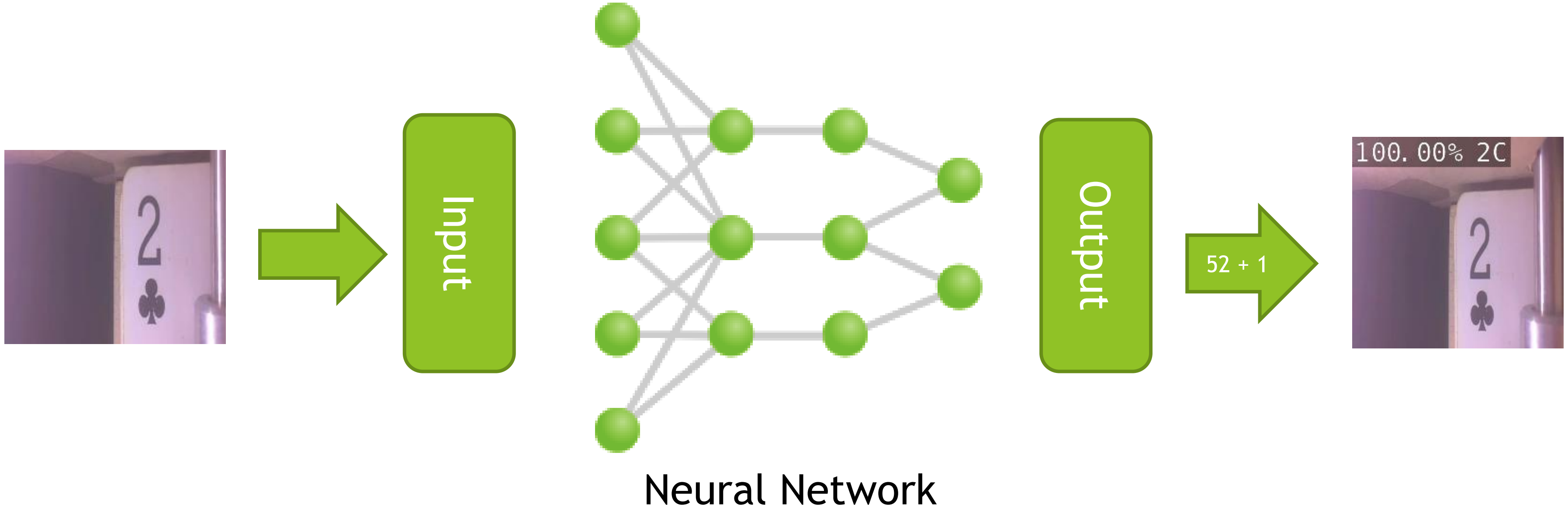
Playing Cards Recognition using Machine Learning (ML)

HP Tuners 2021
Personal Project

Project Goals



- Get into Machine Learning (ML)
- Develop Neural Network (NN) model for playing card recognition
- Test model on real-time system

System Setup / Learning ML Basics

- Acquired / installed Jetson hardware and development tools:

GPU Accelerated Computing:
384 CUDA
48 Tensor
6 ARM
2 DLA
cores

NVIDIA JetPack 4.6

PyTorch

jupyterlab

TensorBoard

- Completed training and quick start tutorials:

Jetson AI Fundamentals

Jetson AI Fundamentals – excellent course for beginners to quickly start ML development on Jetson boards. Includes Docker container with Jupyter lab and notebooks. I used this platform to develop my first ML model and train it for playing cards classification.

HELLO AI WORLD
NVIDIA JETSON

Hello AI World – quick start (with Docker container) for inferencing with TensorRT and Jetson. Learned how to collect datasets, train / ‘transfer learn’ off-the-shelf image classification models with PyTorch and convert / optimize them for embedded platform deployment.

Neural Network – Design

- Selected ResNet-18 based network (pre-trained on ImageNet) also, experimented with other network types pre-trained on ImageNet: AlexNet, GoogLeNet and ResNet-50)

  IMAGENET dataset that spans 1000 object classes and contains 1,281,167 training images, 50,000 validation images and 100,000 test images

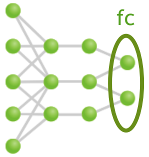
- Used Transfer Learning technique (with PyTorch) to re-train ResNet-18 on playing card images

  Transfer Learning is a technique for re-training a DNN model on a new dataset, which takes less time than training a network from scratch. With transfer learning, the weights of a pre-trained model are fine-tuned to classify a customized dataset.

- Defined Dataset Categories:

```
[ '2C','3C','4C','5C','6C','7C','8C','9C','10C','JC','QC','KC','AC',
  '2H','3H','4H','5H','6H','7H','8H','9H','10H','JH','QH','KH','AH',
  '2S','3S','4S','5S','6S','7S','8S','9S','10S','JS','QS','KS','AS',
  '2D','3D','4D','5D','6D','7D','8D','9D','10D','JD','QD','KD','AD','NONE']
```

- Defined the neural network and adjusted the fully connected layer (`fc`) to match the outputs required for the project:




```
# RESNET 18
model = torchvision.models.resnet18(pretrained=True)
model.fc = torch.nn.Linear(512, len(dataset.categories))
```

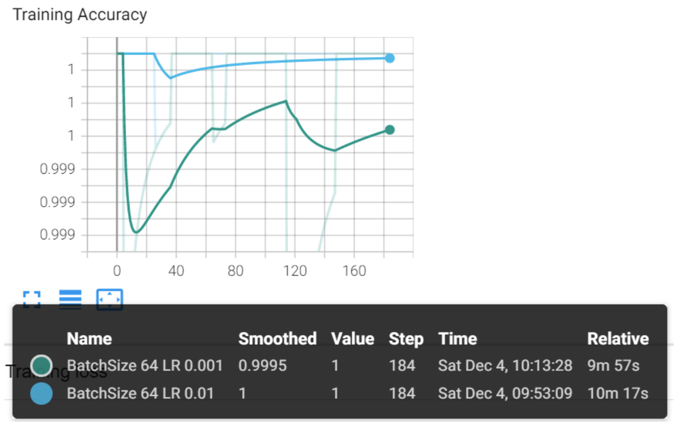
Neural Network - Data Collection / Training

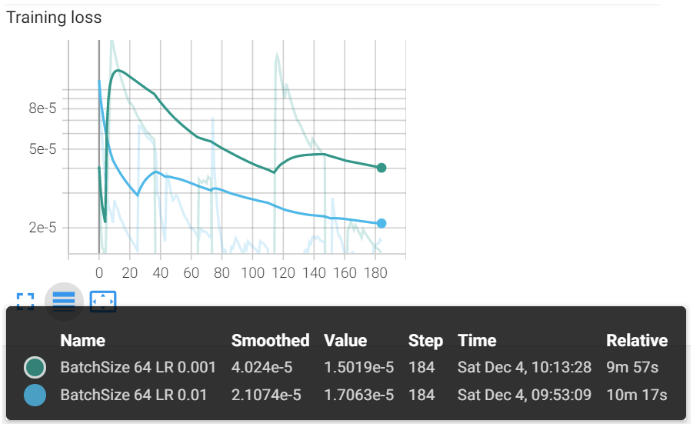
Data Collection:

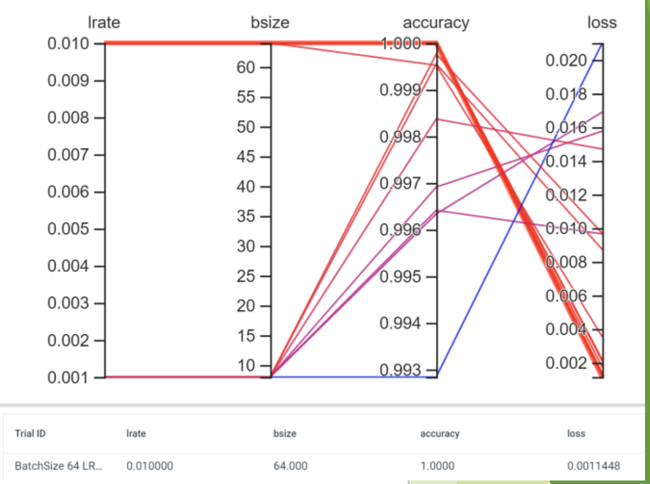
- Initially, I used Jetson tools (from AI tutorials) to manually capture card images for model training, then (when training accuracy reached levels > 85%) I automated data collection with python scripting and playing card dealing machine

Neural Network Fine-Tuning with TensorBoard

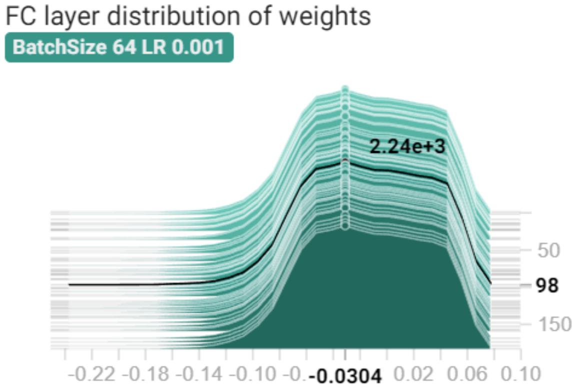
- Finding best training accuracy / loss for different batch size / learning rate values

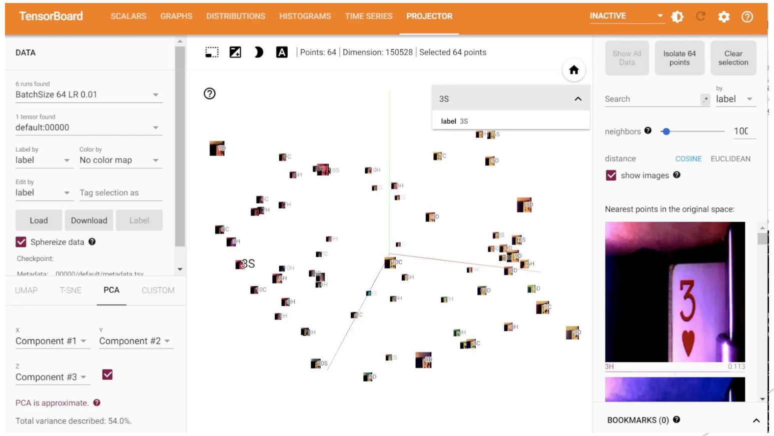




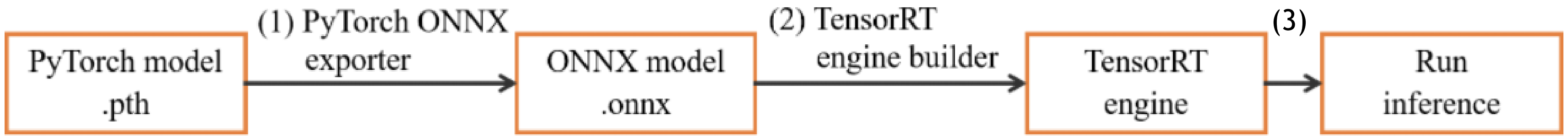


- Plotting distribution of weights in FC layer for each training step and 3D model projector:





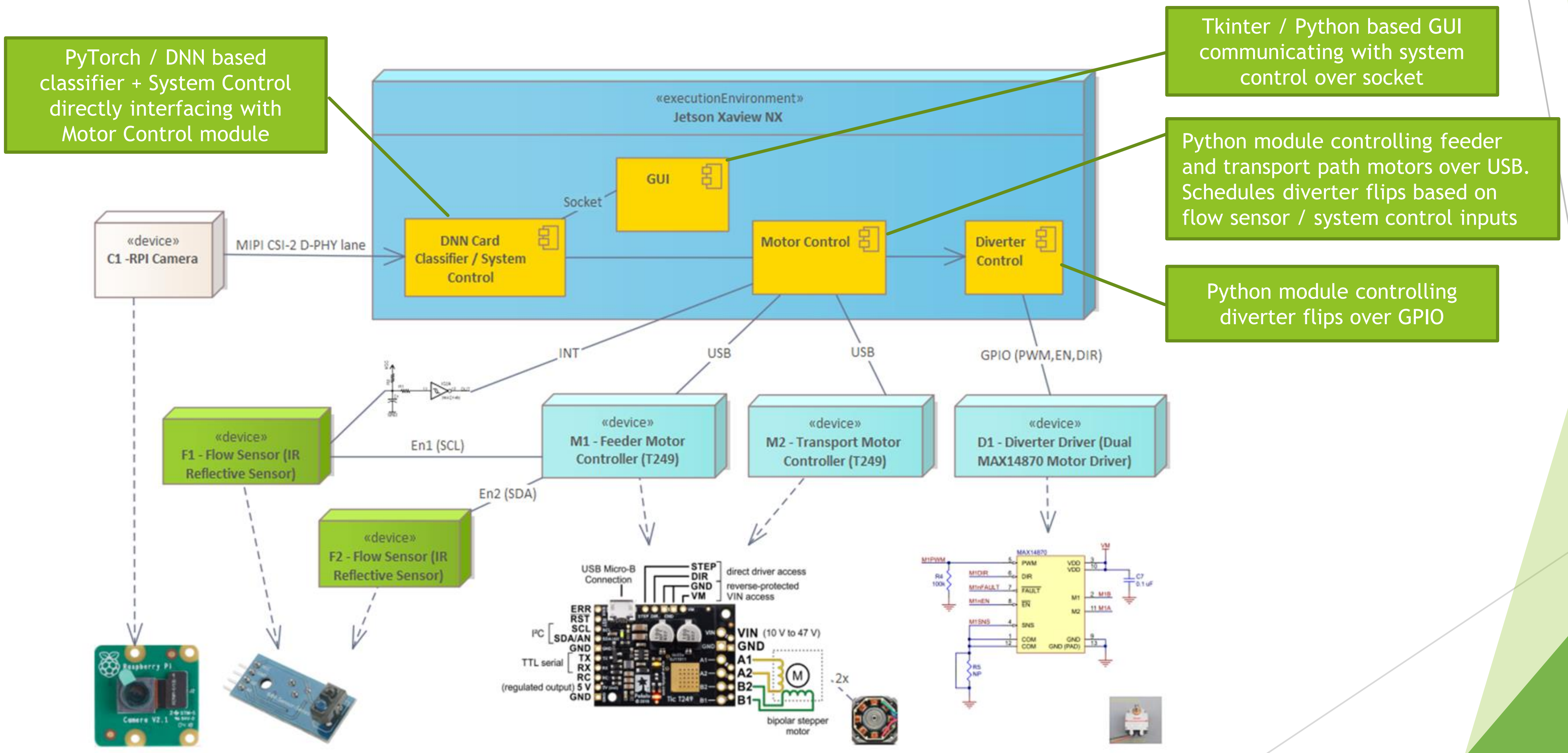
Model optimization for embedded deployment



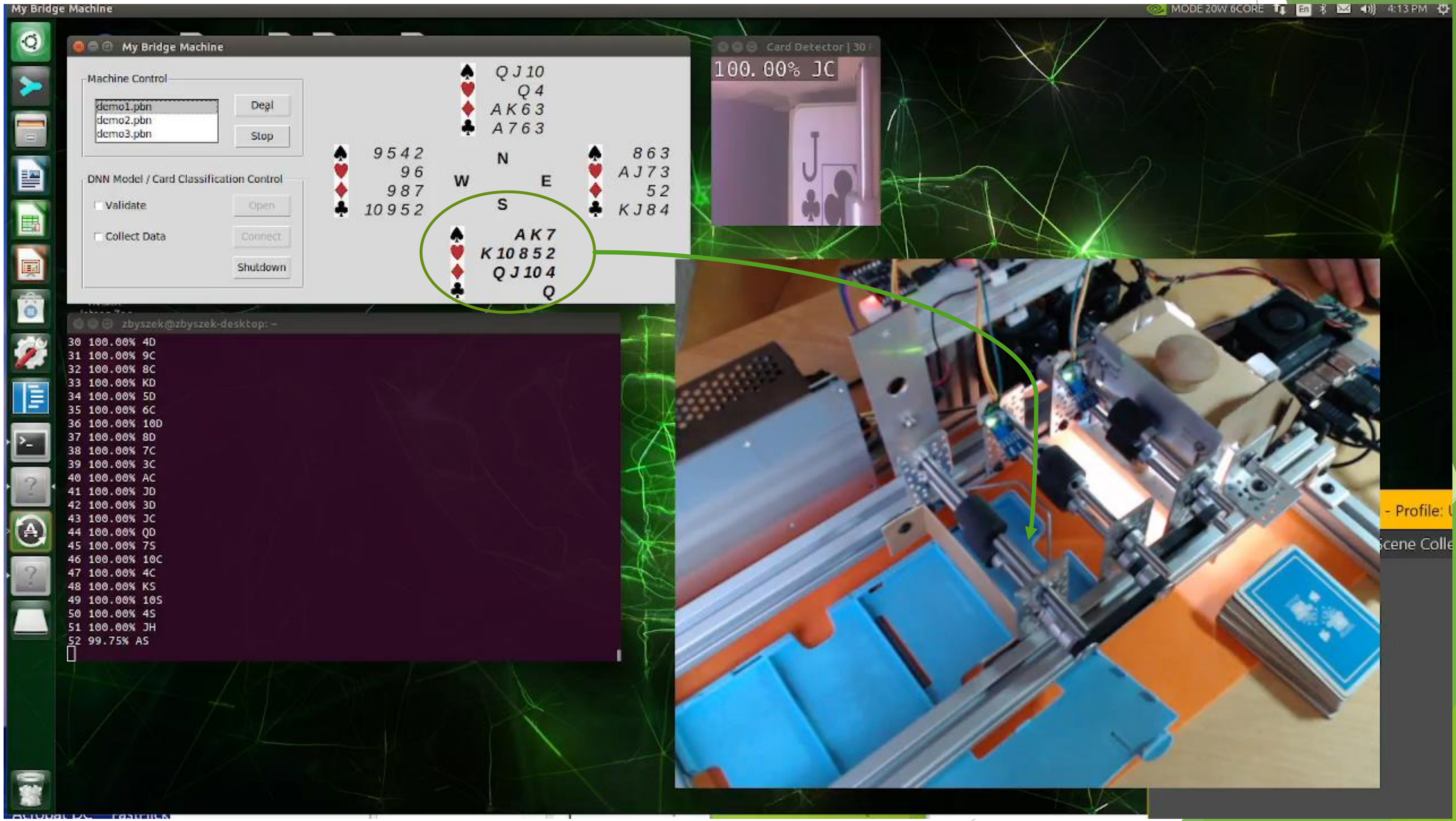
1. After training model using PyTorch framework, model files are in PyTorch model format (.pth)
2. In order to optimize inference speed on Jetson, the PyTorch model needs to be converted to TensorRT engine format. The conversion is done via an intermediate format called ONNX (Open Neural Network Exchange)
3. Accuracy and inference time comparison after TensorRT engine conversion:

Model	Image Size	PyTorch model		TensorRT model		
		Accuracy [%]	Frames/s	Precision	Accuracy [%]	Frames/s
Resnet-18	224x224	100	30	Float32	> 97	> 100

Software Deployment View
GUI, NN Card Classifier and System Control



Validation / Testing



Lessons Learned

- Neural net model design with PyTorch framework, Tkinter / Python GUI design
- How to develop, train optimize model for embedded platform
- How to accelerate ML / neural net inference with TensorRT and NVIDIA GPUs
- How to use TensorBoard to fine-tune, visualize and analyze machine learning / model data

Budget / Scope Review Against Plan

Budget Review

Item	Plan	Actual
Jetson Xavier NX development Kit	$399	$399
Arducam OV9281 1MP Global Shutter Camera Module	$51	
Hardware mounting brackets and miscellaneous	$25	
Seagate NVMe drive (32G SD card was too small for Linux, tools and model / image data)		$62.99
Total	$475	$461.99

Scope Review

Work Item	Plan	Actual
Mechanical	Jetson mounting	More work than I planned. Had to add extra flow sensor mounting and S player stacker wall
Replace rolling shutter camera with global shutter one	Eliminate rolling shutter distortion	Managed to work with rolling distortion by filtering out transient frames and increasing spacing between cards
Hardware enhancements	Replace RPI3 with Jetson, reuse stepper motor controllers, flow sensors and power supply	More work than originally planned: added extra flow sensor to control spacing, extra work to drive diverter motor plus debouncing logic for sensor output to drive interrupt line
Software development	Port over RPI software to Jetson platform, Develop NN based classifier	Software development as planned. Disk space required for training and testing NN turned out to be bigger than expected.

What would I have done differently?

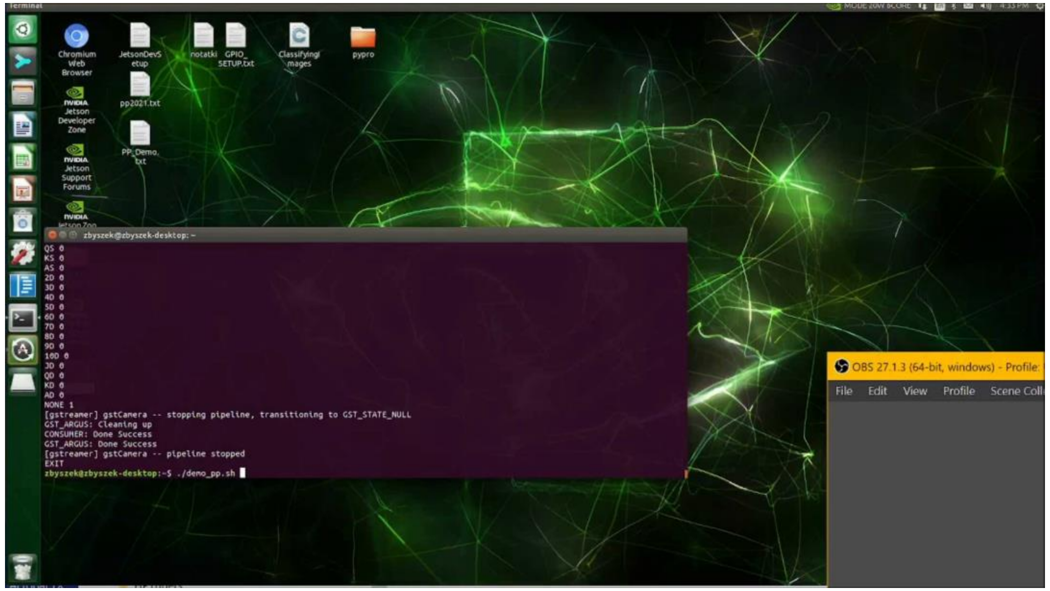
- Use CAD tools to design sensor and Jetson mountings
- Use 3D printing for mechanical parts
- Add overcurrent protection for diverter motor
- Do better project planning
- Order parts ahead of time

Q&A

Appendix A – NN Validation / Testing

Transient Cases

NN Validation



Appendix B – TensorBoard 3D Projector