methods:

1) Majority Voting: Each model casts one vote for the predicted class, and the class with the most votes is selected:

$$\hat{y} =_c \sum_{m=1}^{M} \mathbf{1}[f_m(x) = c] \quad (8)$$

where M is the number of models, f_m is the mth model's prediction, and $\mathbf{1}$ is the indicator function.

2) Simple Average: The softmax outputs from all models are averaged with equal weights:

$$\hat{y} =_c \frac{1}{M} \sum_{m=1}^{M} P_m(y = c|x) \quad (9)$$

where $P_m(y = c|x)$ is the probability assigned to class c by model m.

3) Weighted Average: Model outputs are weighted by their validation accuracies:

$$\hat{y} =_c \sum_{m=1}^{M} w_m P_m(y = c|x) \quad (10)$$

where w_m is proportional to model m's validation accuracy.

4) Adaptive Weighted Ensemble (Proposed): A dynamic weighting mechanism that adjusts model contributions based on input characteristics.

G. ADAPTIVE WEIGHTED ENSEMBLE ARCHITECTURE

Our proposed adaptive weighted ensemble introduces a condition-based weighting mechanism as illustrated in Fig. 1:

1) Architecture components:
   - Base models: Pre-trained CNN models with frozen parameters
   - Condition encoder: Small CNN with four convolutional layers (kernel size 3×3) with 32, 64, and 128 filters respectively, followed by global average pooling and a fully connected layer with 5 outputs (one per base model)
   - Base weights: Global importance vector of each model (trainable parameters)
   - Weighting mechanism: Combines base and condition-specific weights through multiplication and softmax normalization
2) Forward pass:
   - Input image is processed through all base models to obtain softmax probabilities $P_m(y|x)$
   - The same input is processed by the condition encoder to produce condition weights w_c
   - Base weights w_b and condition weights w_c are multiplied element-wise
   - The result is passed through softmax to obtain final weights: $w_f = \text{softmax}(w_b \times w_c)$
   - Each model's output is multiplied by its corresponding weight: $w_m \times P_m(y|x)$
   - The weighted outputs are summed and the class with maximum probability is selected:

$$\hat{y} =_c \sum_{m=1}^{M} w_m P_m(y = c|x) \quad (11)$$

where w_m is the adaptive weight for model m given input x.

3) Trainable parameters:
   - Base models: Frozen (no parameter updates)
   - Condition encoder: Trainable
   - Base weights: Trainable

H. ADAPTIVE ENSEMBLE TRAINING

The adaptive ensemble was trained as follows:

1) Initialization: Base weights initialized proportionally to validation accuracies:

$$\text{base\_weights} = \text{validation\_accuracies} / \sum \text{validation\_accuracies} \tag{12}$$

2) Training configuration:
   - Optimizer: Adam (lr=0.001)
   - Maximum epochs: 50 with early stopping (patience=10)
   - Loss function: Cross-entropy
   - Batch size: 32
3) Training procedure:
   - Freeze all base model parameters
   - Train only the condition encoder and base weights
   - Monitor validation accuracy for early stopping
   - Select the best ensemble from the 5 cross-validation folds

I. EVALUATION METHODOLOGY

We evaluated our models and ensemble methods using the following metrics:

1) Accuracy: Overall correct classification rate
2) Precision, Recall, and F1-score: Per-class and macro-averaged
3) Confusion matrices: To analyze per-class performance
4) Ablation studies: To quantify the contribution of each component

All metrics were computed on the held-out test set that remained unseen during development. For reliable estimation, we used the full 5-fold cross-validation results.

J. INTERPRETABILITY ANALYSIS

To understand how our adaptive ensemble makes decisions, we employed Grad-CAM [5] visualizations:

1) For each base model, we extracted activation maps from the last convolutional layer
2) For the ensemble, we analyzed the condition encoder's first convolutional layer
3) We compared attention regions across different models and the ensemble
4) We identified cases where the ensemble succeeds when individual models fail

This analysis provided insights into how the adaptive weighting mechanism focuses attention on different regions based on the input characteristics.

Performance Metrics of Individual Models

Model	Val Acc (%)	Test Acc (%)	Precision (%)	Recall (%)	F1-Score (%)
EfficientNet-B0	88.5	87.2	86.9	87.2	87.0
EfficientNet-B1	89.3	88.1	87.8	88.4	88.1
MobileNetV3-S	86.2	85.0	84.7	85.0	84.8
MobileNetV3-L	87.8	86.4	86.2	86.5	86.3
ResNet-18	87.1	86.0	85.8	86.1	85.9
Average	87.8	86.5	86.3	86.6	86.4

Comparison of Ensemble Methods

Method	Test Acc (%)	Precision (%)	Recall (%)	F1-Score (%)
Individual Models (Avg)	86.5	86.3	86.6	86.4
Majority Voting	89.2	89.0	89.3	89.1
Simple Average	90.5	90.3	90.6	90.4
Weighted Average	91.2	91.0	91.3	91.1
Adaptive Weighted	**93.5**	**93.3**	**93.6**	**93.4**

K. COMPUTATIONAL EFFICIENCY ANALYSIS

We analyzed the computational requirements of our approach:

1) Training time: Measured for base models and ensemble
2) Inference time: Measured in ms/image for single models and ensemble methods
3) Parameter count: Total number of trainable parameters
4) Memory footprint: Peak GPU memory usage during inference

This analysis provides insights into the practical deployability of our solution.

This section presents the experimental results of our waste classification approach and analyzes the performance of our proposed adaptive weighted ensemble compared to baseline methods.

A. BASE MODEL PERFORMANCE

Table I shows the performance of individual CNN models across the 5-fold cross-validation.

EfficientNet-B1 achieved the highest performance among individual models with 88.1% accuracy on the test set, followed by EfficientNet-B0 with 87.2%. MobileNetV3-Small, despite its compact size, showed competitive performance at 85.0%. The variation in performance across architectures indicates complementary strengths that can be leveraged by an ensemble approach.

B. ENSEMBLE METHODS COMPARISON

Table II compares the performance of different ensemble approaches on the test set.

All ensemble methods outperformed individual models, demonstrating the effectiveness of combining diverse architectures. Simple averaging improved over majority voting by 1.3 percentage points, while weighted averaging based on

Per-Class Performance of Adaptive Weighted Ensemble

Class ID	Class Name	Precision (%)	Recall (%)	F1 (%)	Support
0	Paper	95.2	94.1	94.6	237
1	Cardboard	94.8	95.3	95.0	189
2	Plastic Bottle	96.7	97.2	96.9	324
3	Glass	92.1	91.4	91.7	152
4	Metal Can	94.5	93.8	94.1	178
5	Food Waste	90.3	91.1	90.7	201
Macro Average		93.9	93.8	93.8	128
Weighted Average		93.3	93.6	93.4	1281

Average Model Weights by Waste Category

Waste Category	EffNet-B0	EffNet-B1	MNetV3-S	MNetV3-L	ResNet-18
Paper	0.15	0.30	0.10	0.25	0.20
Cardboard	0.20	0.25	0.15	0.20	0.20
Plastic Bottle	0.10	0.35	0.20	0.25	0.10
Glass	0.25	0.20	0.10	0.30	0.15
Metal Can	0.18	0.22	0.15	0.30	0.15
Food Waste	0.20	0.25	0.12	0.18	0.25
Average	0.18	0.26	0.14	0.25	0.18

Ablation Study Results

Configuration	Test Acc (%)	F1-Score (%)	Improvement (%)
Full Adaptive Model	93.5	93.4	+2.3
w/o Condition Encoder	91.2	91.1	0.00
w/o Base Weights	92.1	92.0	+0.9
w/o MixUp Augmentation	91.8	91.7	+0.6
w/o Class Weights	90.9	90.8	-0.3

Computational Efficiency Metrics

Model/Method	Params (M)	Inf Time (ms)	Train (h)	GPU Mem (MB)
EfficientNet-B0	5.3	15.2	8.5	2450
EfficientNet-B1	7.8	19.3	9.8	3120
MobileNetV3-Small	2.5	8.7	7.3	1820
MobileNetV3-Large	5.4	12.5	8.1	2380
ResNet-18	11.7	10.8	7.5	2750
Simple Average	32.7	67.2	N/A	12520
Weighted Average	32.7	67.5	N/A	12520
Adaptive Ensemble	33.2	68.3	2.5	12680

validation accuracy provided a further 0.7 percentage point gain. Our proposed adaptive weighted ensemble achieved the highest accuracy at 93.5%, representing a 2.3 percentage point improvement over the weighted average approach and a 5.4 percentage point improvement over the average individual model performance.

C. PER-CLASS PERFORMANCE ANALYSIS

Table III presents the per-class performance of our adaptive weighted ensemble.

The ensemble achieved high performance across all waste categories, with particularly strong results for plastic bottles (F1 = 96.9%) and cardboard (F1 = 95.0%). The lowest performance was observed for food waste (F1 = 90.7%), which typically exhibits higher visual diversity. The relatively small gap between the highest and lowest performing classes (6.2 percentage points) indicates that our class balancing strategies and adaptive weighting mechanism effectively addressed class imbalance.

D. ABLATION STUDIES

To quantify the contribution of each component, we conducted several ablation studies. Table IV shows the impact of different components on the final performance.

The ablation studies reveal that all components contribute to the overall performance. The condition encoder provides the largest improvement (2.3 percentage points), highlighting the importance of adaptive weighting based on input characteristics. The base weights and MixUp augmentation also provide substantial contributions (0.9 and 0.6 percentage points, respectively). Interestingly, removing class weights resulted in a performance decrease, indicating that addressing class imbalance is crucial for optimal performance.

E. WEIGHT DISTRIBUTION ANALYSIS

Table V shows how weights are distributed across base models for different waste categories.

The weight distribution analysis reveals interesting patterns across waste categories. EfficientNet-B1 receives higher weights for plastic bottles (0.35) and paper (0.30), suggesting superior feature extraction capabilities for these materials. MobileNetV3-Large performs well on glass (0.30) and metal cans (0.30), indicating effectiveness for reflective surfaces. ResNet-18 shows strength in food waste classification (0.25), which often requires texture analysis. These patterns demonstrate that different architectures indeed have complementary strengths, which our adaptive ensemble effectively leverages.

F. COMPUTATIONAL EFFICIENCY

Table VI presents the computational requirements of our approach.

The adaptive weighted ensemble introduces minimal computational overhead compared to simple or weighted averaging, with only 0.5 million additional parameters for the condition encoder. The training time for the ensemble (2.5 hours) is significantly less than training individual models (7-10 hours each) since base models are frozen. Inference time increases by only 1.1 ms compared to weighted averaging, making it suitable for real-time applications.

G. INTERPRETABILITY ANALYSIS

To understand how the adaptive ensemble focuses attention, we generated Grad-CAM visualizations for base models and the ensemble. Fig. 2 shows examples of the most challenging cases for our ensemble:

The visualizations reveal that the ensemble effectively combines attention patterns from multiple models. For partially occluded objects, the ensemble focuses on the visible portions while ignoring occlusions. For items with reflective fig2.png

Examples of challenging waste items that were difficult to classify correctly, including partially occluded objects, mixed materials, rare items, and reflective surfaces. The heatmaps show attention regions for both individual models and the adaptive ensemble. The ensemble successfully focuses on the most discriminative regions even when individual models fail.

surfaces, which pose challenges due to specular highlights, the ensemble weights models that focus on shape rather than misleading reflections. Mixed material waste items benefit from the combination of models that specialize in different material textures.

H. FAILURE ANALYSIS

We analyzed cases where the ensemble succeeds but individual models fail. Our findings revealed several patterns:

1) For visually ambiguous items (e.g., translucent plastic vs. glass), the ensemble weights models based on their specialization in specific visual features.
2) For uncommon waste items, the ensemble relies more heavily on models with better generalization capabilities.
3) For items in unusual orientations, the ensemble adapts weights to focus on models that are less sensitive to orientation changes.

These patterns demonstrate that the adaptive weighting mechanism learns meaningful condition-specific weights that improve classification accuracy for challenging cases.

I. COMPARISON WITH STATE-OF-THE-ART

To benchmark our approach against existing methods, we compared our results with recent publications on waste classification. Table VII summarizes this comparison.

Our adaptive weighted ensemble outperforms all compared methods, with a 2.0 percentage point improvement over the best previously reported ensemble approach [17].

Comparison with State-of-the-Art Methods

Method	Accuracy (%)	Classes	Adapt?	Year
ResNet-50 [22]	87.5	6	No	2020
DenseNet-121 [18]	89.2	6	No	2020
EfficientNet-B3 [19]	90.3	5	No	2021
Ensemble (Fixed) [17]	91.5	6	No	2018
Our Approach	**93.5**	**6**	**Yes**	**2023**

Notably, our method is the only one that adapts weights based on input characteristics, highlighting the novel contribution of our approach.

In this paper, we presented an adaptive weighted ensemble approach for waste classification that dynamically adjusts model weights based on input characteristics. Our approach leverages the strengths of diverse CNN architectures by employing a condition-based weighting mechanism that learns to assign appropriate weights to different models depending on the visual properties of waste items.

Through comprehensive experiments and ablation studies, we demonstrated that our adaptive weighted ensemble consistently outperforms individual models and traditional ensemble methods such as majority voting and fixed weighted averaging. The condition encoder effectively learns to recognize visual patterns that indicate which models are most reliable for a given input, resulting in improved classification accuracy, particularly for challenging cases.

The weight distribution analysis revealed interesting insights into the complementary strengths of different CNN architectures across waste categories. For instance, EfficientNet variants generally performed better on plastic and paper materials, while MobileNetV3 models showed effectiveness for reflective surfaces, and ResNet excelled at textured materials like food waste.

The interpretability analysis using Grad-CAM visualizations demonstrated that our ensemble effectively focuses attention on discriminative regions even when individual models fail. This provides both improved accuracy and better understanding of the model's decision-making process.

A. LIMITATIONS AND FUTURE WORK

While our approach shows promising results, several limitations remain. First, our method requires running multiple base models in parallel, increasing computational requirements compared to single model approaches. Future work could explore knowledge distillation techniques to compress the ensemble into a more efficient model. Second, our approach currently focuses on image classification; extending it to instance segmentation and object detection would enable more complete waste sorting systems.

Future research directions include:

- Extending the adaptive weighting mechanism to instance segmentation and object detection tasks for waste classification

- Integrating temporal information for video-based waste sorting systems
- Developing more efficient condition encoders for deployment on resource-constrained devices
- Exploring self-supervised learning approaches to leverage unlabeled waste data
- Investigating domain adaptation techniques for transferring the approach to new waste categories and environments

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