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A Methodical and Intuitive Image Classifier for Trash Categorization Based On Deep Learning

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Abstract

Segregating renewable waste is a huge problem for several countries across the world. In addition to manual waste segregation, there are a number of automatic waste segregation processes. Manual waste segregation has its own set of drawbacks, including negative impacts on human wellbeing. As a result, an effective waste segregation system is required. The article proposes an effective IoT (Internet of Things) and a garbage sorting system based on deep learning that aids in classifying the custom dataset under consideration (garbage classification-12 classes) as well as real-time images taken from waste bin cameras. The classification scheme is intended to effectively mark the disposal of the collected wastes faster and more efficient. Thus, the model is learned to identify images into 12 waste classes: biotic, cardboard, clothing, metal, paper, plastic, shoes, brown glass, white glass, green glass, battery, and others(trash), utilizing image processing.The proposed framework is based on the updated Xception paradigm and is trained on an open source pooled dataset, with 96 percent test accuracy. As a result, the proposed system will be able to improve separation efficiency and intelligence without needing or minimizing human interference.

Keywords: Open source dataset, 12 classes, xception model, automated, garbage segregation

Introduction

The present-day system of waste/garbage separation is most pre-dominantly hand-picking method, wherein someone is hired to segregate the various objects/materials. The person who separates waste is vulnerable to pathogens because of the dangerous chemicals in the garbage. The housing characteristics, residential and household situation, and satisfaction associated with eco-social relationship of trash pickers in León, Nicaragua are investigated in this study performed by Vázquez , J. J., Suarez, A. and Berríos A [31]. The majority of trash pickers live in slums, according to the findings. Although a significant number of trash pickers are dispersed across the city's various neighborhoods, a large proportion of them live in residential segregation. In light of this, a waste-sorting technique that is automatic has been proposed. Compared to the manual process, this system can sort waste in less time and with better precision. The big concerns that arise as a result of poor waste management are human health risks, environmental issues, and so on. As a result, an unhealthy environment is created in which to live. Recycling wastes is ineffective since segregation of wastes at junk yards is tedious as well as time-consuming process. These disadvantages can be mitigated by adequate waste management at home. The primary goal of suggested by B. R. S. Kumar, N. Varalakshmi, S. S. Lokeshwari, K. Rohit, Manjunath and D. N. Sahana [31] in their paper is to develop efficient methods for collecting waste and segregating at the household level, based on their composition, such as metal, plastic, and biodegradable waste, which is then stored in the appropriate segments of the dustbin. Burning waste is another common method of waste disposal, but this can cause air pollution and the spread of hazardous waste products into the air, which can cause cancer. Recycling waste is also vital to protect the atmosphere and human health, and people can separate waste into several components that could be recycled in various ways. There are several machine learning models developed already to segregate the wastes and contribute to the environmental well-being. Our proposal focuses on providing a better solution to the existing system. The system in place provides for the recycling and conversion of valuable separated waste into electricity and power for economic growth.

Literature Survey

OlugbojaAdedeji, Zenghui Wang [1] suggested a residual network composed of fifty layers (resnet50) and a SVM classifier which provides 87% accuracy by classifying the wastes into 6 classes namely glass, plastic, metal, paper etc. Rismiyati, S. N. Endah, Khadijah and I. N. Shiddiq [2] suggested an approach based on transfer learning to enact classification tasks on TrashNet dataset. They have also used ImageNetpretrained VGG16, ResNet-50, and Xception model for the study. C. Bircanoğlu, M. Atay, F. Beşer, Ö. Genç and M. A. Kızrak[3] proposed an Inception-Resnet, Inception-v4 models that outperformed other models with 90 percent test precision with no pre-trained weights.DenseNet121 provided better performance with 95 % test accuracy and fine-tuned weight parameters using ImageNet. Huang, G-L, He, J, Xu, Z, Huang,G. A[4] suggested a modern architecture paradigm for processing the ImageNet database based on three pretrained CNN models (VGG19, DenseNet169, and NASNetLarge), which revealed considerable outputs. Syed Ayaz Imam, M. Monica Subashin[5] addressed the implication of the VGG-16, VGG-19, InceptionV3, and Xception frameworks which was imbibed to the classification system for military induced waste.

M, Aghilan and M, Arun Kumar and TS, Mohammed Aafrid and A, Nirmal Kumar and S, Muthulakshmi[6] presented a multi-layer perceptron that was trained and tested manually labeled objects, and achieved total classification accuracy greater than 90% in two separate testing frameworks, surpassed a reference CNN-based approach that uses image inputs. M, Aghilan and M, Arun Kumar and TS, Mohammed Aafrid and A, Nirmal Kumar and S, Muthulakshmi [6] suggested a sustainably viable model, as well as traditional machine learning algorithms, which showed how advanced machine learning could be employed to solve real-world issues in Smart Waste Management system.White, Gary, Christian Cabrera, Andrei Palade, F. Li and S. Clarke [7] suggested a classification model where paper, glass, metal, plastic, cardboard, and others are divided into 6 groups. The model had a prediction accuracy of 97 percent on the test dataset. This stage of classification precision would cater with certain typical problems associated with smart bins, such as recycling pollution, which happens when different types of waste are combined with recycling waste, contaminating the bin. Brintha V.P., Rekha R., Nandhini J., Sreekaarthick N., Ishwaryaa B., Rahul R[8]elucidated a system to identify wastes as biodegradable or non-biodegradable, where an automated garbage recognition system based on a deep learning algorithm was implemented. Yunyi Liao [9] lined up to utilize a picture as an input and determine which trash group it belongs to. Web crawlers were created that can capture photos. They turned out with about 14,000 images after pre-processing.On the dataset, they compared CNN, a ResNet50 model, and VGG16 model, among others. The experiments showed that ResNet50 model outperformed the others.

Satvilkar, Mandar [10] suggested a Convolutional Neural Network (CNN) model with Extreme Gradient Boosting that was employed to see if it could outperform a CNN.Wang, Ying & Zhang, Xu [11] targeted using a deep learning methodology to detect garbage automatically by making use of a Faster R-CNN with area proposal network and ResNet network algorithm. G. E. Sakr, M. Mokbel, A. Darwich, M. N. Khneisser and A. Hadi[16] used deep learning using convolution neural networks (CNN) along with support vector machines (SVM) for their target garbage classification. Using just a 256X256 colored waste image which is of PNG format, each algorithm generated different classifier that divides waste into three major categories namely plastic, metal and paper. S. Sudha, M. Vidhyalakshmi, K. Pavithra, K. Sangeetha and V. Swaathi[17] suggested an automatic recognition method that uses a deep learning algorithm to segregate objects into biodegradable and non-biodegradable, where the system could detect real-time objects and classify them correctly after being trained with an initial dataset. Using and comparing multiple AL approaches in two separate application domains, Ahmad, N. Said, B. Qolomany, J. Qadir and A. Al-Fuqaha[18] suggested an AL-based FL architecture. They demonstrated that AL is effective in federated and unified learning by attaining sustainable outcomes with data labeled manually using smaller samples in the selection of training data through an elaborate experimentation setup.

Xu, X.; Qi, X.; Diao, X[19] constructed the rebuilt network which was used extracting features, and the features are inserted into the SVM to realize the detection of 6 types of trash by migrating and restoring the lightweight neural network MobileNetV2. Using 2527 samples of garbage labelled data available in the TrashNet dataset, the model was learned and verified. Hussain, A.; Draz, U.; Ali, T.; Tariq, S.; Irfan, M.; Glowacz, A.; Antonino

Daviu, J.A.; Yasin, S.; Rahman, S [20] suggested a conventional model which is a combination of k-nearest neighbours algorithm (KNN) and logistic regression and a long short term memory (LSTM) network-based deep learning algorithm for the notification of warning messages about bin status and detecting the quantity of air pollutant carbon monoxide (CO) present in the air at a particular case. Constantine E. Kontokosta, Boyeong Hong, Nicholas E. Johnson, Daniel Starobin [21] suggested a regression model with gradient boost to predict the residential and urban garbages. Initially, they measured building-level waste on a daily and weekly basis and recycling tonnage using a comprehensive dataset for the waste generation in NYC. In New York City, their concept encompasses over 800,000 residential houses. Md. Shafiqul Islam, M.A. Hannan, Hassan Basri, Aini Hussain, Maher Arebey [22] proposed a Multi-Layer Perceptron (MLP) classifier to define the level of the waste bin and approximate the quantity of waste within the bin. To measure classifier output, the region under the Receiver Operating Characteristic (ROC) curves was used. The established system's findings are similar to those of previous image processing-based systems. Based on the predicted bin level, the model was used to refine waste collection routing. Using advanced image processing and load cell technology, Jagtap S, Bhatt C, Thik J, Rahimifard S [23] an automated and real-time device based on Internet of Things (IoT) principles was suggested to calculate total amount of waste as well as causes for waste production in real-time. To assess a possible explanation for potato waste generation, a deep learning architecture called the convolutional neural network (CNN), is used. During the training phase, a limited collection of samples yielded a 99.79 percent accuracy.

M.A. Hannan, Maher Arebey, R.A. Begum, Hassan Basri [24] created a new model in response to environmental issues around trash cans and the types of garbage that are exposed of in them. To remove the bin image texture, a grey level aura matrix (GLAM) solution was proposed. The optimum values of GLAM parameters, such as adjacent structures, were investigated. Mesut Toğaçar, Burhan Ergen, Zafer Cömert [25] created an AutoEncoder network which was used to recreate the dataset used for waste classification. Convolutional Neural Network (CNN) architectures were used to derive feature sets from two datasets, which were then merged. On the combined feature collection, the Ridge Regression (RR) approach decreased the number of features while still revealing the productive features.

The proposed model definitely stands out as it proposes an efficient classification algorithm using the pre-trained model Xception with twelve different classes which adds novelty and accuracy to the system. Since the system classifies wastes into twelve classes, it easily facilitates for green recycling and efficient disposal of wastes. The proposed work also facilitates the real-time segregation of trash.

Materials and methods

The suggested work in this paper incorporates transfer learning methodology to sort images of trash or garbage. The use of transfer learning allows for the use of a pre-defined model called Xception, as well as the addition of a few layers to improve the classification system's accuracy.

Data Collection

A. N. Kokoulin, A. I. Tur and A. A. Yuzhakov [26] provided a concept for automated recycling of plastic as well as metal waste, which is an alternative method for the end-user economic incentive-a discount and bonus scheme in large trade networks. These devices were as inexpensive as possible while also providing a high level of reliability and protection. Traditionally, IoT devices such as controllers and single-core computers have been used to construct the basic components of this system, which have severe memory and computing limitations. Nonetheless, using cameras, these controllers were capable to distinguish the trash forms and provide classifying and preprocessing. They suggested using IoT to incorporate CNN for reverse vending machines. Using the TensorFlow paradigm and a pre-trained object detection model, T. J. Sheng et al [29] was able to identify objects and classify waste. This model is trained with waste images to create a inference graph, which is then used to detect objects using a camera connected to the Raspberry Pi 3 Model B+ as the core processing unit. Each waste compartment contains an ultrasonic sensor that monitors the amount of waste filling. A GPS module is built in to map the real-time bin's position. The LoRa communication protocol is used to submit data about the bin's location, real-time state, and filling speed. An RFID module has been embedded for identifying waste management staff. All such implementations are highly expensive and not really practical in real time scenarios. The suggested method categorises garbage images into 12 distinct groups. It employs the “Xception” paradigm, which has been pre-trained on the ImageNet dataset. The ImageNet dataset includes a vast amount of data, with over 14 million images categorised into about 22,000 groups. This paper considers a simplified and optimised version of the ImageNet dataset, which includes 1000 categories. The custom dataset is generated by a series of real-time images from the waste bins based on IoT architecture (UV cameras). The model is used to predict the real-time new images from the custom dataset, which was trained on the optimised ImageNet dataset.

Methodology of Transfer Learning

The standard garbage classification dataset has six classes of household garbage namely cardboard, plastic, metal, trash, glass and paper. Adedeji, O., & Wang, Z. [14]used 6 classes of garbage images. Most of available datasets hold 2 to 6 classes of garbage. The more the available classes, the more would be the capability of the trash to be recycled. The hypothesis of web scraping was employed to retrieve images for certain classes like food remains, rotten fruits, clothes, shoes. Therefore the obtained dataset holds 15,510 images with 12 classes of household wastes namely cardboard, biotic, plastic, metal, green-glass, brown-glass, white-glass, clothes, shoes, batteries and others (trash).

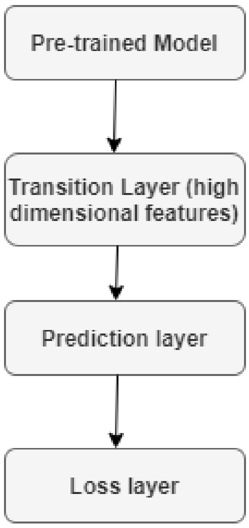


Fig 1 – General workflow of transfer learning model.

The above Fig 1 provides the general workflow of transfer learning architecture. A lot of data is normally needed to train a neural network from scratch, but access to that data is not always feasible. Transfer learning comes into play in this situation. Transfer learning can be used to build a solid machine learning model with relatively few training data since the algorithm has already been pre-trained. We can simply restore the original model and retrain any of the layers for our mission if it was designed with TensorFlow. Transfer learning, on the other hand, only succeeds if the features learned in the first challenge are general, ensuring they can be applied to another task. In addition, the model's feedback must be the same size as it was when it was first trained. N. Baras, D. Ziouzios, M. Dasygenis and C. Tsanaktsidis [27] proposed a low-cost, high-efficiency Smart Recycling Bin that makes use of cloud technology to help with waste classification. A structured Information System (IS) gathers data from smart bins placed in the city and uses Artificial Intelligence and neural networks to classify the waste in each bin. Their implementation was able to identify various forms of waste with a 93.4 percent precision while holding deployment costs and power usage to a minimum.

Weiss, K., Khoshgoftaar, T.M. & Wang, D [12] cited the transfer learning methodology which enables to make use of an already trained model on a subsisting problem thereby to transfer the obtained knowledge of pre-trained model and additionally learn new features rather making the model learn from scrape. The scraped

ImageNet dataset has more images than the traditional Garbage classification dataset, so the transfer learning approach is used here to improve the precision and accuracy of our predictions. L. Omar, R. Oscar, T. Andres and S. Francisco [28] They demonstrated an efficient garbage segregator (TrashCan) that would eliminate recycling bins by collecting trash and separating it into separate containers using a multimedia embedded processor and pattern detection to allow for garbage collection, which is very expensive.

C. Data preparation

Data preparation is one of the essential primary steps in machine learning where the raw data is transformed into better information to gain insights or make predictions. The data preprocessing phase is considered due to complicated issues such as missing or inconsistent records, anomalies, unstructured data, categorical variables that are non-standardized, sparse attributes.

D. Importance of Data Preparation

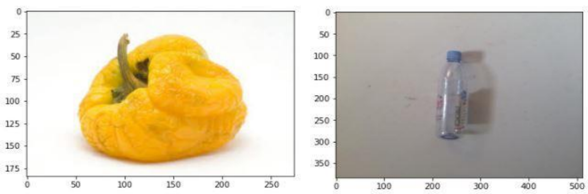
Datasets will almost always need some planning before they can yield useful insights, as most machine learning algorithms require data to be formatted in a certain way. Any datasets have values that are either incomplete, incorrect, or otherwise impractical for an algorithm to process. The algorithm is unable to use data that is missing. Some datasets are comparatively clean but require shaping (aggregated or pivoted), while others simply lack valuable business context, necessitating feature enrichment. Clean and well-curated data is produced by good data preparation, resulting in more realistic and precise model outcomes.

The figures obtained from the obtained Garbage collection dataset are labeled in accordance with the classes such as

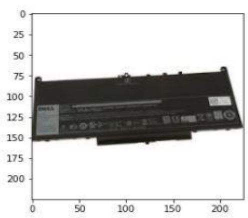
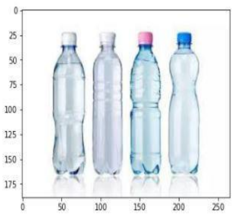
S.NO	Class Name	Category
1	Paper	0
2	Cardboard	1
3	Plastic	2
4	Metal	3
5	Trash	4
6	Battery	5
7	Shoes	6
8	Clothes	7
9	Biotic	8
10	Green-glass	9
11	Brown-glass	10
12	White-glass	11

CATEGORIES OF LABELLED IMAGES

The various classes of images are labeled in table 1 and are grouped into a data-frame. The figure visualizes a few sample images derived out of the dataset.



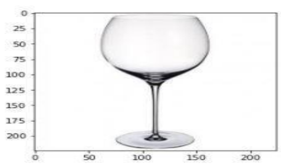
(a) Biotic (b) plastic

(c) Battery (d) plastic

(e) Clothes (f)Green-glass

(g) Metal (h) white-Glass

Fig 2 Sample images of the dataset – 12 classes

Proposed method

The proposed method incorporates the utilization of pre-defined Xception model accompanying modified CNN layers. The model is constructed by freezing the layers of the xception model excepting the final layer, followed by the addition of a series of convoluted layers.

A, Traditional Xception Model

F. Chollet, [13] suggested a modified deep learning system called Xception, an improved version of Inception V3 model. A depth-wise separable convolution is cited to be "separable convolution." To create the initial depth-wise separable convolution, the depth-wise convolution is followed by a point-wise convolution. A depth-wise convolution, which is a spatial convolution done separately over each channel of an input, and a point-wise convolution, which is a 1x1 convolution that projections the channels output by the depth-wise convolution into a new channel space.

B. Xception Architecture

The Xception architecture is a linearly layered depthwise separable convolution layer stack with residual relations**.** Since this modern model uses depthwise separable convolutions, the word "Xception" means "Extreme Inception."

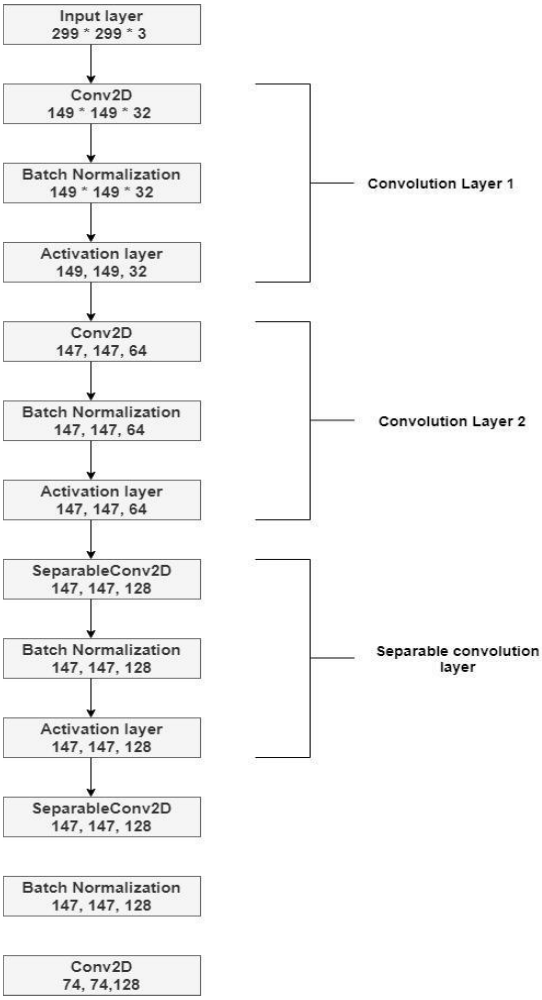


Fig 3. Xception model – predefined architecture

C. Proposed Model

To achieve transfer learning, a pre-trained model is used. To reuse a pre-trained model, the layers are loaded first and then frozen to prevent any of the information they provide from being lost in subsequent rounds. Followed by then the standard classifier portion is deleted and replaced with a new one that better suits our needs.

D. Requisite for the Xception Model

Zabir, M. &Fazira, N. & Ibrahim, Zaidah&Sabri [15] made constructive comparison between AlexNet and GoogLeNet. For transfer learning, the Xception model is used as a foundation.Instead of inception modules, extreme inception, or Xception, uses a depth-wise convolution model. It is a stack of linear depthwise separable convolution layers with residual relations.

On the defined ImageNet dataset, Xception marginally excels in performance of the Inception v3, but massively outperforms on a broader image segregation dataset. It also has the identical model parameters as Inception, suggesting higher computational efficiency. Xception's architecture is now powering Google's mobile vision applications via MobileNet, despite the fact that it is still relatively new.

System Architecture

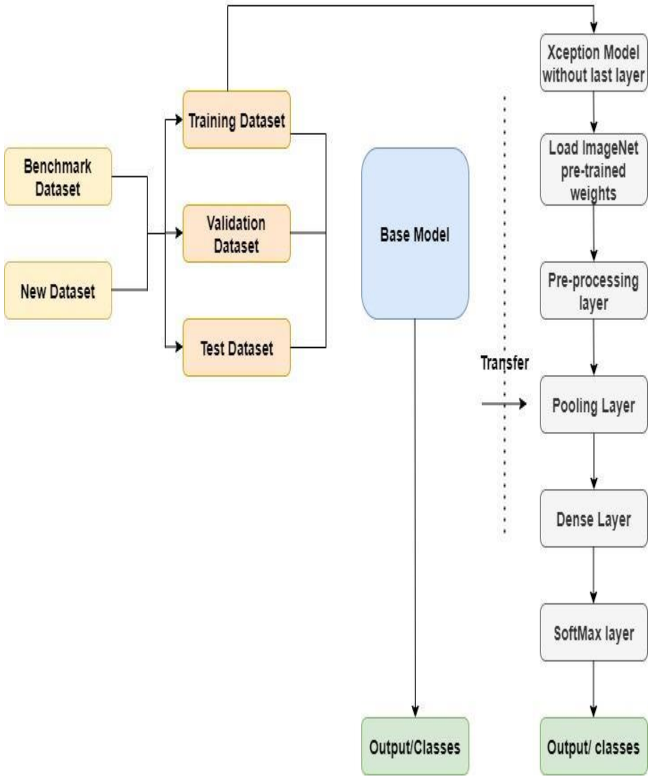


Fig 4. Proposed model architecture

The fig3 depicts the architecture of the Xception model, which has a 299x299 input dimension. Two main concepts underpin the effective architecture: depthwise separable convolution and convolution block shortcuts. The model's feature extraction base is made up of approximately 36 convolutional layers. Batch normalization is applied on both Convolution and Separable Convolution layers. For both separable Convolution layers, the depth multiplier is one.

Except for the last layer, the pre-trained model layers are frozen. The ImageNet model weights are loaded, and the default xception model's lambda expression for the pre-processed layer is retrieved. A pooling layer (This layer's primary goal is to shrink the size of the convolved feature map in order to reduce computational costs. This is accomplished by reducing the relation between layers and operating independently on each function map. There are various types of Pooling operations, depending on the system used. Usage of 2D Global Average pooling operation is demonstrated). After that, there's a softmax activation function. (They're used to learn and approximate some kind of continuous and dynamic network variable-to-variable relationship. It induces non-linearity in the network.)

K. Akhmetzyanov and A. Yuzhakov [30] suggested a hyperparametric optimization algorithm and manual search of architectures to conduct an intuitive search for the architecture for the original efficient neural network. The built neural network must meet the following criteria: fast image processing, low memory requirements, and high object recognition accuracy under a variety of lighting, backgrounds, angles, and geometric deformations.

Implementation

The study was carried out on the Google collaborative framework making use of the Keras library as an API and TensorFlow backend. Google Colab provides free access to a versatile GPU as well as a fully optimised deep learning runtime. The pre-trained Xception model was loaded into Imagenet, with the exception of the last layer. This is the convolutional basis for feature extraction. On top of this base model, a global average pooling layer, which will act as the classifier part, is applied, followed by a dense layer. (an additional dropout layer to avoid overfitting) and its output is fed directly into the softmax enabled layer.

A. Model Training

The training set was categorized into three parts:

- ❖ The training set is the set where the model was trained on.
- ❖ The validation set: is to ensure that the model is not over-fitting the training set, and that it can generalize to data other than the training data.
- ❖ The test set is used to estimate the model's performance on new data that varies from the training data. Splitting the data only into training and validation sets could be able to achieve the highest possible accuracy without having to properly estimate how accurate the model is.

The dataset was divided into two parts: 80% training sets, 10% cross-validation, and 10% test sets. To take advantage of model strength, fine tuning of the weights is performed on the selected best performing model. For fine tuning, network ran through 20 epochs at first and then 50 epochs later. The last layer was frozen, and the remainder of the layers were tweaked. With a default learning rate of0.001, the Adam optimizer was used. For all of the training tests, a batch size of 16 was used. As performance metrics, the network's train and validation accuracies, as well as their respective losses and an uncertainty matrix, are measured and mapped.

B. Algorithm

Step 1: Download the required libraries

Step 2: Load input images from dataset

Step 3: Perform data augmentation and pre-processing

Step 4: Split the train and test set

Step 5: Batch size =16, No of classes = 12

Step 6: Load the transfer learning model

Step 7: Build the classifier layer

Step 8: Compile the model

Step 9: Train the model.

Step 10: Perform hyper-parameter search and fine tune the model

Results and discussion

During the model's initial training, the model had an accuracy about 90% for the validation set and training accuracy of around 93 percent. In order to increase the model's performance, it was fine-tuned. The validity accuracy of the previous model was increased to 96 percent by fine-tuning the weights. Due to hardware limitations, the training lasted about 20 epochs and the fine tuning took 50 epochs. It takes about 20 minutes to complete the simulated GPU training on Google colab Notebooks. The optimizer function used for the training process is Adam optimizer, with a learning score of 0.001.

To see if their model is overfitting, a method known as cross-validation is used where the data is divided into two parts: the training set and the validation set. The validation set is only used to test the model's performance, while the training set is used to train it. We divided the training dataset into two sections with an 80:20 split ratio. Rather than breaking the dataset at the beginning, it is split at each epoch. The dataset is shuffled at each epoch to ensure that the training and validation datasets are still separate. This offers a deeper explanation of the model's results. If the validation loss is very much greater than training loss, it means that our model is over-fitting. If the validation loss is very much less than training loss, it may be referred to as under-fitting.

The graph shows the training and validation loss, accuracy obtained. When using a pre-trained deep model to extract features from a small dataset, it was discovered that the model was much accurate and faster than the baseline model, also in CPU mode.

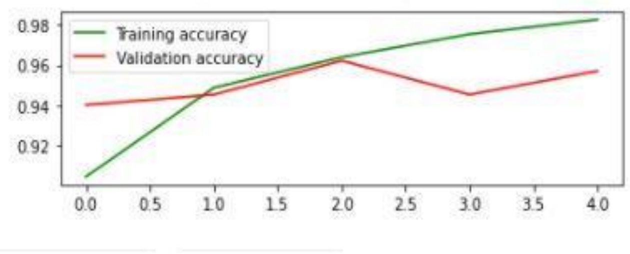


Fig 5. Plot on Training and validation accuracy

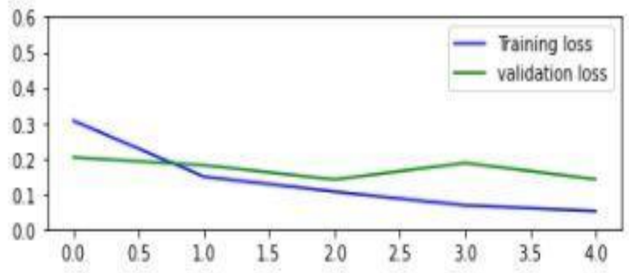


Fig 6. Plot on Training and validation accuracy

This demonstrates that when high precision is required and time required is limited, very deep models are preferable to shallow models. The maximum and minimum training losses are respectively 5.0 percent and 1.0 percent.The model should lose as little as possible, and a declining value indicates that it is learning during the training.If the loss does not decrease, early stopping could be performed (ie) training can be stopped at any time. TensorFlow Lite was employed to transform the learned model. The model was quantized by transforming the weights from floating point to integers. This reduces lag while having only a minor effect on accuracy.Both the size and the latency of the model have been optimised.

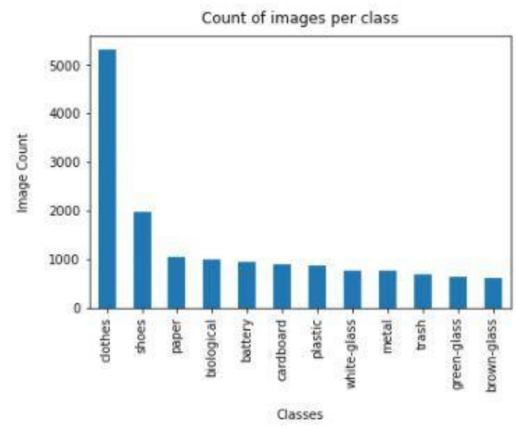


Fig 7. Count of images in the dataset for the respective 12 classes. It could be seen that

The table below indicates the classification report of the different classes classified and their respective precision, recall and F1-score.

class	Precision	Recall	F1-score
Battery	0.93	0.98	0.95
Biological	0.98	0.95	0.96
Brown-glass	0.87	0.96	0.91
Cardboard	0.99	0.90	0.94
Clothes	0.98	0.99	0.99
Green-glass	0.91	0.85	0.88
Metal	0.80	0.89	0.84
Paper	0.93	0.93	0.93
Plastic	0.92	0.87	0.89
Shoes	0.99	0.95	0.97
Trash	0.92	0.96	0.94
White-glass	0.95	0.83	0.84

classification report of the model

Metrics	[33]	[34]	Proposed model
Test Accuracy	94.5 %	94.22%	95%
Average Precision	93.20%	90.24%	94.98%
Average F1 Score	91.30%	91.20%	96.21%
Loss	0.857	0.567	0.789

Table III :classification report of the model

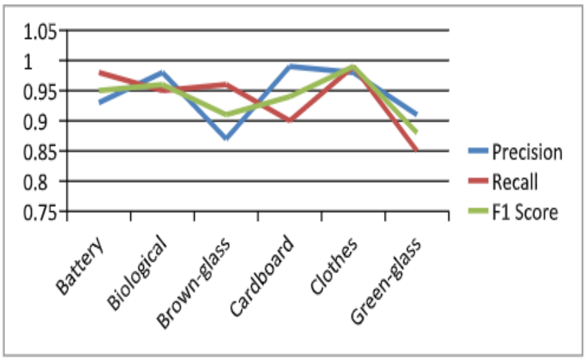


Fig 8.1. classification metrics (precision, recall, F1 score) for first 6 classes

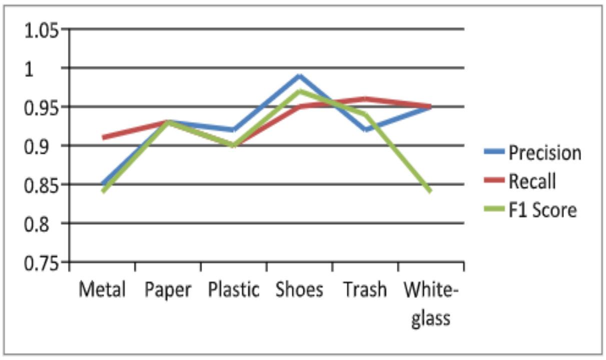


Fig 8.2. classification metrics (precision, recall, F1 score) for other 6 classes

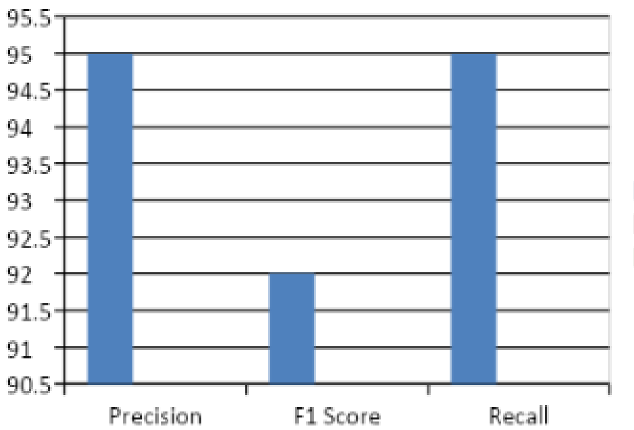


Fig 9. Overall performance of the model (based on computational metrics - precision, recall, F1 score)

The fig (8.1) and (8.2) denotes the graph obtained for the 12 different classes of waste classification which portrays the precision, accuracy and recall score of the categorization model. The graph (9) denotes the overall performance of the proposed model measured with respect to precision, F1 score, recall values. The table III indicates the constructive comparison between two other models and it is concluded that the proposed architecture outperforms well.

Conclusion

The paper proposed a waste sorting system that could classify waste into separate categories. On the qualified model, the model achieved 95 percent accuracy. The model is also capable of classifying the wastes into 12 different categories which provides better insights for trash segregation. The model's optimization would result in still more latency reduction. The use of computer vision on edge devices will expand in the future as deep learning models increase in accuracy and processor processing capacity increases. The system outputs expected results from the experiment, and the network shows its efficient generalization capacity when small area artefacts appear. The identification of garbage in urban scenes in near-real time and with high precision is achieved, which has a high functional value. Finally, it is agreed that this will be a right step in terms of using technology to assist in protecting our environment.

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