

Group 4: Autonomous Sorting of Trash Objects Based on Structure using Gazebo Robot Simulation

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Introduction

Goal: Create autonomous robot that can detect and sort various trash objects

Reason: Assisting with proper disposal and sorting of waste

Objectives:

- Detecting and Differentiating between various objects
 - DOPE - Deep Object Pose Estimation
 - Image Classification with Tensorflow
- Consistent and Accurate Grasping of objects
 - MoveIt Motion Planning Framework

Related Work - DOPE

Pre-trained Models for Pose Estimation

- Utilized pre-trained models for initial pose estimation.
- Requires all objects to be known ahead of time
 - Useful for small dataset testing in simulation
 - Potentially not as useful in real world circumstance, too many shapes and objects to train all of them

ROS Implementation Challenges

- Struggled to get working on our systems. Missing certain files and libraries
- If implemented successfully, would require additional training for additional models if needed
- May attempt implementation again in future

Related Work - Image Classification

Model summary

```
Model: "sequential_8"
```

Layer (type)	Output Shape	Param #
conv2d_25 (Conv2D)	(None, 222, 222, 32)	896
max_pooling2d_25 (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_26 (Conv2D)	(None, 109, 109, 64)	18496
max_pooling2d_26 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_27 (Conv2D)	(None, 52, 52, 128)	73856
max_pooling2d_27 (MaxPooling2D)	(None, 26, 26, 128)	0
flatten_8 (Flatten)	(None, 86528)	0
dense_16 (Dense)	(None, 128)	11075712
dense_17 (Dense)	(None, 2)	258

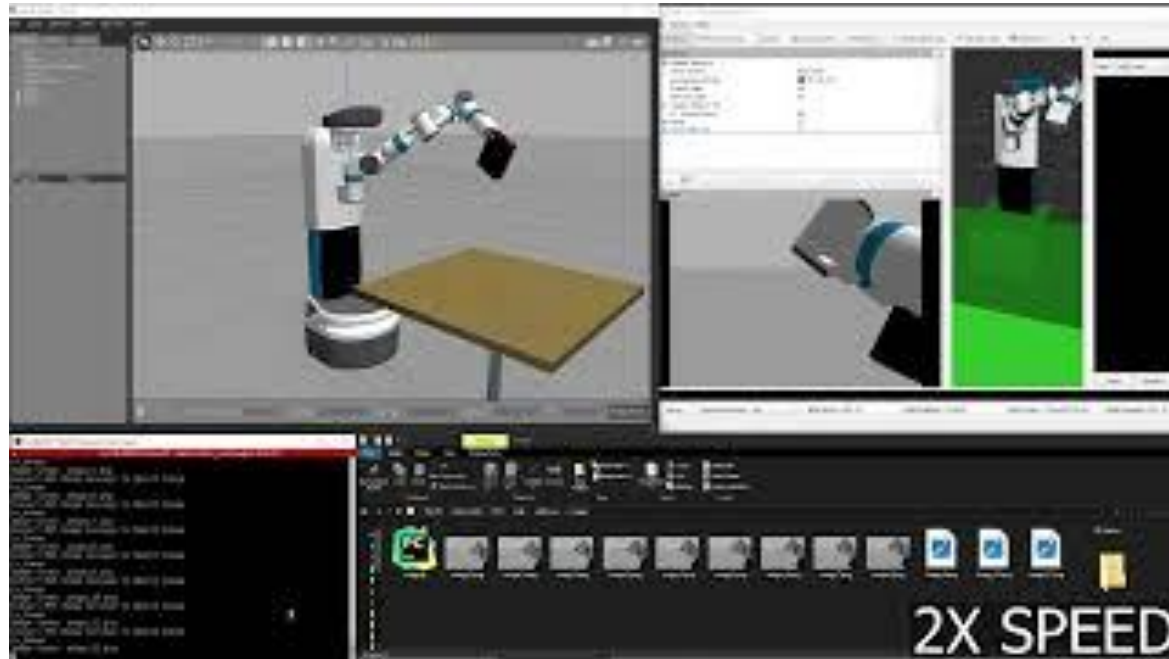
```
=====  
Total params: 11169218 (42.61 MB)  
Trainable params: 11169218 (42.61 MB)  
Non-trainable params: 0 (0.00 Byte)
```

Implementation

- Gazebo for Simulations and Collecting Classification Images
- MoveIt for Grasping
- Classification using Tensorflow
- Current Model trained on boxes and cans

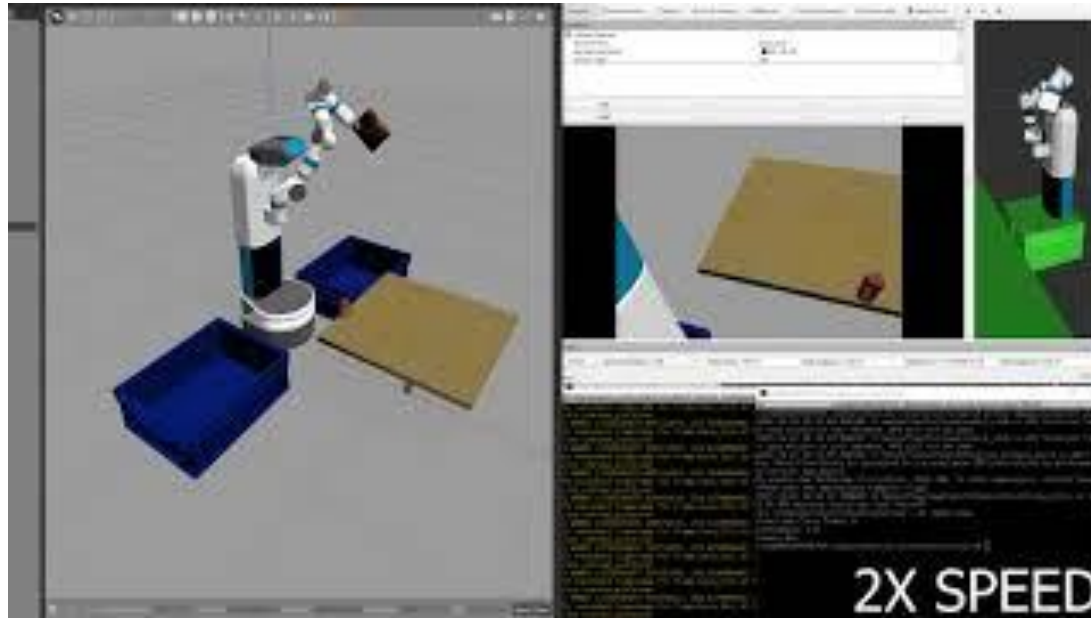


Collecting Sample Input Images Demo



<https://youtu.be/Qx4bh3ISySg>

Demonstration of Current Implementation



<https://youtu.be/W6Qgg94Xr7E>

Experiments and Data

Dataset stats:

Train:

Box:50

Can:51

Val:

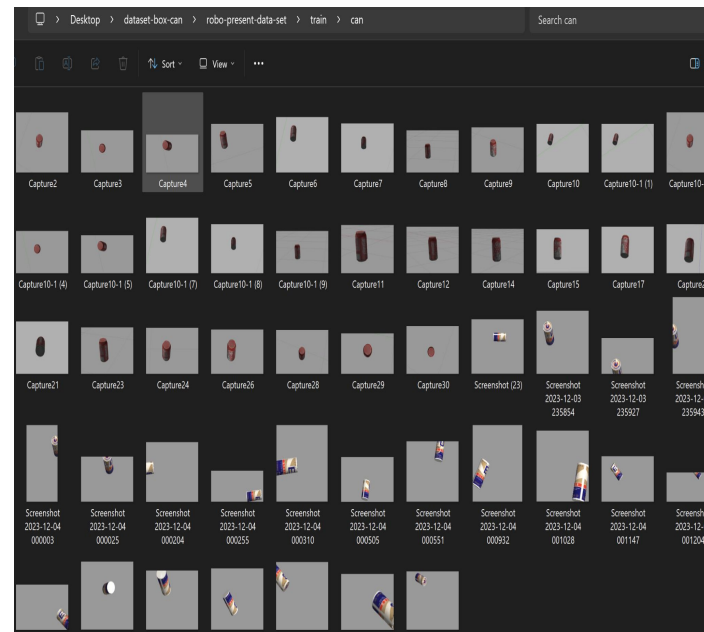
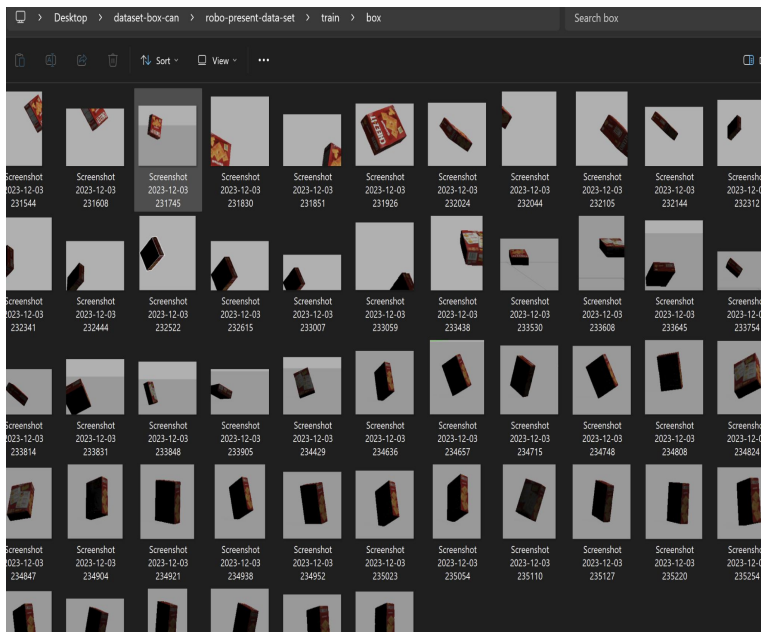
Box:15

Can:15

Test:

Box:10

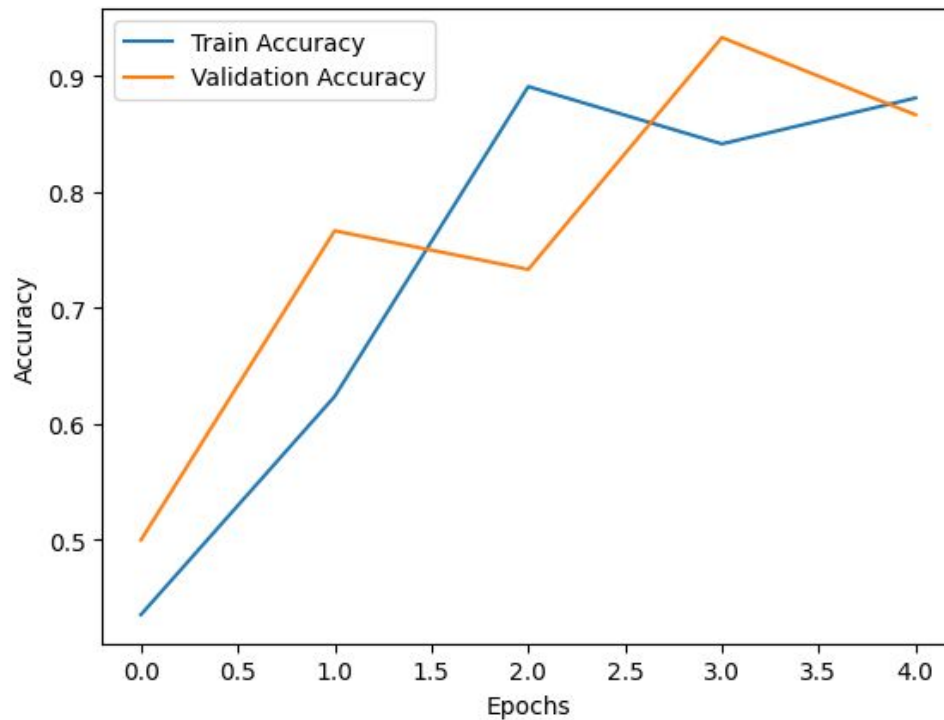
Can:10



Experiments and Data

Training and Validation accuracy

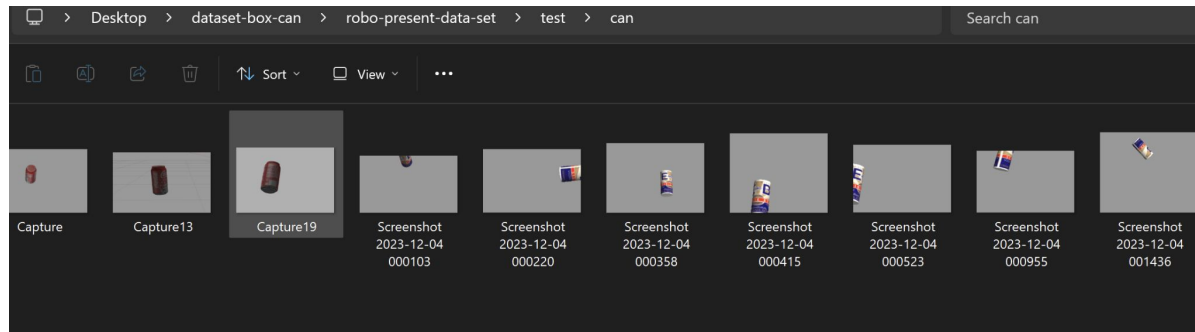
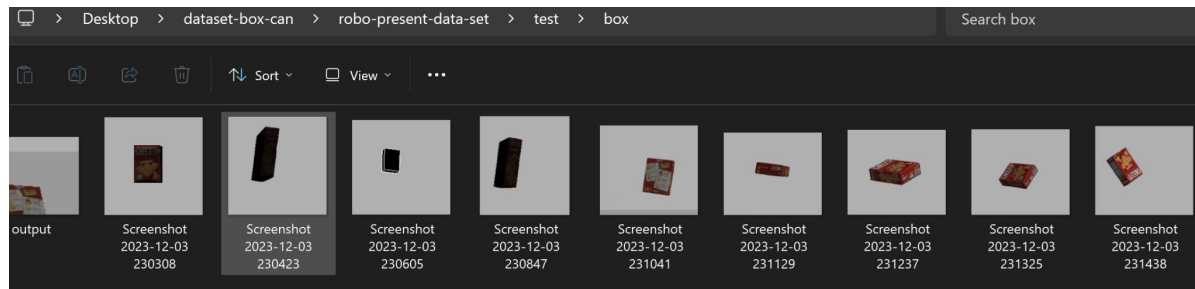
Graph(5 epochs)



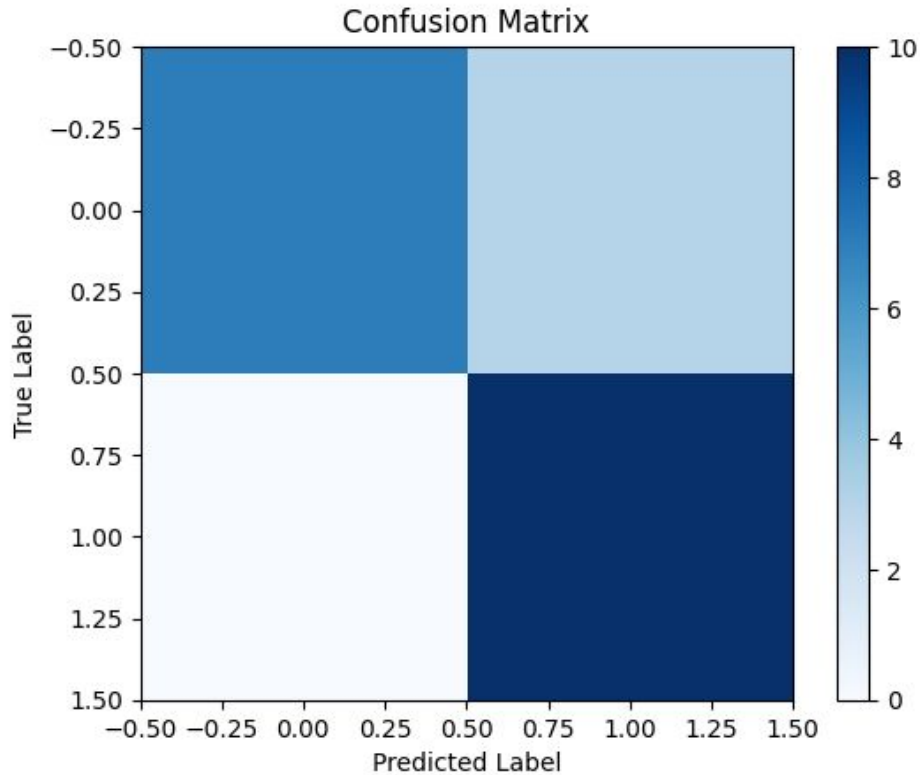
Analysis of Results/Limitations

Testing Data sample

To evaluate the model



Analysis of Results/Limitations



Confusion matrix

Box [[7, 3]

Can [0, 10]]

Accuracy: 0.85

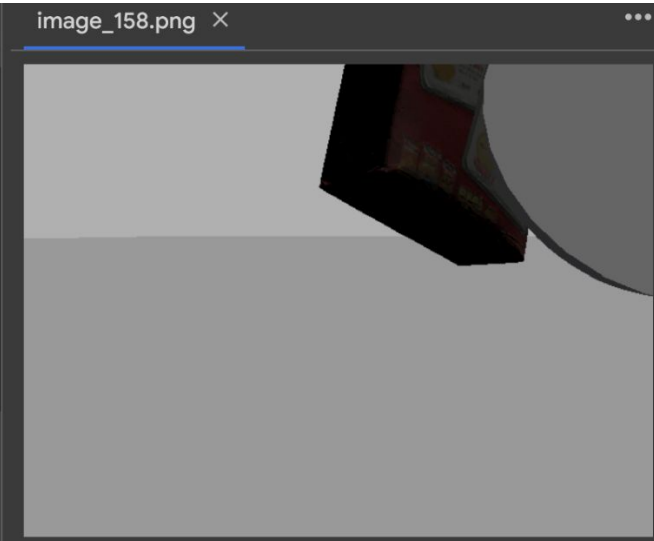
Testing model on the fetch robot camera

```
model.save('custom_image_classifier_box_can.h5')
# Provide the path to the image you want to classify
image_path = '/content/image_158.png'

# Make a prediction
class_index, class_confidence = classify_image(image_path)

# Print the result
print(f"Predicted Class Index: {class_index}")
print(f"Confidence: {class_confidence}")
```

1/1 [=====] - 0s 131ms/step
Predicted Class Index: 0
Confidence: 1.0



Future Work

Improve Object Recognition

- Enhance the robot's ability to recognize diverse trash items.
- Handle deformable or complex objects effectively.
- Distinguish between different materials for precise sorting.

Improve Grasping

- Implement models with defined potential grasps
- Using CNN's for grasp learning
- Focus on top-down grasping instead of 6D grasping

References

- J. Tremblay, T. To, B. Sundaralingam, Y. Xiang, D. Fox, and S. Birchfield, “Deep object pose estimation for semantic robotic grasping of household objects,” arXiv preprint arXiv:1809.10790, 2018.
- X. Zhu, D. Wang, O. Biza, G. Su, R. Walters, and R. Platt, “Sample efficient grasp learning using equivariant models,” arXiv preprint arXiv:2202.09468, 2022.
- Sachin Chitta, Ioan Sucan, and Steve Cousins. Moveit! [rostopics]. IEEE Robotics & Automation Magazine, 19(1):18–19, 2012.

Thank You

Questions?