Waste classification using Convolutional Neural Network

Mr. Devidas A. Jagtap, P.G. Scholar, Late G.N. Sapkal College of Engineering, Nashik, Maharashtra, India, devidasproject@gmail.com

Prof. Manjusha S. Borse Assistant Prof. E&TC Late G. N. Sapkal College of Engineering, Nashik, Maharashtra, India, Manjusha.borse19@gmail.com

Abstract - **Garbage is one of the most dangours product present onto earth and infact in this thenon-degradable part is veritably dangerous from mortal as well as beast point ofview. So we aimed to make a design which can sagrigate the type of scrap as per its parcels like paper, cupboard, glass, plastic etc. The thing of this design is to contribute to the development and enhancement of machine literacy ways concentrated on working environmental issues like the waste accumulation, global warming, pollution, etc. likewise, it'll be subject to trial by professionals and subject matter experts since its open- source. That trial is crucial when perfecting the performance of models in the field of machine literacy, along with the data gathering and processing ways used in the process.**

Keywords —Waste Classification, Machine Learning, Convolutional Neural Network

I. INTRODUCTION

There are substantially 3 reasons for the scrap pollution in that 1st bone is that absence of recyclable products indeed though society claiming for particulars which are more durable and less dangerous to nature but at one condition they becomes waste.2 nd reason is overpopulation present onto earth, as the product of particulars is veritably huge and due to it there will be further scrap produced as compare to its disposablecapacity.In 3rd reason the main point is less mindfulness of humanity onto global warming, pollution problemsetc. So lack of involvement is there for mortal being regarding scrapre-cycling. To show how the waste produced in form of data check says world population produced 7 to 9 billion data in single time out of which 70 is manhandled available onto landfilled, ocean and contaminating it. This data refers to the total quantum of used, unwanted, and discarded objects that humankind creates. still, there's a distinction between the total waste produced and the so- called Municipal Solid Waste(MSW), which only includes scrap generated in civic centers or their areas of influence. Concerning the quantum of MSW with respect to the rest of the waste, roughly 2 billion tons of civic scrap is produced yearly, with around 33 of that not adequately managed. It means that each person generates from0.1 to4.5 kilograms of waste every day, with an normal of0.7 kg. In addition, it's anticipated that the MSW will increase to3.4 billion tons by the time 2050 due to the fleetly growing global population and the need for the ferocious use of natural coffers for the development of assiduity and the sustaining of our civilization. immaculately, a completely enforced indirect frugality model would basically be an excellent result for the accumulation problem, therefore with the match of technology to problem we need to find the result for separating of this waste so that we can find out which of them is.

II. OBJECTIVE

The scrap collection in India still depends on unorganized collection of waste. The isolation process is still handled by humanity which has numerous health issues, time consuing, expensive and less effective. therefore automatic waste bracket system should be developed which is simple, low cost and fluently adoptable to mortal or we say theworkers. For this we need to use rearmost technology which is CNN. The end of using a Convolutional Network to reuse an image resides in its capability to prize certain patterns or features from images with an invariance in position, gyration, and scale.

III. METHODOLOGY

To make the Convolutional Neural Network programmatically, we will be using Python law running on the web platform Google Colab, which provides a presto, comfortable, and robust pall terrain for training similar large models. likewise, the Python programming language has a wide variety of libraries acquainted to constructing machine literacy algorithms that make training and evaluation much more accessible. similar libraries are

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Tensorflow, Keras, Numpy, Matplotlib, etc. Fig.1 show the detailed workflow of proposed conception of scrap bracket using CNN.Before structure, training, and assessing our model, we must gather a dataset of labeled waste images. There are numerous coffers on the internet where you can download a dataset to use in a machine literacy design, not only images dataset but also numerically grounded datasets like business, deals,etc.

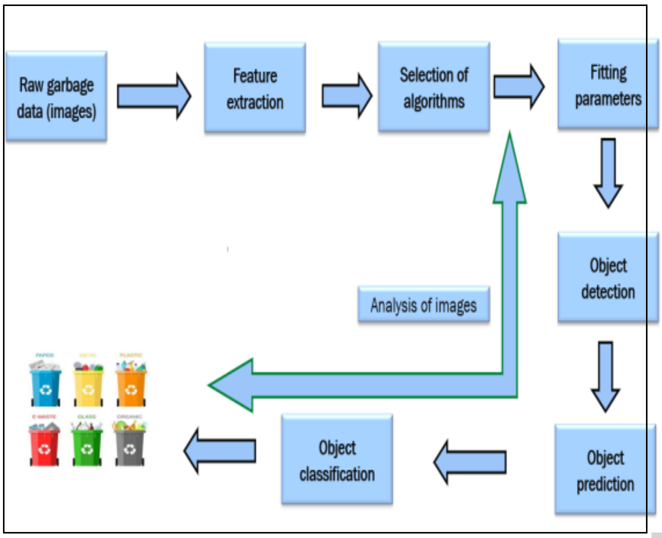

Fig.1 Work Flow of Prposed model

A. Data Collection and Processing

In this design, we will gather the data from Github. After having the data ready, let's start to make the Colab Tablet with all the Python law. But, first, we need to import the libraries that we're going to need. Subsequently, we've to resolve our data into two datasets(train and test). Each of them is only used in the corresponding phase of the design(training and evaluation of the model). This operation is critical to make the model able of generalizing from the handed data to any input that the stoner will use in product. The usual splitting rates are70/30,80/20, and90/10 for training and testing, independently. In this we uses the Keras API of the Tensorflow library to preprocess the dataset located into a brochure by resizing all the images to a standard dimension of 256x256 and setting a batch size of 128, meaning that in the training process, the data will pass through the network in gobbets of 128 images

Also, we can store the number of classes in a variable rooting it from the train dataset object (9 classes in this case) and usetf.data.AUTOTUNE to optimize the performance of both training and testing dataset objects

B. Model Building and Training

As we're dealing with a fairly large dataset(5000 images), it's accessible to use a common fashion when training a model on such an quantum of data called Transfer literacy. That refers to replacing the convolutional part of your model with an formerly trained one. So before training, your model will be suitable to prize useful features from the input images thanks to the trained convolutional part. also, it'll only have to train the last many thick layers, reducing the computing power and time involved. There are a lot of trained convolutional models available, but the most common bones are included in the Keras API that we're presently using for the project. Using the Template Template.

IV. MODEL EVALUATION

The training time it takes depends on the tackle, model complexity, and dataset size. But in this case, with a Google Colab terrain equipped with a Tesla P100 GPU, a dataset size of 5000 images roughly and a model with around 4500000 parameters, only around a million and a half of them trainable, it took about seven twinkles to finish the training process.

After completing the training, we can compass the loss and delicacy values over ages in a graph using the Matplotlib library to check how the model conducted during the process. As you can see on thefig. 1, the delicacy increases during the veritably first ages in a analogous way for both train and test values(one for each dataset) until there comes the point when the test delicacy goes below the train delicacy(blue line).

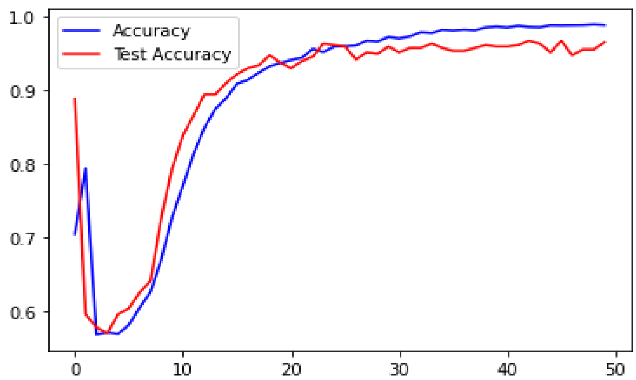

Fig.2 Accuracy Graph

That is an index of overfitting; the lesser the difference between the two values of training and test, the lesser the overfitting and lower generalizable the model is. Despite the loss of conception, there isn't important than 2 of the difference in this case, from98.75 delicacy on training to96.45 on testing, which does not affect in a significant way the results of the model.We can observe the final results by erecting a Confusion Matrix and assessing the model with data from the two datasets. The delicacy attained reaches 98, but the overfitting issue presented ahead can drop this value to 97 or indeed 96. nonetheless, the stylish way to test the model's performance is by planting it to product and assessing it with a large quantum of' unseen' data.

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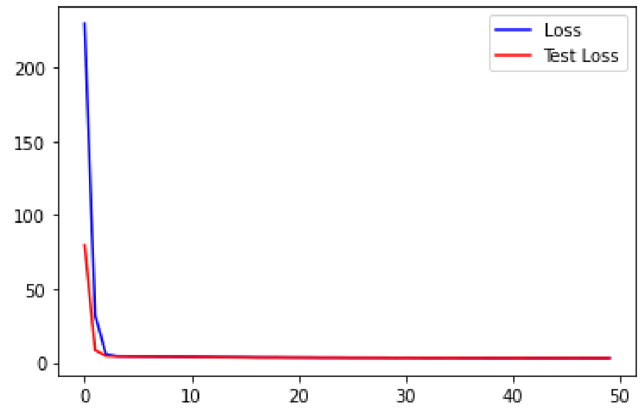

Fig. 3 Loss Graph

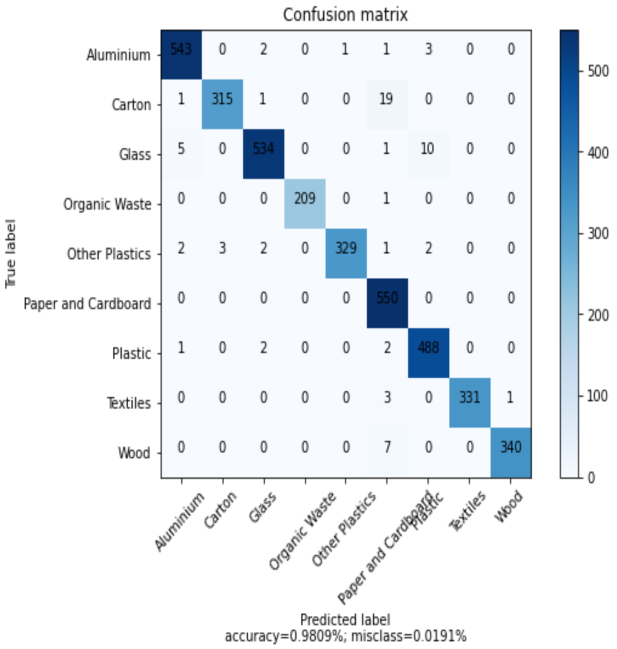

Fig.4 Confusion Matrix

Approach	**Test Accuracy**	**Notes**	**Epochs**
SVM+HOG	47.25%	9,095 train img, 1,013 test img	---
Simple CNN	79.49%	2,276 train img, 251 test img	40
ResNet50	91.40%	2,276 train img, 251 test img	40
HOG+CNN	93.56%	9,095 train img, 1,013 test img	40
SIFT + SVM	63%	1,769 train img, 758 test img	--
RecycleNet	81%	Vertical and horizontal flip	200
Proposed CNN	98.09%	4571 train img, 507 test img	50

Table 1: Performance Comparison Between Different Approaches

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REFERENCES

[1] Shanshan Meng, Wei-Ta Chu,"A Study of Garbage Classification with Convolutional Neural Networks", Indo – Taiwan 2nd International Conference on Computing, Analytics and Networks (Indo-Taiwan ICAN2020)

[2] S. Kaza, L. Yao, P. Bhada-Tata, and F. Van Woerden, What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050. The World Bank, 2018.

[3] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in Proceedings of the 25th International Conference on Neural Information Processing Systems - Volume 1, Lake Tahoe, Nevada, pp. 1097–1105, Dec. 2012, [Online]. Available: https://dl.acm.org/doi/10.5555/2999134.2999257 [Accessed: Sep. 23, 2019].

[4]Y. LeCun, K. Kavukcuoglu, and C. Farabet, "Convolutional networks and applications in vision," in Proceedings of 2010 IEEE International Symposium on Circuits and Systems, Paris, France, pp. 253–256, May 2010. doi: 10.1109/ISCAS.2010.5537907.

[5] N. Dalal and B. Triggs, "Histograms of Oriented Gradients for Human Detection," in 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05), San Diego, CA, USA, vol. 1, pp. 886–893, 2005. doi: 10.1109/CVPR.2005.177.

[6]K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," in arXiv:1409.1556 [cs], San Diego, CA, USA, pp. 1–14, May 2015, [Online]. Available: http://arxiv.org/abs/1409.1556 [Accessed: Sep. 27, 2019].

[7] Z. Wang et al.Classification for plastic bottles recycling based on image recognitionWaste Manage. (Oxford)(2019)

[8] Y. Tachwali et al.Automatic multistage classification system for plastic bottles recycling Resour. Conserv. Recycl.(2007)

 DOI : 10.35291/2454-9150.2022.0499

[9] T. Seike et al.Analysis of the efficacy and feasibility of recycling PVC sashes in Japan Resour. Conserv. Recycl. (2018)

[10] H. Piroozfard et al.Minimizing total carbon footprint and total late work criterion in flexible job shop scheduling by using an improved multi objective genetic algorithm Resour. Conserv. Recycl. (2018)

[11] H. Panwar et al. AquaVision: automating the detection of waste in water bodies using deep transfer learning Case Stud. Chem. Environ. Eng. (2020)

[12] P. Nowakowski et al. Application of deep learning object classifier to improve e-waste collection planning Waste Manage. (Oxford) (2020)

[13] B. Navaneeth et al. PSO optimized 1-D CNN-SVM architecture for real time detection and classification applications Comput. Biol. Med. (2019)

[14] D. Han et al. A new image classification method using CNN transfer learning and web data augmentation Expert Syst. Appl. (2018)

[15] M. Frid-Adar et al. GAN-based synthetic medical image augmentation for increased CNN performance in liver lesion classification Neurocomputing (2018)

[16] Y. Chen et al. Transfer learning with deep neural networks for model predictive control of HVAC and natural ventilation in smart buildings J. Cleaner Prod. (2020)

[17] M. Abdallah et al. Artificial intelligence applications in solid waste management: a systematic research review Waste Manage. (Oxford) (2020)

[18] A. Al-Hyari et al. Design space exploration of convolutional neural networks based on evolutionary algorithms J. Comput. Vision Imag. Syst. (2017)

[19] R.A. Aral et al. Classification of trashnet dataset based on deep learning models

[20] C. Bircanoğlu et al. RecycleNet: intelligent waste sorting using deep neural networks

[21] H.-W. Chen et al. Managing water quality in a river basin with uncertainty Int. J. Environ. Sci. Technol. (2019)

[22] Y. Chu et al. Multilayer hybrid deep-learning method for waste classification and recycling Comput. Intell. Neurosci. (2018)

[23] S. Elagroudy et al. Municipal solid waste management and green economy Glob. Young Acad. (2016)

[24] K. He et al. Deep residual learning for image recognition,Automatic used mobile phone color determination: Enhancing the used mobile phone recycling in China 2022, Resources, Conservation and Recycling

[25] Recycling waste classification using emperor penguin optimizer with deep learning model for bioenergy production2022, Chemosphere

 DOI : 10.35291/2454-9150.2022.0499