Waste Segregation using CNN

Samiksha Gudgude, Yash Gupta, Riddhi Halade, Harsh Laddha

Vishwakarma Institute of Technology, Pune, Maharashtra, India Corresponding author: Samiksha Gudgude, Email: samiksha.gudgude21@vit.edu

Waste Segregation and Disposal has become a crucial mission for sustainable socio economic development and preserving the environment around us. Population in metropolitan and suburban areas has been increasing exponentially which has made this topic more critical since the past decade. Considering the unsurmountable pressure on current infrastructure put in place for waste segregation, upgradation and improvisation is a necessity. The integration of Machine Learning for this purpose will greatly help in addressing this purpose. Numerous Machine Learning techniques have been implemented to come up with an insightful solution. A CNN (Convolutional Neural Network) consists of n neurons which are interconnected with each other to form a network which provides us with an accurate classification model. This revolutionary technique of waste disposal is many folds faster than current waste segregation techniques which is mostly manual and time-consuming. The resultant output of these new systems will not only be useful in this step of segregation, it will also boost the process of recycling and make it more efficient and effective.

Keywords: CNN, Waste segregation, Waste disposal, recycling.

1. Introduction

Centuries ago, people used to dispose of their waste by digging holes in land far from their area which was a good solution for disposing of waste for a certain period of time as the population was very less at that time, and due to that the waste generated was also very less which made waste management very easy but now due to increasing in no of people, waste generation has also increased which has made disposing of waste difficult. Nowadays the waste elements that are produced are of various types like non-biodegradable and inorganic so if this waste is disposed of in landfills it will take a lot of time to get disposed of. Municipal solid refuse is currently discharged around the globe in an annual amount of 2.01 billion tons, and by the year 2050, this amount is expected to reach 3.40 billion tons . In creating Burning and landfilling are the primary refuse control strategies in many nations . Because of this poor administration, there is the pollution of the air, the land, and the vegetation. Even worse, people and other living things are subjected to the heavy metals produced by unregulated solid refuse, which poses significant dangers to public health.

Recycling is one of the most effective methods for processing such kinds of waste materials, and it will not only create a positive impact on the environment but it will also have a positive impact on the national economy. An official of the Vietnamese Ministry of Natural Resources and Environment stated that it is predicted that by the year 2050, there will be 1 billion tons of plastic in use worldwide. Just 14% of that is collected for recycling or repurposing, though [3]. In order to reduce the enormous quantity of plastic waste that is dumped into the environment, we must boost recycling.

2. Materials and Methods

We developed a machine learning model that can accurately classify different types of waste into their respective categories, such as recyclable, organic, and non-recyclable waste.

Data Collection and Preprocessing:

The first step in training our waste segregation model is to gather a comprehensive dataset of waste images. This dataset should contain images representing different types of waste, including recyclable, organic, and non-recyclable waste. The dataset should also include images with different backgrounds, lighting conditions, and perspectives to ensure the model's robustness.

Once the dataset is collected, it needs to be preprocessed before feeding it into the model. The preprocessing steps may include resizing the images to a standard size, normalizing pixel values, and splitting the dataset into training and testing sets. It is crucial to ensure a balanced distribution of waste types in both the training and testing sets to avoid bias in the model's performance.

Model Architecture:

We will utilize the Keras library, which offers a user-friendly and effective interface for creating deep learning models, to train our trash segregation model. Convolutional Neural Networks (CNNs) are well suited for our trash segregation model because they have demonstrated exceptional performance in image classification tasks.

The architecture of our model may consist of multiple convolutional layers followed by pooling layers to extract important features from the images. Subsequently, fully connected layers can be used to classify the features and make predictions. Activation functions like ReLU can be used to introduce non-linearity, and dropout layers can be included to prevent overfitting.

Model Training:

It is crucial to establish a suitable loss function and an optimization strategy before training the model. The categorical cross-entropy loss function is frequently utilized since waste segregation is a multi-class classification problem. As for the optimizer, algorithms like Adam or RMSprop are commonly employed due to their efficiency in handling large datasets.

During training, the model iteratively adjusts its weights based on the computed loss and the gradients obtained from the back propagation algorithm. The model is fed batches of photos during the training process, and the weights are updated after computing the loss. The number of epochs and batch size are hyper parameters that need to be carefully tuned to achieve optimal performance.

Model Evaluation:

We may assess our waste segregation model's performance using a number of criteria, including accuracy, precision, recall, and F1 score. The accuracy is the overall percentage of garbage that has been correctly classified. Recall indicates the percentage of actual positive samples that were correctly classified, whereas precision reflects the percentage of correctly classified positive forecasts. Precision and recall are combined into a single metric called the F1 score.



Figure 1: Classification Output

Figure 1 presents the evaluation of model output represented by a line plot. The x-axis denotes the labels, while the y-axis displays their corresponding probabilities. Each point on the line plot signifies the probability assigned by the model to a specific label.

Additionally, an analysis of the confusion matrix is made to understand the model's performance on different waste categories. This matrix provides insights into how the model is confusing or misclassifying certain types of waste.

Training a waste segregation model using Keras involves collecting and preprocessing a diverse dataset, designing an appropriate model architecture using CNNs, training the model with suitable optimization algorithms, and evaluating its performance using various metrics. By accurately classifying different

types of waste, such models can contribute to effective waste management and environmental sustainability. Further research and development can focus on improving the model's performance, exploring transfer learning techniques, and deploying the model in real-world waste management systems.



Figure 2: System Flowchart

Figure 2 illustrates the sequential process from data gathering via OpenCV, preprocessing steps, model selection, to evaluation metrics application, depicting the interconnected workflow for efficient system operation.

3. Literature Survey

Proper waste disposal and recycling are crucial for sustaining economies. In the 19th century, industrial waste recycling emerged in response to material shortages during the Great Depression. Subsequently, many nations have endeavored to establish modern sorting systems, replacing manual labor, a practice adopted during economic crises. Relying on workers for recycling or disposing of common items like glass, paper, cardboard, plastic, metal, and other waste poses risks to both the workers and the environment. Handling hazardous waste not only jeopardizes the health of workers but also poses

environmental threats, potentially causing severe damage to properties and creating risks to human health and the ecosystem if mismanaged [1].

To automate recycling processes, advanced composting, and incineration, it is crucial to introduce intelligent systems capable of accurately detecting waste components. This is not only beneficial for the economy but also for the overall well-being of our world. Intelligent systems mitigate the risk of harm to humans, as they eliminate the need for direct contact with hazardous waste. However, this technological advancement raises concerns about job displacement, as artificial intelligence may replace traditional roles [2].

Moreover, the segregation of hazardous waste through intelligent sorting systems poses a growing challenge and disruption to many societies. Implementing effective solutions for such sorting becomes increasingly difficult for societies to devise. Numerous countries face financial constraints, lacking the resources to afford these advanced technologies [3]. Additionally, less industrialized nations find these innovations financially out of reach, further hindering their ability to invest in such sophisticated contraptions.

In the relevant literature addressing challenges in the sorting of syringes and batteries, Abdul Mujeeb et al. conducted a review on the recycling practices of injection equipment in Pakistan. Their study focused on highly-trafficked clinical laboratories in Karachi [4]. The findings reveal a concerning scenario, where only 9% of recycled syringes from these clinical labs are processed through healthcare waste recyclers. The remaining laboratories dispose of needles in manners that expose individuals to hazardous waste, posing the risk of injuries and the potential spread of diseases. Notably, these locations include government-collected waste systems and community waste sites, both of which are not designed to handle medical equipment. Moreover, the reliance on human hands for sorting trash, whether as employees or scavengers, introduces potential harm to these individuals.

The research underscores the urgent need for improvements in the disposal of lithium batteries in a manner that minimizes harm. It also highlights the existing limitations in infrastructure that hinder such changes, particularly in the context of Pakistan as a developing country with less industrialization compared to more industrialized nations.

The proposed system [5] comprises two main components: object detection and object measurement. Using a Raspberry Pi camera, frames are captured for processing. In the first part, computer vision techniques are employed to detect and measure objects within the frames. The process involves converting frames to grayscale for efficiency and accuracy, applying the Canny edge detector algorithm to identify objects, and further refining the edges using dilation and erosion algorithms. Non-maximum suppression is then applied to retain local maxima as edges, enhancing the sharpness of the detected objects. The final step involves hysteresis thresholding to distinguish strong and weak edges based on empirically selected threshold values.

In the realm of object detection, various techniques play a pivotal role in analyzing video frames for identifying and measuring objects. Frame differencing, where consecutive frames are compared to estimate differences, serves as a fundamental approach. Optical flow, on the other hand, employs algorithms and self-adaptive techniques to calculate the optical flow field, enhancing accuracy and mitigating noise. Furthermore, two distinct methods for object tracking are explored. The first involves tracking in a sequence of detection, capturing frames at different intervals to analyze an object's movement and calculate its velocity. The second, a more sophisticated approach termed "detection with dynamics," estimates an object's trajectory by predicting its position at various time intervals. This method adds a dynamic dimension to the tracking process, surpassing mere object detection at intermittent intervals. The integration of these object detection and tracking methodologies contributes to the advancement of computer vision systems, enabling efficient analysis and understanding of dynamic visual scenes [6].

4. Results and Findings

Waste segregation is the process of classifying various waste items into distinct groups such plastics, paper, metal, and organic trash. It is a crucial phase in the waste management process that aids in cutting down on the amount of waste transported to landfills as well as in the recycling and reuse of waste products.

OpenCV (Open Source Computer Vision) is a popular computer vision library that can be used to perform image and video processing tasks. Convolutional Neural Network (CNN) is a deep learning algorithm that is widely used for image classification and recognition.

Convolutional Neural Networks (CNNs) have proven to be highly effective in image classification tasks, making them suitable for waste segregation. CNNs can learn intricate patterns and features from visual data, enabling them to distinguish different types of waste based on their visual characteristics.

By training a CNN model on a diverse dataset of waste images, the model can learn to identify and classify waste into specific categories, such as recyclable, organic, and non-recyclable waste. The model can capture intricate details, textures, and shapes that human observers may overlook, resulting in more accurate and consistent waste segregation.



Text(0.5, 1.0, 'Training and Validation Accuracy')

Figure 3: Validation and Training

The figure above has a plot that illustrates the relationship between training and validation accuracy over epochs, providing insights into the model's performance and generalization ability. The x-axis denotes epochs, while the y-axis represents accuracy values, facilitating easy comparison and analysis. The expected results of training the model include overall classification accuracy, class-specific metrics like precision and recall, and the analysis of the confusion matrix. The model's performance can vary based on the dataset quality, complexity of waste categories, and model architecture. Discussions can focus on model performance, dataset quality, model architecture, challenges and misclassifications, and real-world application of the waste segregation model.

By analyzing the results and engaging in discussions, insights can be derived to improve the model's accuracy and address challenges in waste segregation. Considerations for dataset diversity, model architecture, hyper parameter settings, and real-world implementation can guide future enhancements. Ultimately, training a waste segregation model using CNNs contributes to sustainable waste management practices and promotes a cleaner and healthier environment.

5. Conclusion

The waste segregation system can be used to create public awareness about sustainable waste management practices. By educating the public about the benefits of waste segregation and recycling, we can promote a more sustainable and responsible attitude towards waste management.

The integration of CNNs in waste segregation offers several benefits, including resource recovery, waste reduction, environmental protection, and the promotion of a circular economy. Through precise classification of waste items, valuable resources can be identified and recovered, reducing the strain on natural resources.

6. Future Scope

Waste segregation using OpenCV and CNN can be used in smart waste management systems or in industrial settings that can automatically sort and recycle waste materials This can help in reducing the environmental impact of industrial activities.

Further advancements can be achieved by integrating technologies such as the Internet of Things (IoT), real-time data analytics, and machine learning. These advancements can enhance waste management systems, enable real-time monitoring, optimize collection routes, and promote effective recycling practices.

References

- [1] Paul T Williams. Waste treatment and disposal. John Wiley & Sons, 2005.
- [2] Cuneyt Dirican. The impacts of robotics, artificial intelligence on " business and economics. Procedia-Social and Behavioral Sciences, 195:564–573, 2015.
- [3] Manas Chatterji. Technology transfer in the developing countries. Springer, 2016.
- [4] Syed Abdul Mujeeb, Malik Mohummad Adil, Arshad Altaf, Yvan Hutin, and Stephen Luby. Recycling of injection equipment in pakistan. Infection Control & Hospital Epidemiology, 24(2):145–146, 2003.
- [5] Othman, Nashwan Adnan, Mehmet Umut Salur, Mehmet Karakose, and Ilhan Aydin. "An embedded realtime object detection and measurement of its size." In 2018 International Conference on Artificial Intelligence and Data Processing (IDAP), pp. 1-4. IEEE, 2018.
- [6] Chandan, G., Ayush Jain, and Harsh Jain. "Real time object detection and tracking using Deep Learning and OpenCV." In 2018 International Conference on inventive research in computing applications (ICIRCA), pp. 1305-1308. IEEE, 2018.