Waste Management Classification using Convolutional Neural Network

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Abstract. Efficient waste management plays a crucial role in ensuring the sustainability of our environment and safeguarding public health. However, the lack of knowledge and awareness of waste management practices among the public will increase waste production and cause an unprecedented environmental crisis. Waste separation is crucial for addressing environmental problems, but the diversity of household and company waste complicates proper separation. This paper aims to develop a user-friendly mobile application to help with waste sorting processes by identifying various waste materials. This waste separation solution includes image detection using Faster Regional Convolutional Neural Networks (Faster R-CNN). The comprehensive study involved meticulously curating and utilizing a dataset of 250 images of five categories, which consist of glass, metal, paper, cardboard, and plastic. After a thorough pre-processing process, the datasets are then used for training data and testing data. The test consists of 7 trials. Remarkably, the outcomes yielded a good confidence value for cardboard and plastic, which are 97.99% and 95.24% respectively. Meanwhile, paper achieved 87.54%, glass achieved 70.24%, and metal achieved 65.88% in confidence value. This means the algorithm can detect and classify successfully the five waste categories. Furthermore, we embedded this best model in an Android application to demonstrate its potential for consumer and industrial usage, underscoring the transformative potential of technology in enhancing waste management practices and fostering environmental sustainability initiatives.

Keywords: Waste classification, Image detection, Faster R-CNN, Convolutional Neural Networks, Recycle, Mobile apps.

1 Introduction

Improper waste disposal and lack of awareness about sustainable waste management lead to environmental pollution and public health concerns [1]. The main cause of improper waste disposal is the public's lack of knowledge about waste management practices [1]. Many people struggle to correctly identify and dispose of different types of waste [2]. The lack of awareness about proper waste sorting, recycling, and disposal contributes to increment of waste generation and poor waste management. The

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issue of waste management is becoming more critical globally due to the increasing amount of waste being produced [3]. Homes, businesses, and waste management organizations are all impacted by this issue. Daily, households and companies generate a large amount of waste [4]. Waste management companies need to efficiently and cost-effectively handle various types of waste, which can lead to contamination of recyclable materials and an increase in landfill waste, negatively impacting the environment [5].

In recent years, research on image detection for waste management has attracted considerable interest due to its potential for enhancing waste classification, recycling, and overall waste management practices [6]. Studies have focused on the development and evaluation of image detection techniques for various waste management applications [7]. These include refuse sorting and classification, where deep learning-based techniques such as Convolutional Neural Networks (CNNs) are used to accurately categorize waste items into various categories [8]. Besides, the analysis of waste composition using image detection has provided valuable information for waste classification and resource allocation [9]. In addition, image detection-based real-time monitoring and analytics have enabled the tracking of refuse generation patterns, contamination levels, and operational efficiency. The integration of image detection and Internet of Things (IoT) technologies to create intelligent waste management systems has also been investigated [8].

This paper aims to design waste separation solution includes image detection using Convolutional Neural Networks (CNN). The following section consists of related works, methodology and result and conclusion.

2 Related Works

Extensive research has been conducted in this field, leading to the introduction of various proactive waste segregation systems to the modern world. This section provides a review of studies conducted in recent years.

2.1 Existing Waste Management System

Waste management currently a physical and mechanical sector focussing on the collection, sorting, and recycling or incineration of waste material. The waste management technologies are:

i. Trommel separators/drum screens – In waste management, trommel separators are used to sort waste materials by allowing smaller particles to pass through while larger particles are directed to the end of the drum for further processing [10].
ii. Eddy current separator - Commonly used in recycling plants to extract aluminium, copper, and other non-ferrous metals from waste streams. This method is efficient in recovering valuable metals and reducing landfill waste [11].
iii. Induction sorting – Uses electromagnetic fields to separate materials based on their electrical conductivity and magnetic properties. This process in-

duces currents in materials, allowing for the separation of different types of materials [12].

iv. Near Infrared Sensors (NIR) - Detect and analyse near-infrared light wavelengths to identify and separate materials like plastics, paper, and metals in recycling facilities [13].

v. X-ray technology – Employed in recycling to identify and sort materials based on their density, atomic number, and other detectable characteristics using X-ray radiation [14].

vi. Manual method – The manual method involves hand-sorting waste materials and is commonly used for waste segregation [15].

2.2 Convolutional Neural Networks in Waste Classification

Convolutional Neural Networks (CNN) are mainly used to sort and group images based on their similarities and to identify objects in images using artificial neural networks. CNN works with image data as matrices of numbers called tensors. It can recognize 3D objects in big images and is used in tasks like recognizing objects and faces. CNN is a complex part of neural networks, made up of three types of layers: convolutional layers, subsampling layers, and fully connected layers [16].

A study compared different algorithms used for waste classification to understand their strengths and weaknesses. Algorithms like Support Vector Machine (SVM), k-Nearest Neighbor (KNN), Random Forest (RF), Naïve Bayes, Decision Tree, and Convolutional Neural Networks (CNN) were examined. Each algorithm has unique features that can improve the accuracy and efficiency of waste classification [17]. The study found that SVM and CNN are more accurate in classifying image datasets compared to Naïve Bayes, Decision Tree, KNN, and Random Forest. This is because traditional algorithms like Naïve Bayes, Decision Tree, KNN, and Random Forest do not consider spatial relationships in images, leading to lower performance [17]. On the other hand, CNNs can learn complex patterns from raw image data through multiple layers, improving accuracy by considering translation invariance and iterative learning. Therefore, Deep Learning models like CNN play a crucial role in developing waste material classification systems [18].

Hence, the above context demonstrates the significant role of Deep Learning models in creating a waste material classification system [17, 19]. This study combines a novel approach with an android application to aid in waste segregation, a concept that has not been widely explored in existing CNN applications. The main goal is to help individuals identify waste materials and guide them on proper disposal into specific bins, improving the waste separation process with a user-friendly mobile app. The research aims to design a waste separation solution that categorizes waste into five categories- cardboard, plastic, paper, metal, and glass - and develop an easy-to-use android application.

3 Methodology

The methodology was divided into four parts. As depicted in Figure 1, the process begins with the dataset preparation for the deep learning. Second step is image pre-processing. Third process is the training process of the Faster R-CNN. Finally, deploy the model into android application.

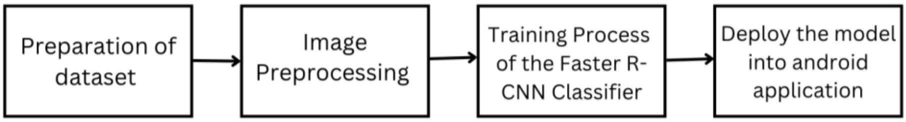

Fig 1. Four phases of methodology

3.1 Preparation of Dataset

The data were gathered by collecting dataset from the Kaggle website [20]. This dataset has 15,150 images from 12 different classes of household garbage: paper, cardboard, biological, metal, plastic, green-glass, brown-glass, white-glass, clothes, shoes, batteries, and trash. The data used in this paper are only six categories, including glass, paper, metal, cardboard, and plastic. The final dataset consists of 250 images.

3.2 Image Preprocessing

The dataset preparation involved sorting and labelling images manually into categories like glass, paper, metal, cardboard, and plastic. Ambiguous images, like those with watermarks or hidden objects, were removed to ensure a clean training set. All images were resized to a standard dimension of 150 x 150. Figure 2 displays sample images from the finalized dataset.

Fig 2. Example of Trash

3.3 Training Process of the Faster R-CNN Classifier

The Convolutional Layer consists of neurons arranged in such a way as to form a filter with length and height (pixels). The function of the Convolutional Layer is to recognize the features of an object. The Convolutional Layer will produce output on the Feature Map. A feature map is a region proposal layer. The anchor box at each location defines a Region Proposal Network (RPN), which in turn makes suggestions at various scales. The bounding box coordinates are classified as objects and are combined with the Feature Map. In the ROI pooling layer, bounding boxes with different sizes and aspect ratios are resized using a maximal merge. The collected feature maps are then classified to obtain an output image with a bounding box and class labels because of the classification.

The training process for this research uses Faster R-CNN with 80 samples of waste images for the training data in the 1st and 2nd trials and 30 and 50 samples for the test data in the 1st and 2nd trials, respectively. In the third and fourth trials, A dataset with 120 samples is required for training and 30 and 50 samples for testing. For the 5th and 6th trials, A dataset with 200 samples serves as training data and 30 and 50 samples serve as test data. The training process runs until the steps reach 3,000, 4,000, 5,000, and 8,000, where each has a loss function parameter.

Table 1. Datasets split table

Trials	Total Training Data	Total Test Data
1	80	30
2	80	50
3	120	30
4	120	50
5	200	30
6	200	50

3.4 Deploy the model into Android Application

Python is used to train and convert a TensorFlow model before incorporating it into an Android app. After completing the training of Faster R-CNN model, next process is to build a TensorFlow model of Faster R-CNN for device training using preprocessed dataset. For a model to be trained and used on a device, it must be able to perform several separate operations, including train, infer, save, and restore functions for the model. After converting the model to TensorFlow Lite and deploying it with the application, the model can be retrain on a device using new data and the train signature method of the model.

4 Result & Discussion

4.1 Image Classification Training

In this part, the results of the image classification training are displayed using a Convolutional Neural Network, a function in Deep Learning. The graphs show the Classification Accuracy, which indicates how well the model classifies images over time, and the Loss over time, which reflects the model's performance and increases when predictions differ from actual labels. These visualizations are important for evaluating the test results in this project, showing how accurately the model can recognize and categorize different types of waste.

According to the training data, the model showed strong understanding, reaching a high accuracy of roughly 96.23% and lowering the training loss to 0.1217, indicating enhanced predictive performance. However, when verified on new, previously unseen data, the model had a significantly lower accuracy of roughly 78.65%, indicating potential generalization issues. The validation loss, which is 0.7695, reflects the model's performance on the validation dataset. In summary, the model performed well on the training data, achieving a high accuracy of 96.23%. However, there is a slight drop in performance on the validation set, where the accuracy is 78.65%.

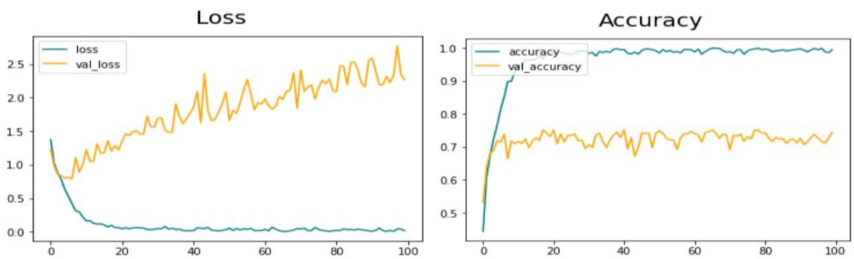

Fig 4. Training and validation loss and accuracy

According to Figure 4, the model initially performed poorly with low accuracy and high loss for the training dataset. As the number of epochs increased, the accuracy improved significantly, reaching a high value around the 15th epoch. A high accuracy indicates that the model can make accurate predictions on new data. The loss per epoch represents the model's average error during training, with lower values indicating better performance. The figures show that the model's performance improved over time, with the loss decreasing for both training and validation datasets. This simultaneous improvement in accuracy and loss suggests that the model is learning effectively and can generalize well. Testing the model on a separate set of data will further evaluate its accuracy in practical scenarios.

4.2 Convolutional Neural Network Accuracy Testing

Table 2. Example of Result of the Classification Task on Test Datasets

Accuracy Test Result : Positive		Accuracy Test Result : Negative		
Test case 1 : Metal		Test case 6 : Metal		
Label	Metal	Label	Metal	Glass
Confidence (%)	65.88	Confidence (%)	45.54	54.46
Test case 2 : Cardboard		Test case 7 : Glass		
Label	Cardboard	Label	Cardboard	Plastic
Confidence (%)	97.99	Confidence (%)	21.12	78.88
Test case 3 : Plastic				
Label	Plastic			
Confidence (%)	95.24			
Test case 4 : Paper				
Label	Paper			
Confidence (%)	87.54			
Test case 5 : Glass				
Label	Glass			
Confidence (%)	70.24			

The material of waste detection module analyses image datasets with readable labels. Table 2 shows seven test examples to demonstrate the model's outcome explanation. If the model correctly labels the waste material in the image, the outcome is positive; otherwise, the result is negative. Cases 1-5 have a positive outcome. Cardboard and plastic with the highest accuracy which are 97.99% and 95.24% respectively. It is due to the characteristics, color, and texture of the waste material. The problem comes when two labels have nearly identical properties, as demonstrated in test cases 6 and 7. Most of the training images for glass and plastic in tests 3 and 7 have a nearly comparable texture, confusing the testing phase and explaining why those test situations suggest high confidence in the different label.

4.3 Deployment into mobile application

When creating the mobile app's user interface, special care was taken to design each page to ensure a seamless user experience. The app will have four main interfaces: a recognition page, a location page, a store details page, and an information page. During the app development, the model was converted to a '.tflite' Flat-Buffer format supported by TensorFlow. Figure 4 demonstrates how the model is incorporated into the mobile application.

Fig 4. Model classify an image in Result Page

The recognition page of the app shows its features after the user clicks the 'Classify Me' button on the main menu page. Users can start image classification by selecting waste images and uploading them from their phone's gallery. The result page displays the images sorted by waste type with their labels. The highest accuracy image for each waste type is shown. The accuracy is converted into a percentage, although this is not shown to users. A table suggests which recycling bin to use based on the classification. Users can reuse the classification tool by uploading new images.

4.4 Discussion

This study has successfully embedded and deploy a Faster R-CNN model in mobile application for detecting materials of the waste, However, there is a slight drop in performance on the validation set, where the accuracy is when new data is added. One major constraint is the observed variance in detection accuracy between the model trained in the Tensorflow environment and its performance after conversion for mobile app deployment. The disparities in accuracy could be attributed to factors such as platform differences, resource constraints, or potential issues arising during the conversion process.

5 Conclusion

This paper concludes with several points. First, the Faster R-CNN successfully classifies images of waste into five categories, metal, paper, plastic, cardboard, and glass waste, which are achieved confidence rate of 97.99% , 95.24%, 87.54%, 70.24%, and 65.88% respectively.This paper also finds that the more images trained, the greater the value of the F1 score, and the greater the number of steps during training, the better the model is at learning object features. In the future, further research needs to increase the number of dataset by adding more objects with different angle to each image and comparing other algorithms as comparisons.

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