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Abstract- *A rapid increase in the enormous volume of waste leads to high separation costs and also impacts on manual separation. There is a major demand for automatic waste segregation. To achieve this, waste needs to be classified into recyclable and non-recyclable types since the recyclable process helps in reusing that waste for various useful future purposes and is helpful for various economic aspects. Trash classification is one of the important tasks for recyclable purposes. In this article, we proposed an automated waste classification for educational institutions that uses computer vision tasks for single waste recognition, which classifies the waste at the time of throwing it into the bin. The model is constructed with the help of resnet-50, Alex net with batch normalization, and Google net. This model classifies the detected waste into six categories. Our proposed trash classification model is used to detect and recognize the waste from the captured image by the camera and also pre-process the image by reducing the actual dimension of the image for better feature extraction.*

Keywords*: Convolutional Neural Network, Recyclability, Image Classification, Feature Extraction*

INTRODUCTION

In recent years, millions and millions of tons of waste are generated but it is quite difficult to monitor, screening and managing of those waste for further recycling and dumping of all waste into the same dustbin leads to contamination of the environment. Waste separating cost in the waste-yard is high and it's a time consuming process. Classification of garbage waste has become an increasingly popular topic. According to the latest report of International LianheZaobao, the volume of garbage will be increased by 70% by 2050 in the world and classification of garbage will be even enormous [1].Plastic degradation in the soil is anticipated to take about 400 years [2]. Glass bottles are thought to take a million years to decompose in the soil on average [3]. Sweep Smart [4], a waste management firm located in the Netherlands, began working with a local vendor running a dry-waste management centre in Bangalore (supported by HasiruDala) [5] and the Electronic City Industrial Township Authority's dry-waste management section in late 2016. (ELCITA). Increased population in the urban areas, has caused increasing accumulation of waste generation. Due to indolent behaviour of the people and lack of dustbins in local regions, disposal of waste has increased rapidly.There are several types of garbage, such as dry, wet, biodegradable, and so on, and separating them is a difficult chore.With technological developments, recycling waste can yield more efficient results. In this system, decomposition of waste still depends on human factors [6].Despite the presence of large-scale industrial waste segregators, it is always preferable to segregate garbage at the source.Manual separation of wastes leads to time consuming process.There is a major

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demand for bin-level sorting while dumping the wastes into it but still automated garbage classification remains a difficult task since camera placed at the bin captures an image which may usually contains noises and the object needs to be localized and image gets preprocessed and dimension needs to be reduced for further recognition task.For reducing various problems, we proposed a single waste detection framework for detecting single waste at a time and classifies accordingly.

RELATED WORKS

The best accuracy is achieved using several strategies proposed for distinct types of garbage detection and classification. Some selective approaches for classification and problems with some proposed models are addressed in this part.

A. Object detection and recognition

Object detection refers to the localization of various objects in an image or video and it comprises two techniques such as single stage detector and two stage detector. Object detection is a basic visual detection problem in computer vision that has been explored extensively over the years. Deep learning-based object detection systems have been extensively researched in recent years.Sylwia Majchrowska [7] addressed certain concerns with data annotations while detecting an item, which were overcome by splitting the method into two stages: region localization and region categorization. After the object has been detected, it gets cropped and added to the classification dataset. Unified learning framework[10] used for object recognition and occurs some negative transfer for domain shift[9] for autoencoder based domain discrimination.[11] proposed some ideas which generally reduces the information cost. [12] A new lightweight neural network has been proposed ,WasNet employs stacked convolutional layers and expands the convolutional blocks, contributing to the garbage categorization and recycling system. The experiment was altered for the number of convolution layers as well as the depth and width of the network, in order to determine the best network architecture for the dataset.

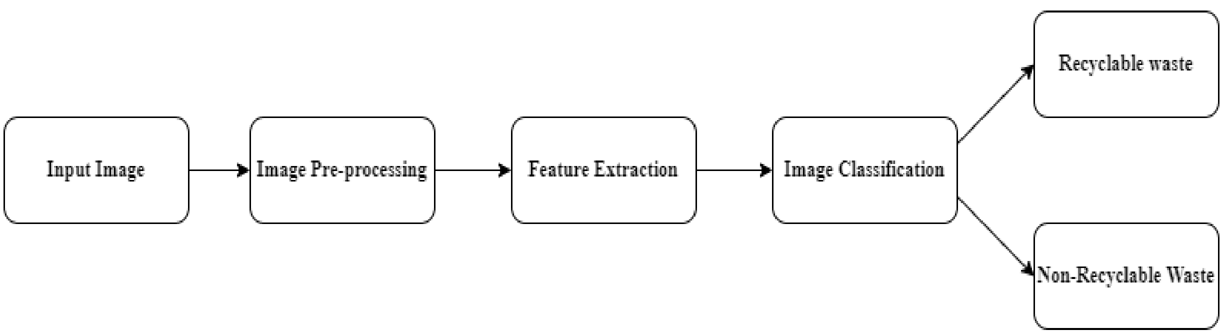

Figure 1 *System flow for Waste Classification*

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B. Garbage Classification

Since et al[17] suggested a residual unit updation in ResNet, garbage waste classification tackles the gradient vanishing problem.Model gets fine-tuned using waste images [14] proposed Reverse vending machine and identifies the best model as AlexNet which is too complicated, hence double LeNet model is introduced for classification task [18] proposed a four-layer CNN approach performance using Alexnet and Res-net models, and uses Arduino to operate the Servo Motor in a specific way, resulting in the camera module taking an image and classifying waste.

C. Multi feature fusion

By merging features from different layers, deep learning provides a fusion technique for retrieved features from the input image.Since Zhuang Kang [14] proposed parallel feature extraction and those parallel extracted features are produced for feature fusion. ResNet and Inception net used for training process and inception net achieves higher depth for the network and also it helps in model generalization for effective fusion process and also double fusion[8] for accurate classification by measuring the fitness criteria by averaging and selecting the highest average score as a resultant image label with waste category name.

D. Transfer Learning

Deep Neural net based models require large amounts of labelled data which can be achieved by using transfer learning [12] approach. The primary detection benchmark was the detect-waste dataset[18], and the object detector was trained and evaluated on all detect-waste subsets. Because it has fewer parameters and uses fewer computational resources, the EfficientDet-D2 [27] network achieved the best evaluation results. Experiments have shown that modifying pseudo-labels for each batch improves accuracy by a tiny margin.

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E. K-Nearest Neighbour

K-nearest neighbour is an effective classification method which is based on the majority of k-nearest neighbours and uses multinomial regression [13] which reduces the complexity of model and also distance similarity measure used for dot-wise operation. K-way classification problem [19] helps in the development of a vision-based waste detection system for determining the recyclability of household waste. The cosine distance [10] is used to find neighbors, and then K-nearest neighbours transforms them into prediction probabilities.

F. Image Classification

Image classification tasks often mitigate the over-fitting problem and retain model accuracy by resisting occlusion [13]. Random selection of rectangular portions in an image is performed, and random erasing is used to erase some pixel values [15]. Label smoothing and mixed up [16] changes with the previous enhancements made in a model. Multi-model Cascaded Convolutional Neural Network[28] for image identification and classification of domestic trash and also used a classification model cascaded with the detection part to determine whether the detection results are accurate in order to suppress false-positive forecasts

G. Instance waste segregation

Waste gets segregated with a sorting system [20] which sorts automatically and ensures

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that any dynamic changes in the environment which do not affect the sensing. A microcontroller-based platform Arduino Mega 2560 board[21] interfaced with Ultrasonic sensor enabled smart bins connected through the cellular networks creates a huge quantity of data and automates the movement of smart-bin from its source to the destination user with the help of deep learning based model.The sensor system is connected to the GSM system via microcontroller. The network of sensor-enabled smart bins connected through cellular networks creates a huge quantity of data, which is processed and displayed in real time to give insights into the city's garbage problem.

PROPOSED WORK

Waste detection and classification are essential for categorising wastes into recyclable and non-recyclable wastes. Single waste placed in the top of the bin gets detected with the help of a camera which captures as an image. Those captured images are supplied to the feature extraction stage, which uses a CNN model for extracting important information from the image and classifies the wastes into recyclable and non-recyclable waste.

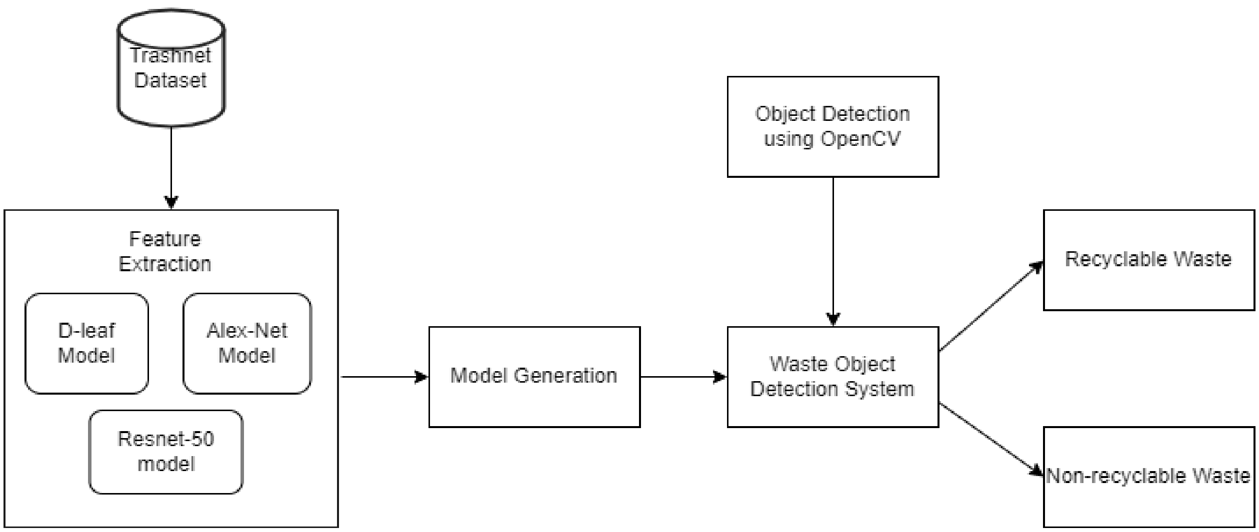

Figure 2 *System design for waste classification*

Dataset

To evaluate the proposed model, TrashNet dataset has been used. In this data set, it consists of 6 classes of common wastes including cardboard, clothes, glass, metal, paper, plastic, trash. The dataset consists of 2527 images of 6 classes of waste in jpg format.

Image Pre-Processing

The original images are unsuitable for study and include complexity in training the model, as it has high pixel values. In this research, the size of images in the TrashNet dataset has been modified. Images in the TrashNet dataset have high resolution as well as dimensions of each and every image is different. The image is resize to desired target size (300*300). As the image was

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taken in a high brightness environment, in order to reduce that, a fraction of the value is multiplied with image pixels. In the ratio of 7:1:2, the dataset is divided into training, validation, and testing.As a result, the above techniques size of the entire dataset is drastically reduced to 25MB from 3.4GB.

Feature Extraction

Feature extraction is used to extract relevant properties from waste images such as form, texture, and colour, which is a major component in this study.

CNN

Convolutional Neural Network is one of the deep learning methods recommended for feature extraction and its primary function is to divide an image into pixels and then combine these groupings of pixels in order to assess the image's matrix. The matrix value for a black-and-white image is 2x2. The matrix value is 3x3 if the image is a colourized image. CNN is a multilayer perceptron in the sense that it learns picture properties using several perceptron layers.. A typical CNN layer is made up of three layers. The convolution stage is the first layer, and it creates feature maps by performing convolution operations on an input image using filters. Non-linear activation functions such as Rectified Linear Unit are used in all feature maps in the second layer..In terms of piecewise linear function, this function would remain linearly close. As a result, many of the properties which allow gradient-based approaches and generalised linear models to optimise will be preserved. The pooling layer is the third layer, which employs a function to reduce and represent the information of a certain layer and comes after the convolution layer, which is used to down sample the retrieved features. Following the stacking of a few convolution layers, the pooling layers and normalization function are applied. The feature maps have been flattened and organised into dense layers. Dropout layers are preferred after dense layers because they alleviate the problem of overfitting.

Proposed model: AlexNet model, d-leaf model and ResNet-50 model are combined and used for object detection mechanism which generates various regions and extracts features from the images.Combining these deep models for waste classification is a more reliable method.

AlexNet

AlexNet is a work of supervised learning and got very good results for our model and it had eight layers, the first five of which were convolutional layers, some of which were followed by max-pooling layers, and the final three of which were fully linked layers[22]. It employed the non-saturating ReLU activation function, which outperformed tanh and sigmoid in terms of training performance and allowed for multi-GPU training.It is not easy to have low classification errors without having overfitting problems.An internal covariate shift issue occurs during neural network training, resulting in varying contrast for the same classes of pictures. This issue is addressed with a batch normalisation layer [23]. A BN layer is inserted before each input layer to improve normalisation for each layer's input data. Normalization will alter the network layer's features and, consequently, this layer has two learnable parameters to increase normalisation, allowing the network to restore its feature distribution, and this issue may be effectively controlled by layering.

ResNet-50

Resnet-50 [24] is one of the most active networks on its own and residual net

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variation of 48 convolutional layers, 1 subsampling layer and 1 average pool layer. Generally, Resnet framework is used for image identification tasks and we used Resnet-50. This network takes an image with a height and width that are multiples of 32 and a channel width of 3. Every ResNet architecture uses 77% and 33% kernel sizes for initial convolution and max-pooling, respectively. The network then enters Stage 1, which is made up of three residual blocks, each with three layers. All three levels of the stage 1 block employ 64, 64, and 128 bit kernels to accomplish the convolution operation. Skip connection was used to avoid overfitting and ensure learning of important features.The convolution layer is used to extract important features from the given input and after that all of the salient features have been extracted, sample average pooling has been utilised to minimise the trainable parameter.

Optimization

Most commonly used optimizers are Adam and SGD. But both have different meanings. Adam leads to faster convergence but lacks generalization. SGD leads to better generalization but slow convergence. In order to obtain an optimal solution, improved generalisation and training stability, Adabelief optimizer [25] is used.It changes the size of its steps based on the gradient's present direction. It gives more reward than Adam in case of reinforcement learning and outperforms Adam, Radam and SGD. Adabelief optimizer has no extra parameters than Adam.

Algorithm 1: Adabelief Optimizer [25]

Initialize $\theta_0, m_0 \leftarrow 0, s_0 \leftarrow 0, t \leftarrow 0$

While θ_t not converged

$t \leftarrow t + 1$

$g_t \leftarrow \nabla_\theta f_t(\theta_t - 1)$

$m_t \leftarrow \beta_1 m_{t-1} - 1 + (1 - \beta_1) g_t$

$s_t \leftarrow \beta_2 s_{t-1} + (1 - \beta_2)(g_t - m_t)^2 + \epsilon$

Bias Correction

$$\widehat{m}_t \leftarrow \frac{m_t}{1-\beta_1^t}, \ \hat{s}_t \leftarrow \frac{s_t}{1-\beta_2^t}$$

Update

$$\theta_t \leftarrow \Pi_{F, \sqrt{\hat{s}_t}} \left(\theta_{t-1} - \frac{\alpha \widehat{m}_t}{\sqrt{\hat{s}_t + \epsilon}}\right)$$

Experimental Results

A. Performance Evaluation Metrics

The suggested model's success rate was measured using performance metrics such as recall, precision, F1-score, and accuracy in this study. The values of the given metrics were computed using the equation below. True positive (TP) and true negative (TN) estimates classified samples properly, but false positive (FP) and false negative (FN) estimates classified samples wrongly.

Accuracy

Accuracy for each of the classes are specified in the same way as for the binary classification. The accuracy for the paper class is the percentage of accurately predicted paper images among all predicted paper images. As a result, the items that our predictor identifies as paper are, in fact, papers. We can compute the accuracy for the remaining five classes in the same way.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

Precision is calculated by dividing the number of relevant classes returned by the total number of classes returned by a result.

$$Precision = \frac{TP}{TP + FP}$$

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F1-Score

The model's overall F1-score for six class problem is calculated by merging the scores of each class into a single value. Precision and recall are used to form an overall assessment of a model's accuracy.

$$F1 = \ 2 * \frac{(Precision * Recall)}{(Precision + Recall)}$$

Recall

The recall for paper class is the number of properly anticipated paper images divided by the number of actual paper images. This signifies that the paper images were classified as paper by our model. We can compute the recall for the remaining five classes in the same way.

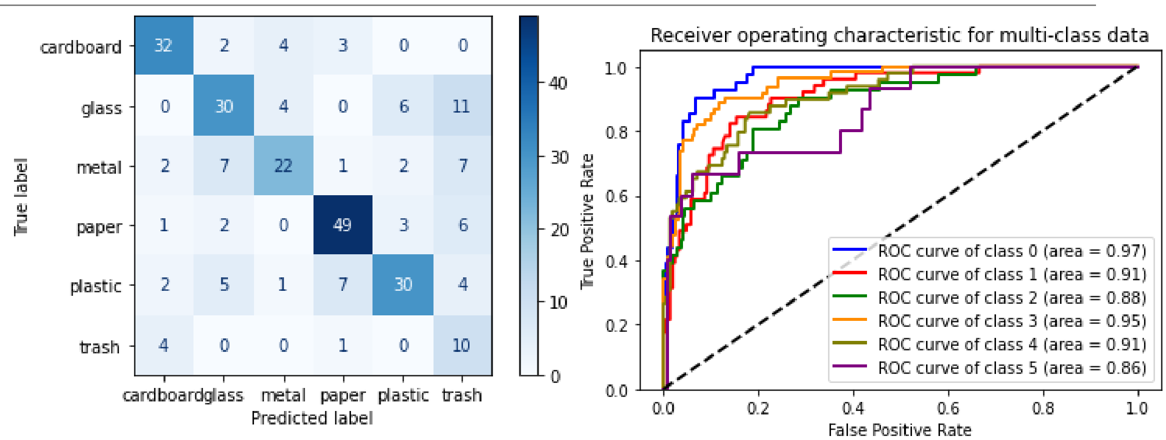
$$Recall = \frac{TP}{TP + FN}$$

B. Model Evaluation

After model training, it gets combined into three models such as Resnet-50, Alexnet and D-leaf model that have higher detection ability.It also seeks to improve accuracy and views the noisy gradient's exponential moving average as a forecast of the gradient at the next time step; if the observed gradient deviates significantly from the prediction, we distrust the current observation and take a short step.

Table 1 Classification Result

	Precision	Recall	F1- Score	Support
Cardboard	**0.78**	**0.78**	**0.78**	**41**
Glass	**0.65**	**0.59**	**0.62**	**51**
Metal	**0.71**	**0.54**	**0.61**	**41**
Paper	**0.80**	**0.80**	**0.80**	**61**
Plastic	**0.73**	**0.61**	**0.67**	**49**
Trash	**0.38**	**0.67**	**0.38**	**15**
Accuracy	**-**	**-**	**0.67**	**258**
Macro average	**0.66**	**0.66**	**0.64**	**258**
Weighted average	**0.71**	**0.67**	**0.68**	**258**



(a) *(b)*

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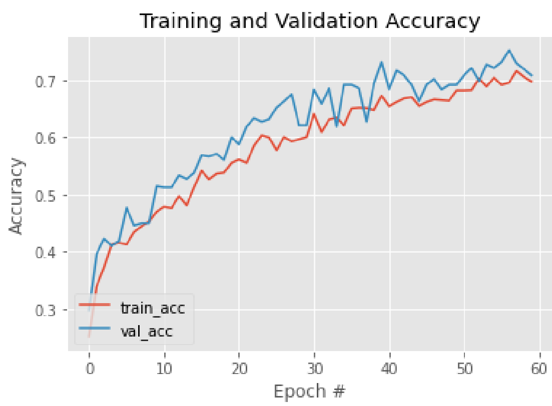
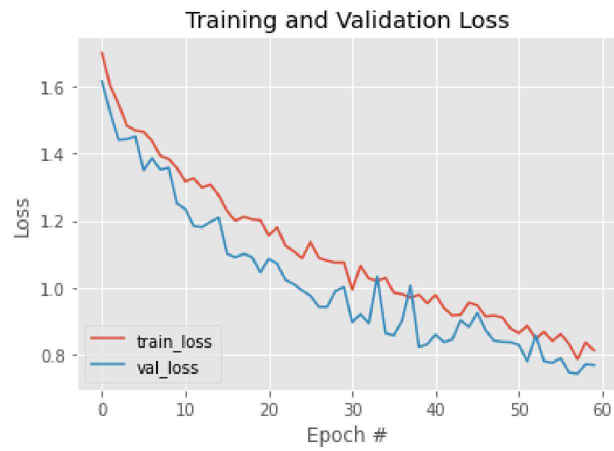
Fig.3. Classification Results. Graph (a) depicts the confusion matrix for six different classes, including cardboard, glass, metal, paper, plastic, and trash, and compares the actual and predicted values. Diagonal values represent results that have been appropriately categorised, and other values in the confusion matrix represent misclassified results. Graph (b) depicts the roc curve for six classes using model prediction.



(c)



(d)

Fig.4. Accuracy and loss. The training and validation accuracy for the Trashnet dataset's resnet-50, alexnet, and d-leaf models are depicted in graph (c).After 60 epochs of training, the model's training and validation accuracy improve dramatically.The training and validation loss for the resnet-50, alexnet, and d-leaf models on the Trashnet dataset is represented by Graph (d). After 50 epochs, the train loss and validation loss deviate and decrease.

CONCLUSION

Garbage classification still remains a complicated task for separating various kinds of waste, and it negatively affects various lives [25]. There is more information that needs to be included for multiple waste classifications. In this study, the main purpose of our proposed work is single waste detection and identifying six types of classes, which is not sufficient for domestic and household waste. Some issues arise, such as misclassification when dumping multiple wastes into the bin.After preprocessing the dataset, images are augmented for the convolutional neural network, and we multiply the data by a value called rescale. Our original images have RGB coefficients ranging from 0–255, but these values are too high for our model to interpret, so we scale with a factor of 1 to achieve target values between 0 and 1. Flip the images in both horizontal and vertical positions and also use a pixel transformation technique to reduce the brightness by a percentage of the value multiplied by the image pixels. In general, we employ a variety of operations on it, but the actual pixel values will not change, and pixel values will not be adjusted as a result of these modifications. Rather, the placement of pixel values will change. Mixed waste is

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generated, necessitating the use of effective sorting techniques. In the future, research will be focused on multiple object detection, which will allow multiple categories of waste to be recognised simultaneously in a single image, facilitating waste sorting and recycling automation.

REFERENCE

[1] R. Geyer, J.R. Jambeck, K.L. Law, Production, use, and fate of all plastics ever made, Sci. Adv. 3 (2017), https://doi.org/10.1126/sciadv.1700782 e1700782.

[2] A. Mohajerani, J. Vajna, T.H.H. Cheung, H. Kurmus, A. Arulrajah, S. Horpibulsuk, Practical recycling applications of crushed waste glass in construction materials: a review, ConstrBuild. Mater. 156 (2017) 443–467, https://doi.org/10.1016/j.conbuildmat.2017.09.005.

[3] E.K. Agbaeze, I.O. Onwuka, C. Agbo, Impact of sustainable solid waste management on economic development – lessons from Enugu State Nigeria, Comput. Eng. Intell. Syst. 5 (2014) 130–139.

[4] M. Cıbuk, U. Budak, Y. Guo, M.C. Ince, A. Sengur,Efficient deep features selections and classification for flower species recognition, Measurement 137 (2019) 7–13, https://doi.org/10.1016/j.measurement.2019.01.041.

[5] M.Togˇaçar,B.Ergen, Biyomedikal Görüntülerde DerinÖgˇrenmeile MevcutYöntemlerinKıyaslanması, FıratÜniversitesiMühendislikBilim. Derg. 31 (2019) 109–121.

[6] N. Bandara, J. Patrick, J. Hettiaratchi, Environmental impacts with waste disposal practices in a suburban municipality in Sri Lanka, Int. J. Environ. Waste Manag. 6 (2010), https://doi.org/10.1504/ijewm.2010.033987.

[7] SylwiaMajchrowska, AgnieszkaMikołajczyk, Maria Ferlin, Zuzanna Kwiatkowska, Marta A, Plantikow, ArkadiuszKwasigroch , Karol Majek “Deep learning-based waste detection in natural and urban environments” in Science direct Journals , December 2021.

[8] A. H. Vo, M. T. Vo, T. Le et al., “A novel framework for trash classification using deep transfer learning,” IEEE Access, vol. 7, pp. 178 631–178 639,2019.

[9] H. Zou, Y. Zhou, J. Yang, H. Liu, H. P. Das, and C. J. Spanos, “Consensus adversarial domain adaptation,” in Proc. AAAI Conf. Artif. Intell., vol. 33,2019, pp. 5997–6004.

[10] Jianfei Yang , Zhaoyang Zeng, Kai Wang , Han Zou , and LihuaXie , GarbageNet: A Unified Learning Framework for Robust Garbage Classification .IEEE transactions on artificial intelligence , Vol. 2, no. 4,August 2021

[11] J. Toutouh, D. Rossit, and S. Nesmachnow, “Soft computing methods for multiobjective location of garbage accumulation points in smart cities,” Annals of Mathematics and Artificial Intelligence, 06 2019.

[12] S. J. Pan et al., “A survey on transfer learning,” IEEE Trans. Knowl. Data Eng., vol. 22, no. 10, pp. 1345–1359, Oct. 2010

[13] Y. Resti, A. S. Mohruni, T. Rodiana, and D. A. Zayanti, “Study in Development of Cans Waste Classification System Based on

Statistical Approaches," J. Phys.: Conf. Ser., vol. 1198, no. 9, p. 92004, 2019, doi: 10.1088/1742-6596/1198/9/092004

[14] A. N. Kokoulin et al. described in their research entitled "Convolutional Neural Networks Application in Plastic Waste Recognition and Sorting"

[15] Z. Zhong, L. Zheng, G. Kang, S. Li, and Y. Yang, "Random erasing data augmentation," arXiv preprint arXiv:1708.04896, 2017.

[16] T. He, Z. Zhang, H. Zhang, Z. Zhang, J. Xie, and M. Li, "Bag of tricks for image classification with convolutional neural networks," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 558–567.

[17] MallikarjunaGowda C. P, Sachin Yadav, "Waste Classification and Segregation: Machine Learning and IOT Approach" in International Conference on Intelligent Engineering and Management (ICIEM) , July 2021

[18] SylwiaMajchrowska , AgnieszkaMikołajczyk , Maria Ferlin, Zuzanna Kwiatkowska, Marta A, Plantikow ,ArkadiuszKwasigroch , Karol Majek "Deep learning-based waste detection in natural and urban environments" in Science direct Journals , December 2021

[19] Jianfei Yang , Zhaoyang Zeng, Kai Wang , Han Zou , and LihuaXie , GarbageNet: A Unified Learning Framework for Robust Garbage Classification .IEEE transactions on artificial intelligence , Vol. 2, no. 4, August 2021

[20] Uppugunduru Anil Kumar ,B.Renuka , G.Kiranmai , G.Sowjanya, "Automatic waste segregator using raspberry Pi". International conference on emerging trends in engineering and science management , 2017

[21] Akshay K N ,GopalakrishnaPrabhu V A , Sharon Biju Easow "Smart-Bin", International Journal of Computer Science and Mobile Computing, Vol.9 Issue.7, July-2020

[22] Krizhevsky, Alex; Sutskever, Ilya; Hinton, Geoffrey E. (2017-05-24). "ImageNet classification with deep convolutional neural networks" (PDF). Communications of the ACM. 60 (6): 84–90. doi:10.1145/3065386. ISSN 0001-0782. S2CID 195908774.

[23] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," ArXiv, vol. abs/1502.03167, 2015.

[24] Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun "Deep Residual Learning for Image Recognition" arXiv:1512.03385v1 [cs.CV] 10 Dec 2015

[25] Juntang Zhuang,Tommy Tang,Yifan Ding,Sekhar Tatikonda,Nicha Dvornek,Xenophon Papademetris,James S. Duncan "AdaBelief Optimizer: Adapting Stepsizes by the Belief in Observed Gradients" arXiv:2010.07468v5 [cs.LG] 20 Dec 2020

[26] E.K. Agbaeze, I.O. Onwuka, C. Agbo, Impact Of Sustainable Solid Waste Management On Economic Development – lessons from Enugu State Nigeria, Comput. Eng. Intell. Syst. 5 (2014) 130–139.

[27] Tan, M., Pang, R., Le, Q.V., 2020. EfficientDet: Scalable and Efficient Object Detection. In: 2020 IEEE/Cvf Conference on Computer Vision and Pattern Recognition (Cvpr), pp. 10778–10787. https://doi.org/10.1109/CVPR42600.2020.01079.

[28] Jiajia Li,Jie Chen,Bin Sheng,Ping Li,Po Yang,David Dagan Feng,Life Fellow,Jun Qi "Automatic Detection and Classification System of Domestic Waste via Multi-model Cascaded Convolutional Neural Network" IEEE Transactions on Industrial Informatics, Vol. 18, No. 1, January 2022