Project Report

Project Overview

Distribution centers play a crucial role of modern supply chain and logistics operations. These centers are responsible for receiving, storing, and shipping products to retail outlets, customers, or other distribution hubs. Inventory Monitoring is one of the main challenge distribution center faces during these operations which is essential to ensure that products are available for shipment in a timely manner, and that the right quantities are dispatched for customer orders. Inventory Monitoring involves tasks like sorting, tracking, and packaging products into different bins, boxes, or pallets. Performing these tasks manually is time consuming and error prone. We can automate most of tasks using robots, automated systems or ML agents. A critical challenge in such environments is ensuring accurate inventory tracking and verifying that the correct number of items are packed and shipped. This becomes even more complicated when bins contain multiple different objects. Manual counting of items within each bin is inefficient and error-prone, especially when dealing with large volumes of goods. We will be using machine learning as a solution for the manual counting of items in the bin

Problem Statement

One of the key tasks of inventory monitoring in distribution centers is the accurate counting of objects within bins. Bins may contain a variety of items, and having a precise count of each item is essential for tasks such as inventory tracking, quality control, and ensuring the accuracy of shipping consignments. An error in the number of items could lead to overstocking or understocking of products, delays in order fulfillment, or even customer dissatisfaction.

For example, when preparing a shipment, it is critical that the correct number of products are included in each bin, as discrepancies could lead to incomplete orders or incorrect shipments. Manually counting items inside a bin is labor-intensive and prone to errors, especially when bins contain hundreds or thousands of small items.

To address this issue, a solution is needed that can automatically count the number of objects in each bin during the inventory monitoring distribution center. An automated system that can detect and count the objects within bins will help reduce human error, improve accuracy and performance during inventory monitoring in distribution centers.

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Solution

Machine Learning can provide solution to this problem of counting the objects in bin. By training a machine learning model on images or sensor data of bins, it is possible to develop a system that can accurately count the number of objects in each bin. The model can be integrated with the automation systems, allowing it to make real-time inventory updates which increases the performance in distribution centers ultimately leading to customer satisfaction.

In this project, the goal is to build an object counting model using machine learning techniques, which can process images of bins, analyze the contents, and accurately count the number of items within. The machine learning model will be trained using labeled data that is images of bins with the corresponding object counts and deployed in the distribution center to assist with automated inventory tracking and shipment verification.

Data Exploration and Visualization

Amazon is one of leading supply chain and logistics company and has lot of distribution centers. For this project, we will use the Amazon Bin Image Dataset which consists of 500,000 images of bins, each containing one or more objects. These images were captured in various scenarios to reflect real-world conditions that might be encountered in distribution centers. Each image in the dataset contains an assortment of items, ranging from small objects to larger, more complex items. The variety of objects and bin configurations within the dataset is important, as it allows the model to generalize across different types of bins and object arrangements. Since there is lot of data I will be taking a smaller set of the entire data. Below is the bin count and the number of images containing that bin count.

{'1': 1228, '2': 2299, '3': 2666, '4': 2373, '5': 1875}

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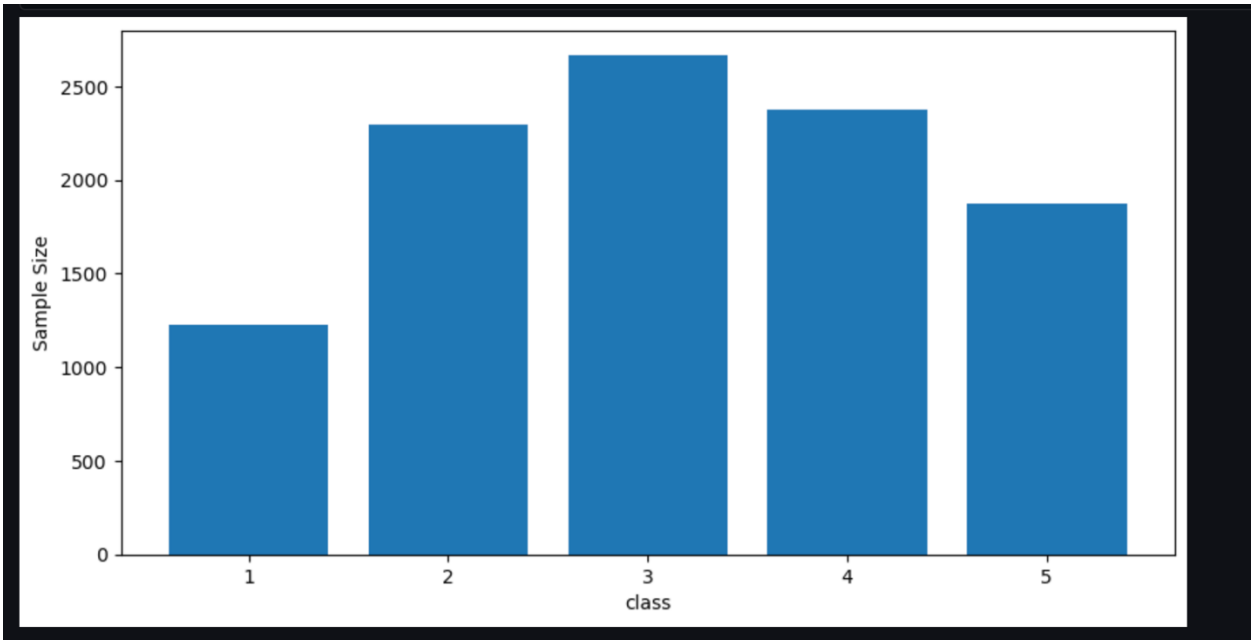

We have this file file_list.json (https://github.com/udacity/nd009t-capstone-starter/blob/master/starter/file_list.json) which contains the metadata images of all these images. We will this meta data to download the images from the s3 bucket aft-vbi-pds
More info can be found here: https://registry.opendata.aws/amazon-bin-imagery/

Some of the images of the bins with different Item count

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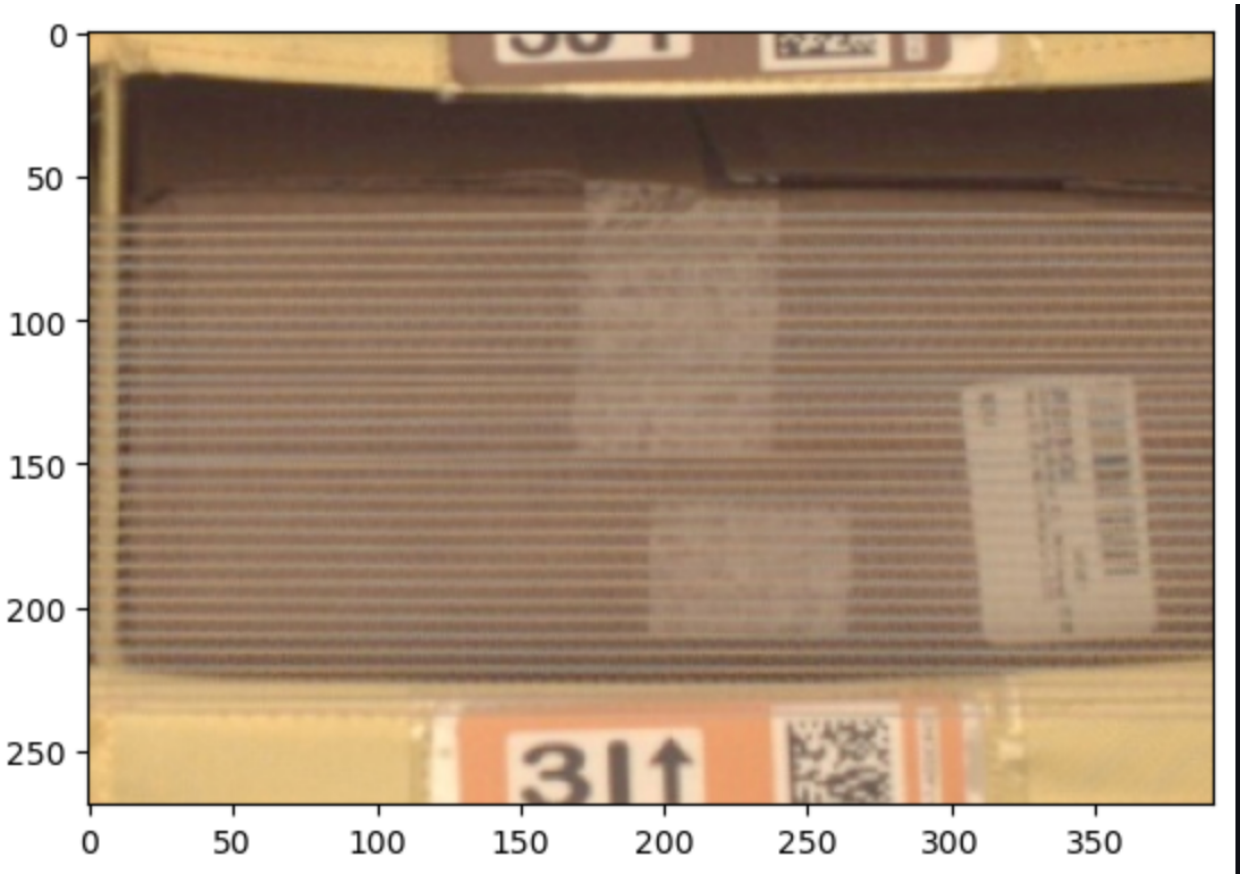

Bin with 1 Item Count

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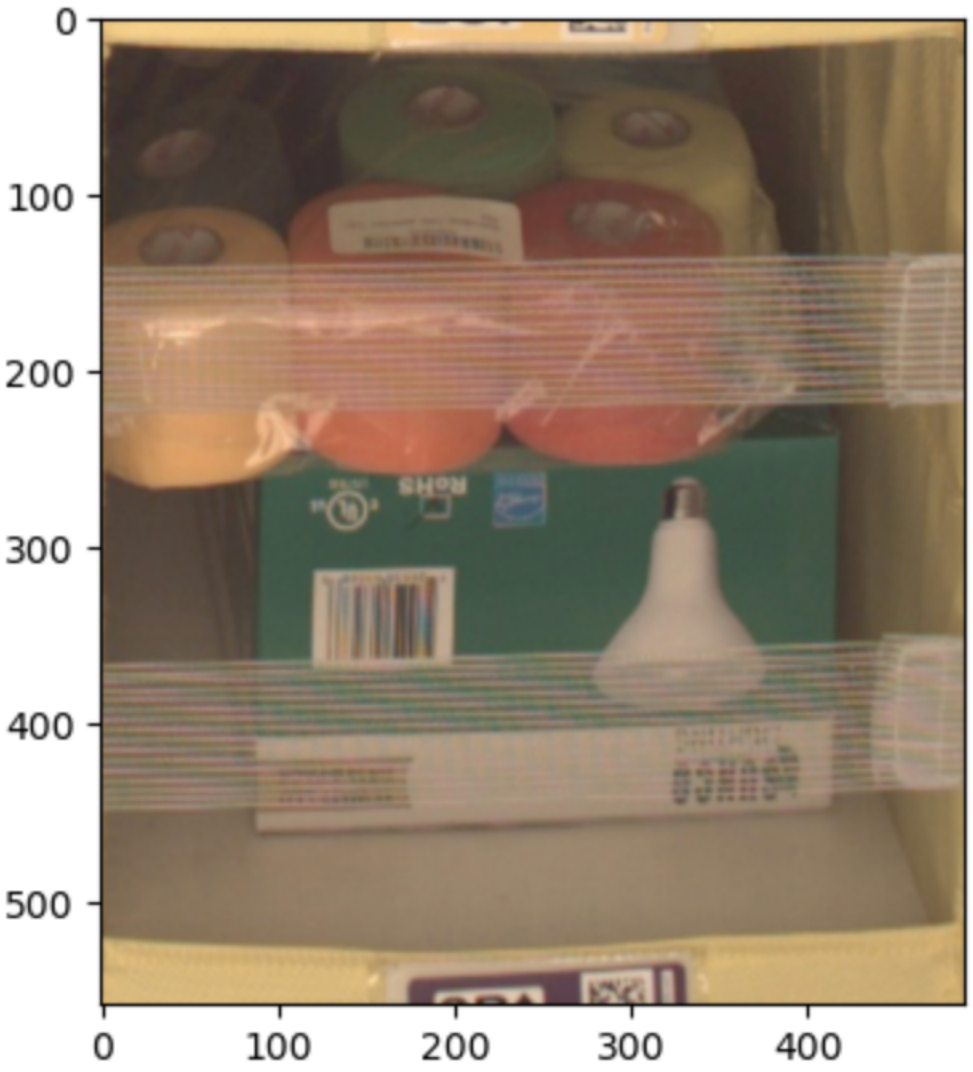

Bin with 2 Items Count

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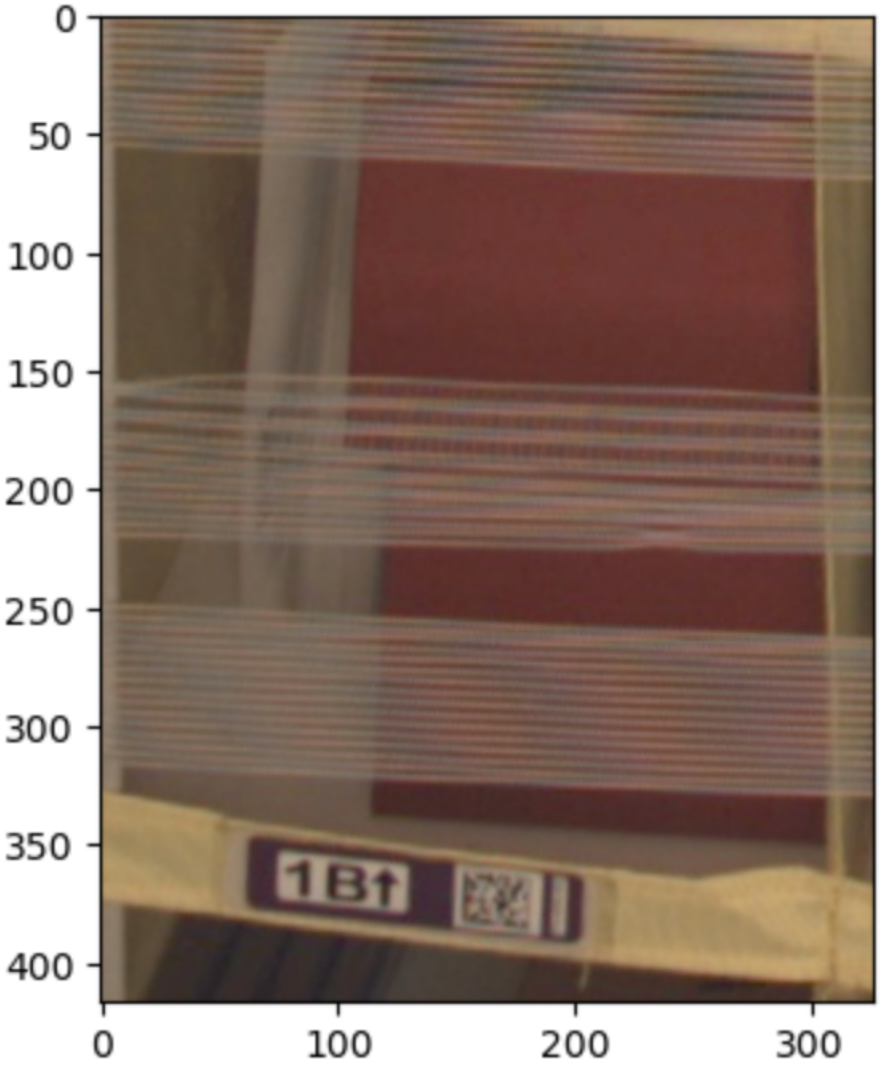

Bin with 3 items Count

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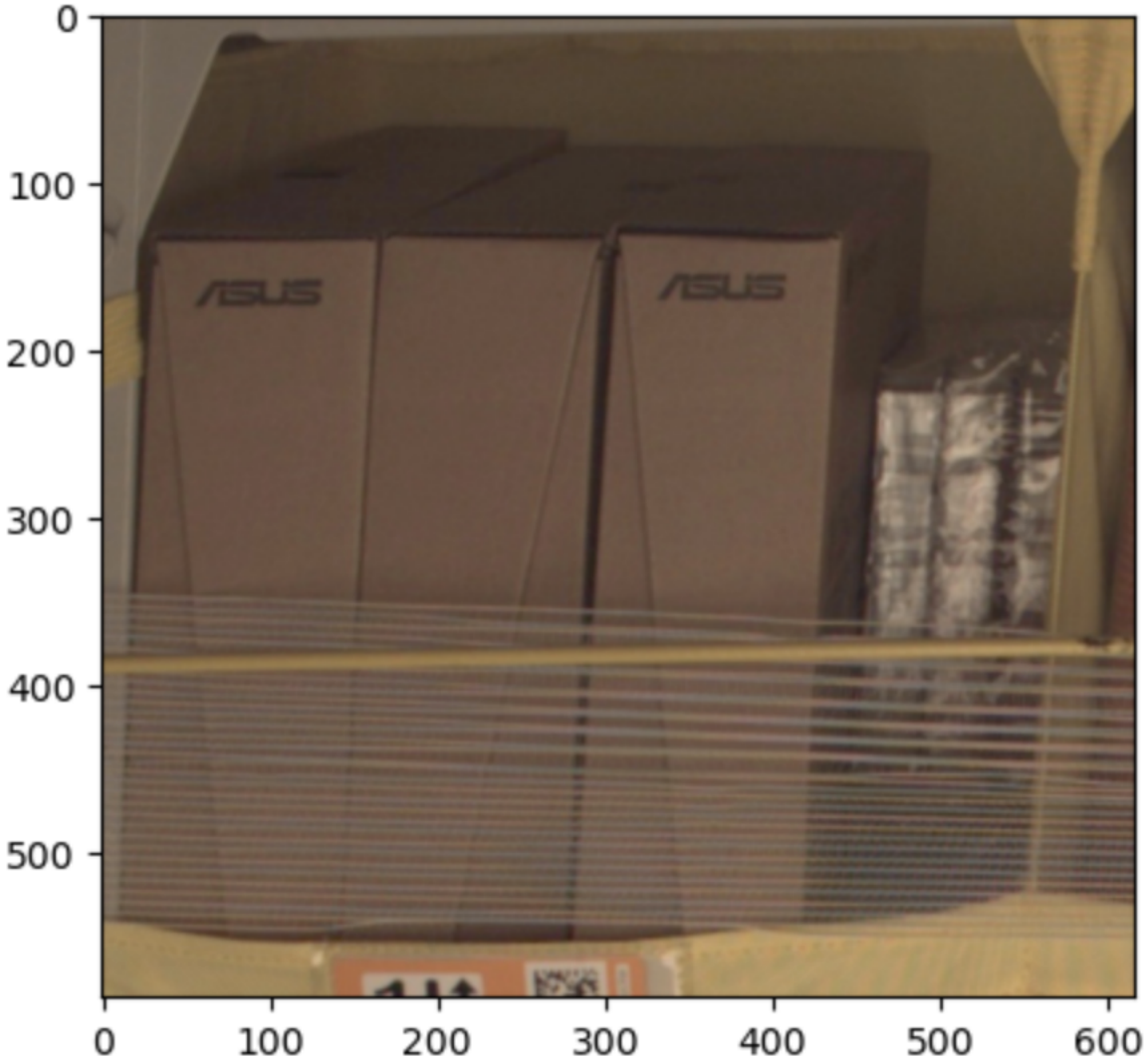

Bin with 4 items count

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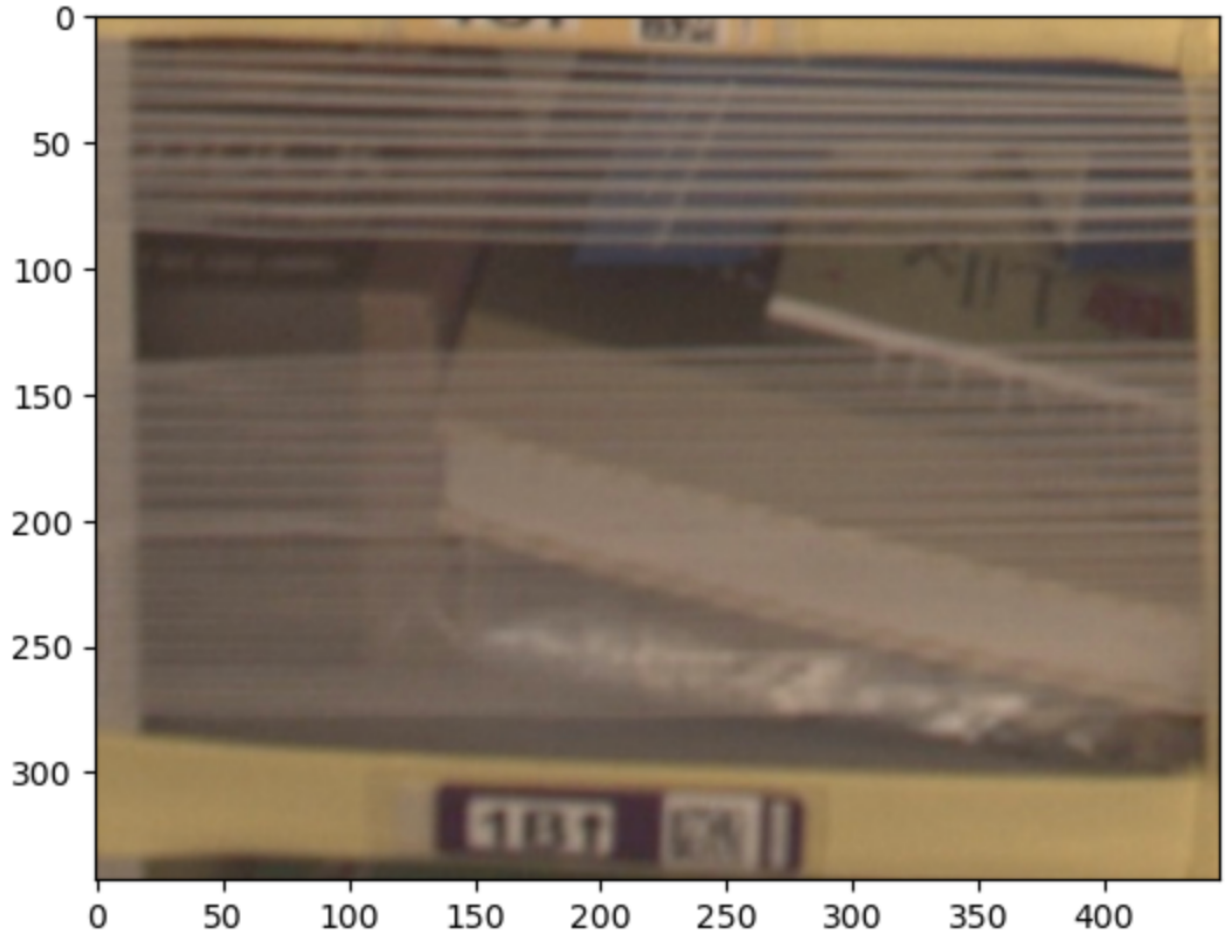

Bin with 5 items count

The subset of data from amazon bin data set is further split into Train, Test and validation dataset. The crux here is we cannot randomly split the 20 percent entire subset to test data and this may result in choosing the entire 20 percent from one of the class of the images that contains the bin with specific number of items. This will result in bias while training and incorrect evaluation during test. We have the same issue while splitting the validation dataset. To overcome this Split is done on each class(bin images with specific item count) and aggregated to the final test and validation set.

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```
data moving for class 1
took random samples to test for size 245
took random samples to valid for size 196
Moving files to test_folder...
Moving files to valid_folder...
data moving for class 2
took random samples to test for size 459
took random samples to valid for size 368
Moving files to test_folder...
Moving files to valid_folder...
data moving for class 3
took random samples to test for size 533
took random samples to valid for size 426
Moving files to test_folder...
Moving files to valid_folder...
data moving for class 4
took random samples to test for size 474
took random samples to valid for size 379
Moving files to test_folder...
Moving files to valid_folder...
data moving for class 5
took random samples to test for size 375
took random samples to valid for size 300
Moving files to test_folder...
Moving files to valid_folder...
```

From the above logs we can see that split for train and validation data set is done on each class to prevent overfitting and underfitting of the model.
So the final trainset will have 245 images which have bins with 1 item, 459 images which have bins with 2 items, 533 images which have bins with 3 items, 479 images which have bins with 4 items, 375 images which have bins with 5 items. That is 20 percent from each class of the total data set we considered. We uploaded the split data into s3 which can be used for model training.

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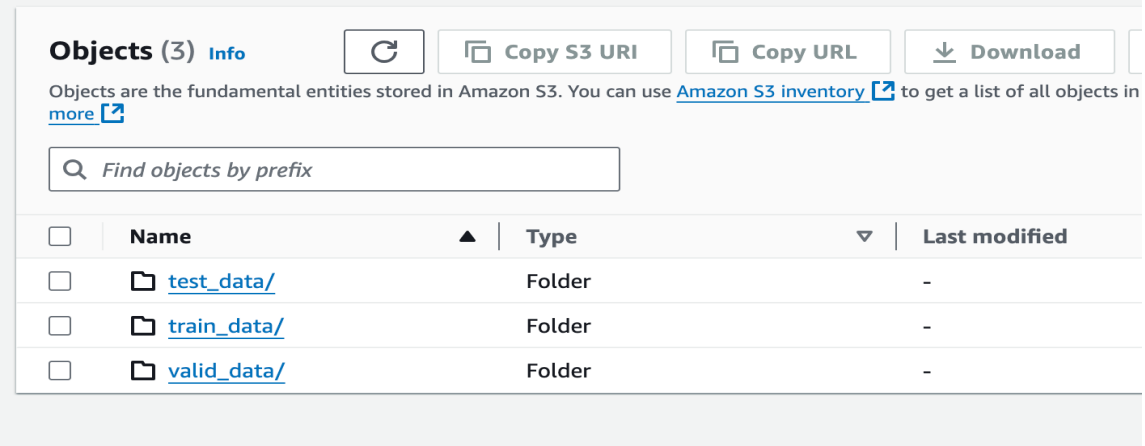
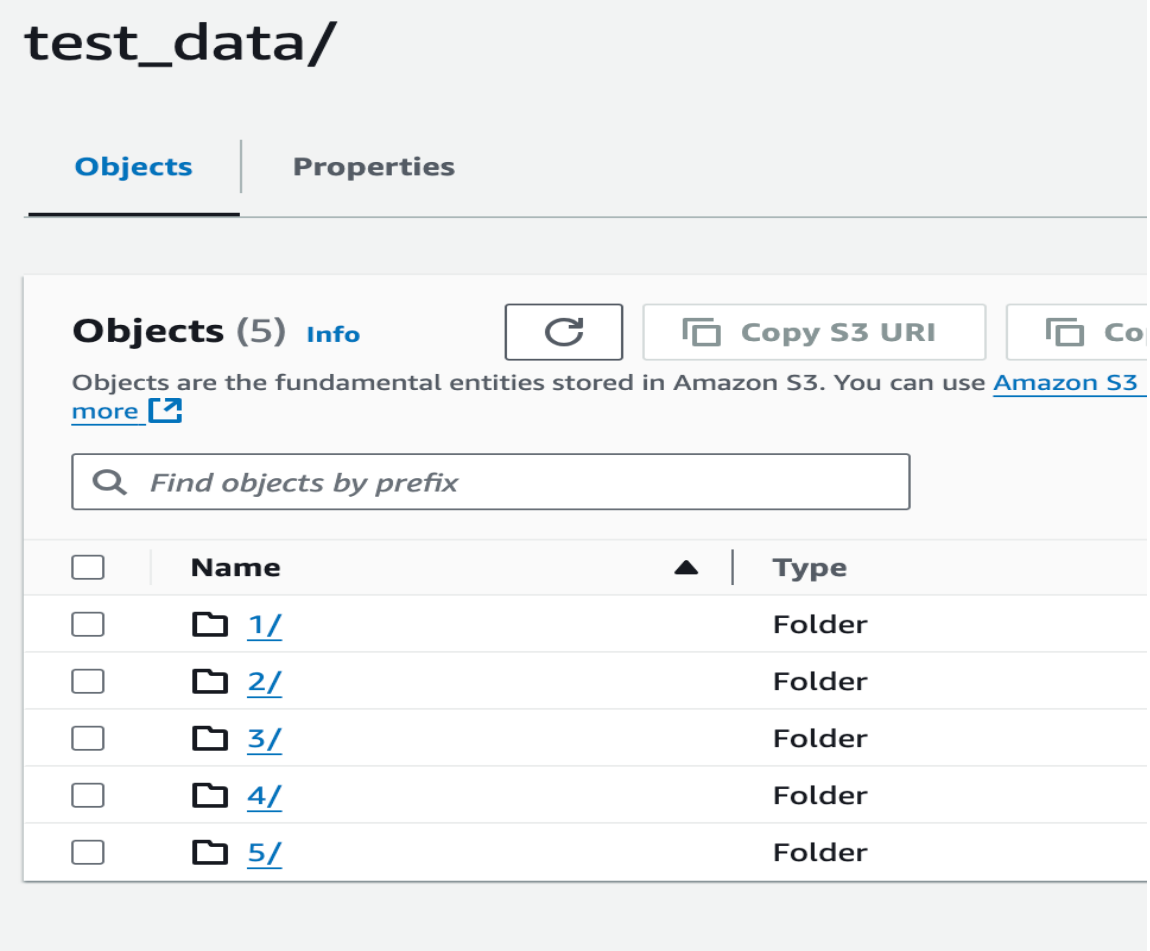


Where each of the folder will have all the classes and the images that belong to them inside it



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Benchmark Model:

Image Classification Based On CNN will be taken as Base Model. It is CNN model for image classification with good results.
Elngar AA, Arafa M, Fathy A, Moustafa B, Mahmoud O, Shaban M, Fawzy N. Image classification based on CNN: a survey. Journal of Cybersecurity and Information Management. 2021 Apr;6(1):18-50.

Model

To address the challenge of counting objects in bins within a distribution center, I am building an efficient machine learning solution based on a pretrained neural network. Instead of training a model from scratch, which can be computationally expensive and time-consuming, I will leverage the power of transfer learning. By fine-tuning a pretrained model, I can adapt an already trained neural network to our specific problem of object counting, saving significant development time while achieving high accuracy.
The core of this solution involves modifying the architecture of a pretrained neural network by adjusting the layers to better suit the object counting task. Specifically, I will focus on replacing or fine-tuning the final layers of the network to ensure it can output the correct number of objects for each bin. This approach will allow the model to learn not just to recognize individual items, but to estimate the total count of objects present in the bin based on visual features. I will also be focusing on to find the right hyper parameters for the model.
Using this strategy, the model will take input images or data related to the bins, process the information through the modified neural network, and output the predicted object count. By leveraging AWS Sage Maker, I will streamline the model training, validation, and deployment process, ensuring an end-to-end solution that is scalable, reliable, and ready for integration into real-world distribution center operations.
This solution demonstrates a practical application of transfer learning and neural network fine-tuning, while also showcasing how pretrained models can be adapted and optimized to solve domain-specific problems in a more efficient and effective manner.

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Environment & Platform:

- AWS Sage maker – to develop, train, tune and deploy
- AWS S3 – for storage

Algorithms:

- Torch
- Residual Network - convolutional neural network (Base Model)

Hyper parameter Tuning:

Hyper parameter Tuning plays a crucial role in model development as it helps maximize the performance of your machine learning model by finding the best configuration of hyperparameters. This is done using the HyperparameterTuner of Sage maker. Three parameters that were tunes are learning Rate, batch size and epochs.

```
hyperparameter_ranges = {
    "lr": ContinuousParameter(0.001, 0.1),
    "batch_size": CategoricalParameter([16, 32, 64, 128]),
    "epochs": CategoricalParameter([5, 10])
}
```

Below are the four training jobs that were run using the hyperparameter tuning

	batch_size	epochs	lr	TrainingJobName	TrainingJobStatus	FinalObjectiveValue	TrainingStartTime	TrainingEndTime	TrainingElapsedTimeSeconds
2	"128"	"5"	0.058185	pytorch-training-241114-1958-002-dc2fa01c	Completed	1.596853	2024-11-14 19:59:44+00:00	2024-11-14 20:12:02+00:00	738.0
3	"64"	"10"	0.088724	pytorch-training-241114-1958-001-390d8933	Completed	1.583377	2024-11-14 19:59:43+00:00	2024-11-14 20:18:18+00:00	1115.0
0	"128"	"5"	0.051661	pytorch-training-241114-1958-004-c1653c5a	Completed	1.537071	2024-11-14 20:18:30+00:00	2024-11-14 20:25:50+00:00	440.0
1	"16"	"5"	0.012927	pytorch-training-241114-1958-003-d5a7fe3c	Completed	1.528551	2024-11-14 20:13:54+00:00	2024-11-14 20:21:15+00:00	441.0

Using the hyperparameters of the best model we train the final model that will be deployed.

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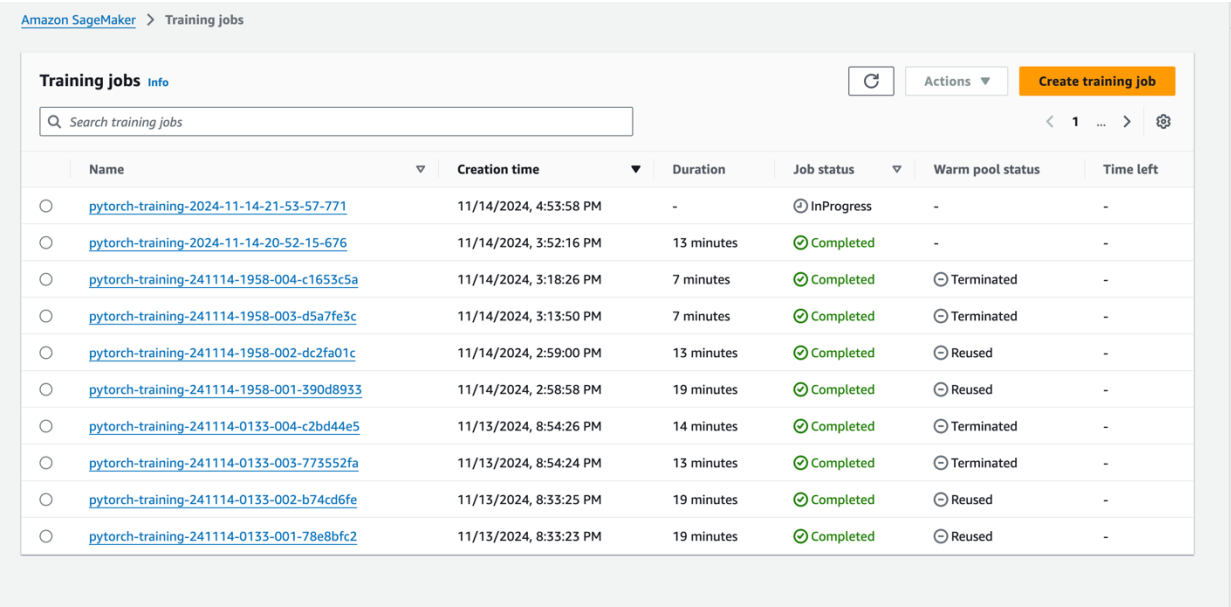

Name	Creation time	Duration	Job status	Warm pool status	Time left
pytorch-training-2024-11-14-21-53-57-771	11/14/2024, 4:53:58 PM	-	InProgress	-	-
pytorch-training-2024-11-14-20-52-15-676	11/14/2024, 3:52:16 PM	13 minutes	Completed	-	-
pytorch-training-241114-1958-004-c1653c5a	11/14/2024, 3:18:26 PM	7 minutes	Completed	Terminated	-
pytorch-training-241114-1958-003-d5a7fe3c	11/14/2024, 3:13:50 PM	7 minutes	Completed	Terminated	-
pytorch-training-241114-1958-002-dc2fa01c	11/14/2024, 2:59:00 PM	13 minutes	Completed	Reused	-
pytorch-training-241114-1958-001-390d8933	11/14/2024, 2:58:58 PM	19 minutes	Completed	Reused	-
pytorch-training-241114-0133-004-c2bd44e5	11/13/2024, 8:54:26 PM	14 minutes	Completed	Terminated	-
pytorch-training-241114-0133-003-773552fa	11/13/2024, 8:54:24 PM	13 minutes	Completed	Terminated	-
pytorch-training-241114-0133-002-b74cd6fe	11/13/2024, 8:33:25 PM	19 minutes	Completed	Reused	-
pytorch-training-241114-0133-001-78e8bfc2	11/13/2024, 8:33:23 PM	19 minutes	Completed	Reused	-

Evaluation Metrics

As this is a Classification Model, we will use Accuracy and Root Mean Squared Error to evaluate this model.
Accuracy= Number of correct predictions/ Total number of predictions

Formula for RMSE:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Where:

- n is the number of observations (or test samples).
- y_i is the true count for the i^{th} observation.
- $\hat{y}_i$ is the predicted count for the i^{th} observation.

Calculated the Accuracy for the model evaluation. We can see it logs

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Model evaluation and validation

The accuracy when compared to benchmark model is far less but can be improved with increasing the training data. The base model is just for recognizing an object where this model counts the items in the image. So it little complicated considered to base model.
For evaluating the model which calculated the accuracy and loss with test data separated in the beginning

for each prediction we calculated the loss and correction

```
 running_loss += loss.item() * inputs.size(0)
running_corrects += torch.sum(preds == target.data).item()
```

using the above values added we calculated the total loss and accuracy

```
total_loss = running_loss / len(test_loader.dataset)
total_acc = running_corrects / len(test_loader.dataset)
```

The model's accuracy is 29 percent and loss is 1.5

▶	2024-11-14…	'levelName:'INFO, 'ts':2024-11-14 20:15:27,798, pathname: train.py, message: for epoch= 0 load= train, loss and accuracy are epoch_loss=1.9233093203959202,…
▶	2024-11-14…	'levelName:'INFO, 'ts':2024-11-14 20:15:42,717, pathname: train.py, message: for epoch= 0 load= valid, loss and accuracy are epoch_loss=1.5441920822290978,…
▶	2024-11-14…	'levelName:'INFO, 'ts':2024-11-14 20:16:41,176, pathname: train.py, message: for epoch= 1 load= train, loss and accuracy are epoch_loss=1.5985223522310354,…
▶	2024-11-14…	'levelName:'INFO, 'ts':2024-11-14 20:16:56,055, pathname: train.py, message: for epoch= 1 load= valid, loss and accuracy are epoch_loss=1.5667759590051786,…
▶	2024-11-14…	'levelName:'INFO, 'ts':2024-11-14 20:17:54,171, pathname: train.py, message: for epoch= 2 load= train, loss and accuracy are epoch_loss=1.5881166801300037,…
▶	2024-11-14…	'levelName:'INFO, 'ts':2024-11-14 20:18:09,221, pathname: train.py, message: for epoch= 2 load= valid, loss and accuracy are epoch_loss=1.6259217233697836,…
▶	2024-11-14…	'levelName:'INFO, 'ts':2024-11-14 20:19:08,074, pathname: train.py, message: for epoch= 3 load= train, loss and accuracy are epoch_loss=1.550403799304018, …
▶	2024-11-14…	'levelName:'INFO, 'ts':2024-11-14 20:19:23,128, pathname: train.py, message: for epoch= 3 load= valid, loss and accuracy are epoch_loss=1.5583122449409754,…
▶	2024-11-14…	'levelName:'INFO, 'ts':2024-11-14 20:20:22,635, pathname: train.py, message: for epoch= 4 load= train, loss and accuracy are epoch_loss=1.5318043778897117,…
▶	2024-11-14…	'levelName:'INFO, 'ts':2024-11-14 20:20:37,924, pathname: train.py, message: for epoch= 4 load= valid, loss and accuracy are epoch_loss=1.5521682082999602,…
▶	2024-11-14…	'levelName:'INFO, 'ts':2024-11-14 20:20:37,924, pathname: train.py, message: training done successfully
▶	2024-11-14…	'levelName:'INFO, 'ts':2024-11-14 20:20:57,513, pathname: train.py, message: Testing Accuracy: 28.906999041227227, Testing Loss: 1.528551061338569

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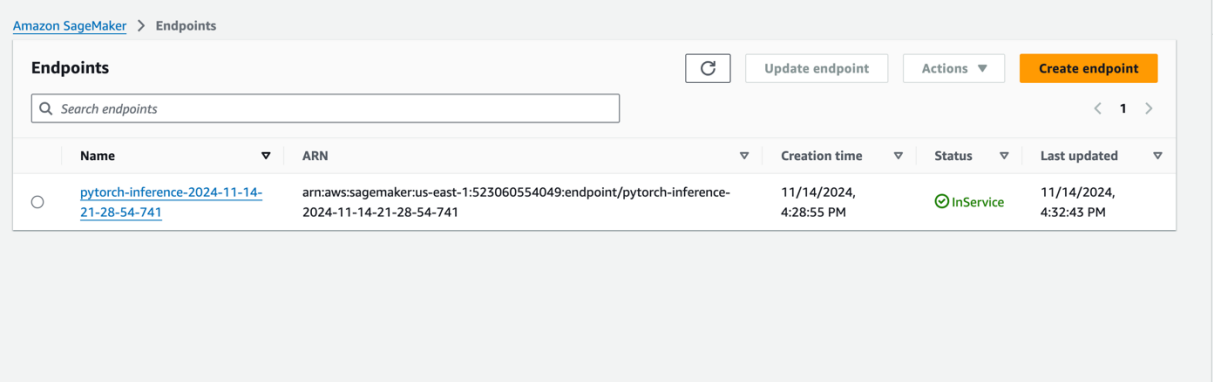
Deployment

The trained model with the best hyperparameters is deployed and created an endpoint which can used for the prediction.



During a inference call the input object need some transformation to be used as a model input so the inference call has this transformation step embedded

```
transforms.Compose([
transforms.Resize((224, 224)),
transforms.ToTensor(),
])
```

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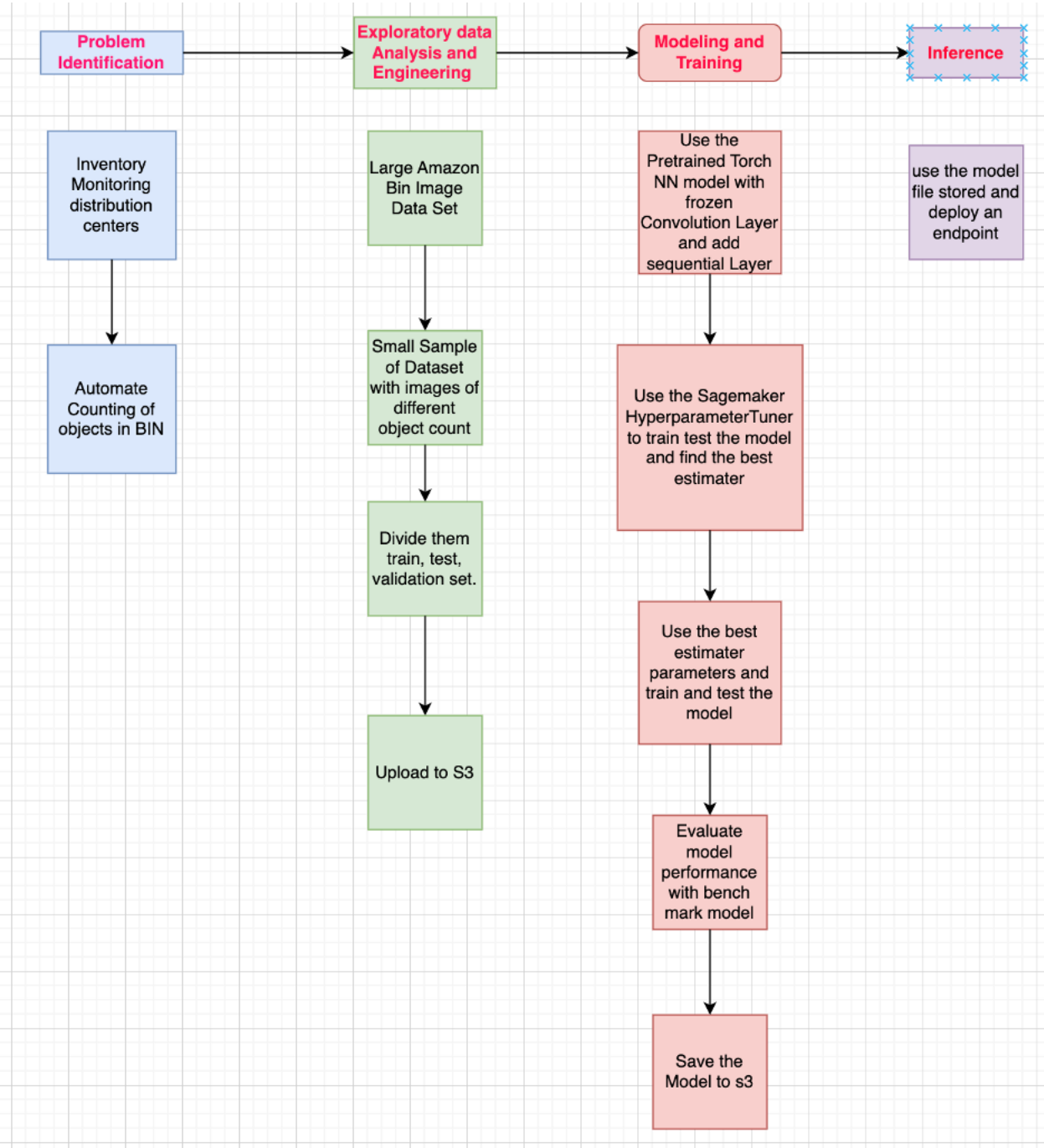
Design



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Justification

When this model is compared to the benchmark model both use the CNN as the base model, but the accuracy of the bench model is around 96 percent where this model accuracy is 29 percent. This model accuracy is far less than the base model because the benchmark model is just recognizing the object in the image where this model is used to count the objects in the image. To improve the accuracy, we can train this model more data may be full set of Amazon BIN dataset. The justification for choosing transfer learning and fine-tuning a pretrained CNN for the object counting task lies in the combination of efficiency, scalability, and adaptability. Transfer learning allows for faster convergence and better generalization, particularly in situations where large labeled datasets are not readily available. The modification of the pretrained CNN to handle a regression task (object counting) allows the model to leverage the power of CNN-based feature extraction, while also addressing the unique requirements of counting objects in images.

In conclusion, while the CNN benchmark model excels in image classification, the proposed model's use of transfer learning for object counting provides a more tailored and computationally efficient solution for the specific problem at hand. The fine-tuning process ensures the model is well-suited to the task, and the integration with AWS SageMaker enhances its scalability and real-world applicability.