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# Evaluating the Performance of MobileNetV2, DenseNet169, and the Concatenated Model in Waste Classification

*Josephine Dela Cruz, Heidi Batara, Raquel Bautista,*

*Jp De los Trinos, Leonardo Gavino III, Karl Adrian Laroya,*

*Rodolfo Aaron Mercado & Rianne Justin Policarpio*

*Saint Louis University*

*jdelacruz@slu.edu.ph, 2200055@slu.edu.ph, 2200311@slu.edu.ph,*

*2205437@slu.edu.ph, 2200042@slu.edu.ph, 2200591@slu.edu.ph,*

*2202631@slu.edu.ph, & 2200848@slu.edu.ph*

## Abstract

*As waste accumulates daily, waste management becomes an issue. Solutions have been proposed and developed by implementing machine learning to transform from traditional to more automatic and efficient methods for managing waste. Based on studies, problems were: there is a demand for a more significant waste dataset, the majority did not use preprocessing, and a few attempted concatenated or fused models. Hence, this study was conducted to develop a unique good-performing model that classifies wastes into seven categories: sanitary, plastic, paper, metal, glass, cardboard, and biodegradable. It aimed to assess the relevance of image preprocessing and concatenation to a large dataset in developing a predictive model. To achieve this, the researchers compared a raw dataset from a preprocessed one and utilized two classification models, which are MobileNetV2 and DenseNet169. The extracted features from the two models were combined to develop the Concatenated Model. Based on the findings, raw* *datasets yielded better metrics than preprocessed data, and the Concatenated Model performed better than MobileNetv2 and DenseNet169 regarding waste classification. The Concatenated model is then integrated into a gamified web application called YASS: Youngsters Automated Segregation System to improve waste segregation knowledge as a proof of concept.*

***Keywords:*** *Gamification, Image Classification, Waste Segregation.*

## Introduction

Waste is a state of an abandoned object and is harmful to the environment. As evident in numerous parts of the world, waste is an inevitable by-product of humans. In addition to that is the rampant waste contribution of industrial manufacturing, which is still in operation due to our constant need for their products. In the Philippines, 31,751 - 40,000 tons of waste are produced daily (Flores & Tan, 2019; Ortaliz et al., 2020). The amount of waste and improper disposal causes pollution that is seriously harmful to the environment.

Countries began investigating recycling which led to the development of waste treatment plants to reduce pollution (Briones et al., 2018). For the Philippines, Republic Act 9003 targets to reduce the number of waste. Many methods were considered, like recycling, recovery, and treatment, but for these to work, proper segregation of waste should be implemented (Ortaliz et al., 2020). Given these solutions, it is still believed that prevention is always the best cure. It is prevention in the sense that the people are being educated for them to apply waste management as a long-term practice. A common site for this idea is commonly seen in educational institutions when partnered with local external communities, who are advocates of the environment.

Regarding waste segregation, the Philippines still uses the traditional way, exposing the persons involved to harmful chemicals and infectious agents (Flores & Tan, 2019; Raamesh et al., 2021). Another reason is that human error can lead to inefficiencies in waste management, such as missed incorrect sorting of recyclables. With that, there is a need to create a management system to simplify the process and have less human involvement (Adedeji & Wang, 2019). Also, as a society in the computer age, these solutions can evolve and reach greater heights. An intelligent waste management system can help improve the process's accuracy.

Nowadays, implementing machine learning is typical in transforming all these traditional solutions into something more intelligent and automatic. Machine learning uses data and algorithms to imitate human thought processes (IBM, n.d.). An example of machine learning is the Automated Waste Segregation System from the University of St. La Salle. It uses material and optical sensors, image datasets, and a trained Convolutional Neural Networks (CNN) model to achieve its system's waste identification ability (Ortaliz et al., 2020). The effectiveness of such a machine learning product is further proven with the help of descriptive and predictive analyses. A descriptive analysis produces information based on data patterns and calculations (Rawat, 2021). The predictive analysis combines data and machine learning to determine possible outcomes based on historical data (SAS, n.d.). However, it can continue with what machine learning can provide.

There are still some voids regarding waste classification in machine learning. One is the need for an adequate dataset. Based on several related studies, one standard recommendation of the prior researchers is to have an extensive dataset to enhance the model's accuracy since these studies only used approximately 1,000 to 3,870 images. Additionally, studies claim the relevance of preprocessing (Raamesh et al., 2021), and others do not. Thus, data preprocessing is the one area of focus in this study. Another gap is the need for studies utilizing simple feature concatenation from different models. One related research has tried fusing four classification models and used concatenation as an initial stage (Ahmad et al., 2020). However, their processes were complicated and comprised different sub-processes. Aside from having a reliable machine-learning model, other factors must also be considered.

One factor in instilling waste segregation knowledge in children is the entertainment value and immersion they can get from experience. The waste management system can be incorporated into a game to help create an accessible learning environment (Janakiraman et al., 2018). Gamification in an educational setting is the implementation of a medium of play in the pursuit of sending information and knowledge (Magista et al., 2018). Applying gamification acknowledges the positive justifications from "The Fun Theory" by Volksvagens (Di Dio et al., 2019). The study targets children because it has shown that children should be educated about waste segregation to develop a mindset for protecting the environment. This concept could be applied in schools and promote environmental education (Eder, 2016). Education is vital since it could solve today's environmental problems and promote a sustainable future.

Other studies created mobile games, while some built physical prototypes that children can interact with and learn. In this study, the researchers created a web-based game of waste segregation and integrated an artificial intelligence model. It is said to have potential and is appropriate for young students if it respects behavioral theories and is developed with an effective gaming mechanic (Magista et al., 2018). To fully achieve this system, the objectives must be fulfilled.

First, as recommended by most studies, the study aims to gather a larger dataset by adding sanitary wastes. Second, the study aims to compare the model's performance that is trained with the preprocessed versus the raw datasets. The researchers considered different preprocessing techniques by combining the approach of other studies. Third, the study aims to develop a reliable model for classifying wastes that utilize an early fusion method called the simple concatenation, which is applied to the features extracted using the pre-trained models: DenseNet169 and MobileNetV2. It also compares the performance of the developed Concatenated model with the standalone DenseNet169 and MobileNetV2. Fourth, the study aims to integrate the best-performing model into a web-based game. Hence, the study requires the researchers to develop a game that provides a practical gamified experience of waste segregation for school children.

This study focuses on the UN sustainable development goals: quality education and sustainable cities and communities. The game application where the model will be integrated can be a learning tool for children on waste classification. Educational institutions may use the model if embedded in their learning applications. The developed model can be a fresh perspective for future image-processing researchers since it is relatively new. The model can also initiate the development of better waste classification models and future research topics.

## Review of Related Literature

This section includes the related studies of the four main topics of this research. It centers around aspects that will help improve this study, concentrating primarily on the potential of deep learning in waste segregation among schools with an introduction to gamification.

### Waste Segregation in Schools

Focusing on school waste segregation is an area a few studies have looked into recently. One study developed an education robot for children, challenging and teaching primary students about recycling (Castellano et al., 2021). In Italy, however, it focused on preschool students. It emphasized the necessity to teach new generations about environmental protection through an educational game (Di Dio et al., 2019). Another study conducted in an elementary school in

Calamba City, Philippines, found that eco-centers have given opportunities to the students to accomplish segregation responsibly and adequately (Matsumoto & Saizen, 2017). In line with the studies mentioned, this study will focus on primary students to aid the need to teach younger generations about waste management.

**Waste Segregation and Machine Learning**

One of the most prominent ways of doing waste segregation is for a human to manually identify biodegradable, non-biodegradable, and recyclable materials. Although this approach is simple, its effectiveness has long since decreased with the amount of waste in circulation, especially in urban areas (Rajendran et al., 2019). With the statements above in mind, computer vision, or retrieving data from images, can be utilized along with machine learning to classify waste efficiently (Costa et al., 2018).

Several studies have already been produced and published, utilizing different kinds of pre-trained deep learning models with varying degrees of success. A recent study in India produced an Automated Waste Segregator (AWS) that classified waste according to type by utilizing various sensors. This model utilized the YOLOV3 deep learning algorithm and produced an accuracy score of 83.60% (Meena et al., 2020). Another study also produced similar results using another deep learning framework called MobileNetV2. This model garnered a maximum 83.46% accuracy score with a larger dataset than the previous study (Qin et al., 2021).

Similarly, another study from India netted an accuracy score of around 84% by utilizing the primary Convolutional Neural Network (CNN) architecture (Hulyalkar et al., 2018). As observed, the different deep learning models and algorithms used in the three studies produced similar results. From this, this similarity is generally prevalent among the different deep-learning algorithms.

When improving upon these pre-trained models, a study was done to "fuse" multiple algorithms by extracting their features into classifiers and combining their outputs through a method termed "double fusion" (Ahmad et al., 2020). Doing this would prove to be a success as it yielded an accuracy of 94.58%, which is noticeably higher than just utilizing one pre-trained model from the results of past studies. This fusion method is relatively new, with plenty of room for improvement, such as utilizing newer and up-to-date pre-trained models on which the research is focused.

Upon analyzing the related works that develop different waste classification models, they have yet to introduce sanitary wastes as a classification. Hence, the said classification has been added to the categories used in the current study's web application game to educate children about sanitary classification. The other waste categories are based on related works (Ahmad et al., 2020; Fernando et al., 2019). Related research also recommended the addition of a sanitary classification in waste segregation classifications (Meena et al., 2020).

Regarding data preprocessing, most related studies on model training opted not to utilize image preprocessing techniques for their datasets. It raises the question of whether these techniques affect the model's accuracy, which no related literature in the waste segregation field has expounded on so far. When comparing the results of the studies that utilized image preprocessing, which they claimed as an essential step (Raamesh et al., 2021), and those that did not, the accuracies still vary with no clear inference on whether they have a positive effect. Although their scores may differ, it could be attributed to the differences in dataset size. With this in mind, data preprocessing is the second central area of focus.

**Gamification in Waste-Related Systems**

Researchers have developed an innovative method to motivate society to manage waste by adding gamification to their systems—one study utilized environmental education through an action-puzzle game (Fernando et al., 2019). Another study used a method where it used containers to create a junk box inspired by a jukebox that helped playfully educate children. Through this, it can attract the users' interest, especially the kids; hence, schools can use the system (Di Dio et al., 2019). However, the children needed to be physically present to play the game. Due to the pandemic, this was considered impractical as there were possible health issues. Hence, the current researchers integrated their game through a web application. Trash Attack (Fernando et al., 2019) and iTrash (Eder, 2016) are about educating people about the ideas regarding waste segregation. However, their shortcomings are possible because education can only go so much without application. Hence, the active application of proper waste segregation techniques and their importance is much more effective than education alone.

The effectiveness of gamification can be seen in another related study that increased the participation of the citizens up to 32.2%. The study used a reward-penalty system (Briones et al., 2018). With this approach, offering rewards can motivate residents to manage their waste and recycle properly, which the current researchers also integrated into their system. This claim was supported by another research, as adding an educational and fun approach will produce a positive emotional involvement and result in a high success rate for children to segregate their waste correctly (Castellano et al., 2021). Thus, based on these related works, there are many approaches that the current researchers can utilize in their proposed system.

## Methodology

This section presents the relevant data analysis methodologies, research design, and method. Also, it includes the areas about the population and its sampling method, materials, and procedures. As shown in Figure 1, the research framework consists of input through data collection, a machine learning process, and the output of a waste classification model integrated into a web application.

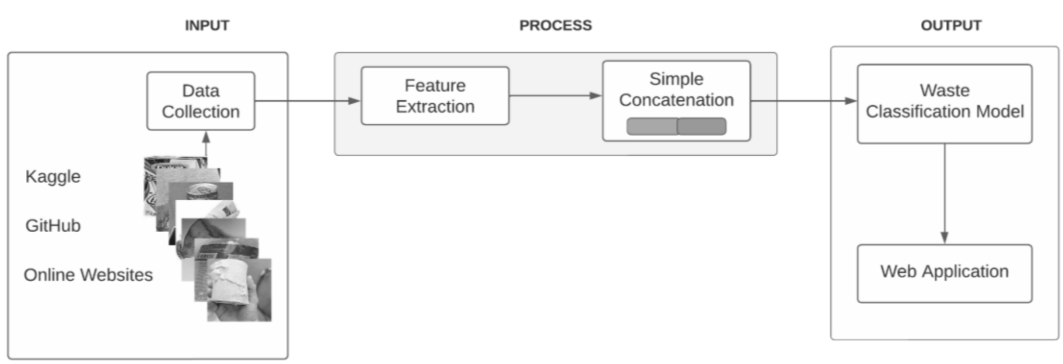
### Research Methods

The researchers applied the quantitative approach, which explains a phenomenon based on accumulated numerical data analyzed using mathematical methods (Idowu, 2015). The phenomenon in question is the performance of the gamified waste segregation application.

The application mainly yields results, which are evaluated to determine the application's credibility in becoming a valid technique of waste segregation for elementary students. As the application is also process-driven, it must be evaluated based on its performance. It is to determine the application's reliability in meeting the required results.

**Figure 1**

*Research Framework*



**Research Population**

The study could likely be applied to various cities nationwide with the underlying garbage problem. The target population of the web application would be elementary students in the Philippines. It is to ensure children can learn, through their participation, the importance of waste management and give them and the people around them a sense of consistency and responsibility.

**Sampling**

The deep learning model (DLM) data is divided into training, validation, and testing data. The training data subset trains the model to predict what waste classification an image input falls. The validation data subset is used to verify the accuracy of the trained DLM. Lastly, the test data subset tests the completed DLM's accuracy after being adjusted according to the validation data subset. The reason for using another subset for testing instead of just using validation data is to prevent bias (Baheti, 2023).

The 50-25-25 split based on the "general rule" (Hastie et al., 2004) determines the training, validation, and test subsets. Training data has the highest percentage out of the three because, in data science, the general principle for training data is that the higher the amount, the better (Chawla, 2020). The validation and test data are split evenly to prevent further metric bias.

**Research Materials**

Images of items that fall into these seven categories: biodegradable, cardboard, glass, metals, papers, plastic, and sanitary, and could be considered waste, were used as datasets for the research. Images were retrieved from five different datasets from Kaggle and GitHub (Thung, 2017; Dragicevic, 2021; Hsu, 2021; Vaduva, 2021; Nakkas, 2022), except for sanitary waste. The researchers came up with their dataset for the said category. Researchers considered having

1,000 to 1,500 images per classification. Based on several related studies, one standard recommendation of the previous researchers is to have a large dataset to improve the model's accuracy since these studies only used one dataset that contains approximately 1,000 to 3,870 images. With all categories combined, the researchers have 8,747 photos in their dataset, which is already adequate for processing.

The Python programming language was used to develop the Concatenated model as it specializes in machine learning concepts. The Python machine-learning libraries used were Tensorflow, Keras, and Sklearn. The Django web framework is the primary material used for the web application where the Concatenated model was embedded. It helped rapidly develop a secure and functional web application. On the front-end aspects, HTML, CSS, and Javascript were used. As a collaborative effort, GitLab retrieved each other's progress.

**Research Procedures**

The complete process in the research framework is shown in Figure 2. The first step was to gather data by finding appropriate datasets online. After collecting the required data, a sampling technique was employed. The collection of images is then compiled in a new singular dataset. Afterward, the researchers preprocessed the data in the new dataset to produce one already standardized and cleaned version of the dataset. Three preprocessing techniques were applied to generate the preprocessed dataset: applying an image-sharpening kernel makes blurry images more apparent to a certain extent. The cropping method crops out the background of the trash image. The images were resized to improve the performance of the next step, which is feature extraction.

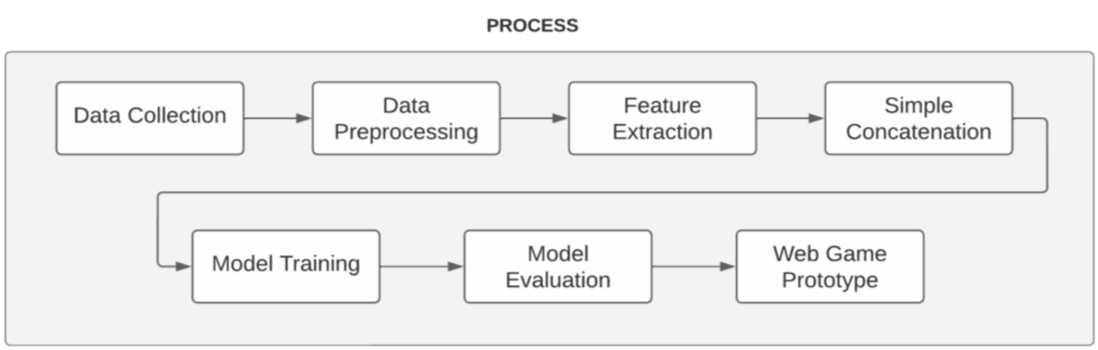
Next, feature extraction was done using the DenseNet169 and MobileNetV2 CNN models to further minimize the footprint of the dataset without losing any of the essential or relevant information in the process. It made the dataset easier to digest by a machine, increasing the learning speed and saving valuable time.

Simple concatenation is then applied to the extracted features of DenseNet169 and MobileNetV2. It is called early fusion since it is done before the machine learning process. The goal here is to have varying feature sets of different compositions made possible by the two CNN models, which the classifier can then use to have a more varied training dataset, further increasing the classification accuracy comes validation or testing.

Then, a sequential model was trained to the features extracted from DenseNet169, MobileNetV2, and the concatenated features. The training took 80 epochs for better training and utilized ReduceLROnPlateau. The models are initially trained with 20 epochs, which is then increased to 80 to see if there is a pattern on how much the two datasets perform over increasing epochs. A study on the comparative analysis of different pre-trained CNN models noticed that after a certain number of epochs, the performance of the models stopped improving (Gyawali et al., 2020). With this in mind, 80 epochs were considered the limit because, after multiple tests, the models started to overfit and ceased to improve their accuracy on validation data beyond 80 iterations.

**Figure 2**

*Process*



Constructing the prototype follows after training, testing, and evaluating the model. The prototype is a website simulation demonstrating the game mechanics and waste classification process. The Concatenated model is housed inside the prototype to classify uploaded images.

**Data Analysis**

For data analysis, the researchers utilized the accuracy, precision, recall, and F1-score performance metrics to evaluate the algorithms. As a supplement, these data are backed up with descriptive analytics, specifically concerning measures of central tendency.

Comparisons were made to supplement the realizations regarding the better case of the dataset and the model. The first comparison is the accuracy between the created model that used the preprocessed dataset and the developed model that used the non-preprocessed dataset. The second comparison is the accuracy results between the models trained with extracted DenseNet169 features, MobileNetV2 features, and concatenated features.

## Discussion of Results

This section presents the results and discussion based on the experiment conducted by the researchers.

**Raw vs. Preprocessed Dataset**

This section showcases MobileNetV2, DenseNet169, and the Concatenated Model with formalized parameters. Moreover, both use raw and preprocessed datasets for the sake of comparisons. In this case, higher percentages of accuracy dictate the better nature of the dataset.

For MobileNetV2, the training, validation, and test accuracies from using the raw dataset are higher than the preprocessed dataset (see Table 1). Hence, training with a raw dataset when using MobileNetV2 is better.

**Table 1**

*MobileNetV2 Model Accuracies for 80 Epochs*

| Dataset | Train | Validation | Test |
|---|---|---|---|
| Raw | 99.84 % | 86.18 % | 86.18 % |
| Preprocessed | 99.43 % | 81.47 % | 81.20 % |

For DenseNet169, the training, validation, and test accuracies from using the raw dataset are higher than the preprocessed dataset (see Table 2). Thus, training with a raw dataset when using DenseNet169 is better.

**Table 2**

*DenseNet169 Model Accuracies for 80 Epochs*

| Dataset | Train | Validation | Test |
|---|---|---|---|
| Raw | 99.34 % | 88.29 % | 88.29 % |
| Preprocessed | 99.04 % | 85.04 % | 85.04 % |

For the Concatenated Model, the training, validation, and test accuracies from using the raw dataset are higher than the preprocessed dataset, as shown in Table 3. Hence, training with a raw dataset using our Concatenated Model is better.

**Table 3**

*Concatenated Model Accuracies for 80 Epochs*

| Dataset | Train | Validation | Test |
|---|---|---|---|
| Raw | 90.81 % | 88.47 % | 88.47 % |
| Preprocessed | 83.81 % | 83.49 % | 83.49 % |

Overall, even with the change in parameters, better results can be observed from models that have utilized the raw dataset. It would imply that in the pursuit of developing a well-performing prediction model, it is optional to preprocess the data. To fortify the integrity of the results, the researchers also tried to train the model using datasets that only utilized one preprocessing technique, either sharpening or cropping, to verify if these datasets' accuracies were still lower than the raw dataset. To do this, the researchers used the DenseNet169 model with 80 epochs compared to all models; it produces the highest validation and test accuracies.

Based on the results, the dataset that utilized both preprocessing techniques performed lower than if the data used image sharpening or cropping only. As per observation, the sharpening procedure to the images introduced a lot of "white pixels" to the images, resulting in data loss. In the case of biodegradable, where rotten fruits or vegetables have their specific colors, their original color has been replaced. It needs more data for the model to train on.

However, in contrast to the raw dataset, the said dataset still yielded the best performance, 88.29% for both validation and test accuracies. As for the cropping technique, only some images are overcropped. With that, it also affects the sharpness of the images. Thus, it further supports the claim that using a raw dataset is better than a preprocessed one in developing a predictive model.

**Comparison of the Models**

The following comparison of the models: MobileNetV2, DenseNet169, and Concatenated model, was done on the raw dataset, considering the abovementioned results.

The corresponding classification report for the MobileNetV2 model is shown in Table 4. It shows that the overall accuracy of the model is 86%. Biodegradable and sanitary classes have performance scores for precision, recall, and F1-Score above 90%. The other classes' scores range from 80% to 88%.

**Table 4**

*MobileNetV2 Classification Report with Raw Data*

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Biodegradable | 0.90 | 0.97 | 0.94 | 273 |
| Cardboard | 0.88 | 0.86 | 0.87 | 304 |
| Glass | 0.80 | 0.84 | 0.82 | 338 |
| Metal | 0.86 | 0.85 | 0.86 | 329 |
| Paper | 0.83 | 0.83 | 0.83 | 257 |
| Plastic | 0.85 | 0.80 | 0.82 | 375 |
| Sanitary | 0.92 | 0.91 | 0.91 | 310 |
| Test Accuracy: 0.86 | | | | |

Also, the following is the number of samples that lie per class, given that 25% of the dataset belongs to the validation. Specifically, there were 273 biodegradable, 304 cardboard, 338 glass, 329 metal, 257 paper, 375 plastic, and 310 sanitary images, totaling 2,186 samples. Moreover, Table 5 presents the classification report of DenseNet169 using raw data that produces an accuracy of 88%.

**Table 5**

*DenseNet169 Classification Report with Raw Data*

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Biodegradable | 0.92 | 0.97 | 0.94 | 273 |
| Cardboard | 0.88 | 0.89 | 0.88 | 304 |
| Glass | 0.87 | 0.85 | 0.86 | 338 |
| Metal | 0.88 | 0.88 | 0.88 | 329 |
| Paper | 0.84 | 0.82 | 0.83 | 257 |
| Plastic | 0.87 | 0.86 | 0.86 | 375 |
| Sanitary | 0.92 | 0.93 | 0.92 | 310 |
| Test Accuracy: 0.88 | | | | |

The classification of biodegradable and sanitary shows an outstanding performance hitting above the 0.90 line for the precision, recall, and F1-score. Classifications of cardboard and metal are next in line, ranging from 88% to 89%.

The Concatenated model produced results with an accuracy of 88% through the raw data shown in Table 6. For the classifications, similar to the other models, biodegradable and sanitary have the highest performances compared to the rest, with performances above 90%. Cardboard, plastic, and metal follow with having at least one performance of 90% or above. Other classifications have performances above 90%.

**Table 6**

*Concatenated Model Classification Report with Raw Data*

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Biodegradable | 0.91 | 0.98 | 0.95 | 273 |
| Cardboard | 0.93 | 0.88 | 0.91 | 304 |
| Glass | 0.89 | 0.84 | 0.87 | 338 |
| Metal | 0.81 | 0.92 | 0.86 | 329 |
| Paper | 0.83 | 0.86 | 0.84 | 257 |
| Plastic | 0.90 | 0.82 | 0.86 | 375 |
| Sanitary | 0.93 | 0.91 | 0.92 | 310 |
| Test Accuracy: 0.88 | | | | |

Based on the accuracy of the three models, the DenseNet169 model and the Concatenated model yielded the highest with a result of 88%. However, the average precision, recall, and F1 scores were computed to see which model performed better based on their corresponding classification reports. It can be seen in Table 7.

**Table 7**

*Average Performance Scores of the Models*

| Model | Avg. Precision | Avg. Recall | Avg. F1-Score |
|---|---|---|---|
| MobileNetV2 | 0.8629 | 0.8657 | 0.8643 |
| DenseNet169 | 0.8828 | 0.8857 | 0.8814 |
| Concatenated | 0.8857 | 0.8871 | 0.8871 |

With this, it shows that even though both models have the same accuracy, they still differ on some performance metrics, which makes them perform better than the others. Based on Table 7, compared to the DenseNet169, the Concatenated model performed better, with an average of 89% and 89% for precision and recall, respectively. This indicates that when it predicts waste classifications, for instance, waste is a metal, it is correct around 89% of the time. Moreover, of all the waste labeled as biodegradable or any of the seven categories, 88.71% or 89% are correctly predicted. Lastly, given the F1-score, which takes the precision and recall score of the model into account, the Concatenated model has a higher average F1-score of 89%.

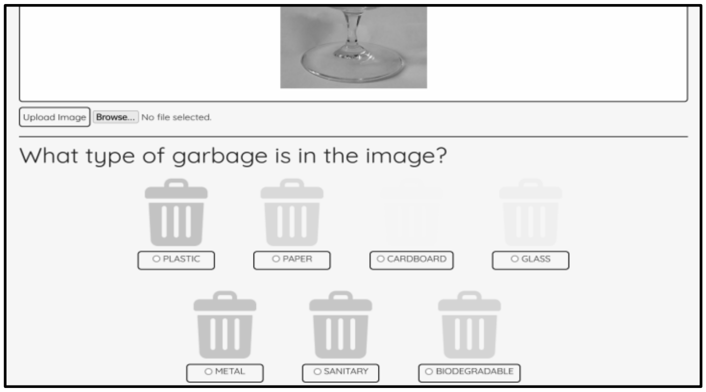
Hence, the Concatenated model performs better than the rest of the models, which makes it the best fit to be integrated into the gamified web-based application that will encourage children to segregate waste and teach them about proper waste segregation.

**YASS Game, the Web-based Game**

The YASS Game is a quiz-type game that asks the players what type of waste is in an image. The player uploads a picture of waste, and the Concatenated model will then predict whether it is plastic, paper, and cardboard, glass, metal, biodegradable, or sanitary. Afterward, the question "What type of garbage is in the image?" is asked, and they can choose which bin it belongs to (see Figure 3). If their choice matches the value for the correct answer, the player will be notified that they are correct and will receive 100 points. If not, the player will be notified that they are wrong and will lose 50 points. A particular case in the game interface denies some uploaded pictures. If the prediction model has a prediction confidence score below 0.60, the uploaded picture is considered undistinguishable, and the system will request the player to upload a different picture. It is to lessen the probable incorrect predictions that can inconvenience the player during their answering phase.

**Figure 3**

*The Questioning Phase of the Game Interface*




Additionally, there is a ranking system that boosts the immersion of the game. As the player's total score increases, their expected rank is higher. For it to become a fully functioning application, essential features such as login, logout, sign-up, input validation, and player profiling have been implemented.

## Conclusion

This research aims first to utilize a larger dataset. The second objective is the application of data analysis to specify the result of preprocessing image data on the accuracy of predictive models. The third objective is to produce a waste classification model using image features by implementing feature concatenation or early fusion.

Utilizing a larger dataset has contributed to a better model with an average accuracy of 88%. Additional sanitary waste is also a good edge for the study as it provided a variety and more data for which the model was trained.

Based on the training, validation, and test accuracies, the models trained using the raw dataset have higher accuracies by the majority compared to the models trained through the preprocessed dataset. Thus, it is essential to use data analysis, such as the comparison of raw and preprocessing, to understand and improve the model training process.

The experiments performed by the researchers showed that a sequential model trained through concatenated features extracted from the DenseNet169 and MobileNetV2 models yields higher performance than DenseNet169 and MobileNetV2 individually. It makes it the best fit to be integrated into the gamified web-based application to encourage and teach children proper waste segregation.

## Limitations and Recommendations for Future Research

Future researchers should improve the model's performance so that its accuracy is close to at least 95% and above. This improvement will limit the number of false negatives or instances where the user's input is correct, but the system responds incorrectly. They should also look into the concatenation of other models and double fusion, as this study only used simple concatenation due to a large dataset. Also, the use of data preprocessing is optional in waste classification. However, if researchers would like to preprocess, they should be wary about sharpening and cropping as they may result in data loss. Additionally, while the web application was created, it has not yet been proven that it is an effective way of teaching waste segregation knowledge to children.

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