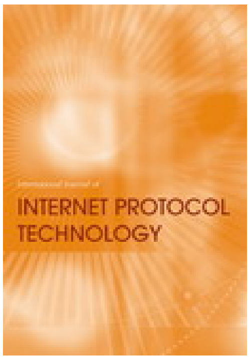

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Deep learning models-based classification of solid waste

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Abstract: In order to give the best socio-economic qualities – such as environmental preservation, economic sustainability and a decrease in health-related issues – Municipal Solid Waste (MSW) management currently needs to be carefully studied. Wastes might be identified by computer algorithms, which would also facilitate their conversion into useful energy. Owing to their high error rate and low accuracy, the present methods of trash classification in municipal solid waste continue to have issues. Convolutional Neural Networks (CNNs) and CNNs built from the ground up using ResNet V2 models trained by transfer learning are intended for the purpose of picture classification. The percentage of occurrences in the validation data set that were correctly classified is known as the validation accuracy, and it stands at 0.938. The model effectively adapts what it learnt from the training data set to the validation data set, as seen by the validation accuracy of 93.8%.

Keywords: waste classification; waste data sets; work flow; efficient net raining.

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1 Introduction

The management of waste necessitates the implementation of essential procedures and activities from the beginning of the process until its conclusion. Trash can be divided into three main categories: solid, liquid and gaseous. There are specific categorisation schemes, disposal methods and management strategies needed for each of these waste categories. 'Waste management' is the process of handling waste of any kind, including biological, organic, industrial, radioactive and municipal waste as well as garbage from biomedical applications. Any item that is unnecessary or has no potential value is referred to as 'waste'. Trash management entails a variety of procedures, including collecting, moving and properly disposing of waste. Approximately 423 million tonnes of garbage, or 56% of all residential waste, were recycled by the European Union (EUROPA) in 2016.

Reports indicate that the recycling process requires effective management of garbage from households in order to be successful (Liu et al., 2020). To meet the basic wants of their people and keep giving them a good level of service, bigger towns will need infrastructure that lasts a long time and a waste management system that works well.

Either by hand or via the use of a series of filters, traditional recycling techniques sort waste materials into several categories. Therefore, in order to satisfy the fundamental demands of their residents and maintain a decent level of service, larger cities will need highly sustainable infrastructure and an effective waste management system. The enormous increase in processing power has led to a great deal of advancement in the domains of image processing and computer vision. One form of deep learning architecture that has been deemed crucial in this regard is the Convolutional Neural Network (CNN).

The identification and categorisation of waste materials may be completed more quickly and efficiently with the use of deep learning, which reduces costs associated with time and human resources and benefits the environment.

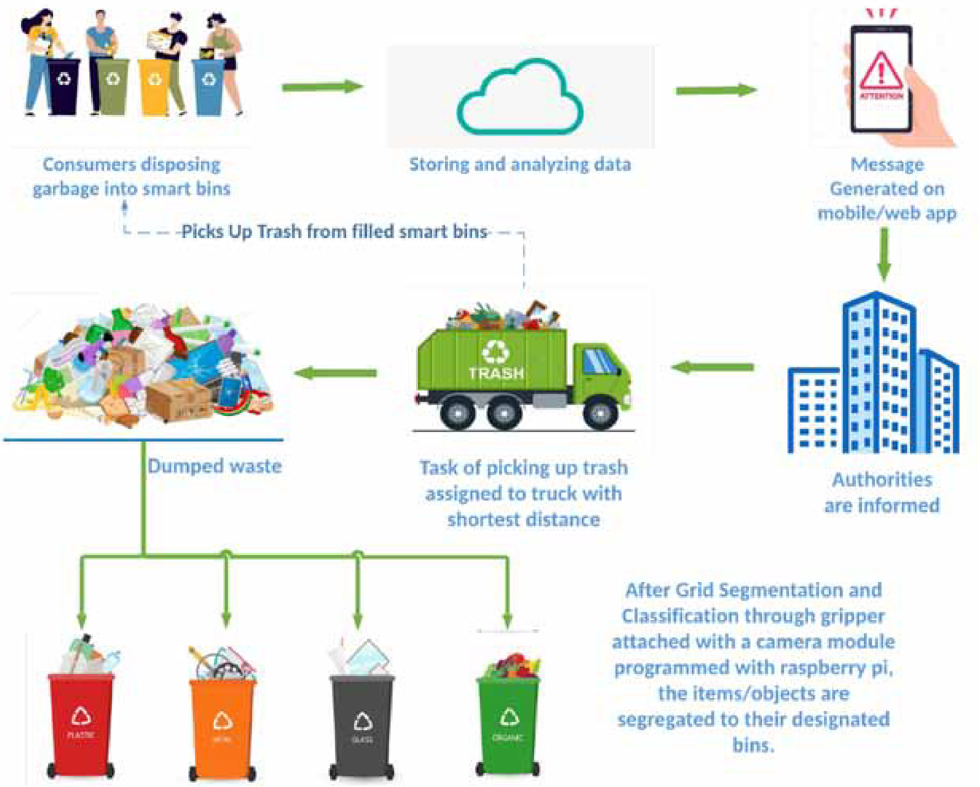
Approximately 127 new devices are connected to public networks every second, according to a FUSON analysis (Lagakos, 2020). As a result of this rapid expansion, 328 million new gadgets are imported every single month. According to STATISTA, by the time 2023 ends, the Internet of Things market is expected to be valued $1.1 trillion. These figures show that the Internet of Things is rapidly becoming the focal point of contemporary computing methods. The internet of things (IoT), Machine Learning (ML) and Deep Learning (DL) in a variety of systems are phenomena made possible by the modern web. These systems include Radio Frequency Identification (RFID), sensors, actuators and Wireless Sensor Networks (WSNs) (Hajian-Tilaki, 2013).

To get the most accurate results, prediction methods like clustering and classification are also used in place of depending only on human labour. People's daily lives have been profoundly impacted by this programme because a city may experience improved living standards and a better way of life if its waste is effectively collected, managed and categorised (Zheng et al., 2023). The following research topics are addressed by our investigation, which contains a more in-depth investigation, a solution and answers:

- *RQ1*: For the landfill area, what are some ways that we may undertake garbage segmentation?
- *RQ2*: Through the development of a smart system, what are some ways that we might immediately categorise waste products into distinct categories?

In addition, a solid plan for trash collection, waste transportation to a designated location, waste monitoring, and waste preparation and recycling are all necessary. The challenge lies in more than just having to pick up trash from door to door (Bagri et al., 2021). Therefore, we designed and built a smart waste management and classification system that utilises cutting-edge technology (cloud computing, edge computing and fog computing) and enables the proper actions to be performed in waste management in order to handle the massive issue of garbage collection, management and classification (Zhang et al., 2021). Waste materials were sorted and classified using a system that made use of wireless sensors, cameras, Deep Learning algorithms, the Internet of Things (IoT) and the Global Positioning System (GPS). Many different types of sensors are used in this project.

Figure 1 Intelligent waste classification (see online version for colours)



Through the proper implementation of waste management and categorisation activities, their objective is to collect information about waste material and, as a result, improve the infrastructure of the city (Rahman et al., 2020). Components such as garbage bins, a fleet of trucks, a gripper, a landfill and other such items make up the physical infrastructure of our system. To begin, the garbage from households is gathered in our intelligent waste bin, the information of which is kept in the cloud. When the bin reaches its capacity, a notification is automatically created on the web or mobile application (Ramsurrun et al., 2021). After that, the authorities will designate a garbage collection truck to remove the trash from the waste container and transport it to the disposal location. Subsequently, the garbage will be divided and categorised in line with the Figure 1.

A particular application domain, segmentation and waste management categorisation are the areas of concentration for our company (Pires et al., 2020). This waste segmentation is accomplished by the use of a grid segmentation method, which creates waste segments. Following that, a gripper equipped with a camera and a Raspberry Pi begins the process of picking up trash things (Mao et al., 2021).

Following the completion of the categorisation, it deposits the particular object in the bin that has been assigned for it. Trash is first divided into two groups in this way: bio waste and non-bio garbage (Nañez Alonso et al., 2021). Subsequently, the non-bio waste group is further separated into three subcategories: glass, metal and plastic (Altikat et al., 2022). This system was put into operation in a controlled setting that included a designated place for waste disposal. An overview of the contributions our research has made is provided below.

We created a Waste Classification Model (WCM) that separates garbage into biodegradable and non-biodegradable components, such as plastic, metal, glass and other comparable materials, using the image classification technique. Through the use of the segmented grid picture that was acquired by a camera that was positioned on the raspberry pie, we put into action an architectural development process for a smart garbage dump (Fuson et al., 2022). We devise a novel technique that lowers the overall latency and improves energy efficiency to provide an intelligent real-time trash disposal monitoring system (STATISTA, 2022). As a hybrid computing phenomena, we merge the cloud data processing mechanism with the edge processing mechanism. The suggested system performs better overall as a result of this (Salmador et al., 2008). The outcomes of the suggested system are subjected to a performance analysis and evaluation (Sheng et al., 2020).

2 Related work

2.1 Waste classification

Waste categorisation is the process of identifying and grouping waste products according to their characteristics and contents. Waste classification is an alternative term for this procedure (Esmaeilian et al., 2018). This is often carried out in order to recycle the trash, dispose of it appropriately, or discover other environmentally friendly ways to handle it. A variety of techniques, such as chemical analysis, visual inspection and machine learning methods, can be used to classify trash. Examples of typical waste categories that are often categorised include biological waste, electronic waste, hazardous waste and municipal solid waste (Agarwal and Sharma, 2011). During the course of our investigation, we will be using sophisticated approaches to deal with the categorisation of garbage (Markoulidakis et al., 2021).

2.2 Waste data sets

For the purpose of categorising wastes into various groups, several researchers have used a variety of distinct classification systems (Bansal et al., 2019). The most often used approach to achieve this is to use deep learning and machine learning algorithms. One of these studies is a waste picture collection with over 2800 images of various waste products, including cardboard, metal, plastic, paper, bottles, metals and electronic waste. Two thousand and five hundred (2500) photos of various types of waste, including cardboards, metal, plastic, paper, glass and metals, are included in the Trash net + image scrapping.net data set. There has been a use of this data set that is 80% training and 20% testing (Agarwal and Sharma, 2011) as shown in Figure 2.

The trash Net data set, which includes 2527 images total and displays six different categories of waste, has been used. These images include images of trash, cardboard, glass, metal, paper and plastic, as seen in Figure 3 (Howard et al., 2023).

Figure 2 displays the 2313 image database that researchers in Rishma and Aarthi (2022) were able to gather. The average accuracy rate of recognition while using a Raspberry Pi 3B+.

Furthermore, the initial data collection included objects including bottles, papers, cans, milk cartons, batteries and paper cups. The garbage net data set is used by another module and goes by the name (Yang and Thung, 2016). This collection of 2527 waste images is broken down into six categories: cardboard, paper, metal, glass and trash. Training, validation and testing are the three distinct sets of TrashNet's components, with respective overall ratios of 70%, 13% and 17%.

A total of 2751 images relating to waste are produced by using a compose net data set that has been enhanced by the Trash Net data set. The following categories are used to group these images: garbage, cardboard, metal, glass, paper and plastic-based goods (Bansal et al., 2021).

There are four categories in the WasteRL data set (volume 20): recyclables, organic waste, hazardous waste and miscellaneous wastes. It recently came out. The variety of rubbish in each photograph is becoming wider. As an example Figure 4, the data set was used as a basis for training, validation and testing (Valente et al., 2019). To provide a more complete analysis of their performance, the models were assessed in the verification phase after being taught in the training phase Srivatsan et al. (2021). The initial testing stage, which is succeeded by the review-stage validation phase.

Figure 2 Trash net data set (see online version for colours)

Figure 3 Raspberry PI 3B+ average recognition accuracy (see online version for colours)

Figure 4 WasteRL picture data set (see online version for colours)

To address the problem of photo classification, many kinds of algorithms have been enhanced in machine learning and deep learning. These algorithms include, among others, CNN, Resnet-50, SVM, Random Forest and Decision Tree (Wu and Lin, 2022).

3 Proposed methodology

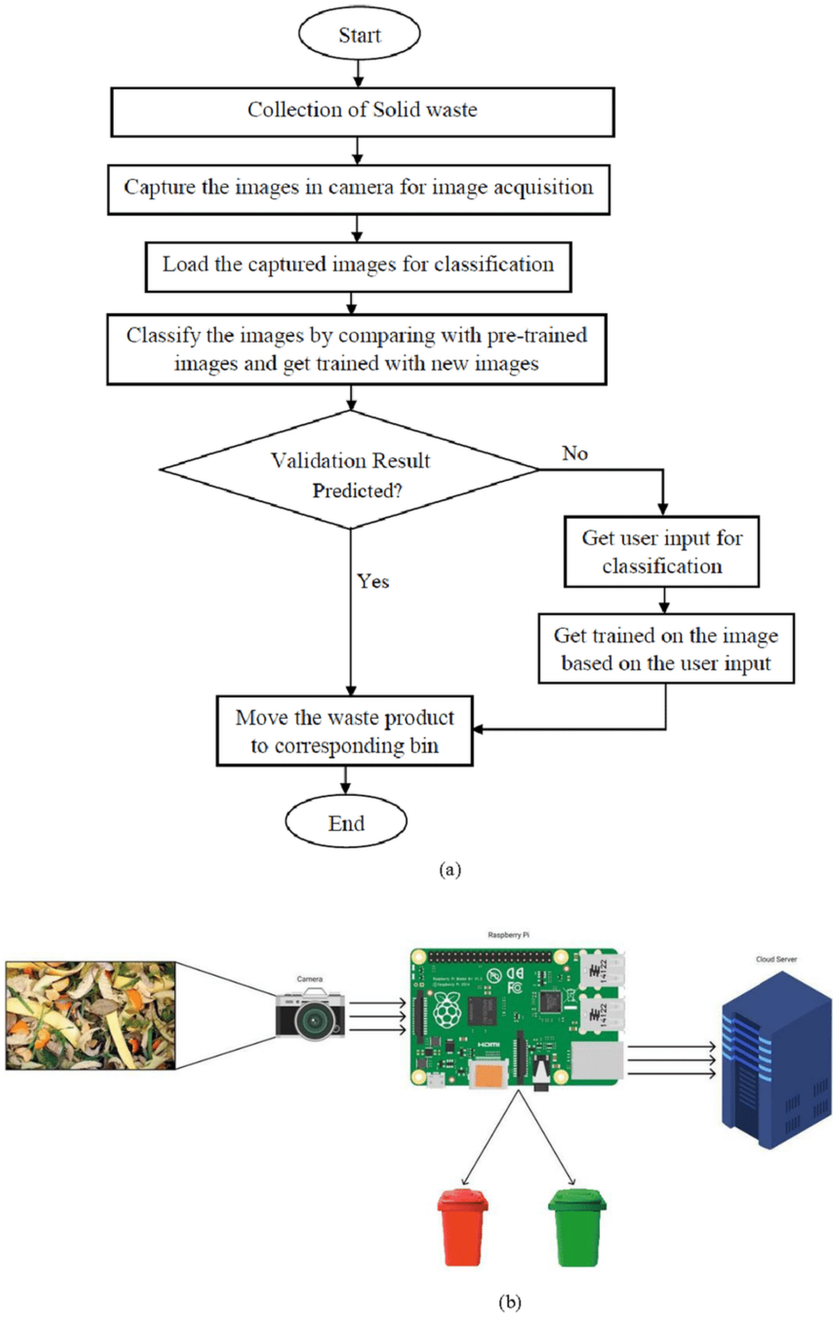
The goal of this research is to decrease the number of errors and improve the accuracy of garbage classification by proposing a CNN-based design method for managing municipal solid waste. Sorting the collected waste materials into categories is the main purpose of the CNN-based method. The next parts provide thorough descriptions of the workflow, how to build a CNN-based machine learning model, how to train and retrain the model and how to determine the evaluation criteria.

3.1 Work flow

When the intake is empty, the camera module will transition to sleep mode in order to reduce the amount of power that it consumes. The second step consists of the categorisation of garbage based on the photos that were recorded and placed into the waste classification module that had its training completed beforehand.

Based on the analysis being done, the image classification module is in charge of validating the collected images and categorising the solid wastes so that they are deposited in the appropriate bin. In addition, the model provides individuals with information on the types of waste materials that are collected by means of an automated audio message that has been prepared. Pre-programmed control device sends the necessary information automatically to play pre-recorded audio stored in the cloud. To be more explicit, the system asks the sanitation personnel to characterise the waste particles that are unknown or unexpected by presenting the photos. The suggested model is able to self-train the system for future prediction by using the input that is obtained from workers in the sanitation industry. In order to do the same thing, more human interventions are not necessary since this is a one-time operation. The technique of the CNN for training and retraining is described in the section under ‘Training and Evaluation’.

Figure 5 Waste categorisation model concept, hardware model (see online version for colours)



3.2 *Machine learning model creation*

There are three processes involved in building a machine learning model from start. During these stages, digital data is gathered, pre-processed, classified and a deep learning algorithm is used to develop a model. In the context of waste management systems, TensorFlow facilitates the building of a deep learning-based categorisation model from scratch. Moreover, TensorFlow offers a high-level programming interface for neural network construction. CNN is one of the most popular deep learning algorithms that can learn data sets with weights and biases. Neurons using learnable weights and biases of the derived input characteristics enable real-time training picture monitoring. For a deep learning model to be successful in garbage categorisation, a lot of training data is required. Large image data sets may be utilised to train the learning model via Kaggle, an online tool for collecting and organising data.

In the process of developing a successful machine learning model, the pre-processing of data is likely the stage that demands the greatest attention and effort. One other name for this technique is 'data cleaning'. Through the provision of the optimal fit, rescaling and resizing are able to lower the loss function. In addition, it provides data processing pipelines that are completely autonomous, adaptable and accurate. In the process of data pre-processing, the Keras pre-processing layers are used to resize the photos and rescale the pixels before transforming them into trustworthy forms. This approach improves the accuracy of picture categorisation, as well as the performance and abstraction of the process. During the data augmentation process, images taken in normal field situations are used in order to enhance the variety of the data that has been trained.

The most time-consuming step is selecting the optimal model through a process of trial and error, and then fine-tuning its hyper-parameters. Model selection is the process that picks the best model. Image categorisation has been shown to be a particularly successful use of CNN architecture. CNN performs much worse when it comes to large-scale data set training and procedures like Maxpool. Using Google's Inception Resnet V2 architecture, a CNN architecture was built to categorise the trash. The intended waste management system incorporated this design. Resnet V2 is capable of handling large data sets, including testing with 50,000 pictures from ImageNet and training with 1.2 million photographs, without increasing the number of mistakes that occur during training. Resnet V2's introduction into CNN simplifies and speeds up calculation, provides a sharp gradient to descend and yields an Inception network with excellent performance. Convolution layers, a normalisation approach, a Rectified Linear Unit (ReLU), pooling layers, a flattening layer, dropout, dense layers and fully linked layers are all components of the CNN model that has been presented. Normalisation is the subsequent layer, which provides enhanced network performance, a higher learning rate, straightforward weight activation and the ability to regularise picture recognition using neural networks. In the model that has been suggested, batch normalisation is a method that is used to normalise the input layers. To do this, the alterations that are unacceptable are rescaled and adjusted, and then the modifications are regularly moved into new distribution places. ReLU uses batch normalisation, which sits between convolution layers and a non-linear layer, to increase the classifier's pace of learning.

The subsequent layer is known as pooling, and it is an essential component in the process of minimising network parameters and achieving smoother feature extraction. Local or global pooling is often used by CNN in order to expedite the computing process. Three different criteria can be used to categorise pooling layers: maximum pooling, minimum pooling and average pooling. In contrast, the min pooling layer takes into account the lowest possible value from each cluster of neurons that were present in the layer before it. The usage of min pooling layers in CNN is not implemented because to the high computational cost involved.

3.3 Training and evaluation

A total of 25,077 images were utilised in the training and assessment of the CNN model. Out of the total number of images in the data set, 80% were used for training, 10% were used for testing and 10% were used for validation. When correctly captured and pre-processed photos (10% of the testing sets and 10% of the validation sets) are used, accuracy is good. Split validation makes ensuring that the model and the data are correctly matched. Cross-validation is the most used data separation technique. Keras-based *K*-fold cross-validation may be used to assess models with better performance and fewer data samples. The suggested model divides the training data sets and assesses the model with ideal performance parameters using a five-fold cross-validation procedure.

It also prevents the training model from being too precise and offers accurate image classification when it comes to evaluation. The model receives the whole training data set as input, and it goes through fifty epochs until reaching its global optimum state. A training cycle known as an epoch may be chosen by taking into consideration the least amount of fluctuation in the loss and accuracy functions.

The suggested CNN model is retrained using transfer learning on a particular data set in order to improve its performance. Transfer learning preserves the neural network and results in a significant improvement in accuracy. Retraining the learning model makes it possible to use previously acquired image classifier data. Fine-tuning is then carried out to increase the waste items categorisation accuracy in a waste management system. Using the same collection of photos, CNN is retrained using the ResNet V2 model developed by Google. The retrained networking model, which has 164 layers and can categorise photos into thousands of distinct object categories, is the result of a comprehensive analytical procedure. Using the trained ImageNet data set, the model's reliability in garbage categorisation is further evaluated. The whole collection of retraining data must also be input into the model fifty times in order to reach the point at which the system reaches its global optimality. All of the weight modifications are made correctly using the normalisation method after the model has been retrained.

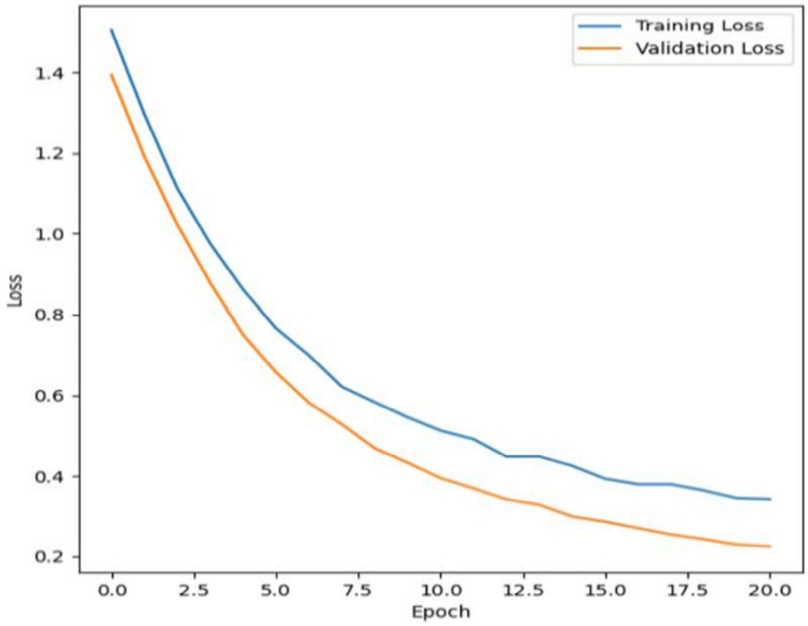
3.4 Evaluation standard

The F1 score was computed using the accuracy and recall metrics of each design model in order to determine which of the suggested models gave the most accurate representation of the world. It is possible to express the F1 score of the learning model as where Precision is equal to TP divided by TP plus FP, and Recall is equal to TP divided by (TP plus FN), where TP stands for true positive, TN is for true negative, FP stands for false positive and FN stands for false negative.

$$F1 = 2 \cdot \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$MCC = \frac{(TP \times TN) - (FP + FN)}{\sqrt{(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)}}$$

Figure 6 Lost EfficientNet training/validation curves (see online version for colours)



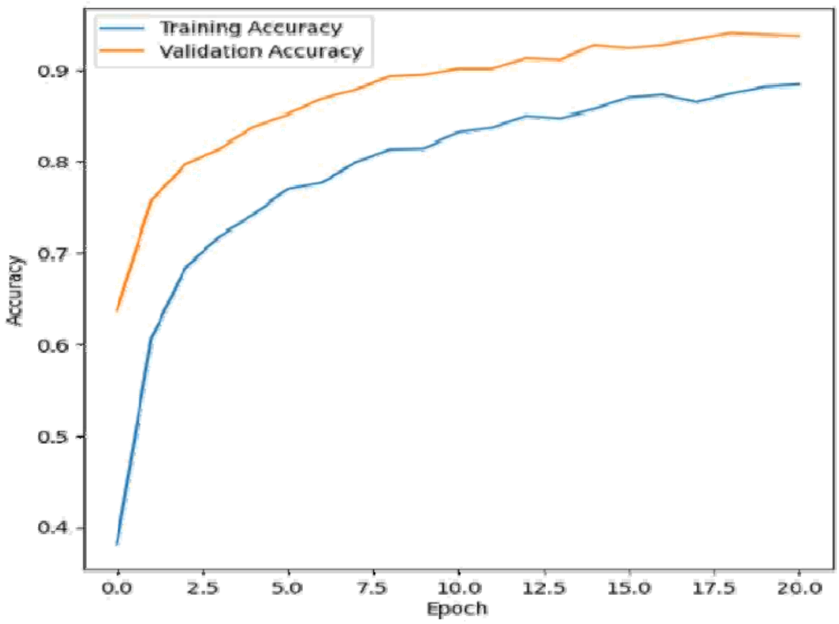
4 Result

4.1 *Comparison of EfficientNet training and validation*

The results of training and validating an EfficientNet model applied to a classification task are presented in this thesis. the most recent deep learning architecture EfficientNet is well acknowledged for its exceptional effectiveness and efficiency in applications pertaining to transfer learning and image classification. We trained the EfficientNet model for a total of 22 epochs throughout the course of our investigation. Throughout this period, we tracked the accuracy and loss in training and validation to evaluate the overall performance and generalisation capabilities of EfficientNet.

1. A training loss that is smaller than average shows that the model has successfully learnt the patterns and characteristics that were present in the training data.
2. This outcome, which is different from the training data set, demonstrates the error that the model made on the validation data set. There is a 0.2245 validation loss. In comparison to the training loss, the validation loss is much smaller, which indicates that the EfficientNet is able to display excellent generalisation when applied to data that is novel to it.

Figure 7 Curves showing EfficientNet training and validation accuracy (see online version for colours)



The percentage of occurrences in the training data set that were successfully classified is reflected in the training accuracy, which stands at 0.885. The percentage of occurrences in the validation data set that were correctly classified is known as the validation accuracy, and it stands at 0.938. The model effectively adapts what it learnt from the training data set to the validation data set, as seen by the validation accuracy of 93.8%. In this classification assignment, the EfficientNet model performs very well. This is shown by the strong training and validation accuracies and the very low training and validation losses. It's very astonishing that EfficientNet can generalise to data that it has never seen before, as shown by the fact that its validation accuracy is higher than its training accuracy. These outcomes might be used as a foundation for further optimisation, adjustment, or model application to related activities.

4.2 *VGG16 training versus validation*

Drawing conclusions from the metrics supplied, it can be said that the deep convolutional neural network model VGG16 performs very well in the presented data set. The VGG16 model, which is well-known for its efficiency in picture classification tasks, shows promise in both training and validation. Efficiency is a well-known feature of the VGG16 model. With the model's training loss being 0.2634 and validation loss being 0.2668, respectively, both the training and validation losses are very low. These low loss values show that the model is effectively assimilating the underlying patterns in the data and can correctly extrapolate to examples it hasn't yet seen.

The VGG16 model can correctly identify 90% of the training data with a 90% training accuracy. This suggests that the model yields precise outcomes. An further indication of the model's generalisability is its 91% validation accuracy. This is because the model correctly categorises 91% of the validation data, which is comprised of samples that have not been seen before.

Consequently, the VGG16 model exhibits good performance in the data set provided, as shown by the low training and validation losses and high training and validation accuracies. These results show that the model is a dependable option for picture classification jobs as it can efficiently learn from the data and generalise to new instances.

4.3 *Precision confidence curve/ROC*

The Receiver Operating Characteristic Curve is what the acronym ROC stands for in exact terms. The precision of the model varies with a change in the confidence threshold, as seen by the curve representing the link between accuracy and confidence. There will be no shortage of positive predictions. Raising the confidence criterion will result in fewer positive predictions overall but higher accuracy since there will be a greater likelihood that the remaining forecasts will be actual positives. In evaluating a binary classification model's performance, the precision-confidence curve may be useful. This is especially true in circumstances when the proportion of positive to negative classes is not evenly distributed.

Figure 8 VGG16 training and validation losses curves (see online version for colours)

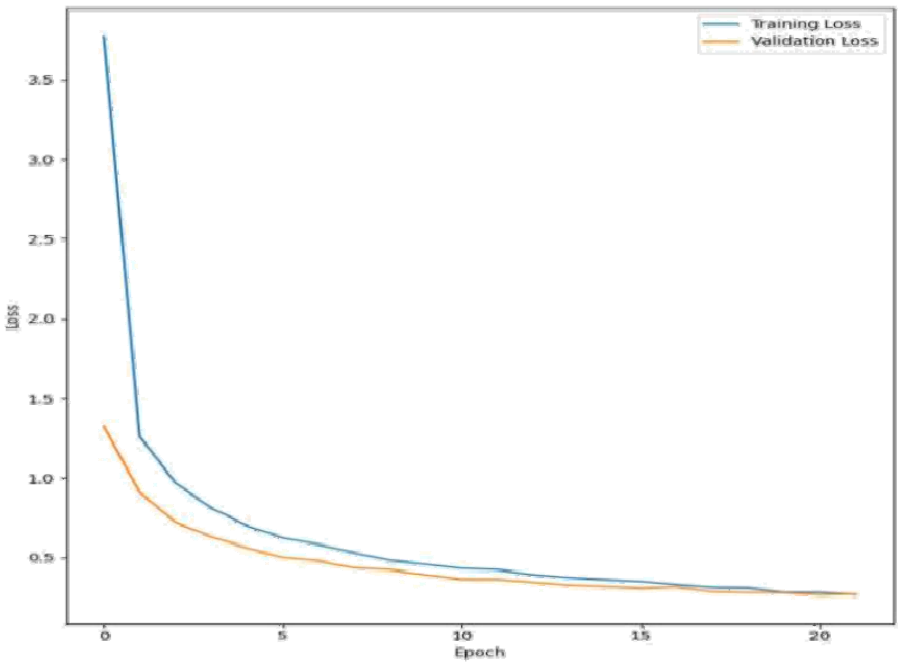
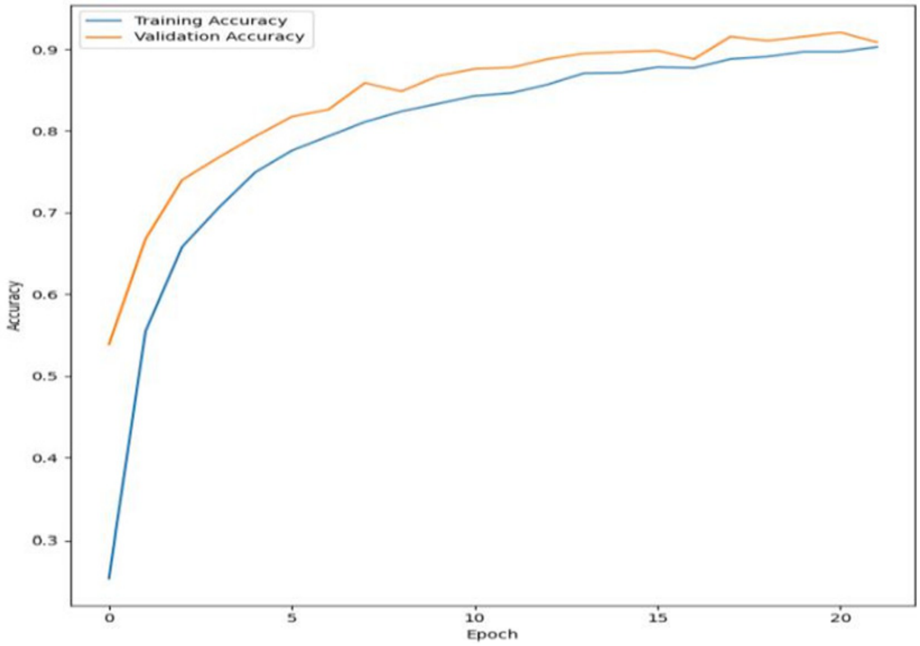


Figure 9 Accuracy curves for VGG16 training and validation (see online version for colours)



4.4 Model accuracy and confidence

Models based on the performance metrics they have, including the number of parameters, training epochs, precision-recall, F1 confidence, and precision confidence. This diagram lists the pros and cons associated with each paradigm.

VGG16 performs very well when it comes to accuracy-recall (97%) and precision confidence (99%), as well as F1 confidence (98%). However, 22 training epochs and a greater number of parameters (15,245,125) are required for it to be implemented.

Table 1 Trust and precision model performance (Hajian-Tilaki, 2023)

Model	*Precision confidence*	*F1 confidence*	*Precision Recall*	*#Parameters*	*Epochs*
VGG16	99%	98%	97%	15,245,125	22
Efficient Net	97%	98%	99%	3,603,489	22
YOLOv8	99%	93%	96.5%	43,633,695	50

4.5 Solid waste label assumptions and misunderstanding

The purpose of this study was to evaluate the predictive performance of three deep learning models: VGG16, EfficientNet, and YOLOv8. The models were used to predict the labels of solid waste items in five different categories. EfficientNet performs well in the Cardboard (95%) and Metal (97%) categories in addition to exhibiting competitive performance in the Glass (91%) and Plastic (92%) classes. It is, however, less accurate than VGG16, which has a higher accuracy rating of 97% in the Paper category.

Table 2 Confusion matrix comparisons (Zheng et al., 2023)

Model	*Cardboard*	*Glass*	*Metal*	*Paper*	*Plastic*
VGG16	91%	87%	92%	97%	92%
EfficientNet	95%	91%	97%	94%	92%
YOLOv8	95%	92%	88%	94%	94%

Excellent overall performance is shown by YOLOv8, which leads in Glass classification with a 92% accuracy rate and matches EfficientNet's accuracy in Cardboard with a 95% accuracy rate.

4.6 ROC comparison of several Yolov8, EfficientNet, and vgg16 models

Within the confines of this study, the effectiveness of three cutting-edge deep learning models is closely analysed:

We are considering the classification of solid waste items using the VGG16, EfficientNet and YOLOv8 algorithms. Finding the mean Average Precision (mAP) and Receiver Operating Characteristic (ROC) values for each material group (Cardboard, Glass, Metal, Paper and Plastic) is the main goal of the study.All material categories show consistent performance from the VGG16 model, with ROC values ranging from 92% for Glass to 98% for Paper. Its overall performance was 95% based on the mAP of 95%.

At 96% accuracy on average, EfficientNet outperformed the others overall. Glass had a grade of 94%, while cardboard, metal and paper received ratings of 97% and 94%, respectively. The highest-rated materials were cardboard, paper and metal. In comparison to VGG16, it also displays a mAP that is 96% higher than the previous value. The YOLOv8 fared better functionally than the other two versions, with an average accuracy mAP of 96.5%. Consequently, ROC values and mAP measurements show that the YOLOv8 model performs better than the VGG16 and EfficientNet models. EfficientNet's performance is still superior than VGG16's, although not being as good as YOLOv8.

Table 3 Comparison of ROC performance (Markoulidakis et al., 2021)

Model	*Cardboard*	*Glass*	*Metal*	*Paper*	*Plastic*	*mAp*
VGG16	95%	92%	95%	98%	95%	95%
Efficient Net	97%	040%	97%	97%	95%	96%
YOLOv8	98.40%	97.70%	92.70%	97.10%	96.60%	96.5%

5 Conclusion

CNN architecture was being used by the system at the time ResNet was developed. The CNN model is constructed from the ground up and taught to understand and categorise the trash photos. The MSW management model with CNN architecture obtained an 87.99% classification accuracy throughout the assessment phase. To increase the precision of image classification during municipal solid waste management, a CNN model created using Inception ResNet V2 is built, trained and assessed using the same set of data samples. With the help of the proposed CNN Inception ResNet model, the accuracy of the photo classification process was raised to 94.44%. This design outperforms the CNN one by around 6.45%. Compared to the models that were previously in use, the CNN model created by Inception of ResNet V2 showed a high accuracy of 19.08% and a loss reduction of 34.97%. When ResNet was first created, the suggested CNN had a high degree of accuracy, an F1 score and an MCC score for distinguishing biodegradable trash from non-biodegradable waste. This was shown by comparing the proposed model with current practices. Additionally, the pre-trained model improved the accuracy of millisecond image prediction. There may be less rubbish stored in landfills without being separated if municipal solid waste management uses this trash classification method. It is possible that the technique that has been suggested might lessen the negative impact that incorrect disposal of waste that has accumulated in landfills without effective separation has on the environment.

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