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Waste Classification for Sustainable Development Using Image Recognition with Deep Learning Neural Network Models

Meena Malik [1], Sachin Sharma [2,*], Mueen Uddin [3], Chin-Ling Chen [4,5,6,*], Chih-Ming Wu [7], Punit Soni [8] and Shikha Chaudhary [9]

1 Department of CSE, Sagar Institute of Science & Technology, Bhopal 462036, Madhya Pradesh, India; meenamlk@gmail.com
2 Department of CSE, Koneru Lakshmaiah Education Foundation, Vijaywada 522502, Andhra Pradesh, India
3 College of Computing and Information Technology, University of Doha for Science and Technology, Doha 24449, Qatar; mueenmalik9516@gmail.com
4 School of Information Engineering, Changchun Sci-Tech University, Changchun 130600, China
5 School of Computer and Information Engineering, Xiamen University of Technology, Xiamen 361024, China
6 Department of Computer Science and Information Engineering, Chaoyang University of Technology, Taichung 41349, Taiwan
7 School of Civil Engineering and Architecture, Xiamen University of Technology, Xiamen 361024, China; chihmingwu@xmut.edu.cn
8 Department of CSE, Chandigarh University, Mohali 140413, Punjab, India; punit.e9880@cumail.in
9 School of Computing and IT, Manipal University Jaipur, Jaipur 303007, Rajasthan, India; shikha.chaudhary18@gmail.com
* Correspondence: rj14.sachin@gmail.com (S.S.); clc@mail.cyut.edu.tw (C.-L.C.); Tel.: +91-9887469909 (S.S.)

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Abstract: The proper handling of waste is one of the biggest challenges of modern society. Municipal Solid Waste (MSW) requires categorization into a number of types, including bio, plastic, glass, metal, paper, etc. The most efficient techniques proposed by researchers so far include neural networks. In this paper, a detailed summarization was made of the existing deep learning techniques that have been proposed to classify waste. This paper proposes an architecture for the classification of litter into the categories specified in the benchmark approaches. The architecture used for classification was EfficientNet-B0. These are compound-scaling based models proposed by Google that are pretrained on ImageNet and have an accuracy of 74% to 84% in top-1 over ImageNet. This research proposes EfficientNet-B0 model tuning for images specific to particular demographic regions for efficient classification. This type of model tuning over transfer learning provides a customized model for classification, highly optimized for a particular region. It was shown that such a model had comparable accuracy to that of EfficientNet-B3, however, with a significantly smaller number of parameters required by the B3 model. Thus, the proposed technique achieved efficiency on the order of 4X in terms of FLOPS. Moreover, it resulted in improvised classifications as a result of fine-tuning over region-wise specific litter images.

Keywords: litter classification; convolution neural networks; machine learning; EfficientNet-B0

1. Introduction

A major environmental issue that poses a critical challenge in almost all developed and developing countries is the disposal of garbage. It turns out to be the most important challenge for sustainable development and ecological balance. A number of non-government organizations (NGOs) are actively working for this cause and drawing the attention of government organizations toward this direction, as it is their purpose to act in the public interest. Apart from NGOs, the World-Wide Fund for Nature (WWF) holds a dominant position in this domain [1,2]. There are organizations formed by intellects and nature-lovers; people drive such agendas within their own regions all over the world.

The problem of garbage disposal has increased many fold in recent years because of the massive production of disposable goods [3] in almost every industry; ranging from potable drinking water packaged in plastic bottles to takeaway coffee cups, foam to medical waste, and lightbulbs to plastic bags, the list is endless. The primary motivation behind the proper handling of waste is the compelling requirement for ecological balance, which has already been disturbed by mankind, to a large extent, only in the past 200 years. We considered, as a baseline, the statistics of the United States Environmental Protection Agency (US-EPA) [1]. It is estimated that the total generation of Municipal Solid Waste (MSW) is about 292.4 million tons, which is approximately 2.22 kg per person per day [4]. MSW is a collective term for various items consumers throw away after they are used. It includes cans, bottles, disposable glasses, chip packets, food, chairs, sofas, computers, tires, and refrigerators. As indicated above, MSW includes items that belong to categories of both hazardous and non-hazardous and disposable and non-disposable items. While there are specific techniques for specific types of disposal, the recommended usage of types of (non) disposable items follows the hierarchy shown in Figure 1.

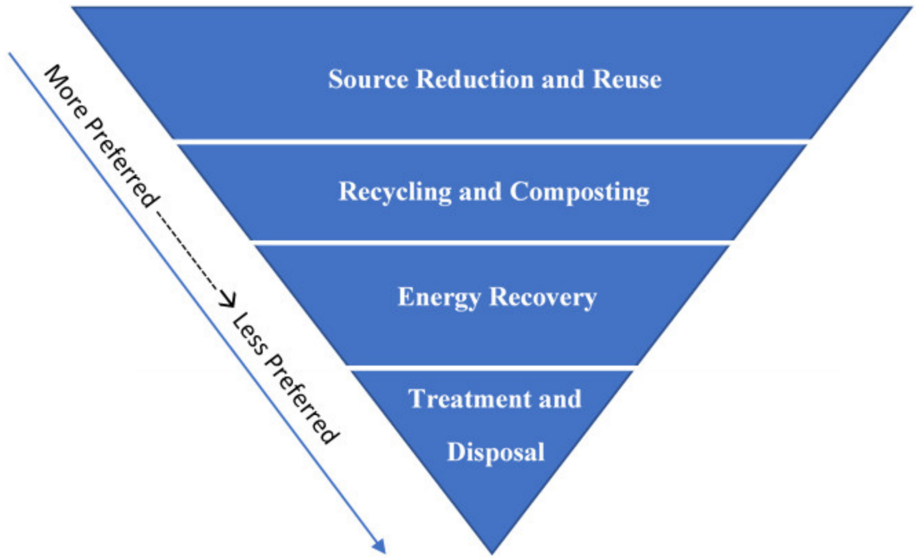

Figure 1. Preferred model of waste management.

For governments operating at the level of countries and states and local bodies operating at the town level, proper disposal of waste is a challenging issue. This includes the reduction in waste at the source before it enters the waste stream and the recovery of generated waste for recycling, composting, or other methods. It also includes environmentally sound waste management through combustion with energy recovery and conversion, as well as landfilling practices that meet current standards or newly emerging waste conversion technologies.

As indicated in [1], broadly, only 10 percent of materials are recycled. One possible solution for this is suggested to be the circular economy. Stated with the highest abstraction, we take materials from the earth, process them, and then dump them as waste. This process is linear. Instead, the circular economy suggests the circular way in which there is no endpoint of the line; rather, there is a loop that disposes of the waste (after converting it into a suitable form) back to mother earth. A circular economy is a collection of policies and frameworks to tackle global challenges, such as global climate, waste disposal, and pollution. In the context of plastic materials, the waste generated must be recyclable or compostable and recyclable. The point is to circulate the plastic items so that they can stay in the economy and out of the environment.

Figure 2 shows the classification of the waste into its types as per the US-EPA statistics of 2018 [4]. The figure gives a brief outline of all types of waste that belong to representative classes, along with their proportions in the overall MSW generated in 2018.

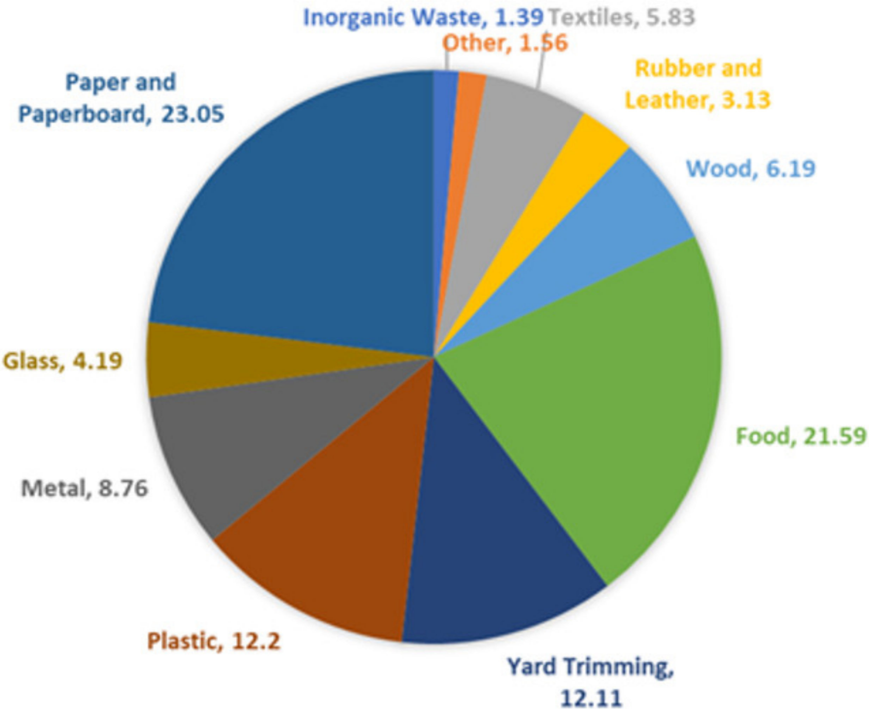

Figure 2. Types of Municipal Solid Waste (MSW) Types.

Recycling refers to a collection of processes to convert the waste material into a new material or object. There can be a possible recovery in energy and/or useful resources in said process. The material is recyclable only when it has the ability to reacquire the original state properties.

Composting refers to a natural process of recycling organic matter into manure. Both recycling and composting are preferred techniques in solid waste management. The percentages to which the MSW has been recycled as compared to the quantity in which it was produced initially is roughly estimated in Table 1, wherein the specific MSWs' are listed with their estimated percentages of recycling, as per the US-EPA statistics of 2018 [4].

Table 1. Specific Types of MSWs and their normalized percentage proportion [4].

Item\Year	1960	1970	1980	1990	2000	2005	2010	2015	2018
Paper and Paper-Board	17	15	21	28	43	50	63	67	68
Glass	2	1	5	20	23	21	27	28	25
Plastic	<0.05	<0.05	1	2	6	6	8	9	9
Yard Trimmings	<0.05	<0.05	<0.05	12	52	62	58	61	63
Lead Acid Batteries	<0.05	76	70	97	93	96	99	99	99

The aforesaid points clearly indicate the motivation towards the development of techniques for the efficient handling of MSW items. There is a requirement to automate this process, thereby reducing human effort and cost. One of the important aspects of this automation is the efficient classification of MSW items. One of the revolutionary techniques for solid waste classification is the Deep Learning Technique based on Convolution Neural Networks (CNN) [5]. A CNN is a deep-learning model which is extensively used for image recognition. Through this technique, a given image can be annotated with an appropriate label. Deep learning is still a research subject, but it has migrated from research labs into the commercial mainstream, revolutionizing several application areas. A framework of image processing techniques over the existing dataset is considered for the classification of the litter among the images and for the subsequent classification of the litter.

2. Review of the Techniques for Litter Localization and Classification

The automatic identification of litter (localization) and labeling under its proper class, recyclable or non-recyclable (classification), is an important aspect of automated waste management [6]. Several research papers have already been published in this area. The focus on this domain is continuously increasing due to its importance in ecological balance and sustainable development; Table 2 gives an overview of the most cited articles in the field of automatic litter classification.

Table 2. A Review of Techniques for Litter Classification Using Deep Learning Models.

Paper Title	Authors	Year	Aspects Considered	Aspects Compromised
Deep learning-based waste detection in natural and urban environments [1]	Sylwia Majchrowska, Agnieszka Mikołajczyk, Marta A. Plantykow	2022	The paper suggests a technique to localize urban environment waste considering all cases in which the litter might be present indoor, outdoor, or underwater. It further classifies the waste into seven categories, viz; glass, bio, metal and plastic, non-recyclable, paper, unknown litter, and others.	The model fails to consider the provision for localization of any object having dimensions comparatively very small as compared to nearby objects. This includes cigarette buts, small pieces of wreckage, etc.
A Waste Classification Method Based on a Multilayer Hybrid Convolution Neural Network [7]	Cuiping Shi, Cong Tan, Tao Wang, Liguo Wang	2021	The proposed techniques classify the litter into a number of categories; viz; cardboard glass, Trash, metal, plastic, paper, etc.	The proposed techniques do not indicate any classification of recyclable and non-recyclable waste. Additionally, the approach fails to achieve the desired accuracy in multiclass classification as compared to the benchmark approaches.
Intelligent waste management system using deep learning with IoT [8]	Md. Wahidur Rahman, Rahabul Islam, Arafat Hasan et. al.	2020	The methodology proposed classifies the litter into trash, plastic, paper, glass, metal, and cardboard using deep learning-based image classification.	The paper takes into account only five categories for MSWs. Due to the use of only two sensors in the proposed model, the proposed technique is certainly inefficient in locating trash holes, thereby reducing the localization efficiency.
Deep Reinforcement Learning Enabled Smart City Recycling Waste Object Classification [9]	Mesfer Al Duhayyim, Taiseer Abdalla Elfadil Eisa, et. al.	2022	The proposed technique is a two-stage DRL scheme that classifies the solid waste into six waste classes: trash, plastic, paper, glass, metal, and cardboard, using Q-learning and MR-CNN based image classification.	The top-1 accuracy is significantly less than that of EfficientNet models. Moreover, the training of the models for the waste categories with a core CNN is susceptible to overfitting and underfitting.

Table 2. *Cont.*

Paper Title	Authors	Year	Aspects Considered	Aspects Compromised
Detection of Waste Materials Using Deep Learning and Image Processing [10]	Arghadeep Mitra, et al.	2020	The article suggests a technique to automatize waste detection and segregation in order to reduce human intervention by using DL. It uses a fast R-CNN for categorization and image processing through using TensorFlow's Object Detection API for object recognition as per shape, size, dimension, color, etc.	The paper does not indicate any requirement for parameter tuning. Thus, it might result in relatively lower accuracy, precision, and recall w.r.t. actual and predicted labels.
Machine Learning and IoT-Based Waste Management Model [11]	Rijwan Khan, Santosh Kumar, Akhilesh Kumar, Srivastava	2021	Provides ML- and IoT-based an efficient and smart schemes as well as its hardware prototype for waste management to accomplish a pollution-free and clean environment. Organic, plastic, e-waste, biomedical waste, hazardous waste, etc.	Little emphasis has been given to waste localization and classification techniques using machine learning classifiers. Thus, the model can work as a subsystem for a complete deployment of the architecture for solid waste management.
Waste Management System Using IoT-Based Machine Learning in University [12]	Tran Anh Khoa Cao Hoang Phuc, et.al.	2020	The article suggests a method of obtaining an assessment of the waste level in the bins, indicating which bins are on the verge of being filled up and require attention in one way or the other.	The proposed architecture provides a hardware approach with a little focus on waste segregation through machine learning techniques.
An Assessment of Machine Learning Integrated Autonomous Waste Detection and Sorting of Municipal Solid Waste [13]	Sonam Chaturvedi, Bikarama Prasad Yadav and Nihal Anwar Siddiqui	2021	The litter categories considered in the classification model include cardboard, glass, metal, paper, and plastic wastes. Although the classifier works reasonably well, it requires a large training set.	The model works for a subset of classes from among the diversified set of waste categories. As such, the model is not scalable and thus, cannot be implemented meticulously for MSW classification.
An Automated Machine Learning Approach for Smart Waste Management Systems [14]	David Rutqvist, Denis Kleyko, and Fredrik Blomstedt	2019	The primary focus of the research is on the detection of empty bin containers. The same has been implemented by a sensor approach using smart sensors. It utilizes bare minimum image classification for the detection of litter from the images.	The paper does not include any classifier for automatic segregation. As such, the model is not feasible for deployment in realistic scenarios where the garbage categories are diversified and need to be disposed of separately.

Table 2. *Cont.*

Paper Title	Authors	Year	Aspects Considered	Aspects Compromised
Household Waste Management System Using IoT and Machine Learning [15]	Sonali Dubey, Pushpa Singh, Piyush Yadav, Krishna Kant Singh	2020	The research proposes the classification of organic and inorganic waste at the first level. It further segregates the organic waste into subcategories at a later stage.	The application of back-to-back binary classifiers for the classification of organic–inorganic waste and further classification of organic waste is a suboptimal strategy to be deployed in real-world scenarios.

The authors in [1] proposed a deep learning framework using a two-stage detector to identify and classify garbage into seven categories with a level of accuracy up to 75%. The first stage manages litter localization without focusing on its class type with the help of EfficientDet-D2, and the second phase follows the classification of the identified waste into seven categories where the training of the classifier is undertaken by the un-labeled images in a semi-supervised manner. The scheme suggests a mobile application using Deep learning which can precisely identify the category of the waste item.

The model presented in [7] considers a TrashNet dataset that is analyzed for waste image classification. To improve the detection technique, a simply structured and efficient waste classification method with fewer parameters has been proposed with the help of a multilayer hybrid convolution neural network resulting in an accuracy of up to 92%. The basic model has been suggested with four successive improved versions back-to-back in order to analyze the best classification and accuracy. An adequate Heat Map comparison in the form of images is also presented in order to achieve rich feature extraction. Lastly, a comparison of the proposed scheme with existing ones has been represented in terms of accuracy, parameters, and complexity.

The authors in [8] proposed a deep learning model along with IoT-based smart bins, which uses a microcontroller and sensors for the real-time monitoring and sorting of waste into digestible and indigestible using a CNN. For indigestible items, the classification is conducted across six categories using machine learning with an accuracy of up to 95%. A detailed working principle for a smart bin is represented along with the functionality of both the camera and sensor. The scheme is proposed to be deployed for real-time monitoring as well as segregation of house waste. It can be directly concluded that the accuracy can be further improved by using multiple kinds of sensors, such as MQ Gas sensors, IR sensors, etc.

The authors in [9] have designed an inventive DRL scheme (IDRL-RWODC) for the identification and classification of waste, especially for smart cities, with the help of two stages of processing: the first phase, with Mask Regional (MR-CNN) using a Dense-Net model for detecting objects followed by deep reinforcement learning referred to as the Q-learning network scheme for classification. To improve efficiency at the first stage, the Dragonfly algorithm is used as a hyperparameter optimizer. The results represented the better performance of the proposed scheme over existing ones, and it can be deployed in smartphones as a mobile application for classifying objects in real-time. Here, the simulation was performed using Python 3.6.5, and the classification was prepared with the dataset from the Kaggle repository.

In [10], the authors developed a framework to automatize and expedite the entire process of waste detection and segregation in order to reduce human intervention by using DL. A faster R-CNN was used for categorization and image processing by using TensorFlow's Object Detection API for object recognition as per shape, size, dimension, color, etc. The data for the training purposes were obtained from the GitHub Repository, available online. Approximately 2527 pictures were considered and used for the labeling of different images; the LabelIMG tool was used. The latter part of this study recommends implementing the proposed schemes in a mobile application.

The author of [11] offers an ML- and IoT-based smart scheme with a hardware prototype for waste management to accomplish a pollution-free and clean environment. The scheme tries to automate and trace all of the necessary activities related to waste management through a GPS system, especially focusing on a garbage collection system, truck activities, and meetings in order to minimize the price, distance, and fuel. The prototype is equipped with an Arduino UNO microcontroller connected to an ultrasonic sensor to monitor the waste level in the dustbin and a moisture sensor to verify the waste status: whether it is wet or dry. A buzzer indicates when the maximum level in the dustbin is reached. The scheme offers efficiency by using smart bins, dynamic changes in route, and generating collection orders for vehicles.

The author of [12] offers a novel, low-cost scheme to manage waste in smart bins under real-time monitoring by predicting the probable garbage level in a bin using logical regression and graph theory to help identify the shortest route, thus, saving time for waste collection. A scenario for the scheme has been implemented using a LoRa module on the university campus of Ton Duc Tang University (Vietnam) to evaluate the system performance. The offered system was found to be simple, cheap, and effective, leading to the deployment of the scheme to the full university campus. The scheme offers cost-saving operations, optimizes the workload of employees, and on-demand data collection.

In [13], a smart mechanism for the prediction and forecasting of waste production is proposed. For the preprocessing and integration of data, CNN, along with an air-jet structure, is used. The results obtained from the model indicate that the proposed technique is very efficient for the detection of different categories of waste with high accuracy. The work mainly aims to solve waste-related issues in a famous city, Dehradun, India. The developed model can easily identify and segregate garbage using both CNN and decision-tree algorithms. The model offers automatic waste identification with little human intervention, therefore resulting in better control over pollution and diseases.

In [14], the authors propose machine learning to solve waste management issues using binary classification to detect empty recycling containers. The model outperforms the existing frameworks by using the data preprocessing techniques, which are used meticulously in this approach. It uses a feature engineering approach to generalize the model, thereby achieving a greater accuracy compared to traditional approaches without feature engineering. Performance optimization was performed on the three baseline approaches, viz. the feature engineering model, traditional machine learning with standard features, and with extended features.

In [15], the system offers a smart bin for home-waste localization and segregation using IoT and ML techniques. The authors propose a framework for waste management using traditional ML techniques. The proposed technique is based upon a K-Nearest Neighbor (KNN) model for the segregation and classification of MSW. The proposed scheme uses a pipeline architecture comprising of segments, where the first module performs house-level segregation into organic and inorganic waste classes, and the second module segregates into further subclasses at the society level. The KNN model outperforms the existing approaches with a 93.3% accuracy.

Most smart city planning and development consider litter management as one of the prime concerns, as it is directly related to the quality of living and health issues of the residents of that area. Automatic litter classification is a problem that has been investigated by researchers for a long time. The revolution in this domain has come after the success of deep learning models, which have recently achieved human-comparable accuracy in these domains. The state-of-the-art deep-learning models perform remarkably well and sometimes exceed human intelligence for certain specialized tasks. In the next section, an introduction to EfficientNet model is presented. These models perform reasonably better than existing CNN models.

2.1. Efficient Nets for Image Classification

The domain of image classification has seen some of the most cutting-edge AI research in the past few years. The most efficient models for image classification have recently been introduced in the form of Efficient Nets [16]. As the name suggests, these are highly efficient implementations of Convolutional Neural Networks (CNN), having a large number of input layers, ranging from 237 in EffficientNet-B0 to 813 in EfficientNet-B7.

EfficientNet are the CNN models proposed by computer researchers Mingxing Tan and Quoc V. Le, in May 2019, in their benchmark paper "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks [17]." The motivation behind the use of Efficient Nets in proposed litter classification is that it exhibits remarkably high accuracy of 84.3% over ImageNet while having 8.4 times smaller memory requirements and being 6.1 times faster than the best existing Convolutional Neural Networks for image classification [18]. Figure 3 gives the overall performance of EfficientNetB0-B7 for image classification as compared to those of the other state-of-art models.

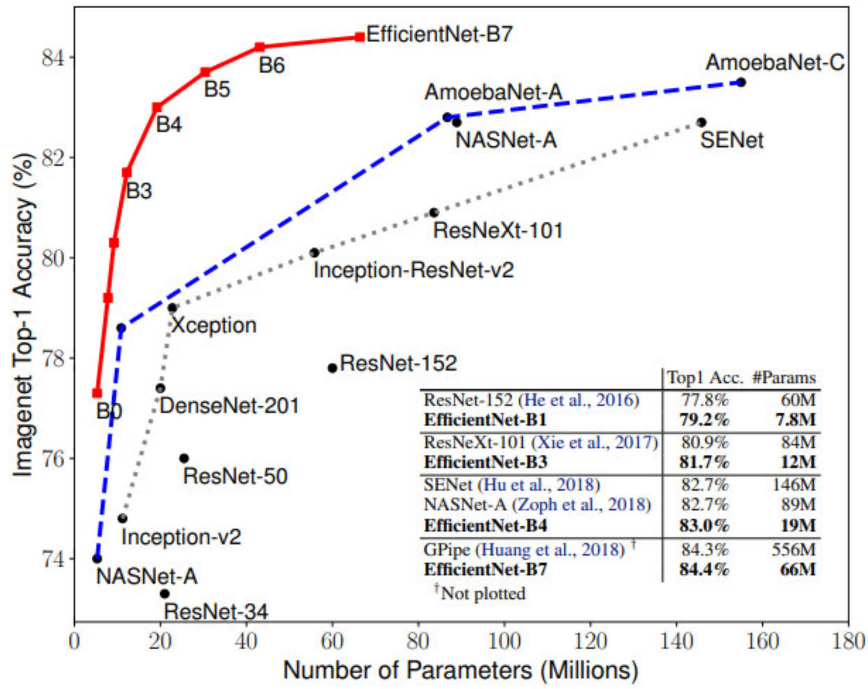

Figure 3. Efficiency of benchmark CNNs over ImageNet. Image Courtesy, Mingxing Tan et al. [17]. EfficientNet-B1-B7 Top1 Accuracy Score and #Params [19–23].

ImageNet is one of the most widely used image databases, constructed in the form of a tree data structure and consisting of hundreds and thousands of images at each node. It is used as a reference by CNNs and other models for accuracy metrics. The following graph illustrates the accuracy given by NN models over ImageNet. Another promising reason behind the use of EfficientNet-B0-B7 for the proposed litter localization and classification architecture is that these are pretrained models over ImageNet. Thus, an additional training dataset is required only for performance improvement over the baseline already achieved by these models.

The motivation behind the use of EfficientNet-B0 in the classification model, as compared to the use of B3 in the benchmark approach for litter classification, is validated in view of the following factual points as stated below.

1. For B0 to B7 base models, the input shapes are different. The input image shapes expected for these models are listed in Table 3.

Table 3. Image Resolution Requirements for EfficientNet Models.

Model	Input Image Resolution-Expected
EfficientNet-B0	224
EfficientNet-B1	240
EfficientNet-B2	260
EfficientNet-B3	300
EfficientNet-B4	380
EfficientNet-B5	456
EfficientNet-B6	528
EfficientNet-B7	600

It accounts for the use of more storage space in augmenting with training data even for a pretrained classifier in the case of B7 as compared to B0.

2. The requirement of Floating-Point Operations Per Second (FLOPS) for B0 is 0.39B (B for Billion; 10^9) which is 21% of 1.8B; the requirement in the case of B3. In the case of B7, the same is 37B. EfficientNet-B0 base architecture, particularly Keras implementation, can be hosted on commodity hardware, whereas the same cannot be performed using B3 to B7.

2.2. Vision Transformers for Image Classification

The discussion related to the topic, "deep learning for image classification", at the time of writing, cannot be complete without giving an introduction to a new and emerging technique in this domain, Vision Transformers (ViTs). These are Neural Network architectures that have been introduced quite recently by Dosovitskiy et al. [24]. A detailed discussion regarding the application of ViTs for litter detection can be found in [25]. A ViT is basically a transformer-like architecture. ViTs are primarily used for text processing, in which the *sequence* is significant. The same is not applicable to images where the concept of a sequence is irrelevant. The images are mostly processed by CNNs that have convolution layers for successively summing up, using a sliding window, and using max-pooling, which finally converges to a class representing the final annotation of the image. However, recent research in ViTs enables this architecture to classify images in an efficient manner. A ViT model eliminates the need for the Convolution Block used in CNN. A given image is partitioned into regions, mostly of identical dimensions, and these form the initial input for the ViTs.

A pure transformer model applies *Attention*, which refers to a quadratic operation between each pair of inputs. It accounts for a very large number of quadratic operations in the case of images, where the input sequence comprises pixels. For example, in the case of an image of dimension 512×512, the total count of pixels is 512^2, and the pairwise count is ${}^{512\times512}C_2$. This is indeed a large number of computations on a general-purpose computer. ViTs handle this issue by partitioning the image into small regions, each of which is further subjected to the *Attention* operation. Transformer architectures are able to achieve comparable accuracy with state-of-art, pretrained CNNs. However, this is too early to say that transformers will eventually replace CNNs. Most recent CNN models introduced by researchers have efficiency comparable to human beings.

3. Proposed Framework for Litter Localization and Classification

The proposed framework is a part of a larger system of automatic collection and disposal of solid waste. The system requires an automatic vehicle, preferably an all-terrain vehicle. The robotic arm mounted on the vehicle can pick and put the solid waste, as per the decision-support system described herewith. The proposed model for efficient localization and detection is depicted as shown in Figure 4.

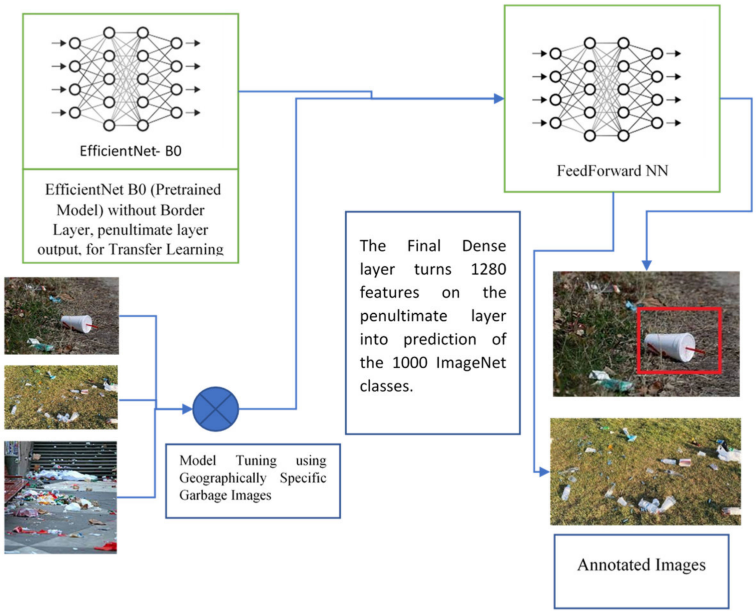

Figure 4. Image Localization Architecture Using Transfer Learning Model over EfficientNet-B0.

As a next step of the process, the 34 categories are mapped to 10 base classes that deal with the types of recycling and composting plants. Thus, it is reasonable to map the 34 classes to 10 higher-order classifications so that the corresponding item will be repository mapped to the correct type of recycling/composting facility. This is illustrated in Figure 5.

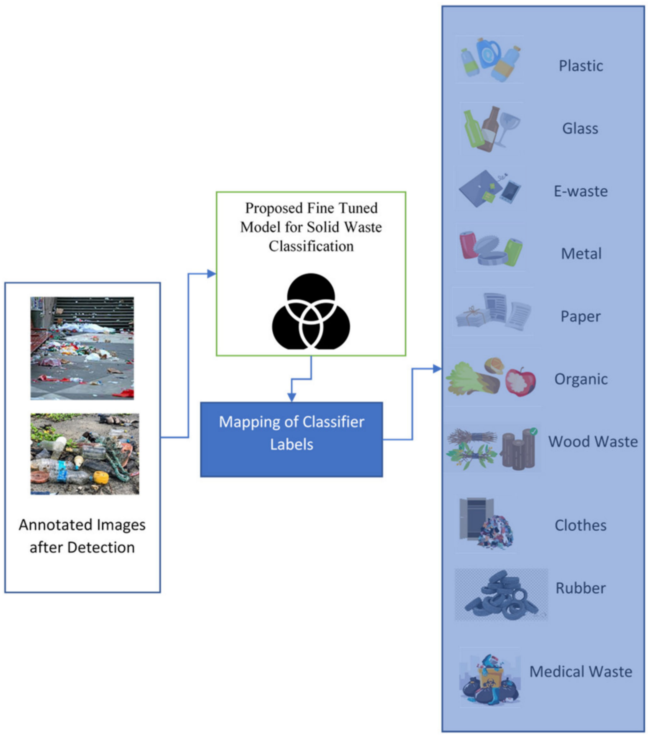

Figure 5. MSW classification architecture using transfer learning model through label mapping.

As most of the implementation for garbage collection is undertaken through mobile units roaming across a definite physical zone, wherein the count of required units is significant, the B0 implementation with a semi-resolution camera is the most cost-effective alternative with the same desired accuracy as given by B3 with moderately high-resolution images.

3.1. Framework for Classification of Solid Waste Images

The efficient model is imposed in TensorFlow over Python. The reason for the selection of TensorFlow is its wide acceptability in almost all production environments. The Efficient models are used through the Keras implementation of the model over Python.

CNNs are usefully deployed as a model with fixed resources, viz, a specific number of layers of prespecified width. These models are then scaled up where there are more training datasets. The scaling is conducted in width, i.e., the number of parameters inputs to the model (e.g., image resolution), or the depth, i.e., the number of hidden layers to the model. However, this process of scaling is time-consuming and often results in compromised accuracy, as in cases where the datasets are incompatible.

EfficientNet uses a compound scaling process for CNN so as to expand the CNN in a structured and systematic way in both width and depth. Unlike traditional scaling, which scales up the model in arbitrary ways, the EfficientNet rethinking model uses a compounding process, which scales the model uniformly in each dimension with a fixed set of scaling coefficients. The process of compound scaling is depicted in Figure 6.

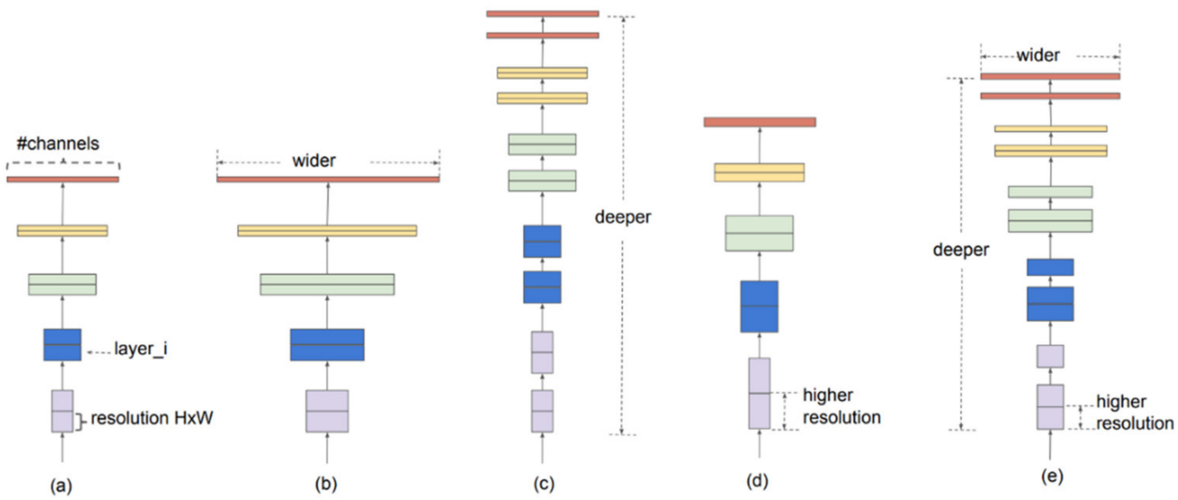

Figure 6. Efficient Net Model Scaling [17]. (**a**) Baseline; (**b**) Width Scaling; (**c**) Depth Scaling; (**d**) Resolution Scaling; (**e**) Compound Scaling.

In this research, the CNN model, EfficientNet B0, is considered for the classification of solid waste. The architecture of the Efficient Net B0 is shown in Figure 7.

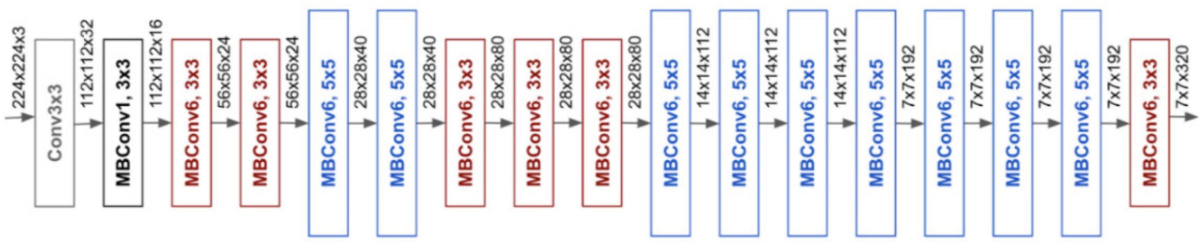

Figure 7. Layered Architecture of EfficientNet [17].

3.2. Proposed Framework for Classification Using EfficientNet-B0

1. The model EfficientNet-B0 is a pretrained model using ImageNet with 1000 classes of objects. The model is used as a baseline model for solid waste classification.
2. The internal layers of B0 models are frozen to avoid any loss of information contained in them. The model is used with penultimate-layers output. The output serves as an input to a CNN in a pipelined manner, which is further trained over the secondary dataset.

3. A secondary dataset refers to the specific dataset of the solid waste image, which is specific to the particular region under consideration. For example, in coastal areas, the solid waste comprising of coconut shells is common, whereas, in dry regions, potable water bottles and cold-drink cans are most common.
4. The secondary dataset of images and class is used to train a set of layers only. These layers would learn to map the old features into predictions over the new dataset, thus, implementing Transfer Learning over the CNN model through pretrained EfficientNet.
5. The additional layers can be thought of as a new CNN model, having input from pretrained EfficientNEt-B0 and secondary image datasets.
6. The proposed system gives a record accuracy of 81.2%, which approximately matches B5 while being 20 times smaller than EfficientNet B7 and 23X times smaller than the best Convolutional Neural Network for Image classification.

4. Results and Analysis

In the proposed research, a number of solid-waste types are considered, which represent large general classes of solid waste categories. The solid-waste categories that are included in this manuscript represent the most general category of FMCG (Fast Moving Consumer Goods Items) that are representative of most solid-waste management research work.

These general classes of solid waste relate to most of the urban cities in the modern world [26]. Thus, this classification is useful for a broad class of applications meant for such cities.

In particular, we have classified municipal solid waste into 34 categories, as shown in Figure 8.

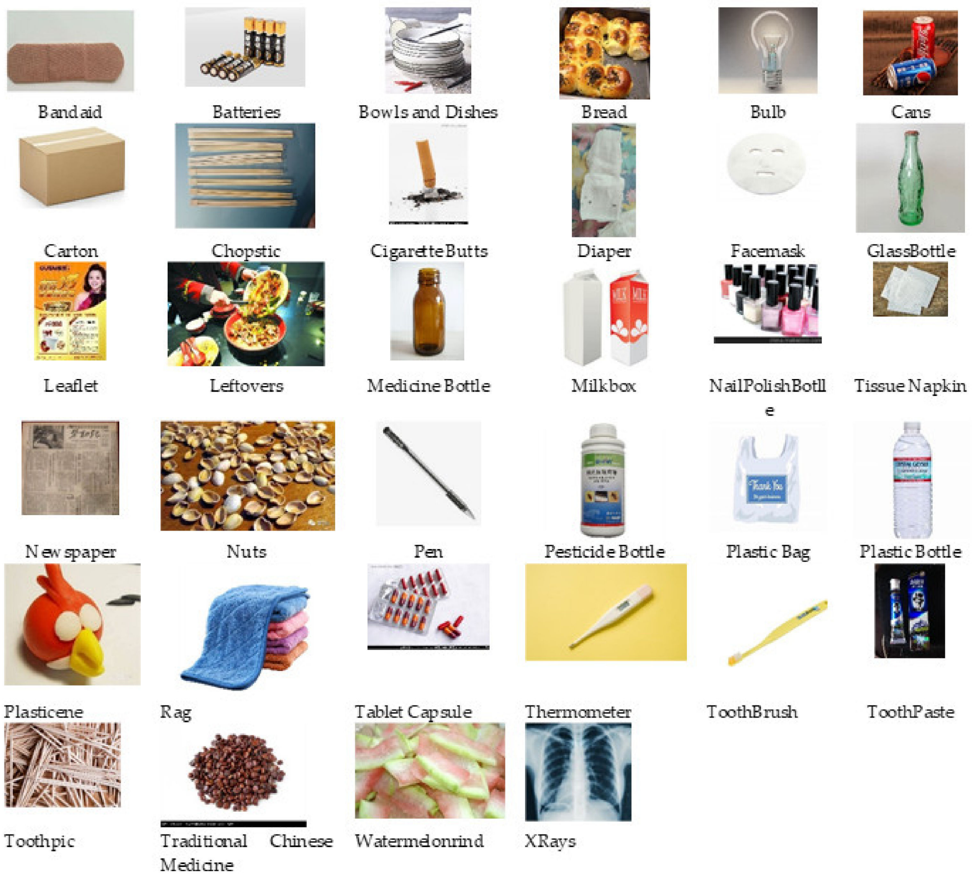

Figure 8. Solid Waste Categories for Overall Classification and Fine Tuning of Efficient-Net B0.

A dataset of images corresponding to these 34 different categories of solid waste was obtained from the Kaggle data repository. The same is used to perform fine-tuning of the EfficientNet-B0 model. The 1000 ImageNet Classes consist of a number of labels pertaining to Solid Waste Categories. The indicative list of the class labels of ImageNet is shown in Table 4.

Table 4. Indicative List of ImageNet Classes.

Class ID	Class Label
0	tench, Tinca tinca
1	goldfish, Carassius auratus
2	great white shark, white shark, man-eater, man-eating shark, Carcharodon caharias',
...	...
...	...
20	water ouzel, dipper
...	...
475	car mirror
...	...
494	chime, bell, gong
...	...
647	measuring cup
...	...
653	milk can
...	...
700	paper towel
...	...
772	safety pin
...	...
788	shoe
...	...
809	soup bowl
...	...
845	syringe
...	...
999	toilet tissue

Most of the ImageNet categories can be mapped to the 34 Base Classes of MSW. These can be further mapped to the broad classification of the MSW, thereby providing a fine-tuned model for customization to the least level of granularity. A significant number of those that are in the original list of 1000 item labels can be mapped to 34 classes and then to 10 representative classes of solid waste considered in the proposed architecture.

Analysis of the Proposed Architecture over CNN Model

An indicative dataset of images in the programming environment is shown in Figure 9.

We have investigated the images dataset with 34 categories through the approach of the Convolution Neural Network model. For the purpose of efficient operations, both the test and the training datasets are considered to have jpeg images of the dimensions 224×224 with three color channels, namely red, green, and blue.

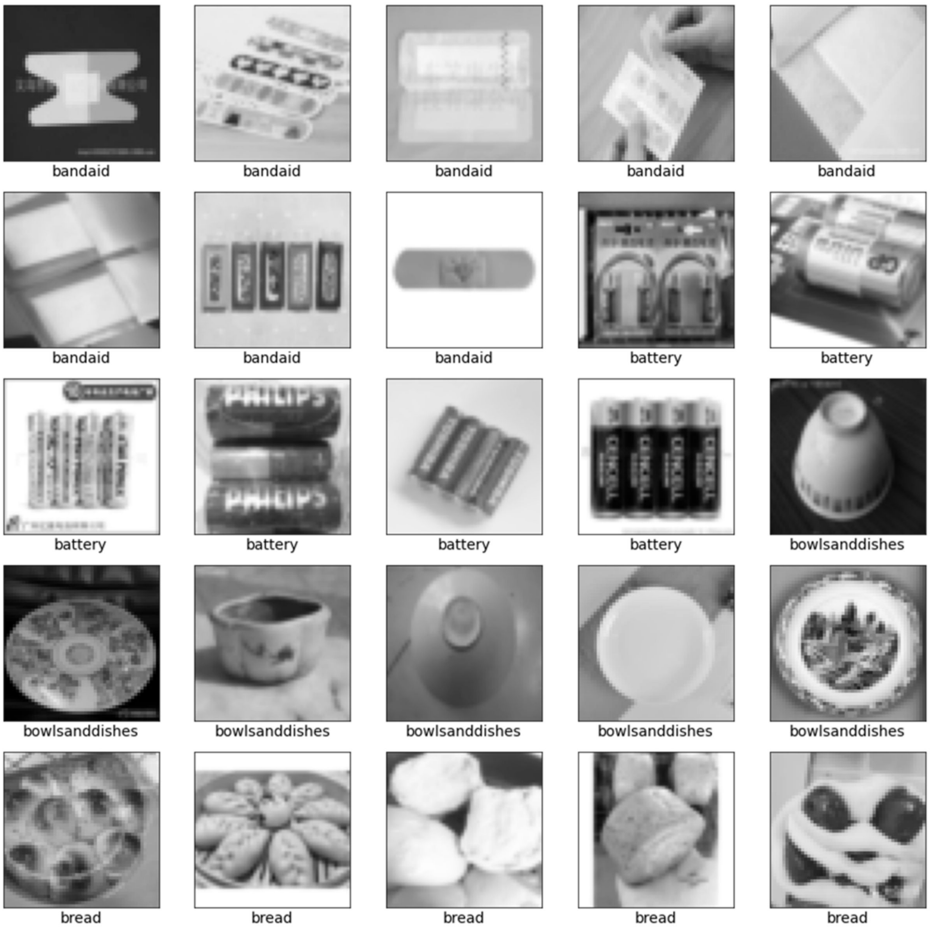

Figure 9. Image Samples (Indicative first five rows).

The specifications of the B0 model are shown as a model summary in Figure 10. These are rethinking models that are pretrained over the ImageNet for 1000 image annotations. These models utilize compound scaling that results in a much-improved efficiency over the same scale provided by other benchmark networks.

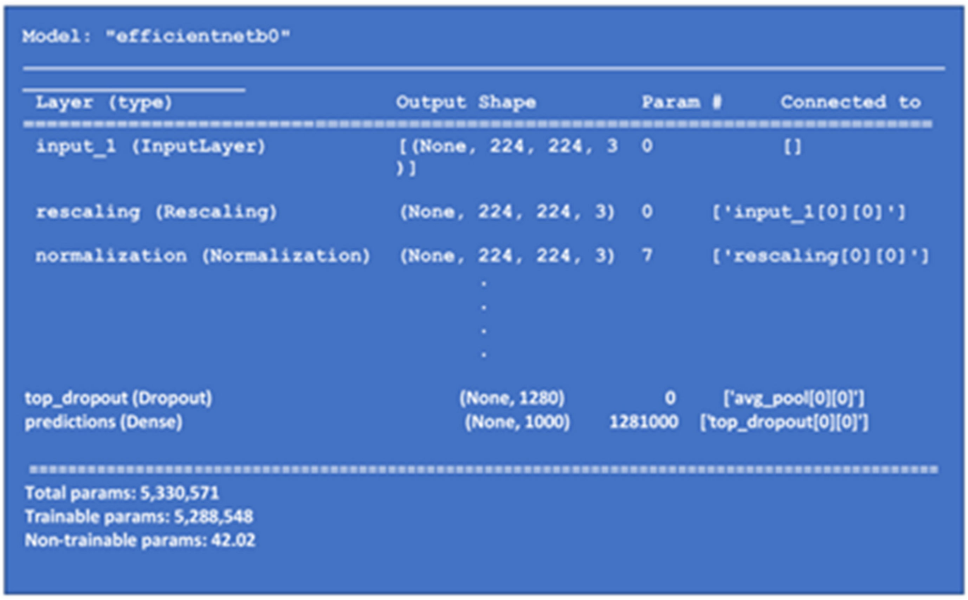

Figure 10. Model summary of the EfficientNet-B0 model accessible using TensorFlow in Python.

It is evident from the layer summary that the input layer accepts the input tensor of the order 224 × 224 × 3. The last layer has 1000 neurons corresponding to 1000 classes of objects that can be classified over the model. The model consists of a total of 237 layers grouped into five modules.

The training dataset consists of 34 classes of solid waste categories that are distributed over the directory structure of category labels, consisting of train and test directories, consisting of 23,628 files, including the testing and training datasets. We have performed a random sampling of the dataset using the test–train-split method in Python. The model ROC over the dataset, using a sequential model of CNN, is depicted as shown in Figure 11.

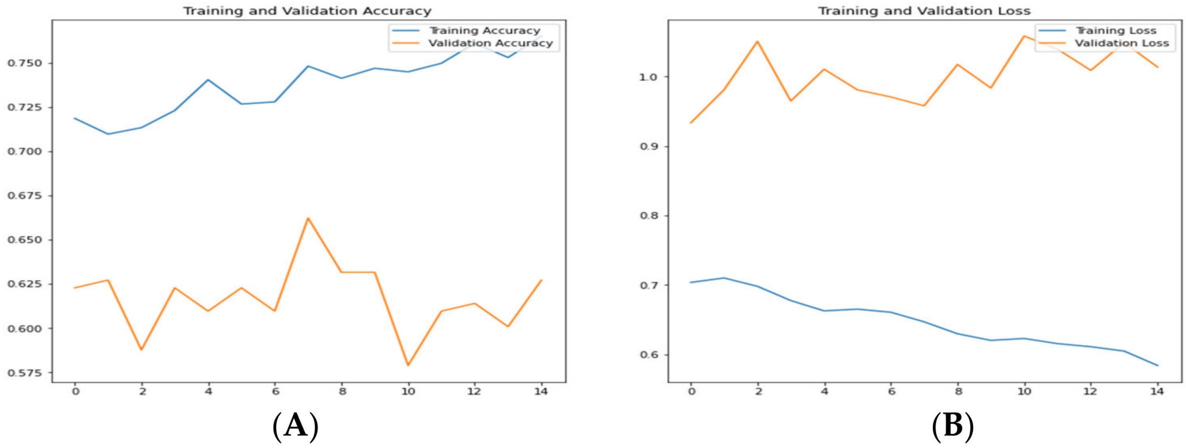

Figure 11. The horizontal axis represents the epochs and the vertical axis shows (**A**) Accuracy, and (**B**) Validation Loss.

It can be seen from Figure 11 that the maximum achievable accuracy with the traditional NN models is only 67%. However, this can serve as a solution as the model is inexpensive in terms of FLOPS and operates on images of dimension 224 × 224 × 3. Improvising the resolution of the images from 224 × 224 × 3 to 240 × 240 × 3 results in a slight improvisation of the accuracy, as shown in Figure 12.

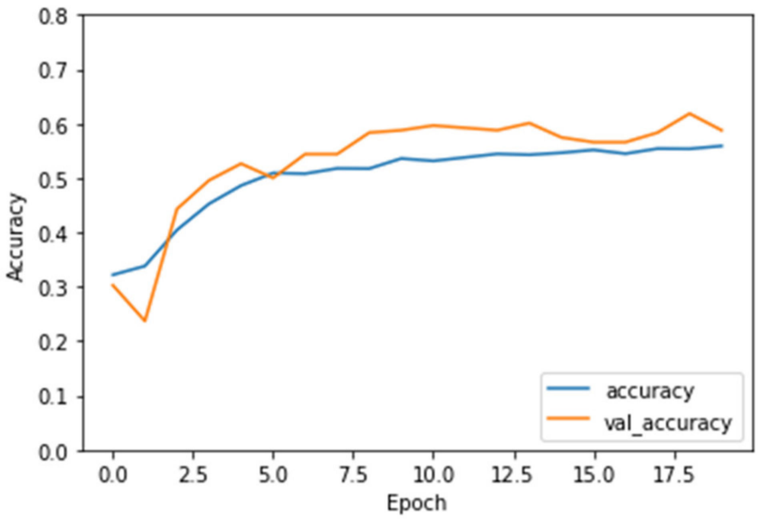

Figure 12. Improved accuracy under the same test-train set. Image Resolution = 240 × 240 × 3.

It is evident from the layer summary that the input layer accepts the input tensor of the order 224 × 224 × 3. The last layer has 1000 neurons corresponding to the 1000 classes of objects that can be classified over the model. The model consists of a total of 237 layers, grouped into five modules.

The ROC curve execution of the model over the categories of solid waste, as indicated in Table 4, is shown in Figure 13. It consists of the classification of 10 categories of solid waste samples using EfficientNet B0. The ROC curve depicts the accuracy of the model over the test–train split.

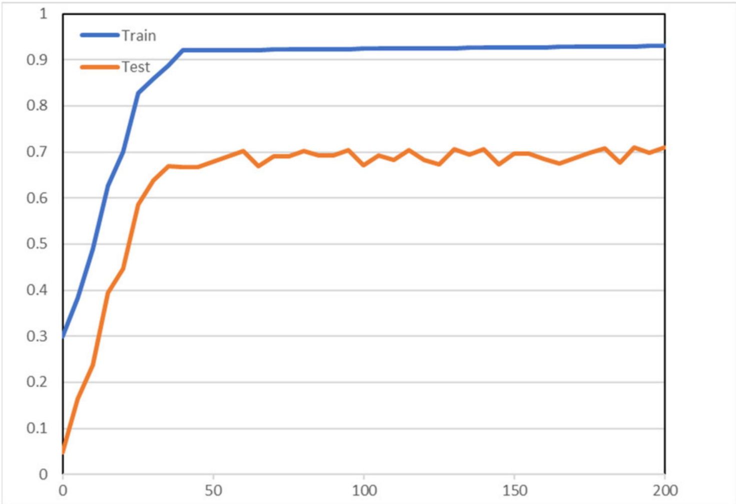

Figure 13. ROC Curve for accuracy of the model over Test and Train Data Sets of 1000 ImageNet classes mapped to 10 solid-waste classes using EfficientNet.

The model accuracy for the classification of 10 categories of solid waste samples, over Feed-Forward Networks, after fine-tuning over the "Solid-Waste-Images" region-specific dataset and transfer learning through EfficientNet B0 is shown in Figure 14.

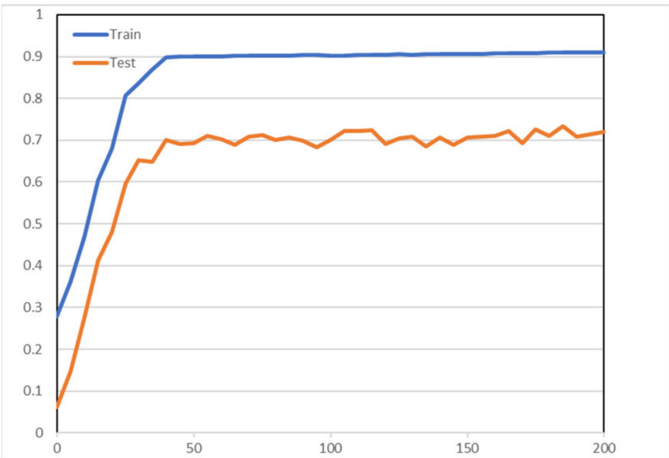

Figure 14. ROC Curve for accuracy of the Feed Forward NN Model, performance tuned with EfficientNetB0 and Dataset of 34 waste Categories of Test and Train Datasets of 34 Classes- Transfer Learning Approach.

It is evident that the transfer learning using EfficientNet-B0 is higher in performance, at a scale of 0.6 percent over the test dataset consisting of 11,823 training images belonging to 34 classes. Moreover, such a performance improvement is with a considerable reduction in the requirement of computing resources. The requirement of Floating-Point Operations per second for B0 is 0.39B, whereas, for B3, it is 1.8B, which gives a reduction of 4.61 times, which accounts for one GPU as compared to a 4GPU cluster. This gives a considerably low and cost-effective design as compared to the one using EfficientNet-B3 proposed in [1].

5. Conclusions and Future Scope

In this work, we have used transfer learning techniques over a base model B0, improvising its classification accuracy for solid waste images, and making it comparable in this particular domain, with the B3 model, thus, achieving an 85% image classification accuracy, with a model of which the upper limit of accuracy was previously 80%. However, this is for a specific group of images that corresponds to litter.

For the future scope of the work, the proposed model can be extended to the identification of subclasses among the same class. As indicated in the popular waste-images dataset consisting of 34 classes, the same will be extended into subclasses. For example, the class "carton" can be extended into large, medium, small, wood, cardboard, plastic, or any other related class. Moreover, transfer learning can be implemented using EfficientNet-B0 to B7, which gives state-of-art accuracy over the ImageNet dataset. Moreover, there is a number of issues that need consideration when implementing the model, for example, as part of a smart city project. These issues include the development of autonomous vehicles mounted with a robotic arm and an HD camera and efficient operation cycles over various types of areas with solid waste content.

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References

1. Majchrowska, S.; Mikołajczyk, A.; Ferlin, M.; Klawikowska, Z.; Plantykow, M.A.; Kwasigroch, A.; Majek, K. Deep learning-based waste detection in natural and urban environments. *Waste Manag.* **2022**, *138*, 274–284. [CrossRef] [PubMed]
2. Sharma, K.D.; Jain, S. Overview of municipal solid waste generation, composition, and management in India. *J. Environ. Eng.* **2019**, *145*, 04018143. [CrossRef]
3. Ceballos-Pinto, L.; Martinez-Jeronimo, F. Mass production of Scenedesmus incrassatulus in 8 and 40 liter disposable polyethylene bags with different culture media. *Rev. Latinoam. Microbiol.* **1995**, *37*, 109–119.
4. Ionescu, G.; Rada, E.C.; Ragazzi, M.; Mărculescu, C.; Badea, A.; Apostol, T. Integrated municipal solid waste scenario model using advanced pretreatment and waste to energy processes. *Energy Convers. Manag.* **2013**, *76*, 1083–1092. [CrossRef]
5. Devi, R.S.S.; Vijaykumar, V.R.; Muthumeena, M. Waste segregation using deep learning algorithm. *Int. J. Innov. Technol. Explor. Eng.* **2018**, *8*, 401–403.
6. Ziouzios, D.; Tsiktsiris, D.; Baras, N.; Dasygenis, M. A distributed architecture for smart recycling using machine learning. *Future Internet* **2020**, *12*, 141. [CrossRef]
7. Shi, C.; Tan, C.; Wang, T.; Wang, L. A waste classification method based on a multilayer hybrid convolution neural network. *Appl. Sci.* **2021**, *11*, 8572. [CrossRef]
8. Rahman, M.W.; Islam, R.; Hasan, A.; Bithi, N.I.; Hasan, M.M.; Rahman, M.M. Intelligent waste management system using deep learning with IoT. *J. King Saud Univ. Comput. Inf. Sci.* **2020**, *34*, 2072–2087. [CrossRef]
9. Al Duhayyim, M.; Eisa, T.A.E.; Al-Wesabi, F.N.; Abdelmaboud, A.; Hamza, M.A.; Zamani, A.S.; Rizwanullah, M.; Marzouk, R. Deep Reinforcement Learning Enabled Smart City Recycling Waste Object Classification. *Comput. Mater. Contin.* **2022**, *71*, 5699–5715. [CrossRef]
10. Mitra, A. Detection of Waste Materials Using Deep Learning and Image Processing. PhD. Thesis, California State University San Marcos, San Marcos, CA, USA, 2020.
11. Khan, R.; Kumar, S.; Srivastava, A.K.; Dhingra, N.; Gupta, M.; Bhati, N.; Kumari, P. Machine Learning and IoT-Based Waste Management Model. *Comput. Intell. Neurosci.* **2021**, *2021*, 5942574. [CrossRef] [PubMed]
12. Anh Khoa, T.; Phuc, C.H.; Lam, P.D.; Nhu, L.M.B.; Trong, N.M.; Phuong, N.T.H.; Dung, N.V.; Tan-Y, N.; Nguyen, H.N.; Duc, D.N.M. Waste management system using IoT-based machine learning in university. *Wirel. Commun. Mob. Comput.* **2020**, *2020*, 6138637. [CrossRef]

13. Chaturvedi, S.; Bikarama Prasad, Y.; Nihal Anwar, S. An Assessment of Machine Learning Integrated Autonomous Waste Detection and Sorting of Municipal Solid Waste. *Nat. Environ. Pollut. Technol.* **2021**, *20*, 1515–1525. [CrossRef]
14. Rutqvist, D.; Denis, K.; Fredrik, B. An automated machine learning approach for smart waste management systems. *IEEE Trans. Ind. Inform.* **2019**, *16*, 384–392. [CrossRef]
15. Dubey, S.; Singh, P.; Yadav, P.; Singh, K.K. Household waste management system using IoT and machine learning. *Procedia Comput. Sci.* **2020**, *167*, 1950–1959. [CrossRef]
16. Koonce, B. EfficientNet. In *Convolutional Neural Networks with Swift for Tensorflow*; Apress: Berkeley, CA, USA, 2021; pp. 109–123.
17. Tan, M.; Quoc, L. Efficientnet: Rethinking model scaling for convolutional neural networks. In Proceedings of the International conference on machine learning PMLR, Long Beach, CA, USA, 9–15 June 2019.
18. Córdova, M.; Pinto, A.; Hellevik, C.C.; Alaliyat, S.A.-A.; Hameed, I.A.; Pedrini, H.; Torres, R.d.S. Litter Detection with Deep Learning: A Comparative Study. *Sensors* **2022**, *22*, 548. [CrossRef] [PubMed]
19. He, K.; Zhang, X.; Ren, S.; Sun, J. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016.
20. Xie, S.; Girshick, R.; Dollár, P.; Tu, Z.; He, K. Aggregated residual transformations for deep neural networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA, 21–26 July 2017.
21. Hu, J.; Shen, L.; Sun, G. Squeeze-and-Excitation Networks. 2018. Available online: https://openaccess.thecvf.com/content_cvpr_2018/html/Hu_Squeeze-and-Excitation_Networks_CVPR_2018_paper.html (accessed on 8 April 2022).
22. Zoph, B.; Vasudevan, V.; Shlens, J.; Le, Q.V. Learning transferable architectures for scalable image recognition. In Proceedings of the 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Salt Lake City, UT, USA, 18–23 June 2018.
23. Huang, Y.; Cheng, Y.; Chen, D.; Lee, H.; Ngiam, J.; Le, Q.V.; Chen, Z. Gpipe: Efficient training of giant neural networks using pipeline parallelism. *arXiv preprint* **2018**, arXiv:1808.07233.
24. Dosovitskiy, A.; Brox, T. Generating images with perceptual similarity metrics based on deep networks. In Proceedings of the Advances in Neural Information Processing Systems (NIPS), Barcelona, Spain, 5–10 December 2016; pp. 658–666.
25. Huang, K.; Lei, H.; Jiao, Z.; Zhong, Z. Recycling Waste Classification Using Vision Transformer on Portable Device. *Sustainability* **2021**, *13*, 11572. [CrossRef]
26. Ziouzios, D.; Baras, N.; Balafas, V.; Dasygenis, M.; Stimoniaris, A. Intelligent and Real-Time Detection and Classification Algorithm for Recycled Materials Using Convolutional Neural Networks. *Recycling* **2022**, *7*, 9. [CrossRef]