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Self-Adaptive Waste Management System: Utilizing Convolutional Neural Networks for Real-Time Classification †

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Abstract: This research presents a novel Self-Adaptive Waste Management System (SAWMS) that integrates advanced technology to address the pressing challenges of waste sorting and classification. SAWMS leverages Convolutional Neural Networks (CNNs) in conjunction with conveyor belt technology to achieve real-time object classification and self-training capabilities. The system utilizes sensors for object detection and a camera for image capture, enabling an accurate initial classification of waste objects into predefined categories such as food waste, metal, and plastic bottles. Notably, our proposed system sets itself apart by its unique ability to adapt and self-train based on classification errors, ensuring ongoing accuracy even in the face of changing waste compositions. Through dynamic adjustments of the conveyor belt's destination, it efficiently directs waste objects to their appropriate bins for disposal or recycling. This research demonstrates the potential of SAWMS to revolutionize waste management practices, offering an agile and sustainable solution to the evolving challenges of waste sorting and disposal.

Keywords: waste management; convolutional neural networks; self-adaptive systems; waste segregation; recycling; sustainability

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1. Introduction

The management and disposal of waste materials have emerged as critical global concerns, driven by rapid population growth, urbanization, and increasing consumption patterns. Inefficient waste handling not only contributes to environmental degradation but also poses significant health risks. Traditional waste sorting methods, often reliant on manual labor, are characterized by their susceptibility to human error, limited adaptability to evolving waste streams, and an inherent lack of scalability. In response to these challenges, there is a growing imperative to develop innovative and automated waste management systems that not only enhance the efficiency and accuracy of waste sorting but also remain agile in the face of dynamic waste compositions.

Automation, propelled by advancements in artificial intelligence and robotics, has emerged as a promising solution to the inefficiencies of manual waste sorting. Within this context, we present our innovative and comprehensive waste management system designed to revolutionize the waste management landscape. Our system seamlessly integrates state-of-the-art technologies, including Convolutional Neural Networks (CNNs) and conveyor belt systems, to achieve real-time waste object classification and dynamic self-training. At its core, our system operates by employing sensors that detect incoming waste objects, a camera to capture high-resolution images of these objects, and a CNN algorithm meticulously trained to categorize waste items into predefined classes such as food waste, metal, plastic bottles, and other recyclable or non-recyclable materials. This initial classification, achieved with high precision, ensures that waste objects are correctly directed to their designated bins, mitigating the risk of cross-contamination, and enhancing recycling efforts. What sets our system apart is its innate ability to self-train and continuously adapt to emerging waste challenges. By leveraging instances of classification errors, the system autonomously updates its knowledge base, ensuring that it remains up to date with shifting waste compositions. This adaptive self-training feature not only enhances classification accuracy but also positions our system as a versatile solution capable of accommodating new waste categories and materials without the need for manual reprogramming.

Furthermore, our system embodies sustainability by dynamically adjusting the conveyor belt's destination in real time, ensuring that each waste object is channeled to its appropriate bin for either recycling or disposal. This feature minimizes waste sent to landfills and maximizes resource recovery, aligning with the principles of a circular economy and sustainable waste management. In this research, we comprehensively explore the development, implementation, and performance evaluation of our system. We present empirical evidence highlighting the system's adaptive capabilities and its impact on waste sorting efficiency. Comparative analyses with traditional manual sorting methods underscore the advantages of automation in waste management. Additionally, we discuss the potential environmental and economic benefits arising from the system's adaptability to the evolving waste landscape.

2. Related Work

Zol Bahri et al. [1] demonstrated a waste separation system utilizing a camera for image sensing and a conveyor belt for waste movement. The waste was sorted into different bins for plastic and paper categories. Sakr et al. [2] compared deep learning and support vector machine (SVM) methods for waste classification. Their study found that SVM outperformed AlexNet. Cenk Bircanoglu et al. and Olugboja Adedeji et al. [3] demonstrated an intelligent waste classification system using a pre-trained residual convolutional neural network. Kancharla Tarun et al. [4] designed a model for sorting plastic and non-plastic waste using Convolutional Neural Network. RFID tags attached during manufacturing were used for waste segregation. The authors developed a real-time machine prototype. Mahmudul et al. [5] developed a waste classification system based on metal, glass, and transparent materials. Their approach incorporated various sensors such as metal and glass sensors, a light-dependent resistor (LDR), LASER, IR transmitter, and receiver. A microcontroller controlled a servo motor to deposit waste into the respective bins. Yin Shen et al. [6] proposed a model classifying impurities in wheat using a Convolution Neural Network. They applied image processing techniques with Wiener filtering and Multi-scale retinex enhancement algorithms. George E. [7] compared multiple deep Convolutional Neural Network architectures (MobileNet, RecycleNet, ResNet50, Inception, ResNet, Xception, Densenet121, Densenet169, and Densenet201) using various optimization methodologies. The training samples were limited. Yijian Liuin et al. [8] presented a hardware module using a Raspberry Pi, SURF-BoW algorithm, and multi-class SVM classifier for waste classification. They categorized waste into batteries, bottles, cans, paper balls, and paper boxes.

3. Methodology

3.1. Dataset and Pre-Processing

In this study, we used a comprehensive image dataset sourced from Kaggle, contributed by ashidutt and anujdutt. The dataset is divided into two main categories, "Biodegradable" and "Non-Biodegradable", with each encompassing four distinct classes. Some of them is shown in Figure 1.

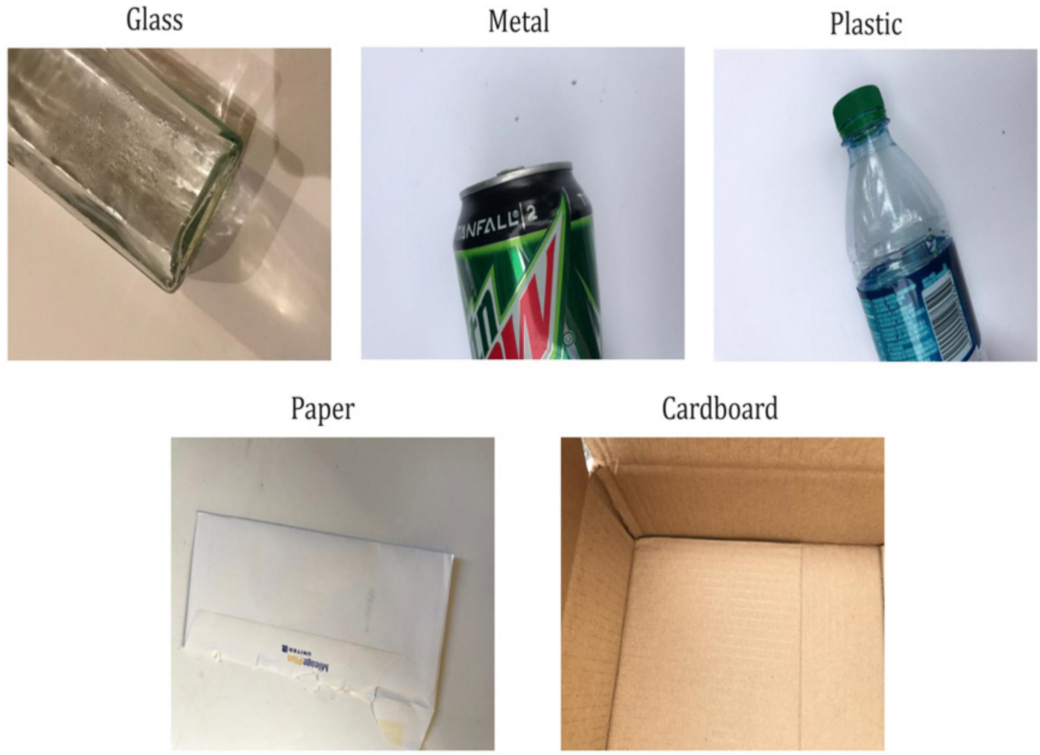


Figure 1. Random samples from the waste segregation image dataset shown with their actual class on top.

For the "Biodegradable" category, the classes are as follows:

- Food waste—10,100 images.
- Leaf waste—1179 images.
- Paper waste—860 images.
- Wood waste—593 images.

For the "Non-Biodegradable" category, the classes are as follows:

- Waste—180 images.
- Plastic bags—200 images.
- Plastic bottles—417 images.
- Metal cans—670 images.

In our study, the dataset was divided into training and testing sets to facilitate the development and evaluation of our waste management system's classification algorithm. To ensure a robust assessment of our model's performance, we adopted a commonly used split ratio of 80:20, where 80 is the training sets and 20 is the testing sets. This partitioning allowed us to effectively train our model on a substantial portion of the data while maintaining a separate, unseen portion for evaluation. By doing so, we aimed to simulate real-world scenarios where the model encounters new, unseen waste objects and assess its ability to generalize and accurately classify them.

Preprocessing of image data is often an essential step when training a Convolutional Neural Network (CNN) for computer vision tasks.

The following are the pre-processing techniques we used to clean our data and make our data ready for training. Sample image after applying pre-processing techniques is shown in Figure 2.

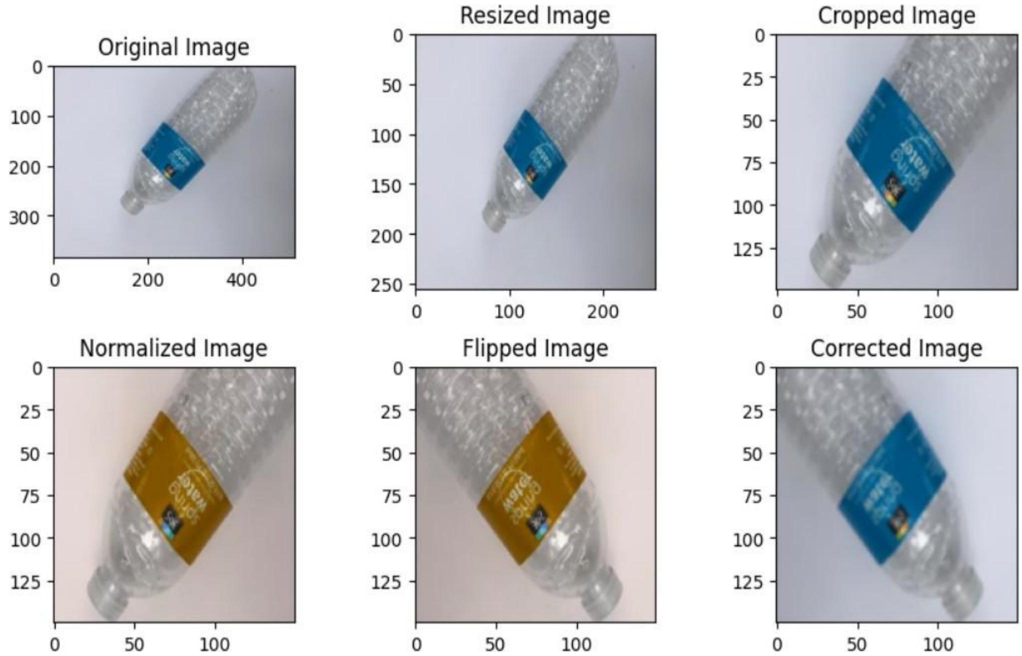


Figure 2. Preprocessing steps that each image has undergone.

- Resizing and cropping: Images in a dataset may come in various sizes and aspect ratios; so, it is often necessary to resize and crop them to a consistent size before feeding them into the CNN.
- Normalization and rescaling: Normalizing and rescaling the pixel values of the images can help to reduce the impact of illumination and contrast variations across the images. Typically, normalization involves subtracting the mean pixel value of the entire dataset and dividing it by the standard deviation.
- Data augmentation: data augmentation techniques, such as flipping, rotating, and zooming, can be used to generate additional training examples and make the CNN more robust to variations in the data.
- Noise reduction: Images can often be noisy due to factors such as compression artifacts, sensor noise, and motion blur. Applying denoising techniques such as smoothing filters can help to reduce the noise in the images and make them easier to interpret.
- Color correction: Color variations can be present in images, especially if they are taken under different lighting conditions. Applying color correction techniques can help to standardize the colors across the images in the dataset.

The dataset-splitting approach, combined with thorough data preprocessing and augmentation techniques, allowed us to develop and evaluate our waste management system's classification algorithm under controlled yet realistic conditions. This methodology enabled us to assess the algorithm's performance accurately and make informed decisions about its effectiveness in classifying waste objects as either "Biodegradable" or "Non-Biodegradable".

3.2. Network Architecture Design

The proposed network architecture for our waste management system is based on a Convolutional Neural Network (CNN) that incorporates several convolutional and pooling layers, followed by dense layers for object classification. CNNs are a well-established deep learning architecture renowned for their effectiveness in image analysis tasks. The input waste object images undergo preprocessing using data augmentation techniques, such as resizing and flipping, to enhance their suitability for classification. The first layer of the CNN architecture consists of a convolutional layer employing a rectified linear unit (ReLU) activation function. This is succeeded by a max pooling layer that reduces the spatial dimensions of the output. The process iterates through additional convolutional and pooling layers, each contributing to feature extraction. The final convolutional layer employs a sigmoid activation function to generate a binary output for object classification. Subsequently, the output from the last convolutional layer is flattened and passed on to two dense layers designed for classification purposes. The first dense layer incorporates a sigmoid activation function, while the second dense layer utilizes a softmax activation function to produce a probability distribution over the object classes. In the context of our waste management system, the softmax layer generates a probability distribution across various waste categories, facilitating efficient object sorting.

This modified CNN architecture is tailored to capture the distinctive features present in waste object images, enabling precise classification. The use of data augmentation techniques ensures that the model is adaptable to variations in object size, orientation, and condition, enhancing its robustness in real-world waste sorting scenarios. Activation functions and pooling layers have been selected based on well-established practices in deep learning for image analysis. To optimize the performance of our system, significant modifications have been made to the architecture, including parameter adjustments, architecture fine-tuning, and training process optimization. These alterations are essential for achieving a higher overall system performance and classification accuracy. In the training process, validation metrics such as accuracy and loss are monitored over training epochs to gauge the network's progress. Visualization tools, such as diagrams and graphs, are employed to represent the architecture and training details, aiding in the interpretation and reproducibility of the results.

3.3. Model Training

The network is composed of various layers, and the functions of the different layers are mentioned below. The convolutional layers perform convolutions on the input data, applying filters to detect different patterns and features as shown in Figure 3. Each convolutional layer learns a set of filters that can detect specific features at different spatial scales. The max pooling layers, on the other hand, reduce the spatial dimensions of the features while retaining the most important information. They achieve this by selecting the maximum value within each pooling region. Together, the alternating sequence of convolutional and max pooling layers allows the network to progressively learn hierarchical features, starting from low-level features (such as edges and corners) in the early layers and gradually building up to more complex and abstract features in the deeper layers.

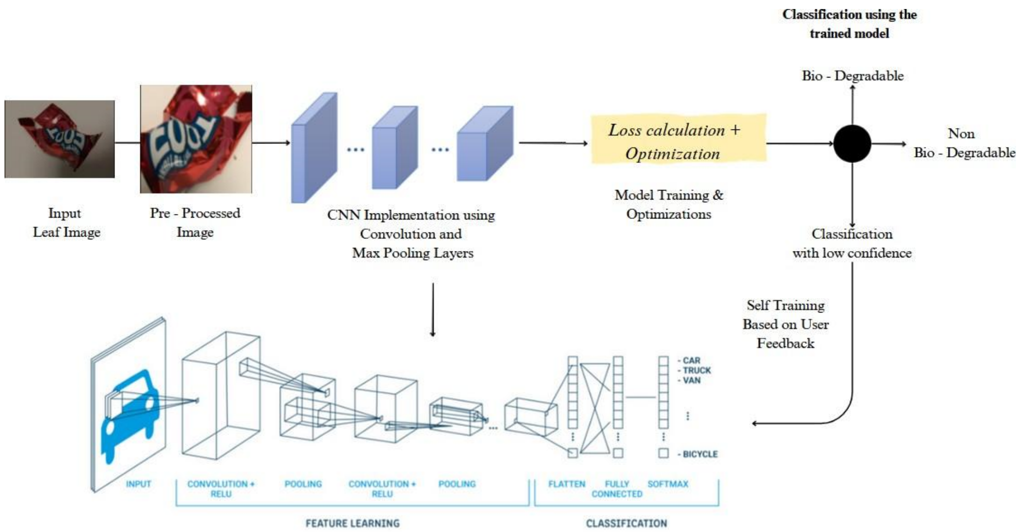


Figure 3. Flowchart of the proposed deep learning architecture for waste class analysis. (https://www.run.ai/guides/deep-learning-for-computer-vision/deep-convolutional-neural-networks (accessed on 25 October 2023)).

The final layers of the network, which include the flattening layer and the dense layer, are involved in the classification task. The flattening layer reshapes the output of the previous layer into a 1D vector, effectively preparing the features for input into the dense layer. The dense layer, also known as the fully connected layer, receives the flattened features as input and performs the classification based on those features. It connects every neuron in the previous layer to every neuron in the dense layer, allowing for complex decision making and mapping of the learned features to specific classes or labels.

The proposed garbage analysis model is trained using a combination of the steepest gradient function and Adam optimizer. The learning rate is set to 0.05, which controls the step size of the gradient descent algorithm during training. The training is performed using the proposed architecture, which includes multiple convolutional and pooling layers, followed by two dense layers for classification. The dataset has been split into three disjoint subsets, namely, the training set, test set, and validation set. The training set comprises 70% of the dataset and is used to train the model. The test set, which constitutes 20% of the dataset, is used to evaluate the model's performance on previously unseen data. Finally, there is the validation set, which accounts for 10% of the dataset. The use of a validation set is important because it allows for the evaluation of the model's generalization performance on data that are not part of the training set. By fine-tuning the hyperparameters on the validation set, one can avoid overfitting the model to the training data, which may result in poor generalization performance on new data. The use of a separate test set, in turn, allows for the unbiased evaluation of the model's performance on previously unseen data, and provides a measure of the model's ability to generalize to new data. The steepest gradient descent function is a widely used optimization algorithm in machine learning that updates the model parameters in the opposite direction of the gradient of the loss function with respect to the parameters. Mathematically, given a loss function L, and a model parameter vector $\nabla_\theta L$, the update rule for steepest gradient descent is as follows:

$$\theta_t = \theta_{t-1} - \alpha \nabla_\theta L \tag{1}$$

where α is the learning rate, which controls the step size of the update. The gradient $\nabla_\theta L$ is calculated using backpropagation algorithm, which efficiently computes the gradient of the loss with respect to each parameter in the model. The Adam optimizer is a popular optimization algorithm that uses a combination of the first and second moments of the gradients to update the weights. This algorithm is known to converge faster than other optimization techniques and has been shown to work well with deep neural networks. Specifically, the Adam optimizer calculates an adaptive learning rate for each parameter, which is based on the estimated first and second moments of the gradients. This allows the optimizer to adjust the learning rate for each parameter based on the historical gradient information, leading to faster convergence and better performance.

The update rule for Adam Optimizer is as follows:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{2}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \tag{3}$$

$$\theta_t = \theta_{t-1} - \alpha \sqrt{m_t} / [\underline{v}_t + \varepsilon] \tag{4}$$

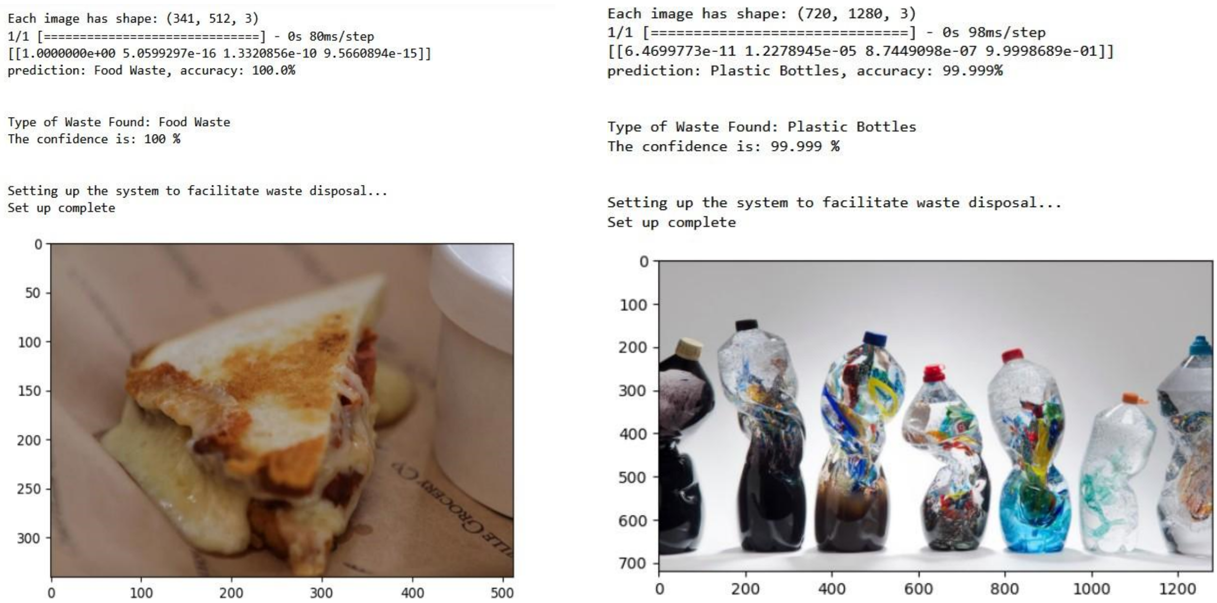
where m_t and $\underline{v}_t$ are the first and second moments of the gradient, g_t is the gradient of the loss at time t, β_1 and β_2 are the exponential decay rates for the moving averages, and ε is a small constant added for numerical stability. The training procedure involves feeding the preprocessed waste images to the model and using a loss function to compute the error between the predicted and actual outputs. The Adam optimizer is used to adjust the model weights based on the computed error, while the steepest gradient function is used to determine the direction of the weight updates. The training is continued until the validation accuracy saturates and stops increasing. The training progress can be monitored by plotting the validation accuracy and loss over epochs. The model is saved after training, and the saved model can be used for inference on new waste images. The proposed architecture and training procedure are based on the extensive literature on deep learning for image analysis and are designed to capture the intricate features present in waste images. The use of the steepest gradient function and Adam optimizer ensures that the model converges to the optimal solution quickly and efficiently.

3.4. Model Evaluation

To evaluate the performance of the proposed mammogram analysis model, several evaluation metrics were used. These metrics included accuracy, precision, recall, and F1 score. The model was evaluated on both the test and validation datasets to ensure the generalization of the model. Precision is the ratio of true positives to the sum of true positives and false positives, measuring the accuracy of positive predictions. Recall is the ratio of true positives to the sum of true positives and false negatives, measuring the completeness of positive predictions. F1 score, the harmonic mean of precision and recall, provides a balanced measure. In medical diagnosis, where positive cases are often less frequent, F1 score is a more meaningful evaluation metric than accuracy, which may be misleading due to class imbalance.

3.5. Front End Implementation

Our system is developed to enhance waste segregation by combining machine learning algorithms with a user-friendly front-end interface as shown in Figure 4. The front-end is composed of four integral components:



(**a**) (**b**)

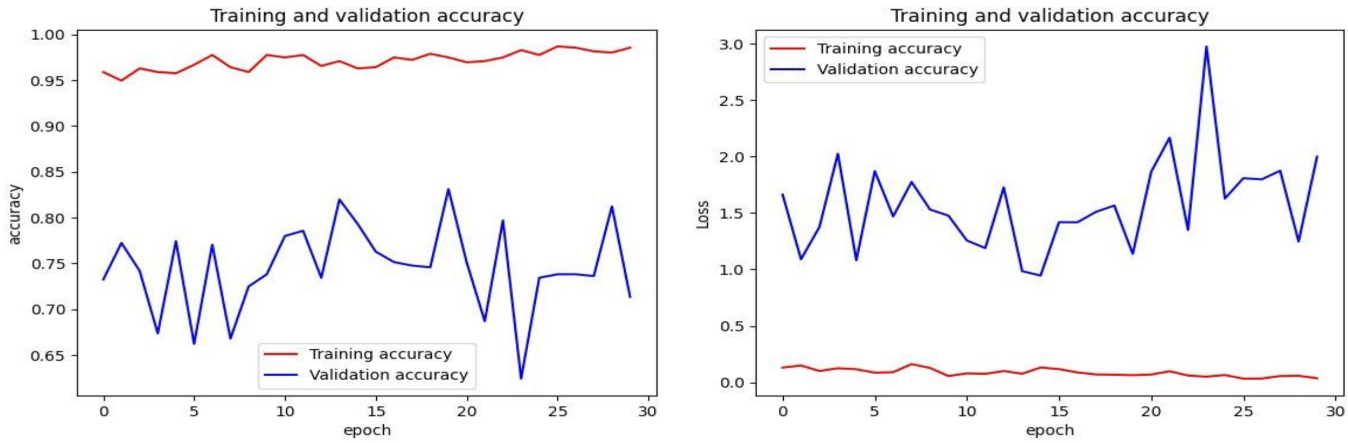
Figure 4. (**a**) Prompt shown as output when a food waste is set up for classification. Result captured in Jupyter Notebook. (**b**) Prompt shown as output, when a plastic bottle is setup for classification. Result captured in Jupyter Notebook.

Following the algorithmic processing, the third component displays segregation predictions to users on the front-end interface. Users receive guidance on proper waste segregation based on the predictions, utilizing a probabilistic model that factors in waste type, history, and additional relevant information. The initial phase involves users uploading waste images via the front-end interface, acting as the primary data source for segregation predictions. In the subsequent stage, waste images undergo preprocessing, including normalization, contrast enhancement, and resizing. These processed images are then fed into a machine learning algorithm utilizing convolutional neural networks (CNNs) for effective image classification. Following the algorithmic processing, the third component displays segregation predictions to users on the front-end interface. Users receive guidance on proper waste segregation based on the predictions, utilizing a probabilistic model that factors in waste type, history, and additional relevant information. The fourth component centers on continuous learning. Users are encouraged to provide feedback on segregation predictions, particularly in cases of misclassification. The system utilizes this feedback to update its database and retrain the machine learning model. Transfer learning techniques are applied to adapt pre-trained CNNs to the unique features of the waste dataset, and retraining incorporates backpropagation and stochastic gradient descent (SGD) to minimize prediction errors.

This continuous learning approach aims to improve segregation accuracy over time, providing users with a clearer understanding of segregation results and enabling them to take informed actions. The user-friendly front-end interface accommodates a diverse user base, including those unfamiliar with machine learning or waste management terminology. The system's goal is to optimize waste management practices, contributing to more effective segregation and positive environmental outcomes.

4. Results and Discussion

The waste images from the dataset were trained using the TensorFlow library in Python. The Figure 5 shows the training was carried out until the validation accuracy values became saturated and stopped increasing.



(**a**) (**b**)

Figure 5. (**a**) Plot of the training and validation accuracy changing with epochs while training the Neural Network. Here, we can observe that the training accuracy reached about 98% and the validation accuracy saturates at about 80%. (**b**) This plot shows the training and validation loss decreasing with increasing epochs.

5. Conclusions

The Self-Adaptive Waste Management System (SAWMS) introduced in this study marks a significant advancement in waste sorting and classification. By combining Convolutional Neural Networks (CNNs) with conveyor belt technology, SAWMS achieves real-time and precise waste object classification while uniquely adapting and self-training to ensure sustained accuracy amidst changing waste compositions. Although hardware details are briefly addressed, the system's standout features include its automation, reducing contamination risks, promoting recycling, and dynamically adjusting the conveyor belt for sustainable waste management. The adaptability, efficiency gains, and economic benefits showcased in this study position SAWMS as a promising solution for future waste management challenges, emphasizing the role of technology in transforming waste sorting systems.

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References

1. Razali, Z.B.; Madasamy, S. An application of image processing for automated mixed household waste sorting system. In Proceedings of the International Conference on Man-Machine System (ICoMMS2012), Perlis, Malaysia, 27–28 February 2012; Volume 27, pp. 28–32.
2. Bircanoglu, M.C.; Atay, M.; Beser, F.; Kazak, M.A. Recyclenet: Intelligent waste sorting using deep neural networks. In Proceedings of the 2018 Innovations in Intelligent Systems and Applications (INISTA), Thessaloniki, Greece, 3–5 July 2018; pp. 1–7.
3. Adedeji, O.; Wang, Z. Intelligent waste classification system using deep learning convolutional neural network. *Procedia Manuf.* **2019**, *35*, 607–612. [CrossRef]
4. Tarun, K.; Sreelakshmi, K.; Peeyush, K. Segregation of plastic and non-plastic waste using convolutional neural network. *Conf. Ser. Mater. Sci. Eng.* **2019**, *561*, 012113. [CrossRef]
5. Russel, M.H.; Chowdhury, M.H.; Uddin, M.S.N.; Newaz, A.; Talukder, M.M.M. Development of automatic smart waste sorter machine. In Proceedings of the International Conference on Mechanical, Industrial and Materials Engineering 2013 (ICMIME2013), RUET, Rajshahi, Bangladesh, 1–3 November 2013; Volume 1, p. AM-012.
6. Shen, Y.; Yin, Y.; Zhao, C.; Li, B.; Wang, J.; Li, G.; Zhang, Z. Image recognition method based on an improved convolutional neural network to detect impurities in wheat. *IEEE Access* **2019**, *7*, 162206–162218. [CrossRef]
7. Liu, Y.; Fung, K.C.; Ding, W.; Guo, H.; Qu, T.; Xiao, C. Novel smart waste sorting system based on image processing algorithms: Surf-bow and multi-class svm. *Comput. Inf. Sci.* **2018**, *11*, 35–49. [CrossRef]
8. Sakr, G.E.; Mokbel, M.A.; Darwich, A.; Khneisser, M.N.; Hadi, A. Comparing deep learning and support vector machines for autonomous waste sorting. In Proceedings of the 2016 IEEE International Multidisciplinary Conference on Engineering Technology (IMCET), Beirut, Lebanon, 2–4 November 2016; pp. 207–212.