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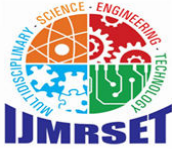
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International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

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Trash Collection and Transportation Monitoring System

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ABSTRACT: It is an essential responsibility with considerable significance for waste management to oversee the rubbish collection and detection process. Instead of managing the entire process, previous research has mostly concentrated on detecting particular kinds of rubbish. In order to increase trash categorization performance, we suggest a supervision strategy in this study that is based on an upgraded CNN model. We add triplet attention to the model's foundation in order to deal with the problems of low location precision and multi-target scenarios. With the help of this method, the model may automatically discover cross-dimensional interactions, improve the weights of powerful feature channels, and better its ability to extract features.

Additionally, concentrating on categories like empty, full, and typical garbage, we gathered a dataset for waste categorization supervision using photos provided by a city environmental protection. Numerous tests were run on this dataset, and the outcomes show that the enhanced CNN model algorithm works better than other detection techniques. The average accuracy attained was 99.91%, which is 0.7% more accurate than the baseline CNN model. The model's average detection speed is 14.6ms/it, which satisfies the needs of real-time regulation and the supervision system's environmental complexity. We predict considerable improvements in waste management and recycling efforts by utilizing our enhanced CNN model for waste classification, resulting to a more effective and sustainable waste management system.

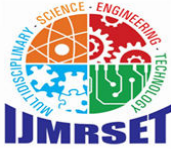
I. INTRODUCTION

The fast expansion in squander yield, driven by financial turn of events, urbanization, and worked on expectations for everyday comforts, has placed huge tension on squander assortment and handling frameworks. To reduce this strain and advance economical waste administration, an efficient trash grouping and it is urgent to reuse framework. Trash characterization includes the capacity, detection, and reuse of waste as indicated by unambiguous principles, expecting to change squander into public assets. The course of trash characterization basically centers around the order stage. Appropriate waste characterization empowers compelling reusing and lessens the weight on landfills. The Chinese government has as of late accentuated the significance of trash grouping, with urban communities carrying out severe waste arranging guidelines. Executing a productive and exact waste order framework can essentially add to squander the board endeavors.

Our examination plans to work on the effectiveness and precision of waste arrangement by proposing a better CNN model. We center around the characterization of waste into three classes: empty, full, and normal. By utilizing PC vision methods and utilizing the abilities of the superior CNN model, we intend to improve the presentation of waste order frameworks.

While past examinations have tended to squander arrangement utilizing PC vision calculations, our exploration explicitly focuses on the order stage and the three characterized classes. By working on the precision and proficiency of waste arrangement, we can work with better waste administration rehearses, advance reusing, and diminish the burden on landfills.

Our proposed arrangement means to add to the advancement of reasonable waste administration frameworks.



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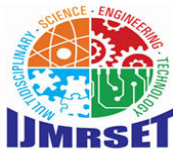
II. REVIEW OF LITERATURE

1. F. Liu, H. Xu, M. Qi, D. Liu, J. Wang, and J. Kong (2022) Currently, how to deal with the massive garbage produced by various human activities is a hot topic all around the world. In this paper, a preliminary and essential step is to classify the garbage into different categories. However, the mainstream waste classification mode relies heavily on manual work, which consumes a lot of labor and is very inefficient. With the rapid development of deep learning, convolutional neural networks (CNN) have been successfully applied to various application fields. Therefore, some researchers have directly adopted CNNs to classify garbage through their images. However, compared with other images, the garbage images have their own characteristics (such as inter-class similarity, intra class variance and complex background). Thus, neglecting these characteristics would impair the classification accuracy of CNN. To overcome the limitations of existing garbage image classification methods, a Depth-wise Separable Convolution Attention Module (DSCAM) is proposed in this paper. In DSCAM, the inherent relationships of channels and spatial positions in garbage image features are captured by two attention modules with depth-wise separable convolutions, so that our method could only focus on important information and ignore the interference. Moreover, we also adopt a residual network as the backbone of DSCAM to enhance its discriminative ability. We conduct the experiments on garbage dataset. The experimental results demonstrate that the proposed method could effectively classify the garbage images and that it outperforms some classical methods.

2. Z. C. Chen, H. N. Jiao, J. Yang, and H. F. Zeng (2021) A garbage image classification method based on improved MobileNet v2 was proposed aiming at the problems of poor real-time performance and low classification accuracy of existing garbage image classification models. A lightweight feature extraction network based on MobileNet v2 was constructed. The parameter numbers of the model were reduced by adjusting its width factor, channel and spatial attention modules were embedded in the model to enhance the network's ability to refine features, a multi-scale feature fusion structure was designed to enhance the adaptability of the network to scale, and transfer learning was used to optimize the model parameters to further improve the model accuracy. Experimental results show that the average accuracy of the algorithm on the self built dataset was 94.6%, which was 2.0%, 3.4%, 3.2%, 2.3% and 1.2% higher than that of MobileNet v2, VGG16, GoogleNet, ResNet50 and ResNet101 models, respectively. The proposed algorithm achieved good performance in two public image classification datasets, CIFAR-100 and tiny-ImageNet. The parameter numbers of the model was only 0.83 M, which was about 2/5 of the basic model. The single inference on edge device JETSON TX2 took 68 ms, which proved the improvement of inference speed and prediction accuracy.

3. Q. Li, Y. Q. Gong, W. Zhang, C. Liu, J. Li, D. Han, D. F. Liu, W. H. Mei, and X. Dong (2021) As the rate of garbage generation gradually increases, the past garbage disposal methods will be eliminated, so the classification of garbage has become an inevitable choice. The multi-category classification of garbage and the accuracy of recognition have also become the focus of attention. Aiming at the problems of single category, few types of objects and low accuracy in existing garbage classification algorithms. This paper proposes to use the improved YOLOV4 network framework to detect 3 categories, a total of 15 objects, and find that the average accuracy is 64%, Frame per second 92f/s. It turns out that the improved YOLOV4 can better detect garbage categories.

4. Z. Zheng, P. Wang, D. Ren, W. Liu, R. Ye, Q. Hu, and W. Zuo (2022) Deep learning-based object detection and instance segmentation have achieved unprecedented progress. In this article, we propose complete-IoU (CIoU) loss and Cluster-NMS for enhancing geometric factors in bounding-box regression and no maximum suppression (NMS), leading to notable gains of average precision (AP) and average recall (AR), without the sacrifice of inference efficiency. In particular, we consider three geometric factors, that is: 1) overlap area; 2) normalized central-point distance; and 3) aspect ratio, which are crucial for measuring bounding-box regression in object detection and instance segmentation. The three geometric factors are then incorporated into CIoU loss for better distinguishing difficult regression cases. The training of deep models using CIoU loss results in consistent AP and AR improvements in comparison to widely adopted \ln -norm loss and IoU-based loss. Furthermore, we propose Cluster NMS, where NMS during inference is done by implicitly clustering detected boxes and usually requires less iteration. Cluster-NMS is very efficient due to its pure GPU implementation, and geometric factors can be incorporated to improve both AP and AR. In the experiments, CIoU loss and Cluster-NMS have been applied to state-of-the-art instance segmentation (e.g., YOLACT and Blend Mask-RT), and object detection (e.g., YOLO v3, SSD, and Faster R-CNN) models. Taking YOLACT on MS COCO as an example, our method achieves performance gains as +1.7 AP and +6.2 AR 100 for object detection, and +1.1 AP



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and +3.5 AR 100 for instance segmentation, with 27.1 FPS on one NVIDIA GTX 1080Ti GPU. All the source code and trained models are available at <https://github.com/Zzh tju/CIoU>.

5. S. Chen, J. Huang, T. Xiao, J. Gao, J. Bai, W. Luo, and B. Dong (2020) The GHGs contributions (tally by carbon emissions) during treatment of domestic food waste and residual waste from pilot communities (contained 2365 families) in Shanghai, China, under different Modes induced by garbage classification were investigated. It was found that under the present condition of garbage classification in Shanghai, 51.8% of the food waste could be separated finally. With garbage classification, the load of landfill was saved by 17.3% (Mode 2) and 16.5% (Mode 3), the moisture of garbage for incineration was reduced by 13.6%, and the lower heating value (LHV) of garbage was increased by 16.2%. Applying the life-cycle assessment (LCA) methodology and Life Cycle Inventory (LCI) with material flows, net carbon emissions during the treatment of garbage were found to be in the following order: Mode 3 (1.60×10^{-3} kg CE/kg waste) < Mode 2 (4.85×10^{-3} kg CE/kg waste) < Mode 1 (4.94×10^{-3} kg CE/kg waste) < landfill (1.49×10^{-2} kg CE/kg waste). Mode 2 and Mode 3 were replaceable patterns of Mode 1, and anaerobic digestion was the recommendable strategy to recover energy from food waste. Especially, there was no obvious benefit of increasing the separation proportion of food waste to 60% (or above) for reducing net carbon emissions in the process.

III. EXISTING SYSTEM

- A garbage image classification method based on improved Mobile Net v2 was proposed aiming at the problems of poor real-time performance and low classification accuracy of existing garbage image classification models. A lightweight feature extraction network based on Mobile Net v2 was constructed.
- The parameter numbers of the model were reduced by adjusting its width factor, channel and spatial attention modules were embedded in the model to enhance the network's ability to refine features, a multi-scale feature fusion structure was designed to enhance the adaptability of the network to scale, and transfer learning was used to optimize the model parameters to further improve the model accuracy. Experimental results shows that the highest accuracy.

Existing System Disadvantages

- The problem of negative transfer.
- Only works if the initial and target problems are similar enough for the first round of training to be relevant.

IV. PROPOSED SYSTEM

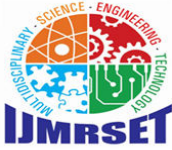
We intend to concentrate on garbage classification and management within the municipal environment in the suggested system. The goal is to provide a framework that is insightful and instructive and makes effective waste classification possible. It should be emphasized, nevertheless, that the system does not offer real-time data.

We suggest an enhanced Convolutional Neural Network (CNN) model that can oversee the trash classification procedure as a follow-up to this research. However, we will turn our emphasis away from transportation and towards a project to classify waste. Waste will be sorted into categories like empty, full, and normal as part of the initiative. This system of classification will help make recycling and waste management operations generally better.

We hope to improve the efficiency of garbage classification systems and ultimately contribute to better municipal wastemanagement by applying this upgraded CNN model for waste classification.

Proposed System Advantages

- CNN model has the advantages of detection speed and accuracy.
- This helps to reduce the computational complexity of the model.
- It has a large number of backbone network parameters.



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V. SYSTEM ARCHITECTURE

The figure illustrates a Convolutional Neural Network (CNN) architecture designed for image classification tasks. The system processes an input image of dimensions $28 \times 28 \times 128 \times 28 \times 1$, indicating a grayscale image with a single channel. The architecture begins with **Conv_1**, a convolutional layer utilizing a $5 \times 5 \times 5$ kernel and **valid padding**, which reduces the spatial dimensions to $24 \times 24 \times n_1 \times 24 \times n_1$, where n_1 denotes the number of feature maps or channels generated by this layer. This is followed by a **Max-Pooling** operation with a $2 \times 2 \times 2$ kernel, reducing the spatial dimensions further to $12 \times 12 \times n_1 \times 12 \times n_1$, effectively downsampling the feature maps to extract prominent features and reduce computational complexity.

The next stage, **Conv_2**, applies another $5 \times 5 \times 5$ convolution with valid padding, yielding feature maps of size $8 \times 8 \times n_2 \times 8 \times n_2$, where n_2 is the number of filters in this layer. Another **Max-Pooling** operation reduces the dimensions to $4 \times 4 \times n_2 \times 4 \times n_2$. At this stage, the feature maps are **flattened** into a onedimensional vector, preparing them for fully connected layers.

The network includes two fully connected layers: **fc_3**, which applies a RELU activation function to introduce nonlinearity, and **fc_4**, which serves as the final classification layer. Dropout is implemented to reduce overfitting by randomly disabling neurons during training. The output layer consists of 10 neurons, corresponding to the possible classes (e.g., digits 0-9). This architecture efficiently combines convolutional, pooling, and fully connected layers to learn hierarchical features for image recognition.

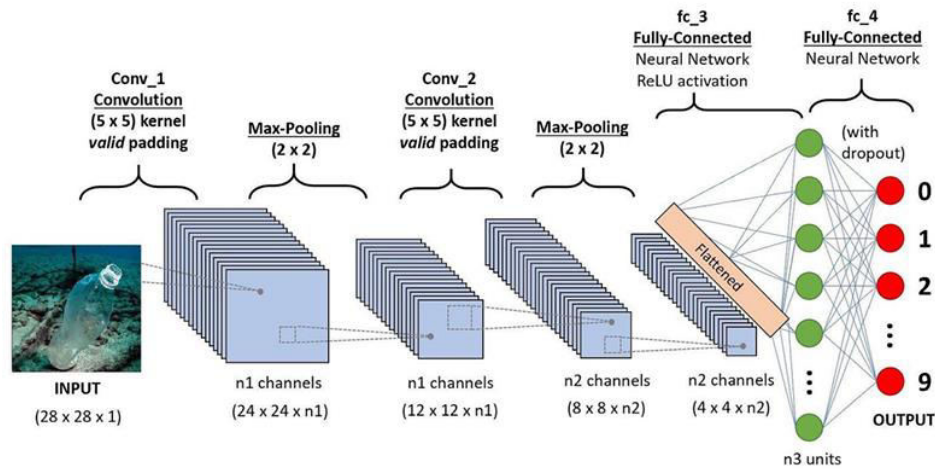


Figure A:- SYSTEM ARCHITECTURE

Fig 1.1 System Architecture

VI. METHODOLOGY

The system involves installing IoT-enabled sensors in waste bins to monitor fill levels in real-time. These sensors use technologies like ultrasonic or infrared to detect waste volume and trigger alerts when bins are nearly full. Additionally, cameras or embedded systems equipped with machine learning algorithms can classify waste into categories such as organic, recyclable, or non-recyclable. The collected data is transmitted to a cloud-based platform for monitoring, analysis, and efficient waste management planning.

A CNN (Convolutional Neural Network) model is essential for improving the process of identification and detection. The CNN classifier validates the model once it has been trained on synthetic marker datasets to guarantee precise



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detection even under different circumstances. To increase the system's resilience, a variety of training data is produced during the synthetic dataset production process

VII. MODULES

1. Dataset:

In the first module, we developed the system to get the input dataset for the training and testing purpose. We have taken the Waste Collection image dataset for Waste Classification.

The dataset consists of 1166 Waste Collection images

2. Importing the necessary libraries:

We will be using Python language for this. First we will import the necessary libraries such as keras/ tensorflow for building the main model, ImageDataGenerator for splitting the training and test data & for image alignments like height and width, PIL to open & read images, numpy for converting data into array of numbers, BytesIO for taking input in bytes format, expanding dimensions & finding argument maximum and other libraries such as pandas, webbrowser, flask and save.

3. Retrieving the images:

We will retrieve the images and their labels. Then resize the images to (224,224) as all images should have same size for recognition. Then convert the images into numpy array.

4. Splitting the dataset:

Split the dataset into train and test. 80% train data and 20% test data.

5. Building the model:

For building the model, we will use sequential model from keras/ tensorflow library. Then we will add the layers to make CNN Architecture. In the first Conv2D layers we have used 32filters and the kernel size is (5, 5). A rectified linear unit (ReLU) is an activation function that introduces the property of non-linearity to a deep learning model and solves the vanishing gradients issue. "It interprets the positive part of its argument.

In the MaxPool2D layer we have kept pool size (3, 3) which means it will select the maximum value of every 3 x 3 area of the image. By doing these dimensions of the image will reduce by factor of 3. In dropout layer we have kept dropout rate = 0.25 that means 25% of neurons are removed randomly.

In the Dense, it was developed specifically to improve the declined accuracy caused by the vanishing gradient in highlevel neural networks. In simpler terms, due to the longer path between the input layer and the output layer, the information vanishes before reaching its destination. In the Dense layer we have used 512 filters.

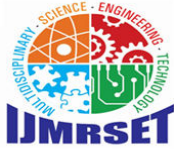
We apply these 1st& 2nd layers again with some change in parameters. Then we apply flatten layer to convert 2-D data to 1-D vector. This layer is followed by dense layer, dropout layer and dense layer again. The last dense layer outputs 3 nodes as the Waste Classification. This layer uses the softmax activation function which gives probability value and predicts which of the 3 options has the highest probability.

6. Accuracy on test set:

We got an accuracy of 99.91% on test set

7. Saving the Trained Model:

Once you're confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into an .h5 file using a library like save.



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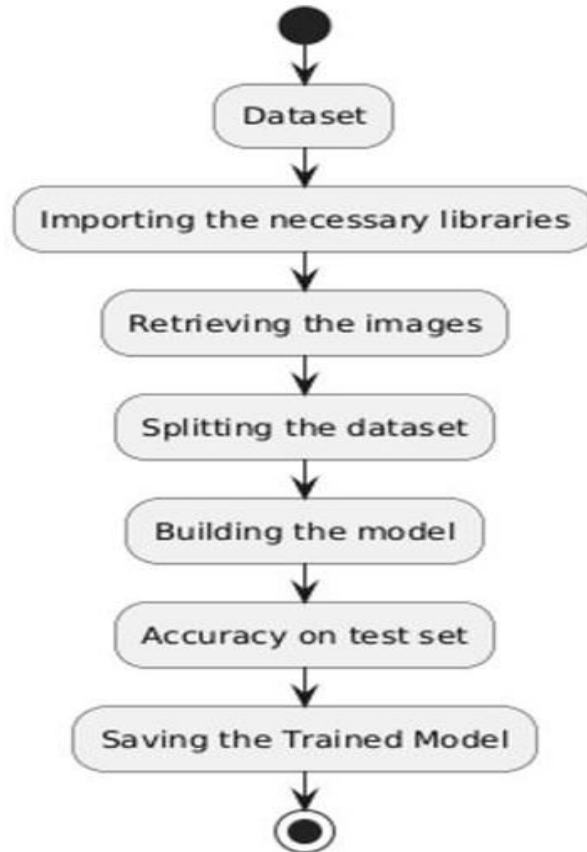


Figure B:- MODULE DIAGRAM

VIII. IMPLEMENTATION

Algorithm:-

1. Set up the environment and dataset:

- Prepare the dataset with labeled images for waste classification categories such as organic, recyclable, and nonrecyclable.
- Ensure necessary dependencies, such as TensorFlow, Keras, or PyTorch, are installed.

2. Import the necessary libraries:

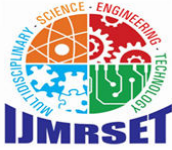
- Import libraries like NumPy, OpenCV, and machine learning frameworks for preprocessing, model training, and classification.

3. Load and preprocess images:

- Retrieve images from the dataset and resize them to a uniform size (e.g., 224x224 pixels).
- Normalize pixel values and apply data augmentation techniques like rotation, flipping, and scaling to improve model generalization.

4. Split the dataset:

- Divide the dataset into training, validation, and test sets (e.g., 70% training, 20% validation, 10% testing).



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5. Build the classification model:

- Use a pre-trained CNN model (e.g., ResNet, VGG) or create a custom architecture.
- Define layers for feature extraction, activation functions, and fully connected layers for classification.

6. Train the model:

- Use the training dataset to train the model with a specified loss function (e.g., categorical cross-entropy) and optimizer (e.g., Adam).
- Monitor accuracy and loss on the validation set for early stopping or tuning hyperparameters.

7. Evaluate the model:

- Test the trained model on the test dataset to compute accuracy, precision.

8. Save the trained model:

- Save the trained model in a format like .h5 or .pth for later use in real-world.

9. Real-time classification loop:

- Use a camera or input images for real-time classification.

10. Display classification results:

- Overlay classification results (e.g., "Recyclable," "Organic") and confidence scores on the image or video feed.

11. Exit loop:

- Press a key (e.g., 'q') to exit the real-time classification loop.

12. Release resources:

- Release the camera, close any active windows, and free up resources.

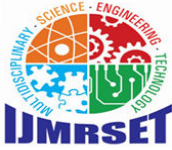
IX. EXPERIMENTAL RESULTS

HOME PAGE:

Home Page of Trash Collection and Transportation Monitoring System consists of featuring options such as HOME and LOGIN.



Figure:-HOME PAGE



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LOGIN PAGE:

This page represents a Login Page showing up a popup message saying “Login Success” after entering the login details and then clicking on the Login button at the bottom.

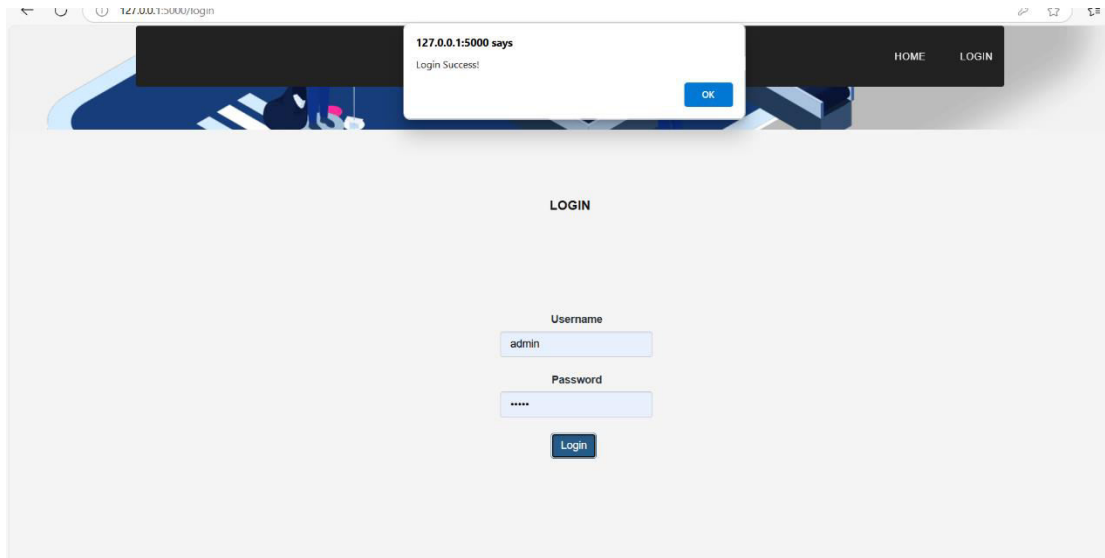


Figure:-LOGIN PAGE

UPLOAD FILE PAGE:

This page shows a file selection window opened as part of the waste classification system interface. Users are navigating through available image files to select one for upload. Once an image is chosen, it can be processed through the system for waste detection and classification.

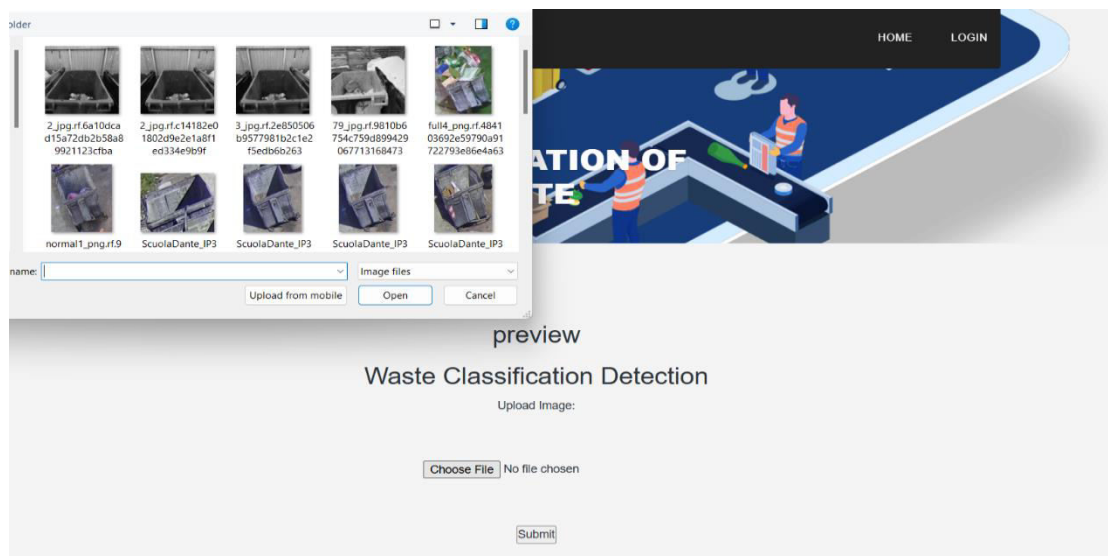


Figure:-UPLOAD FILE PAGE



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RESULT PAGE:

The result page shows the prediction about the uploaded image whether it is full, normal or null and the confidence percentage which represents the percentage of the prediction to be correct. And a “Upload Again” field to upload another image.

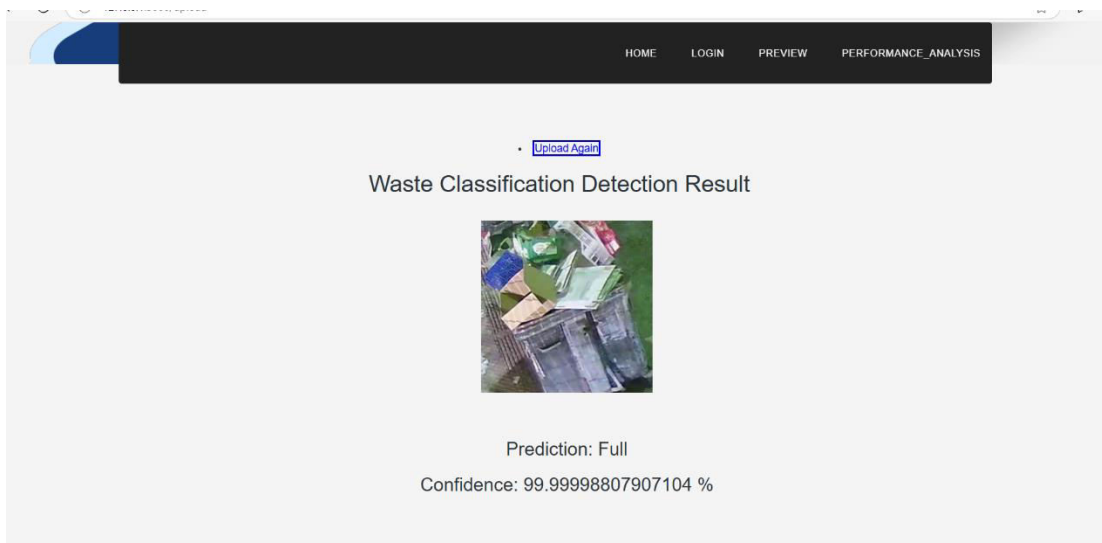


Figure: -RESULT PAGE

PERFORMANCE ANALYSIS:

This page shows the performance analysis of the waste classification system which provides the System’s Accuracy percentage as 99.91 based on the previously uploaded images.

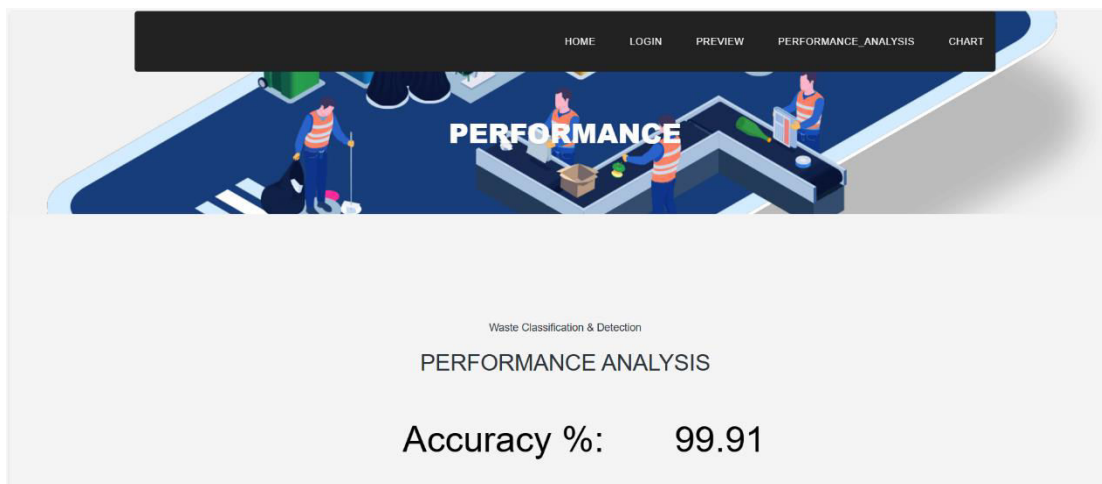
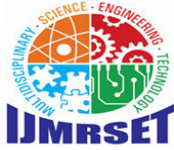


Figure:-PERFORMANCE ANALYSIS



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X. CONCLUSION

We propose an improved CNN model network to supervise the waste detection and collection process. The model is improved by several methods to adjust the characteristics of the garbage can dataset. Through the experiment we found that the identification between close-full and close-empty need more detailed features so we introduced Triplets Attention at the backbone of the CNN model, which under the circumstance of almost no extra parameters and the cross dimensional interaction is established thus improving the precision of the network. Meanwhile, this paper replaces the standard convolution of 3×3 in CNN model with a depth-separable convolution, which greatly reduces the number of parameters and computation of the model and improves the detection speed.

Finally, we demonstrate these advantages through experiments and the results of comprehensive experiments and analysis show that our approach can enhance the accuracy of the detections as well as meet the requirement of speed detection. Computer vision and deep learning still have a profound appliance on garbage collection and detection supervision. The next step will be to study how to identify the color of garbage cans to determine whether the type of garbage collected is correct or not, and to study how to combine the target detection algorithm with the actual operation scenario and be able to integrate it into the urban garbage collection and detection management system.

XI. FUTURE ENHANCEMENT

In the future with the use of technologies including AI and IoT the efficiency and accuracy of garbage classification can be improved.

REFERENCES

1. S. Chen, J. Huang, T. Xiao, J. Gao, J. Bai, W. Luo, and B. Dong, "Carbon emissions under different domestic waste treatment modes induced by garbage classification: Case study in pilot communities in Shanghai, China," *Sci. Total Environ.*, vol. 717, May 2020, Art. no. 137193, doi: 10.1016/j.scitotenv.2020.137193.
2. Y. Tong, J. Liu, and S. Liu, "China is implementing 'garbage classification' action," *Environ. Pollut.* vol. 259, Apr. 2020, Art. No. 113707, doi: 10.1016/j.envpol.2019.113707.
3. K. H. Yu, Y. Zhang, D. Li, C. E. Montenegro-Marin, and P. M. Kumar, "Environmental planning based on reduce, reuse, recycle and recover using artificial intelligence," *Environ. Impact Assessment Rev.*, vol. 86, Jan. 2021, Art. no. 106492, doi: 10.1016/j.eiar.2020.106492.
4. X. Meng, X. Tan, Y. Wang, Z. Wen, Y. Tao, and Y. Qian, "Investigation on decision-making mechanism of residents' household solid waste classification and recycling behaviors," *Resour. Conservation Recycling*, vol. 140, pp. 224–234, Jan. 2019, doi: 10.1016/j.resconrec.2018.09.021.
5. W. Zeng, S. Y. Yin, and F. Zhang, "Research on recognition and location algorithm of waste plastic bottle based on computer vision," *Electron. Meas. Technol.*, vol. 44, no. 23, pp. 12–17, Jul. 2021, doi: 10.19651/j.cnki.emt.2107427.
6. T. Mahmud, M. A. Rahman, and S. A. Fattah, "CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization," *Comput. Biol. Med.*, vol. 122, Jul. 2020, Art. no. 103869, doi: 10.1016/j.combiomed.2020.103869.
7. B. Sun, J. Li, M. Shao, and Y. Fu, "LRPRNet: Lightweight deep network by low-rank point wise residual convolution," *IEEE Trans. Neural Network. Learn. Syst.*, early access, Nov. 13, 2021, doi: 10.1109/TNNLS.2021.3117685.
8. J. W. Feng and X. Y. Tang, "Office garbage intelligent classification based on inception-v3 transfer learning model," in *Proc. 4th Int. Conf. Control Eng. Artif. Intell (CCEAL) Singapore, 2020*, Art.:No.012008.
9. Z. Chen, J. Yang, L. Chen, and H. Jiao, "Garbage classification system based on improved Shuffle Net v2," *Resour. Conservation Recycling*, vol. 178, Mar. 2022, Art. no. 106090, doi: 10.1016/j.resconrec.2021.106090.
10. F. Liu, H. Xu, M. Qi, D. Liu, J. Wang, and J. Kong, "Depth-wise separable convolution attention module for garbage image classification," *Sustain-ability*, vol. 14, no. 5, p. 3099, Mar. 2022, doi: 10.3390/su14053099.
11. V. Ruiz, A. Sánchez, J. F. Vélez, and B. Raducanu, "Automatic image-based waste classification," in *Proc. Int. Work Conf. Interplay between Natural Artif. Comput.*, 2019, pp. 422–431.



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

12. Q. Q. Chen and Q. H. Xiong, "Garbage classification detection based on improved YOLOV4," *J. Comput. Commun.*, vol. 8, no. 12, pp. 285–295, Dec. 2020, doi: 10.4236/jcc.2020.812023.
13. Z. Wang, H. Li, and X. Yang, "Vision-based robotic system for on-site construction and demolition waste sorting and recycling," *J. Building Eng.*, vol. 32, Nov. 2020, Art. No. 101769, doi: 10.1016/j.job.2020.101769.
14. Z. C. Chen, H. N. Jiao, J. Yang, and H. F. Zeng, "Garbage image classification algorithm based on improved Mobile Net v2," *J. Zhejiang Univ. Eng. Sci.*, vol. 55, no. 8, pp. 1490–1499, Mar. 2021. Available: <https://www.zjournals.com/EN/abstract/abstract42032.shtml>
15. M. Gao, Y. H. Chen, Z. H. Zhang, Y. Feng, and W. G. Fan, "Classification algorithm of garbage images based on novel spatial attention mechanism and transfer learning," *Syst. Eng.-Theory Pract.*, vol. 41, no. 2, pp. 498–512, Jun. 2021, doi: 10.12011/SETP2020-1645.
16. Q. Li, Y. Q. Gong, W. Zhang, C. Liu, J. Li, D. Han, D. F. Liu, W. H. Mei, and X. Dong, "Attention YOLOv4 algorithm for intelligent waste sorting," *Comput. Eng. Appl.*, vol. 58, no. 11, pp. 260–268, Nov. 2021, doi: 10.3778/j.issn.10028331.2111-0098.
17. B. Fu, S. Li, J. Wei, Q. Li, Q. Wang, and J. Tu, "A novel intelligent garbage classification system based on deep learning and an embedded Linux system," *IEEE Access*, vol. 9, pp. 131134–131146, 2021, doi: 10.1109/ACCESS.2021.3114496.



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