SEQUENTIAL DEEP LEARNING FOR OBJECT RECOGNITION ON A MOBILE ROBOT

Watch as our robot, Bandit, correctly recognizes objects in the room completely on its own! Train it, introduce a new object, and it'll identify individual objects!

INTRODUCTION & BACKGROUND

- Our team chose this project because we wanted to challenge ourselves by undertaking a project at the forefront of machine learning research. The main idea is that despite modern advancements in Neural Networks, it is difficult to train machines to both remember old information and still learn from new data.
- We hypothesize that by adjusting the mathematical model to weight certain knowledge advancements over others, our intelligent robot could not only recognize objects but continue to learn more about its environment over time via a process known as, Sequential Lifelong Learning.
- Our Goal is to train the Fetch robot on 5 different common objects and have it predict the class of new objects 80% of the time or better. Additionally, the intelligent robot must be able to retain old information about previous objects and learn more about their specific features over time such as: logos, shape, color, and owner. Because our intelligent agent is learning about its environment, this architecture could be used to train robots to assist humans in numerous applications.

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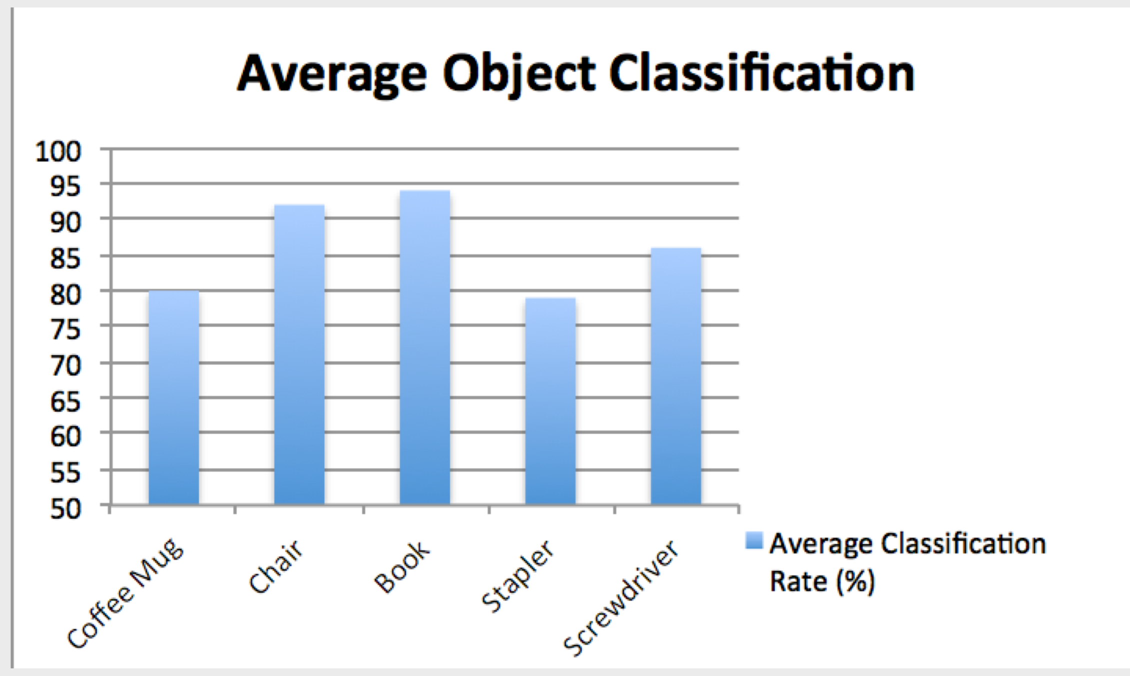
DESCRIPTION

To create a highly accurate image classification program, we designed a software pipeline to interact with the Fetch mobile robot platform. After Bandit gathers images in the first stage of the pipeline, the program performs data preparation, convolutional neural network (CNN) training, and prediction. The CNN is then updated sequentially by Bandit to accomplish online learning over time.

For each proposed step in the pipeline, we compared and contrasted modern algorithms and techniques to ensure our project is utilizing state of the art technology. As part of the research project, we also tested alternative hardware and software options to infer how our system might scale in different computing environments. We examined how we may accomplish these same tasks in more resource efficient ways, or with access to larger budgets and more advanced hardware.

Our classification system is general enough to train itself on whatever objects it finds in its environment. With this in mind, we created our data set out of a variety of staplers, mugs, chairs, screwdrivers, and books to represent realistic use cases in an environment outside our own. These objects fit into categories with different key features and dimensions, and individual objects have distinguishing features the intelligent agent can recognize.

RESULTS



After creating a dataset and implementing the full software pipeline, the model classified 5 objects at an average classification success rate of 87%, which was above our starting goal of 80%!

The average training time of our model with 500 images on an Nvidia GeForce GTX 970 GPU was 6 hours.

CONCLUSIONS

As we hypothesized, this model was able to differentiate between objects it had previously seen and new ones. It was also able to identify the object's overarching class and was able to continuously learn new traits about old objects.

We believe that our sequential lifelong learning model isn't just useful for object recognition, there are many different industries that would benefit from our technology. The most basic application of our architecture would be to train this model to assist researchers in a lab by retrieving objects and providing useful environmental diagnostics (think JARVIS from Iron Man).

Another possible application could be within Swarm Robotics. This architecture can be ported to larger distributed systems of robots known as, "Swarms." A swarm of interconnected security or peace-keeping machines could use this technology to learn and monitor an environment, then detect and report changes and oddities.

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