Increase Recycling Efficiency with Deep Learning

June 11, 2023

1 Introduction

Increasing human population and industrialization have increased the consumption of natural resources and the world has faced the problem of resource consumption [13]. When the wastes reached a level that would harm human health, the search for solutions gained importance. One of these solutions is recycling. Recycling protects ecosystems and wildlife, contributes to the economy, conserves energy, reduces air and water pollution, reduces greenhouse gases, and conserves natural resources, reduces demand for raw materials.

The large variety of products in recycling can cause difficulties in sorting. It is expected that the detection and separation of recycling materials with artificial intelligence will save time and cost. The aim of the project is to identify and classify recycling products with deep learning that can take the first step of the process for groups that do not have awareness of garbage classification. The project can be integrated into the robot arm, the product line. It is desired to increase efficiency in recycling by minimizing operator errors.

2 Literature Review

Costa, Bernando S. et al. used image processing technique to classify recycling wastes. Using VGG-16, AlexNet, Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and Random Forest (RF) models, they divided waste into four classes as glass, paper, metal and plastic. This study reached an accuracy rate of 93% [4]. Gupta, Praveen Kumar et al. studied to use modern technology methods in smart waste management and recycling by using sensors or artificial intelligence techniques embedded in trash cans. In this study, the waste levels in the trash can are shown and it is aimed that there are no uncontrolled trash cans by moving on different routes. As a result, it is desired to create a cleaner society with reduced costs and less effort[6] Wilts, Henning et al. They conducted a study on the evaluation of the performance quality of the training and operation of the robotic sorting system based on artificial intelligence. The robot was hand fed and trained to recognize 13 materials. An average of 90% success rate was achieved in 13 material recognition. The robot has shown difficulties in object detection with overlapping objects. As a result of the study, it is planned to increase capacity and identify new materials[14]. Qu, Donqxu worked by using artificial intelligence in the collection and separation of waste processes. With this study, an artificial intelligence technology-based proposal was made to improve the waste classification recycling performance at the university [9]. Wahab et al. He worked on shape analysis, feature extraction and classification, and the development of an automated sorting system using image processing techniques for plastics recycling. As a result, 95% correct definitions were provided. With this work, it was sought to provide a cleaner and more cost-effective method for plastic recycling[12].Tachwali et al. worked on an artificial intelligence-based plastic bottle sorting system for recycling plastic bottles. This study resulted in 94% accuracy [11]. Yu, Kan Hua et al. used machine learning and graph theory for environmental planning to optimize the waste management process, and as a result, they observed that the current method improves performance and accuracy when compared to other methods[15]. Lai, Shih et al. established an object detection system for recycling using SSD, Faster-RCNN and VGG methods in their study. In this project, which interacted with the camera, the accuracy rate was recorded as 97% [8] Erkinay Özdemir, Merve et al. conducted analysis studies focusing on machine learning algorithms used for classification and better separation of materials in a recycling application.[5].

3 Project Proposed Approach

The social problem, which increased with the food, water, agricultural land crises and the increase in consumption, brought along the search for recycling solutions. One of the biggest obstacles to the recycling process is the improper sorting of materials. In this study, it is aimed to use YOLO and deep learning approach in real-time material separation in recycling. The intended effect of the study is to meet the need for models to perform material separation and to minimize the need for workers, with the camera system installed on waste bands in recycling facilities.

Datasets belonging to 4 different classes, namely glass, plastic, metal and paper, were used [1]. The data set consists of 2967 data. The distribution of the data set is shown in Figure.1.

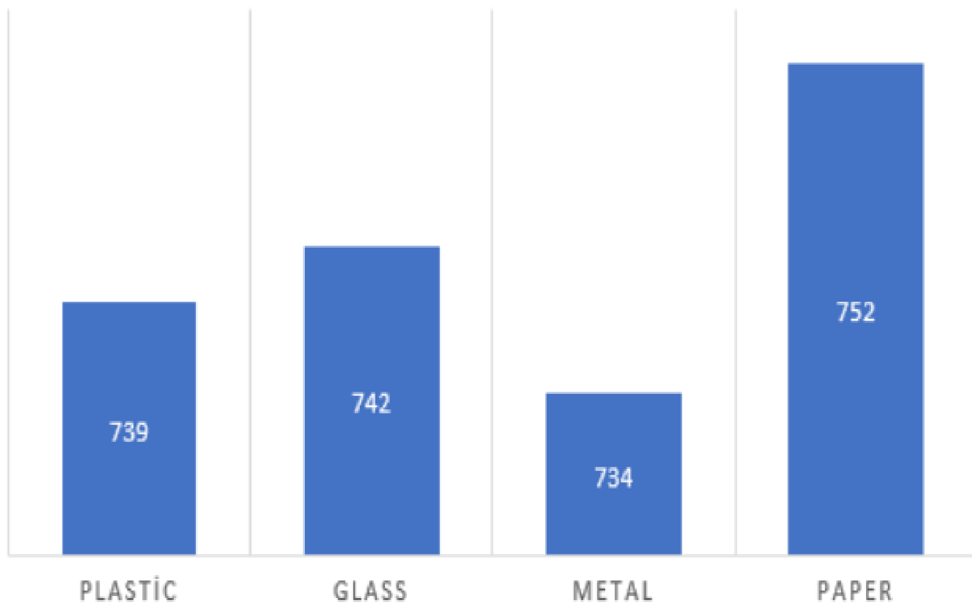

Figure 1: Data Count

Figure.2 shows examples from the dataset. Unlabeled data at source were labeled glass, metal, paper, and plastic, respectively, using the labelImg application. Class indexes are shown in LabelImg as in Table.1. LabelImg is a tool that allows you to draw boxes around the object you want to classify in the images you upload[2]. It saves the positions of the picture you marked according to the format you selected. It provides a free and easy way to tag your images.

Class	Epoch
plastic	0
glass	1
metal	2
paper	3

Table 1: Indexes by Class

Object detection is a technique that allows us to identify and locate objects in an image or video. An example of this is to identify what a dog, cat, car, and human are in a picture. Object recognition has a great place in the field of deep learning. Many object detection algorithms such as Faster R-CNN, Single Shot Detector (SSD) and YOLO (You Only Look Once) are used today. In this study, the YOLO algorithm was chosen to be applied to the data. YOLO is more successful in real-time object detection than other algorithms.

Figure 2: Data Examples

The reason is that it predicts the class and coordinates of all objects in the picture by passing it through the net at once. Other algorithms require a view of the object to be predicted from multiple angles and different locations. They can perform classification and localization processes in line with these images. Unlike these algorithms, YOLO works with a single image and divides the image into regions. These separated regions see a data box and different weights are given to these boxes by applying the neural network. Thus, less data, and higher accuracy value is achieved with neural network. In the YOLO algorithm, the grids travel the picture and understand whether there is an area of that object or not, and if it is within its midpoint. If its midpoint is in it, it finds its length, height, and what class it belongs to. In short, it is responsible for the box drawn during object detection. Accordingly, YOLO creates a separate prediction vector for each grid.

In a real-time sample study, YOLO showed the best results in real-time vehicle type detection with the sum of speed and success. The fastest model, the Faster-RCNN model, does not have enough FPS. Mobile-V1, on the other hand, could not achieve a sufficient success rate.[7] Figure.3 shows the comparison of Retina-Net algorithms with YOLO on the COCO dataset[10].

GPU support provides efficiency in object recognition and classification. Since it provides GPU support, model training and development will be done on Google Colab.

4 Results

This study first tried with the YOLOv3 model and correct results could not be obtained in the validation data. Then, a 12-hour training was performed with YOLOv8 by setting the hyperparameters epoch = 10 batch = 32 loss = 0.01. As a result of this model, the hyperparameters were changed because the data could not be fully learned. nd correct results could not be obtained in the validation data. Then, about 35-hour training was performed with YOLOv8 by setting the hyperparameters epoch = 20 batch = 32 loss = 0.001. Stochastic gradient descent was chosen as the optimization algorithm.

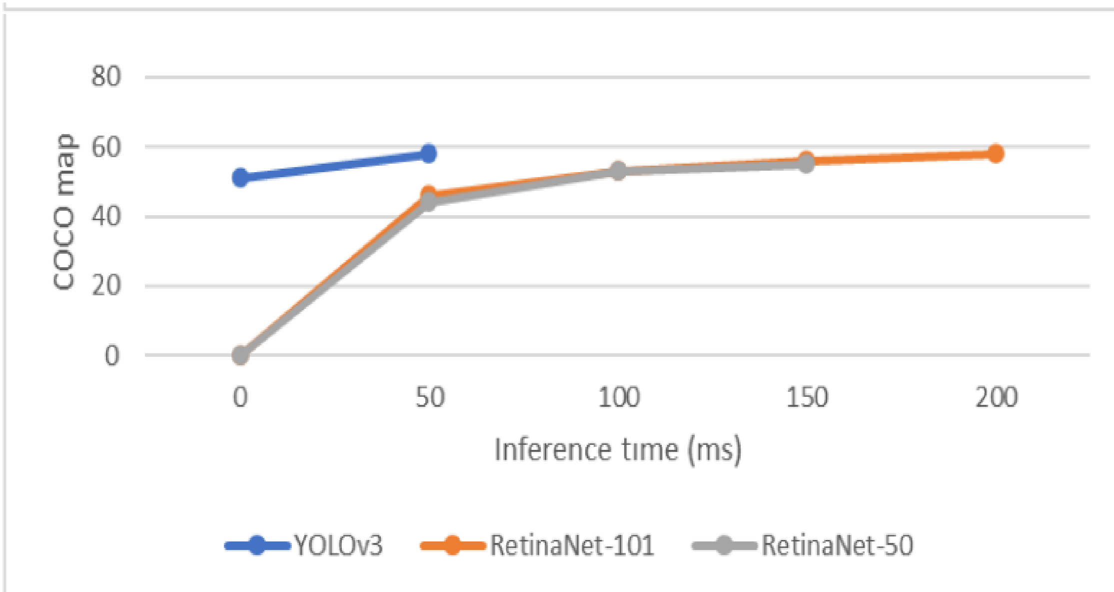

Figure 3: Comparison of Models

YOLOv8 is designed to be fast, accurate and easy to use, making it an excellent choice for a object detection and image classification[3] .The learning rate determines the step size used during the optimization of the model. If the learning rate is high, the optimization is faster, if learning rate is low the optimization starts to give slower but more accurate results. Batch number means how many pieces of data will be processed at the same time during the training of the model. The model updates its weights by backpropagation with the split data. Finding the best model, this process is called epoch.

After training the model, graphs of precision, recall and confidence distributions were drawn. Confidence Score is a number between 0 and 1 that represents the probability that the output of a deep learning model is correct and satisfies a user's request. If the confidence score is between 0.2 and 0.7, the forecast and demand are partially satisfied. If the confidence score is above 0.7 then the prediction is a strong candidate to answer the user query. As can be seen in Figure 4, the comparison of classes in terms of precision and confidence has followed a consistent path, with results close to each other. Model got the highest precision score after the 0.8 confidence score. By looking at this, we can conclude that the training is successful.

When recall score and confidence score values are compared, it is seen that recall takes the full value of 1 in confidence score values between 0 and 0.8. The model recall score represents the model's ability to accurately predict positives from true positives. It is also known as sensitivity of the true positive rate. As seen in Figure 5, an increase in the downward slope of the recall value after a confidence score of 0.8 is observed in successfully trained models. The absence of a breakpoint in the curve of the graph indicates that the training is reliable. This result reflects the consistency of the model. The fact that metal and paper classes intersect with all classes curve and give a closer result shows that more reliable results will be obtained in these classes compared to the metal class.

The F1 score is used to evaluate binary classification systems that classify samples as either 'positive' or 'negative'. The F-score is defined as the harmonic mean of the model's precision and recall. As seen in Figure 6, we can see a similar curve to Recall Score - Confidence Score curve. Before the 0.8 confidence score the curve slightly goes up to 0.9 valued F1 score and after the 0.8 confidence score, curve goes down to 0.0 F1 score. The breaking point which is near to 0.9 confidence score shows us after the critical 0.8 value of confidence score, balance between recall and precision score is not reliable In the case of this model, choosing a confidence score of 0.8 seems to be optimal, as the F1 value appears to be about 0.95 before it hits the breakeven point. The break point after a confidence score of 0.8 and then the curve going down indicates that confidence scores higher than 0.8 will not yield sufficiently harmonic results.

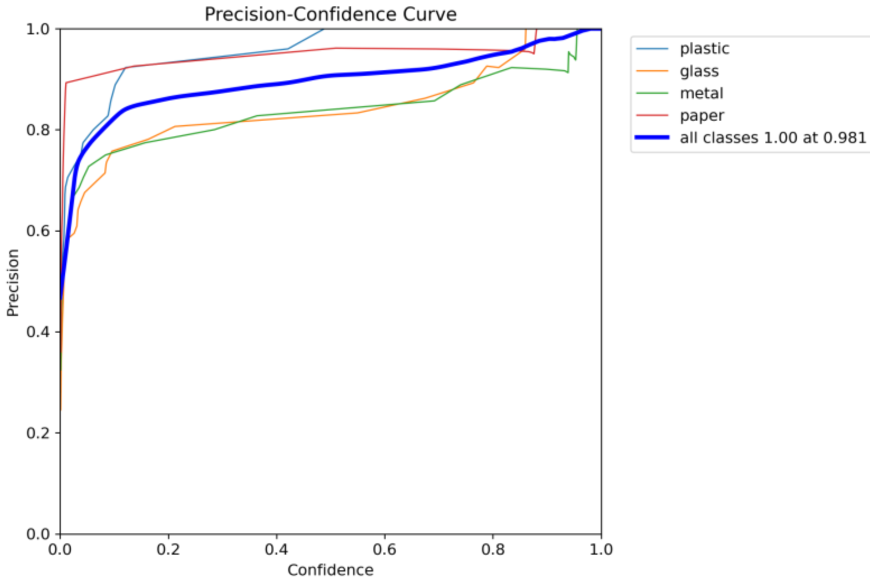

Figure 4: Precision-Confidence Curve

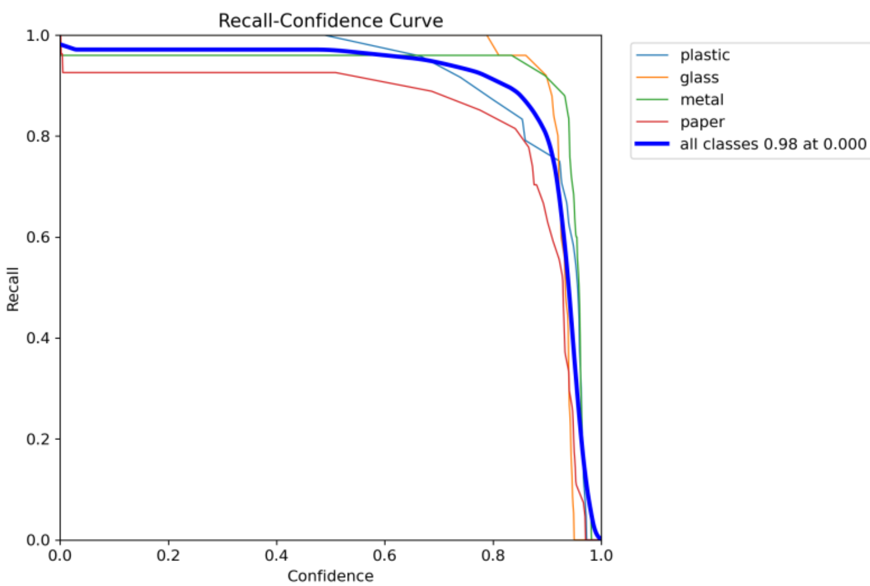

Figure 5: Recall-Confidence Curve

The algorithm's precision, recall and accuracy values are calculated according to the output calculation and TP (true positive), FP (false positive), FN (false negative), TN (true negative) classifications are made. Confusion matrix is created according to the TP, FP, FN, TN results obtained and the success rate of the algorithm can be observed. As can be seen in the obtained confusion matrix, the dark diagonal structure stands out and the deviations due to the result outside this diagonal are few and light colored as Figure 7. By looking at the confusion matrix, it can be said that the accuracy of the model is high and the deviations are low.

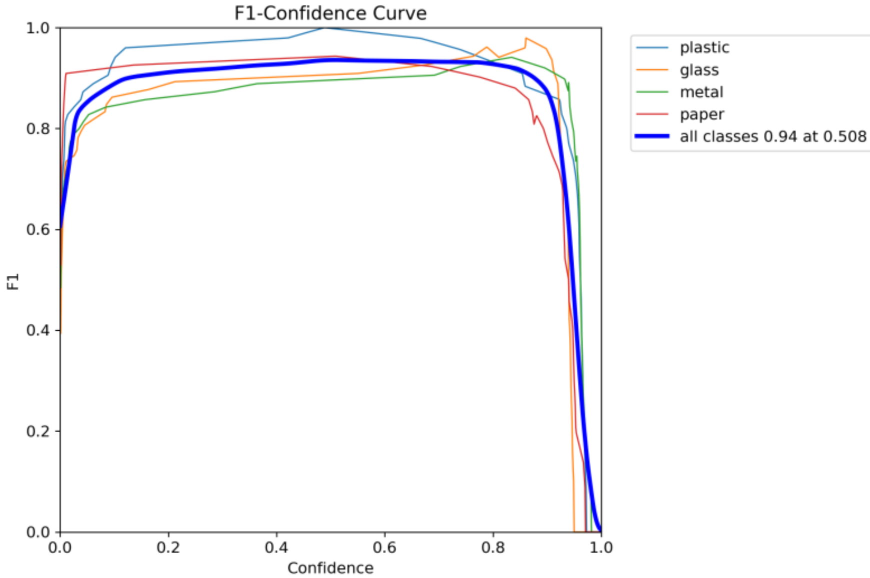

Figure 6: F1-Confidence Curve

The graphics of the model are shown in the Figure 8.The graphics of the old model are shown in the Figure 9. It was understood that the old model could not learn because It has more breakpoints so hyperparameters changed for this reason and the parameters were changed for this reason.

A website has been developed for the use of the project. The model has been uploaded here. Tested with validation data, webcam and video upload feature.The design of the website is shown in Figure 10 and Figure 11. Video upload and webcam were tested in real time and the model is tested with high accuracy as shown in Figure 12, Figure 13, Figure 14, Figure 15.

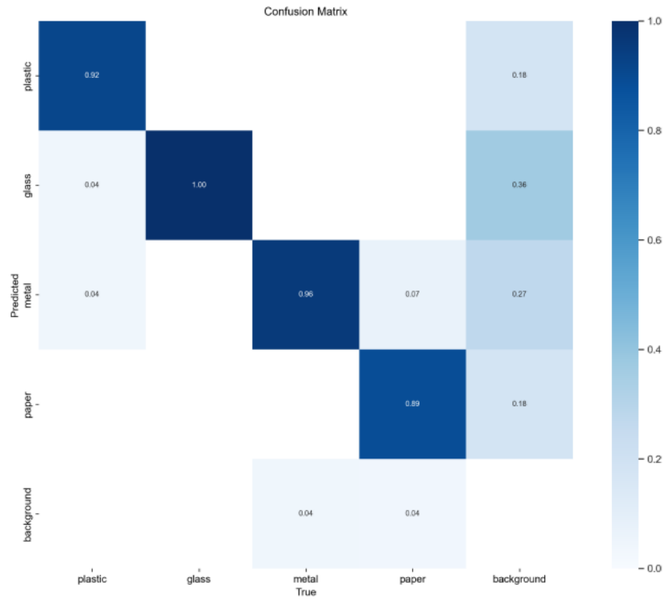

Figure 7: Confusion Matrix

As a result, YOLOv8 has been tested on labeled data. Video and webcam features have been tried on the website and successful results have been obtained.

Figure 12: The Metal Sample Tried on the Website with Video

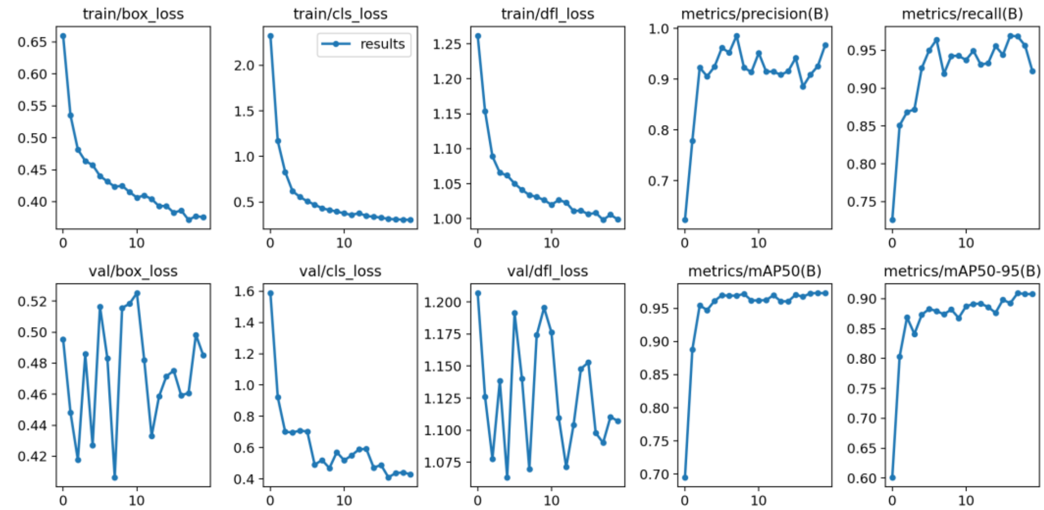

Figure 8: Last Trained Model

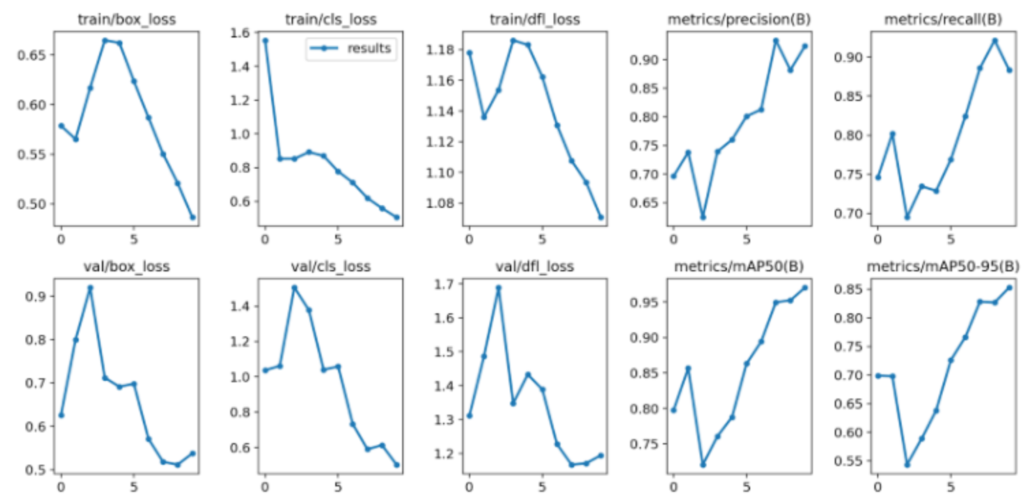

Figure 9: First Trained Model

Figure 13: The Plastic Sample Tried on the Website with Webcam

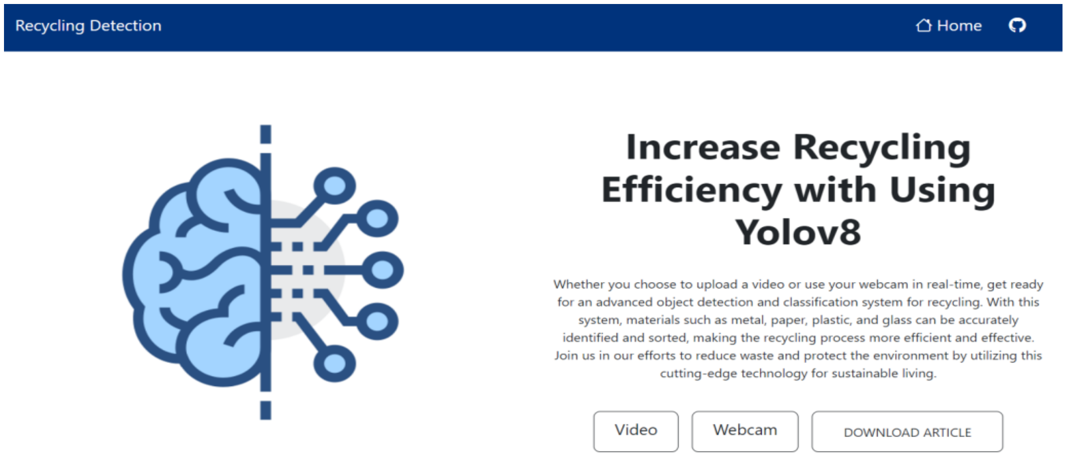

Figure 10: Model Loaded Website Homepage Design

Figure 11: Model Loaded Website Homepage Design

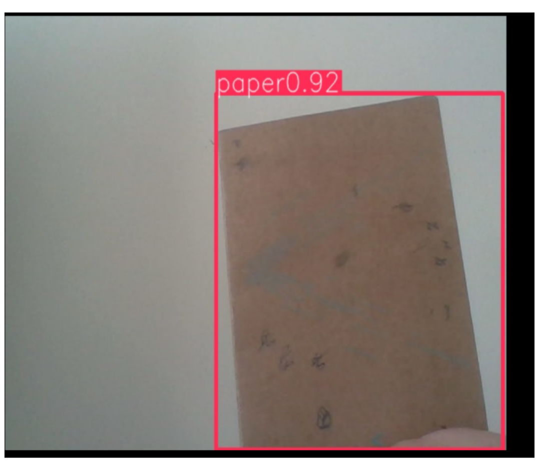

Figure 14: The Paper Sample Tried on the Website with Webcam

Figure 15: The Glass Sample Tried on the Website with Video

5 Discussion and Conclusion

In this study, an artificial intelligence-based recycling system is making significant progress in waste management and recycling processes. This system aims to increase the speed and efficiency of the recycling process by accurately classifying waste. While traditional recycling processes can be time-consuming and prone to errors, AI-based systems help overcome these challenges. With the use of an AI-based system, less effort will be required from humans to classify and direct waste properly. This will make recycling more appealing and encourage people to engage in recycling willingly.

The AI-based recycling system can accurately categorize waste by using various detection and classification techniques. For example, with the use of a trained model, it can recognize materials such as plastic, paper, glass, and metal, and direct them to separate containers. Additionally, depending on the type of waste, the system can automatically manage different steps in the recycling process. This minimizes human errors and enables a more efficient recycling process. The AI-based recycling system can also optimize the recycling process by analyzing large amounts of data. It can monitor waste quantities, recycling rates, and the capacities of recycling facilities. As a result, smarter and more informed decisions can be made regarding waste management and recycling planning. Moreover, the system can analyze trends to identify potential improvements in the recycling process and develop new strategies. With the widespread adoption of such AI-based technological advancements, more efficient and environmentally-friendly solutions can be achieved in waste management and recycling. By reducing errors caused by human factors, the recycling process becomes more reliable, and the rate of waste recovery can increase. This enables more effective utilization of natural resources and constitutes a significant step towards achieving environmental sustainability goals.

In the recycling industry, there are a variety of recycling waste types, and using more data for accurate classification is an important factor. Additionally, optimization processes and additional metrics can be used to increase the accuracy of the existing model. The next step would involve adding more data to increase the data quantity. This will enable the recognition of objects of different types with high success rates. More data will help the model learn in a more generalizable manner and achieve better results. Furthermore, you can improve the success rate by monitoring the optimization processes in the current model more closely. Steps such as adjusting the hyperparameters used during training, optimizing data preprocessing methods, and modifying the network architecture can be taken to improve performance. In future projects, new models that increase accuracy and reduce hardware costs can be used. Advanced and faster models, such as transitioning from YOLOv3 to YOLOv8, can be employed. Such updates can provide better performance and more efficient processing times.

One of the biggest challenges in the project is the low success rate in differentiating between glass and plastic. To address this issue, future work should focus on more detailed detection of glass and plastic objects. In the upcoming process, our goal is to develop high-accuracy and intelligent waste classification models for smart devices and recycling facilities systems by creating optimized models reinforced with more data. To enable the use of these models in recycling facilities, camera systems will be installed on pre-classified waste. This will make it easier to continue the model's learning process and collect more data. The smart waste classification models to be used in recycling facilities will enable the automatic classification of waste and increase the efficiency of the recycling process. These models will be trained to accurately classify various objects, materials, and waste types with high precision. To ensure that the developed models can be used in recycling facilities, it is important to continuously update the algorithm with real-time data. Therefore, great importance will be placed on the data collection process, and the overall performance of the model will be enhanced by incorporating data from various sources.

This project is a significant step towards achieving sustainability goals. The use of intelligent waste classification models will make the recycling process more effective, thereby helping us conserve natural resources and playing a crucial role in waste management. This work will contribute significantly to a cleaner and more sustainable world in the future.

References

[1] Garbage classification. https://www.kaggle.com/datasets/asdasdasasdas/garbage-classification. Accessed: 2023-11-04.

[2] Labelling images for object detection with labelimg. https://www.altisconsulting.com/insights/labelling-images-for-object-detection-with-labelimg/. Accessed: 2023-11-04.

[3] Ultralytics yolov8. https://github.com/ultralytics/ultralytics. Accessed: 2023-30-04.

[4] Bernardo S Costa, Aiko CS Bernardes, Julia VA Pereira, Vitoria H Zampa, Vitoria A Pereira, Guilherme F Matos, Eduardo A Soares, Claiton L Soares, and Alexandre F Silva. Artificial intelligence in automated sorting in trash recycling. In *Anais do XV Encontro Nacional de Inteligência Artificial e Computacional*, pages 198–205. SBC, 2018.

[5] Merve Erkinay Ozdemir, Zaara Ali, Balakrishnan Subeshan, and Eylem Asmatulu. Applying machine learning approach in recycling. *Journal of Material Cycles and Waste Management*, 23:855–871, 2021.

[6] Praveen Kumar Gupta, Vidhya Shree, Lingayya Hiremath, and Sindhu Rajendran. The use of modern technology in smart waste management and recycling: artificial intelligence and machine learning. *Recent advances in computational intelligence*, pages 173–188, 2019.

[7] Jeong-ah Kim, Ju-Yeong Sung, and Se-ho Park. Comparison of faster-rcnn, yolo, and ssd for real-time vehicle type recognition. In *2020 IEEE international conference on consumer electronics-Asia (ICCE-Asia)*, pages 1–4. IEEE, 2020.

[8] Yeong-Lin Lai, Yeong-Kang Lai, Syuan-Yu Shih, Chun-Yi Zheng, and Ting-Hsueh Chuang. Deep-learning object detection for resource recycling. *Journal of Physics: Conference Series*, 1583(1):012011, jul 2020.

[9] Dongxu Qu. Application of artificial intelligence in waste classification management at university. In *Proceedings of the International Conference on Intelligent Vision and Computing (ICIVC 2021)*, pages 330–343. Springer, 2022.

[10] Joseph Redmon and Ali Farhadi. Yolov3: An incremental improvement. *arXiv preprint arXiv:1804.02767*, 2018.

[11] Y Tachwali, Y Al-Assaf, and AR Al-Ali. Automatic multistage classification system for plastic bottles recycling. *Resources, Conservation and recycling*, 52(2):266–285, 2007.

[12] Djuraidah Abdul Wahab, Aini Hussain, E Scavino, MM Mustafa, and Hassan Basri. Development of a prototype automated sorting system for plastic recycling. *American Journal of Applied Sciences*, 3(7):1924–1928, 2006.

[13] Minxi Wang, Ping Liu, Zhaoliang Gu, Hong Cheng, and Xin Li. A scientometric review of resource recycling industry. *International journal of environmental research and public health*, 16(23):4654, 2019.

[14] Henning Wilts, Beatriz Riesco Garcia, Rebeca Guerra Garlito, Laura Saralegui Gómez, and Elisabet González Prieto. Artificial intelligence in the sorting of municipal waste as an enabler of the circular economy. *Resources*, 10(4):28, 2021.

[15] Kan Hua Yu, Yue Zhang, Danni Li, Carlos Enrique Montenegro-Marin, and Priyan Malarvizhi Kumar. Environmental planning based on reduce, reuse, recycle and recover using artificial intelligence. *Environmental Impact Assessment Review*, 86:106492, 2021.