Enhanced Classification of Garbage Images Using an Adapted Multi-Branch Deep Learning Model

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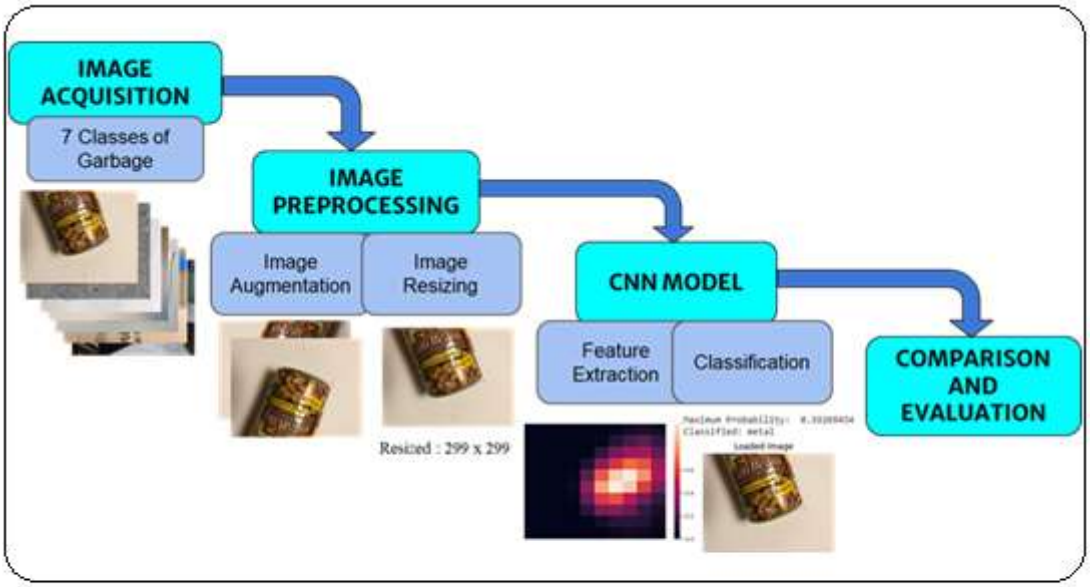
Graphical Abstract



Abstract

With the emergence of newer technologies and cities every day, the accumulation of tons of waste has become an adverse concern in the field of waste management. Municipal waste management department faces several challenges, including inadequate technical facilities and health concerns of workers during segmentation of solid wastes. Hence, it is of great value to rapidly and accurately detect garbage from images in the application of intelligent waste management using convolutional neural network (CNN). In the proposed research work, e-waste and packaging waste are also included. The TrashNet dataset with live image for 7 classes of garbage is used for training the model. Image pre-processing such as image resizing and image augmentation is done to obtain target size and overcome the class imbalance. Xception CNN Model is used to classify the TrashNet dataset, the accuracy of 98.57% is achieved. The Xception CNN Model is further modified in its middle flow core structure and

improved accuracy of 100% is obtained. The proposed is compared with various deep learning models and it is outperforms than others.

Keywords: CNN, TrashNet, Xception, Image classification.

I. Introduction

Garbage or trash can be referred as any waste that is discarded by humans, having a perceived lack of utility. In the present circumstances, the discovery of new technologies every day has also resulted in newer types of garbage. This has resulted in an adverse waste management system as manual labour is the commonly employed method, which has caused significant health hazards to humankind and the environment raising cause of global concern over the growing heaps of untreated trash. Many Garbage image classification systems have been developed and deployed but have become futile mostly due to the various types of garbage [1, 2]. The processing of garbage images includes many types of techniques and operations such as image resizing and augmentation, feature extraction, classification and presentation. In the past decade, thanks to the development of computing power and theoretical system, Deep learning realized a period of rapid development. Now, all aspects of computer vision have been penetrated by deep learning and it has achieved exciting leads in the field of image classification and target detection [3]. Leveraging the various aspects of Deep Learning and the existing knowledge in this field, the images of garbage are classified into different classes [4, 5]. The objective of this project is to develop a robust system using an efficient CNN model to identify and classify images of Garbage into separate classes of trash with high precision and accuracy. The scope of the proposed work is to effectively reduce, reuse and recycle garbage by classifying it using deep learning. Xception is the model chosen for this work as it is one of the most accurate and efficient CNN models currently [6]. The Xception models architecture are modified in this work and they have resulted in improving accuracy, running time and classification.

With the event of human society, the matter of environmental pollution is becoming more and more serious and environmental pollution has great harm to the world and everyone its organisms. Among them, most of the pollution is caused by domestic garbage. The decomposition of some domestic garbage may cause the high concentration of chemical substances within the environment, damaging the ecological environment. The World Bank report of the year 2018 showed that there is almost 4 billion tons of waste created around the world every year and the urban populace alone contributes a lot to this number, with the waste predicted to increase by 70 percent in the year 2025.

2. Literature Review

Disposing of waste has huge environmental impacts and can cause serious problems. Recently various works are carried out to manage the waste effectively. Some of them are discussed here.

In 2019, Olugboja proposed the waste classification system which is able to separate different components of waste using the Machine learning and ResNet50 model. This system can be used to automatically classify waste and helps in reducing human intervention with an accuracy of 87% [7]. Cuiping Shi [8] suggested a method in the year 2020 to greatly improve

the network performance. The author made full use of feature information at slight additional computational cost. Compared with the Xception network, the M-b Xception network provides higher accuracy on the TrashNet data set.

The waste classification framework was done by Mas Rina Mustaffa able to classify the waste accurately based on the feature extraction steps achieving an accuracy rate of 94.4%. Each of the waste image is represented by few shape-based properties which are perimeter, area, major axis length, and eccentricity. Quadratic Discriminant Classifier was utilised to classify into appropriate categories [9].

The objective of the research work is to develop a robust system using an efficient CNN model to identify and classify images of garbage into separate classes of trash with high precision and accuracy. The scope of the work is to effectively reduce, reuse and recycle garbage by classifying it using deep learning.

This paper has been organized as a brief description of the work, in the order of their chronological significance. Section 1 gives a detailed description of garbage, types of garbage and its environmental impact as overview. Section 2 describes the literature review done regarding the work. Section 3 explains about the proposed methodology for the classification system to obtain the desired results. Section 4 includes the results and discussion. Finally, section 5 includes conclusion and future work. The key references are listed at the end of the paper.

3 Methodology

The proposed framework consists of image acquisition, pre-processing, feature extraction and classification. The overall block diagram of this work is shown in figure 1. Garbage images from various sources including the internet and live images have been obtained and compilation of all the image data into an image dataset in the image acquisition process. Image augmentation and image resizing are used as pre-processing methods. In the prescribed work, Convolutional Neural Network (CNN) is used to extract the features from the images in the dataset. The Xception (CNN) architecture extracts a total of 2048 features from an input image which can be fed into fully connected layers to get the classified output. The various metrics that we can use to evaluate our model include accuracy, precision, recall and F1-score. These metrics are calculated by using the values from the confusion matrix.

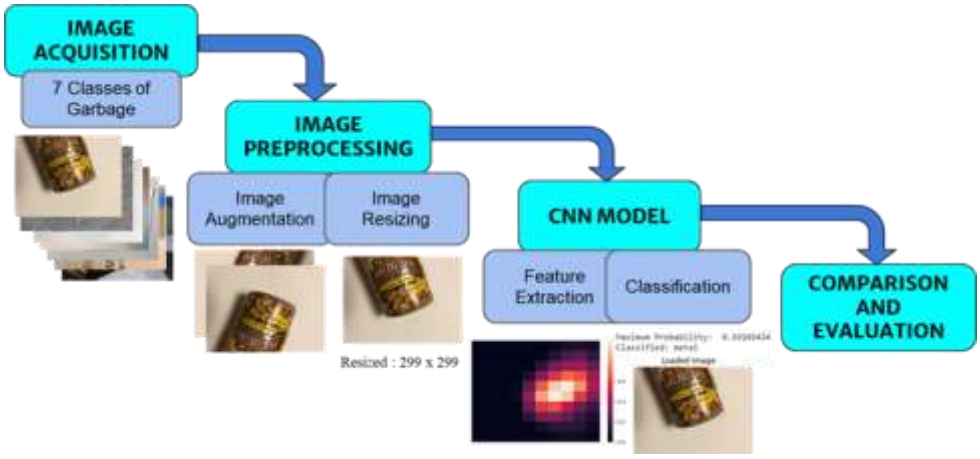


Figure 1. Block diagram of the proposed system

3.1. Xception CNN model

The Xception CNN model is chosen whose architecture is shown in figure 2. There are 36 convolutional layers in the Xception architecture which form the feature extraction base of the network. These 36 convolutional layers are restructured into 14 modules, all of which have linear residual connections, except for the first and last modules. The Xception architecture can be modelled as a stack of depth wise separable convolution layers arranged in a linear fashion with residual connections. A total of 2048 features extracted from the input image by the Xception architecture, which can then be fed into fully connected layers to produce the classified output.

. The Xception model uses modified depthwise separable convolutional layers, which helps in reducing the overall convolutional computations. Depthwise Convolution is followed by Pointwise convolution. Modified Depthwise convolution changes this order of convolution, by performing pointwise convolution first, followed by Depthwise convolutions [9].

3.2. Modified Xception Architecture

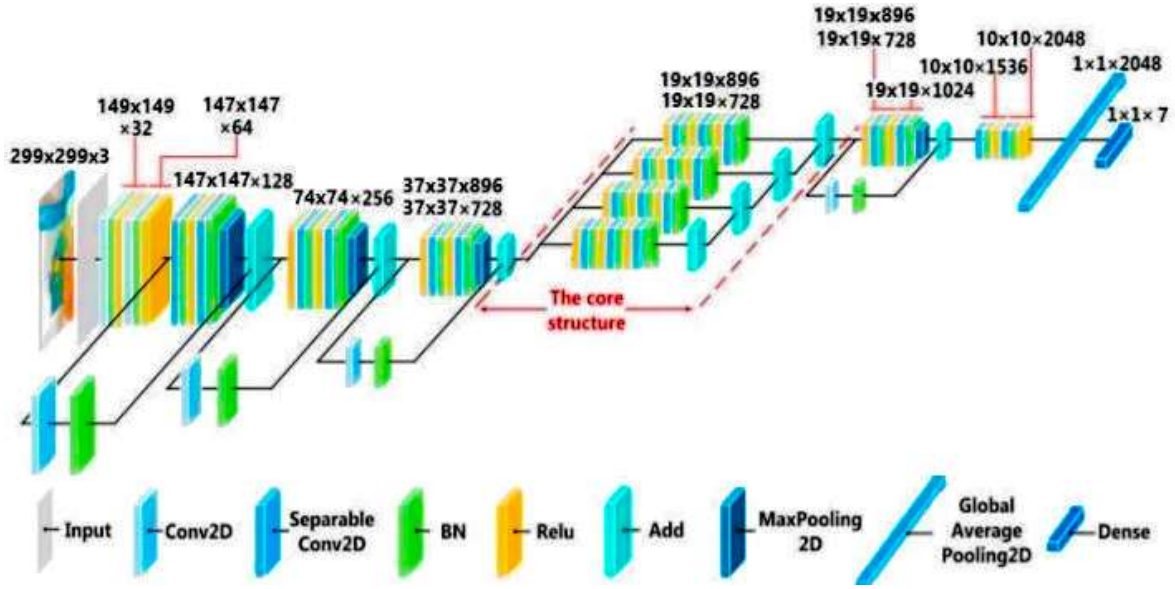


Fig 2. Modified Xception Architecture

In the middle flow of the core structure of the Xception architecture, the convolutional layer modules are repeated 8 times sequentially which is modified as shown in Figure 2. The part of the network receiving 19 x 19 x 728 images is called the core structure part. This is done to reduce the number of convolutional computations that might be redundant, thereby resulting in faster network convergence, resulting in improved network performance and classification accuracy for the TrashNet dataset.

4. Results and Discussion

The accuracy plot shows the performance of the model where how the model learns to be more accurate over many iterations or epochs. The training and validation accuracy tracks well with each other, thus showing a good accuracy for the Proposed Modified Xception. The plot shown in Figure 6 is evident in showing that the proposed Modified Xception shows higher accuracy than the original Xception model for TrashNet dataset.

Fig 3. Accuracy Plot

From figure 3, it is observed that even though both Xception models have a good learning rate, it is evident that the Proposed Modified Xception shows lesser loss than the Xception model.

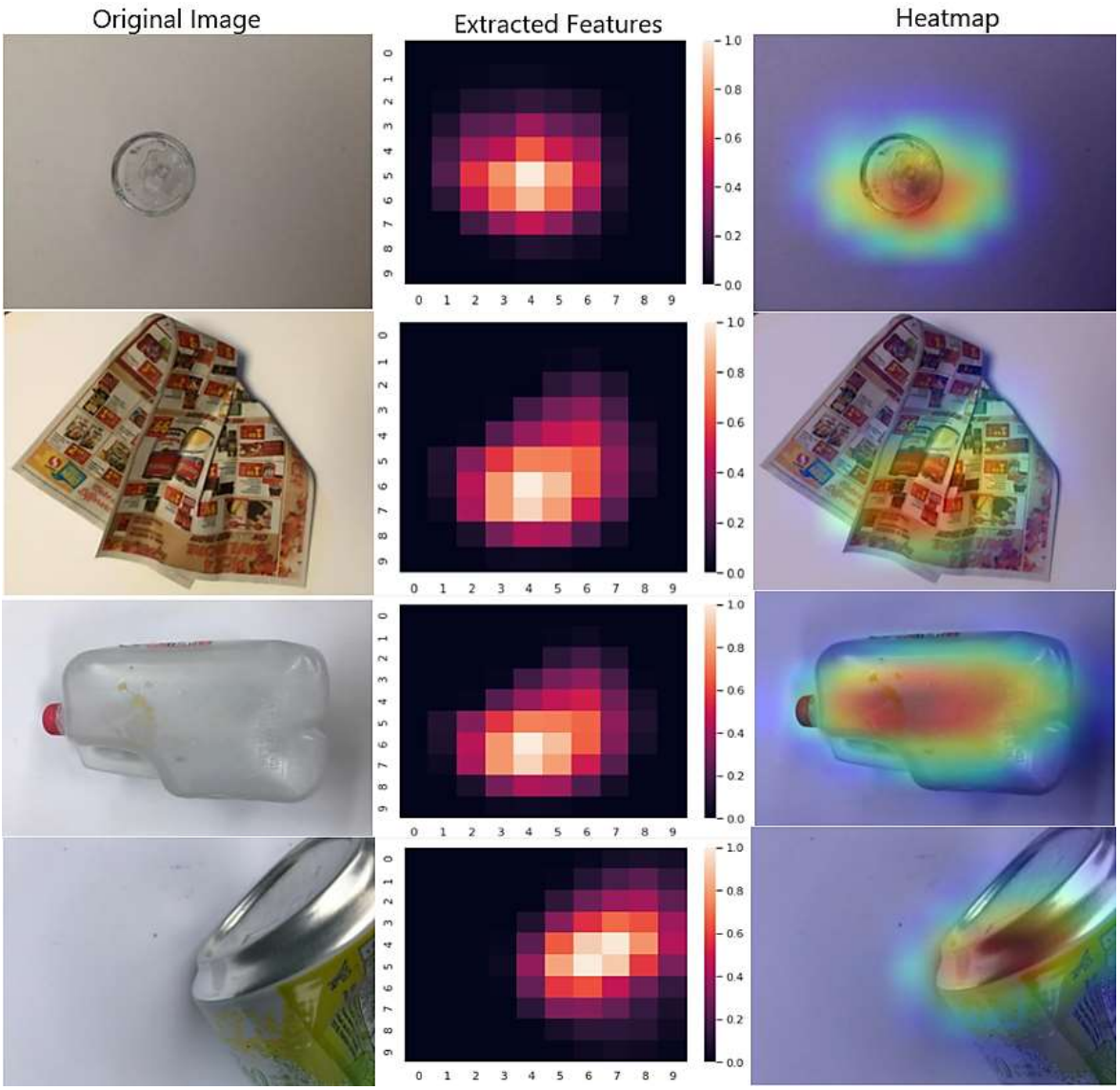


Fig 4. Grad-CAM visualization of extracted features

A Grad-CAM visualization which produces a localization map to highlight the important regions in an image has been used to visualize the features of an image extracted using the proposed network. The images in Figure 4 shows the extracted features visualized using GRAD-CAM visualization over the original input image. It can be inferred that the model is indeed looking at the correct patterns in the image and activating around those patterns.

From Figures 5 and 6, it can be seen that both Confusion Matrices show good performances of the models. On closer observation, we can infer that the performance lag in Paper and Metal Classes in Xception is overcome in the Proposed Modified Xception showing exceptional performance for Paper and Metal classes. Thus, from Figures 5 and 6, it is quite evident that the Confusion Matrix of Proposed Modified Xception shows that this model provides higher performance and effectiveness than the Xception model. The table 1 and Figure 7 show the model metrics for each class. From the Table, it is evident that the Proposed Modified Xception shows very good metric scores for each class.

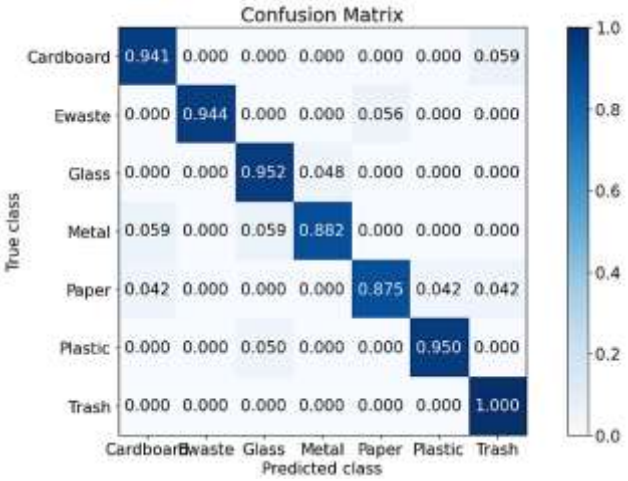


Fig 5. Confusion Matrix of Xception

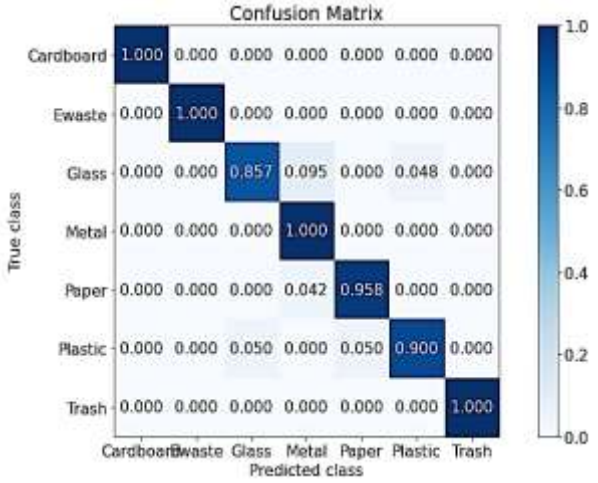


Fig 6. Confusion Matrix of Proposed Modified Xception

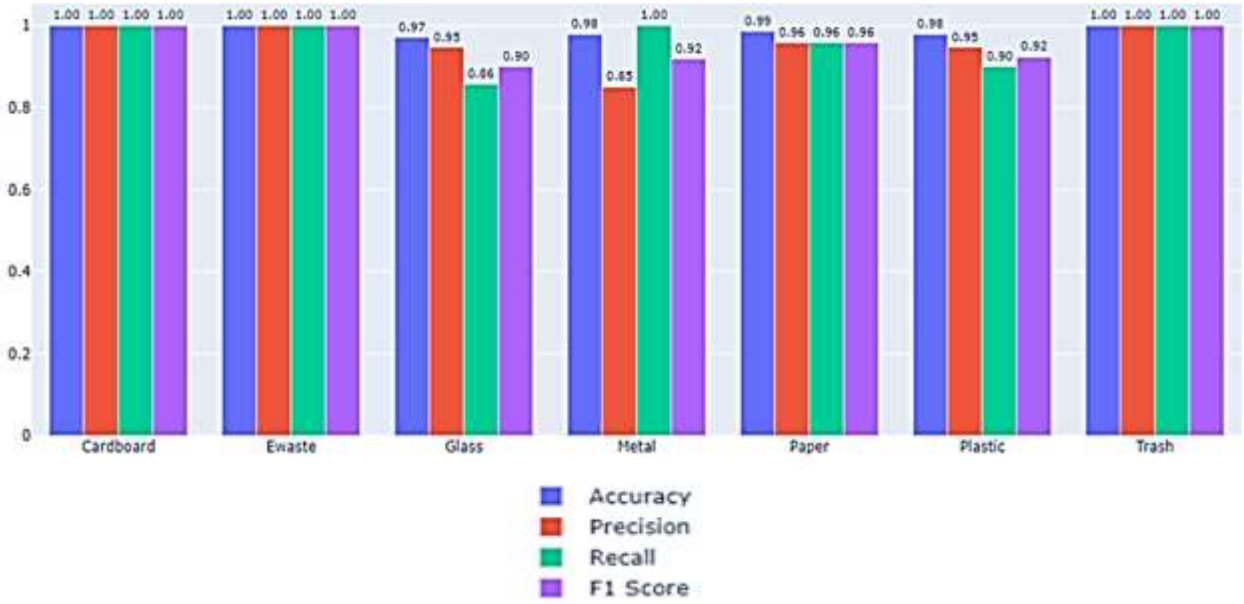
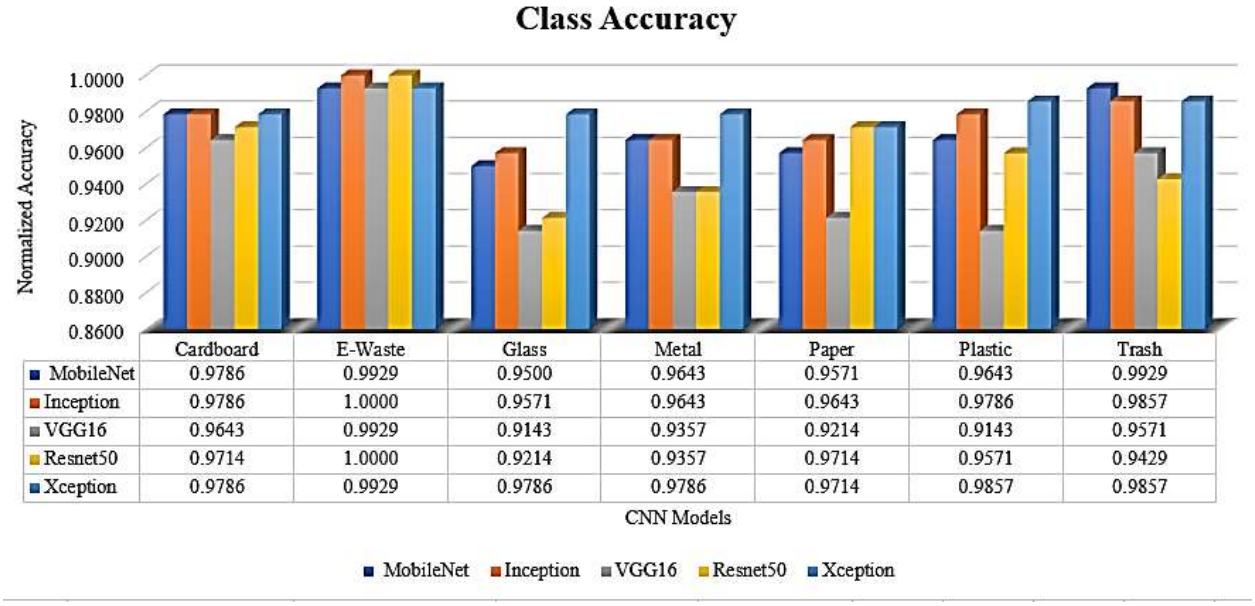


Fig 7. Model Metrics for each class

Table 1. Performance metrics of Proposed Modified Xception

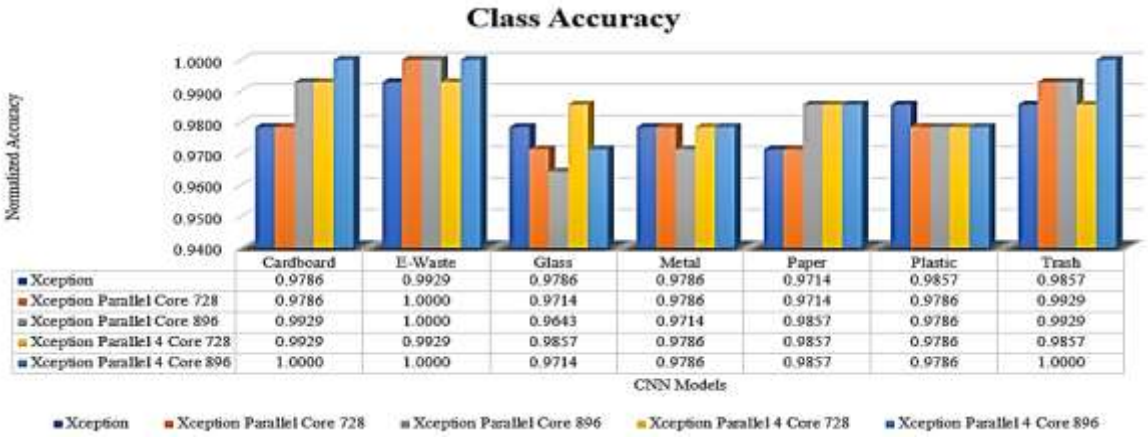
Model Metrics	Normalized Values
Accuracy	0.9571
MCC	0.9503
Cohen's Kappa Coefficient	0.9499

` Figure 8 shows the comparison of class accuracy over different models. It is evident from the figure 8, that the Xception model has the best class accuracy among the models compared. Figure 9 shows the comparison of class accuracy among different Modified Xception models. It is observed and infer that the proposed Modified Xception model – Xception Parallel 4 Core 896 model shows the best accuracy for each class among the modified Xception models. From the figure 9, it is evident that the Proposed Modified Xception - Xception Parallel 4 Core 896 model shows the best class accuracy.



	Cardboard	E-Waste	Glass	Metal	Paper	Plastic	Trash
MobileNet	0.9786	0.9929	0.9500	0.9643	0.9571	0.9643	0.9929
Inception	0.9786	1.0000	0.9571	0.9643	0.9643	0.9786	0.9857
VGG16	0.9643	0.9929	0.9143	0.9357	0.9214	0.9143	0.9571
Resnet50	0.9714	1.0000	0.9214	0.9357	0.9714	0.9571	0.9429
Xception	0.9786	0.9929	0.9786	0.9786	0.9714	0.9857	0.9857

Fig 8. Class Accuracy comparison of different models



	Cardboard	E-Waste	Glass	Metal	Paper	Plastic	Trash
Xception	0.9786	0.9929	0.9786	0.9786	0.9714	0.9857	0.9857
Xception Parallel Core 728	0.9786	1.0000	0.9714	0.9786	0.9714	0.9786	0.9929
Xception Parallel Core 896	0.9929	1.0000	0.9643	0.9714	0.9857	0.9786	0.9929
Xception Parallel 4 Core 728	0.9929	0.9929	0.9857	0.9786	0.9857	0.9786	0.9857
Xception Parallel 4 Core 896	1.0000	1.0000	0.9714	0.9786	0.9857	0.9786	1.0000

Fig 9. Class Accuracy comparison of modified Xception models

VI. Conclusion

The Xception architecture has been successfully modified in its core structure to obtain improved accuracy of classification. The Proposed Modified Xception model – Xception Parallel 4 core 896 provides high accuracy of classification of Garbage images which have been pre-processed. The proposed modified Xception model also shows a more balanced predicting ability, which allows it to be more suitable for implementation in practical applications. High accuracy is obtained especially in categories such as e-waste and trash, which are extremely crucial categories for real-life applications in both the present and the near future. On comparison with other models such as Inception, MobileNet, Resnet50 and VGG16, this model has proved to perform much better in terms of accuracy. This system of classifying images of garbage may also prove to be useful to sort out materials on a large scale without the need for human intervention, thus reducing costs as well as preventing the dangers associated with it. 47 As automation is speculated to be the law of the future, this system can be optimized and implemented into robotic waste management systems to have efficient and safe waste disposal and recycling without human intervention. Our work can be implemented in mobile phones to provide a portable efficient waste management system in future. We hope to create a safe and sustainable world and a harmonious future with our work to safeguard the sanctimonious peace of earth.

6. References

[1] Cuiping Shi, Ruiyang Xia and Liguo Wang, “A Novel Multi-Branch Channel Expansion Network for Garbage Image Classification”, IEEE Access, Volume 8, 2020.

[2] Fei Xue, Hongbing Ji, Wenbo Zhang, “Mutual information guided 3D ResNet for self-supervised video representation learning”, IET Image Processing, 2020.

[3] Francois Chollet, “Xception: Deep Learning with Depthwise Separable Convolutions”, IEEE Conference on Computer Vision and Pattern Recognition, 2017.

[4] Janusz Bobulski, Mariusz Kubanek, “Waste Classification System using Image Processing and Convolutional Neural Networks”, IWANN, Volume 11507, 2019.

[5] J. Shi, Z. Li, S. Ying, C. Wang, Q. Liu, Q. Zhang, and P. Yan, ``MR image super-resolution via wide residual networks with Fixed skip connection," IEEE J. Biomed. Health Informat., Volume 23, May 2019.

[6] Kashif Ahmed, Khalil Khan, Ala al-Faqaha, “Intelligent Fusion of Deep Features for Improved Waste Classification”, IEEE Access (Institute of Electrical and Electronics Engineers, Volume 8, 2020.

[7] K. Kawaguchi, J. Huang, and L. P. Kaelbling, “Effect of depth and width on local minima in deep learning," Neural Comput., vol. 31, Jul. 2019.

[8] Khagi, B., Lee, C. G., & Kwon, G.-R., “Alzheimer’s disease Classification from Brain MRI based on transfer learning from CNN”, 11th Biomedical Engineering International Conference, 2018.

[9] Mas Rina Mustaffa, Nuru Amelia Nasharuddin, “Automated Recyclable Waste Classification using Multiples Shape based Properties and Quadratic Discriminant”, IJITEE, Volume 8, Issue-8S, June 2019.

[10] Mohammad Saeed Rad, Andreas von Kaenel, Andre Droux, Francois Tieche, Nabil Ouerhani, Hazim Kemal Ekenel, Jean-Philippe Thiran, “A Computer Vision System to Localize and Classify Wastes on the Streets”, Springer, Volume 10528, 2017.