ResNet-50 with Grad-CAM for Household Waste Classification: Performance Analysis and Interpretability

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***Abstract*—Global waste generation has been increasing annually, with 2.01 billion tonnes of municipal solid waste produced each year. In the Philippines, Filipinos consume 20 kilograms of plastic annually, resulting in 15.43 kilograms per capita becoming waste, with only 9% being recycled. Household waste contributes significantly to these wastes due to limited awareness, inconsistent compliance, and public attitudes towards solid waste management. Recent studies have applied Convolutional Neural Networks (CNNs) using transfer learning with various deep learning models to perform multi-class classifications of trash. However, there is limited research on applying ResNet-50 for classifying household waste into specific categories. This study addresses this gap by training the ResNet-50 deep convolutional neural network to classify household waste into 15 categories. The modified model demonstrated high performance, achieving a training accuracy of 93.88% and a validation accuracy of 90.33%. Additionally, Real-world testing and Grad-CAM visualizations were used to understand the model's decision-making process by highlighting important features for classification. However, real-world testing revealed a reduced accuracy of 71%, likely due to a small number of samples and the model's sensitivity to changes in image quality, lighting, and background noise. Future research should focus on expanding real-world testing to develop a more comprehensive assessment of the model's performance.**

***Index Terms*—ResNet-50, Waste Classification, Deep learning, Transfer learning**

I. Introduction

Global waste generation has been increasing annually, reaching 2.01 billion tonnes of municipal solid waste produced each year [1]. On average, each person generates 0.74 kilograms of waste every day, with at least 33 percent of this waste not managed properly. According to the United Nations Environment Programme (UNEP) [2], municipal solid waste generation is predicted to increase from 2.1 billion tonnes in 2023 to 3.8 billion tonnes by 2050. Southeast Asia stands as one of the leading contributors to the global plastic waste crisis, with the Philippines ranking among the top 5 countries alongside Indonesia, Thailand, Vietnam, and Malaysia [3]. Filipinos are estimated to consume 20 kilograms of plastic annually, resulting in 15.43 kilograms per capita becoming waste, of which only 9% is recycled [4].

As a result, a significant amount of this plastic waste is disposed of in the ocean, making the Philippines the largest contributor to ocean plastic pollution [5]. The country contributes over 350,000 tonnes of plastic waste to the ocean annually, accounting for 36% of global ocean plastic pollution. These wastes originate from various sectors, including residential, commercial, institutional, and industrial. Reports indicate that 57% of solid waste comes from residential sources [6]. Moreover, in densely populated areas like Metro Manila, 74.14% of the waste consists of household waste [7] Recognizing the significant impact of household waste on plastic pollution in the Philippines, DENR Undersecretary Benito Antonio de Leon highlights a pervasive lack of understanding of waste segregation among Filipino households [8]. Environment Secretary Roy Cimatu further emphasizes the importance of solid waste management (SWM) at the household level, urging community officers nationwide to promote waste reduction and proper disposal practices [9]. Moreover, effective household waste segregation supports the country's greenhouse gas (GHG) emission reduction targets under the Paris Agreement on climate change, as noted by Albert Magalang, chief of the DENR Climate Change Information and Technical Support Division [10].

To address these issues, the Environmental Management Bureau of the Department of Environment and Natural Resources (EMB-DENR) has advised for proper waste segregation, promoting the traditional practice among households of manually sorting their waste into recyclables, compostables, and non-recyclables [11]. However, significant challenges remain, including limited awareness, inconsistent compliance, and public attitudes towards solid waste management. A 2018 SWS survey [12] revealed that 35% of Filipinos believe that the lack of household education on waste management contributes to plastic pollution. Additionally, The World Bank Group report [13] emphasizes that household education and awareness determine the success of proper waste segregation.

In their efforts to enhance waste management practices, current studies apply Convolutional Neural Networks (CNNs) based on transfer learning with various deep learning models to perform multi-class classifications of trash. However, they highlight the need for more images for each class to avoid class imbalance and suggest subdividing labels if necessary [14] [15] [16]. To aid this, the study will focus on acquiring more images from different sources with almost equal amounts per class and further separating classes to attain a higher accuracy of the model. Furthermore, the study will apply the ResNet-50 model (short for Residual Network with 50 layers), a deep convolutional neural network architecture designed for handling complex image recognition tasks [17]. This model will be used to identify images of waste and classify them into specific categories. However, it's worth emphasizing that this study exclusively focuses on utilizing the ResNet-50 architecture and does not explore alternative model parameters or architectures.

Moreover, the model will be evaluated using metrics such as training accuracy, validation accuracy, and F1-score to assess its performance in waste classification tasks. Additionally, real-world testing will be conducted to validate the model's effectiveness in classifying unseen data. Grad-CAM will also be used to visualize and provide insights into how the model makes decisions when classifying this new data. By training and testing a ResNet-50 model to classify various types of household waste, the study aims to enhance waste management processes, promote responsible waste disposal practices, and contribute to environmental sustainability.

II. Related Works

A. Loosening Identification of Multi-Bolt Connections Based on Wavelet Transform and ResNet-50 Convolutional Neural Network

ResNet-50 is a deep convolutional neural network (CNN) that has attracted a lot of interest in a variety of study fields because of its strong performance and effective architecture. A study conducted by Li et al. found that ResNet-50's design, which includes residual blocks that increase gradient flow and reduce training problems, corresponds to its superior performance in tasks such as image recognition and segmentation 18. Its ability to handle high-dimensional input while maintaining model integrity has made it a popular choice in recent years, outperforming alternative CNN architectures in terms of accuracy and performance.

B. Implementation of ResNet-50 on End-to-End Object Detection (DETR) on Objects

A study demonstrated the use of ResNet-50 in an End-to-End Object Detection system to improve object detection performance in images [19]. The study showed that ResNet-50, when combined with DETR (DEtection TRansformer), achieved better accuracy than DETR models that did not use ResNet-50. Apart from that, the study found that ResNet-50 + DETR could detect objects more quickly than similar traditional CNN models.

C. Comparing Inception V3, VGG 16, VGG 19, CNN, and ResNet 50: A Case Study on Early Detection of a Rice Disease

Recent studies have highlighted the effectiveness of the ResNet-50 model in various image classification tasks. In a study by Shah et al., researchers focused on the early detection of rice blast disease which has significant issues affecting rice production [20]. They utilized pre-trained models such as Inception V3, VGG16, VGG19, and ResNet50. The Inception V3 model achieved an accuracy of 98.16%, while the VGG16 and VGG19 models performed similarly, with accuracies of 98.47% and 98.56%, respectively. The modified ResNet50 model outperformed all other models, achieving the highest accuracy of 99.75% with a loss rate of 0.33.

D. Deep Learning Approach to Recyclable Products Classification: Towards Sustainable Waste Management

Ahmed et al. conducted a deep learning study on waste classification and found compelling results in classifying recyclable materials using several models such as Convolutional Neural Network (CNN), DenseNet169, MobileNetV2, and ResNet50V2 [21]. The experiment showed that the CNN model obtained an accuracy of 88.52%.In comparison, the pre-trained models demonstrated significantly higher accuracies: DenseNet169 achieved 94.40%, MobileNetV2 reached 97.60%, and ResNet50V2 achieved 98.95%. Among these tested models, ResNet50V2 outperformed all other models with an impressive accuracy of 98.95%.

E. Image Classification with Transfer Learning Using a Custom Dataset: Comparative Study

Deep neural network training is expensive because it requires significant time, computing power, and a large dataset, which are not always available. These challenges can be avoided through transfer learning, where model weights from pre-trained models designed for popular computer vision benchmark datasets are reused. Transfer learning aims to improve generalization in different applications by leveraging information from one domain to another. High-performing models can be downloaded and used immediately, or integrated into new models created to address specific computer vision tasks. As a result, researchers in this study were able to accelerate the training process and enhance the performance of their deep learning model, even with a relatively small dataset [22].

F. Effectiveness of Transfer Learning and Fine Tuning in Automated Fruit Image Classification

A study was conducted by Siddiqi about the effectiveness of transfer learning in image classification of fruit [23]. It has been shown that the best classification accuracy of 99.27% can be achieved by transfer learning with the VGG16 model. Experiments show not only how successful transfer learning and fine tuning are, but also how remarkably well a self-designed 14-layer convolutional neural net performs the task, with a classification accuracy of 96.79

G. Grad-CAM for Visualizing Key Features in Waste Classification

A similar study by Mao et al. on recycling waste classification using DenseNet121 applied Gradient-weighted Class Activation Mapping (Grad-CAM) to demonstrate how the model identifies waste classes by emphasizing relevant features. Grad-CAM generated heatmaps that highlighted the regions of the waste images the model focused on for classification. In the study, the heat maps revealed that the model directed its attention to the necks of bottles to distinguish between glass and plastic materials, and focused on the edges and corners to classify paper and cardboard items. These visualizations allowed the researchers to understand the features that the model considered significant for its classifications [24]

H. RealWaste: A Novel Real-Life Data Set for Landfill Waste Classification Using Deep Learning

A study about landfill waste classification (RealWaste) used only VGG-16, InceptionResNetV2, DenseNet121, Inception V3, and MobileNetV2 to test [16]. Based on the results of training on RealWaste, the potential for the Inception V3 inside waste classification has been demonstrated to be significant. Although, It has indicated to have trouble telling waste materials made of cardboard, paper, plastic, and metal apart. The labeling on these waste kinds makes the mistake understandable, but it also limits the accuracy of landfill modeling estimates. Therefore, it is advised by this paper that future research takes into account the effects of additional label refinement within the dataset and image enlargement for unbalanced labels.

I. Identified Gaps

Research on the application of ResNet-50 transfer learning for the classification of recyclable and non-recyclable household waste is lacking, despite the capabilities of machine learning and transfer learning with this model demonstrated by previous studies.However, more research needs to be done in this topic on elements such as the build of the model, hyper-parameter adjustments, and quality of the dataset.

III. Methodology

This chapter outlines the methodology used in this study to classify household waste using ResNet-50. The process begins with the collection of a dataset of household waste images from various sources. These images undergo preprocessing to prepare the dataset for the model. After preprocessing, the ResNet-50 model is modified with additional layers and trained on the processed images to classify different types of household waste. Following training, the model's classification accuracy is evaluated using various metrics on the training data. Finally, real world testing evaluates the model's performance with unseen data. Through this approach, the study aims to analyze the effectiveness of the ResNet-50 model in classifying different types of household waste. Figure 1 Shows a graphic format of the methodology.

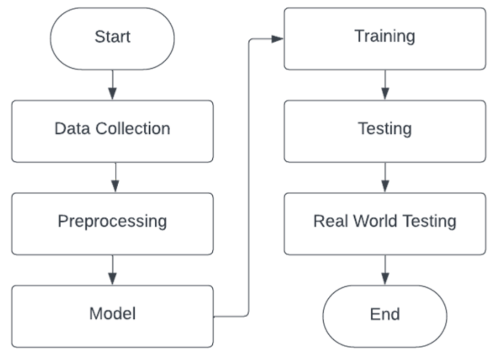

Fig. 1. Methodology Flowchart

A. Dataset

The dataset used in this study contains over 15,000 images representing household waste materials across 15 different classes, including aseptic cartons, batteries, broken glass, cardboard, flexible plastic packaging, glass bottles, metal cans, mugs, paper waste, plastic bags, plastic bottles, plastic jugs, plastic utensils, stained cardboard, and styrofoam, with each category containing 1,000 images. Moreover, the dataset was collected from various sources, including online platforms such as Roboflow (32%) [25] [26] [27] [28] [29] [30] [31] [32] [33] [34] [35] [36] [37] [38] [39] [40] [41] [42] [43] [44]. Kaggle (17.%) [45] [46] [47] [48] [49]. GitHub (15.2%) [50] [51], Google (9.6%), and Hugging Face (6.1%) [52]. Additionally, 19.4% of the dataset consists of images that were self-acquired during the research process. Figure 2 shows the a visualization of the sources of the dataset.

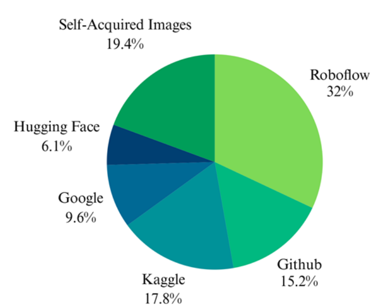

Fig. 2. Dataset Sources

B. Model

The study will use the ResNet50 model, a ResNet architecture consisting of 50 layers that has demonstrated state-of-the-art performance on the ImageNet dataset. This model was chosen for waste classification due to its exceptional performance in image classification tasks. To further optimize the ResNet-50 model, additional layers will be added to the base model. These include GlobalAveragePooling2D, which reduces the spatial dimensions of the input, and BatchNormalization to normalize the data with parameters set as axis=-1, momentum=0.99, and epsilon=0.001. Additionally, Dense layers with 256 units and ReLU activation will utilize L2 regularization, with parameters such as kernel_regularizer=0.016, activity_regularizer=0.006, and bias_regularizer=0.006. Dropout layers will also be included to prevent over-fitting during training. Finally, the output layer will consist of 15 neurons corresponding to the 15 waste classes

C. Training

After adding additional layers and building the modified model, the ResNet-50 model will be trained to classify images of various waste classes. The training dataset will include approximately 800 images per class, and the training will be limited to 15 epochs due to constraints in time and hardware resources.

D. Testing

To evaluate the model's performance, testing will include using metrics such as training validation and the F1 score on the testing dataset. The validation data contains approximately 100 images per class. Additionally, the confusion matrix from scikit-learn will be used to visualize the model's accuracy across different classes in classifying waste.

E. Real World Testing

Real world testing will be conducted to evaluate the model's performance on unseen data. This will involve feeding the model with new images of household waste captured by the researchers. Some of these images will be defaced, weathered, or damaged as they will be taken under different lighting conditions. Due to time constraints, the real world testing will be limited to exactly five images per class. Additionally, GradCAM will be used to generate heatmaps and visualize where the model focuses its attention on these new data. This will provide insights into how the model makes its classifications based on specific features within the images of household waste.

IV. Results and Discussion

The modified ResNet-50 model used to classify different common household waste resulted in a relatively high accuracy in both validation and training in a matter of 15 epochs. The training ended with 93.88% accuracy, while the validation accuracy ended with 90.33% accuracy. Furthermore, the training ended with rather low loss for both training and validation. Training loss ended with 0.6556 and Validation loss ended with 0.7320. Figure 3 and 4 visualizes the accuracy over epoch and loss over epoch.

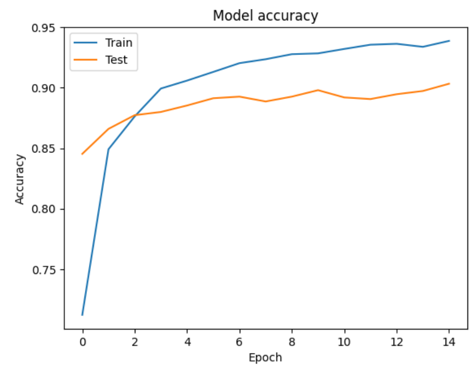

Fig. 3. Accuracy over epoch

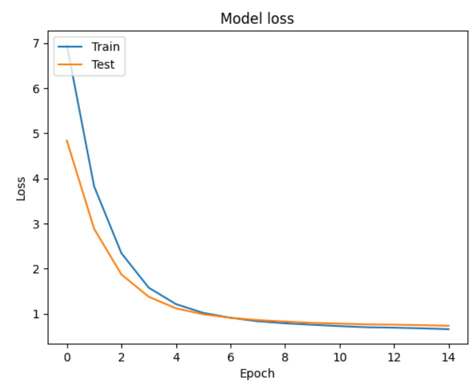

Fig. 4. Loss over epoch

Figure 5 shows the confusion matrix of the testing data, it points out where the model misidentifies and correctly identifies an image.

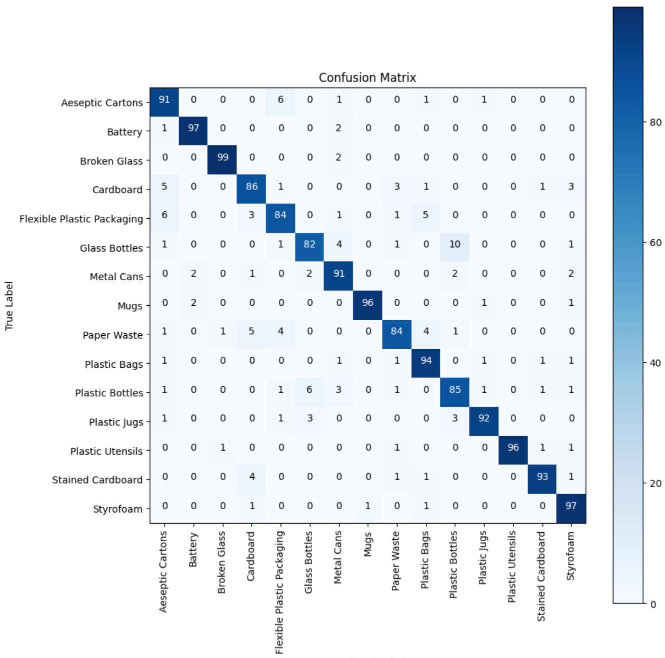

Fig. 5. Confusion Matrix of the Testing Data

Table 1 shows Precision, Recall, and F1-score metrics and the number of supports or samples per class using the Test Data . While Figures 6 shows the Grad-CAM visualization using the Real World images. Furthermore, the titles include the true label, predicted label, and its confidence level.

A. Interpretation of Results

Figures 3, 4 and 5 and Tables 1 shows the different metrics and graphs that support the claim that the model is accurate. Given the model's validation accuracy is at 90.33% this is also supported by the confusion matrix where it mostly classified the test images correctly. However, the model still

TABLE I
CLASSIFICATION REPORT USING TEST DATA

	Precision	Recall	F1-Score	Support
Aseptic Cartons	0.84	0.91	0.88	100
Battery	0.96	0.97	0.88	100
Broken Glass	0.98	0.98	0.98	101
Cardboard	0.86	0.86	0.86	100
Flexible Plastic Packaging	0.86	0.84	0.85	100
Glass Bottles	0.88	0.82	0.85	100
Metal Cans	0.87	0.91	0.89	100
Mugs	0.99	0.96	0.97	100
Paper Waste	0.90	0.84	0.87	100
Plastic Bags	0.88	0.94	0.91	100
Plastic Bottles	0.84	0.85	0.85	100
Plastic Jugs	0.96	0.92	0.94	100
Plastic Utensils	1.00	0.96	0.98	100
Stained Cardboard	0.96	0.93	0.94	100
Styrofoam	0.90	0.97	0.93	100
accuracy			0.91	1501
macro avg	0.91	0.91	0.91	1501
weighted avg	0.91	0.91	0.91	1501

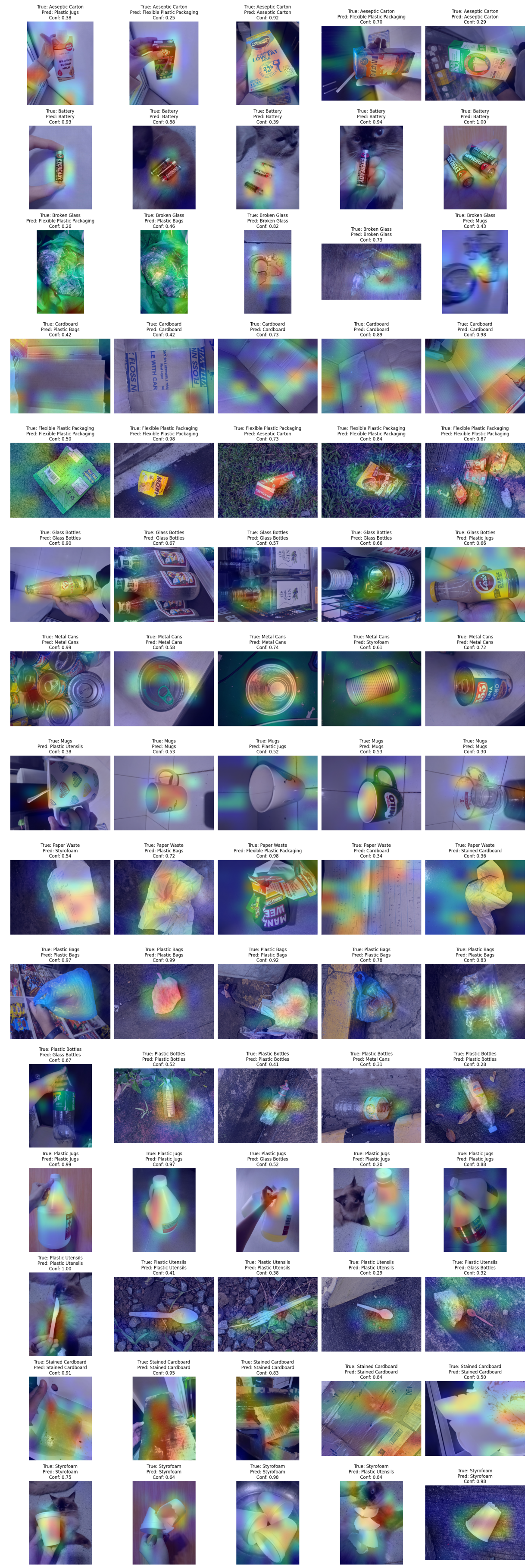

Fig. 6. Grad-CAM Visualization Using Real World Images

TABLE II
CLASSIFICATION REPORT USING REAL WORLD DATA

	Precision	Recall	F1-Score	Support
Aseptic Cartons	0.67	0.40	0.50	5
Battery	1.00	1.00	1.00	5
Broken Glass	1.00	0.4	0.57	5
Cardboard	0.80	0.80	0.80	5
Flexible Plastic Packaging	0.50	0.80	0.62	5
Glass Bottles	0.57	0.80	0.67	5
Metal Cans	0.80	0.80	0.80	5
Mugs	0.75	0.60	0.67	5
Paper Waste	0.00	0.00	0.00	5
Plastic Bags	0.62	1.00	0.77	5
Plastic Bottles	1.00	0.60	0.75	5
Plastic Jugs	0.57	0.80	0.67	5
Plastic Utensils	0.67	0.80	0.73	5
Stained Cardboard	0.83	1.00	0.91	5
Styrofoam	0.67	0.80	0.73	5
accuracy			0.71	75
macro avg	0.70	0.71	0.68	75
weighted avg	0.70	0.71	0.68	75

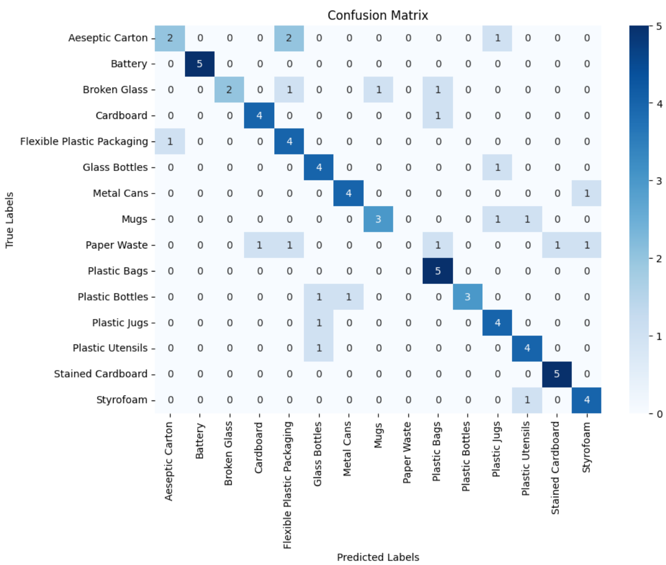

Fig. 7. Confusion Matrix using Real World Data

gets confused especially when it comes to plastic bottles and glass bottles where the model sometimes switches one to another.

The claim that the model is accurate is further solidified by the classification report where the model scored an accuracy score of 91%.

From a visual inspection, the model's loss may have hit its lowest point, meaning the model could overshoot if trained further. Furthermore, the loss graph suggest that the model is at its optimal state as both training and validation loss has converged and this is further supported by the confusion matrix on test data (Figure 5) and classification result on test data (Table 1) However, the confusion matrix using real world data (Figure 7) suggest that the model is less accurate as it does not accurately classify all or most of the images correctly. This is supported by the Classification Result on Table 2 where it shows that the model only has 71% accuracy score using the real-world data. Although, further testing should be implored as this is only 5 images per class or a total of 75 images.

Figure 6 shows the Grad-CAM visualization of the model, it shows where the model focuses to give a prediction. On certain classes such as battery it focuses on the body of the subject, Glass bottles usually focus on the body and or neck of the bottle, metal cans are focused on the lid of the can and mugs are focused on the handle and the body. However, there are classes where all predictions are wrong such as in paper waste, where it did focus on the body but the color of the actual paper and the background itself confuses the model. This suggest further testing by employing more images.

V. CONCLUSION AND RECOMMENDATION

Household waste management is a significant challenge in the Philippines, mainly due to widespread lack of knowledge on proper waste segregation among Filipino households. This study addressed this issue by modifying and training the ResNet-50 model to classify household waste. The study found that the modified model achieved over 90% accuracy in classifying images of common household waste, significantly higher than the 49% achieved by RealWaste. However, when tested with real-world data, the ResNet-50 model's accuracy dropped to 71%. Additionally, while Grad-CAM effectively highlighted key areas, there were instances where it focused on irrelevant features. This misclassification indicates that factors such as lighting, background noise, and image quality can significantly impact the model's accuracy. Furthermore, the real-world testing involved only five images per class, which might not provide a comprehensive assessment of the model's performance in real-world scenarios. Therefore, it is recommended to expand the dataset to include images with varied lighting conditions, backgrounds, and image quality to better enhance the model's generalization and robustness when dealing with real-world data. Future research should also explore longer training durations and increasing epochs to refine the model's weights and improve accuracy. Moreover, adjusting hyperparameters such as learning rate, batch size, and regularization parameters could further enhance performance and address misclassification issues. Ultimately, this study not only highlights the effectiveness of the ResNet-50 model for waste classification but also addresses significant gaps in existing research by including additional classes specifically focusing on household waste. To further enhance accuracy and performance, future research should focus on expanding the dataset, extending training durations, and refining model parameters. These improvements could lead to better waste management practices and address significant waste challenges.

References

[1] W. Bank, "Trends in solid waste management," 2023. [Online]. Available: https://datatopics.worldbank.org/what-a-waste/trends_in_solid_waste_management.html

[2] U. U. E. Programme, "Global waste management outlook 2024," February 2024. [Online]. Available: https://www.unep.org/resources/global-waste-management-outlook-2024

[3] I. S. Arumdani, A. S. Puspita, and M. A. Budihardjo, "Msw handling of top 5 leading waste-producing countries in southeast asia," in *IOP Conference Series: Earth and Environmental Science*, vol. 896, no. 1, November 2021, p. 012003.

[4] C. for Innovative Technology and Missions, "Plastic recycling in the philippines," March 2022. [Online]. Available: https://sustainability.ph/solutions/intelligence/plastic-recycling-in-the-philippines

[5] J. Longley, "Plastic polluters," September 2023. [Online]. Available: https://www.utilitybidder.co.uk/blog/plastic-polluters/

[6] S. E. P. Office, "Philippine solid waste at a glance," November 2017. [Online]. Available: https://legacy.senate.gov.ph/publications/SEPO/AAG_Philippine20Solid20Wastes_Nov2017.pdf

[7] V. Atienza, "Review of the waste management system in the philippines: Initiatives to promote waste segregation and recycling through good governance," 2011. [Online]. Available: https://nswai.org/docs/Review20of20the20Waste20Management20System20in20the20Philippines.pdf

[8] P. N. Agency, "Solid waste segregation remains major challenge in ph: Denr chief," May 2022. [Online]. Available: https://www.pna.gov.ph/articles/1175460

[9] C. Teves, "Solving garbage problem starts at home: Cimatu," November 2018. [Online]. Available: https://www.pna.gov.ph/articles/1053644

[10] ——, "Household waste segregation can aid ph climate action," June 2021. [Online]. Available: https://www.pna.gov.ph/articles/1144229

[11] E. M. B. of the Department of Environment and N. R. (EMB-DENR), "Waste segregation advisory," 2020. [Online]. Available: https://emb.gov.ph/waste-segregation-advisory/

[12] G. A. for Incinerator Alternatives (GAIA), "Sachet economy," July 2020. [Online]. Available: https://www.no-burn.org/Sachet-Economy/

[13] O. K. Repository, "Dspace," March 2021. [Online]. Available: https://openknowledge.worldbank.org/entities/publication/61e2e030-9dc2-5013-a8ff-7565919e17ee

[14] S. Poudel and P. Poudyal, "Classification of waste materials using cnn based on transfer learning," in *Proceedings of the 14th Annual Meeting of the Forum for Information Retrieval Evaluation*, December 2022.

[15] O. Adedeji and Z. Wang, "Intelligent waste classification system using deep learning convolutional neural network," *Procedia Manufacturing*, vol. 35, pp. 607–612, 2019.

[16] S. Single, S. Iranmanesh, and R. Raad, "Realwaste: A novel real-life data set for landfill waste classification using deep learning," *Information*, vol. 14, no. 12, p. 633, December 2023.

[17] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," December 2015. [Online]. Available: https://arxiv.org/abs/1512.03385

[18] X.-X. Li, D. Li, W.-X. Ren, and J.-S. Zhang, "Loosening identification of multi-bolt connections based on wavelet transform and resnet-50 convolutional neural network," *Sensors*, vol. 22, no. 18, p. 6825, Sep 2022.

[19] E. Suherman, B. Rahman, D. Hindarto, and H. Santoso, "Implementation of resnet-50 on end-to-end object detection (detr) on objects," *Sinkron*, vol. 8, no. 2, pp. 1085–1096, Apr 2023.

[20] S. R. Shah, S. Qadri, H. Bibi, S. M. W. Shah, M. I. Sharif, and F. Marinello, "Comparing inception v3, vgg 16, vgg 19, cnn, and resnet 50: A case study on early detection of a rice disease," *Agronomy*, vol. 13, no. 6, p. 1633, Jun 2023.

[21] M. Imran *et al.*, "Deep learning approach to recyclable products classification: Towards sustainable waste management," *Sustainability*, vol. 15, no. 14, pp. 11 138–11 138, Jul 2023.

[22] H. Bichri, A. Chergui, and M. Hain, "Image classification with transfer learning using a custom dataset: Comparative study," *Procedia Computer Science*, vol. 220, pp. 48–54, Jan 2023.

[23] R. Siddiqi, "Effectiveness of transfer learning and fine tuning in automated fruit image classification," in *Proceedings of the 2019 3rd International Conference on Deep Learning Technologies*, Jul 2019.

[24] W.-L. Mao, W.-C. Chen, C.-T. Wang, and Y.-H. Lin, "Recycling waste classification using optimized convolutional neural network," *Resources, Conservation and Recycling*, vol. 164, p. 105132, Jan 2021.

[25] GRPGLMThesis, "thesis dataset," https://universe.roboflow.com/grpglmthesis/thesis-unztx, mar 2023, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/grpglmthesis/thesis-unztx

[26] ——, "Household trash dataset (simple) dataset," https://universe.roboflow.com/grpglmthesis/household-trash-dataset-simple, apr 2023, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/grpglmthesis/household-trash-dataset-simple

[27] nora slimani, "trash-detection dataset," https://universe.roboflow.com/nora-slimani/trash-detection-otdmj, may 2023, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/nora-slimani/trash-detection-otdmj

[28] EcoSmart, "Ecosmart dataset," https://universe.roboflow.com/ecosmart/ecosmart, aug 2023, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/ecosmart/ecosmart

[29] school2, "styrofoam dataset," https://universe.roboflow.com/school2-iqyyf/styrofoam-l0ihw, jun 2023, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/school2-iqyyf/styrofoam-l0ihw

[30] C. Space, "E-waste dataset," https://universe.roboflow.com/circularity-space-nbzxv/e-waste-alwua, may 2024, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/circularity-space-nbzxv/e-waste-alwua

[31] C. Vinarkar, "waste segergation dataset," https://universe.roboflow.com/chinmay-vinarkar/waste-segergation, apr 2023, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/chinmay-vinarkar/waste-segergation

[32] home, "well9 dataset," https://universe.roboflow.com/home-7p8tg/well9-cbyd0, aug 2022, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/home-7p8tg/well9-cbyd0

[33] HCMUT, "milk-box dataset," https://universe.roboflow.com/hcmut-ohque/milk-box, aug 2023, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/hcmut-ohque/milk-box

[34] can, "glass bottle dataset," https://universe.roboflow.com/can-jniv8/glass-bottle-rxvbe, apr 2023, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/can-jniv8/glass-bottle-rxvbe

[35] E. Unal, "detect dataset," https://universe.roboflow.com/erkan-unal/detect-o9dby, aug 2023, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/erkan-unal/detect-o9dby

[36] school, "tetra pak dataset," https://universe.roboflow.com/school-gchcr/tetra-pak, feb 2023, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/school-gchcr/tetra-pak

[37] W. Recognition, "Wastes dataset," https://universe.roboflow.com/waste-recognition-vyhug/wastes-6yna7, mar 2024, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/waste-recognition-vyhug/wastes-6yna7

[38] BangkitCapstone, "Wastecreative dataset," https://universe.roboflow.com/bangkitcapstone/wastecreative, may 2022, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/bangkitcapstone/wastecreative

[39] P. WS, "Batteries dataset," https://universe.roboflow.com/public-ws/batteries, aug 2021, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/public-ws/batteries

[40] school, "batteries dataset," https://universe.roboflow.com/school-gchcr/batteries-1aib9, feb 2023, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/school-gchcr/batteries-1aib9

[41] Dataset, "Plastic bags dataset," https://universe.roboflow.com/dataset-t7hz7/plastic-bags-0qzjp, may 2022, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/dataset-t7hz7/plastic-bags-0qzjp

[42] W. detection, "Clear broken glass dataset," https://universe.roboflow.com/waste-detection-gt6wy/clear-broken-glass-0fj4v, jul 2023, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/waste-detection-gt6wy/clear-broken-glass-0fj4v

[43] FirstWorkspace, "bags dataset," https://universe.roboflow.com/firstworkspace-jg76u/bags-41emo, oct 2022, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/firstworkspace-jg76u/bags-41emo

[44] T. Classification, "Plastic hdpe dataset," https://universe.roboflow.com/trash-classification-mjez0/plastic-hdpe, jun 2023, visited on 2024-06-26. [Online]. Available: https://universe.roboflow.com/trash-classification-mjez0/plastic-hdpe

[45] A. King, May 2024. [Online]. Available: https://www.kaggle.com/datasets/alistairking/recyclable-and-household-waste-classification

[46] S. Sah, March 2023. [Online]. Available: https://www.kaggle.com/datasets/siddharthkumarsah/plastic-bottles-image-dataset/data

[47] M. A. Csizmadia, July 2021. [Online]. Available: https://www.kaggle.com/datasets/markcsizmadia/object-detection-batteries-dices-and-toy-cars

[48] M. Usman, "Cup mug dataset," 2022. [Online]. Available: https://www.kaggle.com/dsv/4022961

[49] S. Kunwar, "Garbage dataset," 2023. [Online]. Available: https://www.kaggle.com/ds/2814684

[50] sam single, "Realwaste dataset," November 2023. [Online]. Available: https://github.com/sam-single/realwaste/tree/main?tab=readme-ov-file

[51] N. V. Kumsetty, A. Bhat Nekkare, S. K. S., and A. Kumar M., "Trashbox: Trash detection and classification using quantum transfer learning," in *2022 31st Conference of Open Innovations Association (FRUCT)*, 2022, pp. 125–130.

[52] M. Yang and G. Thung, "Trashnet: Classification of trash for recyclability status," 2017. [Online]. Available: https://huggingface.co/datasets/garythung/trashnet