AI-Powered Waste Classification Using Convolutional Neural Networks (CNNs)

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Abstract*—In Malaysia, approximately 70%-80% of recyclable materials end up in landfills due to low participation in Separation at Source Initiative. This is largely attributed to the public perception that waste segregation is a foreign idea, coupled with a lack of public knowledge. Around 72.19% of the residents are unsure about waste categorization and proper waste disposal. This confusion leads to apathy toward recycling efforts exacerbated by deficient environmental awareness. Existing waste classification systems mainly rely on manual entry of waste item names, leading to inaccuracies and lack of user engagement, prompting a shift towards advanced deep learning models. Moreover, current systems often fail to provide comprehensive disposal guidelines, leaving users uninformed. This project addresses the gap by specifically developing an AI-Powered Waste Classification System incorporated with Convolutional Neural Network (CNN), classifying waste technologically and providing environmentally friendly disposal guidelines. By leveraging primary and secondary waste image data, the project achieves a training accuracy of 80.66% and a validation accuracy of 77.62% in waste classification. The uniqueness of this project lies in its utilization of CNN within a user-friendly web interface that allows the user to capture or upload waste image, offering immediate waste classification results and sustainable waste disposal guidelines. It also enables users to locate recycling centers and access the dashboard. This system represents an ongoing effort to educate people and contribute to the field of waste management. It promotes Sustainability Development Goal (SDG) 12 (Responsible Consumption and Production) and SDG 13 (Climate Action), contributes zero waste, raises environmental awareness, and aligns with Malaysia's goals to increase recycling rates to 40% and reduce waste sent to landfills by 2025.

Keywords*—*Convolutional neural networks; CNN; deep learning; waste classification; recycling; zero waste; SDGs

I. Introduction

Cities around the world are struggling with a large amount of waste generation because of the rapid urbanization. According to a study by [1], the annual global waste production is projected to reach a staggering 27 billion tons by 2025. Malaysia, a country that is heavily relies on landfill disposal for waste management. It handles approximately 89% of the waste generated daily, which amounts to around 33,120 tons per day [2]. Notably, households in Malaysia are the main contributors to the waste stream, with recyclable materials constituting a substantial 70% to 80% of the landfill-bound waste [3].

To tackle the waste issue, the Malaysian government introduced “Separation at Source Initiatives” (SSI) under Act 672 starting in 2015 [4]. This plan requires households to separate their waste into recyclable and non-recyclables. Nevertheless, this plan has not been very effective because many people lack knowledge and understanding about waste segregation. Around 72% of residents are confused about waste segregation and do not know what the purpose of doing it [5]. Other efforts such as the #Asingkan campaign and KitaRecycle have also been organized, but the responses are not that active [6].

There is a widespread lack of public knowledge about proper waste disposal, recycling practices, and the environmental benefits of recycling [7]. Research conducted by [5] found that approximately 72.19% of the population is uncertain about the best waste disposal practices. This lack of awareness is often compounded by confusion about waste segregation. People are not sure which waste items belong to which categories. This confusion and lack of awareness lead to the perception that individual recycling efforts have little impact on environmental issues. As a result, people become indifferent and less motivated to recycle [8].

Moreover, the absence of well-defined policies and a sense of responsibility among Malaysians compounds the issue of limited environmental awareness [9]. A significant number of Malaysians believe that the primary responsibility for waste management lies with local authorities and municipal waste collectors. This perception creates a gap in knowledge and waste segregation practices at the household level [10]. The lack of environmental consciousness and inadequate enforcement has led to the development of a “tidak apa” (indifferent) culture among Malaysians [11].

By using the deep learning technique, the proposed system solves the issue of confusion and aligns the Malaysia 12th Pan while promoting the Sustainable Development Goals (SDGs). The proposed system aims to serve as an education platform that provides knowledge and utilizes the power of deep learning to eliminate people’s confusion in waste classification, at the same time educating people about sustainable waste management practices. In short, the authors intend to influence the user positively through this system. The flow of the proposed system can be viewed in Fig. 1.

A. Problem Statement

In Malaysia, approximately 70%-80% of recyclable materials end up in landfills due to low participation in Separation at Source Initiative [3]. This is largely attributed to the public perception that waste segregation is a foreign idea, coupled with a lack of public knowledge [6]. Around 72.19% of the residents are unsure about waste categorization and proper waste disposal [5]. Consequently, this confusion leads to apathy toward recycling efforts [7] exacerbated by deficient environmental awareness [3].

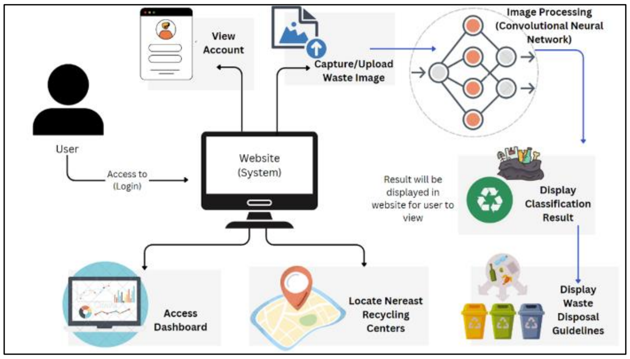

Fig. 1. System flow.

B. Research Question and Objectives

This research paper was written to fulfill the research objective via the questions stated below:

RQ1: What are the current waste management challenges?

RQ2: How effective are Convolutional Neural Networks for waste image classification?

RQ3: What features should the web-based waste classification system have to address the challenges?

RQ4: How effective is the developed system to solve the challenges?

The above research questions are to be answered through the research objectives necessary for this study.

RO1: To study the current waste management issue to recognize the challenges in terms of waste segregation and recycling.

RO2: To investigate the effectiveness of Convolutional Neural Networks in waste image classification.

RO3: To develop a web-based waste classification system.

RO4: To conduct testing and evaluation on the developed system.

This paper is organized as follows: Section II provides a comprehensive literature review, examining existing research and identifying gaps relevant to waste classification. Section III details the methodology employed in this study, outlining the processes from data collection to system development. In Section IV, the results and their implications are discussed, offering the effectiveness of the system. Finally, Section V concludes the paper by summarizing the key findings and presenting recommendations for future research in the field of waste management.

II. Literature Review

The rapid increase in waste generation in Malaysia, coupled with low recycling participation rates underscore the urgent need for effective waste management strategies. Waste classification is a key aspect of this challenge because it facilitates proper recycling and waste reduction. This section reviews current research related to waste management challenges, waste classification using CNN algorithm and the development of user-friendly systems, addressing the research objectives of this paper.

Studies indicate that waste management in Malaysia is not mature enough. The research in [4] emphasized that waste segregation and recycling are the most effective ways to reduce the waste sent to landfills. Referring to the Malaysia Solid Waste Management Policies and Plans Transformation [11], waste segregation and recycling gradually become the main objectives to target. Various organizations, both governmental and non-governmental, have made efforts to raise public awareness about the importance of these practices. One of the impressive programs is “Separation at Source Initiatives” (SSI). However, the outcome is not that positive due to a widespread lack of public knowledge and understanding about proper disposal practices, recycling guidelines, and the environmental benefits of recycling [7]. This confusion often leads individuals to feel uncertain about which waste items belong to specific categories, contributing to a perception that personal recycling efforts have minimal impact on environmental issues, as a result, many lack motivation to recycle [8]. There is a pressing need for innovative solutions to educate the public about recycling, clarify waste segregation, and raise awareness of proper disposal methods. Achieving these goals is essential for reducing waste and meeting the national target by 2025, while also promoting SDG 12 and 13.

Real-life practical applications prove that deep learning performed better than traditional machine learning in image classification tasks [12-14]. Among different deep learning models, Convolutional Neural Networks have demonstrated the highest efficiency in image classification tasks [15]. Several studies have concentrated on enhancing waste classification accuracy. The study in [16] developed the Deep Neural Network for Time Classification (DNN-TC) model using a deep transfer learning approach, achieving impressive results with 94% and 98% accuracy on Transnet and VN-trash datasets. The study in [17] focused on automatic image-based waste classification, achieving 88.66% accuracy using ResNet architecture. These studies underline the effectiveness of CNN in accurate classification of waste items. The choice of using CNN pre-trained models or using scratch depends on time and resource availability [18]. Most studies utilized pre-trained models such as Visual Geometry Group (VGG), Residual Network (ResNet), and Mobile Network (MobileNet) for image classification tasks because they performed well with the ability of the transfer learning technique to recognize a different task [18]. This research validates the use of CNNs in waste classification and directly supports the objective (RO2) to investigate the effectiveness of CNNs in waste image classification.

Upon comparing and analyzing the existing similar waste classification systems, important gaps are found. Existing systems rely only on classifying common waste and it is too general. A good waste classification system should be aligned with the country’s waste management guidelines and missions. The implementation of deep learning for waste classification systems in real-life scenarios is less as the authors found that existing system requires the user's input to search waste items through its database such as the 101 Trash [22], which can be time-consuming. At the same time, for those systems that consist of a deep learning model for classification features such as DeepWaste [19] and EcoScan [20], it only shows the waste classification result without displaying the next step to guide users on what to do. Most studies focus primarily on the technological aspects, often neglecting the necessity of public engagement and comprehensive disposal guidelines. Furthermore, the datasets used for the existing systems are considered less, and probably this is one of the reasons that lead to inaccuracy.

To sum up, the literature outlines significant advancements in waste classification technologies but also reveals critical gaps that must be addressed. By integrating technological solutions with community engagement strategies, this research aims to develop a more effective waste classification system that enhances both efficiency and public participation.

III. Methodology

In the journey of developing the proposed system, the authors followed a structured research methodology, as shown in Fig. 2, which is a combination of the System Development Life Cycle (SDLC) and Cross-Industry Standard Process for Data Mining (CRISP-DM).

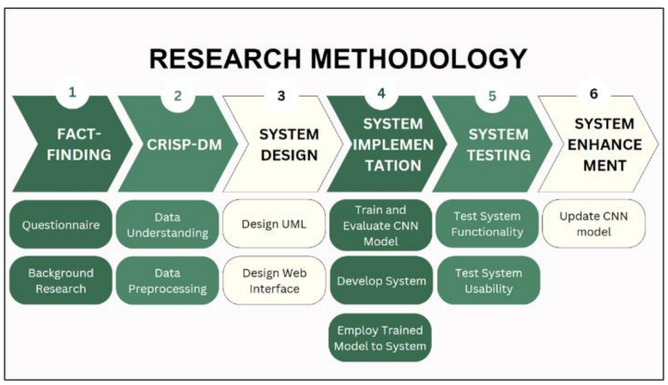

Fig. 2. Research methodology.

The research methodology used includes fact-finding, data collection, system design, system implementation, and system testing. Future enhancement would be done by regularly updating the CNN model training dataset to increase the model's accuracy and ensure that the system can classify more waste items.

A. *Phase 1: Fact-Finding*

The purpose of the above question is to get an overview of the waste materials commonly generated by Malaysian households. As shown in Fig. 3, plastic waste emerged as the main concern, acknowledged by 88.6% of respondents, highlighting its pervasive nature. Paper and cardboard waste were prevalent, reported by 64.8% of respondents, underlining their common use. Other categories included organic waste (55.2%), e-waste (30.5%), and clothing waste (31.4%). The high recognition of general waste, including waste such as tissue paper and masks achieved 78.1%. It reflected contemporary challenges related to pandemic-including waste.

In short, the findings highlight the necessity for targeted waste management strategies, particularly for plastics and general waste, emphasizing the importance of sustainable practices such as 3R (Recycling, Reuse, Reduce) culture and public awareness.

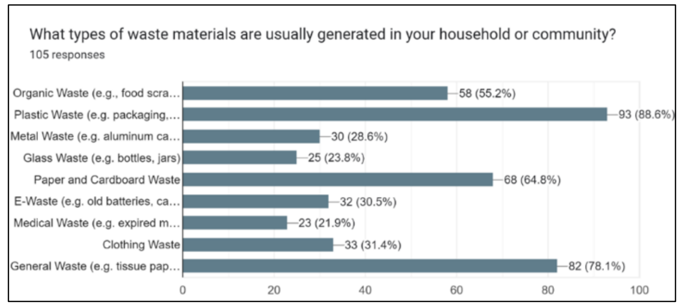

Fig. 3. Common household waste generated.

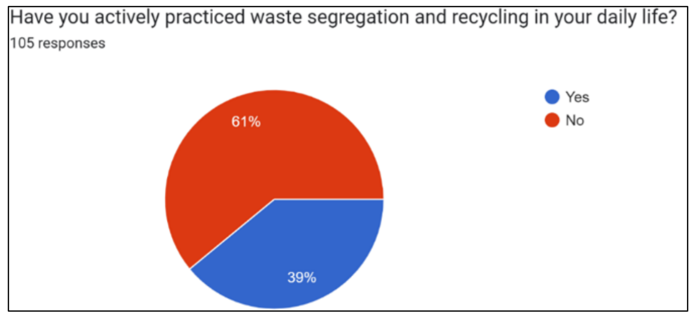

Fig. 4. Activeness in waste segregation and recycling practice.

The purpose of the above question is to understand how many respondents actively practice waste segregation and recycling in their daily lives, providing insights into their engagement with sustainable waste management. As shown in Fig. 4, only 39% of respondents actively participated in these practices. It indicates that there is a considerable portion of the population incorporating eco-friendly habits into their daily lives. Nevertheless, the majority of them, 61%, reported not actively engaging in such practices. The findings highlight a need for innovative solutions to improve community involvement in waste segregation and recycling efforts.

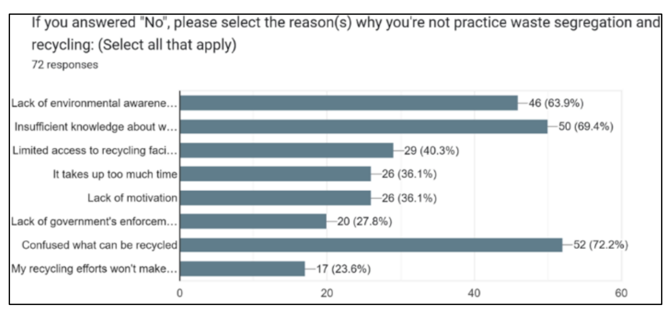

Fig. 5. Insights into the barriers that hinder sustainable waste management practices.

The main purpose above question is to figure out the reasons behind respondents not actively practicing waste segregation and recycling. It provides insights into the barriers that hinder sustainable waste management practices. As shown in Fig. 5, a significant number of respondents, about 72.2%

expressed confusion about what can be recycled. Additionally, the results indicate that the most prevalent reasons include a lack of environmental awareness (63.9%) and insufficient knowledge about waste segregation (69.4%). There are 23.6% of respondents voted for the reason that their recycling efforts would not make a significant difference to the planet. All this information is important for having educational plans and platforms to overcome specific challenges.

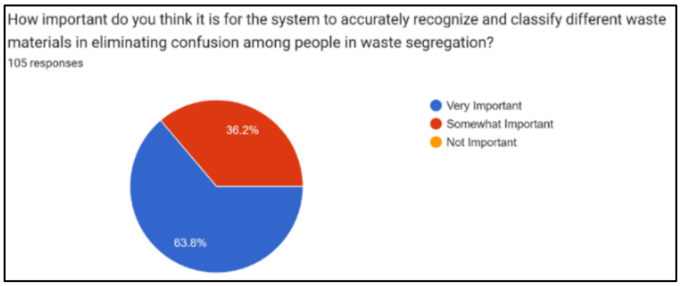

Fig. 6. How important respondents think if the system can recognize and identify waste accurately.

The purpose of asking about the importance of accurate waste material recognition and classification in the proposed system was to gain the respondents' perspective on the significance of leveraging the power of technology in addressing the issue of confusion during waste segregation. As shown in Fig. 6, 63.8% consider it "Very important", which underscores a strong consensus on the important role of technology in enhancing waste management practices. This result suggests a recognition among respondents that an AI-powered waste classification system capable of accurately classifying different waste materials could contribute to eliminating confusion during waste segregation. The positive response toward the importance of technology in waste management aligns with the objectives of the proposed system.

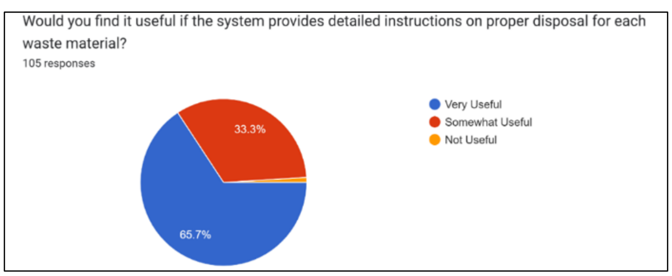

Fig. 7. How useful the system can provide instructions on waste disposal.

The purpose of including the above question in the questionnaire is to understand the users' expectations and preferences regarding the features of the proposed waste classification system. As shown in Fig. 7, the majority of respondents, 65.7%, find it "Very Useful", indicating a strong desire among respondents for a system that not only classifies waste materials but also provides comprehensive guidance on proper disposal. This result suggests that users value not only the identification aspect but also practical guidance on waste management. The demand for detailed instructions aligns with the system's goal of promoting responsible waste disposal practices. It reinforces the importance of integrating informative features within the proposed system to enhance user experience and contribute to more effective waste management habits.

B. Phase 2: CRISP-DM Framework

Following the CRISP-DM framework, the authors collected data from primary and secondary sources [21] to ensure the trained model directly reflects Malaysia's waste context. A total of 12 waste classes are labeled as shown in Fig. 8.

Fig. 8. Sample waste image from dataset for CNN model training.

Fig. 8 shows some sample waste image datasets used for CNN training. Before training, the authors removed the corrupted and low-resolution waste images to maintain the data quality. The images are pre-processed by utilizing data augmentation techniques, including rotation and flipping to improve its ability to recognize more waste variations.

C. Phase 3: System Design

The system is designed by using one of the famous UML diagrams, a use case diagram as shown in Fig. 9 to understand how each component in the system works with each other. By using a use case, the authors can easily figure out how users interact with a system. Use cases help the authors understand the system's functionality, behavior, and interactions in a structured and understandable form. They are valuable for guiding the design, development, and testing of software systems, ensuring that they meet the needs and expectations of users.

D. Phase 4: System Implementation

The authors utilized the power of Jupyter Notebook, Python Programming Language, TensorFlow, and Keras libraries to build and train the deep learning model, Convolutional Neural Network. The authors tried both methods in training the CNN model: train from scratch and train using a pre-trained model. The results from these two methods have shown a large difference.

Fig. 9. System design.

By training the CNN model from scratch, the model achieves a training accuracy of 83.82%, and a validation accuracy of 68.49% (see Fig. 10(a)). In contrast, by using a pre-trained model, which is Visual Geometry Group 16 (VGG16) as the base architecture, it achieves a training accuracy of 80.66% and an increased validation accuracy of 77.62% in waste image classification (see Fig. 10(b)). This further proves the efficacy and performance of using a pre-trained model as a base architecture, as highlighted in previous literature reviews [12] [18].

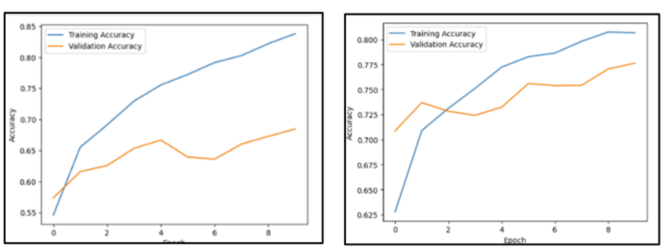

Fig. 10. (a) and (b) show the accuracy of two different methods for training the CNN model.

Transitioning to the system development, the authors used a combination of VS Code, PHP, HTML, CSS, and JavaScript to craft the user interface and system functionalities. What ties everything together is the Flask. By leveraging the Flask framework, the authors successfully integrate the trained CNN model with higher validation accuracy into the system, enabling the user to capture or upload waste images, thus getting immediate waste classification results. At this moment, users can choose to view the customized waste disposal guidelines based on their preference.

E. Phase 5: System Testing

Two main tests were conducted: unit testing and usability testing. The overall unit testing achieved a high pass rate, meaning that the majority of test cases passed successfully. Those test cases that failed will need further investigation and improvement. Some key observations are concluded. Firstly, the CNN model can classify the waste moderately well, but still, some misclassifications were detected, particularly in cases that involve complex waste images.

The result from the usability testing shows that the system consistently provides accurate waste classification results and value disposal guidance to users. Many of them expressed appreciation for the user-friendly interface for completing the tasks given. They are impressed by the power of deep learning in classifying waste images and the sustainable disposal tips provided by the system.

IV. Result and Discussion

This section presents the findings from the development and testing of the proposed waste classification system. The authors begin with system development results by displaying the interfaces, highlighting its design elements that enhance usability and facilitate efficient waste management. Next, the authors present the results of the waste classification testing, which is the main core of the system to showcase the system's accuracy and performance metrics to demonstrate its effectiveness in identifying various waste types. Finally, the authors compare the proposed system with existing solutions, illustrating its advantages in terms of classification capabilities and overall user experience. Through this discussion, the authors aim to provide a comprehensive understanding of the system's contributions to waste management practices.

A. System Development Result

The developed system consists of several features: an informative homepage, waste capture or upload, view classification results and customized disposal guidelines, locate recycling centers, and a dashboard as shown in Fig. 11, Fig. 12, Fig. 13, Fig.14 and Fig.15.

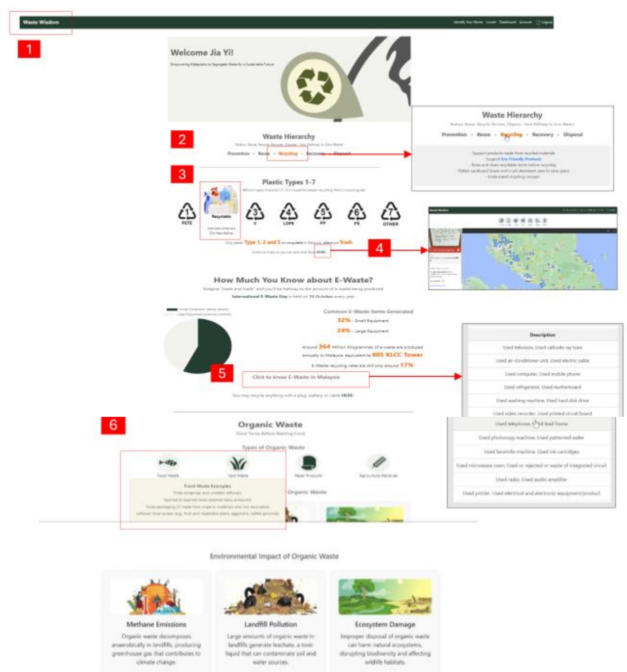

Fig. 11. Informative home page.

Fig. 11 illustrates the system's home page, which provides various useful educational resources and information. This page is designed to help users access essential content related to waste management and recycling.

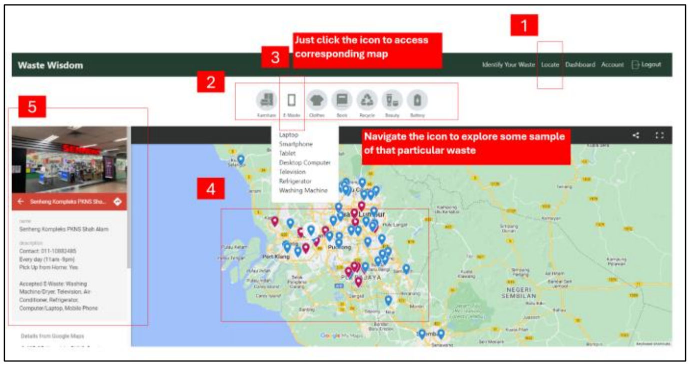

Fig. 12. Locate recycling centers.

Fig. 12 illustrates the system page where it displays the recycling center's location of each different recyclable item. Users can easily navigate through a row of clickable icons representing various items for recycling. For instance, if a user wishes to recycle furniture, they can simply click the furniture icon, and the corresponding map will be displayed.

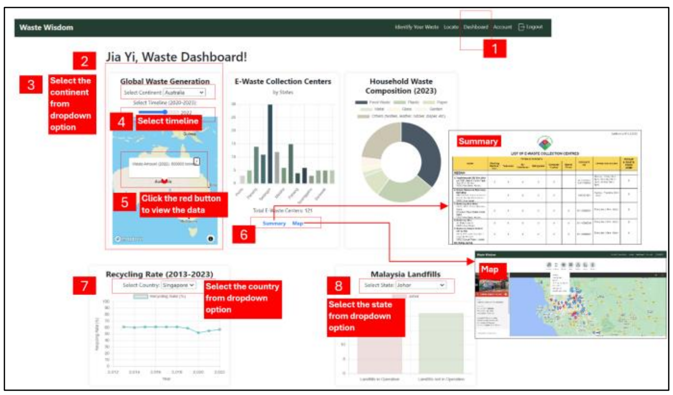

Fig. 13. Dashboard.

Fig. 13 illustrates the dashboard, including global waste statistic, Malaysia e-waste collection centers by states, Malaysia household waste composition, recycling rate by country and Malaysia landfill status.

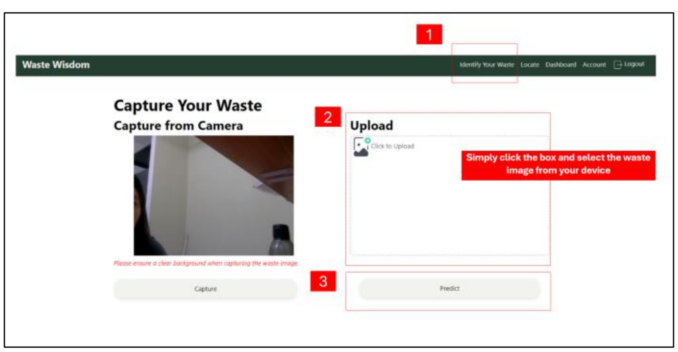

Fig. 14. Capture waste image.

Fig. 14 illustrates the system page where the user can either capture or upload the waste image.

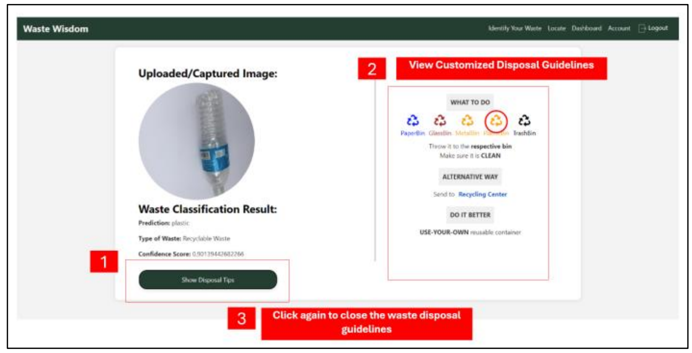

Fig. 15. Waste classification result and guidelines.

Fig. 15 illustrates the system page where the waste classification result and confidence score are displayed. Users can click the "Show Disposal Tips" button to access guidelines for classified waste.

B. Waste Classification Testing Result

This segment presents the results of the waste classification testing, detailing the accuracy and reliability of the system. The findings demonstrate the effectiveness of the classification algorithm, highlighting how well the system identifies various waste types and the confidence scores associated with each prediction.

Fig. 16. Waste items from various categories for testing.

Table I shows the predicted classifications, along with their scores, and indicates whether the model's predictions are considered a pass or fail based on the 60% threshold. The results were derived from the various waste items displayed in Fig. 16. The model correctly classifies 11 out of 12 items, showing that it performs well across a variety of waste types. Even when confidence is lower, it still makes the right prediction in most cases.

TABLE I. WASTE CLASSIFICATION TESTING RESULT

No	Expected	Predicted	Score	Pass/Fail
1	cardboard	cardboard	0.6518	Pass
2	paper	paper	0.5376	Pass
3	glass	glass	0.9991	Pass
4	organic	organic	0.6804	Pass
5	metal	metal	0.9949	Pass
6	plastic	plastic	0.8644	Pass
7	charger	glass	0.6522	Fail
8	mouse	mouse	0.5518	Pass
9	smartphone	smartphone	0.9717	Pass
10	battery	battery	0.9854	Pass
11	laptop	laptop	0.8799	Pass
12	trash	trash	0.4855	Pass

The model performed exceptionally well for categories such as Glass (0.9991), Metal (0.9949), Battery (0.9854), and Smartphone (0.9717). These high scores indicate that the model is highly confident in these predictions, likely due to clear and distinctive features that help distinguish these waste types. Predictions such as Cardboard (0.6518), Organic (0.6804), and Plastic (0.8644) also passed, with confidence scores above the 60% threshold. Although the confidence for these items is slightly lower, the model still correctly identified the waste types, demonstrating good performance overall. On the other hand, the predictions for Paper (0.5376), Mouse (0.5518), and Trash (0.4855), while below the 60% threshold, were correctly classified. The model successfully identified the correct waste category despite its lower confidence. This suggests that even in cases where the model is less sure, it can still make accurate classifications, which is a positive sign for real-world applications.

The only failure in the table is the misclassification of "Charger" as "Glass", with a confidence score of 0.6522. This is possibly due to poor image quality. Another reason might be the image itself's complexity which makes the system confused and misclassifies the waste category. Although the confidence score exceeds the threshold, the predicted output was incorrect. This indicates a specific issue in differentiating Charger from Glass. Therefore, it is important to ensure that the background is clear when capturing or uploading the waste image and further fine-tuning is needed to help the model better differentiate chargers from other materials. But overall, the trained CNN model performed reasonably well in recognizing and classifying common waste.

C. Comparison of Existing and Proposed Systems

This segment compares the proposed system with existing waste classification systems to illustrate the advantages of the proposed system. By comparing important aspects such as key features, model used, dataset, accuracy and user experience, the authors highlight how the proposed system offers enhanced capabilities and improved recycling efficiency, addressing the limitations of current solutions.

Table II shows a clear comparison of key features and models used across several waste classification systems, including DeepWaste [19], EcoScan [20], 101 Trash [22] and proposed system. The proposed system uses a larger and more diverse dataset, specifically tailored to the Malaysian waste context. Since waste generation patterns vary across countries due to cultural differences, this localized focus allows the system to better reflect the types of waste commonly found in Malaysia, enhancing its relevance and accuracy for the target region.

TABLE II. COMPARISON BETWEEN EXISTING SYSTEM AND PROPOSED SYSTEM

Aspects	Deep Waste	Eco Scan	101 Trash	Proposed System
Require Login	X	X	X	/
Model Used	Deep Learning	Not publicly disclosed	X	Deep Learning (CNN – VGG16)
Dataset Used	More than 1,200 waste images	Not publicly disclosed	101 types of trash	Primary waste images source and garbage waste dataset (15,497 images) from Kaggle
Accuracy	88.1%	X	X	77.62%
Capture Waste Image	/	/	X	/
Classification Feature	/	/	X	/
Confidence Score	/	X	X	/
Waste Disposal Guidelines Feature	X	X	/	/
Access Dashboard Feature	X	X	X	/
Locate Feature	X	X	/	/
Country-Based	X	X	/	/
Platform	Mobile	Mobile	Website	Website

a. / indicates the feature is present; **X** indicates the feature is absent

Although the proposed system has an accuracy of 77.62%, which is lower than Deep Waste's 88.1%, it uses the VGG-16 deep learning model. This choice provides a strong foundation for improving accuracy with further adjustments and tuning.

In terms of the classification feature, DeepWaste classifies the waste into three categories: Recycle, Trash and Compost [19], whereas EcoScan only differentiates between two categories: Paper and Glass [20]. This demonstrates the proposed system's ability to offer a more complete waste classification approach to enhance the waste segregation practice. It is believed that with more classification options, the system can improve recycling efficiency and support better waste disposal practices.

Key features such as confidence scoring, classification types, and waste disposal guidelines make the proposed system competitive and user-friendly. It also includes a dashboard and location-based functionality, ensuring its utility in local waste management. While its accuracy can be enhanced, the proposed system's transparency, dataset size, and feature-rich design indicate its potential to outperform existing solutions with further development.

V. Conclusion and Future Work

In conclusion, the developed system is considered to reasonably effectively address the challenges outlined in the problem statement by providing a practical solution to waste classification and waste disposal technologically. The first development of this system can accurately classify common household waste.

By acting as an educational platform, the developed system aims to eliminate people's confusion about waste segregation and educate them about sustainable waste management practices, contributing to a greener environment and, at the same time promoting SDG 12 and SDG 13. By consistently using the system, it is believed that the user can influenced by the system gradually as it provides different essential knowledge about recycling practices and provides details about where they can recycle their specific waste items. Also, the dashboard info might act as an important element to raise people's awareness to start taking action to reduce waste.

In addition, future works would be done by regularly updating the CNN model training dataset and expanding the application to mobile-based. Other than that, rather than focusing on image classification tasks, waste object detection can be taken into future consideration to make it more appealing and allow for real-time processing.

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References

[1] Kumar, A. and Agrawal, A. (2020). Recent trends in solid waste management status, challenges, and potential for the future Indian cities – A review. Current Research in Environmental Sustainability, 2, p.100011. doi:https://doi.org/10.1016/j.crsust.2020.100011.

[2] Yu, P.L., Ab Ghafar, N., Adam, M. and Goh, H.C. (2022). Understanding the Human Dimensions of Recycling and Source Separation Practices at the Household Level: An Evidence in Perak, Malaysia. Sustainability, 14(13), p.8023. doi:https://doi.org/10.3390/su14138023.

[3] Shakil, N.S.M., Azhar, N.A.Z.M. and Othman, N. (2023). Solid Waste Management in Malaysia: An overview. Information Management and Business Review (ISSN 2220-3796), 15(1), pp.86–93.

[4] Razali, F., Daud, D., Weng-Wai, C. and Anthony Jiram, W.R. (2020). Waste separation at source behaviour among Malaysian households: The Theory of Planned Behaviour with moral norm. Journal of Cleaner Production, 271, p.122025. doi:https://doi.org/10.1016/j.jclepro.2020.122025.

[5] Law, J., Lye, C.-T. and Ng, T.-H. (2023). Can environmental literacy and integrated behavioral factors encourage green practices at home? Evidence from Malaysia. Cleaner and responsible consumption, pp.100134–100134. doi:https://doi.org/10.1016/j.clrc.2023.100134.

[6] Abu Bakar, I.A., Ramayan, S.K. and Sangaran, V.S. (2020). Public Inclination Towards Waste Segregation Programme (A Case Study on the Effectiveness Of #Asingkan Campaign in Klang Valley). Idealogy Journal, 5(2), pp.185–198. doi:https://doi.org/10.24191/idealogy.v5i2.241.

[7] Cheng, K.M., Tan, J.Y., Wong, S.Y., Koo, A.C. and Amir Sharji, E. (2022). A Review of Future Household Waste Management for Sustainable Environment in Malaysian Cities. Sustainability, 14(11), p.6517. doi:https://doi.org/10.3390/su14116517.

[8] Chen, B. and Lee, J. (2020). Household waste separation intention and the importance of public policy. International Trade, Politics and Development, 4(1), pp.61–79. doi:https://doi.org/10.1108/itpd-03-2020-0008.

[9] Shakil, N.S.M., Azhar, N.A.Z.M. and Othman, N. (2023). Solid Waste Management in Malaysia: An overview. Information Management and Business Review (ISSN 2220-3796), 15(1), pp.86–93.

[10] Tang, Y.Y., Tang, K.H.D., Maharjan, A.K., Abdul Aziz, A. and Bunrith, S. (2021). Malaysia Moving Towards a Sustainability Municipal Waste Management. Industrial and Domestic Waste Management, 1(1), pp.26–40. doi:https://doi.org/10.53623/idwm.v1i1.51.

[11] Ahmad, I., Chelliapan, S., Abdullah, N. and Ahmad, M.D. (2019). Sanitary Landfill is a Solution in Solid Waste Management or a Silent Threat to Environment: Malaysian Scenario. Open International Journal of Informatics (OIJI), 7, pp.135–146.

[12] Shahab, S., Anjum, M. and Umar, M.S. (2022). Deep Learning Applications in Solid Waste Management: A Deep Literature Review. (IJACSA) International Journal of Advanced Computer Science and Applications, 13(3), pp.381–395.

[13] Alzubaidi, L., Zhang, J., Humaidi, A.J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M.A., Al-Amidie, M. and Farhan, L. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. Journal of Big Data, [online] 8(1). Available at: https://journalofbigdata.springeropen.com/articles/10.1186/s40537-021-00444-8.

[14] Kufel, J., Bargieł-Łączek, K., Kocot, S., Koźlik, M., Bartnikowska, W., Janik, M., Czogalik, Ł., Dudek, P., Magiera, M., Lis, A., Paszkiewicz, I., Nawrat, Z., Cebula, M. and Gruszczyńska, K. (2023). What Is Machine Learning, Artificial Neural Networks and Deep Learning?—Examples of Practical Applications in Medicine. Diagnostics, [online] 13(15), p.2582. doi:https://doi.org/10.3390/diagnostics13152582

[15] Surono S., Rivaldi M., Dewi D.A., Irsalinda N. (2023). New Approach to Image Segmentation: U-Net Convolutional Network for Multiresolution CT Image Lung Segmentation. Emerging Science Journal. Vol 7, No 2 (2023). doi: https://www.ijournalse.org/index.php/ESJ/article/view/1444/pdf

[16] Vo, A.H., Hoang Son, L., Vo, M.T. and Le, T. (2019). A Novel Framework for Trash Classification Using Deep Transfer Learning. IEEE Access, 7, pp.178631–178639. doi:https://doi.org/10.1109/access.2019.2959033

[17] Ruiz, V., Sanchez, A., F. Velez, J. and Raducanu, B. (2019). Automatic Image-Based Waste Classification.

[18] Albashish, D., Al-Sayyed, R., Abdullah, A., Ryalat, M.H. and Almansour, N.A. (2021). Deep CNN Model based on VGG16 for Breast Cancer Classification. 2021 International Conference on Information Technology (ICIT). doi:https://doi.org/10.1109/ICIT52682.2021.9491631.

[19] Narayan, Y. (2021). DeepWaste: Applying Deep Learning to Waste Classification for a Sustainable Planet. 34th Conference on Neural Information Processing Systems (NeurIPS 2020), Vancouver, Canada.

[20] EcoScan (2019). EcoScan - Recycle Waste and Get Rewarded. [online] EcoScan app. Available at: https://www.ecoscanapp.eu/.

[21] Mohamed, M. (2020). Garbage Classification (12 classes). [online] www.kaggle.com. Available at: https://www.kaggle.com/datasets/mostafaabla/garbage-classification.

[22] Zero Waste Malaysia (2021). 101 Trash. [online] trashpedia.zerowastemalaysia.org. Available at: https://trashpedia.zerowastemalaysia.org/en/101trash/.