**SPROJ\_EECE\_7398\_MXX\_V06\_Milestone\_6**

Welcome to the final lesson in our FiDIP tutorial series. In our previous lesson, we monitored the training progress and discussed reproducibility. Now it's time to evaluate our trained model and summarize what we've learned throughout this project.

After training completes, or using our pre-trained model, let's evaluate the results by using this command. Nice. Let's look at the metrics and compare them with the results reported in the paper. As you can see, the output of the command actually gave us the same results reported in the paper. And visually, the model was reporting back every visual results in every epoch. Now that we have our results, let's discuss how to interpret them. The metrics we're seeing are the EP and AR. They are in standard for pose estimation. Average precision and average recall are different. IOU threshold-- give us comprehensive views of the model performance.

With small data sets, even state-of-the-art approaches might not reach the performance levels seen in data-rich domains. This FiDIP approach shows impressive results despite the data limitations. FiDIP's domain adaptation strategy has effectively leveraged the larger adult post data sets to improve performance on small infant post data sets. This demonstrates the power of transfer learning and domain adaptation in small data regimes.

Look at which keypoints or poses have lower accuracy. These could be areas where the domain gap is larger, or where more specific data collection might help. With small data sets, we need to be extra careful about generalization. Good performance on the test set is promising, but real-world deployment might encounter more variability. Let's see our model in action on a new image.

Let's run this command on this test image and see the results. This visualizes the predicted key points on the test image, allowing us to qualitatively assess the model performance. Now because we are computer vision people, we like to see and observe visual results. So we always encourage students to develop a small demo script that can be used easily to test the model developed. Here, we are showing a demo using Streamlit, an open source web-based interactive tool to showcase models.

With just a few lines of code, Streamlit allows us to create an interactive web interface where users can upload their own images and get the pose estimation. You can always play with different settings, like the confidence threshold. And you can see the visual results. The code for this demo is available in the repository, and I encourage you to try building your own interactive demos for your future machine learning projects.

This kind of interactive demo is invaluable for quickly validating your model's performance on new data. Sharing your work with non-technical stakeholders and getting feedback from domain experts, like pediatricians. Congratulations on completing this guided projects. You've successfully set up a research repository, prepare the environments and data, trained a model in a small data regime, evaluated and compared with benchmarks.

Here are some key takeaways from working with FiDIP. Domain adaptation is powerful. When target domain data is scarce, leveraging a data-rich source domain with appropriate adaptation techniques can yield impressive results. Synthetic data can help. The project uses synthetic infant poses to supplement the limited real data, demonstrating how synthetic data generation can be a valuable tool for small data problems. Starting with pretrained models significantly improves performance when fine-tuning on small data sets. Research code navigation. You've gained experience navigating a real research code base, a valuable skill for implementing cutting-edge techniques.

Throughout this tutorial, we've highlighted special considerations for small data problems-- from training, to evaluation, to reproducibility. For your next steps, I encourage you to experiment with different hyperparameters to see their impact on model performance. Try the other backbones mentioned in the paper, such as simple baseline, pose MobileNet.

Explore the synthetic data generation code to understand how the synthetic data was created. Remember when working with small data sets, techniques like domain adaptation, transfer learning, and synthetic data generation are your allies. The FiDIP project demonstrates how these approaches can be combined effectively to tackle a challenging real-world problem.

Great job following along this tutorial series. And I hope you feel more confident tackling small data machine learning projects in the future. If you have any questions, please post them in the course forum and I would be happy to help. Good luck with your future machine learning projects.