Plastic in Grocery Stores: An Image-Based Classification Model for Assessing Packaging Waste

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***Abstract*—With increasing global concern about plastic pollution and sustainable development, this study proposes a deep learning-based image classification method for assessing plastic consumption in grocery store sales. This paper conducts an experiment to compare the performance of ResNet18 and the combination of ResNet18 and *Support Vector Data Description (SVDD)* models in classifying product images to the four categories of no plastic, some plastic, heavy plastic, and no image (non-product), resulting in an efficient and accurate image classification model. The method utilizes over 6,000 product images for training, providing robust scientific support for plastic consumption assessment in grocery store sales. The proposed method aims to quantify plastic consumption through image analysis, providing insights into plastic waste in grocery sales. This study provides robust scientific support for plastic pollution reduction and sustainable development research, and offers practical tools and methods for implementing effective environmental measures.**

***Index Terms*—Plastic consumption, Image classification, Deep learning, ResNet18, Support Vector Data Description (SVDD)**

I. Introduction

Plastic pollution has been described as a global environmental crisis, with devastating impacts on marine life, ecosystems, and human health [1]. Grocery stores, as major retail outlets, contribute significantly to plastic waste through product packaging [2]. With increasing public awareness about the negative effects of plastic pollution and the need for sustainable development, there is a growing demand for accurate and efficient methods to assess plastic consumption in grocery store sales.

In recent years, deep learning, a subset of machine learning, has shown promising results in image recognition tasks and has the potential to revolutionize the way we evaluate plastic consumption in grocery stores. Deep learning algorithms can accurately classify product packaging images into different categories of plastic consumption, providing a data-driven approach to quantify plastic waste.

In response to this need, this study proposes a deep learning-based image classification method for evaluating plastic consumption in grocery stores. The research team developed an image classification model using a large dataset of over 6,000 product images that were labeled into categories of no plastic, some plastic, heavy plastic, and no image (non-product). The proposed method aims to quantify plastic consumption through image analysis, providing valuable insights into the extent of plastic waste in grocery sales.

The outcomes of this study are expected to provide robust scientific support for plastic pollution reduction and sustainable development research. Additionally, the proposed deep learning-based image classification method has the potential to offer practical tools and methods for implementing effective environmental measures in grocery stores and other retail settings, contributing to a more sustainable future [3], [4].

II. Related Work

Plastic pollution and its impacts have been the subject of extensive research and awareness-raising efforts in recent years. Here, we review some of the relevant studies and approaches related to plastic consumption assessment in grocery stores, including the use of deep learning models such as ResNet18 and *Support Vector Data Description (SVDD).*

Several studies have focused on quantifying plastic consumption in grocery stores using various methods. For example, some studies have employed manual sorting and weighing of plastic waste generated by grocery stores to estimate plastic consumption [5], [6]. Others have conducted surveys and interviews to gather data on plastic packaging usage and waste generation in grocery stores [7]–[9]. However, these methods can be labor-intensive, time-consuming, and prone to human error.

In recent years, there has been increasing interest in utilizing image analysis and machine learning techniques for plastic consumption assessment in grocery stores. For instance, researchers have developed computer vision algorithms to automatically classify plastic waste based on images captured from grocery store waste bins [10]. Other studies have used image recognition to identify and quantify microplastics in environmental samples [11], [12]. However, these studies often rely on traditional machine learning algorithms, which may have limitations in handling complex image features and achieving high accuracy.

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Deep learning, a subset of machine learning, has shown significant advancements in image recognition tasks, including image classification. Deep learning models, such as convolutional neural networks (CNNs), can learn hierarchical representations from large datasets, enabling them to accurately classify images with high accuracy [13]. One of the popular deep learning models is ResNet18, proposed by He et al. [15], which has been widely used for various image recognition tasks, including plastic pollution assessment in some recent studies [3], [4], [14]. ResNet18 has shown promising results in achieving high accuracy in image classification tasks, making it a suitable choice for our proposed method.

In addition to traditional deep learning models, other techniques such as Support Vector Data Description (SVDD) have been applied in plastic consumption assessment. SVDD is a type of one-class classification method that learns a representation of the target class based on the available data and can be used for detecting anomalies or outliers in new data [16]. SVDD has been used in some studies for plastic pollution assessment, including identification of plastic debris in environmental samples [17]. SVDD has shown effectiveness in detecting anomalies or outliers in datasets, making it a potential approach for our proposed method.

In this study, we propose a deep learning-based image classification method for assessing plastic consumption in grocery stores. We build on the existing literature on plastic pollution assessment and image recognition using deep learning, including the use of ResNet18 and SVDD, and aim to contribute to the field by developing a robust and accurate method for quantifying plastic consumption in grocery store sales.

III. Methodology

In this section, we describe the methodology used in our experiments for image classification into four classes: ”no_image” (invalid images), ”no_plastic” (images without plastic), ”some_plastic” (images with some plastic), and ”heavy_plastic” (images with a significant amount of plastic). We also explain the methodology used for binary classification into ”no_image” and ”valid_image” (valid images), and further three-class classification of ”valid_image” into ”no_plastic”, ”some_plastic”, and ”heavy_plastic”.

A. Dataset Split

We divided the dataset into training and testing sets with a ratio of 4:1. The same training set split was used for all the models in our experiments, ensuring consistency in training data across different models.

B. Image Preprocessing

All images were resized to a resolution of 256×256 pixels. We performed channel-wise mean and standard deviation normalization on the images to bring them to a similar scale and reduce the impact of illumination variations.

C. Model Architecture

We used the following models for classification:

1) **ResNet18 for 4-class Classification:** We used a pre-trained ResNet18 model to train a 4-class classification model, where the classes are ”no_image”, ”no_plastic”, ”some_plastic”, and ”heavy_plastic”.
2) **SVDD for binary-class Classification:** We trained a binary-class classification model using SVDD on the ”no_image” data and ”valid_image” data, considering it as a single class. This model was applied to further classify the ”valid_image” data into ”no_plastic”, ”some_plastic”, and ”heavy_plastic”.
3) **ResNet18 for 3-class Classification:** We used a pre-trained ResNet18 model to train a 3-class classification model, where the classes are ”no_plastic”, ”some_plastic”, and ”heavy_plastic”. This model was applied only to the ”valid_image” data from the binary classification.

D. Model Training and Hyperparameter Tuning

In the training process of our model, we utilized various hyperparameters that needed to be tuned for optimal performance. We conducted a thorough hyperparameter tuning process to determine the best hyperparameter values for our experimental setup. The hyperparameters we tuned include:

TABLE I
Hyperparameters and their Ranges

Hyperparameter	Range
Learning Rate	10^{-3} - 10^{-2}
Batch Size	16, 32, 64
Number of Epochs	5, 10, 15
Regularization Strength	0.001, 0.01, 0.1

We employed a grid search approach to systematically search through different hyperparameter combinations. For each combination of hyperparameter values, we trained the model multiple times and evaluated its performance using cross-validation on a validation set. The hyperparameter values that resulted in the best validation performance were selected as the optimal hyperparameter values for our model.

The hyperparameter tuning process was performed using Python and the scikit-learn library. We used a combination of manual experimentation and automated hyperparameter search techniques to find the best hyperparameter values. The optimal hyperparameter values obtained from the tuning process were then used in the final training of our model to ensure the best possible performance.

Our SVDD model was trained with a regularization parameter of 1, gamma set to ’scaled’, and a kernel type of ’rbf’. These hyperparameters were not included in the hyperparameter tuning process, as they were determined to be optimal based on prior knowledge of the dataset and the characteristics of the SVDD algorithm.

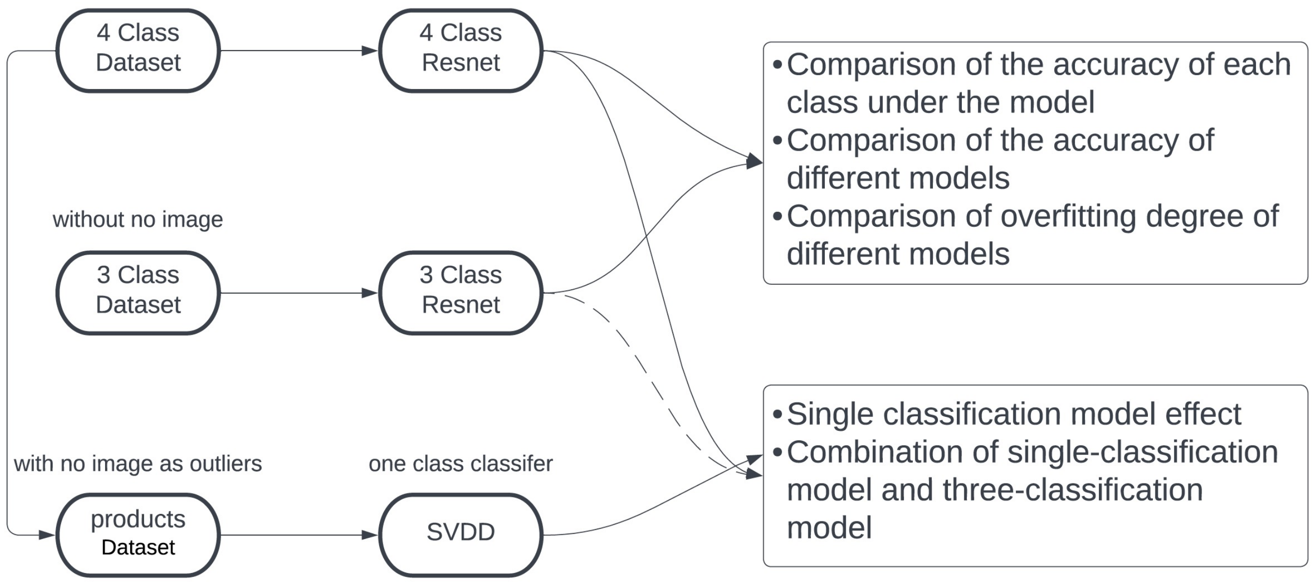

Fig. 1. The architectures for the classification methods described in Section 3.

E. Evaluation Metrics

We used the following evaluation metrics to assess the performance of the models:

1) **ResNet18 Model for 4-class Classification:** We evaluated the overall accuracy and class-wise accuracy of the 4-class classification model.
2) **ResNet18 Model for 3-class Classification:** We evaluated the overall accuracy and class-wise accuracy of the 3-class classification model.
3) **SVDD Model:** We evaluated the classification accuracy of the binary-class classification model using AUC (Area Under the Curve), which measures the model's ability to correctly classify positive samples while controlling the false positive rate.
4) **Integration of SVDD Results:** We evaluated the accuracy of the 3-class classification model after integrating the results of SVDD on the "valid_image" data, by considering the SVDD model's classification results as additional information.

IV. Experiments

In this section, we provide a detailed description of the experimental setup, data collection process, and analysis of the experimental results.

A. Experimental Setup

The experiments were conducted on a dataset of 6,000 product images that were classified into four categories: "no plastic", "some plastic", "heavy plastic", and "no image" (non-product)2. The dataset was randomly divided into training and testing sets with a 80:20 split ratio.

We used the pre-trained ResNet18 model as the base model for our image classification task. The ResNet18 model was fine-tuned using transfer learning to adapt it to our specific task. We also integrated the SVDD algorithm into the classification pipeline to improve the accuracy of the models.

Fig. 2. Plastic packaging image dataset

All experiments were conducted on a computer with an Intel Core i7 CPU, 16GB RAM, and an NVIDIA GeForce GTX 1080 GPU. We implemented the deep learning models using the PyTorch library and trained them using stochastic gradient descent (SGD) optimizer with a learning rate of 0.001 and a batch size of 32.

B. Data Collection Process

The dataset used in our experiments was collected by Professor Amanda Welsh and her group as part of their research program at NU. The images were resized to a resolution of 256x256 pixels to match the input size of the ResNet18 model. Prior to training, the images were preprocessed using a sequence of transformations: first, the images were converted to PIL image format; then, they were resized using the ”Resize” transformation from the ”transforms” module in PyTorch; next, the images were converted to tensors using the ”ToTensor” transformation; and finally, the pixel values of the images were normalized using the ”Normalize” transformation with mean and standard deviation values of [0.7564, 0.7176, 0.6869] and [0.3128, 0.3258, 0.3480], respectively. These transformations were applied to the images during the training process to increase the diversity of the training data and improve the model’s ability to generalize to new images.

C. Experimental Results

In this section, we present the results of our experiments on the classification of the given dataset.

The SVDD model was fitted using the radial basis function kernel with 5357 samples and 196608 features. The fitting process took 309.0179 seconds and resulted in 139 support vectors, which accounts for 2.5947% of the total samples. The model achieved an accuracy of 90.0504% and an AUC of 19.2466%. For the provided data, the prediction process was completed in 36.7964 seconds and resulted in 58 alarm samples out of 1340. The model achieved an accuracy of 89.7761% and an AUC of 13.9464%.

Our main focus is on comparing the performance of our 4-class and 3-class classification models, as well as analyzing the accuracy differences between different classes within each model.

We present the results of our experiments in terms of training and testing accuracy for each model. Figures 3 and 4 show the training and testing accuracy of our 3-class and 4-class classification models, respectively. Figure 5 shows the training accuracy of both models on a single plot, and Figure 6 shows the testing accuracy of both models on a single plot.

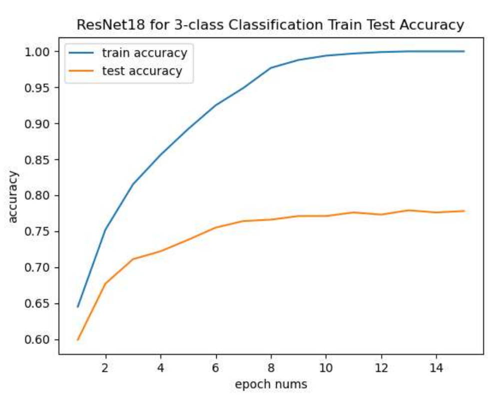

Fig. 3. Training and testing accuracy of the 3-class classification model

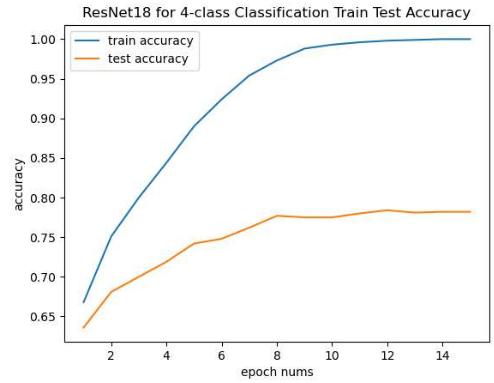

Fig. 4. Training and testing accuracy of the 4-class classification model

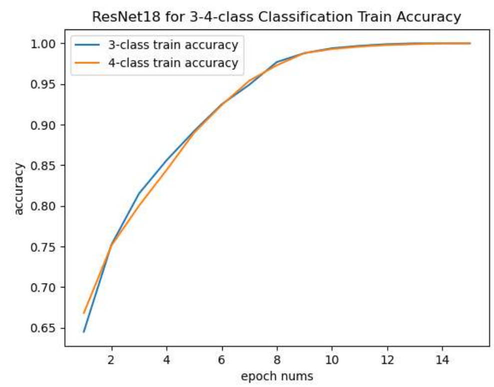

Fig. 5. Training accuracy of the 3-class and 4-class classification models

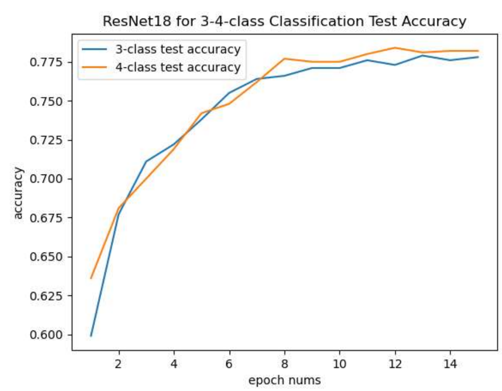

Fig. 6. Testing accuracy of the 3-class and 4-class classification models

From the figures, we observe that both the 3-class and 4-class classification models achieved high training accuracy, reaching almost 98%. However, the testing accuracy of both models was significantly lower, with a close to 75% accuracy rate. Additionally, we can see that the accuracy varies significantly for different classes within each model.

To further analyze the performance of our models for each individual class, we plot the accuracy for each class separately in Figures 7 and 8.

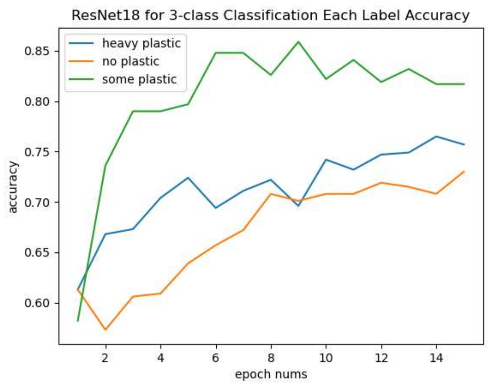

Fig. 7. Accuracy of each class in the 3-class classification model

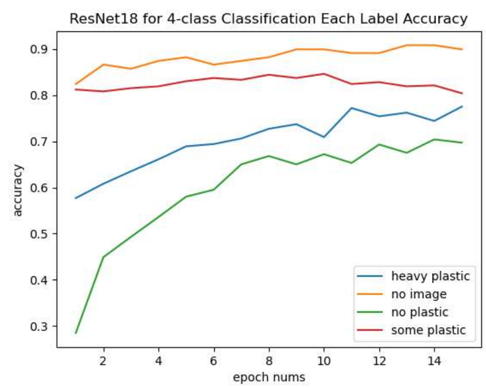

Fig. 8. Accuracy of each class in the 4-class classification model

D. Analysis of Results

The results shown in Figure 3 and Figure 4 provide valuable insights into the performance of both the 3-class and 4-class models. After training for 15 epochs, both models achieved a high level of accuracy on the training dataset, which was nearly 98%. However, the accuracy rate dropped significantly when tested on a separate dataset, where it was only 75%. This discrepancy could be due to overfitting, which is a common issue that arises when a model becomes too complex and starts to fit the training dataset too closely. As a result, the model loses its ability to generalize and perform well on new, unseen data.

Moreover, by comparing the performance of both models on a single graph (Figure 5 and Figure 6), we can observe that both models achieved high accuracy rates on the training dataset. The blue and yellow lines were almost indistinguishable after 15 epochs, suggesting that both models performed similarly well. However, the difference in accuracy rates between the two models on the test dataset was more pronounced. The delta between the two models fluctuated between positive and negative until the 10th epoch, after which the accuracy rate of the 4-class model surpassed that of the 3-class model and remained better until the end of the epochs.

Based on the data presented in Figure 7 and Figure 8, we can analyze the performance of the 3-class and 4-class models. The 3-class model achieved a higher accuracy rate on the "No Plastic" and "No Image" categories, with an accuracy rate of 70% and 89.8% respectively. On the other hand, the 4-class model achieved a slightly higher accuracy rate on the "Some Plastic" and "No Image" categories, with an accuracy rate of 80.3% and 90.2% respectively.

Both models achieved similar accuracy rates on the "Heavy Plastic" category, with the 3-class model achieving a slightly higher accuracy rate of 74.9% compared to the 4-class model's accuracy rate of 74.5%.

Overall, both models achieved relatively high accuracy rates on the different categories, indicating that they are able to differentiate between the different types of waste to a certain degree. However, the 3-class model had a slightly higher accuracy rate on the "No Plastic" category, which could be because it only had to distinguish between two categories ("Plastic" and "No Plastic"), while the 4-class model had to distinguish between three categories ("No Plastic", "Some Plastic", and "Heavy Plastic").

It is also worth noting that the accuracy rate of both models on the "Some Plastic" category was relatively high, indicating that they were able to distinguish between small amounts of plastic and non-plastic waste. This is an important distinction to make since small amounts of plastic waste can have a significant impact on the environment if not properly disposed of.

Overall, while both models performed well in differentiating between the different types of waste, the choice of model may depend on the specific task and the importance of correctly identifying certain categories of waste. Further testing and evaluation may be necessary to determine which model is more suitable for a particular task.

TABLE II
CLASS-WISE ACCURACY FOR 3-CLASS AND 4-CLASS MODELS

Class	**3-class Train**	**3-class Test**	**4-class Train**	**4-class Test**
No Plastic	99.6%	70.0%	99.6%	64.6%
Some Plastic	98.2%	80.6%	98.6%	80.3%
Heavy Plastic	97.6%	74.9%	97.6%	74.5%
No Image	-	-	98.2%	90.2%

V. CONCLUSION

In conclusion, we have investigated the use of machine learning methods for classifying product images into different plastic presence categories in the context of grocery store sales. We compared two approaches: the first one using SVDD to separate images into "no_image" and "valid_image" categories, and then using a ResNet18-based three-class classification model to classify the ”valid_image” data into ”no_plastic”, ”some_plastic”, and ”heavy_plastic” categories; and the second one directly training a ResNet18-based four-class classification model on all images to classify them into ”no-plastic”, ”some-plastic”, ”heavy-plastic”, and ”no-image” categories. Our results indicate that both models achieved high training accuracy, with around 98% accuracy on both the three-class and four-class models. However, the testing accuracy was lower, at around 75%, suggesting that the models may be overfitting to the training data.

In terms of label accuracy, we found that for both models, the ”some_plastic” category had the highest accuracy, followed by ”heavy_plastic” and then ”no_plastic”. Interestingly, the four-class model achieved over 90% accuracy on the ”no-image” category, while the ”no-plastic” category had the lowest accuracy at around 65%. On the other hand, the three-class model achieved over 80% accuracy on the ”some_plastic” category, around 75% accuracy on the ”heavy_plastic” category, and around 70% accuracy on the ”no_plastic” category.

Based on these findings, we conclude that removing the ”no_image” category and training a three-class classification model on the remaining ”valid_image” data is likely to result in higher accuracy compared to directly training a four-class model on all images. However, further optimization of the models and more diverse data may be needed to improve their performance in real-world settings. Overall, our study demonstrates the potential of machine learning methods for plastic waste reduction efforts in the retail industry.

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