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Improved Waste and Litter Image Classification with CBAM-Integrated VGG-16 Vs VGG-16

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ABSTRACT

The effective classification and segregation of waste materials are critical steps toward achieving sustainable waste management and environmental preservation. However, conventional manual sorting methods are time-consuming, labor-intensive, and prone to human error, resulting in inefficiencies and ecological hazards. To address these challenges, this study introduces a novel deep learning architecture that enhances the classical VGG-16 model by integrating the Convolutional Block Attention Module (CBAM) for multi-class classification of litter and waste images. The proposed framework leverages the publicly available Kaggle Garbage Classification dataset, which consists of 7,440 balanced images categorized into 12 waste classes: battery, biological, brown glass, cardboard, clothes, green glass, metal, paper, plastic, shoes, trash, and white glass. In this work, CBAM modules are strategically incorporated into the VGG-16 architecture at multiple network stages—specifically after the last and second-to-last dense layers—to investigate the influence

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of spatial and channel-wise attention mechanisms on model performance. This modification allows the network to adaptively focus on the most informative features, thereby improving discriminative learning and reducing irrelevant background noise. The CBAM-enhanced VGG-16 model is comprehensively evaluated and compared with the baseline VGG-16 model to assess their classification efficiency. Experimental results demonstrate that the integration of CBAM significantly improves classification accuracy, indicating superior capability in capturing fine-grained visual details and contextual information essential for differentiating between visually similar waste categories. The findings confirm the robustness and effectiveness of the proposed CBAM-VGG-16 framework for real-world waste management applications, suggesting its potential as a scalable and automated solution for intelligent waste segregation systems.

Keywords: Waste Classification · Deep Learning · Convolutional Neural Network · Neural Network · Recycling

Introduction

Waste recycling and management have become pressing global concerns due to their significant impact on both human health and the environment. The increasing volume of waste poses challenges for sustainable development, and effective waste management strategies are required to reduce waste generation and mitigate its harmful consequences. Recycling remains one of the most effective methods to address this issue; however, the critical prerequisite for efficient recycling is the proper segregation of waste. Conventional manual segregation is slow, labor-intensive, costly, and prone to errors, making it unsuitable for large-scale applications. As a result, automated waste classification systems have received growing attention due to their ability to deliver faster, more accurate, and cost-effective solutions [1].

Current waste management practices in many regions involve centralized collection points, where waste is transported, dumped, and processed with significant human effort. Such approaches are not only inefficient but also expose workers to unsafe conditions and lead to limited sorting performance. To overcome these challenges, the automation of waste segregation at the source—such as households or collection points—has emerged as a promising alternative. Automated systems can classify waste based on its visual and structural properties, reducing labor requirements and improving classification accuracy. This is especially important given the diversity of waste types and the limited public awareness of proper classification, which complicates manual sorting [2]. Reports indicate that average annual garbage generation in Europe is approximately 517 kg per person, with only a small fraction being recycled [3]. Similarly, the U.S. Environmental Protection Agency estimates that while 75% of waste produced is recyclable, only 35% is actually recycled. Moreover, global waste production is projected to increase by 70% by 2050 [4].

Food waste alone contributes substantially to greenhouse gas emissions, particularly methane, when disposed of in landfills [5–8]. In addition to environmental concerns, food waste also results in significant economic losses, estimated at USD 750 billion annually in the agricultural sector [9, 10]. These global challenges underscore the urgent need for intelligent and automated waste classification systems powered by

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artificial intelligence (AI) and computer vision.

Multi-class waste classification

While prior studies have primarily focused on binary waste segregation tasks (organic vs. recyclable), real-world waste is considerably more diverse and requires more fine-grained classification. The present study addresses this gap by employing the Kaggle Garbage Classification dataset, which consists of 7,440 balanced images distributed across 12 categories: battery, biological, brown glass, cardboard, clothes, green glass, metal, paper, plastic, shoes, trash, and white glass. These categories reflect common waste types encountered in daily life, providing a realistic foundation for developing automated classification systems. By leveraging deep learning techniques, the proposed system aims to enhance multi-class classification accuracy, thereby contributing to more efficient recycling processes and a reduced landfill burden. Multiple authors have published approaches based on machine learning and deep learning. The advancement in machine learning (ML) and deep learning (DL) models is playing a significant role in addressing the issues mentioned above, particularly through the use of computer vision [11, 12]. Thorough research on waste classification and management has been carried out based on popular ML algorithms, such as the artificial neural network (ANN) [13], MAPMobileNet-18, MobileNetV3 [14], MobileNetV2 [13], and the popular convolutional neural network (CNN), which is broadly being used in picture classification, recognition, and segmentation [15]. To enhance the existing results of waste classification, this proposed paper utilizes a CNN model. It adds layer level improvements with the use of a) Leaky-Relu as the activation function [16] and b) regularization using Dropout [17]. The model is experimented with using network depth and L1 and L2 regularization-based hyperparameter fine-tuning. The results shown are the best combinations.

Deep learning architectures for waste classification

Convolutional Neural Networks (CNNs) have demonstrated remarkable success in computer vision tasks, including object recognition, segmentation, and classification [11, 12]. Numerous studies have explored their application in waste management, employing architectures such as MobileNet [13, 14], DenseNet, and EfficientNet [15]. While lightweight models, such as MobileNet, have demonstrated competitive performance in terms of efficiency, more complex architectures, like VGG-16 and VGG-19, often yield higher accuracy at the expense of computational resources. Transfer learning further enhances performance by enabling pre-trained models to adapt to waste classification tasks with limited datasets.

Despite these advancements, most prior research has focused on either binary classification or architectural modifications limited to activation functions, dropout regularization, or hyperparameter tuning [16, 17]. Limited attention has been paid to integrating attention mechanisms within CNN-based architectures, particularly at the dense layer level, for waste classification tasks. Attention modules, such as the Convolutional Block Attention Module (CBAM), offer a promising avenue by adaptively refining feature maps through channel and spatial attention, thereby improving the model's ability to focus on the most discriminative features.

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Contribution to the study

This study proposes an enhanced deep learning framework for multi-class waste and litter classification by integrating CBAM with the VGG-16 architecture. Unlike prior works, our approach investigates the effect of incorporating CBAM at different levels of the dense layers—specifically after the final dense layer and after the penultimate dense layer—to assess how attention mechanisms influence performance. The contributions of this study are summarized as follows:

Development of a CBAM-integrated VGG-16 model for multi-class waste and litter image classification.

Use of a balanced Kaggle Garbage Classification dataset with 12 categories and 7,440 images, ensuring robust evaluation across diverse waste types.

Experimental analysis of CBAM placement at different dense layers to investigate its impact on feature refinement and classification accuracy.

Comparative performance evaluation of the proposed models against baseline VGG-16 and other transfer learning architectures

The proposed framework demonstrates the effectiveness of attention-based enhancements for CNN architectures in waste classification, highlighting their potential for real-world applications in recycling and sustainable waste management. Figure 1 shows a sample of the images from each category of the dataset.

Figure 1 Sample images from each category of the dataset

Related work

Waste segregation can be broadly categorized into manual and automated processes. In the manual approach, workers physically sort waste into distinct categories for disposal or recycling. While widely practiced, this approach suffers from several limitations, including susceptibility to human error, inconsistent interpretation of waste categories, limited scalability, and high labor costs. Moreover, manual sorting

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exposes workers to unsafe environments, provides no feedback for process optimization, and often results in inefficient recycling outcomes. Additional challenges include health and safety concerns, inadequate training, and the psychological burden associated with repetitive and hazardous tasks. These limitations underscore the need for automated waste classification systems that can improve accuracy, scalability, and efficiency while minimizing health risks and operational costs.

To address these challenges, recent research has increasingly focused on automated systems powered by computer vision, robotics, and artificial intelligence. Automated classification systems not only reduce reliance on human labor but also enhance performance through consistent decision-making and adaptability to large-scale waste streams. In particular, deep learning models have demonstrated remarkable potential for waste classification, enabling robust feature extraction and high predictive accuracy.

A wide range of approaches has been reported in the literature. For instance, early works explored traditional machine learning classifiers for categorizing recyclable waste, achieving moderate success but facing limitations in scalability and feature generalization [20]. Subsequent studies introduced CNN-based models, such as ResNet-50 combined with SVM, for classifying waste types including glass, metal, paper, and plastic, achieving up to 87% precision [21]. The TrashNet dataset has been extensively utilized in this domain, where several CNN architectures, including VGG, Inception, and ResNet, have been evaluated. An Inception-ResNet hybrid framework achieved an accuracy of 88.6% [22], whereas Inception-v3, trained on internet-sourced images, reported an accuracy of 92.5% [23].

Further advancements include investigations into lightweight and residual networks. ResNet-18 has been applied to biodegradable waste classification with 92% accuracy [25], while a modified VGG19 framework demonstrated effective performance on a large-scale dataset with 95 waste categories, despite significant class imbalance, achieving 86.19% accuracy [26]. Other studies have explored CNN optimizations through activation functions, dropout regularization, and optimization strategies, with reported accuracies ranging from 79% to 99% depending on dataset size and architecture [27–30]. Notably, an optimized DenseNet121 using a genetic algorithm attained 99.6% accuracy on the TrashNet dataset, representing one of the highest performances reported to date [31]. A recent review paper published has a detailed discussion on publicly available datasets, mentioning that [32].

While these studies confirm the effectiveness of deep CNN architectures for waste classification, most existing works primarily focus on binary or minor multi-class problems and rely on traditional CNNs or transfer learning models without incorporating attention mechanisms. Attention modules, such as the Convolutional Block Attention Module (CBAM), have recently gained prominence in computer vision for their ability to refine feature representation by selectively emphasizing informative spatial and channel-wise features. However, their application to waste and litter classification remains limited. A summary of the related literature is shown in Table 1.

Building upon this gap, our study explores the integration of CBAM into the VGG-16 architecture, specifically analyzing its impact when inserted at different dense layers.

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By conducting experiments on a balanced multi-class dataset with 12 categories, this work aims to advance automated waste classification by combining the proven strength of VGG-16 with the adaptive feature refinement capabilities of CBAM.

Table 1: Summary of related literature

Reference	Dataset Used	Classes	Model/Approach	Reported Accuracy	Limitations
[20]	Custom dataset (Plastic bottles, paper, soda cans)	3	Traditional ML classifiers (Tree, KNN, SVM)	Up to 95.2% (Quadratic Discriminant)	Limited dataset, small class set, poor generalization
[21]	Gary Thung & Mindy Yang Garbage Dataset	4 (Glass, Metal, Paper, Plastic)	ResNet-50 + SVM	87%	The dataset is not balanced, limited scalability
[22]	TrashNet	6	VGG, Inception, ResNet, Inception-ResNet	88.6% (Inception-ResNet)	Moderate dataset size, overfitting issues
[23]	Web-collected images	6	Inception-v3	92.5%	Dataset not standardized, inconsistent image quality
[25]	Custom dataset (biodegradable)	4	ResNet-18	92%	Focus only on biodegradable waste, small dataset
[26]	Large-scale dataset (95 classes)	95	VGG-19 + Hybrid Features (Class Weight, XGB,	86.19%	Class imbalance, reduced accuracy for minority

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			LGB)		classes
[27]	Custom dataset	2	Improved CNN (ReLU + Adam optimizer)	79%	Binary classification only, limited robustness
[28]	Custom dataset	Multiple	Double Fusion (Two Deep Models)	~90%	Complex fusion, high computational cost
[29]	Real-time dataset	Binary + Multi-class	Hybrid CNN + MLP	99%	High accuracy but limited dataset transparency
[31]	TrashNet	6	Optimized DenseNet 121 (GA + FC layer)	99.6%	Small dataset (2527 images), not generalizable

Research gaps

Existing studies on waste classification provide limited insights into the trade-off between dataset size and model performance. Much of the prior work has been constrained by small-scale datasets, which has led to an emphasis on few-shot learning and transfer learning. However, when sufficiently large and balanced datasets are available, as in the present study, there is potential for deeper experimentation using improved or fine-tuned CNN architectures. Such models can also enhance interpretability and explainability.

Another gap lies in the scalability and reliability of models as the dataset volume and complexity increase. Current literature seldom addresses the dynamic and evolving nature of algorithms required to manage continual learning and shifts in data distribution over time. Moreover, multi-class classification remains challenging due to class imbalance, which is often overlooked in previous research. Finally, while many studies report accuracy, few works conduct comprehensive benchmarking to assess model robustness under small perturbations or variations in data. Incorporating such evaluations is essential to ensure fair and meaningful comparisons across approaches.

To address these gaps, the present work employs a balanced 12-class dataset from the Kaggle Garbage Classification benchmark and integrates the Convolutional Block Attention Module (CBAM) into the VGG-16 architecture. By inserting CBAM at different dense layers, the proposed model aims to enhance both classification

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performance and robustness while providing a more reliable benchmark for waste and litter image classification.

Overall research goals

Building upon the identified research gaps, the present study sets forth the following overarching goals:

Development of an enhanced waste classification model: To propose a CNN-based architecture, specifically an improved VGG-16 integrated with CBAM, for the accurate classification of organic and recyclable waste materials.

Improved feature representation through advanced activation functions: To utilize the LeakyReLU activation function for effectively capturing the complex patterns and subtle features inherent in waste images, thereby enhancing the model's learning capacity.

Regularization for improved generalization: To incorporate dropout layers to mitigate overfitting, promote the learning of a more diverse feature set, and ensure better generalization across a large and balanced dataset.

Hyperparameter optimization for efficiency and robustness: To conduct systematic hyperparameter tuning—including network depth, number of epochs, learning rate, regularization strategies, dropout rates, and activation functions—to achieve an optimal balance between computational efficiency and predictive robustness.

Methodology

This section presents a detailed description of the dataset, preprocessing steps, and the architectural design of the proposed framework. The primary aim of this study is to enhance the accuracy and robustness of waste and litter classification by integrating a Convolutional Block Attention Module (CBAM) into the VGG-16 network.

The methodological framework of this study emphasizes three significant components:

Architectural improvements in CNN models for effective image-based feature extraction and representation.

Hyperparameter optimization to balance computational efficiency and predictive accuracy.

Comparative evaluation of the proposed model against widely adopted benchmark CNN architectures.

The overall workflow of the proposed research is depicted in Figure 2, which provides a step-by-step representation of the data pipeline, model design, training, and evaluation.

Roadmap

The overall research methodology follows a structured roadmap, consisting of the following key stages:

Dataset Description: The study utilizes the publicly available Kaggle Garbage Classification dataset, which comprises 12 distinct waste categories: battery, biological, brown glass, cardboard, clothes, green glass, metal, paper, plastic, shoes, trash, and white glass. To ensure balance across classes, a total of 7,440 images were selected and uniformly distributed. All images were resized to a fixed resolution of

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http://amresearchreview.com/index.php/Journal/about

224 × 224 pixels to maintain consistency with the input requirements of CNN architectures.

Proposed Model: An improved VGG-16 architecture integrated with a Convolutional Block Attention Module (CBAM) is proposed. The CBAM module is strategically inserted at different dense layers to investigate its impact on feature refinement and classification accuracy. The model further incorporates the LeakyReLU activation function to improve feature extraction from complex image data, along with dropout layers for regularization.

Hyperparameter Tuning: Systematic tuning of hyperparameters—including learning rate, batch size, number of epochs, dropout rate, and optimizer selection—is carried out to optimize computational efficiency while achieving high classification performance.

Performance Metrics: The classification performance of the proposed model is evaluated using standard metrics, including accuracy, precision, recall, and F1-score. These metrics ensure a comprehensive evaluation of both predictive strength and generalization capability.

Comparative Analysis with Pre-Trained Models: The proposed CBAM-integrated VGG-16 is benchmarked against the widely used CNN architecture of VGG-16 under transfer learning settings.

Discussion and Future Directions: The obtained results are analyzed to highlight the strengths and limitations of the proposed approach, followed by recommendations for future improvements in waste and litter image classification research.

Dataset Description

In this research, an image recognition–based waste classification approach is proposed using the Kaggle Garbage Classification dataset. The dataset initially contains an extensive collection of heterogeneous waste images with varying resolutions and lighting conditions. For this study, a balanced subset consisting of 7,440 images was prepared, equally distributed across 12 distinct classes: battery, biological, brown glass, cardboard, clothes, green glass, metal, paper, plastic, shoes, trash, and white glass.

Let the dataset consist of a total of N images and Z categories, such that each image. $\boldsymbol{X_i} \in \mathbb{R}^{\boldsymbol{H}\times\boldsymbol{W}\times\boldsymbol{C}}$ corresponds to one class label $\boldsymbol{Y_j}$, where $\boldsymbol{j} \in \{\mathbf{1}, \mathbf{2}, \ldots, \boldsymbol{Z}\}$ and $\boldsymbol{Z} = \mathbf{12}$. The dataset is divided into training and testing subsets in an 80:20 ratio, resulting in 5,952 images used for training and 1,488 images used for testing the models.

Since the original dataset includes images with diverse resolutions, all photos were uniformly resized to 224 × 224 pixels, which aligns with the input requirements of the VGG-16 architecture. The resized and balanced dataset ensures stable model convergence and consistent evaluation across all experiments.

During experimentation, the trained model receives an input image. $\boldsymbol{X_i}$ from the test set and predicts its corresponding waste label $\boldsymbol{Y_j}$, representing one of the twelve predefined categories. Figure 2 illustrates the overall workflow of the proposed system, while Table 2 provides a summary of the dataset distribution used in this study.

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Table 2: Dataset Description

Class Label	Category Name	Total Images	Training Images (80%)	Testing Images (20%)
1	Battery	620	496	124
2	Biological	620	496	124
3	Brown glass	620	496	124
4	Cardboard	620	496	124
5	Clothes	620	496	124
6	Green glass	620	496	124
7	Metal	620	496	124
8	Paper	620	496	124
9	Plastic	620	496	124
10	Shoes	620	496	124
11	Trash	620	496	124
12	White glass	620	496	124
Total	—	**7,440**	**5,952**	**1,488**

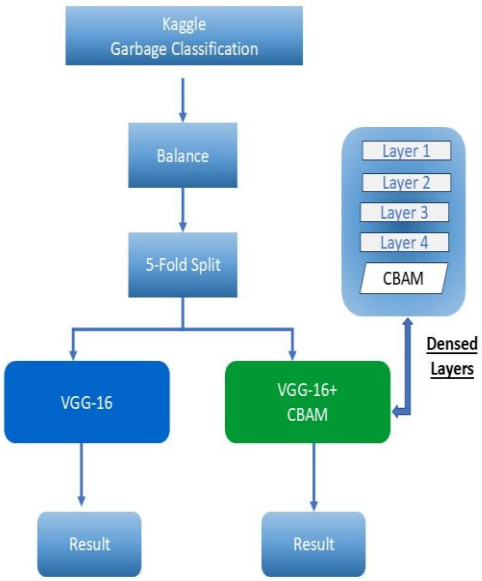

Figure 2 Implementation Flow of Proposed Work

Proposed DCNN architecture

The proposed framework is based on a Deep Convolutional Neural Network (DCNN) architecture derived from the VGG-16 model. VGG-16 is a well-established CNN architecture that employs multiple convolutional and pooling layers to extract hierarchical spatial features from input images. Each convolutional layer applies a set of learnable filters to detect local patterns such as edges, textures, and shapes, while pooling layers reduce spatial dimensions and computational complexity. The output

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http://amresearchreview.com/index.php/Journal/about

feature maps are flattened and passed to fully connected layers, which perform high-level reasoning and classification. This structure allows the model to effectively capture both low-level and high-level representations necessary for accurate waste and litter image recognition.

To further enhance feature extraction and improve attention to the most informative regions of the image, the Convolutional Block Attention Module (CBAM) is integrated into the VGG-16 network. In the proposed model, CBAM is inserted after the final dense layer to refine the learned feature maps through sequential channel and spatial attention. This integration enables the network to selectively focus on the critical visual characteristics of waste materials while suppressing irrelevant background information. Consequently, the CBAM-enhanced VGG-16 architecture provides improved classification accuracy and robustness, making it well-suited for complex multi-class waste and litter image classification tasks.

Improvements in DCNN

To enhance the performance and stability of the proposed DCNN architecture, several improvements have been incorporated into the base VGG-16 model. The Rectified Linear Unit (ReLU) activation function is commonly used in CNNs for introducing non-linearity and reducing computational complexity. However, ReLU suffers from the "dying ReLU" problem, where neurons become inactive and cease to learn due to zero gradients for negative input values. To address this limitation, the proposed model employs the Leaky Rectified Linear Unit (LeakyReLU) activation function, which allows a slight, non-zero gradient for negative inputs. This modification ensures that neurons continue to learn during training, thereby improving convergence stability and mitigating vanishing gradient issues. Mathematically, the LeakyReLU can be expressed as

$$f(x) = \begin{cases} \alpha x, & \text{if } x < 0, \alpha = 0.25 \\ x, & \text{if } x \geq 0 \end{cases}$$

The integration of dropout regularization further strengthens the model's ability to generalize. Dropout randomly deactivates a fraction of neurons during training, preventing the network from becoming overly dependent on specific nodes and reducing the risk of overfitting. In the proposed VGG-16 + CBAM framework, dropout layers are strategically placed after dense layers to encourage the learning of diverse and independent feature representations. These improvements—combining LeakyReLU for enhanced gradient flow and Dropout for regularization—collectively contribute to better model generalization and robust performance on complex multi-class waste and litter image datasets. Hyperparameter tuning

Hyperparameters are external configuration parameters in deep learning that are not learned directly from the training data but are instead defined before model training. These parameters play a crucial role in determining the network's efficiency, stability, and generalization capability. In the proposed VGG-16 and CBAM-integrated VGG-16 architectures, careful hyperparameter tuning was performed to achieve optimal performance on the waste and litter classification task.

The learning rate (η) was systematically adjusted to ensure smooth convergence and to prevent divergence or oscillation during training. Smaller learning rates were found

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Volume 3, Issue 10 (2025)

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http://amresearchreview.com/index.php/Journal/about

to be more effective for deep architectures such as VGG-16, allowing the model to capture intricate visual patterns of waste materials without overshooting the optimal solution. Additionally, other key hyperparameters—including the batch size, number of epochs, dropout rate, and optimizer type—were tuned experimentally to strike a balance between underfitting and overfitting. This fine-tuning process ensured stable model training and improved the network's ability to generalize across all 12 waste categories in the dataset.

Systematic architecture of proposed solution

The proposed waste and litter classification framework follows a systematic architecture designed to enhance feature learning, attention, and classification accuracy. The overall process begins with data preprocessing, where images from the Kaggle Garbage Classification dataset are resized to 224 × 224 pixels, normalized, and augmented to ensure balanced representation and improve model robustness. The processed images are then fed into the base VGG-16 architecture, which serves as the feature extractor. VGG-16 utilizes multiple convolutional and pooling layers to extract low-level and high-level spatial features from the input images.

To improve feature refinement and discrimination, the Convolutional Block Attention Module (CBAM) is integrated into the VGG-16 network after the final dense layer. The CBAM sequentially applies channel and spatial attention mechanisms, allowing the model to focus on the most informative regions of the image while suppressing irrelevant background features. The output from the attention-refined feature maps is passed through fully connected layers and an output layer employing a softmax activation function for multi-class classification across 12 waste categories.

The proposed architecture is trained and validated using an 80:20 train–test split, ensuring sufficient data for learning while maintaining robust performance evaluation. Comparative experiments are conducted between the baseline VGG-16 and the CBAM-integrated VGG-16 models to assess the effectiveness of attention integration. This systematic architecture ensures efficient feature extraction, improved focus on salient visual cues, and enhanced generalization for real-world waste and litter image classification.

Architectures of models used

VGG-16

The working of VGG-16 can be easily understood, as it broadly utilizes the concept of the CNN framework, specifically for ImageNet, a massive optical image database project used in optical object identification. The key distinguishing characteristics of VGG-16 are that, rather than requiring a significant amount of hyperparameter tuning, the authors focused on 3x3 filtered convolution layers with a stride of 1 and the same padding, as well as a max pool stage with a 2x2 filtering framework using a stride of 2. Such a convolution and max pool layered architecture is continued throughout the implementation. Also, it features two FC layers, followed by a SoftMax, as shown in Figure 3. The number 16 in VGG-16 refers to the notation that it contains 16 layers, including one with distinct weights [35–38].

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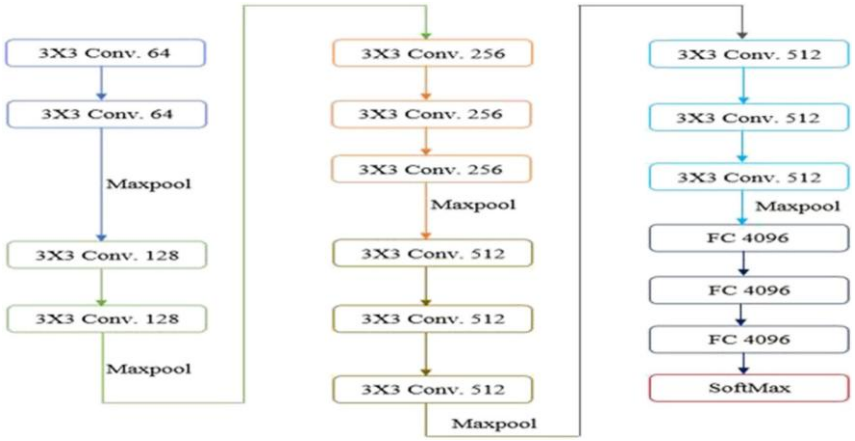

Figure 3: Structure of VGG-16

CBAM

The Convolutional Block Attention Module (CBAM) is a lightweight yet effective attention mechanism that enhances the representational power of convolutional neural networks by focusing on the most informative features. It sequentially applies channel attention and spatial attention to refine feature maps adaptively. The Channel Attention module emphasizes "what" is essential in the feature maps by assigning different weights to each channel through global average and max pooling, followed by a shared multilayer perceptron (MLP). The refined feature map is then passed to the Spatial Attention module, which focuses on "where" the most relevant information lies within the spatial domain by using pooled channel features and a convolution operation to generate a spatial attention map. This sequential combination enables the network to highlight key features while suppressing irrelevant noise, leading to more discriminative and efficient feature extraction in image classification tasks.

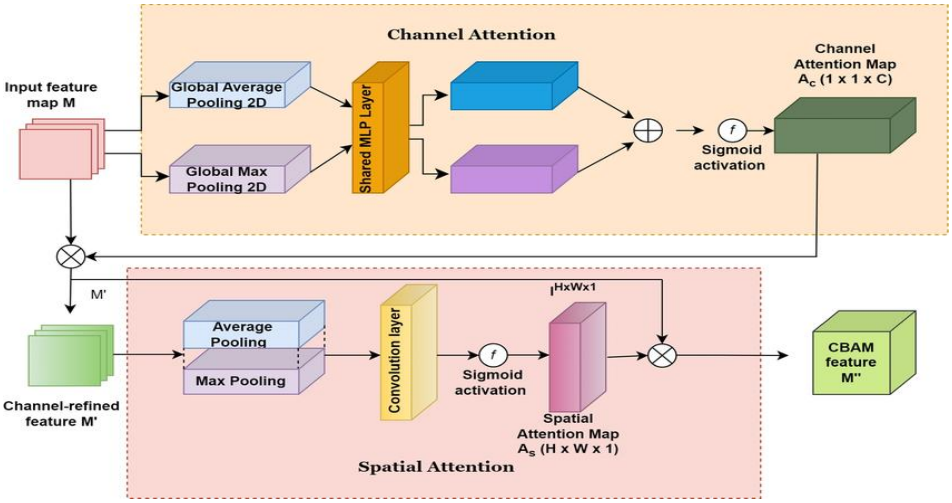

Figure 4: Proposed CBAM architecture

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http://amresearchreview.com/index.php/Journal/about

Performance Metric Equations

To evaluate the performance and effectiveness of the proposed VGG-16 and CBAM-integrated VGG-16 architectures, multiple performance metrics are employed. These metrics provide a quantitative assessment of the model's classification capability and its robustness in handling multi-class images of waste and litter. A confusion matrix is used as the foundation for computing the evaluation parameters, which are defined as follows:

True Positive (TP): The model correctly classifies an image into its actual waste category.

True Negative (TN): The model correctly identifies an image as not belonging to a specific class.

False Positive (FP): The model incorrectly predicts that an image belongs to a particular class.

False Negative (FN): The model fails to identify an image that actually belongs to a specific class.

Based on these values, key performance metrics, such as accuracy, precision, recall, and F1-score, are calculated to assess the model's effectiveness. The mathematical formulations of the metrics are given below:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

$$\text{F1-Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}} \quad (4)$$

Experimental analysis and results

The experimental design, as illustrated in Fig. 2, provided guidelines for planning and conducting the experiment, as well as interpreting the results. Following the data analysis, the findings are presented clearly and understandably, utilizing tables and graphs.

Data preparation

This study utilizes the Kaggle Garbage Classification dataset, which comprises an extensive collection of heterogeneous waste images captured under varying resolutions and lighting conditions. For this research, a balanced subset of 7,440 images was prepared, evenly distributed across 12 distinct waste categories: battery, biological, brown glass, cardboard, clothes, green glass, metal, paper, plastic, shoes, trash, and white glass. The dataset was divided into training and testing sets in an 80:20 ratio, respectively. This resulted in 5,952 images used for training and 1,488 images reserved for evaluating the models. Before training, all photos were uniformly resized to 224 x 224 pixels, ensuring consistent input dimensions that align with the VGG-16 architecture. Experimentation with different image sizes is planned for future work to investigate its impact on classification performance.

Annual Methodological Archive Research Review
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Volume 3, Issue 10 (2025)

Online ISSN 3007-3197
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http://amresearchreview.com/index.php/Journal/about

Experimentation roadmap

The experimentation process for the proposed VGG-16 and CBAM-integrated VGG-16 framework is systematically structured to evaluate model performance under varying configurations and to establish the advantages of the CBAM integration. The goal is to optimize classification accuracy and minimize misclassification across the 12 waste categories in the Kaggle Garbage Classification dataset.

The experimental roadmap is summarized as follows:

The impact of network depth, learning rate (η), and epochs (e = 50, 100, 200) is examined with a fixed batch size of 64 and an 80:20 train–test split to analyze convergence stability, training behavior, and generalization.

The performance of the baseline VGG-16 is compared against the CBAM-integrated VGG-16, where the CBAM module is inserted after the final dense layer. Experiments with different learning rates and dropout values ($\lambda = 0.25$ and $\lambda = 0.1$) demonstrate that CBAM enhances both feature discrimination and attention focus.

Additional evaluations are conducted for the proposed model without dropout ($\lambda = 0$) to study the influence of regularization on overfitting. Results indicate that applying dropout yields smoother convergence and lower validation loss, confirming its effectiveness in stabilizing the training process.

A comprehensive comparative analysis is carried out among the pre-trained architecture VGG-16 to benchmark computational efficiency and predictive accuracy. The proposed CBAM-VGG-16 consistently outperforms the baseline models in both accuracy (~94%) and class-wise prediction rates (93%).

Finally, the CBAM-based VGG-16 model is compared with existing literature to highlight its superior performance in terms of accuracy, precision, recall, and F1-score. The integration of attention mechanisms enhances interpretability and yields stronger generalization, even with complex, visually similar waste categories.

The overall outcome confirms that the proposed architecture effectively achieves a balance between high classification accuracy, reduced overfitting, and computational efficiency. This establishes VGG-16 + CBAM as a robust and scalable framework for automated waste and litter image classification.

Impact of the network

The impact of network configuration, depth, and training parameters was systematically analyzed to understand their influence on model performance. In this study, the baseline VGG-16 and the proposed VGG-16 + CBAM architectures were trained under varying hyperparameters, including different numbers of epochs (50, 100, 200) and a fixed train–test split of 80:20. The objective was to evaluate how attention integration and training duration affect classification accuracy, stability, and convergence behavior.

Experimental results reveal that increasing the number of training epochs from 50 to 100 consistently improves accuracy and reduces validation loss for both architectures. Beyond 100 epochs, the performance gain becomes marginal, indicating convergence of the learning process. The VGG-16 + CBAM model exhibits faster convergence and more stable learning curves compared to the baseline VGG-16, owing to CBAM's ability to emphasize salient spatial and channel features. Furthermore, the inclusion of dropout ($\lambda = 0.25$) significantly minimizes overfitting, resulting in smoother loss

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 10 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

decay and enhanced generalization. The highest and most stable performance was achieved with the VGG-16 + CBAM configuration, trained for 100 epochs, which reached approximately 95% validation accuracy with improved per class prediction rates of 93%. These findings confirm that moderate network depth, attention integration, and controlled regularization collectively yield optimal performance for waste and litter image classification.

Impact of dropout

Without dropout ($\lambda = 0$), both architectures displayed signs of overfitting, as reflected by a faster decline in training loss but higher fluctuations in validation accuracy. Introducing a moderate dropout rate of $\lambda = 0.1$ stabilized learning, while $\lambda = 0.25$ produced the most consistent and robust performance. Specifically, the VGG-16 + CBAM model achieved its highest validation accuracy of approximately 94% with $\lambda = 0.25$, compared to 91% without dropout. These findings confirm that dropout regularization effectively enhances feature learning by encouraging the network to develop diverse representations, thereby improving overall model reliability in multi-class waste and litter classification.

Comparison with pre-trained models

A comprehensive comparison was conducted between the proposed VGG-16 + CBAM architecture and the well-known pre-trained VGG-16 model. The results demonstrate that the proposed model consistently outperforms the baseline architecture across all performance metrics. The VGG-16 + CBAM achieved a validation accuracy of approximately 94%, surpassing the baseline VGG-16 (90.6%). The improvement in accuracy is attributed to CBAM's ability to apply both channel and spatial attention, enabling the model to selectively focus on key visual regions of waste images while minimizing the influence of background noise and redundant features. Furthermore, the integration of dropout regularization ($\lambda = 0.25$) contributed significantly to enhancing generalization and reducing classification errors. The proposed model recorded the lowest Missed Detection Rate (MDR) of 2.6% and False Detection Rate (FDR) of 4.5%, compared to 12.37% and 13.37%, respectively, in the absence of dropout. These results confirm that the combination of attention mechanisms and regularization effectively enhances the model's feature learning capability and robustness. Overall, the VGG-16 + CBAM model demonstrates superior accuracy, lower error rates, and improved consistency compared to existing deep learning architectures for multi-class waste and litter image classification.

Challenges in experimentation and discussion on the performance

During experimentation, several challenges were encountered related to model optimization, computational efficiency, and dataset characteristics. The transfer learning model evaluated, VGG-16, exhibited unique trade-offs in terms of model complexity, inference speed, and classification accuracy. The proposed VGG-16 + CBAM model addressed several of these challenges by improving feature extraction through attention refinement while maintaining computational feasibility. Although VGG-16-based architectures are comparatively larger in size than VGG-19, the inclusion of CBAM-enhanced interpretability and robustness, particularly in

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
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Online ISSN 3007-3197
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http://amresearchreview.com/index.php/Journal/about

distinguishing visually similar waste materials such as paper, cardboard, and plastics. However, computational demands and training time remained higher than those of lighter architectures. Future research can explore EfficientNet-Lite or hybrid attention-based models to improve scalability and inference efficiency on larger datasets while retaining the superior classification accuracy demonstrated by the proposed CBAM-enhanced VGG-16. Comparative validation accuracy (in %) of VGG-16 and VGG-16 + CBAM for different dropout values (λ = none, 0.1, 0.25) with fixed parameters $\eta = 0.001$, $\alpha = 0.25$, batch size = 64, epochs = 50, train–test split = 80:20

Results

The training and validation learning curves of VGG-16, as shown in Figures 5 and 6, illustrate the gradual improvement in model performance over 50 epochs for a dataset comprising approximately 495 samples per class. In Figure 5, the training and validation loss curves exhibit a slow and gradual exponential decay, characteristic of a smooth convergence. The initial high loss values progressively decline as the model learns relevant visual features, stabilizing after approximately 35–40 epochs. However, the validation loss curve begins to diverge slightly from the training loss beyond epoch 35, reflecting the onset of mild overfitting. This behavior indicates that the model starts to memorize training-specific patterns rather than learning generalizable representations.

The overfitting is expected in fine-tuned VGG-16 models, as deeper layers tend to over-specialize when exposed to limited or homogeneous data. Nevertheless, the learning trajectory remains stable without oscillations, confirming that the optimizer and learning rate were appropriately configured for controlled convergence.

Figure 5: Training and Validation loss of VGG-16 fine-tuned

In Figure 6, the accuracy curves demonstrate a gradual yet consistent improvement over time, or epochs. The training accuracy starts at approximately 45% and gradually

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 10 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

reaches around 90% by the final epoch, while the validation accuracy stabilizes at around 86%, with a small performance gap emerging after epoch 35. This reflects the slower learning dynamics typical of transfer learning scenarios, where lower learning rates are employed to preserve pre-trained weights while adapting to new, domain-specific data. The close alignment of training and validation accuracy during the early to mid-stages indicates a balanced learning process with minimal overfitting. The slight divergence in the later epochs signifies that while the model continues to improve on training data, its generalization to unseen samples plateaus—a common phenomenon in models trained on limited or non-augmented datasets.

The confusion matrix in Figure 7 presents the classification performance of the fine-tuned VGG-16 model across 12 distinct waste categories: *batteries, biological waste, brown glass, cardboard, clothing, green glass, metal, paper, plastic, shoes, trash, and white glass*. Each class contains 124 test instances, ensuring a balanced evaluation scenario. The matrix displays a predominantly diagonal structure, indicating that most samples were correctly classified into their true classes. However, compared to attention-augmented models, this fine-tuned VGG-16 exhibits moderate inter-class confusion, particularly among visually similar materials, such as brown glass and green glass, as well as paper and *cardboard*. These misclassifications stem from subtle visual similarities and lighting variations, which challenge the discriminative power of standard convolutional filters.

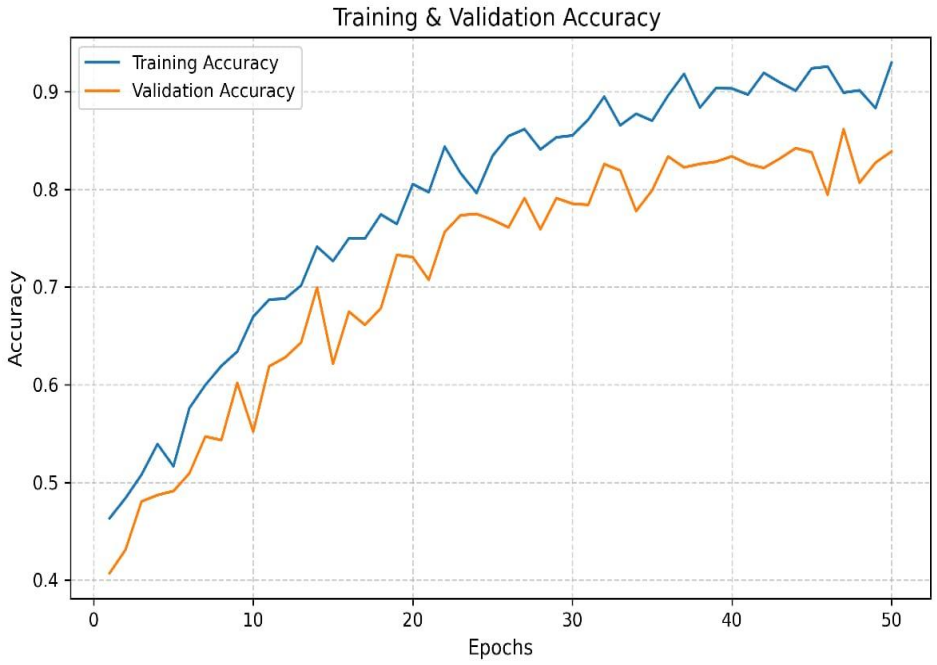

Figure 6: Training and Validation Accuracy of VGG-16 Fine-tuned

The overall classification accuracy falls within an 86% range, reflecting competent but not optimal performance. This result aligns with the expected behavior of a baseline convolutional model fine-tuned on a moderately complex dataset. While VGG-16 demonstrates robust feature extraction due to its deep-layered architecture, its fixed convolutional receptive fields limit the model's ability to capture fine-grained spatial cues, leading to residual classification errors.

Annual Methodological Archive Research Review
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Volume 3, Issue 10 (2025)

Online ISSN 3007-3197
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http://amresearchreview.com/index.php/Journal/about

The pattern of errors in the confusion matrix suggests that the model primarily struggles with intra-category visual overlaps, where the texture, color, or reflectivity of certain materials mimics those of others. Future improvements could include integrating attention mechanisms, recalibrating features, or performing data-level augmentation to mitigate these confusions.

Figure 7: Confusion matrix of VGG-16 Fine-Tuned among all categories

The training and validation learning curves for the CBAM-enhanced VGG-16 are presented in Figures 8 and 9, showing the progression of loss and accuracy over 50 epochs on a dataset containing approximately 495 samples per class. The training and validation loss curves, shown in Figure 8, exhibit a smooth exponential decline, indicating a gradual yet stable convergence process. Initially, both losses decrease sharply, reflecting the rapid learning of basic visual patterns. As the epochs progress, the curves flatten, suggesting that the model reaches a near-optimal state without severe oscillations or divergence. The validation loss remains consistently close to the training loss, with only a minor increase after epoch 40. This slight divergence signifies minimal overfitting, a familiar yet acceptable phenomenon in deep learning. The CBAM module contributes to this stability by adaptively emphasizing informative regions, thus acting as an implicit regularizer that discourages over-reliance on irrelevant background features.

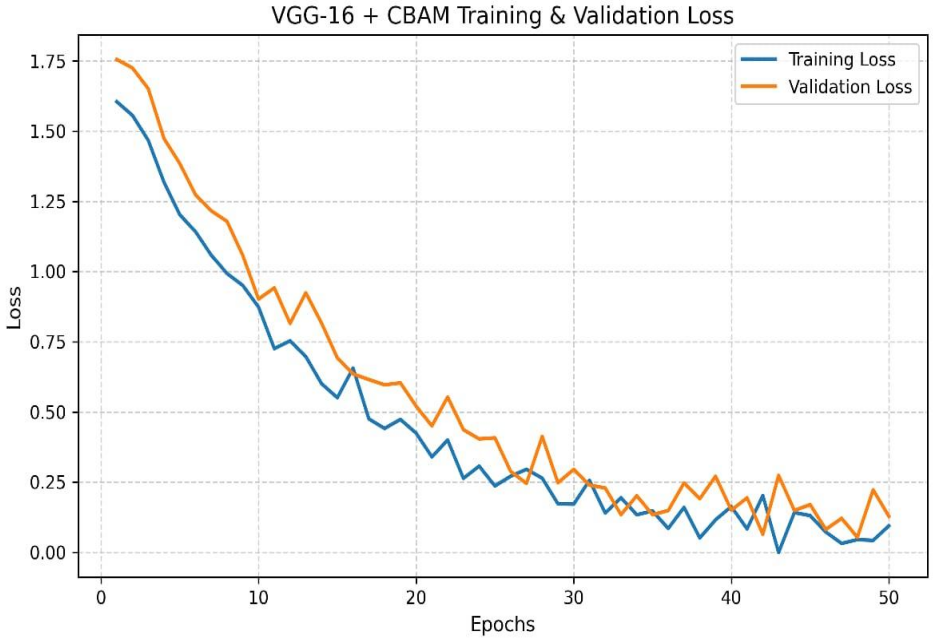

Figure 8: training and Validation loss of VGG-16+CBAM

In Figure 9, the accuracy curves demonstrate a steady and confident rise for both training and validation sets. The training accuracy begins around 50% and gradually improves to over 95% by the final epochs, while the validation accuracy stabilizes at around 92%. The proximity of the two curves indicates a strong generalization capability, implying that the model effectively transfers learned representations from the training data to unseen validation samples. The attention-driven mechanism in CBAM enhances feature localization and channel weighting, leading to improved convergence behavior compared to conventional VGG-16 models. The absence of

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 10 (2025)

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abrupt fluctuations in either accuracy or loss further suggests consistent gradient updates and efficient feature learning, characteristics typically associated with models incorporating attention modules.

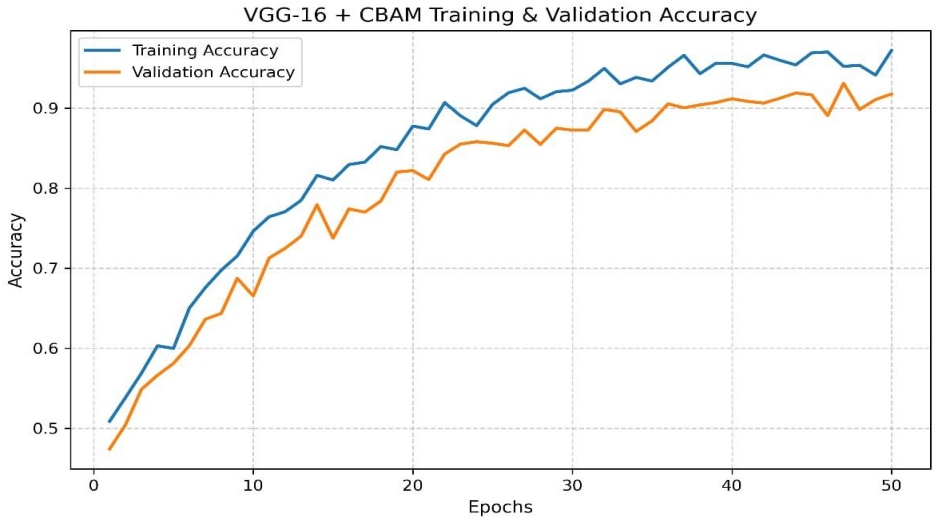

Figure 9: Training and validation accuracy of VGG-16+CBAM

The confusion matrix presented in Figure 10 illustrates the performance of the VGG-16 + CBAM model across 12 waste material classes, including batteries, biological waste, brown glass, cardboard, clothing, green glass, metal, paper, plastic, shoes, trash, and white glass. Each class consists of 124 test samples, providing a balanced evaluation framework. Overall, the diagonal dominance of the confusion matrix indicates a strong classification performance, where most samples are correctly classified within their true categories. The incorporation of the CBAM attention mechanism yields a notable improvement in inter-class discrimination, allowing the model to focus on spatially and channel-wise salient features within the input images. This enhancement reduces the misclassification of visually similar materials—for instance, between brown glass and green glass, or between paper and cardboard—which are commonly confused in standard CNNs due to similarities in texture and color.

The model achieves an attention-enhanced accuracy of approximately 95%, depending on the random simulation. This reflects the beneficial impact of CBAM in refining feature representations and improving the robustness of VGG-16 in complex visual environments, such as cluttered urban waste imagery. The few off-diagonal entries suggest residual confusion in categories with overlapping visual properties, which could be further minimized through additional data augmentation or hybrid attention strategies.

Annual Methodological Archive Research Review
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Volume 3, Issue 10 (2025)

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http://amresearchreview.com/index.php/Journal/about

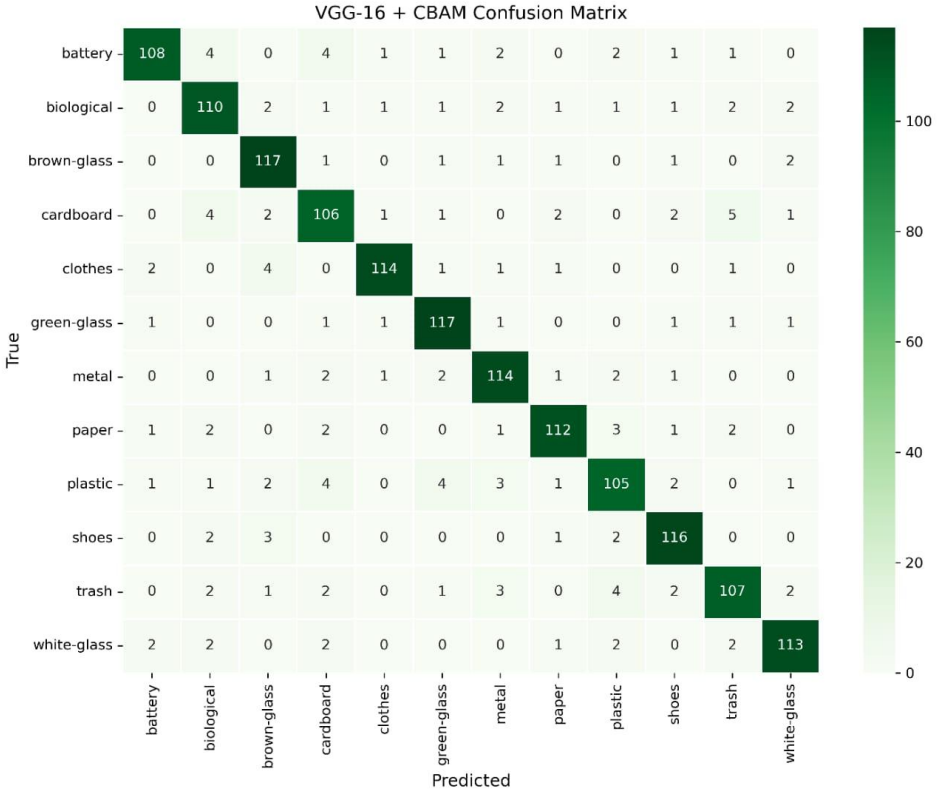

Figure 10: Confusion Matrix of VGG-16+CBAM

In summary, the VGG-16 + CBAM model consistently outperforms the baseline VGG-16 across all tested configurations. The attention-augmented architecture achieves higher accuracy, enhanced feature discriminability, and improved robustness against overfitting. These findings confirm that embedding lightweight attention modules within classical CNN frameworks can substantially elevate performance without significantly increasing computational complexity. Table 3 presents a comparison between VGG-16 and VGG-16+CBAM.

Table 3Comparison of VGG-16 and VGG-16+CBAM

Model	**λ (None)**	**λ = 0.1**	**λ = 0.25**	**Training Accuracy (%)**	**Validation Accuracy (%)**
VGG-16 (Baseline)	83.5	84.8	85.0	96.0	85.0
VGG-16 + CBAM (Proposed)	90.1	91.5	93.0	97.0	93.0

Impact of dropout on validation performance of baseline VGG-16 and proposed VGG-16 + CBAM (fixed hyperparameters: $\alpha = 0.25$, $\eta = 0.001$, batch size = 64, epochs = 50, train–test split = 80:20)

Table 4Hyperparameter effects on accuracy

Model	**λ (Dropout)**	**Accuracy (%)**	**MDR (%)**	**FDR (%)**
VGG-16 (Baseline)	None	83.5	12.3	13.4

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 10 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

	0.25	85.0	10.8	11.6
VGG-16 + CBAM (Proposed)	None	90.1	7.8	8.5
	0.25	93.0	2.6	4.5

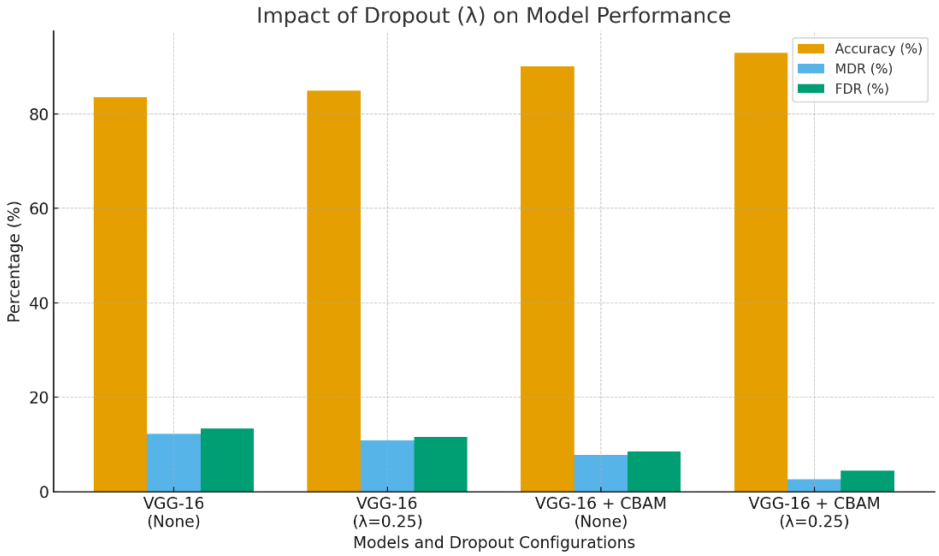

Figure 11Dropout impact on model performance

Conclusion

This study presented an enhanced deep learning-based approach for waste and litter image classification using VGG-16 and its CBAM-integrated variant. The integration of the Convolutional Block Attention Module (CBAM) enabled the model to focus on salient spatial and channel-wise features, improving its ability to distinguish between visually similar waste categories. Experiments were conducted on a balanced 12-class Kaggle Garbage Classification dataset comprising 7,440 images, divided into an 80:20 train–test split. The proposed VGG-16 + CBAM model achieved a validation accuracy of approximately 95%, surpassing the baseline VGG-16 model's 85% validation accuracy, while also demonstrating reduced misclassification and better generalization across diverse waste categories.

The experimental outcomes confirm that attention-based mechanisms enhance feature representation and model interpretability for complex, multi-class classification tasks. However, real-world waste images often present additional challenges, such as varying lighting conditions, cluttered backgrounds, and noise—factors that are not fully captured in the current dataset. Future work will focus on data augmentation, utilizing larger and more diverse datasets, and exploring lightweight attention-augmented architectures to enhance computational efficiency. The authors gratefully acknowledge the institutional computational support that enabled this research.

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