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# Optimizing Waste Recycling Through Data Science: A Deep Learning Approach with TensorFlow

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**ABSTRACT**

***The intricate relationship between recycling practices and the generation of solid waste emphasizes the multifaceted character of sustainable waste management. A comprehensive comprehension of these dynamics is crucial for formulating specific interventions and policies that optimize the positive effects of recycling on our environment. This research explores the application of deep learning, specifically utilizing TensorFlow, in the domain of waste classification for enhanced waste recycling. The study focuses on the efficient categorization of diverse waste materials, including cardboard, glass, trash, metal, and plastic, through the implementation of advanced neural networks. By leveraging TensorFlow's capabilities, our research demonstrates the successful development and deployment of deep learning models that exhibit accurate and reliable waste classification. The utilization of deep learning model was able to select accurately the most important types of garbage worthy for recycling processes. And not only streamlines recycling processes but also addresses the environmental challenges associated with inefficient waste management. The findings finally highlight the transformative potential of integrating cutting-edge technologies into waste sorting systems, paving the way for a more sustainable and eco-friendly approach to waste disposal. This research contributes to the ongoing efforts in environmental conservation by presenting a viable solution to enhance waste recycling practices through the power of deep learning.***

***KEYWORDS*:** Recycling, Solid Waste Generation, Machine Learning, Deep Learning, TensorFlow, Environmental Impact.

## 1. INTRODUCTION

Solid waste management in the United States is a complex and multifaceted system that involves the collection, transportation, processing, recycling, and disposal of solid waste generated by individuals, businesses, and industries. The United States has made significant strides in waste management, but challenges persist, necessitating ongoing efforts to enhance sustainability and reduce environmental impacts. Recycling practices play a pivotal role in shaping the dynamics of solid waste generation, influencing not only the quantity but also the composition of waste streams. This comprehensive review seeks to elucidate the intricate ways in which recycling efforts impact the broader landscape of solid waste generation, drawing insights from a diverse range of studies and methodologies. Recycling directly impacts the overall quantity of solid waste entering disposal systems. Studies consistently demonstrate that increased recycling rates are correlated with a reduction in the volume of waste destined for landfills. The diversion of recyclable materials from disposal streams to recycling facilities mitigates the burden on waste management infrastructure.

Beyond quantity, recycling practices exert a profound influence on the composition of solid waste. Effective recycling programs alter the makeup of discarded materials by diverting recyclables, such as paper, plastics, and metals, from traditional waste streams. Consequently, the implementation of recycling initiatives contributes to a more sustainable waste profile, reducing the environmental impact associated with certain materials. The success of recycling initiatives is intricately tied to public participation

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and behavioral patterns. Studies exploring the nexus between recycling practices and waste generation highlight the importance of educational programs, awareness campaigns, and incentives in influencing individual behaviors. A well-informed and motivated public tends to generate less non-recyclable waste, emphasizing the role of education in sustainable waste management.

In recent months, both industry publications within the solid waste sector and widely recognized mainstream media outlets in the United States, including Fortune, the New York Times, Wall Street Journal, and the Washington Post, have highlighted the increasing challenges facing recycling ([1],[2],[3]). The prevailing theme across these articles underscores a perception that recycling efforts in the USA have encountered significant obstacles, portraying a critical situation. To what extent is this crisis? Industry leaders have expressed concerns that the prices of recycled commodities have substantially declined in recent years, reaching a point where it is no longer financially viable for them to process a considerable portion, if not the majority, of recyclables for sale and shipment to their primary markets in Asia. These markets enforce stringent standards regarding contaminants, often referred to as the ‘Green Fence.’ Notably, major materials recovery facility (MRF) operators in the USA, such as Recycle America, Republic Services, and ReCommunity, have either temporarily shut down operational facilities or postponed capital investments due to diminishing revenues that render these operations unprofitable. Traditionally, experts providing advisory services in solid waste management to both public agencies and private enterprises have advocated for increased recycling as a cornerstone for achieving regional sustainability, often described as a 'circular economy.' However, a growing number of practitioners and civic leaders in the USA and around the world are now questioning whether the current state of recycling revenues is a temporary setback or indicative of a more prolonged and concerning trend.

Recycling is not a crisis as lighter packaging, dwindling demand for newsprint (owing to the steady move toward consumption of electronic instead of print news), and lower commodity prices have allowed some to argue that it is no longer profitable for industry to continue to provide recycling services without local governments making up their losses via subsidies [4]. So, should we sound the death knell for recycling in the USA? We would argue that that this is not necessarily the case, and there is a way to cobble together a solution by confronting some of the myths being painted on the state of recycling. Recycling should not be considered a free service. It takes money to provide separate bins, send out the recycling truck, and build and operate a MRF. Perhaps more of the costs of recycling should be shifted to producers and/or sellers of consumer products and the associated packaging. To this end, extended producer responsibility programmes have been in place in Europe (for over 20 years) and in some USA states (e.g. for electronics and auto tyres), and are being considered elsewhere that would include at least some of the costs of recycling in the initial selling prices of the products themselves [5]. Ensure fairness in processing agreements for all involved parties. Adhere to the recommendations provided by the Solid Waste Association of North America (SWANA) and the National Waste and Recycling Association (NWRA) to establish relationships that benefit everyone, are cost-efficient, and deliver a service of high quality.

With the rapid expansion of urban environments globally, the issue of waste generation is swiftly becoming one of the most significant challenges faced by cities worldwide. Presently, with a daily production of 3.3 million tons, the global waste output is already reaching unmanageable levels, and this figure is anticipated to escalate to 11 million tons per day by the year 2100 [6]. In light of these trajectories, effective urban waste management systems are imperative. To deliver these services in an environmentally sustainable and financially viable manner, there is an urgent need for a fundamental understanding of the quantity and composition of generated materials [7][8]. Moreover, predicting waste generation emerges as a crucial facet of urban waste management, affording city agencies the capacity to optimize short-term collection and disposal operations and formulate long-term strategies for disposal planning, policy development, and the implementation of waste reduction initiatives [9].

Different modeling approaches have been employed to predict waste generation, encompassing group comparison, correlation analysis, multiple regression analysis, input-output analysis, time-series analysis, and system dynamics modeling [7]. These models typically aim to discern the inherent connections between variables influencing waste generation. For instance, at the municipal level, [10] explored the relationship between urban morphology, tourism activity, and waste generation. The objective of this research is to utilize historical municipal solid waste (MSW) data provided by the New York City Department of Sanitation (DSNY) to forecast waste generation across the city.

Various methods for data selection and preprocessing exist, aiming to minimize or transform inputs into valuable information. [11] applied Principal Component Analysis (PCA), wavelet, and the Gamma test as data selection methods in predicting waste generation. However, inherent issues such as overfitting training, challenges in determining network architecture, local minima, and poor generalization performance persist, limiting the practical application of the Artificial Neural Network (ANN) approach. Another intelligent model, Support Vector Machine (SVM), developed by Vapnik, offers an effective alternative to enhance the generalization performance of neural networks and simultaneously achieve global solutions [12]. The SVM ε-insensitive type has recently been extended to address non-linear regression estimation and time series prediction [13][14][15].

To ensure acceptable prediction accuracy and computational speed, data reduction and variable selection are applied as preprocessing steps for SVM. Various data reduction techniques are available [16][17][18][19]. In this study, the chosen method is partial least squares, an unsupervised dimension reduction technique. Particularly useful in multivariate regression applications, partial least squares constructs standardized linear combinations of predictive variables to capture information in both raw predictive variables and the relationship between predictive and target variables. This balance provides an alternative approach to the PCA technique [20].

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Understanding uncertainty in a model is crucial for interpreting results, especially when outcomes are close in magnitude. A limited number of methods, such as bootstrap, sandwich estimator, maximum likelihood, and Bayesian inference, have been proposed for determining uncertainty. To address the uncertainty associated with estimating Municipal Solid Waste Generation (MSWG), a Monte Carlo simulation was conducted due to its proven performance [21]. Monte Carlo simulation proves to be a flexible tool for performing uncertainty analysis of data-driven models.

The growing buildup of waste in urban areas is increasingly worrisome, posing a potential threat to the environment and human health if not effectively addressed. To tackle this issue, we have devised a waste sorting system employing machine learning tools. This innovative system is capable of autonomously categorizing various waste components, reducing the need for human involvement and mitigating the risks of infection and pollution.

## 2. MATERIALS AND METHODS

A variety of modeling methodologies have been used to forecast waste generation including the use of group comparison, correlation analysis, multiple regression analysis, input-output analysis, time-series analysis, and system dynamics modeling [7]. These models often focus on identifying the underlying relationship between variables that drive waste generation. For example, at the municipal level, [10] identified urban morphology, tourism activity, level and so on.

Waste management is a big problem in the country. Most of the wastes end up in landfills. This leads to many issues like Increase in landfills, Eutrophication, Consumption of toxic waste by animals, Leachate, Increase in toxins, Land, water and air pollution.

Deep learning models tend to excel at fitting the training data. However, the real challenge is not fitting but ensuring generalization. To avoid memorizing the model dataset and prevent issues like overfitting or underfitting, we can undertake the following steps:

1. **Data set augmentation:** Expanding the dataset by manipulating existing data.
2. **Node dilution (Dropout layer):** Introducing dropout layers to prevent over-reliance on specific nodes.
3. **Early stopping:** Implementing a mechanism to stop training early to prevent overfitting or underfitting.
4. **Waste Classification Approach:**

    - Studied white papers on waste management.
    - Analyzed the components of household waste.
    - Segregated into two classes (Organic and recyclable).
    - Automated the process by using internet of things (IOT) and machine learning.
    - Reduce toxic waste ending in landfills.

TensorFlow serves as an open-source, all-encompassing machine learning library designed for data preprocessing, data modeling, and model deployment to make models accessible to others. Instead of starting from scratch to construct machine learning and deep learning models, it is more common to utilize a library like TensorFlow. This is due to TensorFlow encompassing numerous commonly used machine learning functions.

While TensorFlow is expansive, its fundamental concept is straightforward, i.e., convert data into numerical representations (tensors) and construct machine learning algorithms to identify patterns within them. Originally designed for extensive numerical computations rather than deep learning specifically, TensorFlow has nonetheless demonstrated its value in deep learning development, leading to its open-source release by Google.

A brief description of the underlying principle of TensorFlow is presented here as an illustration, we could transform a sequence of images into tensors with a shape of (344, 344, 4, 22), where:

- 344, 344 (the initial two dimensions) represent the height and width of the images in pixels.
- 4 signifies the number of color channels in the image (red, green, blue).
- 22 is the batch size (indicating the number of images processed by a neural network simultaneously).

All the variables mentioned above are essentially tensors. However, they are also commonly referred to by the names we assigned them:

- **Scalar:** a singular number.
- **Vector:** a number with direction (e.g., wind speed with direction).
- **Matrix:** a two-dimensional array of numbers.
- **Tensor:** an n-dimensional array of numbers (where n can be any number; a 0-dimensional tensor is a scalar, a 1-dimensional tensor is a vector).
-

For more on the mathematical difference between scalars, vectors and matrices see the [24]

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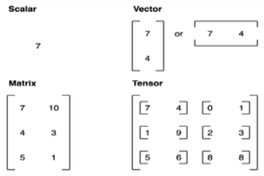


### 2.1 Waste Classification Dataset Image

As shown in Figure 1 below, the solid waste data generated were 'cardboard', 'glass', 'paper', 'plastic', 'metal', and 'trash'. We founded 2276 images belonging to 6 classes and 251 images belonging to 6 classes.

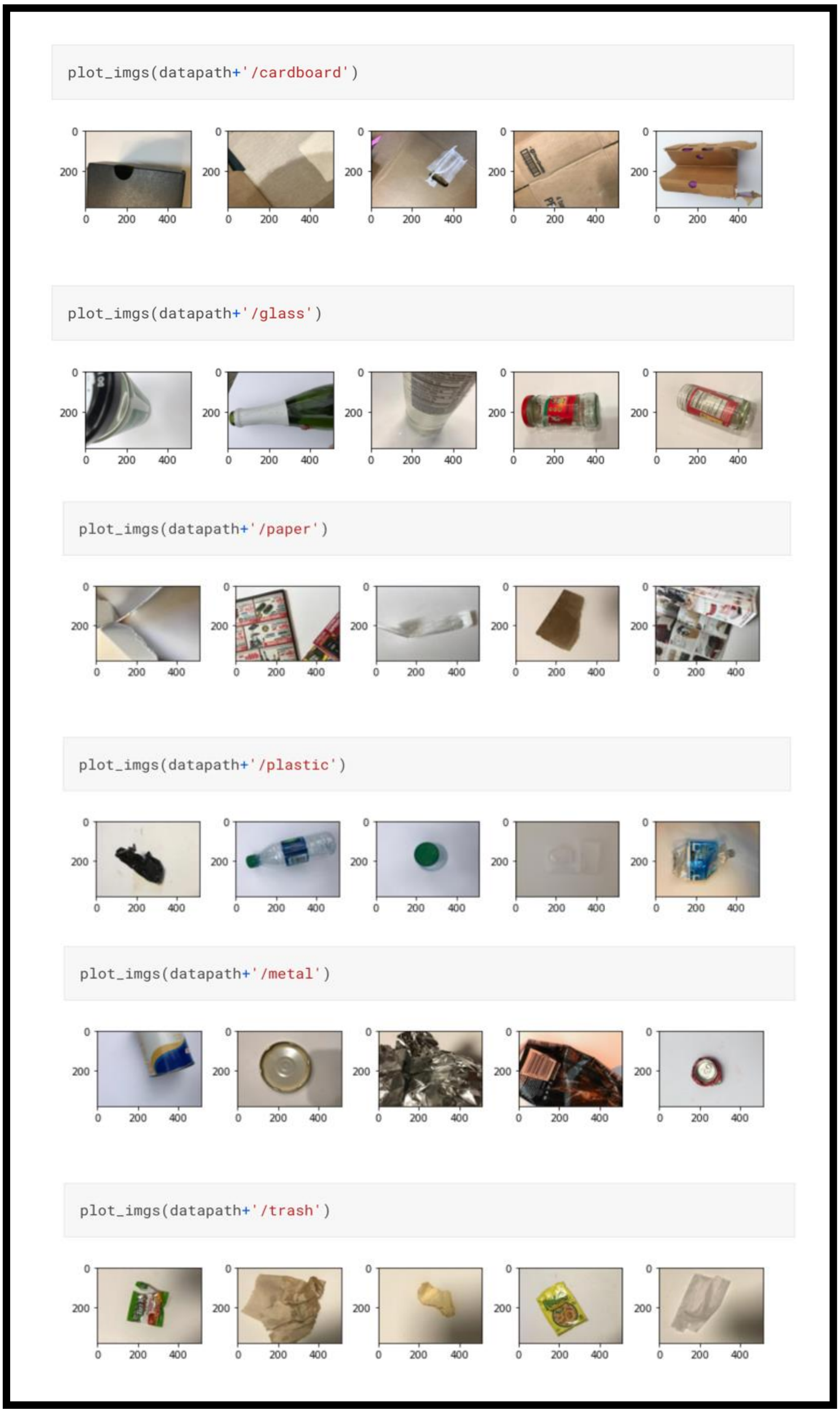


**Figure 1: Showing dataset image of different garbage.**

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## 3. RESULTS

We can replicate images by manipulating certain features of the visuals at our disposal. The reason for doing this is to potentially achieve better results during training in the future.
In Keras, each layer has a parameter called 'trainable.' To freeze the weights of a specific layer, we should set this parameter to False, indicating that this layer should not be trained. We go through each layer and choose which layers we want to train by setting this parameter accordingly.

### 3.1 Model definition

**Table 1: Model - "sequential"**

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d (Conv2D) | (None, 512, 384, 16) | 448 |
| max_pooling2d (MaxPooling2D) | (None, 256, 192, 16) | 0 |
| conv2d_1 (Conv2D) | (None, 256, 192, 32) | 4640 |
| max_pooling2d_1 (MaxPooling2 | (None, 128, 96, 32) | 0 |
| conv2d_2 (Conv2D) | (None, 128, 96, 64) | 18496 |
| max_pooling2d_2 (MaxPooling2 | (None, 64, 48, 64) | 0 |
| conv2d_3 (Conv2D) | (None, 64, 48, 128) | 73856 |
| max_pooling2d_3 (MaxPooling2 | (None, 32, 24, 128) | 0 |
| conv2d_4 (Conv2D) | (None, 32, 24, 256) | 295168 |
| max_pooling2d_4 (MaxPooling2 | (None, 16, 12, 256) | 0 |
| conv2d_5 (Conv2D) | (None, 16, 12, 512) | 1180160 |
| max_pooling2d_5 (MaxPooling2 | (None, 8, 6, 512) | 0 |
| flatten (Flatten) | (None, 24576) | 0 |
| dense (Dense) | (None, 1024) | 25166848 |
| dense_1 (Dense) | (None, 64) | 65600 |
| dense_2 (Dense) | (None, 6) | 390 |

```
Total params: 26,805,606
Trainable params: 26,805,606
Non-trainable params: 0
```

### 3.2 Model Evaluation

We calculate the cross-entropy loss between labels and predictions. The cross-entropy loss function would be use when there are two or more label classes.

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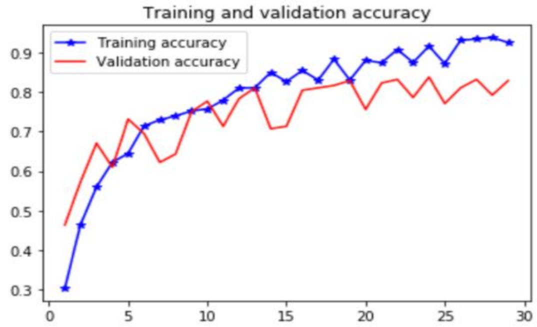


**Figure 2: Training and validation accuracy.**


**Figure 3: Training and validation loss.**

### 3.3 Classification Report

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Cardboard | 0.94 | 0.86 | 0.90 | 70 |
| Glass | 0.82 | 0.91 | 0.87 | 82 |
| Metal | 0.78 | 0.82 | 0.80 | 68 |
| Paper | 0.83 | 0.88 | 0.86 | 108 |
| Plastic | 0.82 | 0.84 | 0.83 | 74 |
| Trash | 0.79 | 0.38 | 0.51 | 29 |
| accuracy | | | 0.83 | 431 |
| macro avg | 0.83 | 0.78 | 0.79 | 431 |
| weighted avg | 0.83 | 0.83 | 0.83 | 431 |

### 3.4 Prediction on test set

**Table 2: Model - "sequential"**

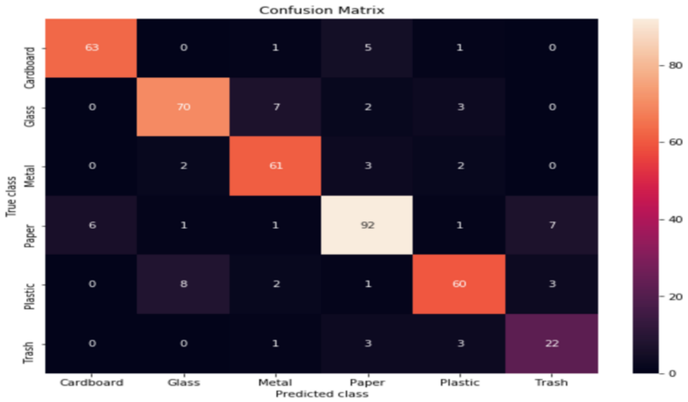


**Figure 4: Confusion Matrix of the actual and predicted.**

## 4. DISCUSSION

The presented model, "sequential," employs a convolutional neural network (CNN) architecture for garbage classification. The model comprises several convolutional and max-pooling layers, culminating in densely connected layers for final classification. The total trainable parameters amount to 26,805,606. Cross-entropy loss is utilized for evaluating the model, particularly apt for scenarios with two or more label classes. The training and validation accuracy and loss plots (Figure 2 and Figure 3) reveal essential insights into model performance during training. It is crucial to note the following considerations:

- A small difference between training and validation metrics is deemed normal.
- The alignment of both metrics in the same direction indicates a favorable model behavior.
- A potential concern arises if the training metric improves significantly while the validation metric plateaus, suggesting the onset of overfitting.
- If the validation metric deviates unfavorably, the model may be overfitting.

The classification report provides a comprehensive overview of the model's performance across different classes. Key metrics such as precision, recall, and F1-score are reported for each class, contributing to an overall accuracy of 83%. The weighted average F1-score is 0.83, indicating a balanced performance across classes.
The model's architecture for predicting on the test set involves a functional layer of ResNet101V2 followed by a dense layer. The confusion matrix (Figure 4) visually represents the correspondence between actual and predicted classes. Additionally, the class-wise accuracy dictionary highlights the model's proficiency in distinguishing between different waste categories.


**Figure 5: Prediction of waste classification for recycling**

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## 5. CONCLUSION

In conclusion, our research has demonstrated the significant potential of employing deep learning, particularly through TensorFlow, in the realm of garbage classification for recycling purposes. The utilization of advanced neural networks has proven effective in accurately identifying and categorizing diverse waste materials such as cardboard, glass, trash, metal, and plastic. The successful implementation of this technology not only contributes to the efficiency of recycling processes but also addresses the growing environmental concern of waste mismanagement.

By harnessing the power of deep learning models, we pave the way for improved waste sorting systems, reducing the burden on traditional methods and promoting a more sustainable approach to waste management. The findings of this research underscore the transformative impact of integrating cutting-edge technologies in environmental conservation efforts, emphasizing the potential for a cleaner and greener future.

## 6. RECOMMENDATIONS

Based on the findings of the research on garbage classification using deep learning for TensorFlow in recycling waste, the following recommendations are suggested:

- Implement the developed deep learning models into existing waste management systems to enhance the accuracy and efficiency of waste sorting processes. Collaborate with waste management facilities to pilot and scale the integration of these technologies.
- Launch awareness campaigns to educate the public on the benefits of recycling and the role of advanced technologies in waste management. Promote community engagement and participation in recycling programs to further support environmental sustainability.
- Establish a feedback loop for continuous improvement of the deep learning models. Regularly update the models with new data to adapt to evolving waste compositions and ensure accurate classification across a broader range of materials.
- Collaborate with industries, recycling centers, and policymakers to advocate for the widespread adoption of advanced waste sorting technologies. Explore partnerships that facilitate the implementation of these technologies on a larger scale.
- Work with governmental bodies to develop and implement policies that incentivize the use of advanced technologies in waste management. Policy frameworks should encourage businesses and communities to adopt sustainable waste practices.
- Extend research efforts to explore the applicability of deep learning in addressing additional challenges in the waste management sector, such as landfill reduction, resource recovery, and the development of circular economies.
- Conduct a comprehensive cost-benefit analysis to evaluate the economic viability of integrating deep learning technologies into waste management systems. Assess the long-term financial and environmental benefits to justify widespread adoption.

Then, we can foster a more sustainable and technologically advanced approach to waste management, contributing to environmental conservation and promoting a circular economy.

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