

EchoSign - Final

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EchoSign - Introduction and Use cases

- **Problem:** Deaf people often struggle to communicate with non-deaf speakers
- **Solution:** Pair of gloves that translate sign language to audible English

Deaf/HH Population: **11 Million**
About **1 Million** Profoundly Deaf



90% BORN TO HEARING PARENTS

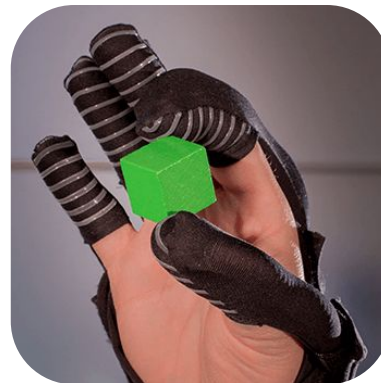


Image from BYU

Qualitative Requirements

Use Case Requirement

Maintain normal signing **speed**



.5 second latency

Glove should be **reliable**



85% sign prediction accuracy

Portable and can withstand
daily activity



100g weight limit per glove

Chosen words **represent**

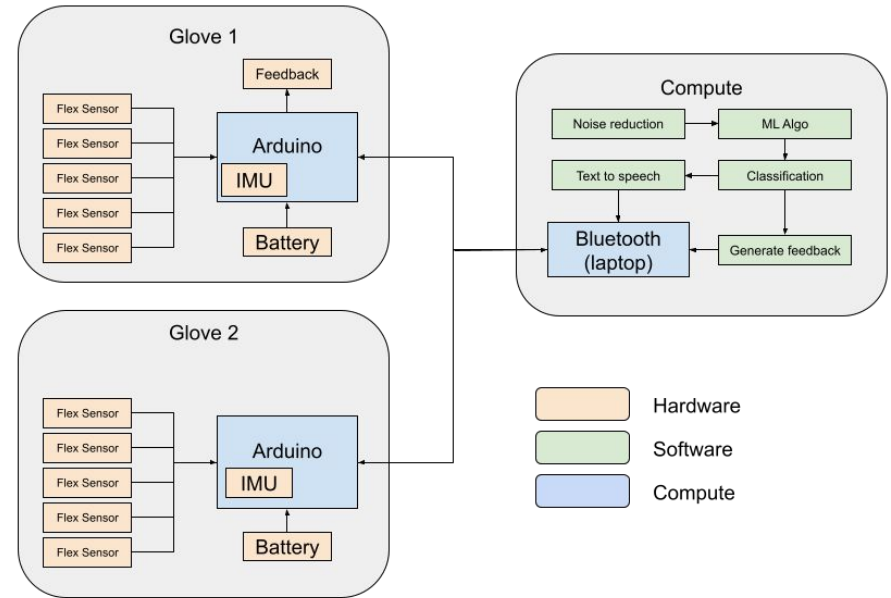


10 of most frequently signed
double-handed ASL words

ASL vocabulary

Solution Approach

- Two battery-powered gloves with sign-to-speech capability over BT
- Design Updates:
 - Got rid of speaker
 - Added PCB
 - Using two ML models (different subsets of the chosen words)
- Bluetooth
 - Python - SimplePyBLE
 - Arduino BLE - Native libraries
- ML
 - Neural Network
 - Two models, two layers, 128 nodes

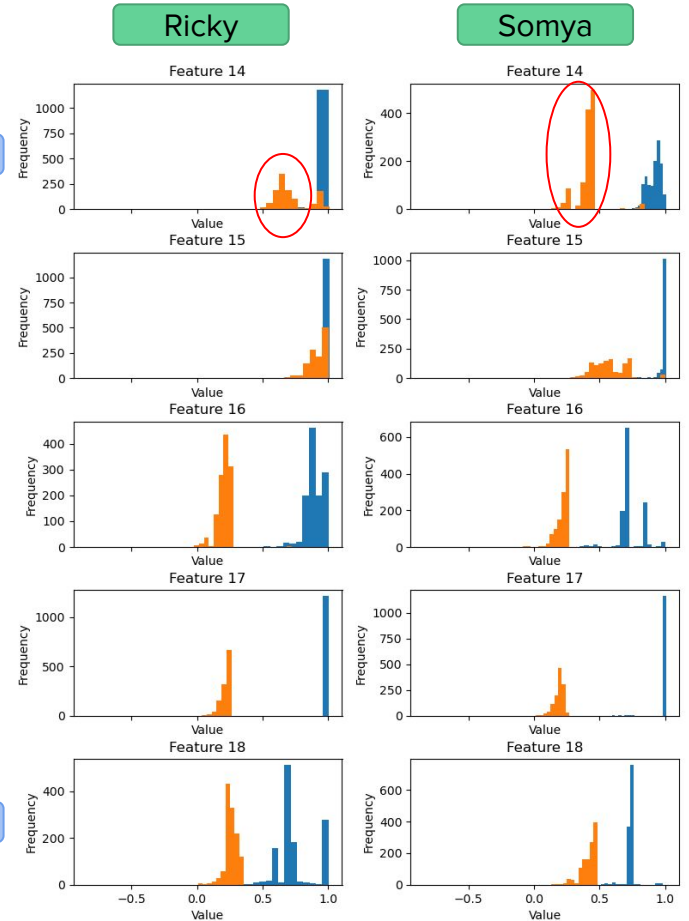


Word: "time"

Solution Approach: Data Collection

- Process details: peripheral setup phase, movement to introduce variation in the data
- 3 people x (1200 data vectors / sign) x (11 signs / person) \approx 39600 data vectors
- Collection via USB vs. Bluetooth
- Manual inspection and verification of sensor data via feature plots (see right figure)
- Noise Reduction Algorithm: calibration phase to normalize flex sensor data

Thumb



Right hand
Left hand

Pinky

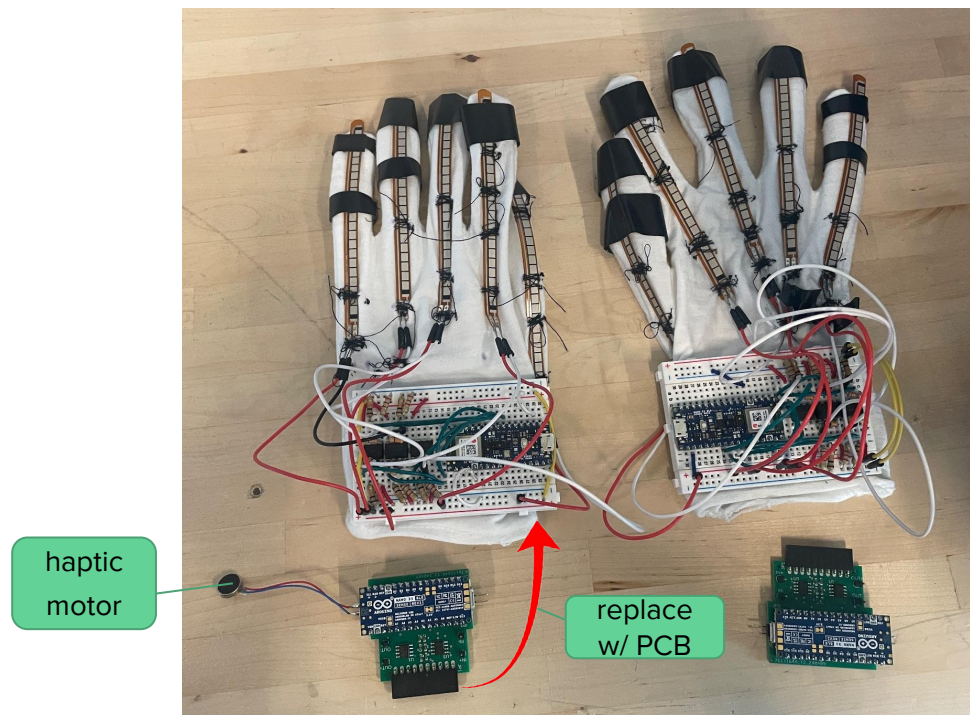
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Complete Solution

- 11 signs (10 double-handed, one 'no sign' state)
- Wireless capability

Category	Double-handed ASL Words
pronoun	<i>what</i>
noun	<i>time, car, church, family</i>
verb	<i>meet, live</i>
adjective	<i>big</i>
adverb	<i>more, but</i>



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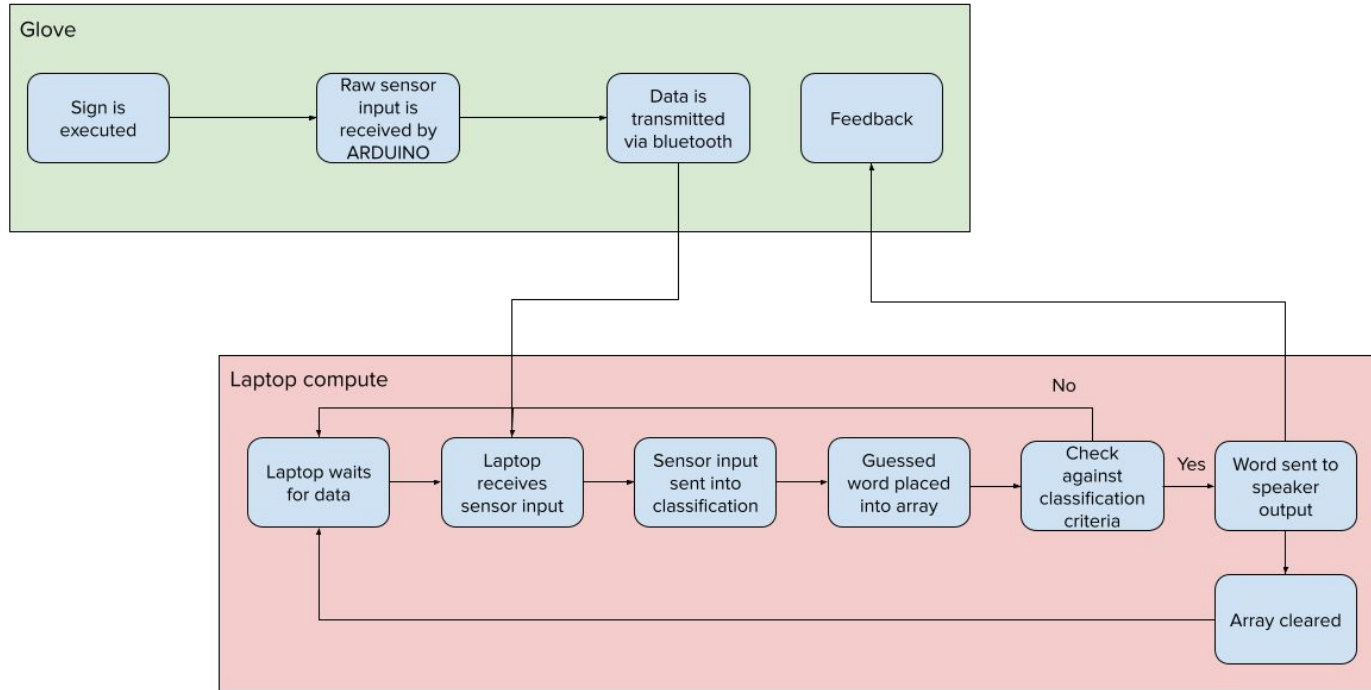
Design Requirements/Testing - ML Model

Requirement	Testing	Metrics
Accuracy	<ul style="list-style-type: none">• Data split into train/test split• Performance of NN evaluated on test set	<ul style="list-style-type: none">• Two layered architecture achieved test accuracy of 97%• Req (> 90%)
Latency	<ul style="list-style-type: none">• Python timing module to compute average speed	<ul style="list-style-type: none">• Model takes an infinitesimal amount of time to compute• Req (< 50ms)
Accuracy (Real-Time)	<ul style="list-style-type: none">• User wears glove and signs a predetermined set of vocabulary• Each word ~10 times	<ul style="list-style-type: none">• Testing reveals that the model performs well on 10/11 of vocab• Overall accuracy of 89%

Design Trade-offs - ML

Issue	Trade-offs	Final Choice
Classification heuristic length - Number of consecutive ML output before speaker output	<ul style="list-style-type: none">● Length of 8 is more robust to noise, latency 2 sec● Length of 2 is more sensitive to noise, latency 0.4 sec	<ul style="list-style-type: none">● Length of 4 balances both accuracy without sacrificing too much in latency
Model Complexity - <ul style="list-style-type: none">● Number of nodes/layers● Number of models	<ul style="list-style-type: none">● Increased model complexity<ul style="list-style-type: none">○ Potential performance boost○ Increase in latency○ More training data required○ Risk of overfitting	<ul style="list-style-type: none">● Two fully connected layers of 128 nodes● Two models for subsets of data● Balances performance, latency, and data requirements

Sign to speech pipeline

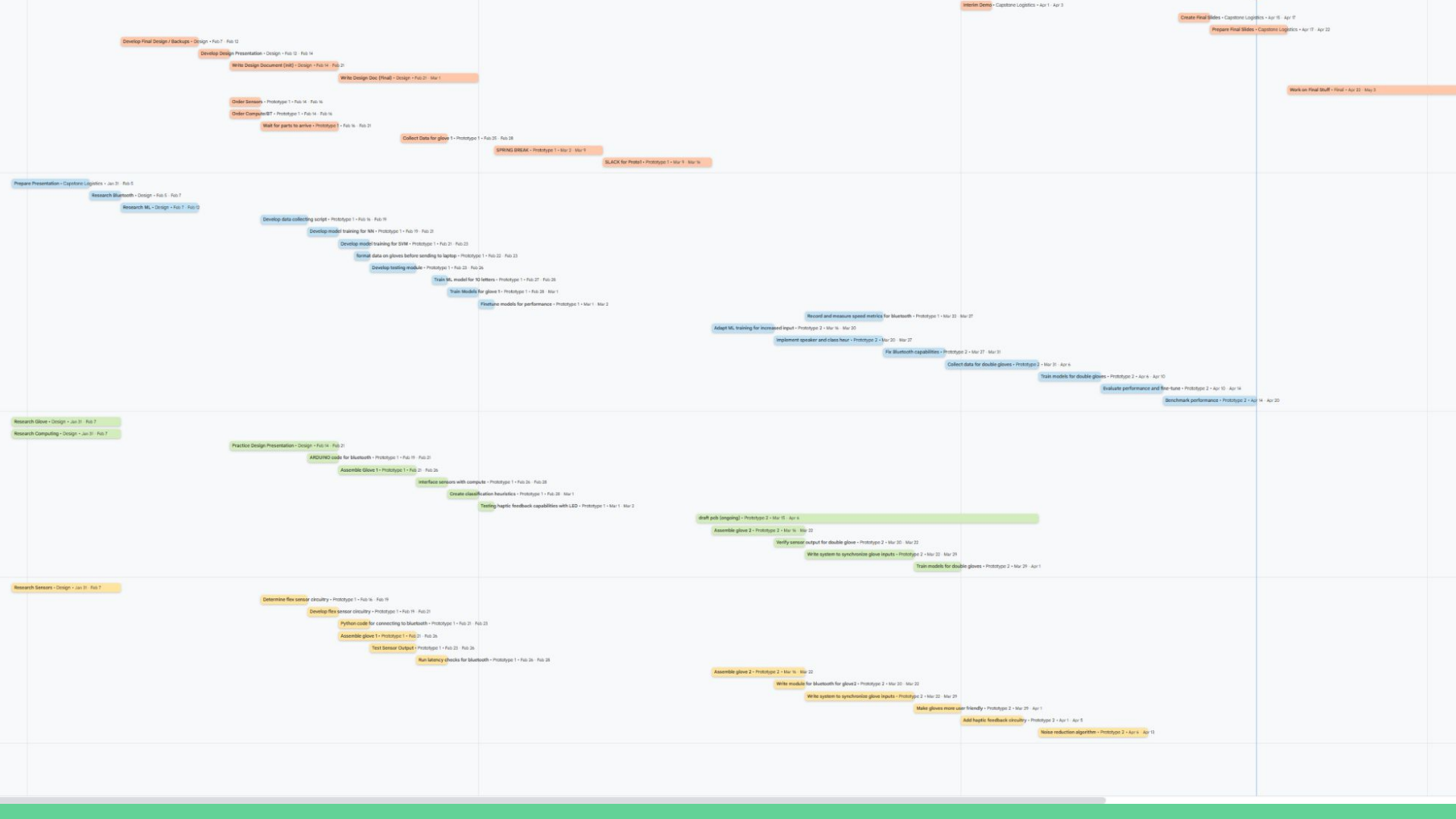


Design Tradeoffs - General

Issue	Trade-offs	Final Choice
Distinguishment of letters that rely on touch	Classification power vs. usability	Omission of touch sensors
Normalizing data discrepancies between different users	Overhead vs. usability	Added calibration phase
On-glove speaker not possible with modules compatible with chosen compute unit	Portability vs. robustness	Speech outputted through laptop
Powering the Arduino Nano wirelessly	Compact and lightweight design vs. battery lifetime	Use two 3.7V LiPo batteries in series at 500mAh
Design was bulky and not secure	Simplicity and flexibility vs. clean design	Printed custom PCB and 3D printed case with velcro strap

Overall - Testing, Verification, Validation

Requirement	Verification	Metrics
<i>Accuracy</i>	<ul style="list-style-type: none">• Evaluate accuracy on separate test data• Evaluate accuracy on real-time performance	<ul style="list-style-type: none">• NN has 97% accuracy on test set• Real-time accuracy of 89% (> 85%)
<i>Latency</i>	<ul style="list-style-type: none">• Evaluate time for ML prediction• Timing from first sensor reception → speaker output	<ul style="list-style-type: none">• NN has infinitesimal time for prediction• Real-time prediction duration: 0.6-0.7 sec (~0.5 sec)
<i>Vocabulary</i>	<ul style="list-style-type: none">• Classification on ten ASL words over multiple POS (noun, verb, adjective, etc.)	<ul style="list-style-type: none">• Classification works well on 10/11 signs

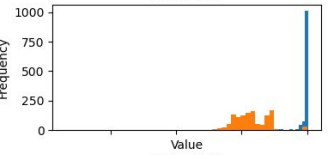
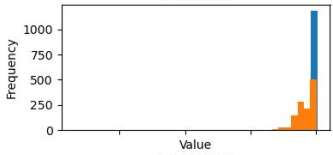
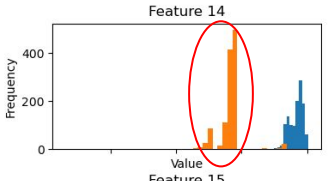
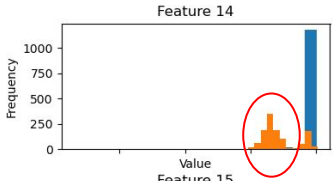
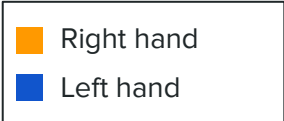


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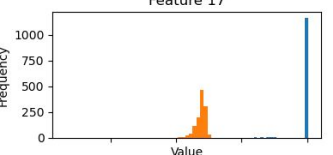
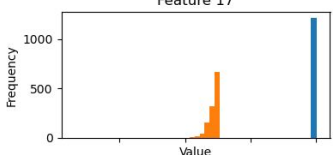
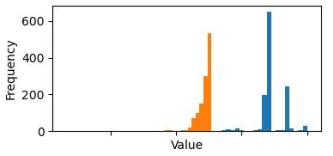
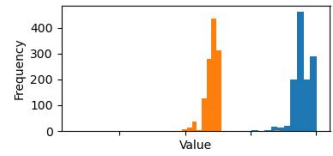
Ricky

Somya

Thumb



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