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Implementation of Xception Algorithm with Convolutional Block Attention Module (CBAM) for Waste Type Detection in Visual Images

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ABSTRACT

The increasing annual volume of waste poses a significant challenge to effective waste management, particularly in the sorting process, which remains suboptimal. Major obstacles hindering the creation of an efficient system include a lack of public awareness and limited facilities for manual sorting. To address this, this study developed a visual waste classification system utilizing the Xception algorithm integrated with the Convolutional Block Attention Module (CBAM) to enhance classification accuracy. The dataset comprised various categories of organic and inorganic waste. Experiments involved integrating CBAM into the Xception architecture, testing data splitting schemes, and conducting hyperparameter tuning using Random Search with ten combinations. Training was performed using Keras and TensorFlow. Results indicated that adding CBAM improved accuracy from 88.38% to 91.29% without significantly increasing training time. Furthermore, the optimal hyperparameter combination—Dense 128, Dropout 0.3, Adam Optimizer, and Learning Rate 0.0001—achieved a highest accuracy of 93.37%. The best-performing model was saved in .h5 format and integrated into a Flask-based web application. This interface allows users to upload images and receive instant waste predictions, thereby assisting the public in easier waste sorting and encouraging active participation in environmentally conscious waste management.

Keyword: Waste Classification, Xception, CBAM, Deep Learning, Flask

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1. INTRODUCTION

The volume of waste in Indonesia continues to increase annually and has become a serious issue in environmental management. According to Government Regulation No. 27 of 2020, waste is defined as the residual matter from daily human activities or natural processes in solid form [1]. Based on the official website of the National Waste Management Information System of the Ministry of Environment and Forestry (KLHK), Indonesia generates over 40 million tons of waste per year. However, only about 46% of this waste is currently being managed properly [2].

Improperly managed waste can lead to environmental degradation and public health concerns [3]. The environmental impacts include soil, water, and air pollution, while from a health perspective, it poses risks of diseases such as dengue fever and malaria. To mitigate these risks, one crucial strategy is waste sorting. Waste sorting is the process of classifying and separating waste based on certain criteria, such as Organic and Anorganic materials [4].

Unfortunately, waste sorting has not yet become a widespread habit among the general public. A survey conducted by GoodStats in November 2024 revealed that only 31.4% of respondents consistently practiced waste sorting, while 48.1% did it irregularly, and 20.5% never sorted their waste at all. The main barriers to optimal waste management are low awareness, insufficient education, and a lack of adequate sorting facilities [5].

To address these challenges, computer vision and deep learning technologies offer efficient approaches for image-based waste classification. Similar research has been conducted comparing several models, wherein the InceptionV3 model achieved the highest accuracy of 89.19% [6]. As a further development, the Xception model is proposed. This model is a Convolutional Neural Network (CNN) architecture that has proven effective in object recognition tasks. Briefly, the Xception architecture consists of a linear stack of depthwise separable convolutional layers with residual connections [7]. To further enhance the model's ability to capture important features, the Convolutional Block Attention Module (CBAM) is integrated as an attention mechanism. CBAM is a lightweight module that can be seamlessly incorporated into CNN architectures [8]. It can be easily integrated into various CNN architectures without introducing significant computational overhead and can be trained jointly with the main network in an end-to-end manner [9]. The combination of Xception and CBAM is expected to improve waste classification accuracy and contribute to more effective environmental management.

2. METHODS

This study employs the Cross-Industry Standard Process for Data Mining (CRISP-DM) as the methodology for data mining and adopts the Rapid Application Development (RAD) model for website development. The research workflow is illustrated in the following figure:

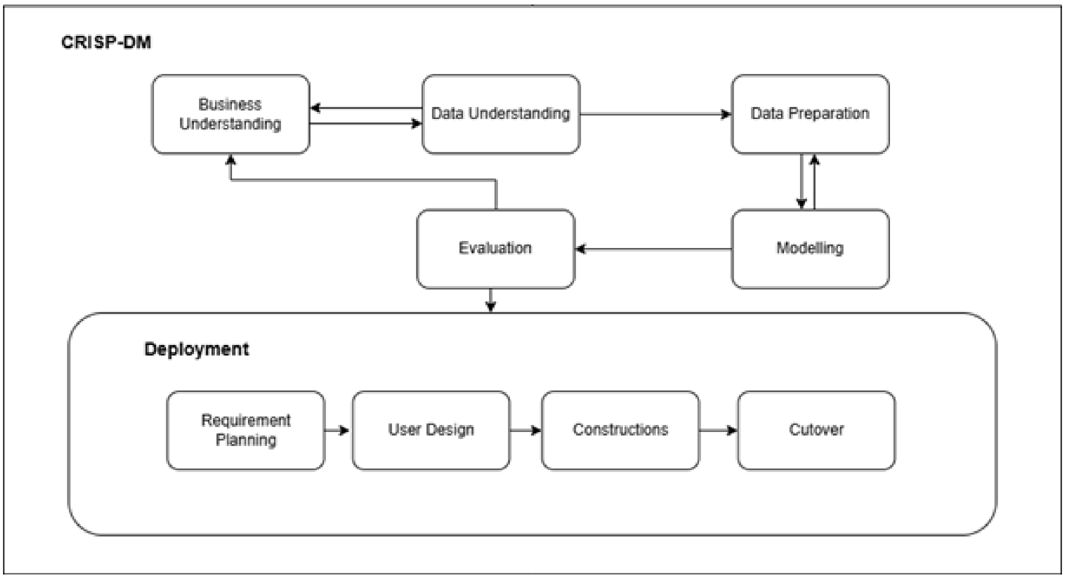


Figure 1 Research Flow

The CRISP-DM methodology consists of six main phases: Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment [10]. Meanwhile, The application development method used is Rapid Application Development

(RAD), with stages: requirement planning, user design, construction, and cutover. The final stage of the RAD model is cut over or the application testing stage which is carried out to ensure the system functions properly, using the Blackbox method. [11].

3. RESULTS AND DISCUSSION

3.1 Data Understanding

This study utilized a secondary dataset sourced from the Kaggle platform titled "Real Waste Image Classification," which contains 4,752 waste images in JPG format with a resolution of 524 × 524 pixels. The distribution of the dataset is presented as follows:

Table 1 Number of Datset

Waste Type	Number of Data
Cardboard	461
Food Organics	411
Glass	420
Metal	790
Paper	500
Plastic	921
Textile Trash	318
Vegetation	436
Miscellaneous Trash	495

In accordance with Indonesian regulations, waste is generally categorized into organic, anorganic, and hazardous (B3) waste. However, this study focuses solely on classifying waste into two primary categories: organic and anorganic, omitting B3 waste due to its relatively small proportion in daily life. The organic category includes food organics and vegetation, while the anorganic category includes cardboard, glass, metal, paper, plastic, textile trash, and miscellaneous trash.

3.2 Data Preparation

Before training the model, the data underwent several preparation stages. The data cleaning stage began with verifying the format and resolution of the images. All images were confirmed to be in JPG format with a resolution of 524×524 pixels and were verified to be correctly labeled.

It was found that the Miscellaneous Trash class exhibited ambiguous characteristics and included images of objects that were difficult to categorize clearly. These inconsistencies could confuse the model in learning visual patterns reliably. Therefore, this class was removed to maintain label consistency and enhance model accuracy. After removal, the final dataset consisted of 4,257 images across 8 classes.

To address class imbalance, oversampling was performed using data augmentation, a technique to artificially increase data diversity by generating new images from existing ones. Each class was augmented to contain 1,000 images using the following parameters: rotation_range=25, width_shift_range=0.15, height_shift_range=0.15, shear_range=0.15, zoom_range=0.20, horizontal_flip=True, and fill_mode="nearest". As a result, the dataset expanded to 8,000 balanced images.

Prior to training, all images were resized from 524×524 to 299×299 pixels to match the input requirements of the Xception architecture. The final step in data preparation was data splitting, to ensure the training and evaluation processes used distinct datasets, thereby allowing for objective model evaluation.

3.3 Model Comparation

An experiment was conducted to compare a baseline Xception model without CBAM to an Xception model integrated with the CBAM module, using identical training parameters. The purpose was to assess the extent to which CBAM improved model accuracy. The results are as follows:

Table 2 Model Comparation

Epoch	Xception		Xception +CBAM	
	Train_acc	Val_acc	Train_acc	Val_acc
5	79.10%	81.71%	83.38%	83.46%
10	84.98%	85.17%	92.43%	88.58%
15	87.81%	87.08%	96.37%	90.42%
20	90.35%	88.38%	98.84%	91.29%

The integration of the Convolutional Block Attention Module (CBAM) into the Xception architecture significantly improved performance. Final validation accuracy increased from 88.38% (baseline) to 91.29% with CBAM, indicating that CBAM enhances the model’s focus on relevant features, resulting in more accurate classification.

Further experimentation was conducted to analyze different data-splitting strategies, with the following results:

Table 3 Data Splitting Comparation

Epoch	Accuracy		
	70:30	80:20	90:10
5	83.46%	84.69%	87.25%
10	88.58%	89.44%	90.38%
15	90.42%	91.69%	92.00%
20	91.29%	92.19%	**93.25%**

The highest accuracy of 93.25%was obtained with a 90:10 train-validation split, suggesting that a larger training set leads to better model generalization.

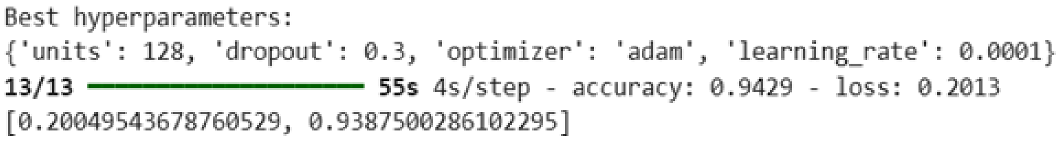
3.4 Parameter Selection

After determining the best-performing model, the next step was to search for the optimal combination of hyperparameters to further enhance model performance. The following table presents the hyperparameter combinations that were tested:

Table 4 Hyperparameter Combinations

No	Dense	Dropout	Optimizer	Learningrate
1	64	0.3	Adam	0.0001
2	128	0.4	RMSprop	0.00001
3	384	0.5	RMSprop	0.00001
4	448	0.4	Adam	0.0001
5	192	0.5	Adam	0.0001
6	192	0.3	Adam	0.00001
7	192	0.6	RMSprop	0.00001
8	128	0.3	Adam	0.0001
9	448	0.5	Adam	0.00001
10	384	0.4	Adam	0.0001
11	448	0.6	RMSprop	0.0001
12	512	0.6	Adam	0.0001
13	384	0.4	Adam	0.00001
14	64	0.4	Adam	0.0001
15	320	0.5	RMSprop	0.00001

Using the Random Search method, 15 different hyperparameter combinations were evaluated based on validation accuracy to identify the most optimal configuration. From these experiments, the best combination was selected is Dense = 128, Dropout = 0.3, Optimizer = Adam, and Learning Rate = 0.0001.



```
Best hyperparameters:
{'units': 128, 'dropout': 0.3, 'optimizer': 'adam', 'learning_rate': 0.0001}
13/13 ━━━━━━━━━━━━━━━━━━━━ 55s 4s/step - accuracy: 0.9429 - loss: 0.2013
[0.20049543678760529, 0.9387500286102295]
```

Figure 2 Best Parameter Combination

A retraining process was carried out on the Xception model with CBAM, using a 90% training and 10% validation data split. The retraining employed the best hyperparameter configuration identified during tuning, selected based on the highest validation accuracy. The training results using this configuration are presented below:

Table 5 Best Accuracy

Epoch	Accuracy	
	Train	Validation
5	88.52%	88.13%
10	95.28%	91.75%
15	98.84%	92.87%
18	99.32%	**93.37%**

These results confirm that the combination of the Xception architecture with CBAM, along with the optimized hyperparameter configuration, is capable of delivering optimal classification performance. The model evaluation was not solely based on accuracy but also considered the classification report and confusion matrix. The classification report is presented as follows:

Table 6 Classification Report

	Precision	**Recall**	**F1-score**	**Support**
Cardboard	0.91	0.93	0.93	100
Food Organics	0.96	0.99	0.98	100
Glass	0.96	0.95	0.95	100
Metal	0.88	0.96	0.92	100
Paper	0.93	0.95	0.94	100
Plastic	0.91	0.81	0.86	100
Textile Trash	0.98	0.93	0.95	100
Vegetation	0.98	0.99	0.99	100
Accuracy			0.94	800
Macro Avg	0.94	0.94	0.94	800
Weighted Avg	0.94	0.94	0.94	800

The following is the confusion matrix, which provides a more detailed overview of the number of correct and incorrect predictions for each class:

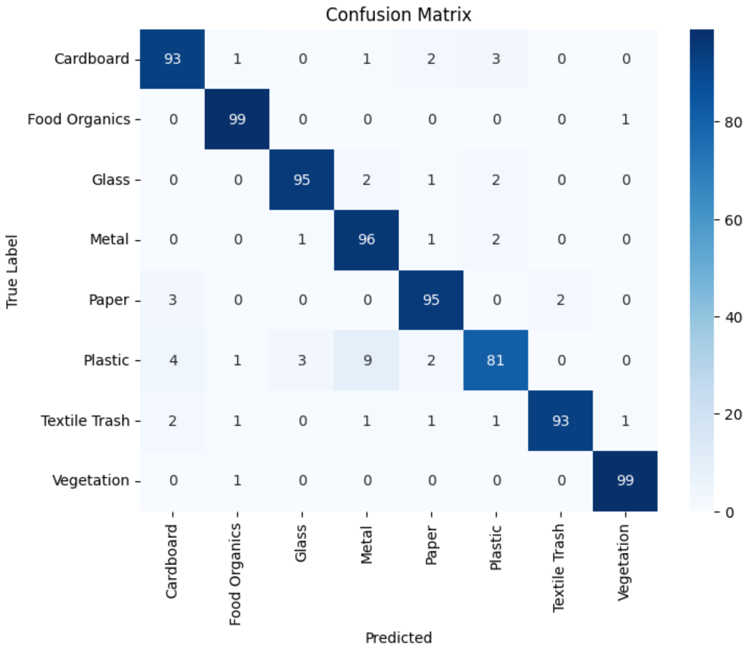
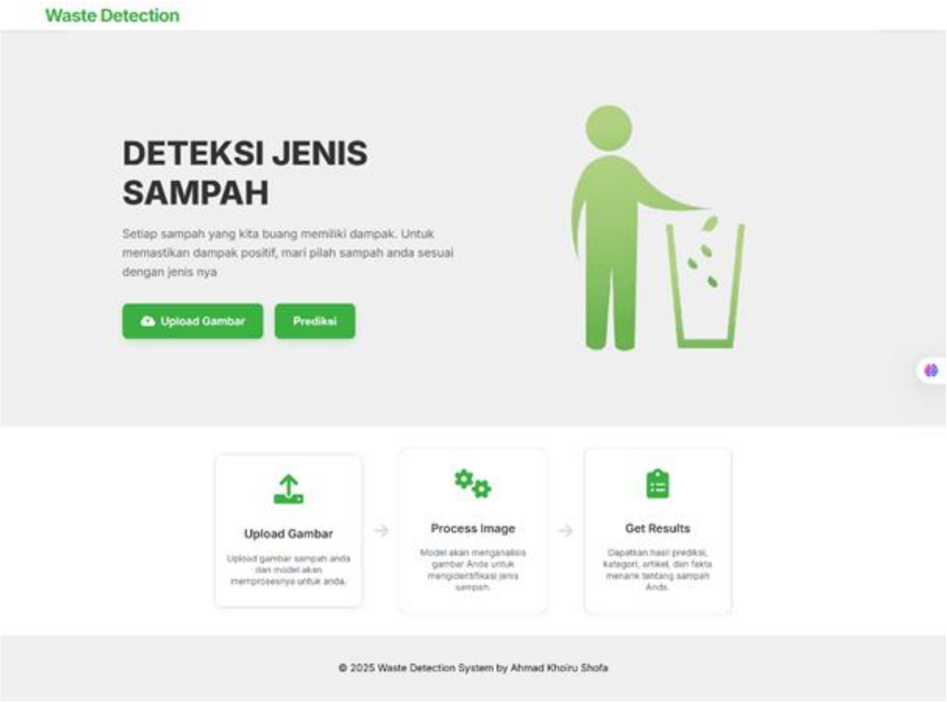


Figure 3 Confussion Matrix

3.5 Implementation

This process integrates the selected classification model, which is the Xception-based model enhanced with the Convolutional Block Attention Module (CBAM), into a Flask application framework. The main objective is to provide a user-friendly interface that allows users to upload waste images and receive prediction results. The following are the interfaces of the main page and the prediction results page:



DETEKSI JENIS SAMPAH

Setiap sampah yang kita buang memiliki dampak. Untuk memastikan dampak positif, mari pilah sampah anda sesuai dengan jenis nya

Upload Gambar

Upload gambar sampah anda dan model akan memprosesnya untuk anda.

Process Image

Model akan menganalisis gambar Anda untuk mengidentifikasi jenis sampah.

Get Results

Dapatkan hasil prediksi, kategori, artikel, dan fakta menarik tentang sampah Anda.

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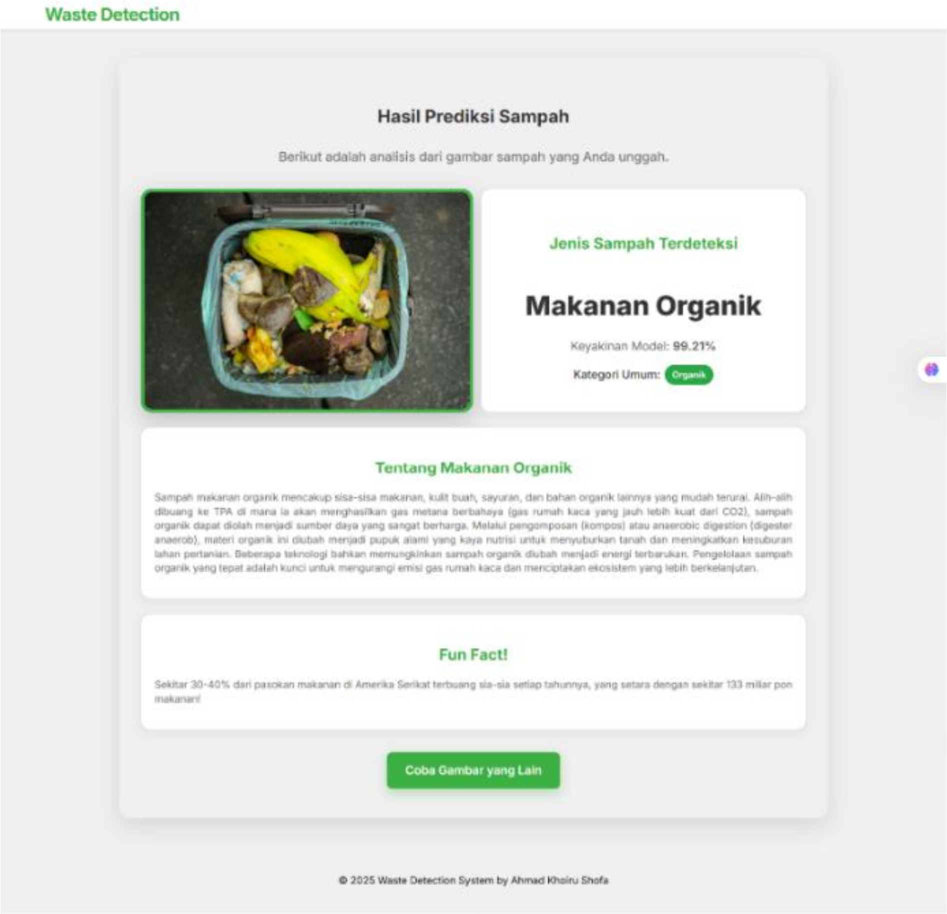
Figure 4 Main Page



Hasil Prediksi Sampah

Berikut adalah analisis dari gambar sampah yang Anda unggah.

Jenis Sampah Terdeteksi

Makanan Organik

Keyakinan Model: 99.21%

Kategori Umum: Organik

Tentang Makanan Organik

Sampah makanan organik mencakup sisa-sisa makanan, kulit buah, sayuran, dan bahan organik lainnya yang mudah terurai. Alih-alih dibuang ke TPA di mana ia akan menghasilkan gas metana berbahaya (gas rumah kaca yang jauh lebih kuat dari CO2), sampah organik dapat diolah menjadi sumber daya yang sangat berharga. Melalui pengomposan (kompos) atau anaerobic digestion (digester anaerob), materi organik ini diubah menjadi pupuk alami yang kaya nutrisi untuk menyuburkan tanah dan meningkatkan kesuburan lahan pertanian. Beberapa teknologi bahkan memungkinkan sampah organik diubah menjadi energi terbarukan. Pengelolaan sampah organik yang tepat adalah kunci untuk mengurangi emisi gas rumah kaca dan menciptakan ekosistem yang lebih berkelanjutan.

Fun Fact!

Sekitar 30-40% dari pasokan makanan di Amerika Serikat terbuang sia-sia setiap tahunnya, yang setara dengan sekitar 133 miliar pon makanan!

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Figure 5 Prediction Page

3.6 Testing

The waste detection website was tested using the Black-box Testing method. This testing approach focuses on the inputs provided and the outputs generated by the system, without examining or modifying the source code directly. The results of the black-box testing are presented in the following table:

Table 7 Black-box Testing

Pages	Test Case	Expected Outcome	Result
Main Page	User uploads an image and clicks the predict button	The website is expected to accept the uploaded image, perform waste classification based on the image, and display educational content on waste management on the prediction page.	✓
Prediction Page	User clicks the "Try Another Image" button	The website should redirect the user back to the main page to allow uploading another image for prediction.	✓

CONCLUSION

Based on the research conducted on the implementation of the Xception model enhanced with the Convolutional Block Attention Module (CBAM) for waste type classification in visual images, several key conclusions can be drawn:

1. The Xception model integrated with CBAM successfully classified waste types from images. The inclusion of CBAM improved the model's ability to focus on important features, resulting in better classification accuracy between organic and anorganic waste.
2. The addition of CBAM increased the model's accuracy from 88.38% to 91.29%. After hyperparameter tuning using the Random Search method (Dense: 128, Dropout: 0.3, Optimizer: Adam, Learning Rate: 0.0001), the highest validation accuracy achieved was 93.37%.
3. The Xception + CBAM model was successfully deployed in a web application using the Flask framework. This application allows users to upload waste images and receive automatic classification results through a user-friendly interface.

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