International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 07 | July 2020 www.irjet.net p-ISSN: 2395-0072

Classification of Waste for Efficient Disposal & Recycling using Deep Learning

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Abstract - *Garbage waste generation and accumulation are increasing at a very fast rate. Treating this waste for proper disposal and recycling has become an important topic. The recycling of waste must be done in a very efficient manner. The aim of this paper is to automate the recyclable waste classification just from their images. The recyclable categories are – metal, paper, plastic and glass. The algorithm for classification of waste used is Faster R-CNN with tensor flow. For classification, it takes the image of the trash objects and provides valid boundaries over the objects based on the recyclable waste categories used. The boundaries comprise of various color boundaries based on the categories for recycling process. The hardware implementation includes real time images being taken and given as an input to the trained model. However, in this paper our focus will be to make multiple types of trash getting recognized through the deep learning process.*

Key Words: **Convolution neural network (CNN), deep learning, object detection, etc.**

1. INTRODUCTION

Increase in urbanization and changing lifestyles has resulted in an increase in volumes of waste in India [1]. The waste increase is estimated to be increased from 64-72 million tons to 125 million tons by 2031. Untreated waste that includes recyclable non-biodegradable waste lies for years at dumpsites where land areas are allocated for disposal of residual waste. Hence, it is important to classify recyclable waste so that it does not get grouped with other waste in the landfills. This will eventually decrease the mixing of recyclable waste with the degradable waste.

The recycling rate of waste in India is comparatively lower than other countries for different categories [1]. If classification of waste is done at the earliest level most of the problem for recycling of waste can be solved easily. In this project, we aim to classify the images of recyclable waste into different categories of recyclable elements. The method used for this classification is with the help of TensorFlow and faster R-CNN method. Through this algorithm, boundaries are created on the recyclable waste indicating which category the waste falls into. Section II contains reviews on the relatable work that has being done in this domain, section III about the data collection process that has being done, Section IV talks about the Fast R-CNN method, Section V contains the training of the dataset in the network, Section VI talks about the result achieved from the model and Section VII talks about the hardware implementation that is been done with the resulted trained network.

2. EASE OF USE

A. Comparing deep learning and SVM for autonomous waste sorting

The paper contained comparative study of deep learning convolution neural network and SVM algorithm for classification of waste for effective waste sorting [2]. The accuracy of SVM was comparatively greater than CNN. However, with increase in data and GPU usage the CNN algorithm will give out greater accuracy and reduce the effect of overfitting.

For the final hardware implementation, the SVM model was implemented for classification. It uses a raspberry pi 3 connected to a high definition camera. The camera takes a snapshot of the waste and the image is saved in a PNG file. The captured image is sent to the preloaded category for classification where according to its category different LED color lights up.

B. Classification of thrash for recyclability status

This was another thrash classification project where they used SVM and CNN at a comparative study base [3]. The impactful contribution was the dataset that they created which included images of various categories thrash being taken under a white background. The dataset included about 400-500 images of each category of thrash which included paper, cardboard, glass, metal, plastic and thrash. The divided the images into training and testing part and compared the end prediction with both the algorithms.

C. Region-based Object Detection and Classification using Faster R-CNN

Faster R-CNN is a major improvement in the deep learning area for object detection [4]. As in the earlier method, as the CNN prediction of the thrash images could only classify single objects to various categories. With Faster R-CNN method multiple objects within a single image can be classified into various categories. For the detection of object in an image the approach for training the data is taken such that the whole image and the region of interest in the image in considered for training so that in the testing phase multiple object detection can take place.

D. RecycleNet: Intelligent Waste Sorting Using Deep Neural Networks

For the training of the Trashnet dataset which included different images of trash objects different CNN architecture were used and a comparative study was being done [5]. By studying different models in deep learning, the authors proposed their own model, called Recyclenet, by bringing in some changes in the overall connection patterns. For training the model high configuration GPU were used in order to reduce the overall time for training. The Recyclenet model gave an accuracy of 81% and showed that their model was more consistent as compared to other models.

3. DATA COLLECTION

The training data was available online in GitHub repository which was used in the classification of thrash for recyclability status [3]. It contained around 2527 images with around 400-600 images of each categories of thrash which were glass, paper, cardboard, plastic and metal [7]. The divisions were made based on images contained in their respective category folder. But in order to train this data in a Faster R-CNN algorithm the region of interest in the image had to be labeled. For this labeling of image, the LabelImg tool was used.

In LabelImg, we had to label the relevant region of the image to the class it belonged. This labeling of image included the procedure of giving boundaries to the thrash object in the image. The image set includes 80% of training images in each category and 20% for testing phase. After labeling the images, the respective csv file for training was created. For testing, the images that were not included during labeling of images were taken into account. The csv of the training images and included the file name, co- ordinates of the relevant region of interest in the whole image and the class to which the thrash object belonged to.

4. METHODOLOGY

For image-based classification CNN algorithm plays an important role [3]. But with simple CNN algorithm only single object in the image can only be classified. Faster R- CNN is an extension towards CNN with Region Propose Network (RPN) [6]. Faster R-CNN algorithm is used because it will help in detecting multiple objects in the same image. Faster R-CNN composed of two modules. The first module is a deep convolution network that will propose regions with RPN and the second module will use the proposed images for classification. In RPN, the output for a given image is a rectangular object proposal which contain an objectness score. The object proposal is referred to as anchors. RPN will help to predict the possibility of objects in a background. For this, a dataset with labeled object in the image has to be processed for training. Region of Interest (ROI) pooling layer is used to reshape the predicted regions. Then it is used to classify the image within the region and predict the offset values of the bounding boxes. Therefore, the accuracy of the final model will depend on the relevant regions which have been proposed correctly. If the regions proposed selects correct region on the basis of object then it can be classified into different class of categories.

5. TRAINING

The training for a huge network in Faster R-CNN requires a lot of computational power. For training our neural network, we used Predator laptop equipped with an Intel i7 processor and an NVIDIA GeForce GTX10. Additional software requirements that were included were the CUDA Toolkit and CUDNN SDK installed for the windows 10 machine. The Tensorflow open source software will give assistance for high performance numerical computation. Its flexible architecture allows easy deployment of computation across variety of platforms. The faster R-CNN inception model was than downloaded from the Tensorflow model. The training CSV file was then used for training the neural network. During the training process, the loss value was initially high. It went on getting lower as training progressed. During the training, the initial loss was about 0.6 and then it gradually dropped to a point at 0.09. The total time taken for the training was about 2 hours and 15 minutes. The number of epochs for the neural network was 22935 steps.

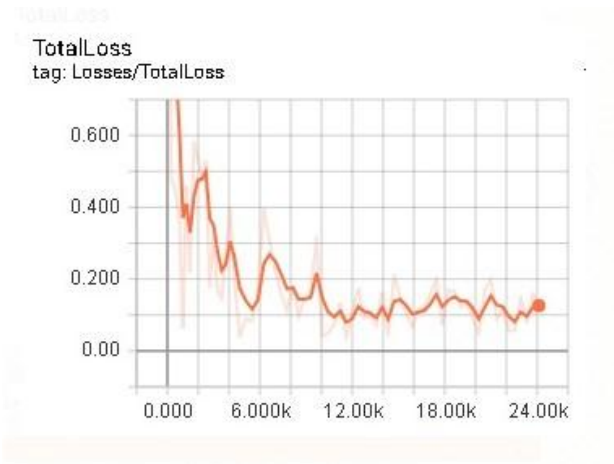

Fig 1. Loss graph during the training period.

6. RESULTS

For testing the model, the images from the testing part was used. In order to make the detection, the testing code was executed with inclusion of the image name that has to be tested. For finding the model accuracy status, we had to manually give file names in the code for each testing images name and check how accurate the model worked. Initially during testing, the region predicted for objects in some images contained multiple boundaries for same object. This error was removed by changing the threshold for the prediction of the boundary. This helped in nullifying the boundaries of the object with lesser threshold values. The prediction of the object showed a well-defined boundary for single thrash object detection in an image.

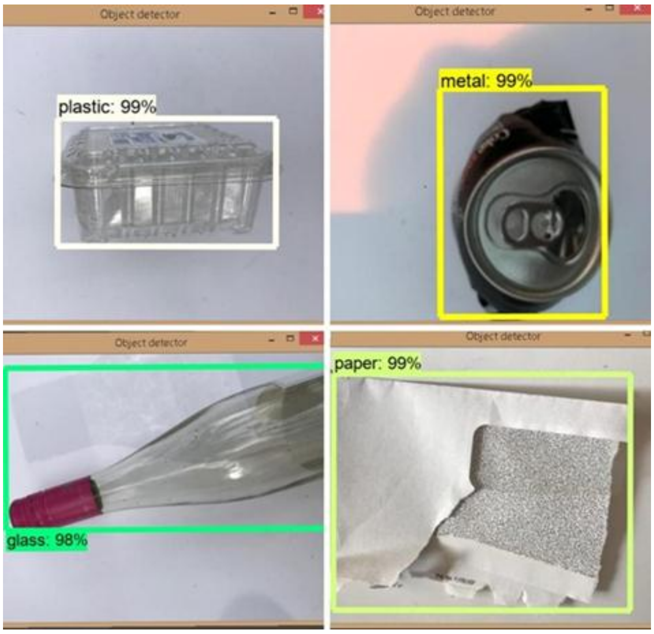

Fig 2. Accurate predictions done by model.

The images of the local thrash objects were taken in a white background and then were provided to the testing program. When images of local thrash object where given for prediction it showed a decrease in accuracy prediction. Wrong prediction of objects was being done since the model was not trained on the local thrash data images.

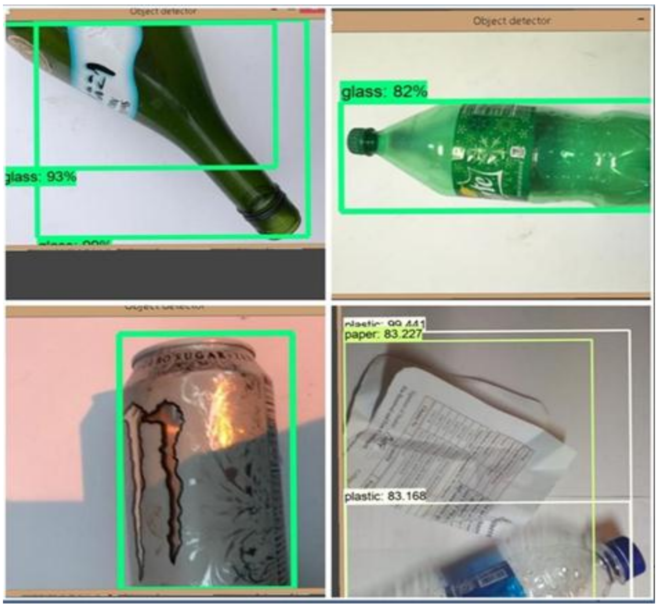

Fig 3. Inaccurate predictions done by model.

Multiple thrash object detection was also done. As the dataset did not contain any multiple thrash object images, we had to provide the multiple thrash object image to the model. For overlapping images, there were comparatively varying prediction were shown. The multiple thrash object image was also taken in a white background image.

Fig 4. Multiple thrash objects predicted by model

Images of the same object but with different orientation were also taken into account for testing result. The prediction for the objects was also done successfully correct. The boundary box for detection for some objects was not seen. This was due to the threshold value included for the prediction of the image. When the threshold value was decreased for that testing phase then the boundary box with the class name associated with it was shown in the image.

Fig 5. Accurate prediction done for same object with different orientation.

7. HARDWARE

In order to give an input for the model a webcam is set up. The GUI representation has also been made. The GUI works in coordination with the webcam. The GUI shows two parts the input from which the real time image is passed on to the model and the output image at its side. The output image contains boundaries with color and name parameters according to the type of class it belongs to.

8. CONCLUSION

In this paper, we have showed how the classification of multiple thrash objects in a single image can be obtained by faster R CNN algorithm. Most of the previous paper included recognition and classification of single thrash objects. With our approach, we have provided an improvement for this problem. The classification of thrash objects into different categories was done with a good accuracy. The main issue was the datasets which included images which were little different from our local thrash objects. Due to this, there was some wrong classification being predicted in it. The future work that can be done with this project would include the same procedure but an improvement in the datasets by including images of local thrash objects. This can help to get some improved classification.

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