

Managing Household Waste Through Transfer Learning

Suman Kunwar

Faculty of Computer Science, Selinus University of Sciences and Literature, Ragusa, Italy

Correspondence: sumn2u@gmail.com

SUBMITTED: 27 January 2024; REVISED: 16 March 2024; ACCEPTED: 21 March 2024

ABSTRACT: As the world continues to face the challenges of climate change, it is crucial to consider the environmental impact of the technologies we use. In this study, we investigate the performance and computational carbon emissions of various transfer learning models for garbage classification. We examine the MobileNet, ResNet50, ResNet101, and EfficientNetV2S and EfficientNetV2M models. Our findings indicate that the EfficientNetV2 family achieves the highest accuracy, recall, f1-score, and IoU values. However, the EfficientNetV2M model requires more time and produces higher carbon emissions. ResNet50 outperforms ResNet110 in terms of accuracy, recall, f1-score, and IoU, but it has a larger carbon footprint. We conclude that EfficientNetV2S is the most sustainable and accurate model with 96.41% accuracy. Our research highlights the significance of considering the ecological impact of machine learning models in garbage classification.

KEYWORDS: Garbage classification; transfer learning; deep learning; waste management; carbon emission

1. Introduction

The escalating global waste crisis, projected to surge by 70% by 2050 without intervention [1], demands innovative solutions. Diverse waste management techniques, from source reduction to education initiatives, strive to combat this issue [2]. Yet, the absence of a standardized waste classification system results in regional disparities [3], emphasizing the need for efficient waste identification, crucial for integrated solid waste management [4]. Recent advancements leverage deep learning (DL) models to streamline waste sorting and management [5]. These models, like RNet and ConvoWaste, exhibit high accuracy, emphasizing the role of accurate waste disposal in mitigating climate change and reducing greenhouse gas emissions.

Some studies incorporate IoT and waste grid segmentation to classify and segregate waste items in real time [6]. Integration of machine learning (ML) models with mobile devices presents a promising avenue for precise waste management [7, 8]. As the advancements are happening, the computing related climate impact of ML models are not explored much. The Information and Communications Technology (ICT) industry contributes to about 1.4% of total global greenhouse gas (GHG) emissions. Out of this percentage, roughly one-third of the emissions are due to the production and management of physical materials [9]. Using transfer learning (TL) [10] various waste classification techniques have been purposed [11, 12] that shows promising results. However, the number of classes used here are quite limited and does not talk about the operational carbon emissions. Besides this, models like EfficientNetV2 that have faster training speed and better parameter efficiency has not been tested [13]. The aim of

this study is to conduct a thorough evaluation of TL models, focusing on various settings and hyperparameters, with a particular emphasis on the Garbage dataset [14]. We also implement model enhancement techniques to improve the performance of the selected model. Additionally, we analyze the computational carbon emissions of the evaluated models to establish metrics for sustainable computing in machine learning.

2. Related Works

The growing challenge of waste management has spurred research into automated classification methods using deep learning. This section explores existing works related to our study, focusing on transfer learning applications, deep learning architecture comparisons, and dataset and model choices. Several studies have demonstrated the effectiveness of transfer learning for waste classification. Lilhore et al. achieved a 95.45% accuracy for two waste categories using a hybrid CNN-LSTM model with transfer learning, highlighting its potential for efficient classification [15]. Similarly, Wulansari et al. employed transfer learning for medical waste classification with an impressive 99.40% accuracy [16], showcasing its adaptability to diverse waste types.

While these studies offer valuable insights, our work specifically focuses on organic and residual waste classification, exploring the impact of transfer learning on both accuracy and training time for VGGNet-16 and ResNet-50 architectures. Comparing the performance of different deep learning architectures is crucial for identifying optimal solutions. Mehedi et al. compared VGG16, MobileNetV2, and a baseline Convolutional Neural Network (CNN) for waste classification, with VGG16 achieving a 96.00% accuracy [17]. Huang et al. proposed a combination model utilizing VGG19, DenseNet169, and NASNetLarge with transfer learning, achieving 96.5% and 94% accuracy on two datasets [18].

These investigations demonstrate the effectiveness of pre-trained models and model fusion, while our work delves deeper into the performance variations between VGGNet-16 and ResNet-50 for organic and residual waste, analyzing their representation capabilities through dimensionality reduction techniques. The choice of dataset and model architecture plays a critical role in determining the success of waste classification systems. Srivatsan et al. used pre-trained models on the CompostNet dataset for 7-class waste classification, achieving 96.42% accuracy with DenseNet121 [19]. Das et al. created a new 17,628-image dataset for 11 trash categories and compared ResNet152, DenseNet169, and MobileNetV2, with DenseNet169 achieving 93.10% accuracy [20]. These examples highlight the importance of dataset size and diversity, and the impact of model selection on specific tasks.

3. Methodology

To classify the waste dataset, a TL approach was undertaken. Various state of the art transfer learning modes are used to train the model using the PyTorch framework. These model were pre-trained with ImageNet dataset and additional data augmentation techniques such as flipping, rotation, cropping, width and height were applied randomly. Additional layers such as GlobalAveragePooling2D, Dense and Dropout were added to improve classification accuracy. Both model training and testing were conducted using the Tesla T4 x2 GPUs available on Kaggle.

3.1. Dataset.

The waste dataset consists of 23672 images, decomposed into ten classes: metal, glass, biological, paper, battery, trash, cardboard, shoes, clothes, and plastic. The number of image files contain in Metal class is 1869, Glass class is 4097, Biological class is 985, Paper class is 2727, Battery class is 945, Trash class is 834, Cardboard class is 2341, Shoes class is 1977, Clothes class is 5325 and Plastic class is 2542. These images are collected from various internet sources and also from the M Waste misclassified images. The dataset contains various sizes of images and has a class imbalance as shown in Figure 1. Some of the sample images are shown in Figure 2. The class imbalance can negatively affect the training results of the model and cause it to be biased towards the largest class.

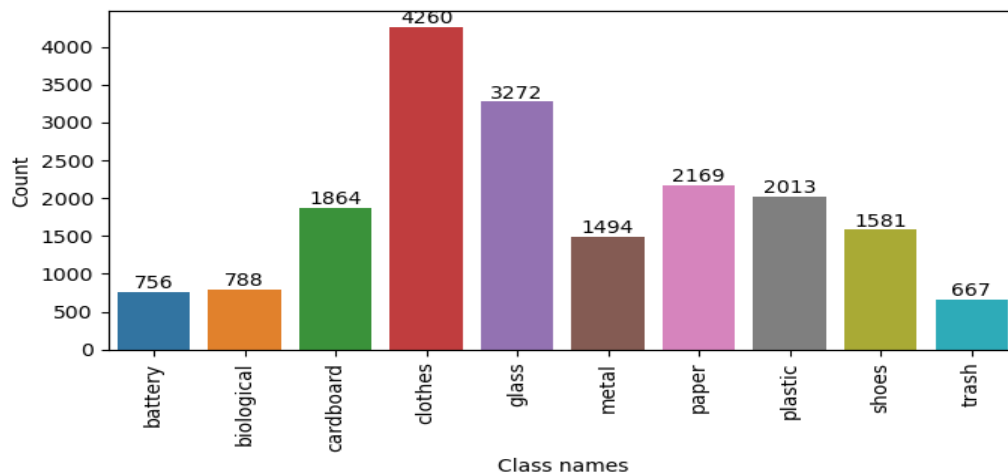


Figure 1. Image count on each class of Garbage Dataset.



Figure 2. Sample images from each class of the Garbage Dataset.

There are different approaches to solving this problem, the applicability of which depends on the problem being solved [21]. We will use the method of insufficient sampling (random undersampling) [22], which consists of randomly excluding some examples from large classes. We limit the number of images in large classes to 1000 images. The updated class distribution is shown in Figure 3. Some classes are still sparse, to solve this data augmentation techniques are applied. The average height and width are calculated from dataset and is applied to the images. The dataset is then divided into three sets: train, test and val. The train data contains 80% of total images that will be used to train the model, the val set contains 10% and

is used for checking during training and adjusting parameters whereas the test contains 10% to evaluate the accuracy of the model on new data not used during training.

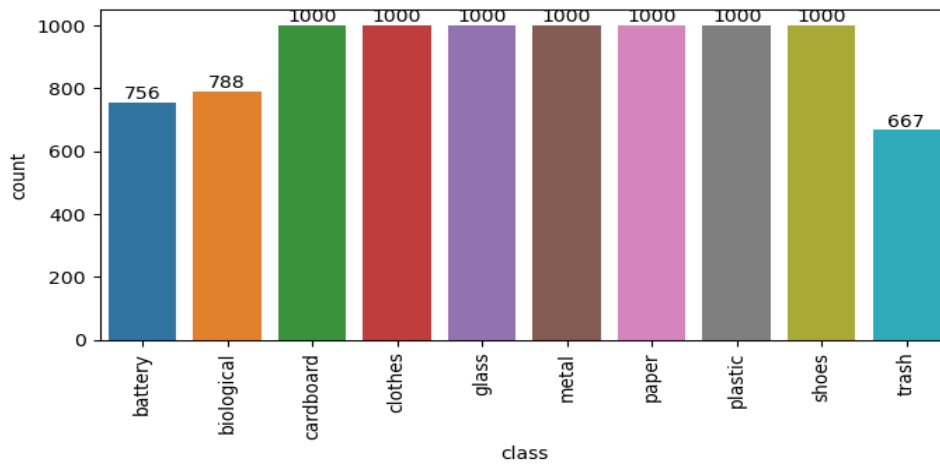


Figure 3. Sample images from each class of the Garbage Dataset.

3.2. Training and evaluation.

Data augmentation techniques were utilized during model training to feed augmented data into the system. Various image transformation techniques [23], such as crops, horizontal flips, and vertical flips, were used for this purpose. The primary objective of this strategy was to prevent the neural network from overfitting to the training dataset, enabling it to generalize more effectively to unseen test data. Since pre-trained models were utilized, the input dataset was normalized to match the statistics (mean and standard deviation) of those models. The model was trained under various settings, and its accuracy was subsequently evaluated. The loss was quantified using categorical cross-entropy loss. To counteract potential issues of vanishing or exploding gradients during training, which could adversely affect the parameters, the gradient clipping technique [24] was employed with a value set to 1.0. The Adam optimizer was used combined with multiple learning rates, due to its proven efficacy in image classification tasks [25]. Regularization strategies, including early stopping, dropout, and weight decay [26], were also implemented to combat overfitting and to optimize time and resources. Various metrics such as accuracy, f1-score, recall, Intersection over Union (IoU) and operational emissions were recorded, including creating and productionalizing an ML model, data storage and processing, model training, and inference with the help of codecarbon. The carbon emission from code carbon is calculated using formula shown in Figure 4.

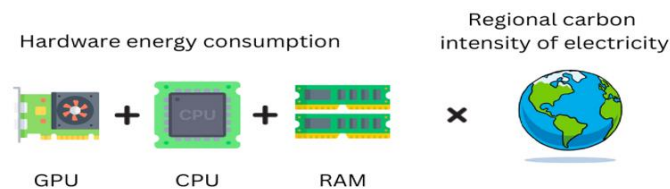


Figure 4. Codecarbon carbon emission formula.

4. Results and Discussion

This section presents the results obtained from EfficientNetV2M, EfficientNetV2S, MobileNet, ResNet-50 and ResNet101 models trained using pre trained transfer learning with

same settings. Metrics such as accuracy, recall, f1-score, IoU and the time taken to train the model are measured. Table 1 shows that the EfficientNetV2M and EfficientNetV2S has higher accuracy along with Recall, F1 score and IoU whereas ResNet50 has higher accuracy, Recall, F1 score and IoU than ResNet101. Meanwhile MobileNet has the least value. Both EfficientNetV2 models have higher IoU indicating superior object detection accuracy with consistent predictions across various levels of confidence and bounding box overlap [27]. The training time for EfficientNetV2M is highest among others and MobileNet has the lowest training time.

Table 1. Comparative experimental results of EfficientNetV2M, EfficientNetV2S, MobileNet, ResNet50 and ResNet101 models with 20 epochs training time.

Model	Training Time	Accuracy	Recall	F1 Score	IoU
EfficientNetV2M	8035.98 sec	96.37%	0.96	0.96	0.963
EfficientNetV2S	6016.56 sec	96.07%	0.96	0.95	0.957
MobileNet	2163.59 sec	68.89%	0.69	0.67	0.661
ResNet50	5868.29 sec	94.63%	0.95	0.94	0.941
ResNet101	7371.51 sec	94.46%	0.94	0.93	0.936

The model's operational carbon emission is also measured which is shown in Table 2. Here we can see that the carbon emission for EfficientNetV2S has lowest carbon emission while preparing data and moderate carbon emission on developing and deploying model. During training, a significant amount of computational resources is consumed [28]. By utilizing the code carbon emissions formula, we can observe that EfficientNetV2M and ResNet50 consume more hardware resources. The MobileNet has lowest carbon emission while developing model and deploying model shown in Figure 5.

Table 2. Carbon emission amount at various stages of EfficientNetV2M, EfficientNetV2S, MobileNet, ResNet50, and ResNet101 models with 20 epochs training time.

Model	Carbon Emission (Kg CO ₂)		
	Prepare Data	Develop Model	Deploy Model
EfficientNetV2M	0.002217	0.151638	0.156662
EfficientNetV2S	0.000483	0.036457	0.037580
MobileNet	0.000974	0.025888	0.027469
ResNet50	0.001111	0.111764	0.114827
ResNet101	0.001383	0.089301	0.092323

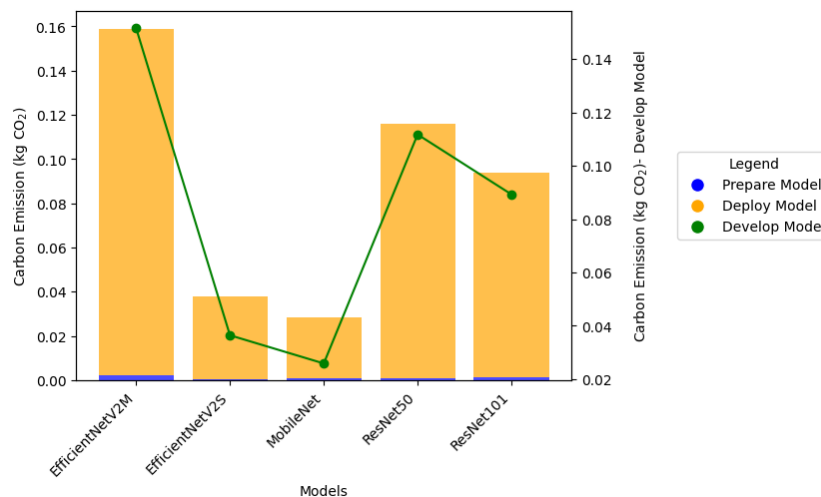


Figure 5. Carbon emission of each model at various stage

The accuracy of the model for EfficientNetV2M, EfficientNetV2S, ResNet50 and ResNet101 increase as it trains longer; whereas, the accuracy doesn't increase for MobileNet after 12 epochs shown in Figure 6 (a). Similarly, the loss decreases for all models except MobileNet after 13 epochs as depicted in Figure 6 (b).

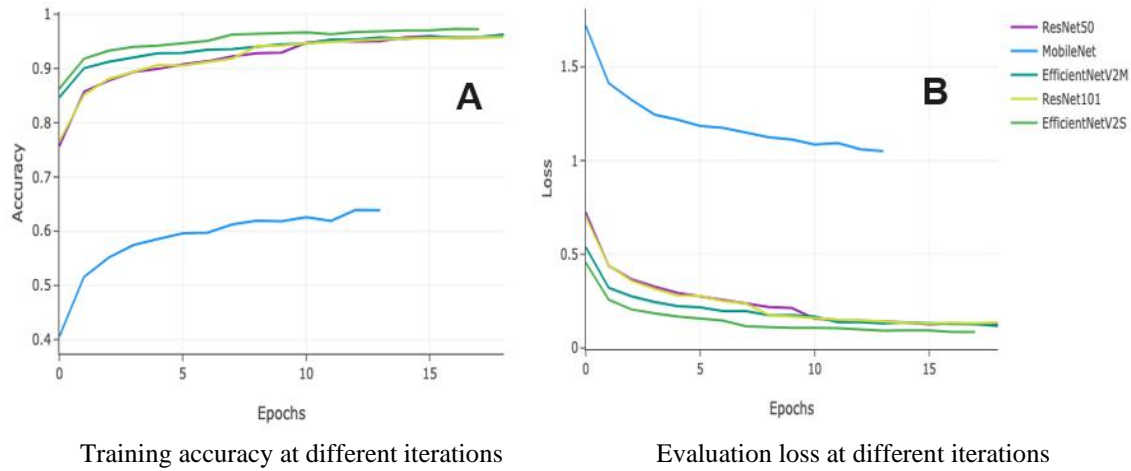


Figure 6. Comparison of loss and accuracy of models at different epochs.

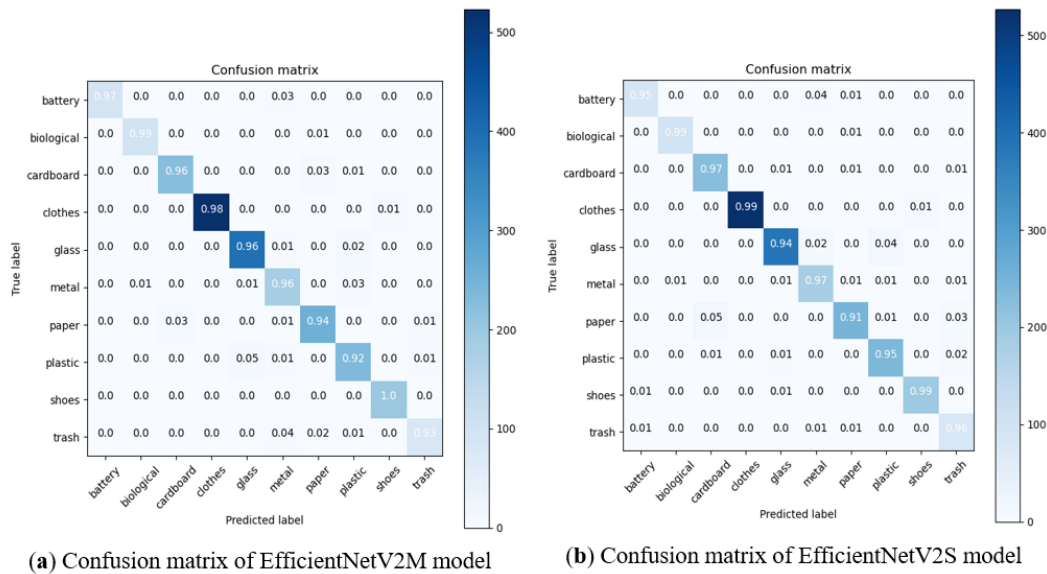


Figure 7. Comparison of loss and accuracy of models at different epochs

The confusion matrix for EfficientNetV2M model is shown in Figure 7(a) and EfficientNetV2S model in Figure 7(b). From our experiment, we found that the EfficientNetV2S has higher accuracy, recall, f1-score and IoU than MobileNet, ResNet50 and ResNet101. Also, carbon emission is moderate for preparing data, developing model and deploying model comparing to others. To find the best hyperparameter we used optuna [29], where we define the objective and get the best value that matches our objective. The best hyperparameter is selected and applied. Figure 8 shows the optimization history plot. After applying the optimal hyper parameters the accuracy increased slightly, the new accuracy is 96.41%.

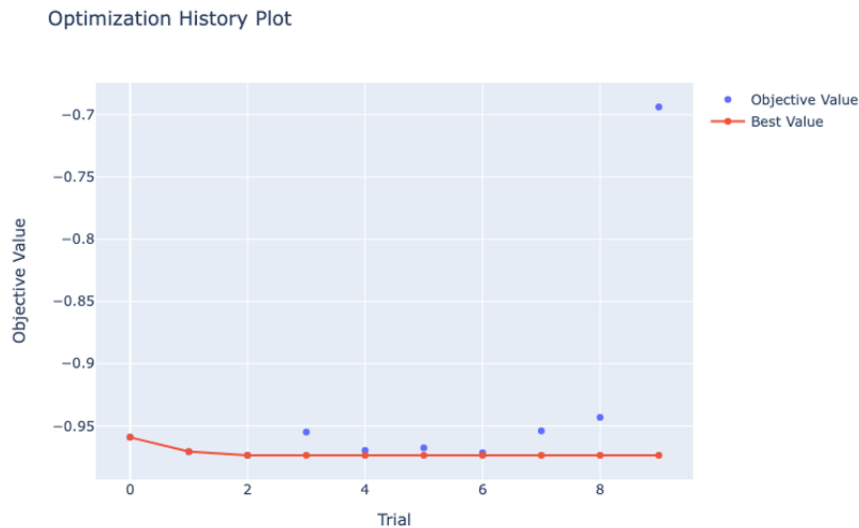


Figure 8. Optimization history plot of EfficientNetV2S model.

5. Conclusions

During our research, we investigated various transfer learning models using a garbage dataset with pre-trained weights. We evaluated the computational carbon emissions of each model and compared their accuracy, recall, f1-score, and IoU. It is essential to note that the data collection process also plays a role in contributing to emissions. Our findings indicate that the EfficientNetV2 family outperforms MobileNet, ResNet50, and ResNet101 in terms of accuracy, recall, f1-score, and IoU. EfficientNetV2M, with more layers than EfficientNetV2S, yielded better results but required longer training time and resulted in higher computational carbon emissions. Conversely, the ResNet family demonstrated moderate accuracy, while MobileNet exhibited the lowest accuracy. We observed that ResNet50 achieved higher accuracy and better recall, f1-score, and IoU values than ResNet110 while requiring less training time. However, ResNet50 had a higher computational carbon emission compared to other models. After comprehensive analysis of the models' training time, accuracy, recall, f1-score, IoU, and computational carbon emissions, we concluded that EfficientNetV2S is the most sustainable model with superior accuracy. Additionally, we found that slight adjustments to hyperparameters contributed to increased accuracy.

Acknowledgments

The author confirm that the data used in this experiment are available at <https://www.kaggle.com/datasets/sumn2u/garbage-classification-v2/> and that the experiments are available at <https://github.com/sumn2u/garbage-classification-tl>.

Competing Interest

The authors declare no conflict of interest.

References

- [1] Kaza, S.; Yao, L.C.; Bhada-Tata, P.; Van Woerden, F. (2018). What a waste 2. 0: a global snapshot of solid waste management to 2050. World Bank: Washington DC, USA. <https://doi.org/10.1596/978-1-4648-1329-0>.

- [2] Mridha, K.; Shaw, R.N.; Ghosh, A. (2021). Intelligent based waste management awareness developed by transfer learning. 2021 IEEE 4th International Conference on Computing, Power and Communication Technologies (GUCON), pages 1–5, Kuala Lumpur, Malaysia. IEEE. <https://doi.org/10.1109/GUCON50781.2021.9573586>.
- [3] Ferronato, N.; Torretta, V. (2019). Waste mismanagement in developing countries: a review of global issues. *International Journal of Environmental Research and Public Health*, 16(6), 1060. <https://doi.org/10.3390/ijerph16061060>.
- [4] Fadhullah, W.; Imran, N.I.N.; Ismail, S.N.S.; Jaafar, M.H.; Abdullah, H. (2022). Household solid waste management practices and perceptions among residents in the East Coast of Malaysia. *BMC Public Health*, 22(1), 1. <https://doi.org/10.1186/s12889-021-12274-7>.
- [5] Liu, W.; Ouyang, H.; Liu, Q.; Cai, S.; Wang, C.; Xie, J.; Hu, W. (2022). Image recognition for garbage classification based on transfer learning and model fusion. *Mathematical Problems in Engineering*, 2022, 1–12. <https://doi.org/10.1155/2022/4793555>.
- [6] Shreya, M.; Nimal Yughan, V.; Katyal, J.; Ramesh, R. (2023). Technical solutions for waste classification and management: A mini-review. *Waste Management & Research: The Journal for a Sustainable Circular Economy*, 41(4), 801–815. <https://doi.org/10.1177/0734242X221135262>.
- [7] Kunwar, S. (2023). Mwaste: An app that uses deep learning to manage household waste. *Clean Technologies and Recycling*, 3(3), 119–133. <https://doi.org/10.3934/ctr.2023008>.
- [8] Narayan, Y. (2021). Deepwaste: applying deep learning to waste classification for a sustainable planet. <https://doi.org/10.48550/ARXIV.2101.05960>.
- [9] Kaack, L.H.; Donti, P.L.; Strubell, E.; Kamiya, G.; Creutzig, F.; Rolnick, D. (2022). Aligning artificial intelligence with climate change mitigation. *Nature Climate Change*, 12(6), 518–527. <https://doi.org/10.1038/s41558-022-01377-7>.
- [10] Pan, S.J.; Yang, Q. (2010). A survey on transfer learning. *IEEE Transactions on Knowledge and Data Engineering*, 22(10), 1345–1359. <https://doi.org/10.1109/TKDE.2009.191>.
- [11] Poudel, S.; Poudyal, P. (2022). Classification of waste materials using cnn based on transfer learning. Proceedings of the 14th Annual Meeting of the Forum for Information Retrieval Evaluation, pp. 29–33, Kolkata India. ACM. <https://doi.org/10.1145/3574318.3574345>.
- [12] Vo, A.H.; Hoang Son, L.; Vo, M.T.; Le, T. (2019). A novel framework for trash classification using deep transfer learning. *IEEE Access*, 7, 178631–178639. <https://doi.org/10.1109/ACCESS.2019.2959033>.
- [13] Tan, M.; Le, Q.V. (2021). Efficientnetv2: Smaller models and faster training. <https://doi.org/10.48550/arXiv.2104.00298>.
- [14] Kunwar, S. (2023). Garbage dataset. <https://doi.org/10.34740/KAGGLE/DS/2814684>.
- [15] Lilhore, U.K.; Simaiya, S.; Dalal, S.; Damaševicius, R. (2023). A smart waste classification model using hybrid CNN-LSTM with transfer learning for sustainable environment. *Multimedia Tools and Applications*, 83, 29505–29529. <https://doi.org/10.1007/s11042-023-16677-z>.
- [16] Wulansari, A.; Setyanto, A.; Luthfi, E. T. (2022). A convolutional neural network based on transfer learning for medical waste classification during pandemic covid-19. 2022 International Seminar on Intelligent Technology and Its Applications (ISITIA), pp. 86–91, Surabaya, Indonesia. IEEE. <https://doi.org/10.1109/ISITIA56226.2022.9855374>.
- [17] Mehedi, M.H.K.; Arafin, I.; Hasan, M.; Rahman, F.; Tasin, R.; Rasel, A.A. (2023). A transfer learning approach for efficient classification of waste materials. 2023 IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC), pp. 0636–0640, Las Vegas, NV, USA. IEEE. <https://doi.org/10.1109/CCWC57344.2023.10099127>.
- [18] Huang, G.; He, J.; Xu, Z.; Huang, G. (2020). A combination model based on transfer learning for waste classification. *Concurrency and Computation: Practice and Experience*, 32(19), e5751. <https://doi.org/10.1002/cpe.5751>.

- [19] Srivatsan, K.; Dhiman, S.; Jain, A. (2021). Waste classification using transfer learning with convolutional neural networks. *IOP Conference Series: Earth and Environmental Science*, 775(1), 012010. <https://doi.org/10.1088/1755-1315/775/1/012010>.
- [20] Das, D.; Sen, A.; Hossain, S.M.M.; Deb, K. (2023). Trash image classification using transfer learning based deep neural network. In Vasant, P., Weber, G.-W., Marmolejo-Saucedo, J. A., Munapo, E., and Thomas, J. J., editors, *Intelligent Computing & Optimization*, volume 569, pp. 561–571. Springer International Publishing: Cham, Switzerland. https://doi.org/10.1007/978-3-031-19958-5_53.
- [21] Devi, D.; Biswas, S.K.; Purkayastha, B. (2020). A review on solution to class imbalance problem: Undersampling approaches. 2020 International Conference on Computational Performance Evaluation (ComPE), pp. 626–631. <https://doi.org/10.1109/ComPE49325.2020.9200087>.
- [22] Hancock, J.; Khoshgoftaar, T.M.; Johnson, J.M. (2022). Informative evaluation metrics for highly imbalanced big data classification. 2022 21st IEEE International Conference on Machine Learning and Applications (ICMLA), pp. 1419–1426. <https://doi.org/10.1109/ICMLA55696.2022.00224>.
- [23] Shijie, J.; Ping, W.; Peiyi, J.; Siping, H. (2017). Research on data augmentation for image classification based on convolution neural networks. 2017 Chinese Automation Congress (CAC), pp. 4165–4170. <https://doi.org/10.1109/CAC.2017.8243510>.
- [24] Zhang, J.; He, T.; Sra, S.; Jadbabaie, A. (2020). Why gradient clipping accelerates training: A theoretical justification for adaptivity. arXiv:1905.11881 [cs, math]. <https://doi.org/10.48550/arXiv.1905.11881>.
- [25] Maji, K.; Gupta, S. (2023). Evaluation of various loss functions and optimization techniques for mri brain tumor detection. 2023 International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE), pp. 1–6. <https://doi.org/10.1109/ICDCECE57866.2023.10151232>.
- [26] Mikołajczyk, A.; Grochowski, M. (2019). Style transfer-based image synthesis as an efficient regularization technique in deep learning. 2019 24th International Conference on Methods and Models in Automation and Robotics (MMAR), pp. 42–47. <https://doi.org/10.1109/MMAR.2019.8864616>.
- [27] Rezatofghi, H.; Tsoi, N.; Gwak, J.; Sadeghian, A.; Reid, I.; Savarese, S. (2019). Generalized intersection over union: A metric and a loss for bounding box regression. 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 658–666. <https://doi.org/10.1109/CVPR.2019.00075>.
- [28] Date, P.; Carothers, C.D.; Mitchell, J.E.; Hendler, J.A.; Magdon-Ismail, M. (2020). Training deep neural networks with constrained learning parameters. 2020 International Conference on Rebooting Computing (ICRC), 107–115. <https://doi.org/10.1109/ICRC2020.2020.00018>.
- [29] Akiba, T.; Sano, S.; Yanase, T.; Ohta, T.; Koyama, M. (2019). Optuna: A next-generation hyperparameter optimization framework. Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2623–2631. <https://doi.org/10.1145/3292500.3330701>.



© 2024 by the authors. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).