



Inventory Monitoring at Distribution Centers

Project Proposal



Domain Background

- This challenge is rooted in the expansive field of robotics and its industry applications, particularly in inventory monitoring and supply chain operations. Many corporations handling physical cargo and overseeing the supply chain of various goods have sought to introduce automation to enhance efficiency and accuracy in these processes. Amazon serves as a prime example, being one of the largest hubs for delivery of a wide range of goods.
- These goods are typically stored in massive warehouses. Given the vast quantity of these items, manual inventory monitoring would necessitate substantial and skilled human resources. However, such an approach is not only costly but also susceptible to errors.
- This is where the utility of robots in inventory monitoring becomes apparent. Robots can be equipped with machine learning models to perform tasks such as object detection, outlier and anomaly detection, and much more. Once trained, these models offer scalability and can be deployed cost-effectively in real-world warehouses and distribution centers, operating on industrial-level robots.

Problem Statement

- Inventory management carried out manually necessitates a considerable workforce and is susceptible to errors, thereby emphasizing the need for an efficient inventory management system.
- A well-optimized inventory management system can significantly enhance productivity and save time for a business. By automating this process, the occurrence of manual errors can be significantly reduced, leading to cost and time savings. For larger organizations, this process can be even more complex.
- However, thanks to recent technological advancements, we now have the ability to address these issues through automated tasks. Computer Vision technology is instrumental in solving this problem.
- Given the surging demand for inventory management, scalability is a critical factor affecting the long-term sustainability of a business. An automated workflow simplifies scalability and enhances cost efficiency.
- The proposed solution can be applied to various objects using their respective datasets for training. The results are quantifiable based on the established evaluation metrics.

Solution Statement

- In order to address our problem statement, we're going to employ computer vision techniques to devise a machine learning model. This model, when provided with an image from our dataset, should be capable of identifying the number of objects present in it. Essentially, we're implementing multi-class image classification, treating each number of objects (from 1-5) as a separate class.
- We'll make use of Convolutional Neural Networks (CNNs) to achieve this. CNNs are a cutting-edge technique for image recognition tasks. To further enhance our model's performance, we'll use pre-trained models and apply transfer learning. This approach enables us to leverage previously learned features from large datasets, thus saving training time and improving prediction accuracy for our specific problem.

Datasets and Inputs

- For this project, we are utilizing the Amazon Bin Image Dataset. This dataset comprises 500,000 images, each showcasing a bin holding one or more items. Alongside each image, there is a metadata file that provides pertinent details such as the number of items in the bin, their dimensions, and their types. Our goal for this project is to develop a system capable of classifying the quantity of objects contained within each bin.

Datasets and Inputs

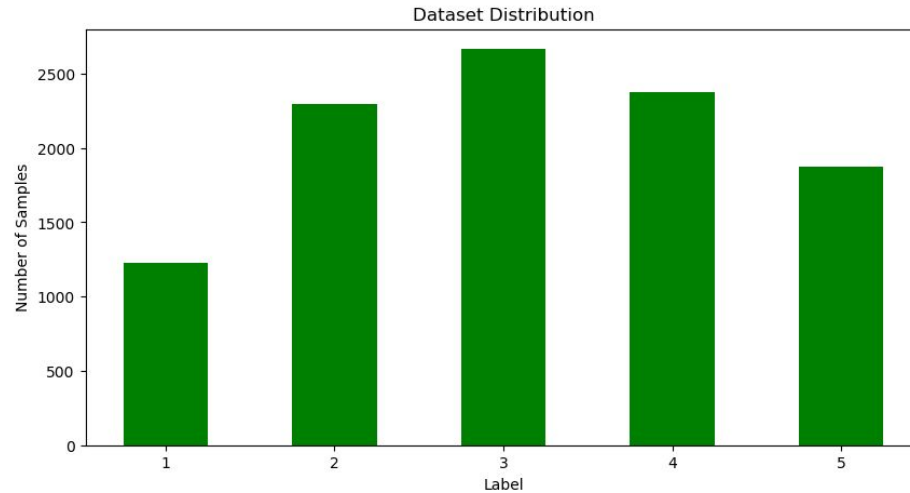


Figure: Distribution of Sample Numbers in the Dataset

Datasets and Inputs



Image example

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{
  "BIN_FCSKU_DATA": {
    "B000ABC50E": {
      "asin": "B000ABC50E",
      "height": {
        "unit": "IN",
        "value": 4.200000000000001
      },
      "length": {
        "unit": "IN",
        "value": 4.7
      },
      "name": "MSR PocketRocket Stove",
      "quantity": 1,
      "weight": {
        "unit": "pounds",
        "value": 0.45
      },
      "width": {
        "unit": "IN",
        "value": 4.4
      }
    },
    "B0064LIWVS": {
      "asin": "B0064LIWVS",
      "height": {
        "unit": "IN",
        "value": 1.2
      },
      "length": {
        "unit": "IN",
        "value": 5.799999999999999
      },
      "name": "Applied Nutrition Liquid Collagen Skin Revitalization, 10 Count 3.35 Fl Ounce",
      "quantity": 1,
      "weight": {
        "unit": "pounds",
        "value": 0.3499999999999999
      },
      "width": {
        "unit": "IN",
        "value": 4.7
      }
    }
  },
  "EXPECTED_QUANTITY": 2,
  "image_fname": "523.jpg"
}
```

Metadata format

Benchmark Model

- The benchmark for our approach to object counting via a convolutional neural network is derived from a specific research paper that employed connected component analysis. The authors of this paper were able to achieve commendable results, serving as an important reference point for our project.

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), Washington, DC, USA, 2016, pp. 1-6, doi: 10.1109/AIPR.2016.8010578.

Evaluation Metrics

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

- In order to assess the performance of our model, we must rely on robust, mathematically sound metrics that correspond with our specific problem statement, and which our model can be optimized against.
- Given that our task is Classification-based, suitable metrics would include Accuracy, Recall, Precision, and F1 scores. These can be applied not only to the dataset as a whole but also to individual classes. This will enable us to discern if our model is demonstrating superior performance in specific classes, or if it exhibits a significant bias towards a certain class. We chose the overall accuracy of the classification to evaluate the performance of the trained model.

Workflow

