AN EFFICIENT CLASSIFICATION OF KITCHEN WASTE USING DEEP LEARNING TECHNIQUES

Dr. A.P. Siva Kumar
Associate Professor Dept. Of CSE, JNTUACEA, Anantapur.
Mail ID: sivakumar.cse@jntua.ac.in
K. BuelaEvanzalina
PG Scholar, M. Tech CSE (AI) Jntuacea, Anantapur
mail:evanjalinejohnson@gmail.com
Chidananda K
Research Scholar (CSE), JNTUA, Anatapur, Andhra Pradesh, India

Abstract: - In the field of environmental protection, recycling of resources and social livelihoods, wasteclassification was always a crucial subject. A deep learning automated waste classification approach is introduced to enhance the efficiency of the front-end waste collection. With the fast increase in global production levels, the problem of garbage disposal is growing severe. Trash classification is an important step towards waste reduction, harmlessness and resource utilization. Increasing trash types and quantities implies that traditional scrap classification algorithms can no longer comply with accurate identification requirements. This study offers a VGG16 neural network model based on the process of attention for classifying recyclable waste. The attention module is introduced to the model after convolution so that the essential information in the feature map may be given greater attention. The algorithm can automatically extract categorization features such as organic, recyclable and non-recyclable waste. Experimental findings reveal that 84 per cent of the algorithm in the recyclable trash classification can effectively categories the garbage.

Key word: - Classification, Deep Learning, CNN, VGG16, Image Classification, Transfer Learning.

1.Introduction:-

Overall, densewaste is projected to exceed 2.1 billion tons per year by 2026, costing waste management $375.6 billion [1]. Improper garbage organization will have huge economic, social and environmental negative effects[1]. The EPA [2] identified public solid waste reprocessing as the second most environmentally completetown waste approach. Efficient trash recycling is helpful both economically and environmentally. It may be used for the recovery of raw resources, conservation of energy, emission mitigation, water pollution, reduction of new sites of waste, etc. [1, 3–6].

In underdeveloped countries, MSWsreprocessing relies on the parting of households through searchers and gatherers trading in profit recyclables [6–8]. Community involvement is increased in the recycling program [9] in industrialised nations. In the industrialised nations several approaches for the automatic trash sorting, for example mechanical categorization and biologicalorganization, are obtainable [10]. Even in the industrialised countries, there is enormous opportunity to enhance trash recycling. In the USAs and European Union, civicreprocessing rates are around 36% and 60% respectively, far lesser than 76% [5,11]. [5].

Waste collection and recycling, especially for major cities, are vital services for modern cities. Recycling is essential in order to prevent pollution and health issues for residents due to a decline in the available natural resources and environmental difficulties created by the rising amount of waste. The average waste produced in Europe is 517 kilogrammes per year, only a tiny fraction of which are recycled [1]. 75% of garbage produced by US citizens is recyclable but only 35% is recycled, according to the Environmental Protection Agency. Most of the process of separation of waste is now carried out manually, creating several health concerns for the employees, taking time and requiring the people' financial taxes [2]. In addition, this waste separation should be made to limit waste contamination by other materials as soon as possible [3].

Alexnet, in 2012, is the sort of architecture of the Convolutional Neural Network (CNN), the winner of the ImageNet Challenge. There is a simple, not deep structure in the architecture employed in that challenge. It's really high performance. The successful performance of AlexNet in the high level of difficulty in an ImageNet competition has encouraged many scientists to work on structures of CNN to solve challenges of image classification. The TechCrunch Disrupt Hackathon team's automatic waste bin is one of the current recycling effort to decide if the rubbish can be recycled using the Raspberry Pi and a camera module. The project method is simply designed to determine if the waste is recyclable or not [2]. Another recycling-related idea aims to use the imagery process to categorise waste as a smartphone application [3]. With the request being implemented, people will be monitored for recycling waste in the vicinity. Data set were acquired to be formed using Bing Image search of the Alexnet model. After the training phase, the accuracy rate is around 87.69%. Faster and more accurate network training was carried out using a pre-trained model. In another investigation, the use of formal characteristics ensured the recycling of metal scrap. The physical characteristics of proposed recycling material were used in this context. Several techniques were employed for the determination of chemical and mechanical waste properties [4]. The Flicker database [5] has been used for the categorization of materials. The Bayesian classification employed the SIFT, colour, micro texture and contour shape characteristics from the picture collection. Yang et al. have carried out a series of features utilising trash classification from pictures using vector support machines and scratch CNN structure. The data collection consists of glass, paper, metal, plastic, carton and other waste. Each class has about 400-500 pictures. Data are slightly different in the data set from the other datasets for deformation and logos of material. Features from SIFT pictures have been retrieved and categorised as CNN. This study was based on several fine-tuned models. Furthermore, the classifier component has been changed [6] for a comparison analysis. As straight and fine-tuned, Cenk et al. have tested several CNN models. With 90% test accuracy, the launch-resnet model in scratch models has obtained the highest grading achievement. Fine-tuned models with DenseNet121 reached 95% test precision. This paper is divided into four pieces. This section only an introduction consisting of broad literature and facts.

The overview of this paper is:

- Kitchen's produce a variety of waste which will require different disposal methods, such as recycling for cardboard and glass and expert removal of knives and chemical waste.
- In this project we have to build the model to classify different types of waste. We used transfer learning models to classify these classes. We are classifying 3 classes like organic, recyclable and non-recyclable.
- In this case we are going to build CNN model with some dropouts and Maxpooling layers. By adding some dropouts we can solve over fitting problem and get best accuracy.
- In our proposed model we are using transfer learning by using transfer we can get best results and time complexity also less.
- In section 2 we use related work based on this work we implemented this project. Section 3 we explain about our proposed model CNN and VGG16, section 4 analyses the results, in last section 5 give final conclusion of this paper.

2.Related Work:-

This section discusses prior work on our model. In terms of machine learning and IoT management, several major contributors had given important traces. In a subsequent study (Bobulski and Kubanek, 2019), the authors have created an image processing and a configuration neural network for trash categorization systems (CNN). They concentrated exclusively on detecting polyethylene during their investigation. The authors also conducted numerous tests on terephthalate, polyethylene, polyethylene, Polyethylene and polystyrene with high-density. The authors utilisedCapsnet (Capsule-Net) to manage hardexcess in a study (Sreelakshmis et al., 2020) and were able to recognise plastics and non-plastic matter. Two public data sets were worked by the writers, and 95.3% and 96.7% were accurate. The whole addition has been created and verified on a number of plans. In this research (Huiyus& O, O.G. &Kims, S. Hs., 2018), the writer suggested to identify the categories of trash utilising profound learning methods using a single classification model. The recycling method has also been used.

The study (Adedeji and Wang, 2019) suggested a technique that automatically identifies the waste with a DL models. The essayists further argued that the approach was also used in the recyclable waste categorization. The authors (Nowakowskin and Pamułas, 2021) proposed the trash categorization technique utilising a pretrained CNN model, the same as ResNet-50 (SVM). 87 percent of the model was accurate and evaluated using a public dataset. The authors examined a new electronic trash identifying and classifying method (Misra et al. 2018) known as e-waste. A CNN model was used for classification and an RCNN model for identification of different e-waste kinds. The detection and classification accuracy has been monitored between 90 and 97 percent by the authors. The authors of the paper (Adedejit and Wong, 2020, Nowakóvski and Pamułan, 2021, Misras et al., 2019, S. G. & H.) intensive exclusively on architecturesproject of waste-classification models using a deep learning system; however the waste managing system wasn't proposed with Iot. (Bobulskis and Kubenek, 2012, Sreelaksmi et al., 2019).

The authors described in their work (Samann, 2017) an important method of automated and resilient trash management. An intelligent waste bin by the ultrasonic device and a variety of vapordevices were shown by the author. The author also offered a real-time vision of garbageutilising the android servers. Over, no techniques to ML have been used. The writer had proposed an economical and smart trash bin to assure waste management in a paper research (Malapur and Pattanshetti, 2017). The writers included a usual of gadgets including Arduinos mini, ultrasonic device and GSMs module because the system was being operated on by IoT. The system would send an SMS to the mobile user through the GSM module if the waste near reached a smallestedge level. A PIRsgesturedevice and a memory card for the assignment of audios messages to the user enhanced the system. The author also submitted that the system's presentation was satisfactory. The article writers (Singoh et al., 2015) had developed a technique of smart city trash managing.

3.Proposed Methodology:-

The CNN Network (CNN) model is the basis of several contemporary Neural Architectures for supervised image categorization. Instead of a generic matrix multiplication, CNN consists by convolutionary layers where neurons are linked such that weight is divided rather than connected. Spatial patterns are thereby created which is invariant to conversions, revolutions and other alterations.

Data Processing: - This article provides a summary of the recyclable waste data gathered and images acquired on the Internet forming a data set for recyclable waste categorization. The data set consists of 3 categories: organic, recyclable, and non- recyclable, 3000 organic, 3000 recyclable and 3000 non- recyclable. The data set is 7:3 and is separated into training set and test sets.

In order to enhance the convergence speed and the capacity for generalisation of the model before model training is carried out. You may read pictures using opencvlibrary and decrease the image's size to 224 dailies224 daily.Since the images acquired are of varying sizes, the training of the model will be quite challenging.The approach of determining the picture size can thereby enhance the model's training pace.

Dataset: - For building machine learning or deep learning models we need dataset based on dataset itself we build the model. We collected this images from kaggle. In this data we used 13966 organic, 8264 recyclable and 3244 non – recyclable images. This is imbalanced dataset. In Fig 1 we printed one image from each class.

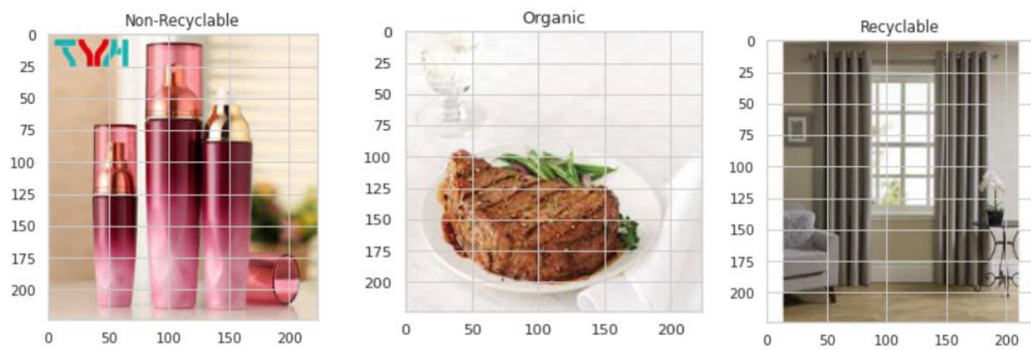

Fig 1 Sample images in dataset

If we have imbalanced data accuracy don't work we have to try some technique to handle imbalanced data like under sampling, oversampling, or smote. In this case we have high amount data we have only basic machine that's why we used under sampling. After balancing the data we randomly spilt it in 70:30 ratio and train the models. In figure 2 we explained about our proposed system.

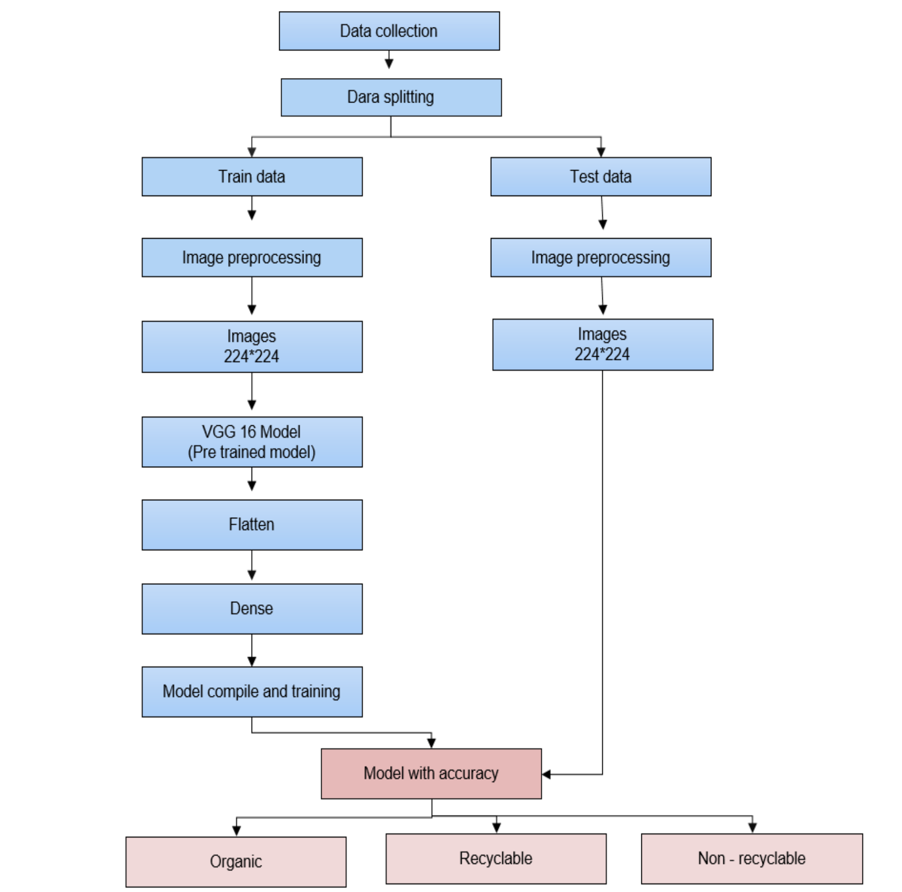

Fig 2 Block diagram of the proposed system

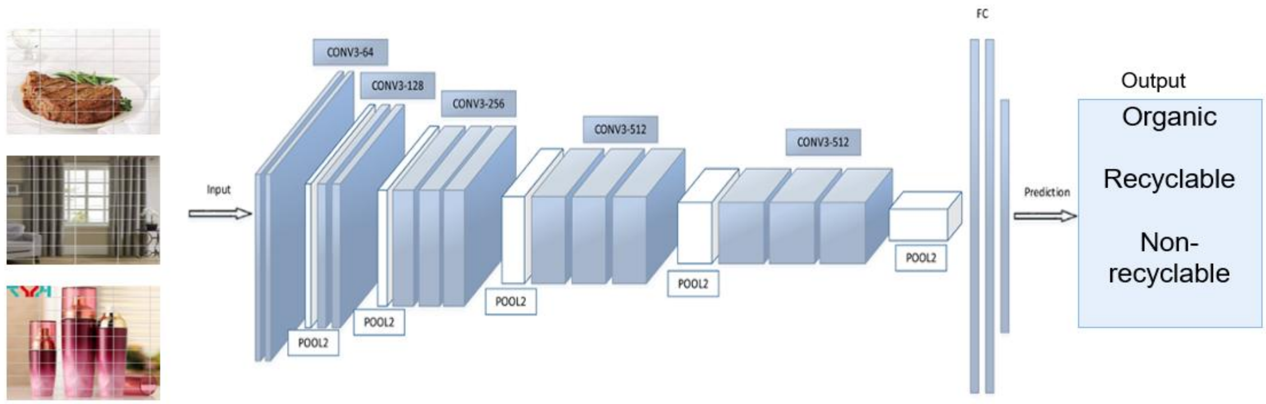

Fig 3 Proposed System Architecture

CNN model: - The objective is to analyses the building of data from humble to complicate by employing multi-layer constructions. In instance, efficient landscapes obtained by CNN simplify the categorization process. The initial layer in the convolutionary network detects the basic structures of the picture, such as recognizable, double-diameter pictures in an attempt to better comprehend convolutional neural webs. Each of anamount of sieves in the layer has to detect the edges of a certain picture. This means that various screenshelp for distinct angles of an edging or for dissimilar forms with other borders when an image's edge data is taken into consideration. The major layer output is the maps with the structural info detected by the filters. These outputs provide information on various image-related edge structures. The next layer of evolution shows relationships on the preceding layer in maps of features. The correlation between the combinatory structures identified in the preceding layer and the picture is analyses in each convolution layer. With this stream, which gains complexity with the number of layers, semantically information is acquired from structural information. Convolutionary Neural Networks (CNN) is a multi-layered neural network specializing in the detection of geometric image processing. A first-school neuron is linked to all the neurons of the following layer in a typical multineural network; a convolutionary layer makes local connections at the output of the previous layer. A matrix multiplication is performed in the completely linked layer. Convolutionary layer employs the method of convolution, a linear algebra. We can see our proposed cnn in figure 3.

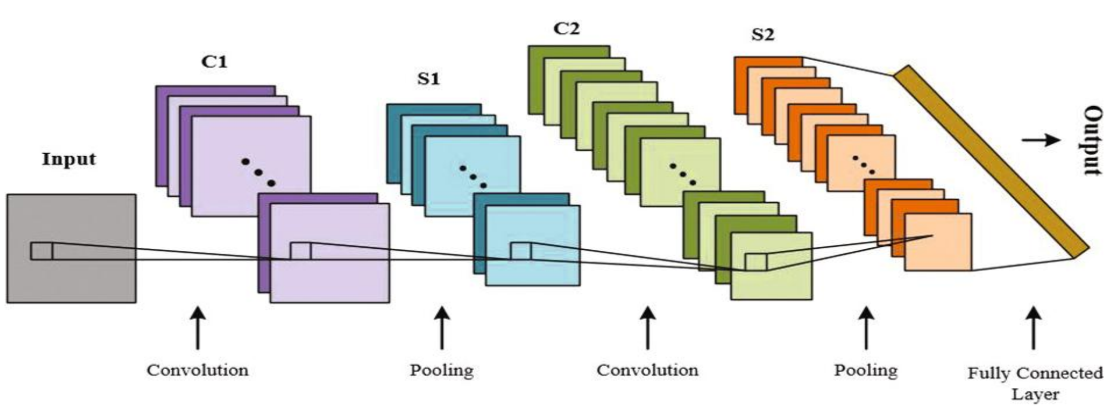

Fig 4: CNN architecture

Transfer Learning:-

Transfer learning is a form of automatic learning. His fundamental notion is to gain information or patterns from one activity, and then apply it to a separate but related independent task, to achieve the objective. Tasks can deliver greater results in learning. When translating learning, you first build a basic dataset and duty network, and then modify or transfer the learned functionality to the second network to train the target data set and task.

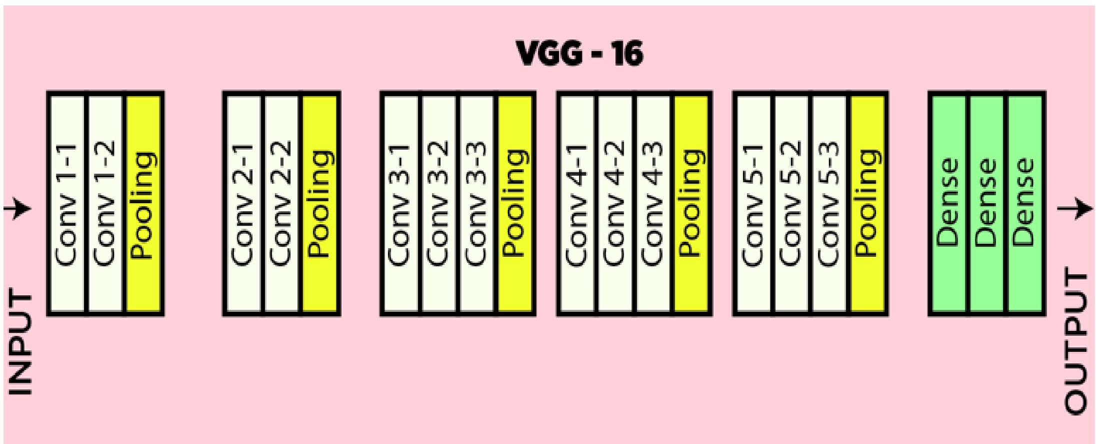

Fig 5: VGG16 model architecture

VGG16 model: - For location and classification tasks on high-resolution pictures, the VGG architecture has been developed [10]. The VGG network consists of several convolutionary layers in all convolutionary layers with increasing depth and with tiny kernels (3 *3). We concentrated on VGG16 models in our paper. The design is composed of a group of thirteen levels of convergence and three completely linked layers in VGG-16[11]. One block, 2 64s-depth cooling layer's with max pooling's, one blocks, 2 128-dept cooling layers, 1 block of 3 256-depth cooling layers with max pooling, 2 blocks, 3 512-deep core cooling layer with max pooling layers, two fully connected layers with 4096 neurons, one fully connected layer with as many neurons as the dataset and so on. The architecture is shown in Fig.5.

4.Results and discussion :-

For categorization of pictures using wastage classification data set, we conducted a comparison analysis. Half of the data set were utilized for difficult data without the usage of any increase approach in this study. The VGG-16 and CNN were utilized as a finely adjusted model as part of our suggested approach. As can be seen in Table 1, we have attempted with two different classifiers to get the best level of accuracy.

The following tables describes the comparison of the proposed method with the previous approaches and it achieved the best accuracy when compared with earlier approaches.

VGG -16	ACCURACY
Cong Tan 1[21]	69.38%
ZHUANG KANG[1]	84.27%
G Sai Susanthet al[13]	80.02%
Liguo Wang [21]	70.58%
Ours	84.62%

Table1 Comparison of the proposed method with previous approaches.

S.NO	MODELS	TEST ACCURACY	EPOCHES
1	CNN	0.60	20
2	VGG16	0.84	10

Table 2 Results comparison table of proposed system

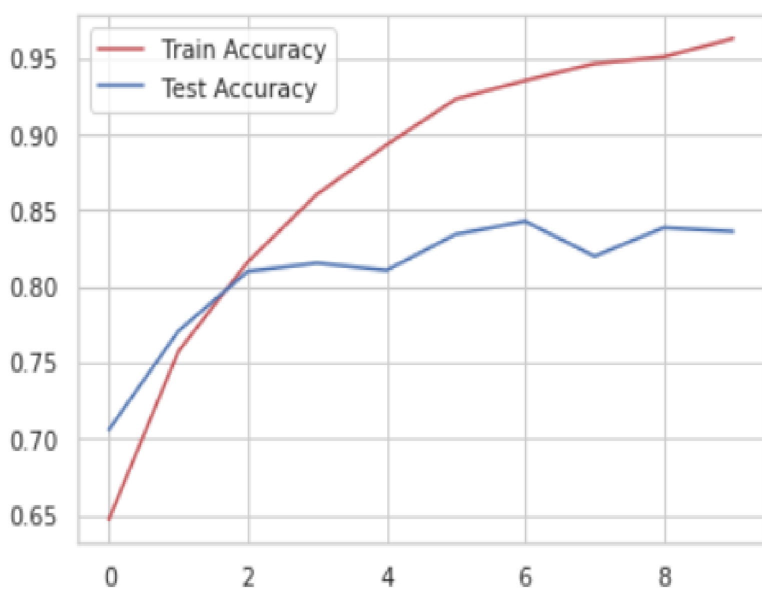

Fig 5: Train and test accuracy graph plot

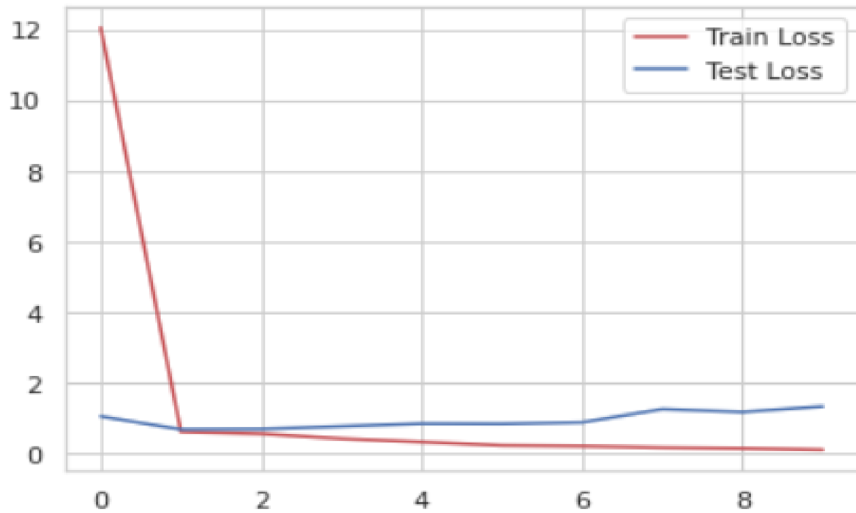

Fig 6: Train and test loss graph plot.

```
#Fit the data or train the model
History_1 = model_1.fit(X_train, y_train, epochs = 10, validation_data = (X_test,y_test),batch_size = 128)

Epoch 1/10
50/50 [==============================] - 106s 2s/step - loss: 35.5688 - accuracy: 0.5671 - val_loss: 1.0682 - val_accuracy: 0.7059
Epoch 2/10
50/50 [==============================] - 62s 1s/step - loss: 0.6365 - accuracy: 0.7513 - val_loss: 0.6991 - val_accuracy: 0.7707
Epoch 3/10
50/50 [==============================] - 62s 1s/step - loss: 0.5251 - accuracy: 0.8169 - val_loss: 0.7081 - val_accuracy: 0.8100
Epoch 4/10
50/50 [==============================] - 62s 1s/step - loss: 0.4512 - accuracy: 0.8603 - val_loss: 0.7854 - val_accuracy: 0.8156
Epoch 5/10
50/50 [==============================] - 62s 1s/step - loss: 0.3271 - accuracy: 0.8977 - val_loss: 0.8639 - val_accuracy: 0.8107
Epoch 6/10
50/50 [==============================] - 62s 1s/step - loss: 0.2148 - accuracy: 0.9251 - val_loss: 0.8587 - val_accuracy: 0.8344
Epoch 7/10
50/50 [==============================] - 62s 1s/step - loss: 0.1765 - accuracy: 0.9399 - val_loss: 0.8982 - val_accuracy: 0.8430
Epoch 8/10
50/50 [==============================] - 62s 1s/step - loss: 0.1656 - accuracy: 0.9491 - val_loss: 1.2719 - val_accuracy: 0.8200
Epoch 9/10
50/50 [==============================] - 62s 1s/step - loss: 0.1509 - accuracy: 0.9542 - val_loss: 1.1913 - val_accuracy: 0.8389
Epoch 10/10
50/50 [==============================] - 62s 1s/step - loss: 0.1326 - accuracy: 0.9645 - val_loss: 1.3491 - val_accuracy: 0.8363
```


Fig. 6. A Sample results on Accuracy and Loss to running the epochs.

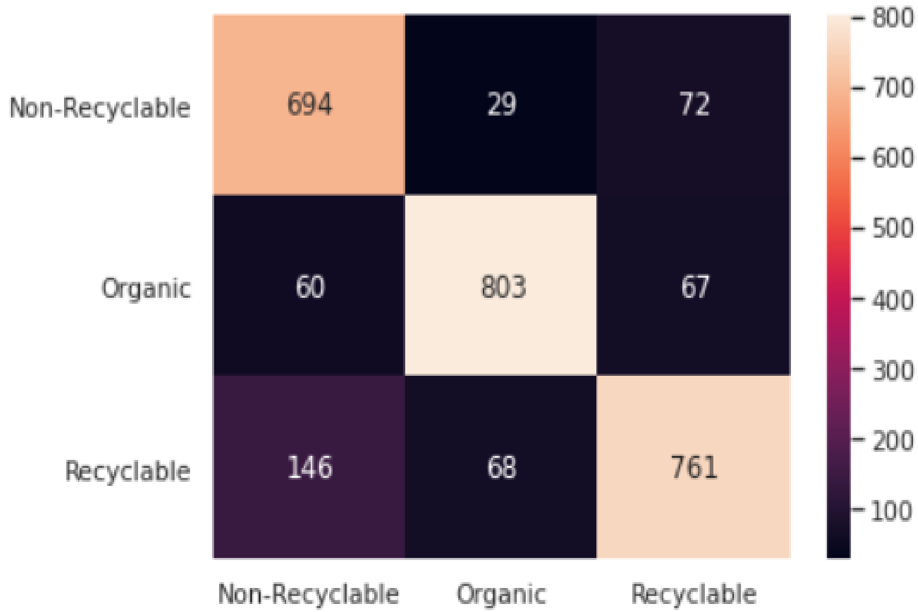

Fig 7:- VGG16 model confusion metric

In Table 1, accuracy of proposed method with fine-tune model vgg16 is reached 84% and CNN we got 60% accuracy. Compared to CNN, VGG16 transfer learning gave best results. In fig 5 and fig 6 we printed train and test data accuracy and loss plots. We printed confusion metric in fig 7. It will show how many data points correctly classified and how many data points misclassified in each classes.

5.Conclusion

In this study our suggested models are categorized into three types of waste: organic, recyclable and non-recyclable; VGG 16 and convolutionary neural network. The model may be enhanced by adding a model VGG16 compared to the standard CNN. In the CNN network without image processing stages, the accurate model is 0.55. The precision of the neural network vgg16 is 0.83 in this article. The experimental findings suggest that the model provided in this document can enhance the accuracy of the vgg16 Network categorization.

References:-

[1]. ZHUANG KANG , JIE YANG , GUILAN LI , AND ZEYI ZHAN "An automatic garbageclassification system Based on Deep learning," School of Electrical Engineeringand Automation, Jiangxi University of Science and Technology, Ganzhou 341000,China.vol.8,Aug.2020,doi:10.

[2]. J. Donovan, "Auto-trash sorts garbage automatically at the techcrunch disrupt hackathon."

[3]. G. Mittal, K. B. Yagnik, M. Garg, and N. C. Krishnan, "Spotgarbage: Smartphone app to detect garbage using deep learning," in Proceedings of the 2016 ACM

International Joint Conference on Pervasive and Ubiquitous Computing, ser. UbiComp ’16. New York, NY, USA: ACM, 2016, pp. 940–945.
[4]. S. Zhang and E. Forssberg, “Intelligent liberation and classification of electronic scrap,” Powder technology, vol. 105, no. 1, pp. 295–301, 1999.
[5]. Liu, L. Sharan, E. H. Adelson, and R. Rosenholtz, “Exploring features in a bayesian framework for material recognition,” in Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on. IEEE, 2010, pp. 239–246.
[6]. Thung, Gary and M. Yang. “Classification of Trash for Recyclability Status.” (2016).
[7]. Bircanoglu, C., Atay, M., Beser, F., Genc, O., &Kizrak, M. A. (2018). RecycleNet: Intelligent Waste Sorting Using Deep Neural Networks. 2018 Innovations in Intelligent Systems and Applications (INISTA). doi:10.1109/inista.2018.8466276.
[8]. A. Hoornweg and P. Bhada-Tata, What a Waste: A Global Review of Solid Waste Management, World Bank, Washington, DC, USA, 2012.
[9]. R. E. Sanderson, Environmental Protection Agency Office of Federal Activities’ Guidance on Incorporating EPA’s Pollution Prevention Strategy into the Environmental Review Process, EPA, Washington, DC, USA, 1993.
[10]. Rodr´ıguez, J. P´erez, and A. Salmador. Intelligent garbage classifier. International Journal of Interactive Multimedia and Artificial Intelligence, 1(1):31–36, 2008.
[11]. S. Sudha, M. Vidhyalakshmi, and K. Pavithra. An automatic classification method for environment, 2016.
[12]. G.E. Sakr, M. Mokbel, A. Darwich, M.N. Khneisser, and Ali Hadi. Comparing deep learning and support vector machines for autonomous waste sorting. In Multidisciplinary Conference on Engineering Technology (IMCET), IEEE International, pages 207–212. IEEE, 2016.
[13]. Garbage Waste Segregation Using Deep Learning Techniques.To cite this article: G Sai Susanthet al 2021 IOP Conf. Ser.: Mater. Sci. Eng.1012 012040.

[14]. G. Mittal, K.B. Yagnik, M. Garg, and N.C. Krishnan. Spotgarbage: smartphone app to detect garbage using deep learning. In Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing, pages 940–945. ACM, 2016.
[15]. M.S. Rad, A. von Kaenel, A. Droux, F. Tieche, N. Ouerhani, H.K. Ekenel, and J.-P. Thiran. A computer vision system to localize and classify wastes on the streets. In International Conference on Computer Vision Systems, pages 195–204. Springer, 2017.
[16]. J.C. Brinez, A. Rengifo, and M. Escobar. Automatic waste classification using computer vision as an application in colombian high schools. 2015.
[17]. O. Awe, R. Mengistu, and V. Sreedhar. Smart trash net: Waste localization and classification. 2017.
[18]. T. Kennedy. Oscarnet: Using transfer learning to classify disposable waste.
[19]. K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014.

[20]. J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. Imagenet: A largescale hierarchical image database. In Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on, pages 248–255. Ieee, 2009.
[21]. A Waste Classification Method Based on a Multilayer Hybrid Convolution Neural Network Cuiping Shi 1,*, Cong Tan 1 , Tao Wang 1 and LiguoWang.College of Communication and Electronic Engineering, Qiqihar University, Qiqihar 161000, China; 2017135251@qqhru.edu.cn (C.T.); 2017051171@qqhru.edu.cn (T.W.)
[22]. A. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1–9, 2015.
[23]. C. Szegedy, S. Ioffe, V. Vanhoucke, and A.A. Alemi. Inception-v4, inception-resnet and the impact of residual connections on learning. In AAAI, volume 4, page 12, 2017.
[24]. European Environment Agency, Waste Recycling, 2018, https://www.eea.europa.eu/data-and-maps/indicators/waste-recycling-1/assessment.
[25]. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” in Proceedings of Neural Information Processing System Conference, Lake Tahoe, CA, USA, December 2012.View at: Google Scholar
[26]. P. Sermanet, D. Eigen, X. Zhang, M. Mathieu, R. Fergus, and Y. Lecun, “OverFeat: integrated recognition, localization and detection using convolutional networks,” in Proceedings of International Conference on Learning Representations, Banff, Canada, April 2014.View at: Google Scholar
[27]. M. D. Zeiler and R. Fergus, “Visualizing and understanding convolutional neural networks,” in Proceedings of 13th European Conference on Computer Vision (ECCV), Zurich, Switzerland, September 2014.View at: Google Scholar
[28]. K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proceedings of Conference on Computer Vision and Pattern Recognition, Las Vegas Valley, NV, USA, June 2016.View at: Google Scholar
[29]. O. Awe, R. Mengistu, and V. Sreedhar, “Smart trash net: waste localization and classification,” arXiv Preprint, 2017.
[30]. G. Thung and M. Yang, “Classification of trash for recyclability status,” arXiv Preprint, 2016.