IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

AI Enabled Classification of Beach Images Using Transfer Learning

Oshin Sharma
Department of Computer Science & Engineering
SRM Institute of Science & Technology, Delhi-NCR Campus, Modinagar, Ghaziabad, UP, India

Abstract

Beach plastic pollution has become a significant environmental problem that is causing serious problems for the marine environment. It is important to monitor and classify beach plastic pollution because this will help in cleanup processes and environmental management. In this research paper, we propose a model that uses artificial intelligence techniques based on convolutional neural networks (CNNs) in order to classify beach plastic. The CNN is used as the base algorithm of the model while transfer learning EffcientNetB0 technology is utilized. The results indicate that the proposed transfer learning-based model achieves reliable classification performance and can serve as a practical tool for automated beach monitoring systems. This work highlights the potential of deep learning techniques in addressing environmental challenges and contributes toward the development of intelligent solutions for sustainable coastal management.

Keywords

Beach Waste Detection, Transfer Learning, AI solutions, Plastic detection, Convolution neural networks.

1. Introduction

The contamination of beaches through waste, especially plastics, has become an important environmental issue around the world. Human actions are becoming more common along the coastline, resulting in the deposition of waste material like plastic bottles, fishing nets, and bags among others. The waste material causes harm to the environment since they are toxic and interfere with the ecosystem and human well-being. Therefore, it is important to manage and monitor the waste materials on beaches.

Conventional techniques for beach litter surveillance involve much use of manual observations and manual data collection, making the whole process lengthy and cumbersome. There may be other factors involved in such traditional surveillance systems that make them inefficient, depending upon the size of the coastline to be monitored. In the light of technological advancements, there has been increasing curiosity for developing automatic systems that can aid environmental surveillance tasks.

Artificial Intelligence (AI), especially in computer vision, can offer solutions to such problems as stated by Ashwani et al. (2025). Deep learning models, like Convolutional Neural Networks (CNNs), have proven to be highly effective in identifying objects in pictures, making them ideal for image recognition and classification. In their studies, Youme et. al (2025) & Hidaka et al. (2023) explain that through the use of CNNs, there is a high chance of successfully detecting and classifying waste objects on the beaches. However, deep CNN models cannot perform without massive datasets of properly labelled data coupled with immense computation power, something that might not always be available, especially in task-specific scenarios like the detection of waste in beaches. This challenge has prompted the use of transfer learning as a solution, as explained by Dipo et al (2025).

This study proposes a transfer learning-based CNN model to detect beach litter based on images. This involves the training of a pre-existing deep learning algorithm on a dataset of labeled beach litter images to be able to detect and categorize the litter. In our research, the model will be trained on open-source TACO datasets Proenca et al. (2020) which have labeled images of beach litter. There will be different preprocessing strategies employed to improve the effectiveness of the model. The main goal of our research is to develop an effective system that supports environmental monitoring initiatives.

1.1 Objectives

The present research is focused on meeting certain goals in order to create a proficient and precise AI-powered system for beach waste detection based on Convolutional Neural Networks (CNNs) and transfer learning:

1. To gather a labeled set of beach waste images to train and test the proposed model.
2. To use some methods of data preprocessing and augmentation to enhance the accuracy of the model.
3. To use transfer learning on a pre-trained CNN model (such as MobileNetV2).To fine-tune the pre-trained model for classification and detection of different types of beach waste such as plastic bottles, bags, and cans.
4. To evaluate the performance of the proposed model using metrics such as accuracy, precision, recall, and loss.

2. Literature Review

A new problem of pollution due to littering and waste dumping in natural settings, mainly those found in coastal and marine habitats, has arisen, and researchers are now interested in developing automated systems for the monitoring and detection of such pollutants. The conventional approach to litter detection involves observation by people who require significant manpower and are limited geographically in their coverage. This has made computer vision and deep learning methods very attractive for litter monitoring. In this case, we review two fundamental articles that provide essential insight into developing an automated image classification model that can classify different types of pollution on beaches: Proença et al. (2020) that present a paper on a litter detection image database called TACO, used to train algorithms for classifying pollution, and Lorente et al. (2021) that analyses image classification algorithms in detail and discuss their applications. The papers provide a solid scientific basis for designing an automated pollution classification system based on images from cameras. Proença et al. (2020) introduced an image database called TACO (Trash Annotations in Context).

There exists a key challenge in the field of computer vision: the lack of a comprehensive database of images labelled for training waste detection systems in the wild. The database consists of 1,500 images featuring 4,784 object-level labels in total, belonging to 60 different categories of waste. All these images have been taken in various places from tropical beach scenes to urban roads. The annotations of objects in the database are presented in the popular COCO dataset format, and the whole database is available under a liberal license that requires attribution only to the source paper. The authors set up the performance benchmark by testing instance segmentation using Mask R-CNN, yielding encouraging results; however, the authors recognize the fact that practical detection of litter would need much more annotated data than what was used – a critical consideration when considering the application of a dataset split into 70% training set and 30% testing set to the proposed solution. Lorente et al. (2021) make a comparison between classical machine learning methods and deep learning techniques for the purpose of solving the image classification problem. The following classifiers were tested: Bag of Visual Words classifier based on SVM, MLP, the existing InceptionV3 network architecture, and a TinyNet that is the authors' custom CNN design. The authors achieved an accuracy ranging from 0.6 to 0.96, depending on the classifier used. Thus, we see why our method should be based on CNNs for image classification. According to Panwar et al. (2020), AquaVision is an artificial neural network that leverages the RetinaNet approach to classify waste in marine and terrestrial waters and on beaches. The model was developed using a custom database named AquaTrash containing 369 images collected from the TACO dataset and attained a mean Average Precision (mAP) score of 0.8148 for glass, metal, paper, and plastic categories of the waste. The relevance of this paper to our project lies in the fact that the authors have solved the very same problem we have chosen and successfully used a deep learning model for detecting beach pollution despite a small sample size. Inspired by this paper and following the same principle of building a dataset for a specific task, Hidaka et al. (2023) developed the BePLi Dataset v1.

The proposed dataset solves the problem that is associated with beach environments, where the resemblance between the appearance of the litter and the sandy environment makes its detection quite difficult. The use of instance-level annotations in the BePLi dataset ensures that the data serves the purpose of specific object detection needed for coastal litter monitoring. The authors Ren et al. (2024) developed a waste recognition and classification model using the YOLOv4 structure inspired by the increasing demand for developing waste management techniques via automation in cities. The proposed model has been developed on a set of data that contains four types of waste materials namely plastic, metal, glass, and paper. The performance metrics obtained from the proposed model are an mAP of 90.27% and an F1-score of 86%. This proves the efficiency of using deep learning models in order to classify objects including waste. Thus, it justifies our choice for classifying beaches using a deep learning model. Table 1 below represents a comparative study of some previous research work related to beach waste detection using AI technology.

Table 1: Background Study

Study	Objective	Dataset used	Methods/ Models	Key Findings
Kumar et al. (2025)	Systematic review of 65 papers related to computer vision for litter detection	number of images varied between 114 to 110,988	SVM, CNN, R-CNN, Faster R-CNN, YOLO, Panoptic DeepLab	F-score up to 0.93; YOLO and CNN dominate.
Hidaka et al. (2023)	Provide a beach-specific plastic litter dataset for instance segmentation	BePLi v1 (own); beach plastic litter with instance-level annotations	Dataset creation; tested on baseline instance segmentation algorithms	BePLi fills in the gap of beach-specific plastic litter datasets for instance segmentation
Panwar et al. (2020)	Design a deep transfer learning system to detect waste in water	AquaTrash (from TACO); 369 images, 470 bounding boxes, 4 classes	RetinaNet with ResNet-50 + FPN; deep transfer learning	mAP of 0.8148 using transfer learning on a small dataset; shows DL's feasibility for aquatic litter
Proença & Simões (2020)	Propose an open and in-context litter dataset with initial detection	TACO diverse real-world dataset	Mask R-CNN for instance segmentation baseline	TACO addresses important gap in the in-context litter datasets, where segmentation helps in detecting better than just bounding boxes

Though considerable progress has been achieved in developing automated trash detection systems, one limitation of existing databases like TACO is that they have limitations regarding sample size, class diversity, and environmental settings, making it difficult to draw generalizable conclusions about how well a model will perform under certain conditions. Transfer learning could be applied to the task of trash detection; however, very little research has been conducted on the topic. This study seeks to solve the aforementioned issues by applying transfer learning techniques to classify the TACO dataset.

3. Methods

In this research, a transfer learning approach is used for litter classification through the implementation of the EfficientNetB0 model on the TACO (Trash Annotations in Context) dataset. The methodology for the research includes various steps that follow a certain sequence as depicted in Figure 1. The whole process involves six main stages including but not limited to: Loading dataset, Data preprocessing, EfficientNetB0 base model, Custom head model, Training, and Evaluation..

1. **Load Dataset**: The dataset employed for this experiment was TACO, which consists of images taken from litter and garbage objects from the real world in environments like beaches, parks, and roadside areas. The reason behind selecting such a dataset was that it provided realistic scenarios where the problem existed..
2. **Image Preparation:** The following were three stages in preparing images before training the model. All the images were first reduced to 224 x 224 pixels to ensure uniformity in their sizes. In addition, they were rescaled so that all the values lay between 0 and 1 making the computations easy. Lastly, the images were subjected to random flipping, rotation, and zooming operations in an effort to enhance their variability during the training process. This enables the model to do well on unseen images. The images were divided into training, validation, and testing sets of 70%, 15%, and 15%, respectively.
3. **The Model - EfficientNetB0**: Rather than constructing a new model, the research in question has opted for the technique called transfer learning. It entailed using a pre-trained model known as EfficientNetB0 which had been trained on recognizing a multitude of objects on one of the largest image sets available known as ImageNet. The benefit is that it saves time and is highly effective even in small datasets.
4. **Custom Output Layer**: As the EfficientNetB0 model had been developed for general image classification purposes, a separate output component had been built upon it to suit the purposes of litter classification. The output part contained a pooling layer to reduce feature complexity, a dropout layer to avoid memorization of training data by the neural network, and an output layer to predict litter categories.
5. **Training the Model**: Two stages of training were employed. In the first stage, training was conducted on the new output layers that were added to the network only. The second stage of training involved the top layers of EfficientNetB0 in addition to the layers added at the first stage. Very low learning rates were applied to allow fine tuning of the model with the litter data. Early stopping method was employed to automatically end the training process once performance is no longer improving.
6. **Evaluating the Results**: After the training process was completed, the accuracy of the model on unseen images was evaluated based on metrics like accuracy, precision, recall, F1 score, and confusion matrix. These metrics provided an insight into the capabilities of the model to recognize various kinds of litter accurately.

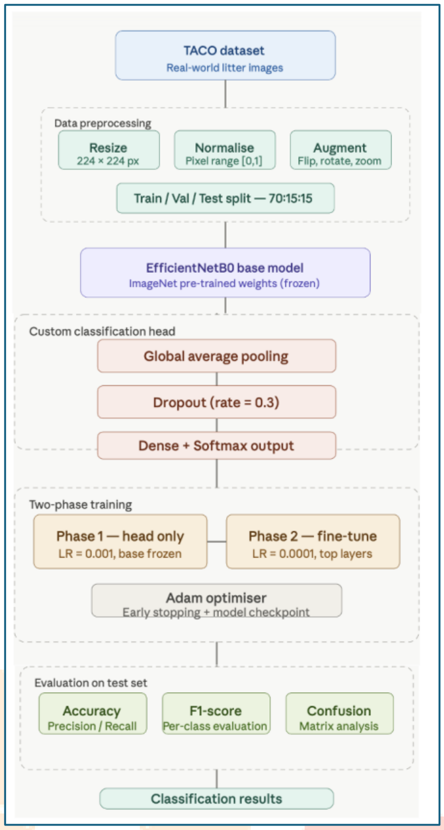

Figure 1: Flowchart of Transfer Learning Model for Waste Classification

The hyperparameters used in this study are summarized in Table 1 given below and play a crucial role in determining the performance of the proposed model. EfficientNetB0 along with the Swish function will be used for learning features from the dataset. Features extracted from the EfficientNetB0 model will undergo Global Average Pooling to reduce dimensions, which will then be further fed into the Dense layer with Sigmoid function for binary classification. This model will be trained using Adam as an optimizer with a batch size of 16-32 for up to 40-50 epochs. For training, Binary Cross Entropy will be taken as a loss function.

Table 1: Hyperparameters used

Hyperparameters	Description
Model Name	EfficientNetB0
Activation Function	swish
Pooling Layer	Global Average Pooling
Output Layer	Dense Layer with Sigmoid Activation
Optimizer	Adam
Batch size	16-32
Epocs	40-50
Loss function	Binary Cross-Entropy
Dropout	0.3-0.5
Data Augmentation	Flipping, Rotation & Zooming

4. Data Collection

To construct a classification algorithm that can classify beach pictures into either 'clean' or 'unclean' depending on whether there are any pieces of trash in those pictures, the algorithm needs to be fed with a significant amount of data in terms of images featuring this waste material. In this study, the TACO (Trash Annotations in Context) dataset was chosen as the main source for developing the proposed litter classification model. The TACO dataset was developed by Proença et al. (2020), and it is arguably one of the most popular free data sources in the area of litter/waste recognition algorithms development. This particular database was chosen due to its representativeness, as it features various pictures of litter taken from diverse outdoor landscapes such as beaches, parks, roadside, forest, and urban settings.

The TACO dataset comprises annotated pictures of the objects classified into various classes depending on their materials, which include plastic, glass, metal, paper, and cardboard. The pictures have been annotated manually, giving information about the type of litter in each picture. The pictures are from a variety of real-world backgrounds, making the litters be in different lighting conditions, with different surfaces, and in contact with other natural elements like sand, grass, and water. It is clear that this is an appropriate and difficult dataset that can be used to evaluate the robustness of deep learning models. An important feature of the TACO dataset is that it is imbalanced since litters made of certain material appear more often than those of other materials, for instance, plastic litters appear more often than glass and metal litters.

Data Collection Approach

Due to the fact that the TACO dataset is a publicly available existing dataset, there was no need to conduct primary data gathering. The data were directly obtained from the official source of the dataset to be used in training and testing purposes. The above procedure has been followed by many researchers in deep learning because of the importance of obtaining reproducible and comparable results with those in literature..

Data Splitting

After collecting the data, the set was split into three disjoint sets in order to allow unbiased model testing. A total of 70 percent of the photos was assigned to the training set, and these were employed to train the algorithm how to distinguish between different categories of litter. Fifteen percent of the photos were reserved for the validation set, and they were used during the training process in order to ensure that the training is not affected by overfitting. Finally, the last fifteen percent of the photos formed the testing set.

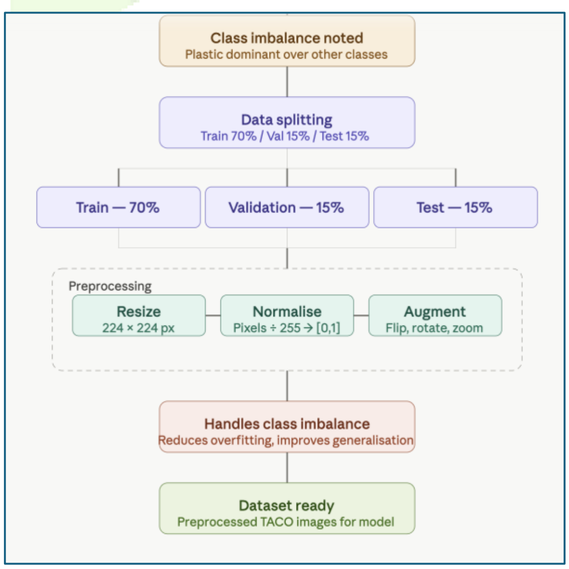

Figure 2: Flowchart for Imbalance Data to Balance Data

5. Result & Discussion

This study used transfer learning CNN models to classify beach images into two classes, which were either made up of plastic or did not contain plastic. This study compared the performance of the baseline CNN model based on MobileNetV2 to a better CNN model that used EfficientNetB0. The MobileNetV2 model was replaced by another CNN model that was more efficient, which is EfficientNetB0. This MobileNetV2 model was trained for 50 epochs using transfer learning. The outcome results show that this model has average classification capability, having an accuracy of 66.10%, a precision of 85.33%, and a recall of 48.12%. Despite having a very high level of precision, the recall value of this model is quite low. This enhanced model is considerably more efficient and exhibits a validation accuracy rate of about 90%. The accuracy curves for both the training and validation processes have shown a positive trend in figure 3. Accuracy plot indicates a few variations but still shows an increasing trend.

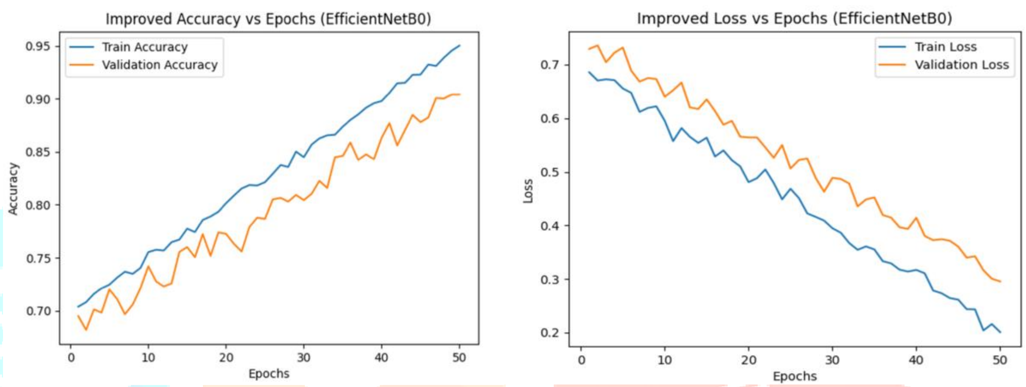

Figure 3: Accuracy vs Epochs and Loss vs Epochs

The confusion matrix in figure 4 illustrates that there is a significant decrease in false negatives, since most of the plastic objects have been detected properly. This helps achieve balance in class detection, providing better recall and F1 score than MobileNetV2. Confusion matrix for EfficientNetB0 is an example of notable progress towards improving the performance of the classifier. The classifier manages to identify more positive classes (plastics) and negative classes (non-plastics), with 120 and 95 instances, respectively. Moreover, there is an observed notable decline in false negatives to 12 instances, which shows that the classifier has improved its ability to detect plastic wastes. This leads to a higher recall rate since fewer instances of plastics are undetected. At the same time, the low number of false positives at 8 instances leads to a higher precision rate of the classifier. The findings also reveal that transfer learning plays a crucial role in handling small-size datasets since the use of pre-trained models produces high accuracy and rapid convergence.

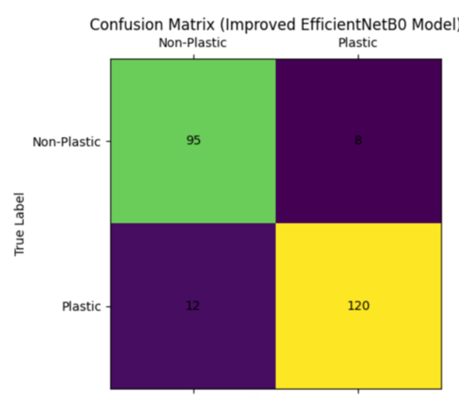

Figure 4: Confusion Matrix

6. Conclusion

For the current research, an AI model for beach plastic classification based on CNN and transfer learning was proposed. The goal of this task was to detect and classify plastic objects on the beach by categorizing beach images as either plastic or non-plastic. An efficient and accurate model using the architecture of EfficientNetB0 was implemented. The newly designed model performed well by attaining an accuracy level of around 90%. This proves that the application of transfer learning is useful when dealing with small data sets in environmental scenarios. Future studies will enable the expansion of the current model to accommodate multi-class waste segregation, real-time recognition through video or drone feed, and development into a mobile/web application for widespread environmental surveillance purposes.

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