SYNTIANT



Training Neural Networks for Sensors

Team Members: Vicki Moran (Fall Lead) Henry Limm (Spring Lead) Taylor Sloop Will McDonald Yaqub Mahsud (Spring Jr) Maxime Vienne (Fall FE) *Liaisons:* Dr. David Garrett Atul Gupta Dr. Sean McGregor

Advisor: Prof. David Harris

Team Members and Primary Focuses

Henry





HMC Senior

HMC Senior Spring Team Leader

> Firmware Development

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Demo and Network Taylor



HMC Senior

Data Collection

Vicki

HMC Senior Fall Team Leader

> Board Design

Yaqub



HMC Junior

Network Training

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Harvey Mudd College Clinic Program

"I gained the idea that engineering was like dancing; you don't learn it in a darkened lecture hall watching slides: you learn it by getting out on the dance floor and having your toes stepped on."

- Jack Alford, Professor of Engineering Emeritus, Cofounder of the Engineering Clinic, Harvey Mudd College 1963

- Teams of four to five juniors and seniors
- Professional design and development projects for industry sponsors
- Objective: to produce useful results on an open-ended authentic project to the sponsor's satisfaction within the constraints of time and budget



Problem Statement

The Syntiant-HMC Clinic team will demonstrate the

versatility and power efficiency of the Syntiant NDP101 chip

by designing a battery-powered application that receives live data from sensor(s) and uses a neural network running on

the chip to detect significant events.





Interpreting our Problem Statement

- Microphones
- Wakewords ("Alexa")
- Small/low-power electronics



Interpreting our Problem Statement

- Microphones
- Wakewords ("Alexa")



• Small/low-power electronics

- Inertial Measurement Unit
- Unique motions and gestures
- Small and low-power smartwatch



Design Alternatives

Application	Be always-on and battery powered	Be an application of machine learning	Be demonstrable and tangible	Be feasible to collect and use data	Be feasible to implement	Be marketable in time and volume
Identify dead pointe shoes	3	3	Constrained by time and shoe dependencies (1)	Limited by existing data and minimal access to many pointe dancers (2)	3	Restricted to niche ballet market (2)
Identify gestures	3	3	3	3	3	3
Identify body movements	3	3	3	3	3	Implemented previously in large battery systems (2)

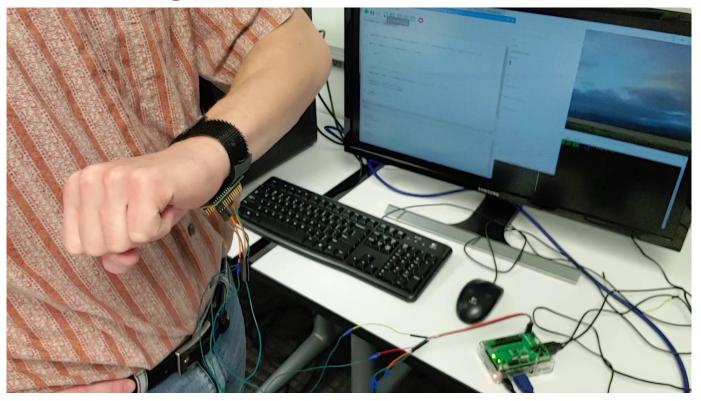


Wrist-Based Gestures

- Time-checking
- Pronating
- Supinating



Watch-Checking Demonstration







Watch-Checking Demonstration





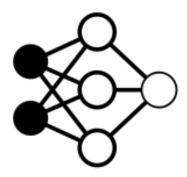


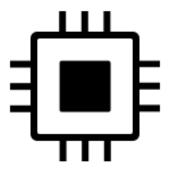
Prototype Breakdown

Data Collection

Neural Network Training NDP101 Demonstration Printed Circuit Board Design













Data Collection



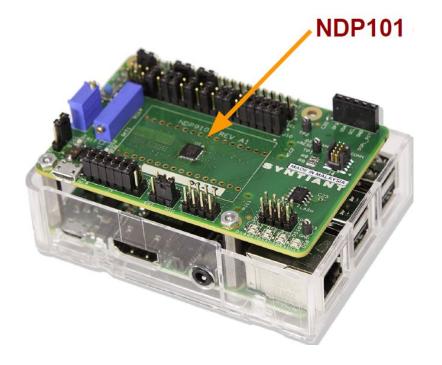


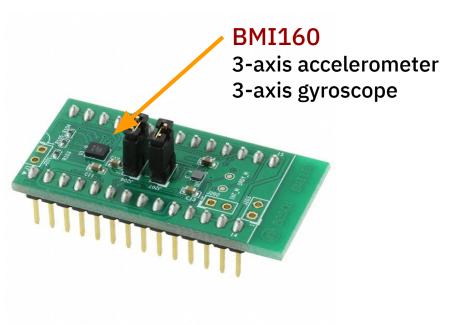


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Data Collection Hardware



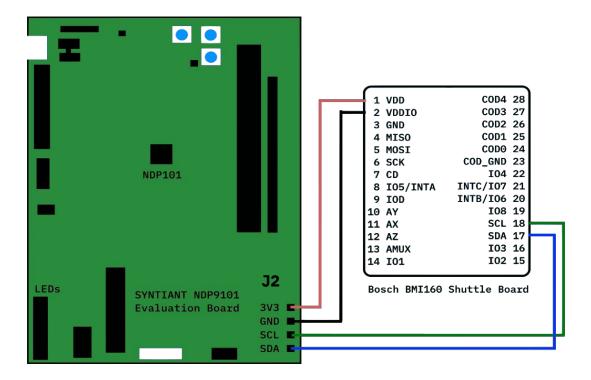








Physical System Schematic



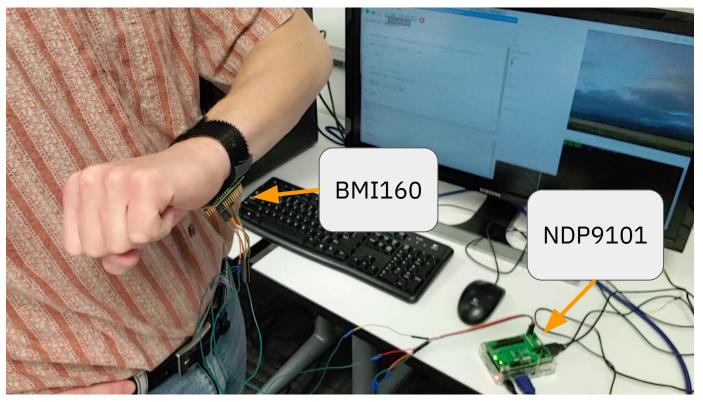




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Demo and Data Collection System



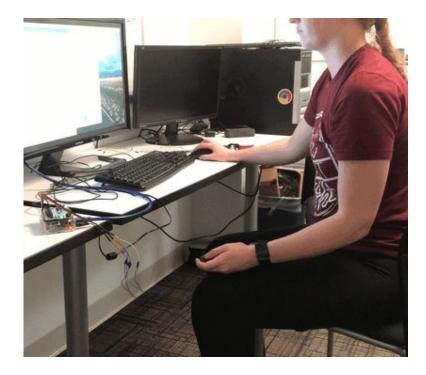


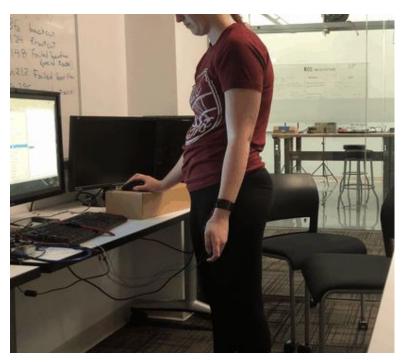


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Data Collection Involves Multiple Gestures



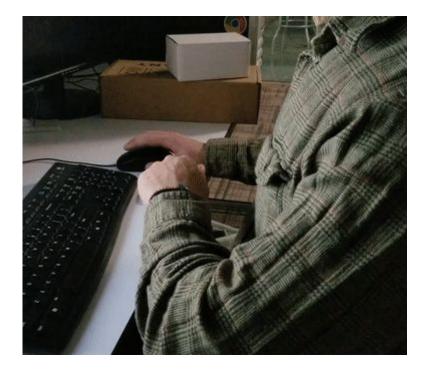


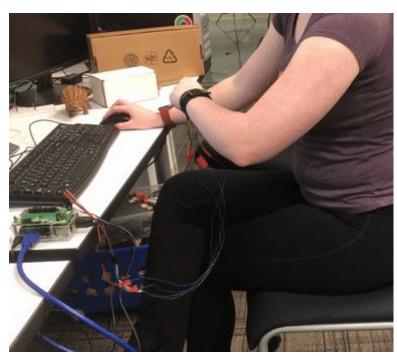






Additional Gestures

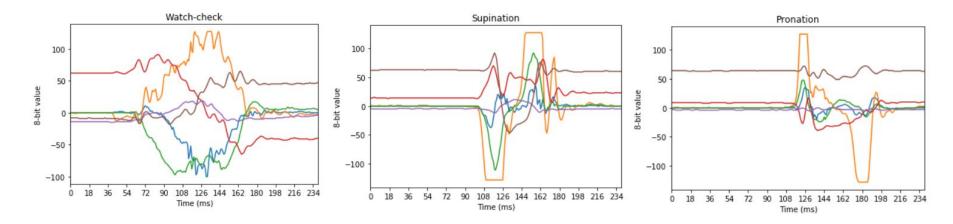








Typical Data Instances

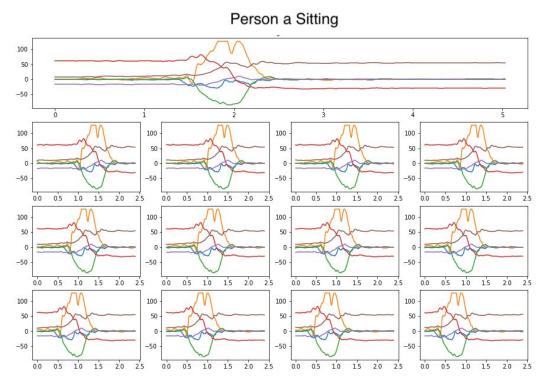


- 2.4 seconds of BMI160 data sampled at 100 Hz.
- 240 sampled values on each axis.





Data Augmentation





Data Collection Composition

Large Scale Collection

- 26 participants and 2 team members
- 10 sitting watch-checking, 10 standing watch-checking, 10 supination, 10 pronation per person
- ~16 augmented samples per original sample

Previous Data Collection

• 300 watch checking by team members

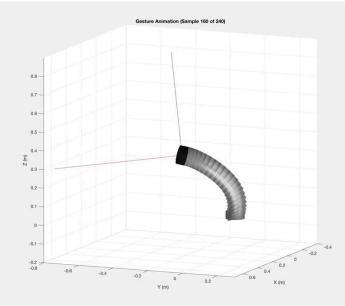






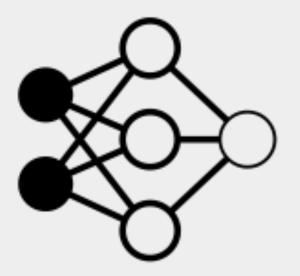
Data Visualization





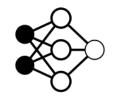


Network Training

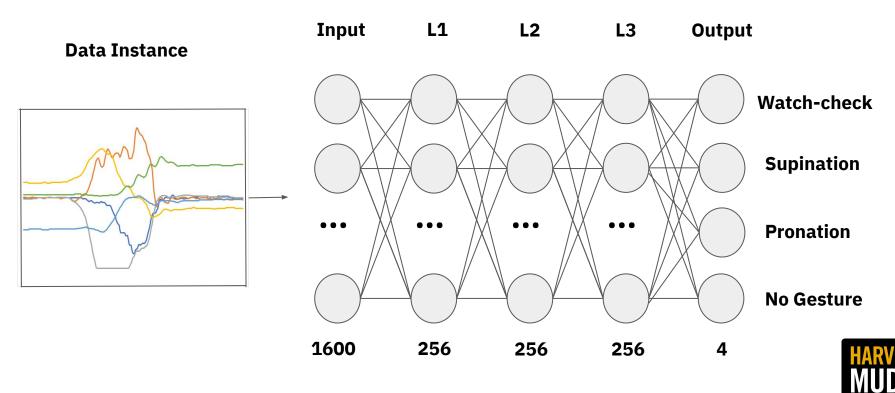








Network Architecture



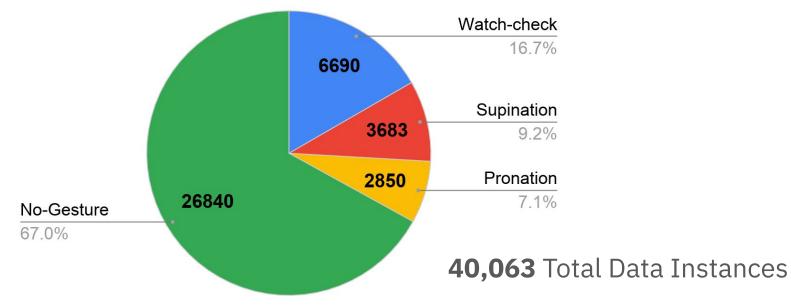
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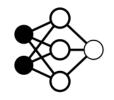
Dataset Composition

Training Set Composition



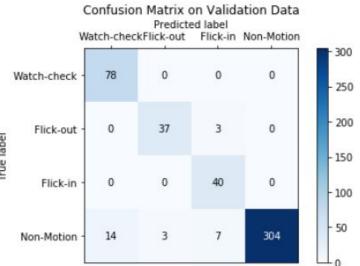






Network Performance

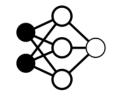
Validation Accuracy	94.44%	
Test Accuracy	96.86%	Watch-(
Precision	85.16%	Flic
Recall	100%	PL FI
False Activation Rate	237/day	Non-M



Partition	Watch-check	Supination	Pronation	No-Gesture	Total
Val. Total	78	40	40	328	486



Effect of Time-Shifting



Implementing time-shifted data increased validation accuracy by 2%

	Time-Shifting	No Time-Shifting
Validation Accuracy	94.44%	92.64%

Partition	Watch-check	Supination	Pronation	No-Gesture	Total
Val. Total	78	40	40	328	486

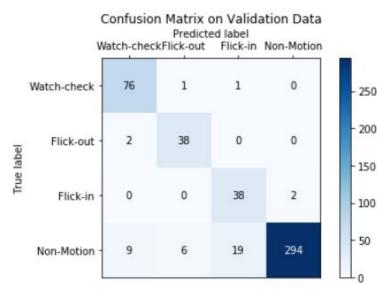




Effect of Time-Shifting

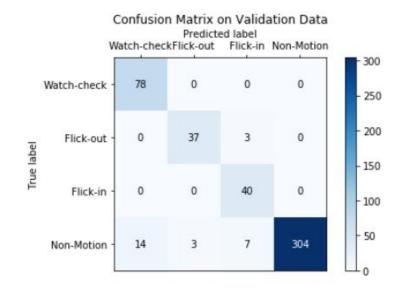
Implementing time-shifted data increased validation accuracy by 1.8%.

No-Time Shifting (92.64%)

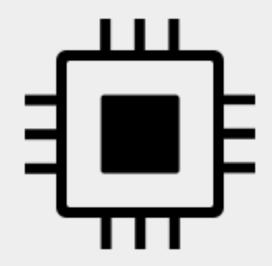


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Time-Shifting (94.44%)



NDP101 Demo



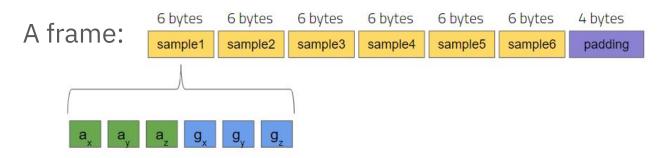




Framing for Input window



Each Data Instance is 1600 bytes - consider as 40 frames of 40 bytes.



All 6 axes sampled from the BMI160 every 10 milliseconds.

Each frame contains 60 milliseconds of consecutive data.

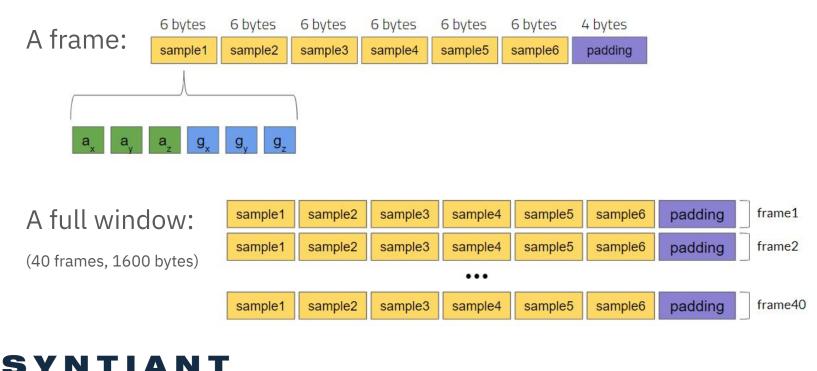




Framing for Input window



Each Data Instance is 1600 bytes - consider as 40 frames of 40 bytes.





Demo Considerations



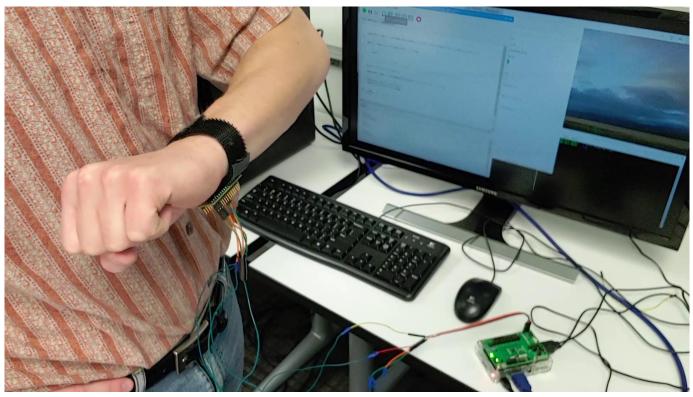
Development of the Demo halted prematurely due to technical freeze.

- Implement and Test Current Network on NDP101
 - Compare test accuracy on the NDP101 to test accuracy on Tensorflow
- Compute actual false activation rate (FAR)
- Reduce latency between gesture and LED response





Watch-Checking Demonstration





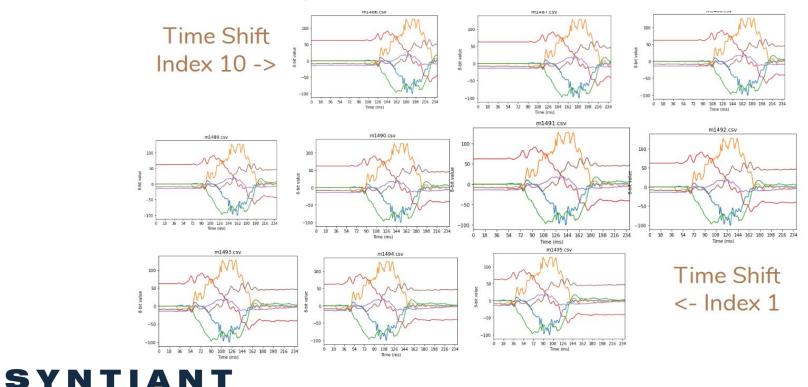


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Demo Latency Experiment



Assess latency of networks with gestures at each of these positions within the NDP101 input window

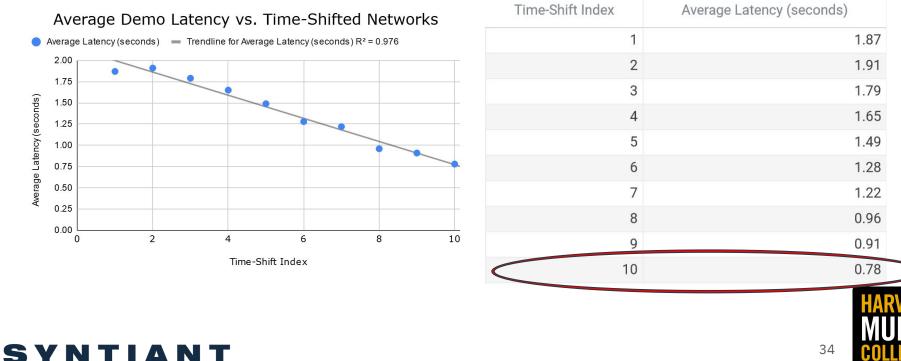




Demo Latency Experiment



Including time-shifted data potentially reduces latency to 0.78 seconds

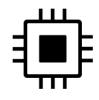


Demo Latency Experiment

Potential cause of remaining latency:

- Frames must be sent to the NDP101 every 60 milliseconds.
- Tested demo iteration sends a new frame every 80 milliseconds.
- Excess 20ms * 40 frames = 800ms
- For a full window, ~.8 seconds latency

Time-Shift Index	Average Latency (seconds)
1	1.87
2	1.91
3	1.79
4	1.65
5	1.49
б	1.28
7	1.22
8	0.96
9	0.91
10	0.78
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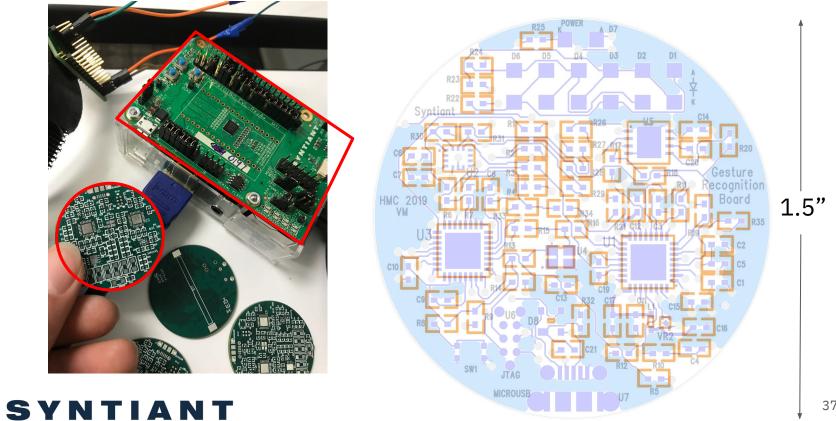
PCB Design





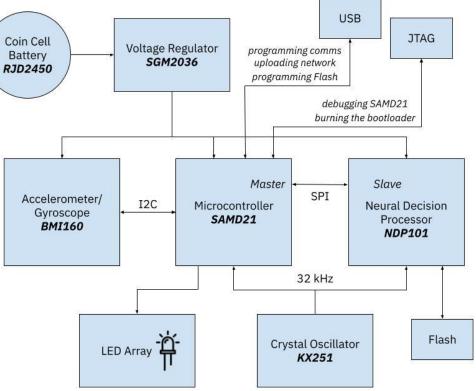


Benefits of a Custom Printed Circuit Board





Implementation of the Board

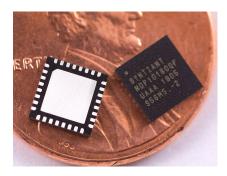




HARVEY MUDD College



Components Consume Minimal Power







Neural Network Chip (*NDP101*) 60 μA

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Accelerometer/ Gyroscope (BMI160) 925 µA **Microprocessor** (ATSAMD21)

2.04 mA

Battery (RJD2450)

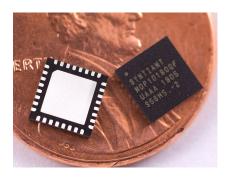
200mAh

Battery Life: **65.4 hours**





Components Consume Minimal Power

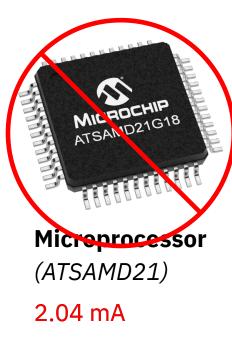




Neural Network Chip (*NDP101*) 60 μA

SYNTIANT

Accelerometer/ Gyroscope (BMI160) 925 µA



Battery (RJD2450)

200mAh

Battery Life: **196 hours**





Other Components Enable Additional Features

D6 ₺ D5 ₺

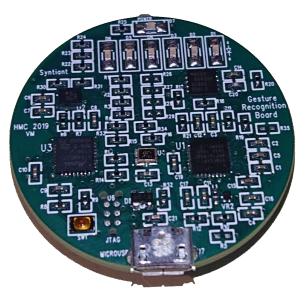
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Assembled Board











Current Progress

- Arduino Bootloader loaded
- Can print to USB serial
- Can blink LEDs
- Cannot use SPI to NDP101

	Auto Format	Ctrl+T
	Archive Sketch	
	Fix Encoding & Reload	
	Manage Libraries	Ctrl+Shift+I
	Serial Monitor	Ctrl+Shift+M
	Serial Plotter	Ctrl+Shift+L
	WiFi101 / WiFiNINA Firmware Updater	
	Board: "Arduino MKRZERO"	>
	Port	>
	Get Board Info	
	Programmer: "AVRISP mkll"	>
	Burn Bootloader	

Serial.println("Hello World");

digitalWrite(LED_PIN_A, HIGH); digitalWrite(LED_PIN_B, LOW);



Conclusion



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Deliverables

Data:

- Original Dataset
- Augmented Dataset
- Data Description File
- Logging scripts

Network:

• Train_accelerometer.py

Demonstration:

- Demo scripts
- GRB firmware

Hardware:

- Raspberry Pis
- NDP9101s
- BMI160s
- Gesture Recognition Boards
- Spare parts for the GRB



Future Work

- Complete board bringup by fully implementing firmware
- Test network features on completed board latency, false activation etc. and tune network as necessary
- Expand data collection to more people



Thanks for Your Time!

Special thanks to

Jay Cordaro and Yao Gao (Board Design Review)

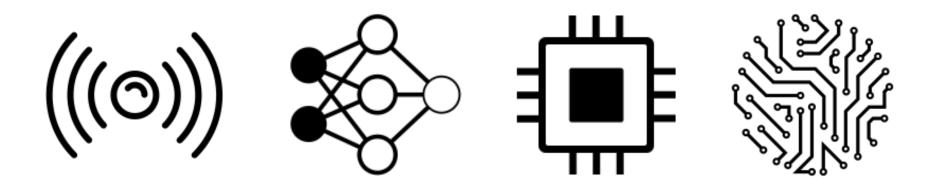
Paul Williams (Board Assembler)

Kaveh Pezeshki (HMC Engineering Server Admin)

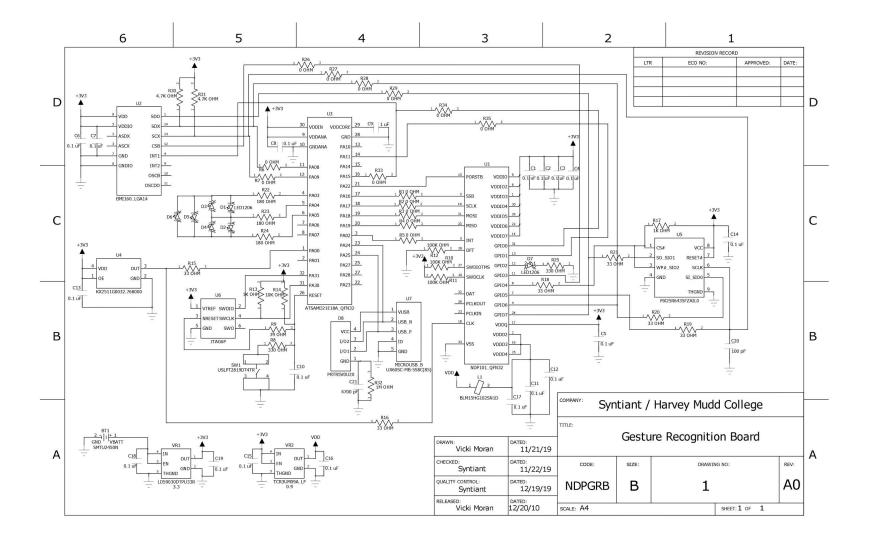




Questions?









How the Prototype Hardware Works

