Baby Boot: Devising a Multimodal Sensor for Enhanced Infant Monitoring

Sritharini Radhakrishnan

Mentors: Dr. Daniel Gulick, Dr. Shiyi Liu, Dr. Jennifer Blain Christen

REU Site sponsored in part
by NSF I/UCRC Award 1659871

Sensor Signal and Information Processing Center
http://sensip.asu.edu

Presentation Agenda

1. ASU Pre-Training
2. Problem Statement and Challenges
3. Proposed Solution
4. Structure of Circuits & Algorithms
5. Research Contribution
6. Results
7. Research Conclusion
8. Next Steps
9. Reflection
10. References

REU Pre-Training

Hands On Technical Training

- MATLAB and Python refresher
  - Activities ranged from noise reduction to digit recognition
- Machine Learning boot camp by Dr. Kristen Jaskie on Colab
  - Clustering + K-means
  - Regression + Prediction
  - Classification + Neural Networks
- Embedded Hardware for ML by Micheal Stanley
  - Learned about factors to consider when a sensor hardware platform

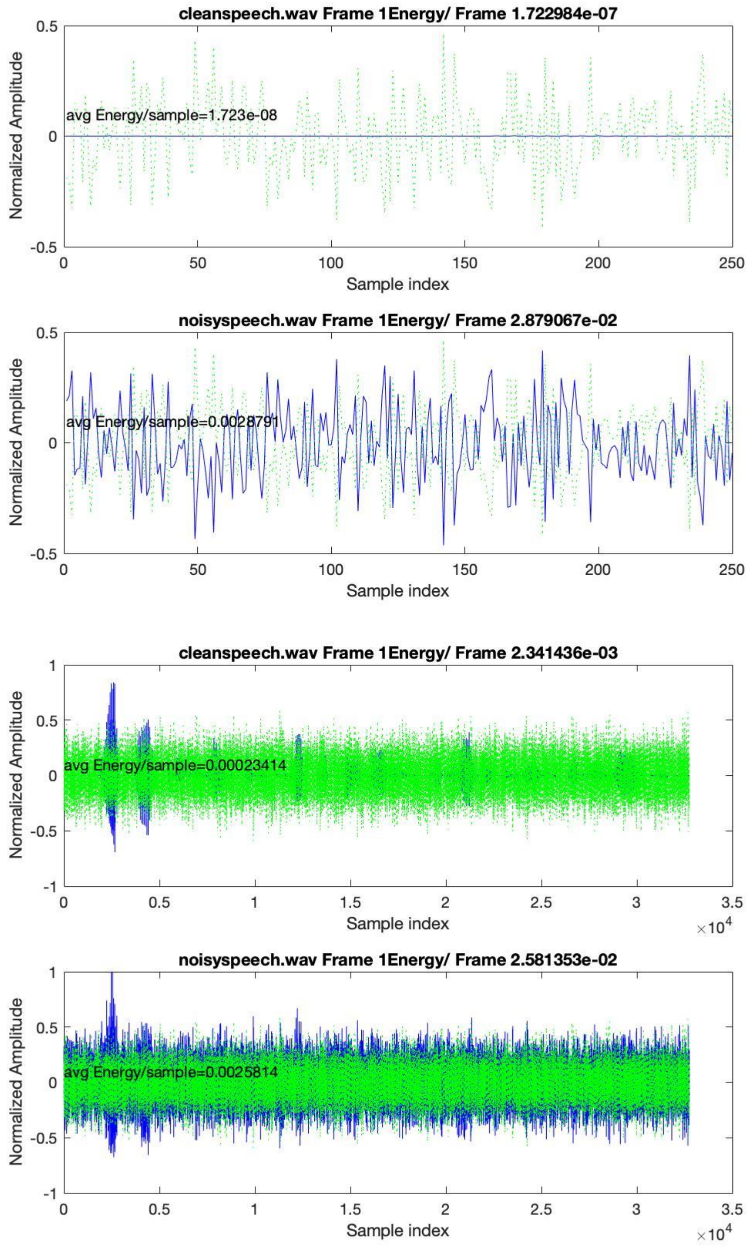

Fig: Noise reduction MATLAB plots

https://sensip.engineering.asu.edu/ret/

Problem Statement

Background

- Unless in immediate medical danger, newborns one hour postpartum are generally placed on the mother's chest to promote critical social bonding.

- During this period, babies are not intensely monitored.

- Without sensors during one-on-one contact, any concerning internal issues developed in the baby as a result of the trauma of birth is allowed to fester. Delayed medical intervention of such symptoms has been linked to hypoxia and cerebral palsy.

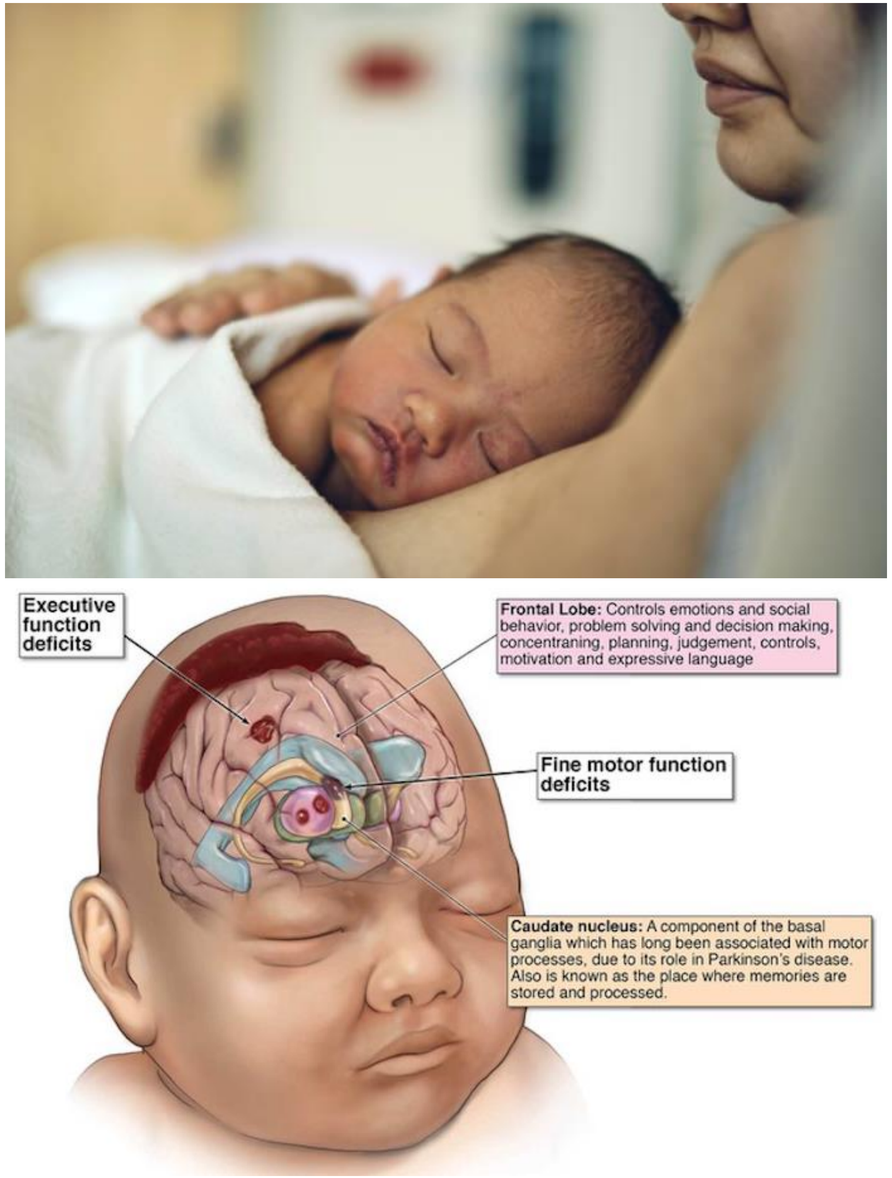

Fig: (Top) Example of crucial skin-skin contact between infant and mother; (Bottom) Hypoxia as it develops in babies

Proposed Solution

Research Goal

- “Baby Boot,” originally pitched by KLS OB-GYNs, is a flexible electronic multimodal sensor that can be easily worn by babies as a “boot”.
- The device will detect and transmit data about crucial analytes: pH, O2, CO2, and glucose levels.
- A machine learning classification algorithm will be used to analyze data and alert doctors of potential health risks.

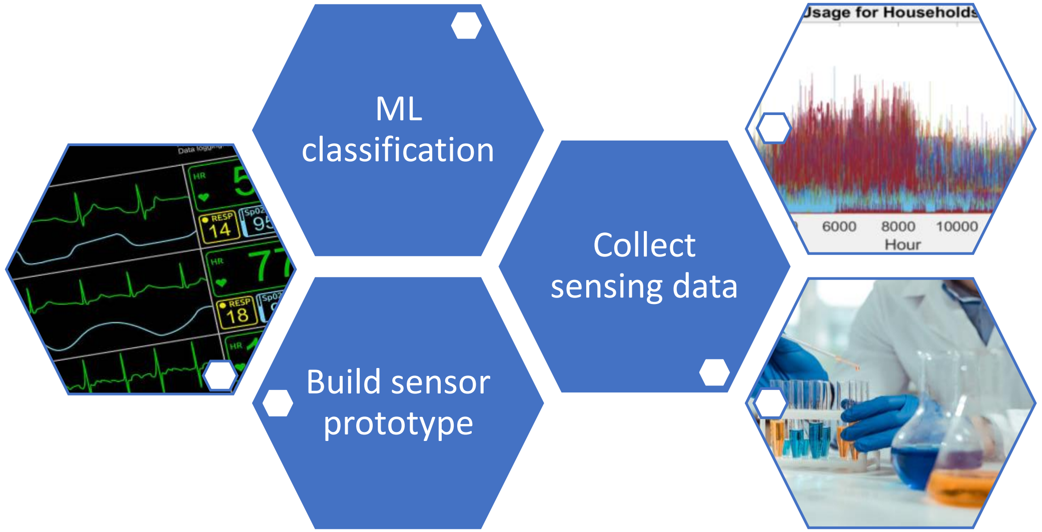

Fig: (Top) Chart that displays the three main components of the project: Data collection. rototyping, and ML Classification; (Bottom) Oxlet commercial (non-medical) baby boot as an example of the proposed sensor design

Structure of Circuits and Algorithms

Research Tools

- Designed and printed glucose sensor for laboratory testing

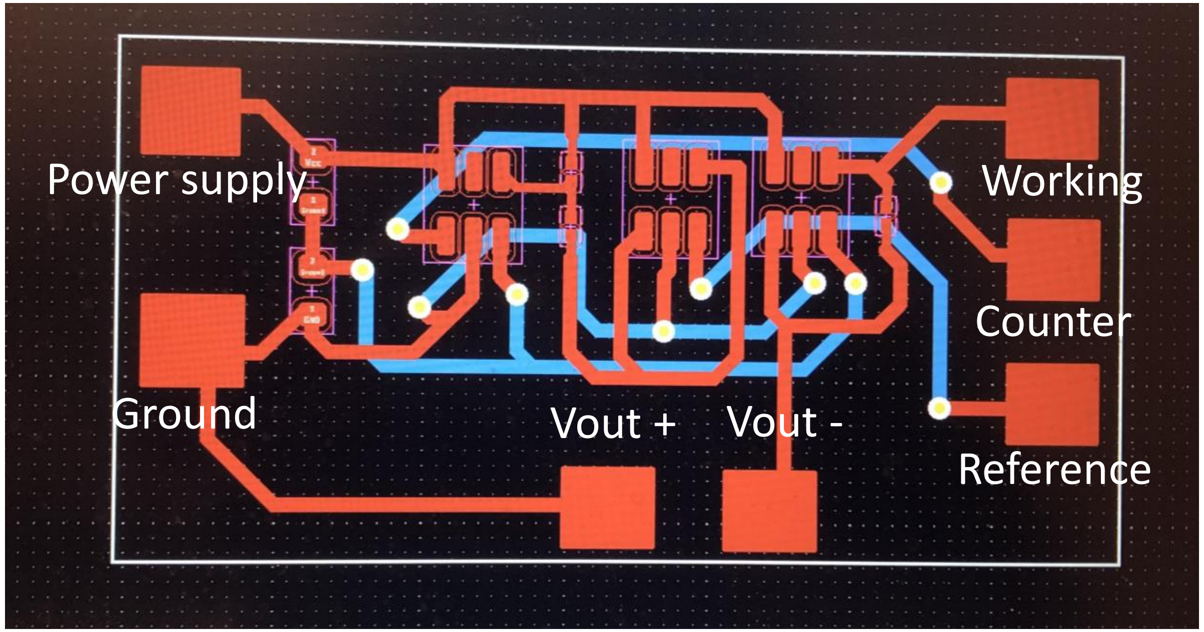

Fig: Circuit schematic of a three-electrode system glucose sensor used in testing

- Logistic regression to classify
  - pH sensor data
  - Glucose sensor data
  - Healthy and unhealthy babies using pH, O2 and base excess

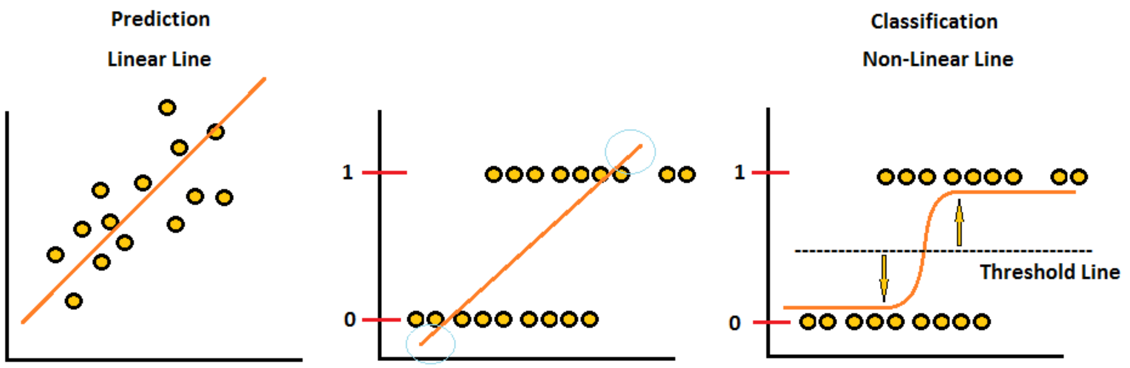

Fig: Diagram explaining classification using logistic regression

Research Contribution

Research Focus Areas

- Sensor selection
  - To devise a protype for testing quickly – through literature/commercial product review was conducted
- Machine learning
  - ML algorithms were explored to test in characterizing benchtop data
  - Determine the importance of analytes in sensor development
    - What analyte is not as crucial for neonatal monitoring?

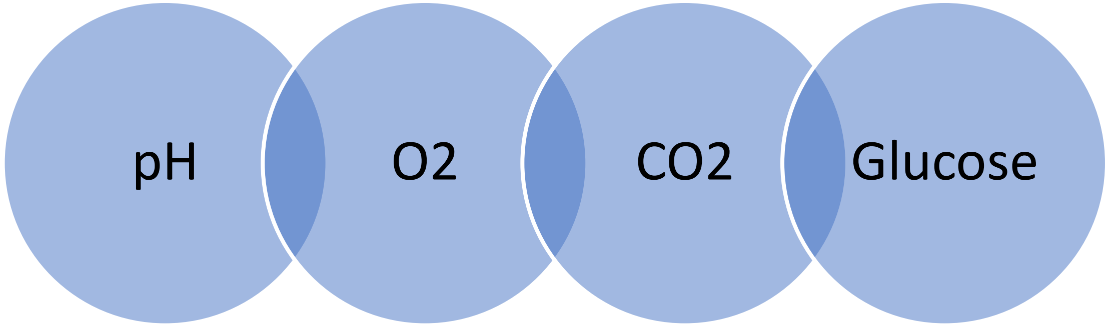

Fig: List of analytes that the sensor will observe

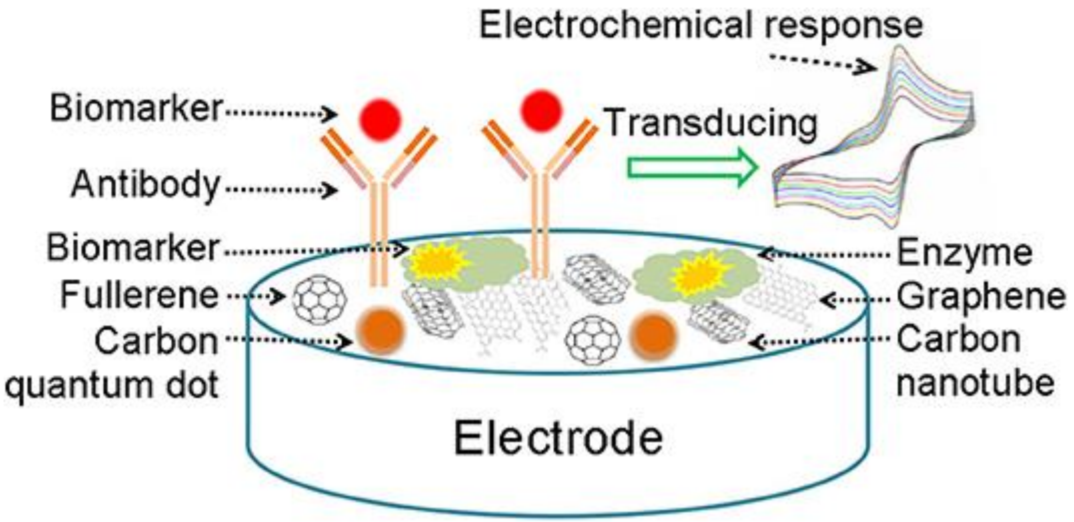

Fig: Diagram illustrates the various considerations in sensor development – from electrode system, modality (invasive/noninvasive), to analyte-detecting enzyme

Results - Sensor Development

- CO_2: commercially unavailable – sparked ML research to determine whether important
- pH: currently being developed in BEST Lab, benchtop experiments to refine accuracy
- Glucose: progression from taking apart/hacking Freestyle glucose sensor, developing circuit
- O_2 – commercially available, easiest to implement
- Set-up Nordic BLE

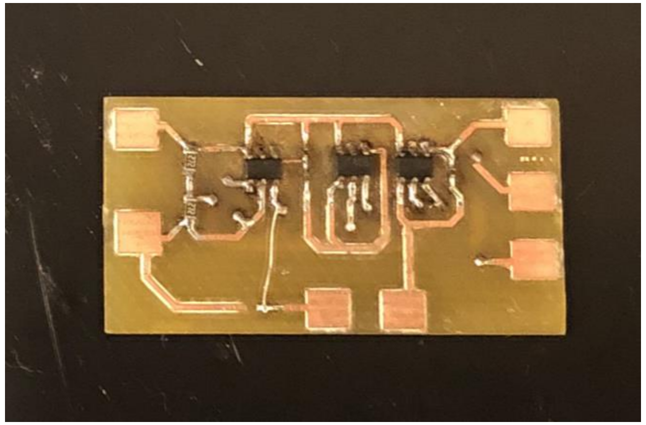

Fig: Printed glucose sensor PCB

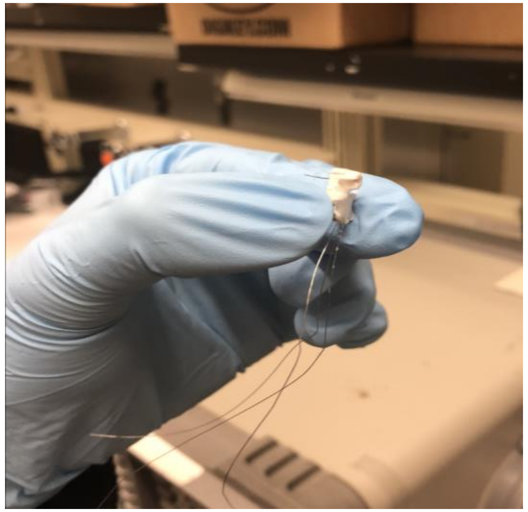

Fig: Disassembled FreeStyle sensor

Fig: pH sensor experimental set-up

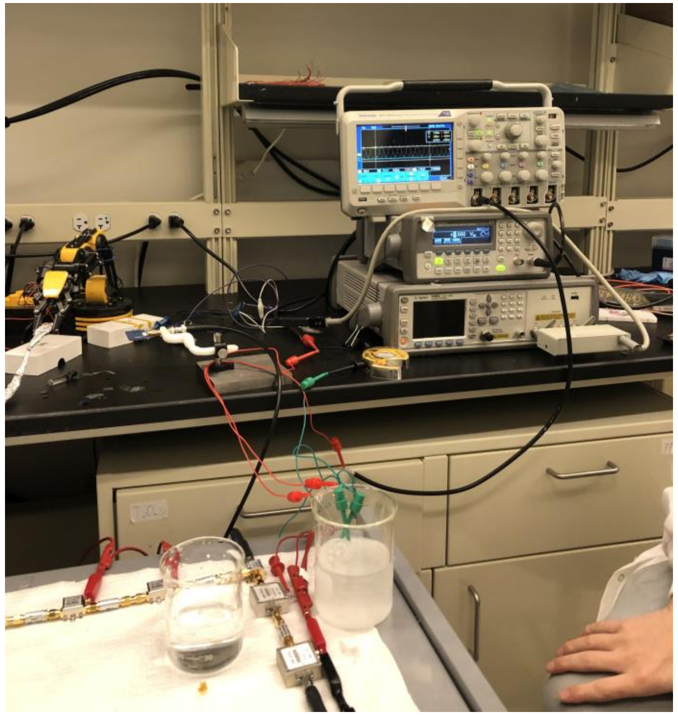

Fig: Glucose experiments for data collection

Results

- Collected pH data and glucose data to train logistic regression ML algorithms
- Utilized KLS dataset to determine healthy vs. unhealthy babies from pH, O2, CO2, and base excess
  - ML algorithm to rank the importance of analytes – to verify accuracy of prototype without CO2

Fig : Keeping Labor Safe (KLS) investors/medical collaborators of the Baby Boot project

Metric	Value
Accuracy	0.98

Fig: pH classification confusion matrix

Fig : Healthy vs. unhealthy confusion matrix

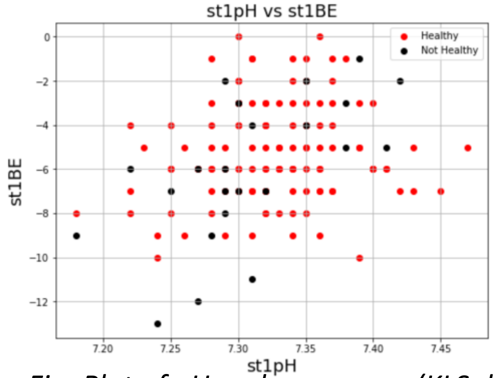

Fig: Plot of pH vs. base excess (KLS data)

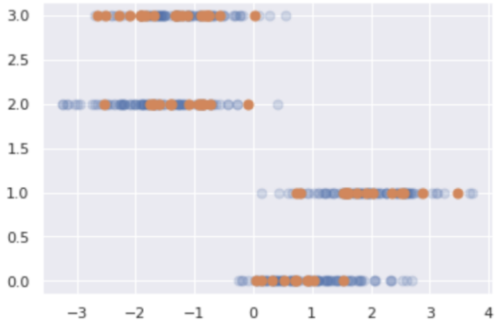

Fig: pH data after logistic regression

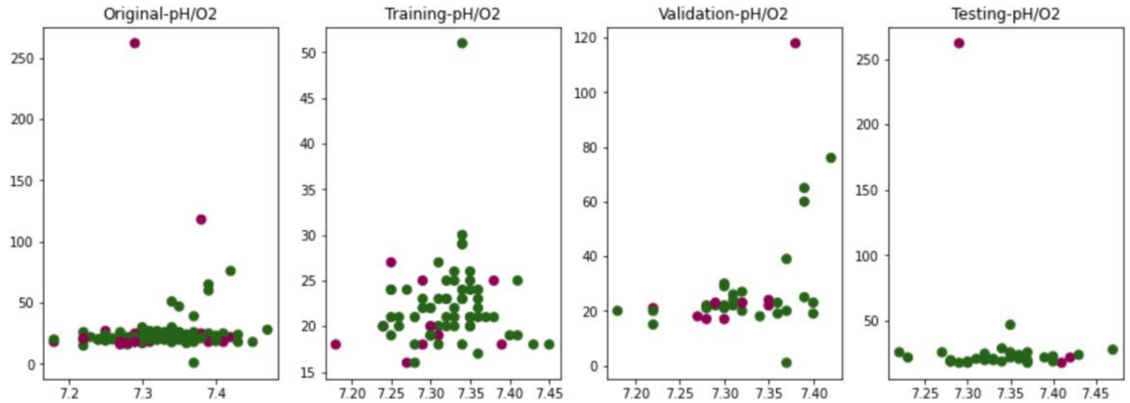

Fig : Illustrates how data is split up to train ML algorithm

Next Steps

Future Plans

- Refine individual sensors developed in lab
  - Glucose, pH
- Integrate sensors in prototype
  - Includes commercial oxygen, CO2 pending
  - KLS agreement to finalize analyte selection, ML to support
- Add Bluetooth capability to sensor
- Begin animal trials on rats

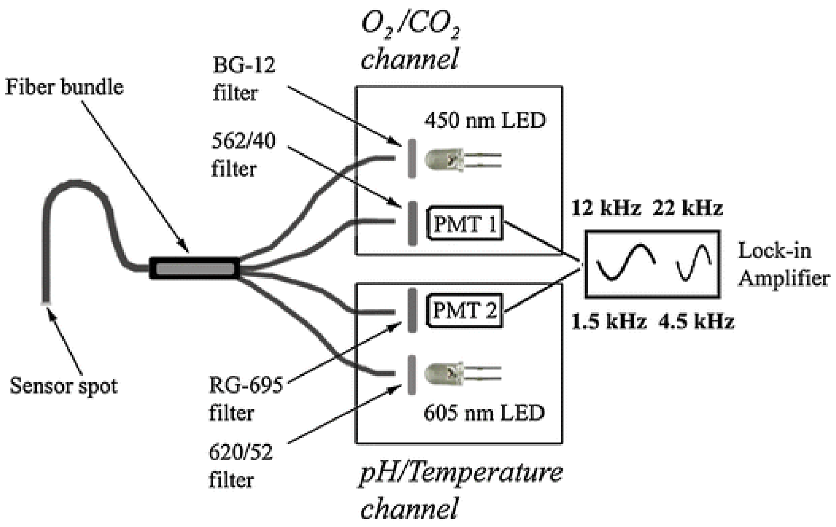

Fig : Illustrates ideal prototype integration, taken from Borisov SM et all [1]

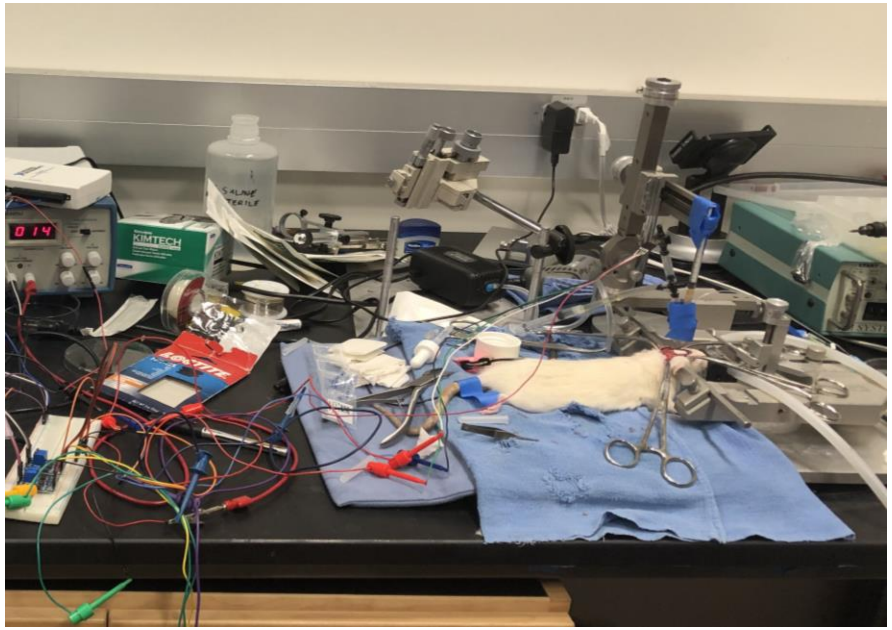

Fig : Rat surgeries conducted in BEST lab to test biomedical sensors

Reflection

- Learned a lot about hardware sensor development
  - Applied textbook principles from Circuits 1&2 in the designing glucose PCB
- First thorough exposure to ML
  - Weekly Friday presentations from all REU students highlighted the versatility of ML
- Working with OB-GYNs from KLS gave insight to biomedical applications of my EE degree
- Valuable community of RET participants, Karl Ernsberger and Raquel Diaz
- Many thanks to Dr. Gulick, Dr. Liu, Ian Akamine, Arnav Bawa, Dr. Jaskie, Dr. Blain Christen, Dr. Spanias, & KLS mentors!

Fig: REU participants

Fig: RET participants

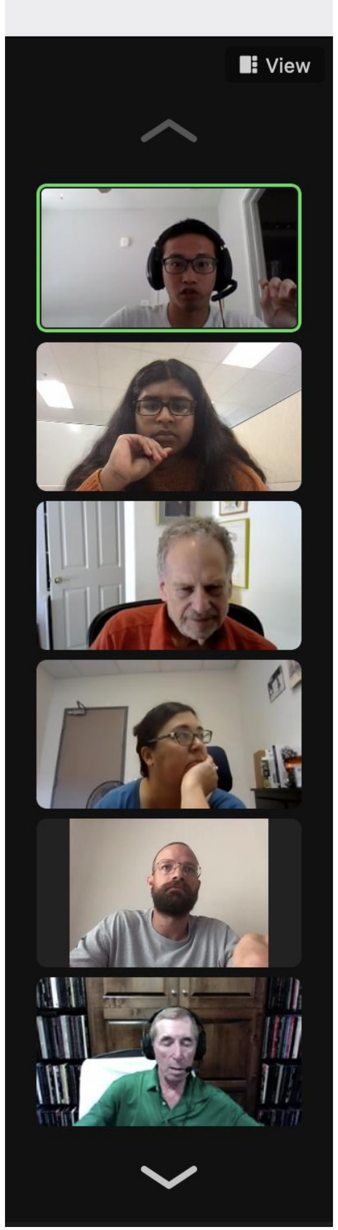

Fig: KLS team

https://sensip.engineering.asu.edu/ret/

References

- [1] Borisov, S.M., Seifner, R. & Klimant, I. A novel planar optical sensor for simultaneous monitoring of oxygen, carbon dioxide, pH and temperature. Anal Bioanal Chem 400, 2463–2474 (2011). https://doi.org/10.1007/s00216-010-4617-4
- Larsen J, Linnet N, Vesterager P. Transcutaneous devices for the measurements of pO2 and pCO2. State-of-the-art, especially emphasizing a pCO2 sensor based on a solid-state glass pH sensor. Ann Biol Clin (Paris). 1993;51(10-11):899-902. PMID: 8210067.
- Sankaran, D., Zeinali, L., Iqbal, S. et al. Non-invasive carbon dioxide monitoring in neonates: methods, benefits, and pitfalls. J Perinatol 41, 2580–2589 (2021). https://doi.org/10.1038/s41372-021-01134-2
- M. Degner, H. Jürß and H. Ewald, "Fast and low power optical CO2-sensors for medical application: New sensor designs for main- and side-stream CO2-sensors are presented in comparison with state of the art capnometers," 2018 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), 2018, pp. 1-5, doi: 10.1109/I2MTC.2018.8409741.
- Ross MG, Gala R. Use of umbilical artery base excess: algorithm for the timing of hypoxic injury. Am J Obstet Gynecol. 2002 Jul;187(1):1-9. doi: 10.1067/mob.2002.123204. PMID: 12114881.
- Verma AK, Roach P. The interpretation of arterial blood gases. Aust Prescr 2010;33:124-9.
- Peng, J., He, X., Wang, K. et al. Noninvasive monitoring of intracellular pH change induced by drug stimulation using silica nanoparticle sensors. Anal Bioanal Chem 388, 645–654 (2007). https://doi.org/10.1007/s00216-007-1244-9
- Mei Qin et al 2019 J. Semicond. 40 111607
- Vivaldi, F.; Salvo, P.; Poma, N.; Bonini, A.; Biagini, D.; Del Noce, L.; Melai, B.; Lisi, F.; Di Francesco, F. Recent Advances in Optical, Electrochemical and Field Effect pH Sensors. Chemosensors 2021, 9, 33/https://doi.org/10.3390/
- Cascales, J.P.; Li, X.; Roussakis, E.; Evans, C.L. A Patient-Ready Wearable Transcutaneous CO2 Sensor. Biosensors 2022, 12, 333. https://doi.org/10.3390/bios12050333