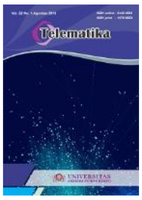


Available online at :
http://ejournal.amikompurwokerto.ac.id/index.php/telematika/

Telematika

Accreditated SINTA "2" Kemenristek/BRIN, No. 85/M/KPT/2020

UNIVERSITAS AMIKOM PURWOKERTO

Garbage Image Classifier using Modified ResNet-50

Bagus Dwi Santoso[1], Nur Nafi'iyah[2]

[1.2] Informatics Engineering, Faculty of Engineering
Universitas Islam Lamongan, Lamongan, Indonesia
E-mail: bagusdwi@unisla.ac.id[1], mynaff@unisla.ac.id[2]

ARTICLE INFO

History of the article:
Received February 7, 2024
Revised August 21, 2024
Accepted August 26, 2024

Keywords:
Garbage classification
Deep learning
ResNet-50
Adadelta
Adamax

Correspondence:
E-mail: bagusdwi@unisla.ac.id

ABSTRACT

This research proposes a deep learning model pretrained with ResNet-50 to classify 12 types of garbage. The model uses a modified ResNet-50 architecture with the Adamax and Adadelta optimizers and varying learning rates (0.1, 0.01, and 0.001). Six experiments were conducted to determine the most optimal training parameter configuration for the proposed model. Results show that the model performed best with the Adadelta optimizer and a learning rate of 0.1, achieving a validation accuracy of 93.85%. In comparison, the Adamax optimizer with a learning rate of 0.001 yielded a validation accuracy of 93.44%. Despite these results, there is a tendency for misclassification in the metal, plastic, and white-glass classes. Future work should focus on addressing these misclassification issues by expanding the dataset for these problematic classes. This can be achieved either by collecting additional images specific to these classes or by employing advanced data augmentation techniques to enhance the existing dataset and improve the model's accuracy.

INTRODUCTION

The escalating growth of the global population and consumption are two primary factors contributing to the serious issue of increasing waste production worldwide. The world generated approximately 20 billion tons of waste, equivalent to an average of 2.63 tons per person per year, and is estimated to skyrocket to reach 46 billion tons by the year 2050 (Maalouf & Mavropoulos, 2023). A study (Qonitan et al., 2021) revealed that the average municipal solid waste (MSW) generation in 10 big cities in Indonesia is 0.69 kg/capita per day. This becomes more concerning by a lack of awareness and the community's difficulties in sorting and reducing waste (Irmawartini et al., 2023).

The technological advancements in recent years have opened new opportunities in waste management, recent studies have successfully built a hardware solution for garbage classification utilizing deep learning as its core (Gupta et al., 2022; Wang et al., 2021), creating a potentially easier garbage sorting solution. The popular techniques used in garbage image classification are machine learning and deep learning (Xia et al., 2022), this includes KNN (Dubey et al., 2020), SVM, Random Forest, Decision Tree, and CNN (Sami et al., 2020). Previous studies revealed that deep learning techniques provide a more accurate results in contrast of machine learning techniques.

One of the approaches to build advanced deep learning model is by utilizing transfer learning, the reuse of a pre-trained model from one task to improve optimization in a related task, especially when dealing with a smaller new dataset (Hussain et al., 2019). (Cao & Xiang, 2020) have applied transfer learning-based CNN for classifying garbage, they use one of transfer learning architecture named InceptionV3 and achieved accuracy of 99.3% and test accuracy of 93.2%. In (Meng & Chu, 2020), they experimented garbage image classification utilizing different transfer learning architecture, this study shows ResNet-50 is able to give accurate classification having accuracy = 95.35%. (Ahmed et al., 2023) obtained great accuracy for garbage image classification using DenseNet69, MobileNetV2, and ResNet50V2 with accuracy of 94.4%, 97.6%, and 98.95% respectively.

Regularization techniques such as Batch Normalization and Dropout can be employed to improve training efficiency. Batch Normalization offers key advantages such as stabilizing learning, reducing required training epochs for convergence, facilitating the use of higher learning rates, and decreasing sensitivity to initialization (Kocaman et al., 2021). Dropout layers randomly deactivates specific neurons during training, diminishing the co-adaptation of features and mitigating overfitting. The primary objective of dropout is to elevate the generalization capabilities of neural networks by creating an ensemble of sub-networks that share parameters and are trained on distinct subsets of the data (Jabir & Falih, 2021).

Based on the previous studies on garbage classification, this study aims to build a garbage image classifier model using pretrained ResNet-50 explore the efficient optimizer and learning rates for the proposed model. In this study, modified ResNet-50 architecture will be used as the basis of the classification model, with optimizer Adadelta and Adamax, learning rates=0.1, 0.01, and 0.001. Based on research (Bircanoglu et al., 2018) by making changes to the optimizer can optimize stochasticity, and reduce overfitting (Cao & Xiang, 2020).

RESEARCH METHODS

1. Research Steps

There are several steps in order to reach the expected goal is shown in Figure 1. These steps include selecting dataset, balancing dataset, splitting dataset into train and validation, training, and evaluation.

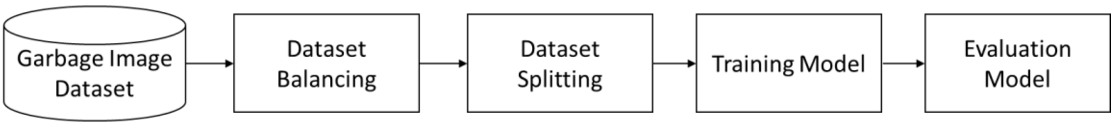


Figure 1. Research Steps

The first stage involves downloading the garbage image dataset obtained from the Kaggle platform. Upon acquiring the dataset, this research perform dataset balancing by employing a down-sampling method, down-sampling method is a way to deal with the unbalance in the training dataset by reducing the number of samples from the over-represented classes (Steiniger et al., 2020). The purpose of this step is to ensure an even distribution of data, an evenly distributed dataset is required to improve overall model accuracy (Chen et al., 2017).

After successfully balancing the dataset, researcher then split the dataset into train and validation with ratio of 80:20. This practice is crucial as it enables the model to learn from a representative portion of the data and subsequently assess its performance on unseen data. Moreover, data splitting serves to prevent overfitting, a situation where the model memorizes the training data but struggles to generalize to new data (Nguyen et al., 2021).

Subsequently, researcher train the model using the ResNet-50 architecture. Researcher opt to employ multiple optimizers with varying learning rates to train the model. The utilization of different optimizers and learning rates allows us to explore various training configurations and select the one that yields the best results.

2. Dataset description

The dataset, curated by (Mohamed, 2021), comprises 15.150 image samples belonging to 12 distinct household garbage classes, namely: battery, biological, brown-glass, cardboard, clothes, green-glass, metal, paper, plastic, shoes, trash, and white-glass. Figure 2 displays sample images for each class within the dataset.

Figure 2. Image Samples of (a) battery, (b) Biological, (c) Brown-glass, (d) Cardboard, (e) Clothes, (f) Green-Glass, (g) Metal, (h) Paper, (i) Plastic, (j) Shoes, (k) Trash, (l) White-glass.

After collecting and analyzing the entire dataset, researcher identified an imbalance in the class distribution as shown in Table 1, necessitating a data balancing method.

Table 1. Dataset Distribution

Class	*Original*	*Balanced*
battery	945	607
biological	985	607
brown-glass	607	607
cardboard	891	607
clothes	5325	607
green-glass	629	607
metal	769	607
paper	1050	607
plastic	865	607
shoes	1977	607

Table 1. Dataset Distribution (Continued)

Class	*Original*	*Balanced*
trash	697	607
white-glass	775	607

The dataset comprised images with distinct features where duplicating minority class images (e.g., brown-glass) will not introduce the necessary variability to balance with the class with most data (clothes with 5325 images). Down-sampling ensured that each class was equally represented without artificially inflating the dataset with near-duplicate images. This involved equalizing the number of samples for all classes, aligning them with the class with the fewest instances, namely brown-glass which had 607 images. The down-sampling was done by randomly selecting 607 samples from each class with more than 607 instances the balanced dataset was then split into training and validation data with an 80:20 ratio.

3. Modified ResNet-50

ResNet-50 (Residual Network) is a variation of the Residual Network (ResNet) which has 50 layers that has undergone training on a dataset of at least one million images from the ImageNet database (Victor Ikechukwu et al., 2021). ResNet effectively addresses common challenges in deep neural networks, such as vanishing gradient and degradation, by employing skip connections or shortcuts (Sarwinda et al., 2021). These connections facilitate learning the residual mapping between input and output layers. Figure 3 illustrates the layer arrangement in the ResNet-50 architecture (Islam et al., 2022).

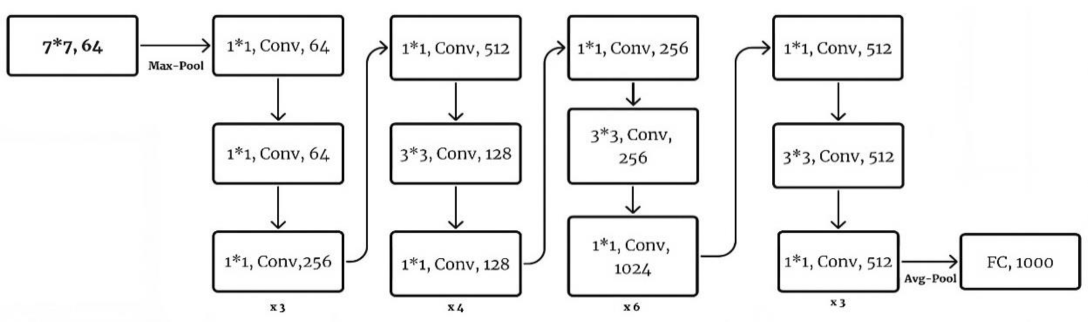


Figure 3. ResNet-50 architecture

This research adds modification of fully connected layers after the pretrained model output. First step is to define the input layer with input size of 224×224×3 followed by the ResNet-50 model, here the weights from ImageNet were loaded and setting it untrainable by freezing all the layers to ensure the loaded weights remain fixed. Finally, researcher construct the complete model by stacking additional layers on top of the frozen base model. The added layers include a flattened layer to convert the 3D output to a 1D vector, BatchNormalization layers for normalization, Dense layers with, Dropout layers to prevent overfitting, and a final Dense layer with a softmax activation function containing 12 units. The complete model modifications can be seen in Figure 4.

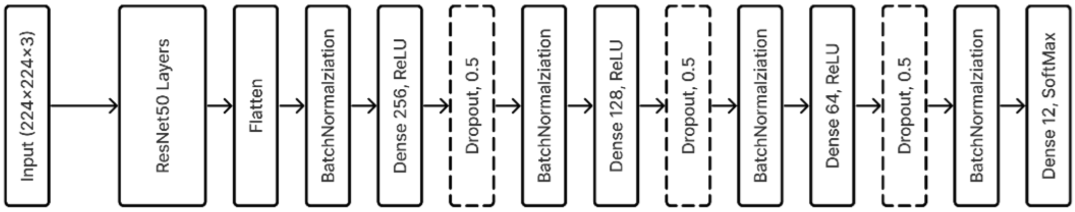


Figure 4. Proposed model's architecture

The model is built sequentially with modifications including the pretrained ResNet-50 layer that has been frozen across all its layers. Following this, a Flatten layer and BatchNormalization are applied before passing the data through three hidden Dense layers, each having 256, 128, and 64 units, respectively. After every Dense layer, there follows a dropout layer and batch normalization, preceding the transmission of data to output Dense layer comprising 12 units. The detailed architecture of this model is depicted in the model summary shown in Figure 5. By stacking the model in this specific way, the researcher ensures that the powerful feature extraction capabilities of the pretrained ResNet-50 are effectively utilized. The additional layers are carefully chosen and ordered to refine these features, normalize the data, and introduce regularization, ultimately enhancing the model's ability to accurately classify garbage images while maintaining generalization (Sarwinda et al., 2021).

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet50 (Functional)       (None, 7, 7, 2048)        23587712

 flatten (Flatten)           (None, 100352)            0

 batch_normalization (BatchN  (None, 100352)           401408
 ormalization)

 dense (Dense)               (None, 256)               25690368

 dropout (Dropout)           (None, 256)               0

 batch_normalization_1 (Batc  (None, 256)              1024
 hNormalization)

 dense_1 (Dense)             (None, 128)               32896

 dropout_1 (Dropout)         (None, 128)               0

 batch_normalization_2 (Batc  (None, 128)              512
 hNormalization)

 dense_2 (Dense)             (None, 64)                8256

 dropout_2 (Dropout)         (None, 64)                0

 batch_normalization_3 (Batc  (None, 64)               256
 hNormalization)

 dense_3 (Dense)             (None, 12)                780

=================================================================
Total params: 49,723,212
Trainable params: 25,933,900
Non-trainable params: 23,789,312
```

Figure 5. Model Summary

4. Performance Measure

Model evaluation process is conducted on the validation subset using various evaluation metrics, including accuracy, which is the ratio of correctly classified results to the total number of all results. In other words, accuracy measures how many predictions the model makes correctly (Ahmed et al., 2023). Accuracy can be defined in Eq. (1).

$$Accuracy = \frac{Correct\ Predictions}{All\ Predictions} \quad (1)$$

In the evaluation of the performance of a multi-class classification model, relying solely on accuracy as a metric is not sufficient. The confusion matrix stands as an essential tool, offering a thorough evaluation of the model's effectiveness. Within this matrix lie key metrics: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Therefore, the confusion matrix offers a detailed overview of the model's performance in predicting each class (Koklu & Ozkan, 2020). Multi-class classification confusion matrix can be represented in Table 2 where $C_1 ... C_n$ represents the classes, $T_1 ... T_n$ indicates how many times class n was correctly predicted, $F_1 ... F_n$ represents the incorrect classifications for class n.

Table 2. Multiclass Confusion Matrix

		Predicted				
		C_1	C_2	C_3	...	C_n
Actual	C_1	T_1	F_{12}	F_{13}	…	F_{1n}
	C_2	F_{21}	T_2	F_{23}	…	F_{2n}
	C_3	F_{31}	F_{32}	T_3	…	F_{3n}
	...	…	…	…	…	…
	C_n	F_{n1}	F_{n2}	F_{n3}	…	T_n

5. Experimental Setup

This research aims to achieve the best training performance, 6 training experiments were conducted as detailed in Table 3. This research utilized the Adadelta optimizer, which, as demonstrated in the study by (Meng & Chu, 2020) provided the best accuracy, and Adamax, known for good performance according to (Yang et al., 2022). Both optimizers were then experimented with varying learning rates=0.1, 0.01, and 0.001.

Table 3. Training Setup

Optimizer	*Learning Rate*	*Num of Epochs*
Adadelta	0.1	100
Adadelta	0.01	100
Adadelta	0.001	100
Adamax	0.1	100
Adamax	0.01	100
Adamax	0.001	100

RESULTS AND DISCUSSION

After defining the model, six training experiments with different optimizers (Adadelta, and Adamax) and learning rates (lr) of 0.1, 0.01, and 0.001 were conducted, it is evident that the proposed model achieves the best accuracy using the Adadelta optimizer with a learning rate of 0.1 achieving validation accuracy of 93.85%. The overall results of the training experiments are summarized in Table 4.

Table 4. Model performance

No.	*Optimizer*	*lr*	*Val Accuracy (%)*
1	Adadelta	0.1	93.85
2	Adadelta	0.01	92.35
3	Adadelta	0.001	82.65
4	Adamax	0.1	92.96
5	Adamax	0.01	93.10
6	Adamax	0.001	93.44

In order to gain a more detailed understanding of how the model behaves during training, the plots of training accuracy and validation accuracy in the training history plots can be examined in Figure 6 (a), (b), (c), and (d), as well as the Confusion Matrix which were done on validation data in Figure 7 (a), (b), (c), and (d). These gives a more comprehensive description of correct and incorrect classification outcomes for each individual class.

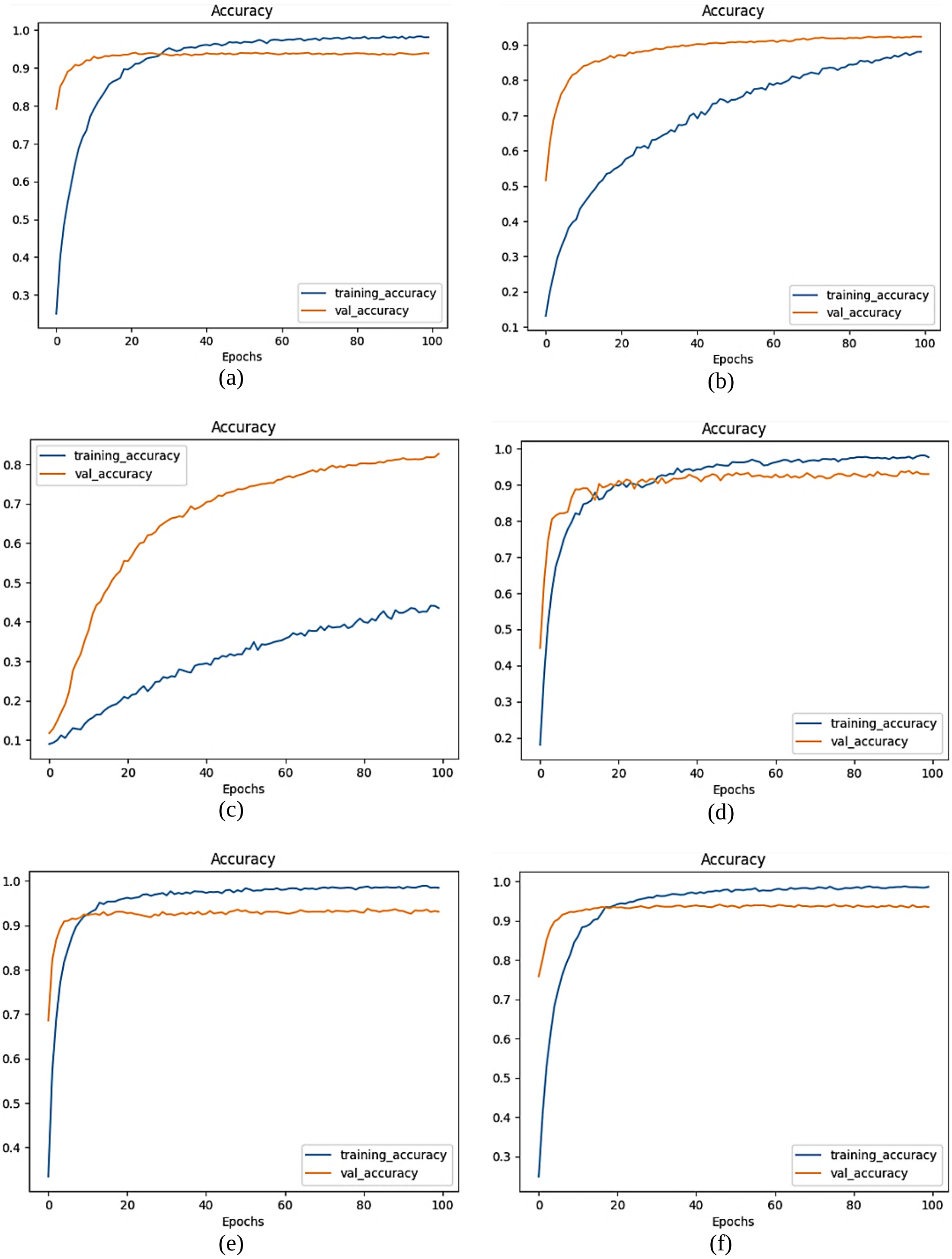
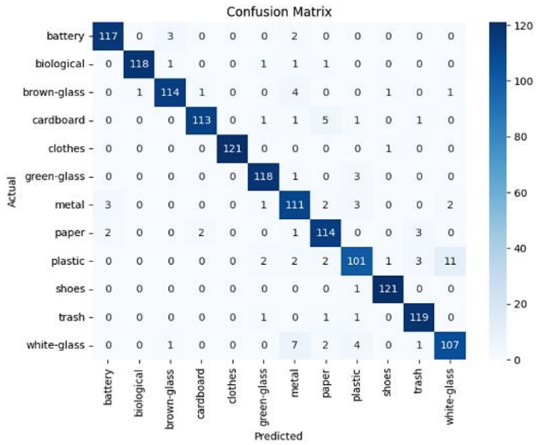


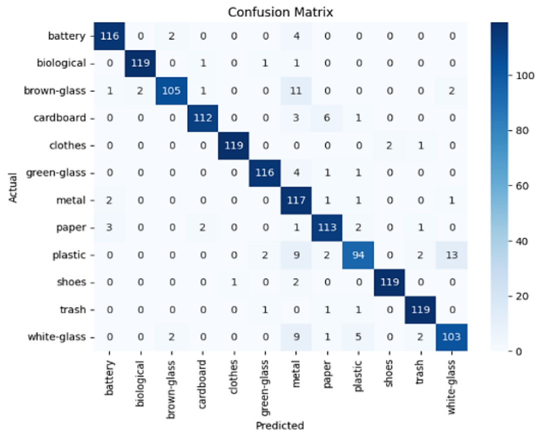
Figure 6. Training history plots for (a) Adadelta – 0.1, (b) Adadelta – 0.01, (c) Adadelta – 0.001, (d) Adamax – 0.1, (e) Adamax – 0.01, (f) Adamax – 0.001.

In Figure 6 (a), (b), and (c), results for the Adadelta optimizer show a trend where the model's performance deteriorates as the learning rate decreases. Additionally, the model converges slower, and validation accuracy consistently exceeds training accuracy suggesting overfitting with learning rate of

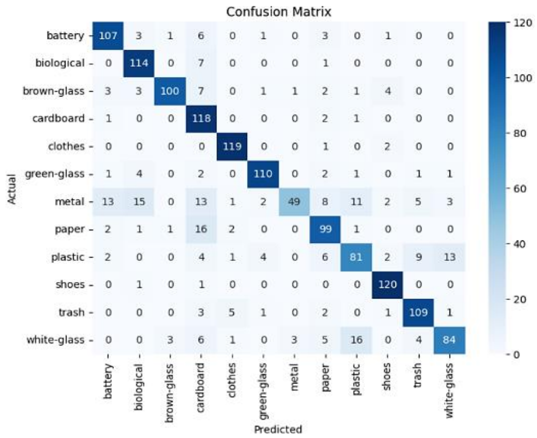
0.001. Conversely, in Figure 6 (d), (e), and (f), using the Adamax optimizer results in robust performance across all tested learning rates. Notably, there is a noticeable trend where the model converges quickly within the first 20 epochs.



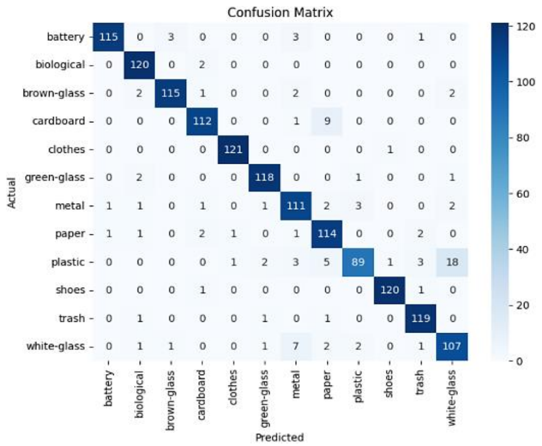
(a)



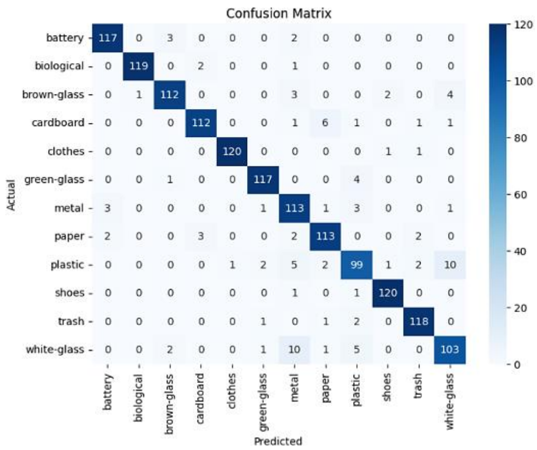
(b)



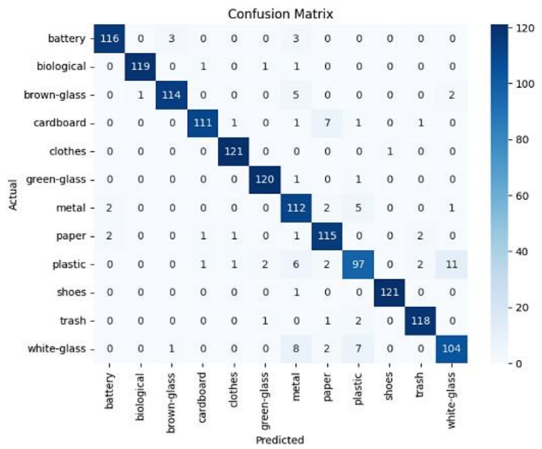
(c)



(d)



(e)



(f)

Figure 7. Confusion matrices of (a) Adadelta – 0.1, (b) Adadelta – 0.01, (c) Adadelta – 0.001, (d) Adamax – 0.1, (e) Adamax – 0.01, (f) Adamax – 0.001.

Figure 7 (a), (b), (c), and (d) illustrate the confusion matrices for each of six training experiments, providing a deeper understanding of the correctness of the proposed model in classifying garbage images on validation data. Specifically, researcher observe a predominant diagonal trend in all training experiments, indicating a high level of correct classification. However, values outside the diagonal signify instances of misclassification. Figure 7 (a) and (b), the model appears to perform well with few misclassifications, with misclassifications occurring in the plastic class. Figure 7 (c) and (d) exhibit clearer off-diagonal elements, indicating higher misclassification rates in the metal, plastic, and white glass classes. Figure 7 (e) and (f) demonstrate a balance between correct and misclassifications, with minor errors in the plastic class.

To provide a comprehensive evaluation of the proposed model, we compare its performance against several established models from previous studies. Table 5 summarizes the validation accuracies of these models, offering insight into how our model stands relative to other approaches in garbage image classification.

Table 5. Performance Comparison between Different Approaches

Model	*Dataset*	*Image Input*	*Validation Accuracy (%)*
Proposed Model	(Mohamed, 2021)	224 x 224	93.85
GoogleNet + SVM	(Bircanoglu et al., 2018)	512 x 384	97.86
Modified InceptionV3	(Cao & Xiang, 2020)	-	93.2
InceptionNet	(Gupta et al., 2022)	224 x 224	96.23
ResNet50	(Meng & Chu, 2020)	384 x 512	95.35
MLH-CNN	(Yang et al., 2022)	64 x 64	96.77

The proposed model performs competitively with a validation accuracy of 93.85%, particularly given its smaller input size of 224 x 224 pixels, which balances accuracy with computational efficiency. While the GoogleNet + SVM and InceptionNet models achieve higher accuracies, they might benefit from larger or unspecified image inputs, which can capture more details at the cost of increased computational requirements.

These comparisons highlight the trade-offs between different models in terms of input size, computational complexity, and accuracy. Our proposed model demonstrates a robust performance, making it a viable option for practical applications where computational resources may be limited. By analyzing the strengths and weaknesses of various approaches, this comparison provides valuable insights for future research and development in the field of garbage image classification.

CONCLUSIONS AND RECOMMENDATIONS

This research proposes a garbage classification model using modified ResNet-50 architecture with the Adamax and Adadelta optimizers with varying learning rates=0.1, 0.01, and 0.001. The results of the training experiments indicate that the model achieves optimal accuracy when configured with the Adadelta optimizer and learning rate of 0.1 having validation accuracy of 93.85%. Adadelta and Adamax both perform well with learning rate of 0.1 while smaller learning rates, such as 0.01 and 0.001, enhance model performance under the Adamax optimizer.

Based on the analysis of the confusion matrix, it can be concluded that the model tends to perform better in identifying some classes compared to others. Although the overall model performance shows high classification rates, special attention needs to be given to the metal, plastic, and white glass classes, where there is a higher rate of misclassification. The research next to this issue is the addition of image data for these classes, which can be achieved by collecting new data for training or augmenting data using data augmentation techniques.

REFERENCES

Ahmed, M. I. B., Alotaibi, R. B., Al-Qahtani, R. A., Al-Qahtani, R. S., Al-Hetela, S. S., Al-Matar, K. A., Al-Saqer, N. K., Rahman, A., Saraireh, L., Youldash, M., & Krishnasamy, G. (2023). *Deep Learning Approach to Recyclable Products Classification: Towards Sustainable Waste Management. 15, no. 14: 11138. https://doi.org/10.3390/su151411138*.

Bircanoglu, C., Atay, M., Beser, F., Genc, O., & Kizrak, M. A. (2018). RecycleNet: Intelligent Waste Sorting Using Deep Neural Networks. *2018 Innovations in Intelligent Systems and Applications (INISTA)*, 1–7. https://doi.org/10.1109/INISTA.2018.8466276

Cao, L., & Xiang, W. (2020). Application of Convolutional Neural Network Based on Transfer Learning for Garbage Classification. *2020 IEEE 5th Information Technology and Mechatronics Engineering Conference (ITOEC)*, 1032–1036. https://doi.org/10.1109/ITOEC49072.2020.9141699

Chen, H., Xiong, F., Wu, D., Zheng, L., Peng, A., Hong, X., Tang, B., Lu, H., Shi, H., & Zheng, H. (2017). Assessing impacts of data volume and data set balance in using deep learning approach to human activity recognition. *2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 1160–1165. https://doi.org/10.1109/BIBM.2017.8217821

Dubey, S., Singh, P., Yadav, P., & Singh, K. K. (2020). Household Waste Management System Using IoT and Machine Learning. *Procedia Computer Science*, *167*, 1950–1959. https://doi.org/10.1016/j.procs.2020.03.222

Gupta, T., Joshi, R., Mukhopadhyay, D., Sachdeva, K., Jain, N., Virmani, D., & Garcia-Hernandez, L. (2022). A deep learning approach based hardware solution to categorise garbage in environment. *Complex & Intelligent Systems*, *8*(2), 1129–1152. https://doi.org/10.1007/s40747-021-00529-0

Hussain, M., Bird, J. J., & Faria, D. R. (2019). A Study on CNN Transfer Learning for Image Classification. In A. Lotfi, H. Bouchachia, A. Gegov, C. Langensiepen, & M. McGinnity (Eds.), *Advances in Computational Intelligence Systems* (Vol. 840, pp. 191–202). Springer International Publishing. https://doi.org/10.1007/978-3-319-97982-3_16

Irmawartini, I., Mulyati, S. S., & Pujiono, P. (2023). Pengelolaan Sampah dari Hulu ke Hilir di Kota Bandung. *Jurnal Kesehatan Lingkungan Indonesia*, *22*(2), 229–236. https://doi.org/10.14710/jkli.22.2.229-236

Islam, W., Jones, M., Faiz, R., Sadeghipour, N., Qiu, Y., & Zheng, B. (2022). Improving Performance of Breast Lesion Classification Using a ResNet50 Model Optimized with a Novel Attention Mechanism. *Tomography*, *8*(5), 2411–2425. https://doi.org/10.3390/tomography8050200

Jabir, B., & Falih, N. (2021). Dropout, a basic and effective regularization method for a deep learning model: A case study. *Indonesian Journal of Electrical Engineering and Computer Science*, *24*(2), 1009. https://doi.org/10.11591/ijeecs.v24.i2.pp1009-1016

Kocaman, V., Shir, O. M., & Back, T. (2021). Improving Model Accuracy for Imbalanced Image Classification Tasks by Adding a Final Batch Normalization Layer: An Empirical Study. *2020 25th International Conference on Pattern Recognition (ICPR)*, 10404–10411. https://doi.org/10.1109/ICPR48806.2021.9412907

Koklu, M., & Ozkan, I. A. (2020). Multiclass classification of dry beans using computer vision and machine learning techniques. *Computers and Electronics in Agriculture*, *174*, 105507. https://doi.org/10.1016/j.compag.2020.105507

Maalouf, A., & Mavropoulos, A. (2023). Re-assessing global municipal solid waste generation. *Waste Management & Research: The Journal for a Sustainable Circular Economy*, *41*(4), 936–947. https://doi.org/10.1177/0734242X221074116

Meng, S., & Chu, W.-T. (2020). A Study of Garbage Classification with Convolutional Neural Networks. *2020 Indo – Taiwan 2nd International Conference on Computing, Analytics and Networks (Indo-Taiwan ICAN)*, 152–157. https://doi.org/10.1109/Indo-TaiwanICAN48429.2020.9181311

Mohamed, M. (2021). *Garbage Classification (12 classes)* [dataset]. https://www.kaggle.com/datasets/mostafaabla/garbage-classification.

Nguyen, Q. H., Ly, H.-B., Ho, L. S., Al-Ansari, N., Le, H. V., Tran, V. Q., Prakash, I., & Pham, B. T. (2021). Influence of Data Splitting on Performance of Machine Learning Models in Prediction of Shear Strength of Soil. *Mathematical Problems in Engineering*, *2021*, 1–15. https://doi.org/10.1155/2021/4832864

Qonitan, F. D., Wayan Koko Suryawan, I., & Rahman, A. (2021). Overview of Municipal Solid Waste Generation and Energy Utilization Potential in Major Cities of Indonesia. *Journal of Physics: Conference Series*, *1858*(1), 012064. https://doi.org/10.1088/1742-6596/1858/1/012064

Sami, K. N., Amin, Z. M. A., & Hassan, R. (2020). Waste Management Using Machine Learning and Deep Learning Algorithms. *International Journal on Perceptive and Cognitive Computing*, *6*(2), 97–106. https://doi.org/10.31436/ijpcc.v6i2.165

Sarwinda, D., Paradisa, R. H., Bustamam, A., & Anggia, P. (2021). Deep Learning in Image Classification using Residual Network (ResNet) Variants for Detection of Colorectal Cancer. *Procedia Computer Science*, *179*, 423–431. https://doi.org/10.1016/j.procs.2021.01.025

Steiniger, Y., Stoppe, J., Meisen, T., & Kraus, D. (2020). Dealing With Highly Unbalanced Sidescan Sonar Image Datasets for Deep Learning Classification Tasks. *Global Oceans 2020: Singapore – U.S. Gulf Coast*, 1–7. https://doi.org/10.1109/IEEECONF38699.2020.9389373

Victor Ikechukwu, A., Murali, S., Deepu, R., & Shivamurthy, R. C. (2021). ResNet-50 vs VGG-19 vs training from scratch: A comparative analysis of the segmentation and classification of Pneumonia from chest X-ray images. *Global Transitions Proceedings*, *2*(2), 375–381. https://doi.org/10.1016/j.gltp.2021.08.027

Wang, C., Qin, J., Qu, C., Ran, X., Liu, C., & Chen, B. (2021). A smart municipal waste management system based on deep-learning and Internet of Things. *Waste Management*, *135*, 20–29. https://doi.org/10.1016/j.wasman.2021.08.028

Xia, W., Jiang, Y., Chen, X., & Zhao, R. (2022). Application of machine learning algorithms in municipal solid waste management: A mini review. *Waste Management & Research: The Journal for a Sustainable Circular Economy*, *40*(6), 609–624. https://doi.org/10.1177/0734242X211033716

Yang, Z., Xia, Z., Yang, G., & Lv, Y. (2022). A Garbage Classification Method Based on a Small Convolution Neural Network. *Sustainability*, *14*(22), 14735. https://doi.org/10.3390/su142214735