

RETAIL INVENTORY MANAGEMENT AND STOCK-OUT PREDICTIONS USING REAL TIME OBJECT DETECTION

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Abstract— Inventory Management System is essential to ensure quality control in businesses handling transactions revolving around consumer goods. This project aims at using real time object detection as the primary means for automating the retail inventory management systems and also for detecting stock-out conditions on shelves. This project adopts an approach in which 24 hours video surveillance of the different aisles of the store continually keep a track of the number of each kind of product that is displayed on the shelves. Object detection is performed using Faster R-CNN. Using the data collected from object counting we perform inventory management in excel. Thus, the efficiency and effectiveness of manually performed operations is improved.

Index Terms— Faster R-CNN; Deep Learning; Retail Inventory Management; Object Detection

INTRODUCTION

In today's competitive retail landscape, the power to regulate and optimize retail execution at the point of sale has never been more crucial. Currently obtainable in-store audit solutions are manual and dilatory. Manually auditing all kinds of merchandise takes close to quarter-hour per class and involves bound physical measurements that are susceptible to human errors and inaccuracies. Measuring the shelving execution standards could be a difficult task. The industry's ability to grow and contend has been challenged by the absence of economical pursuit and analysis tools for retail execution within the stores. With image recognition technology, makers and retailers can currently perceive the marketplace and react in real-time. Using object detection may result in time-saving of audit method with higher accuracy. This ensures that the merchandiser can have correct and reliable data, recognize that products are out of stock at their fingertips. Shelf-out-of-stock is one among the most important motivations of innovation towards the smart shelf. traditionally, for stock renewal, the shop staff perform a visual check, using planogram compliance observation. With image identification capabilities, the CCTV cameras within the retail outlet are often leveraged to sight and count merchandise at to assist the shop employees during this tedious method. The concept of utilising the video camera to count the number of objects has been projected as a new approach of detection and enumeration approach.

The surveillance video from the shops are going to be used by the AI model to sight the merchandise on the shelves and count them using object enumeration methodologies within the morning before the store opens

and there's a count taken at the end of the day post the closing of the shop. This data is stored in an excel file where the remainder of the inventory management takes place. This reduces the likelihood of errors and is both economical and time saving. Accurately counting objects instances in a given image or video frame has been a tough problem to resolve in machine learning. There exists a technique within the field of machine learning and in Deep Learning with Convolutional Neural Networks particularly, known as Region based Convolutional Neural Network (RCNN), where multiple objects and their location on the image are identified. during this project object detection is performed with the help of faster R-CNN.

I. PREVIOUS WORK

The use of object detection has become more significant in industrial processes to identify products involved in inventory management, machining, quality management, packaging etc. A paper on object detection predicated on fast/faster R-CNN employing plenary convolutional architectures fixates on how to employ the plenary convolutional architectures in the fast/faster R-CNN. Faster- R-CNN is 10 times faster than fast- R-CNN and has been one of the most accurate object detection algorithms^[1]. Object detection and counting system centers around six techniques specifically picture securing, picture upgrade, picture division, picture investigation, object tallying and reports. The image is first acquired and then enhanced using gray scaling process which converts the RGB image into gray scale. Picture investigation has been finished utilizing design coordinating method and the number of objects detected was accumulated in the Excel File^[2]. A way to deal with programmed division and including of Red Blood Cells in minuscule platelet pictures was actualized utilizing Hough Transform. This method is cost-effective and time saving and also it can distinguish covering platelets and tally them independently^[3]. Another system based on vehicle detection and counting system came into existence with the help of smart cameras. This work is effective in tackling the traffic control frameworks^[4]. Bayesian following model can deal with a few modes circulations without registering the relationship between track items and location. This item identifier can identify and evacuate shadows, can likewise perform split location and union recognitions which make the direction estimation and article tallying testing task^[5]. A general article checking strategy isolates the info picture into a lot of picture divisions—each completely covering the picture. Each

picture fragment is made out of a lot of district recommendations or uniform pixel cells. The approach learns in an end to end deep learning architecture to anticipate picture level counts from neighborhood picture areas. The strategy joins an including layer which tell object includes in the full picture, by authorizing consistency in tallies when managing covering picture areas ^[6].

II. PROPOSED WORK

A. OBJECT DETECTION

This project utilizes the ideas of object detection and count. Object detection is a technique associated with computer vision and image process which deals with the detection of linguistics objects of a Particular kind or category in pictures and surveillance videos. Object detection methodologies may be classified as machine learning-based approaches or deep learning-based approaches. For Machine Learning Approaches, process the options first and employing a technique like support vector machine (SVM) to do the classification is obligatory. On the other hand, deep learning techniques are that that are ready to do end-to-end object detection while not specifically process options, and are usually supported convolutional neural networks (CNN). Typically, there square measure three steps Concerned in each object detection framework.

1. The regions of interest or regions where the model proposes the existence of associate in nursing object are ridge generated. These proposals region are given as a collection of bounding boxes spanning the whole image.
2. The second step besteht of the extraction of features for every bounding box and their analysis to see did object is present within the planned region supported visual options.
3. In the final post-processing step, overlapping boxes are combined into one bounding box (that is, non-maximum suppression).

B. FASTER R-CNN

Faster R-CNN is a complicated type of the R-CNN and quick R-CNN techniques of object detection. A convolutional neural network (CNN) is employed all told of the on top of techniques. The distinction between them is however the regions to be processed are chosen and the way the classification is finished. Before running the CNN R-CNN and quick R-CNN uses a district proposal formula. The proposal algorithms used methods like Edge Boxes and Selective Search, that aren't dependent on the CNN. Within the case of quick R-CNN, the utilization of those techniques becomes the process bottleneck compared to running the

CNN. This issue is addressed in quicker R-CNN with the usage of CNN for implementing the region proposal mechanism that makes region proposal a region of the CNN training and prediction steps. The model used for training the object detector during this project is that the faster_rcnn_inception_v2_coco_2018_01_28 model. Faster R-CNN was developed by researchers at Microsoft. It is supported R-CNN that used a multi-phased approach to object detection. R-CNN used Selective search to see region proposals, pushed these through a classification network so used an SVM to classify the various regions.

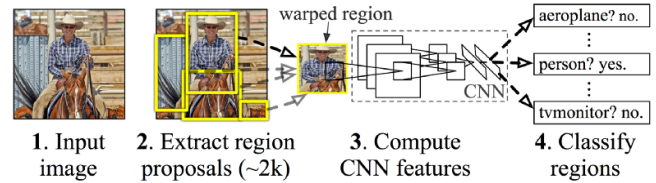


Figure-1 R-CNN Architecture Overview

Faster R-CNN prefers to SSD, is an end-to-end approach. Rather than using default bounding boxes, faster R-CNN encompasses a Region Proposal Network (RPN) to get a set of regions. The RPN permits nearly cost-free region proposals by using the convolutional options from the classification network. The RPN is enforced as a totally convolutional network that generates object bounding boxes and predicts objectless scores at each position.

RPN has a similar setup as the SSD network. A group of proposals are computed with numerous scales and side ratios, at every sliding-window location or anchor. The results of the RPN are adjusted bounding boxes that are based on the anchors.

C. REGION PROPOSALS

Several different approaches exist to get region proposals. Selective search was the rule originally accustomed generates object proposals. It's a clustering-based approach that teams pixels and supported the generated clusters it generates proposals.



Figure-2 Selective Search on an Image

There are few alternative approaches that build use of additional advanced visual features extracted to come up

with region proposals or adopt a brute-force approach to region generation. These regions are automatically generated, without considering the image features.

The number of regions vs. the computational complexity is a very important trade-off that's created with generation of region proposals. The additional amount of regions generated, the additional possible you're to find the object. On the other hand, if you thoroughly generate all proposals, it's attainable to run the object detector in real-time.

D. METHODOLOGY

1. Gathering Pictures

The training images have unwanted objects in the image along with the desired products, and a variety of backgrounds and lighting conditions to train a robust classifier. There are images with products that are overlapping with other products or that are partially obscured. Such flawed images facilitate proper training of the object detector thereby resulting in an efficient software.

2. Labeling Pictures

We use the LabelImg tool for labeling our images. Once each image has been saved and labeled, there is one .xml file for each image in the \test and \train directories. Also, sizeChecker.py was run in order to check if the bounding boxes were of the appropriate size is checked if it is correct by running.

3. Generating Training Data

The TFRecords which are the input data to TensorFlow training model were generated with the help of the labelled images. The xml_to_csv.py and generate_tfrecord.py scripts from Dat Tran's Raccoon Detector dataset are used with some slight modifications to work with the directory structure.

4. Creating Label Map and Configuring Training

Before training a label, map was created and then the training configuration file was edited. From the label map the trainer learns about the object by defining a mapping of class names to class ID numbers. Finally, the object detection training pipeline that defines the model and parameters used in training.

5. Running the Object Counting Model

The trained object counting software is now run and the number of products of each kind are accurately counted. In every five minutes checkpoints are saved by the training routine.

6. Inventory Management and Stock-out Prediction

The products count that are obtained from the object counting model are entered into a spreadsheet where inventory management is performed. These counts as observed before the opening and after the closing of the retail outlet are used for conducting inventory while the product counts taken continuously by the surveillance camera are used to predict stock-out conditions from time to time^[7].

E. ARCHITECTURE DIAGRAM

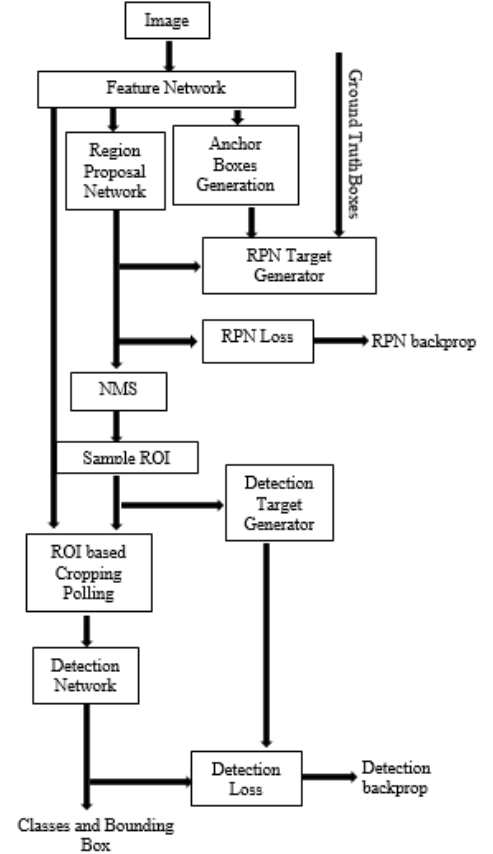


Figure-3 Object Detection Architecture

III. EXPERIMENTAL RESULTS

In this section, we report the comparison of different methods of object detection. We train the Faster R-CNN object detection model in a store. The objects are detected with approximate detection values.



Figure-4 Object Detection in store

Sample Images	Actual Count	CNN		R-CNN		Fast R-CNN		Faster R-CNN	
		Estimated Count	Error in Count	Estimated Count	Error in Count	Estimated Count	Error in Count	Estimated Count	Error in Count
1	3	1	2	2	2	3	1	3	3
2	3	3	2	1	1	2	2	3	3
3	4	2	1	3	3	3	0	4	4
4	3	0	3	1	0	1	3	3	3

Table-1 Observation of Sample Images with various approaches

The values in the table determine the accuracy of the object being detected. This test is done using other object detection approaches like CNN, R-CNN, and fast R-CNN to compare their results with our proposed faster R-CNN object detection model. The test has been performed for different classes of images for better comparison. As a result we have found out that faster R-CNN has matched with the actual values and makes it better than other object detection models. We have represented the results in graph to understand the results of our proposed object detection model.

the stock out condition [8]. As a result, the present methodology automates multiple tasks which were previously implemented manually, thereby enhancing efficiency and effectiveness of inventory management operations to a great extent.

REFERENCES

- [1] Ren, Yun & Zhu, Changren & Xiao, Shunping. (2018) "Object Detection Based on Fast/Faster RCNN Employing Fully Convolutional Architectures", Mathematical Problems in Engineering. 2018, pp 1-7.
- [2] Pornpanomchai, Chomtip & Stheitsthienchai, Fuangchat & Rattanachuen, Sorawat. (2008) "Object Detection and Counting System", IEEE, pp. 61 - 65.
- [3] Maitra, Mausumi & Kumar Gupta, Rahul & Mukherjee, Manali. (2012), "Detection and Counting of Red Blood Cells in Blood Cell Images using Hough Transform", International Journal of Computer Applications, pp 13-17.
- [4] A. Alpatov, Boris & Babayan, Pavel & Ershov, Maksim (2018), "Vehicle detection and counting system for real-time traffic surveillance", pp 1-4.
- [5] Del-Blanco, Carlos & Jaureguizar, Fernando & Garcia, Narciso (2012), "An Efficient Multiple Object Detection and Tracking Framework for Automatic Counting and Video Surveillance Applications" Consumer Electronics, IEEE Transactions on. 58. 10.1109/TCE.2012.6311328.
- [6] Stahl, Tobias & Pintea, Silvia & Gemert, Jan. (2018), "Divide and Count: Generic Object Counting by Image Divisions", IEEE Transactions on Image Processing, pp. 1-1.
- [7] <https://youtu.be/Rgpfk6eYxJA>, "How to Train an Object Detection Classifier Using TensorFlow 1.5 (GPU) on Windows 10".
- [8] <https://patents.google.com/patent/US20090063307A1/en> "Detection Of Stock Out Conditions Based On Image Processing".

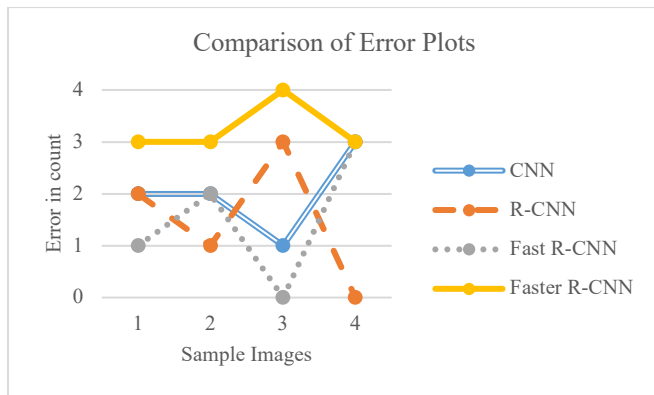


Figure-5 Comparison of Error Plots for various approaches

IV. CONCLUSION

This object detection system is one of the most efficient and effective ones so far as it uses Faster R-CNN. The inventory management is a clean and error free operation when done using this software. Images were analyzed and multiple stock out features within the image were detected. If such features are detected an indication is provided about