DOMESTIC WASTE SEGREGATION USING DEEP NEURAL NETWORKS

MSc Research Project
Data Analytics

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Project Submission Sheet
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Student Name:	Iswarya Yogeashwaran
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Programme:	Data Analytics
Year:	2021-2022
Module:	MSc Research Project
Supervisor:	Dr Giovani Estrada
Submission Due Date:	31/01/2022
Project Title:	DOMESTIC WASTE SEGREGATION USING DEEP NEURAL NETWORKS
Word Count:	4997
Page Count:	19

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DOMESTIC WASTE SEGREGATION USING DEEP NEURAL NETWORKS

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Abstract

Everyone's life has been dramatically affected by significant environmental challenges. Environment and living species suffer from a variety of difficulties because of improper waste disposal. People's negligence, insufficient information about waste types, and bad habits are factors that influence appropriate waste disposal. Generally, rubbish is physically classified. The garbage truck, that separates garbage into biodegradable and non-disposable categories, has innovated this process. The image recognition methodology is used in this system. In this study, the techniques of Custom CNN, VGG16, Mobile-net, and Xception are assessed using analytics to sort garbage into corresponding classes. We may minimize this wrong waste disposal issue at source by developing smart home bins that mishandle fewer items. We expect higher waste segregation efficiency by using smart bins than solutions used at final stages. It transfers far more responsibilities to users and waste collection, and therefore increase the final waste disposal efficiency. A range of techniques, such as VGG16, Custom CNN, Mobile-net, and Xception techniques were tested in this work. In this research, a custom CNN model achieved 90.21% of validation accuracy, 90.27% of validation precision and 90.05% of validation recall. The enhanced model training efficiency allows it to run over 22,564 images, while other models can classify 6443 images in the same allocated time. As Custom CNN has scored really good accuracy even by compiling more data, it is being chosen as Optimum model and implemented into the prototype. This model is saved in a path to integrate with Flask front end to create a web application which has predicted the image into proper category when it has uploaded.

1 Introduction

The major benefits of waste categorization resulted in a reduced amount of infrastructure required as well as the transformation of junk into wealth is explained in this paper (Fakhim Ahmadi et al.; 2010). Some compounds in household garbage have a negative impact on the soil. Humans could categorize recoverable and challenging items to keep those out of the garbage. Recycling old rubbish can assist to reduce the amount of waste produced. Plastics are already being repurposed to make fuel, and repurposing rubbish papers might save trees from being cut down to make lots of paper. Several bottles can be dissolved to make a ton of conventional aluminium block, safeguarding tonnes of aluminium ore. Bottles might also be used to create environmentally sustainable and resource-saving pencil packaging. Biodegradable and non-biodegradable waste are the two categories of garbage. Organic wastes are those that can be broken down in small fragments by microorganisms. Food waste, horticultural trash, papers, and other compostable garbage are instances.Non-biodegradable materials, on the other end, are garbage that cannot be degraded by organic substances. Biowaste destinations include dumps, disposal facilities, repurposed products, and decomposition. The trash cycle must be understood since it relates to the proper disposal items. When materials are sorted into the wrong recycler, they get polluted.

1.1 Motivation

The four Deep learning architectures were used to build 8 transfer learning classifiers in this paper (Guo et al.; 2019). The end up wasting classifiers totaled four, and the disposal classifiers comprised four. Assessment of the Concept For mistake estimates and model identification, the cross-validation approach is well-known. The 10 fold cross-validation analysis was conducted to assess our trash categorization algorithms. The following criteria have been used to assess the project: *"Classification performance"* and *"Identification different classifiers"*. If a trash item is labeled as papers, it is considered reusable. It is a toxic waste if a garbage is a lamp. As a result, the trash category may be deduced from the disposal category. We may utilize the outcome from the disposal classification to determine trash category in order to incorporate the disposal classification algorithm explicitly. Our dataset that contains 20 disposal categories and four disposal subclasses. When trash items are classified at the component level, a 20x20 clustering algorithm is produced. Trash item categories are arranged such that categories of the very same rubbish category are next to one another. As a result, from disposal CNN model, a disposal confusion matrix (4x4) may be constructed (20x20). The observed and forecast disposal categories are added to the disposal cells. After constructing the resulting end up wasting confusion matrix, the efficiency of an end up wasting classification was evaluated using the framework. At both the disposal and disposal levels, our information was balanced. The average total scores of all classes categorized by the system were used to calculate model levels of accuracy.

1.2 Research Question

The application area of this work focuses on segregation of two types of waste: bio- and non-biodegradable. We know deep neural networks are very successful at image classification. The research questions are therefore:

- To what extent can deep learning neural networks be applied for waste segregation?
- Which type of deep neural network architecture is better at classifying bio-degradable and non- biodegradable waste?

Bio-degradable and non- biodegradable waste segregation will be studied using a range of deep learning techniques, such as VGG, CNN, Xception, and Mobile Net. The techniques will be compared and ranked according to their accuracy, precision, and other metrics to find the best deep neural architecture for the application at hand. The best one will be integrated to a web application prototype to show the end-to-end concept.

1.3 Research Objectives

The main objective is to find out what type of deep neural network architecture is more suitable for the waste disposal. In other words, the research will end the study by being able to specify deep neural network factors which emerged as being important for this image classification problem.

Individual steps are described in Figure 1. In the Section 2, the literature survey are evidently analyzed to find the gap of the research.Then, Section 3 explains the methodology of the research and the stages of execution taken part in the research. Further, Section 4 is about the design specifications, which explains the novelty in every stage.The Section 5 describes the implementation works and the usage of tools. The performance of the models is analyzed with evaluation metrics and it is discussed with evident analysis in the section 6.In the Section 8, finally the research work is concluded with the significant reasons and future work to be achieved.

OBJECTIVES	DESCRIPTION	EVALUATION METRICS
OBJECTIVE 1	A Literature work done in the similar field	
OBJECTIVE 2	Exploratory data analysis to get insight	
OBJECTIVE 3	Implementation and evaluation of Custom CNN	Precision, Recall, Accuracy
OBJECTIVE 4	Implementation and evaluation of VGG16	Precision, Recall, Accuracy
OBJECTIVE 5	Implementation and evaluation of Mobile-net	Precision, Recall, Accuracy
OBJECTIVE 6	Implementation and evaluation of Xception	Precision, Recall, Accuracy
OBJECTIVE 7	Comparison of Developed models	
OBJECTIVE 8	Applying Optimum model into the final prototype	
OBJECTIVE 9	Executing the application as end- to-end application	

Figure 1: Research Objective

2 Literature Review

A number of authors have attempted and developed optimized image classification techniques for waste segregation. Moreover, to prevent binmen employees to manually handling potentially dangerous waste, automatic garbage disposal containers are required. Some garbage classification techniques do exist. Perhaps the most popular ones, see below, are neural network approaches.

2.1 Different approaches for Waste segregation

2.1.1 Waste classification using deep learning models

Deep learning (DL) is a novel concept of machine learning that is getting investigated, with the goal of bringing ml models nearer to its selected sites: artificially intelligent. Image identifying, language transformation, speech, and optical object classification, drug investigation, facial character recognition, weather forecasting, and other tasks are all covered by machine learning (Prisyach and Shvetsova; 2018). Deep learning algorithms have been popular over time in computers that do recognition technology. Deep learning, for example, can enable knowledge acquisition via the use of powerful algorithms that allow functionalities, characteristics, and qualities on their own thanks to their deep learning model.

Urban development, general prosperity, and mass migration has contributed to increased trash generation across the world. According to latest statistics, the total amount of solid waste generated garbage created in 2016 was 2.01 billion tons. By 2050, however, it is anticipated that 3.40 billion tons of solid garbage would have been generated. Unfortunately, around 33% of waste is not properly managed, and the material is dumped in unsupervised locations or unregulated dumping (Huang et al.; 2017). Automatic process and new technology have lately been used to try to transform the waste disposal sector for sustainability and efficiency. Waste management systems include non-linear parameters and changeable act in question to several engaged procedures with macroeconomic elements impacting accumulated formations. As a result, obtaining satisfactory performance in management of solid waste while avoiding ecological concerns is a difficult task.

Thus the most significant benefit of Deep Learning techniques over machine learning is that they attempt to acquire increased characteristics from information in a step-by-step way. Level of knowledge and real hardcore extraction of features are no longer necessary.

2.2 Convolutional neural network approach

Transfer learning (TF) is a widely used term in the deep learning area that refers to the process of retraining previously taught algorithms to fulfill additional challenges (Prisyach and Shvetsova; 2018). A pre-trained algorithm is one that was trained on a big validation set to tackle a challenge comparable to the one we're attempting to solve. Training a computational model can require anything from moments to months, dependent on the input and the objective purpose. Due to technology limitations, this was only possible for academic institutions and technological corporations since a few decades ago. However, the circumstance has changed as a result of widely accessible pre-trained algorithms (together with some few other considerations). Developers may now use transfer learning to create deep learning apps that tackle eyesight problems much quicker.

The performance of computerized image recognition has substantially increased as a result of the significant rise in machine rated speed. In the area of picture classification and identification, deep learning methods using CNN (Convolutional Neural Network) as the basis have started to contribute significantly. Convolutional neural networks merge morphological operations and computer vision in the conventional image identification, and they use the actual picture as training dataset. They prevent the complicated image analysis procedure of conventional identification techniques, and they can retrieve the most important characteristics of data that could be derived individually from a restricted group of data specimens, making deep learning acceptance data more accurate and their ability to realize pictures greater in this article (Cai et al.; 2019). As a result, this study offers a VGG16 system based on deep learning for identifying and classifying residential garbage.

In this paper(Md et al.; 2021) a CNN model is presented. It has a fully convolutional set of nodes that contains a dense network. Convolution layers, local connection, and pooling are the cornerstones of image analysis using neural networks. Using shared weights and convolutional networks areas, it may acquire its most important aspects of the information from millions of picture data sets, lowering the amount of variables that must be established during neural net model's development. It may be used to recognize and classify images in a broad lot of formats. The processing unit, feature map, pooling layer, dense layer, and hidden layers are the five fundamental components of a traditional CNN model.

Researchers explain Trash bins in a four-bin design come in four different coloured in this paper (Sreelakshmi et al.; 2019). Common rubbish goes in the blue containers. Bio degradable garbage goes in green bins. Recycled garbage goes in the yellow containers. Dangerous garbage goes in the red containers. Nevertheless, only general-waste and reusable dumpsters are frequently found at prominent venues such as bus stations, parks, and shopping complexes. In that case, reusable things should be placed in the reusable waste bin, whilst other goods should be placed in the standard rubbish bin. Separation of garbage is an essential part of the environmental planning process. When garbage is deposited in the incorrect container, it might lead to further rubbish being deposited in the incorrect location. If multiple non-recyclable trash are detected in the same container, reused or recycled in the reusable bin may wind up being transported to landfills. MSW should be separated as soon as possible when it is created. Disposal might be more challenging than it appears. Nowadays, public areas supply garbage containers with separation labels, but the waste in each bin is combined. Image enhancement, we assume, can make trash separation simple and effective. This would undoubtedly aid in reducing the garbage contamination that our nation, Thailand, is now experiencing. We looked at garbage different classifiers that used transfer learning. The major goal of the research was to see how well different CNNs performed in identifying garbage using the four-bin method.

Deep Neural Networks (ConvNet or CNN) have been successfully applied to a variety of image segmentation, object segmentation, action recognition, object identification, classification techniques, and segmentation problems. When Convolutional networks were used to categorize 1.2 million pictures in the Imagenet, the classification performance was massively improved paper(Munjal and Bhatia; 2019). A variety of CNN designs have been pre-trained on the Dataset. The implementation of deep resnet for machine vision was investigated in the article(Al Mamun et al.; 2014). They employed the ImageNet and CIFAR-10 collections in their research. CNN topologies from the ResNet family were taken into account. The study findings concern the use of Cnns to categorize trash in photos. In this paper(Frost et al.; 2019), researcher analyzed Both AlexNet and support vector as trash categorization systems (SVM). Plastic, cardboard, and metals waste photos had to be separated into 3 groups. The reliability of the SVM classifier was 94.8 percent, whereas the CNN classification was just 83 percent. This article(Li et al.; 2022) established the "RecycleNet" deep network classification algorithm. Papers, glasses, plastics, metals, board, and rubbish were all certified as reusable by RecycleNet. For the RecycleNet concept, the DenseNet121 design was adopted. To provide a quicker forecasting rate, the connecting topologies of the hidden neurons within closely packed blocks were changed. The Trashnet data was used to train and validate the RecycleNet classifier. On the testing data, RecycleNet was 81 percent accurate.

This paper illustrates(Wang; 2020), urban trash disposal seems to have been a major issue in Thailand. Without the need for an appropriate waste categorization method, this issue will not be addressed. The study demonstrated the use of CNN in garbage separation. VGG-16, ResNet-50, MobileNet V2, and DenseNet-121 were all capable of classifying garbage into 4 categories: ordinary trash, organic wastes, discarded materials, and toxic materials. An end up wasting classifiers could be used to classify wastes directly, or it could be generated from the result of an end up wasting classification.

Whenever the training dataset is restricted, inferred categorization might be a viable option.However, generated classifications outscored the others. The Custom CNN graders classified organic wastes and trash kinds equally well.

2.3 VGG16 Approach

A recent paper (Wang; 2020) used VGG16 network for garbage recognition. It presented the VGG16 topology of the network as one of the VGG NET systems. It's a more advanced version of the AlexNet system in 2014. When detecting and categorizing photos, this could more correctly reflect the properties of the data collection. Volumes of data and sophisticated backdrop classification techniques benefit from it. 13 convolution layer, three fully connected layers, and 5 pooling layers make up a network topology. The convolution operation used in the 13 fully connected layers contained in VGG16 is a moderate 3 x 3 matrices with a progressive nature of 1 relative to other systems. The quantity of convolution layers steadily rose from 64, during first level to 128 in the second, 256 in the third, and finally 512 in the protective layer. The accumulation layer's kernel size is 2x2 in length, and the magnitude is 2. It performed best on the retrieved features than other systems with a convolutional kernels diameter of 5 x 5. The VGG16 network structure, on the other hand, offers both benefits and downsides in terms of detailed characterization. The amount of design variables and the difficulty of computations throughout training have risen as the network structure has been deepened, resulting in a long training period and low training efficiency. In this research, we show how to preserve the main characteristics of design extracting without sacrificing identification accuracy while also increasing design production yield.

The strategic priorities are now used to enhance the VGG16 model and minimize the amount of time needed to learn it. Sigmoid and tahh activation functions were substituted with upsampling (RELU) are used in this article(Abdukodirova et al.; 2020). Since the sigmoid and tahh functions correspond to the overloaded non-linear functional class, the algorithm aligns gradually over time throughout training, and the performance suffers as a result. Simultaneously, whenever the sigmoid functional usage increased in the training the model, its magnitude changes gradually, resulting in the emergence of a diminishing slope. This makes it easy for the method to slip into the localized global optimum, making it hard to finish the fully convolutional model's training and attain the desired accuracy rate.

The regular correction factor is a non-saturated and non-linear activation function, unlike non-linear kernel function like sigmoid or tahh. The inclination of the component where predictor variables is much less than Zero is a stable, which can be seen in the program code, hence it will not produce the degradation problem throughout development. Furthermore, the ReLu function might most densely reflect retrieved texture features, as well as cut computation travel time up the model's settling time throughout development.

Researchers illustrate this article(Sirawattananon et al.; 2021) Only after convolutional layers of the VGG16 network, because before the non-linear transition procedure, a pack standardized BN (Batch Normalization) function is built. The initiation value of the DNN will continue moving as during learning phase as the connectivity thorough intensifies or modifications, that is, the feedback is plotted by a non-linear feature for every hidden nodes neuron, and its valuation increment is particularly intense. The source population is compelled to produce a normal curve with a mean of 0 and a deviation of 1 after traversing the BN layer. To stop the issue of slope vanishing, the input following the non-linear transform slips into an area highly responsive to switching element. The model building time is lowered and the stability is increased once the BN level is introduced. The BN level could minimize prediction error as during learning phase, similarly towards how Node is computed to throw out neurons, resulting in improved recognition rate. The acquired trash picture data is treated to data augmentation and visual pre-treatment, as per the experimental procedure outlined in this work. The survey established will be sent to the VGG16 network structure for DCNN training stage, and the testing data comprising 2300 trash pictures is being used to determine the authenticity of the produced deep neural network to recognise household trash upon modifying the activation function and rising the BN surface that after convolutional layers to significantly raise the computational efficiency. By comparison, in retraining, the improvement price is fixed to 0.0001, the number is fixed to 100, and the sampling set recurrent training is completed after about 100,000,000 repetitions. After thorough research, it was discovered that the ultimate identification outcome had the greatest predictive performance. The resolution velocity of the VGG16 system training phase is increased in this article (Koganti et al.; 2021), resulting in a reduction in preparation time. After examining the test data set, it was discovered that the technique in this study had an accurate rate of 75.6 percent. The end result may be used to identify and classify garbage on a daily basis.

The OpenCV vision - based package is used in this study(Zhang et al.; 2010)to conduct data augmentation and picture preparation on the rubbish images obtained. A VGG-16 fully convolutional structure is designed employing TensorFlow as the classifier backdrop, with the ReLu activation and the addition of a BN level to enhance the network resolution speed and highest accuracy percentage. The exact speed of the system discussed in this chapter is 75.6 percent upon checking on the validation set. The system discussed in this chapter could indeed proficiently classify household trash into harmful trash, cooking waste, other trash, and reusable trash, satisfying the requirements of practical uses. However, when comparison to certain other neural project - based learning that employ picture detection and analysis, this development's performance still has to be enhanced.

2.4 MobileNet Approach

MobileNet is a multilayer perceptron in this article(Bircanoğlu et al.; 2018),in which practically single layer is firmly attached to just about every other level in a feed-forward approach. To put it differently, the thick connections that bind every level to all the old levels in an unit. All preceding levels' image features are regarded as independent sources for every layer in this study(Zhang et al.; 2019), whereas their extracted features are being sent out as feeds to all time and within the allocated. This connection design provides region CIFAR10/100 (with or without data augmentation) and SVHN precision. On the huge ILSVRC (2012) ImageNet dataset, MobileNet obtains equivalent accuracy to ResNet by using less than half the set of variables and now almost half the amount of Flip - flop. First of MobileNet's most compelling aspects is its potential to mitigate the problem of such highest derivative by information extraction progressively and reduction in the number of variables. The proposed design has been pushed to the limits on four extremely difficult levels. Compete image retrieval benchmarking events (CIFAR-10, CIFAR-100, ImageNet, and SVHN). MobileNets outperform the condition in some of aspects using less computer power to attain good performance.

These four deep learning techniques achieve better result in these papers separately.

But, when comparing all four, we could tell which is efficient to perform and achieve good accuracy and also by other metric evaluations.

3 Methodology

The Knowledge Discovery in Databases (KDD) has used with some changes in the process step to carry out the research of Domestic waste segregation using deep neural networks, which can be seen in the Figure 2. The novelty of this research is being showcased by highlighted in this process flow diagram.

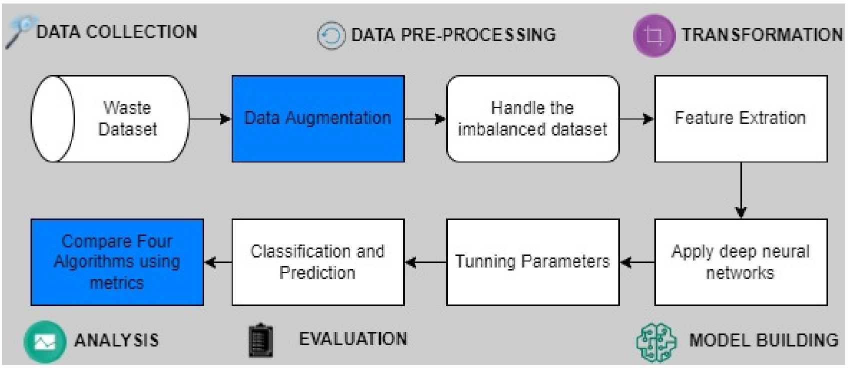

Figure 2: Process Flow of the methodology

3.1 Data Collection

The Waste Images Dataset is found from Kaggle website [1] , which is mentioned below. This dataset is publicly available secondary data. The Folder has two folders such as Train and Test dataset, which is about 55.69% and 44.31% respectively. The Train dataset folder contains two separate files-named Biodegradable and Non-Biodegradable. These images are in JPEG format. It contains around 25,077 images. In which 22564 images in Train dataset and 2513 images in Test dataset. The Biodegradable and Non-Biodegradable folder includes around 12565 images and 9999 images respectively.

3.2 Data Exploratory Analysis

The Random function has used to visualize the Biodegradable and Non-Biodegradable images randomly to check whether the images are labelled correctly, that is shown in the Figure 4.

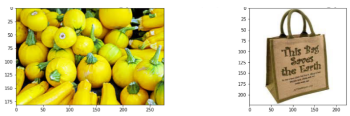

Figure 3: Biodegradable and Non-Biodegradable

The Figure 3 shows the two classes includes Biodegradable and Non-Biodegradable.

[1]Waste images dataset: `https://www.kaggle.com/techsash/waste-classification-data`

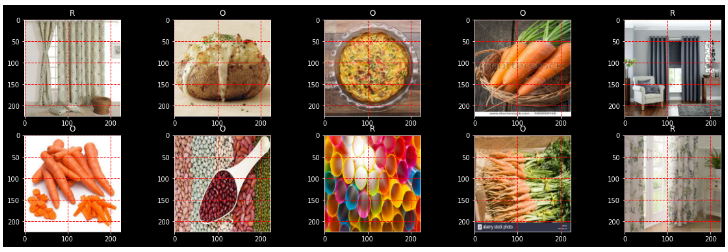

Figure 4: Random images

The Two classes in the waste image dataset are Recyclable(Non-Biodegradable) and Organic(Bio-degradable). Its percentage of images are 44.31% and 55.69% respectively in the Figure 5

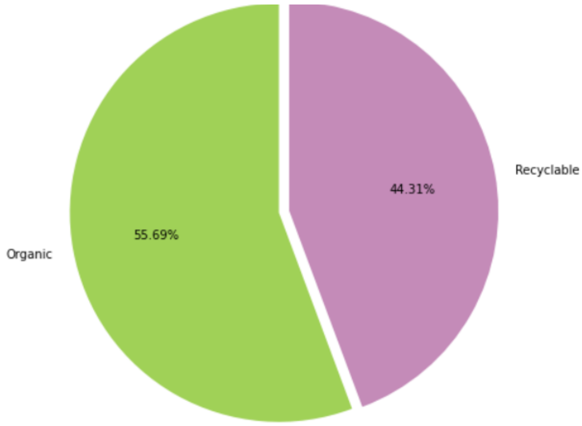

Figure 5: Two Classes

3.3 Data Pre-processing

Pre - processing stage is a significant stage in training a model better accurately. The image data in the dataset are divided by categories, therefore the very first step we took in this dataset was to mapping the images to their labels. Because the dataset comprises high-resolution pictures with varying qualities, the trained model may be developed inappropriately. To solve this problem, we reduced each picture to a constant resolution of 32 x 32 pixels.

3.3.1 Data Augmentation

In analysis of data, data augmentation refers to strategies for increasing the quantity of information by appending toned down replicates of actual data or creating new generated information from previous information is illustrated in this study (Zhang et al.; 2021). During building a deep learning model, it behaves as a preprocessing step and helps in eliminating fitting problem.The ImageDataGenerator class in the Keras deep learning neural framework allows you to fit designs using photographic data augmentation.

3.3.2 Data Rescaling

When dealing with neural network models, data scaling is a suggested pre-processing phase. Order to train a neural network architecture, data preprocessing procedures such as normalizing and standardizing are used to rescale values of the parameters in this paper (Birajdar and Mankar; 2013). The model's parameters are set to minimal sample data and then changed using an optimization approach in accordance to loss predictions on the training sample. Real-valued input and output parameters can be normalized or standardized to accomplish data scalability.

3.4 Model Building

Model Building is the stage where the models are implemented to train the dataset. In this research, Four deep learning techniques such as Custom CNN, Mobile-Net, VGG16, and Xception are the models that were build, which are shown in the Figure 6. The convolutional layers and dense layers are utilized in Custom CNN, Mobile-Net, VGG16, and Xception are (3,2), (3,2), (5,3),(3,2) respectively.There are two classes namely, Biodegradable and Non-Biodegradable.

Transfer method employs deep networks learned on massive data to solve a given goal with minimal data. Generally, the last several layers are fine-tuned on the objective dataset whilst passing acquired knowledge from original function to the training sample. These levels, on the other hand, were created for the original purpose and may not be appropriate for the end purpose. We present a technique for dynamically tweaking Custom Convolutional Neural Networks (CNN) for better transfer learning in this research. Adam Optimizer is used to optimize the CNN layers with information from the original dataset.

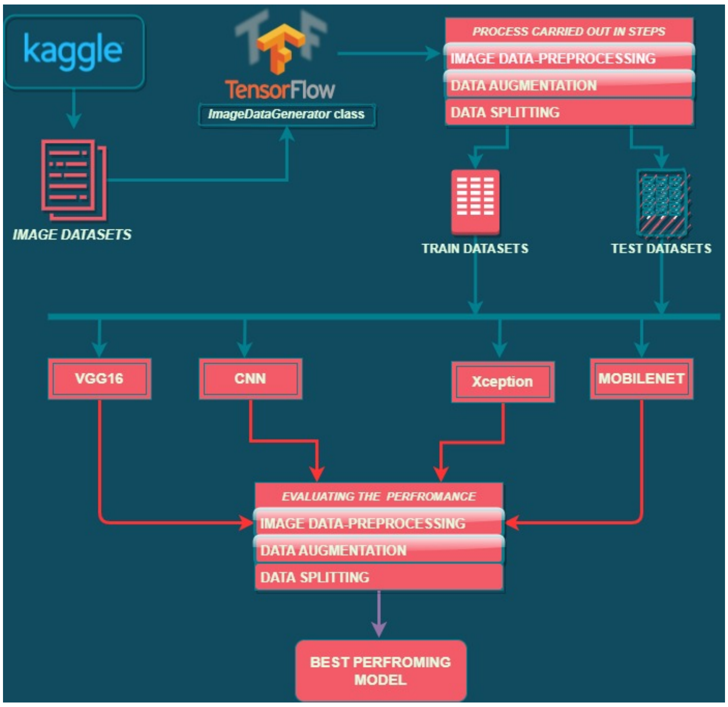

Figure 6: Process Flow of the methodology

Mobile-Net is what we're employing because of its lightweight design. It employs feature extraction convolution layer, that means that instead of merging all three and smoothing the result, it executes a separate convolution on each gray level. With three convolutional layers and two dense layers, Mobilenet is a pre-trained model.

Xception is a deep convolutional neural model. It might import a fully convolutional version of the model from the ImageNet, that has been developed from over a million pictures. As a consequence, the model has learnt a wide array of different image features for a variety of pictures. The network's picture data size is 299 $\times$ 299 pixels.

The VGG16 model may be put into the Keras deep learning framework and utilized there. To use this application, you may develop a VGG16 modeling using pre-trained parameters using it as categorize photos directly.

The waste classification image data set consist of 22,564 images. Since the custom CNN model that I built has a smaller number of layers so the computation time will be less when compared to all the other transfer learning model. So, I used all the images that I obtained from the Kaggle. I also tried using all the images, but my device was not capable (doesn't have RAM and since there is issues in the version between TensorFlow and python, I was not able to programmatically access the GPU of the device). So, this was the reason I used a smaller number of images while training all the other transfer learning models. Since there is large number of images, and the structure of the transfer learning model is also heavy.

3.5 Model Evaluation

In certain cases,optimize one of the metrics, such as recall or precision, at the risk of another. By utilizing accuracy primarily since everyone understands just what implies then because that is the greatest way to do things. Though effectively measurements like recall and accuracy may appear unfamiliar, that already understand why these work more effectively for particular issues like unbalanced classification. Handling all aspects and formulae to compute these metrics are provided by statistical data. When constructing classification techniques, data science is all about having the correct techniques to utilize, and frequently must go above accuracy. Understanding about recall and precision enables to evaluate classification techniques, and that should makes careful of anybody who claims an accurateness alone, particularly for unbalanced situations.

4 Design Specification

By implementing the optimum model from comparing four techniques of deep learning and deploying the prototype as end-to-end web application to check whether the model built is applicable to user friendly. The Tools and frameworks used in the research are listed below. The entire design flow of the research can be seen in the Figure 7

Flask is a Python-based web framework. It features a number of components that make it simple for a web designer to construct apps without having to think regarding protocol administration, process management, and other such concerns. Flask provides us with a number of options for constructing web apps, as well as the technologies and packages to get started. The Response and request packages are imported to handle http response request.HTML is used to structure the webpage of the waste classification application. Furthermore, CSS is added to style the page and Javascript is applied for the purpose of interactive web-page.

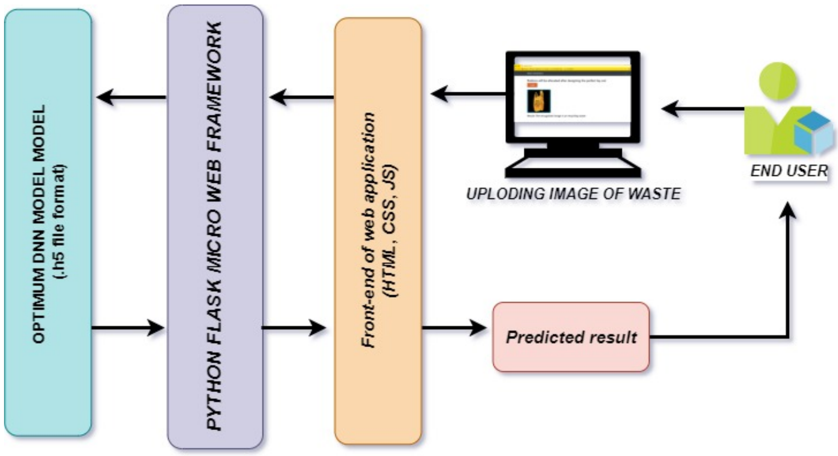

Figure 7: Process Flow

Python packages, such as Keras, and TensorFlow are utilized in the model building of the deep learning techniques. Keras package acts for the distributed training of deep learning techniques. TensorFlow used for developing and training models to create large layers, which is an open source tool.

4.1 Custom CNN

The stacking consecutive different layers of each other to create the neural network. The goal is to minimize the picture's complexity and discover trends associated with each category.Attempt to formulate a sequentially model in the code. A "Conv2D", which is a fully connected layer, plus a "MaxPooling2D" layer make up its first computational block unit. The convolutional layer applies 3 x3 pixel filtration to each region of the picture, yielding extracted features (clusters of activation values) that show where availability of the required are found in the picture. By transforming 2x2 pixel matrices throughout the picture between one pixel that indicates the maximal activating level in that matrix, the max pooling layers decreases the dimensionality of data mappings. In summary,create image features being the same scale as the input images and then compress them down 50%. The custom Cnn model That constructed initially included many of about 5 layers of fully connected layers, in addition towards the top speed strands. Because values were computed using both forward backward propagating, the precision of the five-layer structure was identical with that of the three-layer approach. This has less weights since some variables are identical. Due to this new method, convolution layers are specifically tailored to extracting pertinent data at a limited calculation level.

Verifying at the topology using "model.summary()" prior to actually executing the model.The model must then be compiled. The ADAM optimizer will be used since it enables the training rate will fall with period, which is beneficial for predicting a large connection weights. By using binary cross-entropy as the loss function because we've been generating binary forecasts.Finally, setting up the data generators, a Keras function which developed a new batches of photos from properly trained or testing sets folders. By using an experimental 10 epochs to validate the data and examine how this all works.

4.2 VGG16

The term "sequential model" refers to the arrangement in which the model's layers are structured. We used ImageDataGenerator from keras.preprocessing for this project. The goal of ImageDataGenerator is to make it simple to inserted data with labeling into the model in this study(Wang; 2020). It started by indicating that the model is a sequence of stages when initializing it. The ReLu (Rectified Linear Unit) activating was used on every layer to ensure that no lower values are carried along to the next phase. Transferring the data to the dense layer following completing all of the convolution layers, thus flatten the matrix that emerges from the convolution layer. The modeling is finally ready after the development of the pooling layers. The models has to be compiled. While training the network, Adam used an optimizing compiler to get to the approximate solution. It is visualized training/validation efficiency and losses once the training has been completed.

4.3 MobileNet

Using a lesser network, MobileNet-160, it performs Squeezenet and AlexNet but requiring far less multi-adds and variables. In terms of multi-adds and characteristics, it's likewise comparable to Inception-v3. Finally, MobileNet, which is recommended by Depthwise Separable Complexity, achieves similar results to region techniques but also with a significantly smaller networks in this paper (Thokrairak et al.; 2020).

4.4 Xception

In this article (Rismiyati et al.; 2020), Mostly in traditional identification tests, the Xception architecture outperformed VGG-16, ResNet, and Inception V3. Depthwise Separable Convolution layers are a type of convolution which is meant to be significantly faster than traditional convolutions. XCeption provides a design that consists of Depthwise Separable Convolution blocks + Maxpooling, all coupled using reductions like ResNet versions. In comparison to a depth of similar quality in traditional convolutions, this design results in a small selection of support vectors.

5 Implementation

This research is implemented by 6 stages, that includes Train Data, Algorithms, Evaluation,Test Data, Final Optimum model, Classification, which is shown in the Figure8.

1.Train Data The Input Data(Images) are imported to train the data. The File contains two folders namely Train and Test. The Train dataset is divided into two classes- Biodegradable and Non-Biodegradable, while Test dataset also divided as same. All the images are pushed into the google drive which can be accessed through google colab environment.

2. Algorithms The Models are built by doing data pre-processing stage which includes data augmentation and data rescaling. The Four of the deep learning techniques such as Custom CNN, VGG16, Mobilenet and Xception are built and it was auto tuned and fine tuned again to get better accuracy.

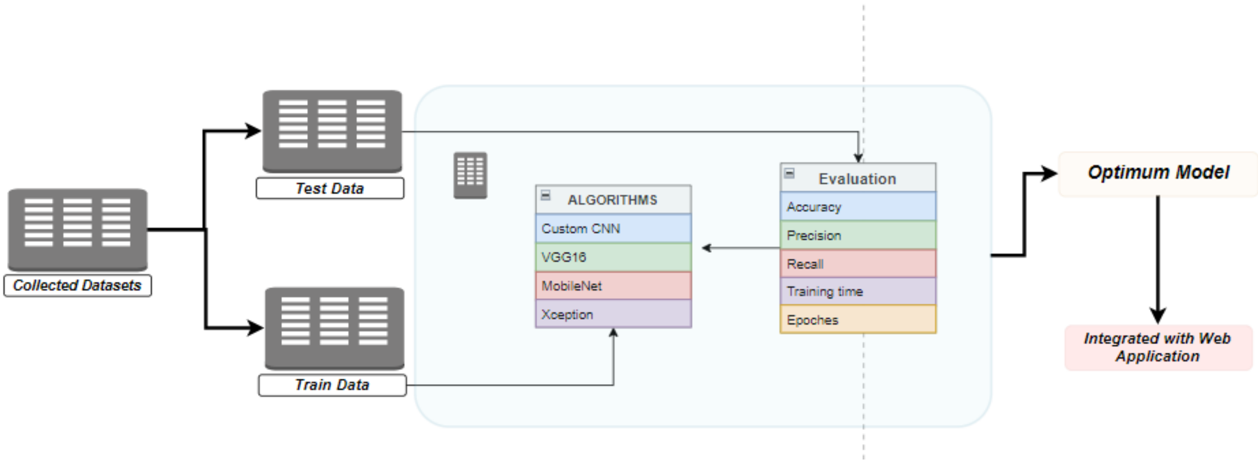

Figure 8: Implementation of Process diagram

3.Evaluation The Models are evaluated not only by accuracy, also by precision, recall. The run time and epochs utilized are considered for evaluating the models.
4.Test data The Trained models are validated to evaluate the results. The test data is accessed by validation accuracy, validation precision and validation recall.
5.Final Optimum model The Models are analyzed and finally selected one optimum model. Adam Optimizer is the optimizer used to compile the model.
6.Classification The Build model is integrated with flask from backend, that optimum model is saved in local device and create a path. The model path is applied to the backend. The front end and back end are integrated to produce end-to-end application. It will show the result of the image whether it is Biodegradable and Non-biodegradable.

6 Evaluation

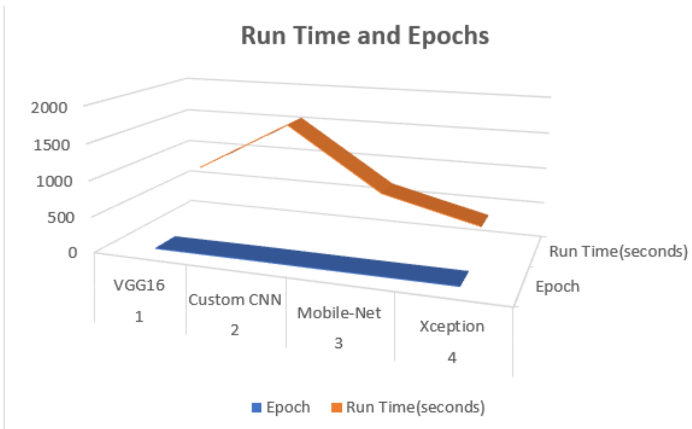

Figure 9: Run Time and Epochs

The Four deep learning techniques such as Custom CNN, MobileNet, VGG16,and Xception are evaluated to find the optimum model. The epochs utilized in Custom CNN, VGG16, Mobilenet, and Xception are 10,6,6,6 respectively. The VGG16 model took 834 seconds to compile the model. The Custom CNN run for about 1562.4 seconds. 689 seconds took for running Mobile-net model. The Xception run for around 356 seconds. Xception was better in compiling the model earlier comparing to all other three models, that is shown in Figure 9.

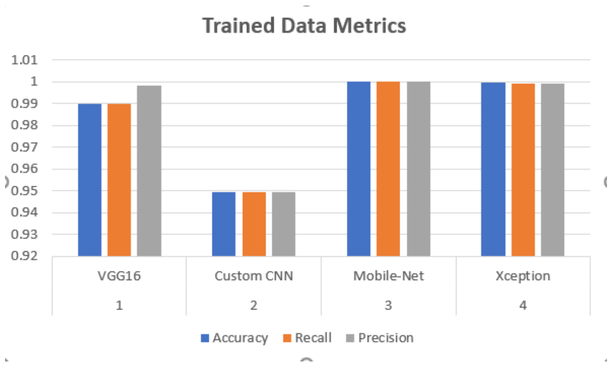

Figure 10: Trained Dataset Metrics

From Figure 10, we can see the metrics used to evaluate the models. They are Accuracy, Precision, and Recall. The Accuracy for Custom CNN, VGG16, Mobile-Net, and Xception in training the dataset are 94.95%, 99%, 1%, and 99.98% respectively. The Mobile-Net model is overfitted model, while Xception and VGG16 are also scored 99% and 99% as accuracy. The Custom CNN acquired 94.95% as its accuracy, which is better among all the four techniques.The VGG16, Custom CNN, Mobile-Net, and Xception obtained Recall are 99%, 94.96%, 1% and 99.94%, Whereas Precision value are 99.81%, 94.96%, 1%, and 99.94% respectively.

6.1 Experiments

The validation metrics for VGG16, Custom CNN, Mobile-Net and Xception are analyzed by Accuracy, Recall and Precision.

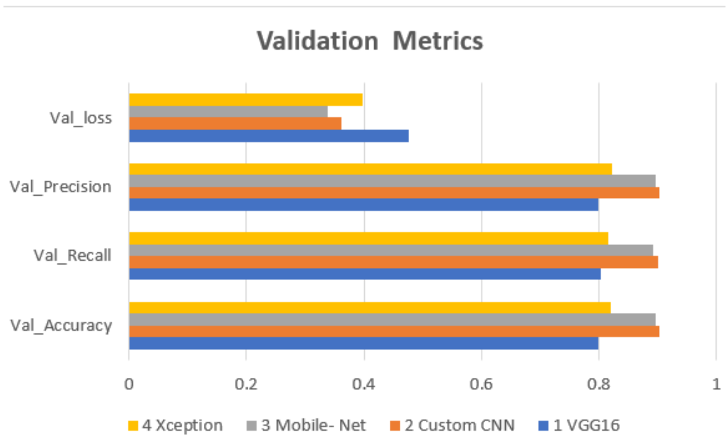

Figure 11: Validation Metrics

Val_Accuracy for VGG16,Custom CNN,Mobile- Net and Xception are 79.86%, 90.21%, 89.65% and 82.07%. Val_Recall for VGG16, Custom CNN, Mobile-Net and Xception are

80.37%, 90.05%, 89.27% and 81.63%. Val_Precision for VGG16, custom CNN, Mobile-Net and Xception are 79.81%, 90.27%, 89.61%, 82.20%. Val_loss for VGG16, custom CNN, Mobile-Net and Xception are 47.66%, 36.16%, 33.88% and 39.69%.

Mobile net is the one which has lowest loss, while on the other hand Custom CNN has the best accuracy value of about 90%. These metrics are seen in the Figure 11.The convolution layer and dense layer for VGG16,Custom CNN,Mobile-Net, and Xception are 5,3,3,3 and 3,2,2,2 respectively, which is shown in the Figure 12.

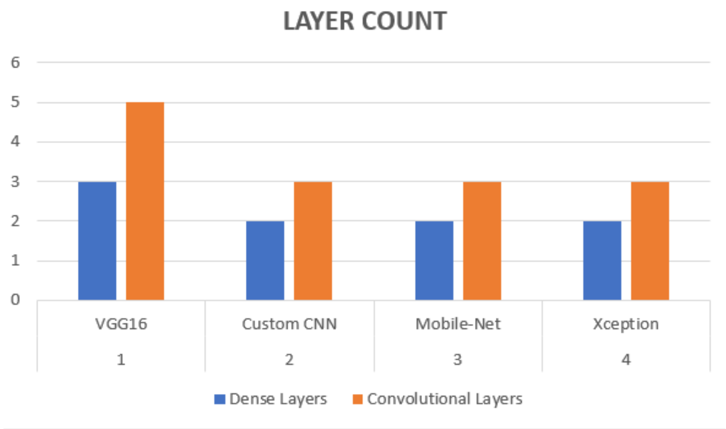

Figure 12: Layer Count

6.2 Discussion

In this research, the waste image dataset is being utilized to train the models.The run time performance is better for Xception, which is around 356 seconds. In trained model accuracy performance is efficient for Custom CNN, that is 94%.

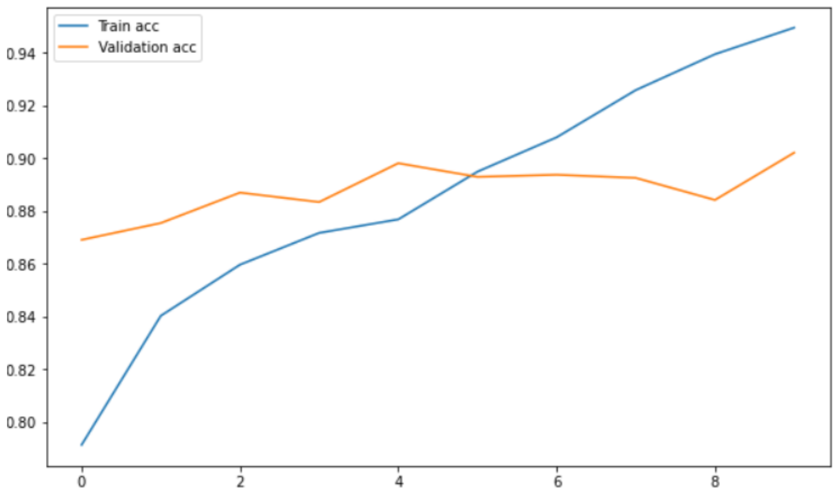

Figure 13: CNN Validation accuracy graph

However, Validation Accuracy is efficient for Custom CNN(90%).By comparing all the models, Custom CNN's validation accuracy is higher and it is not overfitted for the test images. It's Recall value and Precision value are also higher as 90.05% and 90.27% respectively. The trained dataset scored 14.14% as loss value and test data acquired only 36% as loss value. Over all, due to these reasons, Custom CNN is performed really good and therefore this model is selected as Optimum model.

In the Figure 13, Train accuracy and validation accuracy is not over-fitted. Training accuracy is lesser than Validation accuracy, thus it performs really well.

For limitations, the waste image dataset used in Custom CNN model is around 22,564 images. But for all other models, 6,443 images are being trained to compile the models. By training all the images in the dataset, the computational speed was decreased. It reduces the performance. Therefore, Custom CNN performed really good as its computation and run time is efficient along with the accuracy.

7 Conclusion and Future Work

The research aims to classify the two classes of waste namely, Biodegradable and Non-Biodegradable. The waste image dataset was imported into google colaboratory environment. The dataset is pre-processed by data augmentation, data rescaling and then changed into constant size. It is being built as model by using image generator and number of packages such as TensorFlow, Keras to distribute and develop the model training. Therefore Custom CNN is selected as best model among all the four deep learning techniques and integrated with flask to get response in the front page, when any image is uploaded to check that which class that belongs to. It refers to the garbage which will be thrown into the domestic waste bin, then it will capture the image and classify that the trash that it will be belong to which category. It will fall into that side of the category, which has separate bag. This can be implemented as like this in real time situation. This is executed as web application by uploading the image, the category will be predicted in this research. The training process was difficult, and the kernels broke, and the automated reload failure, since its design of the transfer learning approach is so complex to calculate the outcome as comparing to the Custom Cnn architecture that's been built. With all transferring deep learning, the number of cycles and photos expected to accomplish the training phase and exporting the implementing is lowered. As that of the amount of epochs grows, the load in the Custom CNN is modified more frequently, and the line shifts from misclassification to ideal to premature convergence.

In the future work, the performance of Mobile-net, VGG16, and Xception will be improved by increasing the data size for training. As Custom CNN has 22,564 images for training, it took reasonable amount of time to run the model.

8 Acknowledgement

I wish to thank Ibrahim Rinub Babu for facilitating his Google Colab account which was used in the development of this project.

References

Abdukodirova, M., Abdullah, S., Alsadoon, A. and Prasad, P. (2020). Deep learning for ovarian follicle (of) classification and counting: displaced rectifier linear unit (drelu) and network stabilization through batch normalization (bn), *2020 5th International Conference on Innovative Technologies in Intelligent Systems and Industrial Applications (CITISIA)*, pp. 1–10.

Al Mamun, M. A., Hannan, M. A. and Hussain, A. (2014). Real time solid waste bin monitoring system framework using wireless sensor network, *2014 International Conference on Electronics, Information and Communications (ICEIC)*, pp. 1–2.

Birajdar, G. K. and Mankar, V. H. (2013). Blind authentication of resampled images and rescaling factor estimation, *2013 International Conference on Cloud Ubiquitous Computing Emerging Technologies*, pp. 112–116.

Bircanoğlu, C., Atay, M., Beşer, F., Genç, and Kızrak, M. A. (2018). Recyclenet: Intelligent waste sorting using deep neural networks, *2018 Innovations in Intelligent Systems and Applications (INISTA)*, pp. 1–7.

Cai, Y., Wu, J. and Zhang, C. (2019). Classification of trash types in cotton based on deep learning, *2019 Chinese Control Conference (CCC)*, pp. 8783–8788.

Fakhim Ahmadi, H., Rezaee, A. and Miraki, Q. (2010). Gardening waste management - case study: Tehran - iran, *2010 International Conference on Chemistry and Chemical Engineering*, pp. 391–394.

Frost, S., Tor, B., Agrawal, R. and Forbes, A. G. (2019). Compostnet: An image classifier for meal waste, *2019 IEEE Global Humanitarian Technology Conference (GHTC)*, pp. 1–4.

Guo, F., Huang, H., Liu, Y. and Xu, J. (2019). Application of neural network based on caffe framework for object detection in hilens, *2019 Chinese Automation Congress (CAC)*, pp. 4355–4359.

Huang, G., Liu, Z., Van Der Maaten, L. and Weinberger, K. Q. (2017). Densely connected convolutional networks, *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 2261–2269.

Koganti, S. K., Purnima, G., Bhavana, P., Raghava, Y. V. and R, R. (2021). Deep learning based automated waste segregation system based on degradability, *2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC)*, pp. 1953–1956.

Li, J., Chen, J., Sheng, B., Li, P., Yang, P., Feng, D. D. and Qi, J. (2022). Automatic detection and classification system of domestic waste via multimodel cascaded convolutional neural network, *IEEE Transactions on Industrial Informatics* **18**(1): 163–173.

Md, R., Sayed, R. H. and Khan Kowshik, A. (2021). Intelligent waste sorting bin for recyclable municipal solid waste, *2021 International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI)*, pp. 1–5.

Munjal, M. N. and Bhatia, S. (2019). A novel technique for effective image gallery search using content based image retrieval system, *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon)*, pp. 25–29.

Prisyach, E. and Shvetsova, O. (2018). Elements of innovative scenario's development of waste management system in russia, *2018 IEEE International Conference"Management of Municipal Waste as an Important Factor of Sustainable Urban Development" (WASTE)*, pp. 63–65.

Rismiyati, Endah, S. N., Khadijah and Shiddiq, I. N. (2020). Xception architecture transfer learning for garbage classification, *2020 4th International Conference on Informatics and Computational Sciences (ICICoS)*, pp. 1–4.

Sirawattananon, C., Muangnak, N. and Pukdee, W. (2021). Designing of iot-based smart waste sorting system with image-based deep learning applications, *2021 18th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, pp. 383–387.

Sreelakshmi, K., Akarsh, S., Vinayakumar, R. and Soman, K. (2019). Capsule neural networks and visualization for segregation of plastic and non-plastic wastes, *2019 5th International Conference on Advanced Computing Communication Systems (ICACCS)*, pp. 631–636.

Thokrairak, S., Thibuy, K. and Jitngernmadan, P. (2020). Valuable waste classification modeling based on ssd-mobilenet, *2020 - 5th International Conference on Information Technology (InCIT)*, pp. 228–232.

Wang, H. (2020). Garbage recognition and classification system based on convolutional neural network vgg16, *2020 3rd International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE)*, pp. 252–255.

Zhang, S., Shuang, Z., Shi, Q. and Qin, Y. (2010). Improved mandarin keyword spotting using confusion garbage model, *2010 20th International Conference on Pattern Recognition*, pp. 3700–3703.

Zhang, X., Wang, Z., Liu, D., Lin, Q. and Ling, Q. (2021). Deep adversarial data augmentation for extremely low data regimes, *IEEE Transactions on Circuits and Systems for Video Technology* **31**(1): 15–28.

Zhang, Y., Liu, P., Chen, Q., Guo, Y., Liang, J., Yin, H. and Feng, X. (2019). A partially pre-trained dense network for image super-resolution, *2019 6th International Conference on Systems and Informatics (ICSAI)*, pp. 1168–1173.