Inventory Monitoring at Distribution Centers

CAPSTONE PROPOSAL

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1. Domain Background:

Inventory Monitoring is a critical process in a Distribution Center. It is the process of ensuring the right number of products or items present in a particular bin. It is an integral part of the supply chain management, that ensures the flow of goods from manufacturing venue to the warehouse or a distribution center and to the sale location.

Long before the industrial age, keeping track of things consisted of manually counting and tallying items. The earliest form of inventory management dates back over 50,000 years in which people used “tally sticks” to count.

The empowerment of the distribution centers to automate its process through a digital workplace is the need of the hour to manage the demand and supply chain. During the time of the pandemic, there is a huge demand for the logistics services.

2. Problem Statement:

Manual Inventory Management requires a huge workforce, and it is also error prone. So, there is a need for an effective inventory management.

Effective Inventory Management enables the business to save time and increase productivity. The automation of this process would eliminate the manual errors, thus saving cost and time. For larger organization, the process is much complicated.

With the recent advancement in the technology, we could solve the above problem with machine automated tasks. The Computer Vision Process aids us in solving the defined problem.

With the huge rise in the demand for inventory management, scalability is a major concerned that affects the long term run of the business. With the automated workflow, scalability becomes much simpler and cost efficient.

The solution can be replicated to different objects with respective datasets for training and the outcomes are measurable with the proposed evaluation metrics[5].

3. Solution Statement:

The identified problem can be solved using Computer Vision Techniques. By feeding appropriate data to train the machine learning model, a robust model can be produced.

Components:

1. Dataset / Image Source

2. Algorithm
3. Environment or the platform

Dataset or the Image Source:

The **Amazon Bin Image Dataset** is to be used to train the model.

It contains over 500,000 images and metadata from bins of a pod in an operating Amazon Fulfillment Center. The bin images in this dataset are captured as robot units carry pods as part of normal Amazon Fulfillment Center operations.

Documentation about the open source dataset can be found here.

These are some typical images in the dataset. A bin contains multiple object categories and various number of instances. The corresponding metadata exist for each bin image and it includes the object category identification(Amazon Standard Identification Number, ASIN), quantity, size of objects, weights, and so on. The size of bins are various depending on the size of objects in it. The tapes in front of the bins are for preventing the items from falling out of the bins and sometimes it might make the objects unclear. Objects are sometimes heavily occluded by other objects or limited viewpoint of the images.

Algorithm :

1. The Algorithm will be built using the Convolution Neural Network (CNN) architecture.
2. Deep Learning Framework – PyTorch
3. A corresponding Sage Maker instance will be created and data will be fed from the S3 bucket.
4. The model will also be tuned to find out the best hyper-parameters.

Environment or the platform :

1. Amazon Web Services
2. Sage Maker Studio – to train, tune and deploy the model.

S3 – Storage Bucket

Sample Image and JSON Pair :

This is an example of image(jpg) and metadata(json) pair. This image contains 3 different object categories. For each category, there is one instance. So, "EXPECTED_QUANTITY" is 3, and for each object category "quantity" field was 1. Unique identifier("asin") is assigned to each object category, e.g. here "B00CFQWRPS", "B00T0BUKW8", and "B00C3WXJHY"


```
{"BIN_FCSKU_DATA": { "B00CFQWRPS": {
      "asin": "B00CFQWRPS",
      "height": {
        "unit": "IN",
        "value": 2.399999997552
      }, "length": {
        "unit": "IN",
        "value": 8.199999991636
      },
      "name": "Fleet Saline Enema, 7.8 Ounce (Pack of 3)",
      "normalizedName": "(Pack of 3) Fleet Saline Enema, 7.8 Ounce",
      "quantity": 1,
      "weight": {
        "unit": "pounds",
        "value": 1.8999999999999997
      },  "width": {
        "unit": "IN",
        "value": 7.199999992656
      }
    },
    "ZZXI0WUSIB": {
      "asin": "B00T0BUKW8",
      "height": {
        "unit": "IN",
        "value": 3.99999999592
      },
      "length": {
        "unit": "IN",
        "value": 7.899999991942001
      },
      "name": "Kirkland Signature Premium Chunk Chicken Breast Packed in Water, 12.5 Ounce, 6 Count",
      "normalizedName": "Kirkland Signature Premium Chunk Chicken Breast Packed in Water, 12.5 Ounce, 6 Count",
      "quantity": 1,
      "weight": {
        "unit": "pounds",
        "value": 5.7
      },
      "width": {
        "unit": "IN",
        "value": 6.49999999337
      }
    },
    "ZZXVVS669V": {
      "asin": "B00C3WXJHY",
      "height": {
        "unit": "IN",
        "value": 4.330708657
      },
      "length": {
        "unit": "IN",
        "value": 11.1417322721
      },
      "name": "Play-Doh Sweet Shoppe Ice Cream Sundae Cart Playset",
      "normalizedName": "Play-Doh Sweet Shoppe Ice Cream Sundae Cart Playset",
      "quantity": 1,
      "weight": {
        "unit": "pounds",
        "value": 1.4109440759087915
      },    "width": {
        "unit": "IN",
        "value": 9.448818888
      }
    }
  },
  "EXPECTED_QUANTITY": 3
}
```

4. Benchmark Model:

The object counting using convolutional neural network has been introduced with connected component analysis from the following research paper is used as a benchmark to achieve the results. The authors had produced relatedly good results.

N. K. Verma, T. Sharma, S. D. Rajurkar and A. Salour, "Object identification for inventory management using convolutional neural network," 2016 IEEE Applied Imagery Pattern Recognition Workshop (AIPR), 2016, pp. 1-6, doi: 10.1109/AIPR.2016.8010578.

5. Evaluation Metrics:

Since it is a classification problem, **the overall accuracy of the classification and F1 score** can be used to evaluate the performance of the trained model.

6. Workflow: