Fetal Monitoring Signal Optimization Device

SBHSE School of Biological and Health Systems Engineering

LifeCycle | Team7

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Mission Statement

We develop devices that empower every person who gives birth to feel confident, comfortable, and cared for. As an all-women team driven by empathy and research, we are committed to innovation, quality, and collaboration to improve the birthing experience for all.

Clinical Problem

Cardiotocography (CTG) remains the clinical standard for intrapartum fetal monitoring, yet its diagnostic performance is critically limited. Current systems exhibit a false positive rate approaching 99% for adverse fetal event detection,[1] driving unnecessary interventions, including cesarean deliveries that increase hospital costs by 35-85% and carry a 3-15% risk of postoperative complications.[2,3] The root cause is the inability of conventional CTG algorithms to reliably discriminate between overlapping fetal and maternal heart rate signals.

Final Specifications

Hardware filter	
Filter Type	Active bandpass
Passing frequencies	0.15Hz - 40Hz
Op-amp type	LM318
Component tolerence	± 1%
Machine Learning Model	
Language Used	Python
Processing time	< 5s
FHR Precision	> 90.31%

Table 1. Prototype Technical Specifications. A delineation of required components' specifications, values, and tolerances.

Product Architecture

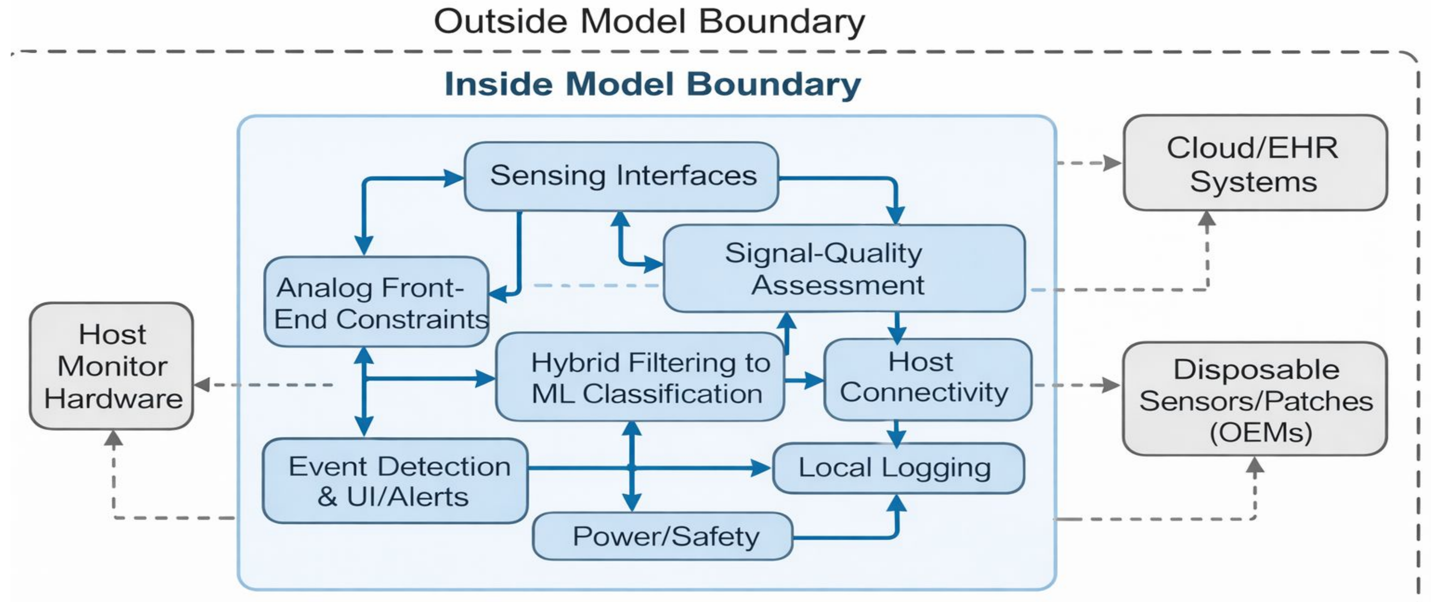

Figure 1. Machine Learning Model Logic. Designed to load data from monitors, compute statistics, perform signal processing steps to reduce noise and detect FHR from filtered data. FHR is compared against reference QRS annotations to calculate performance metrics & event classification.

Prototype

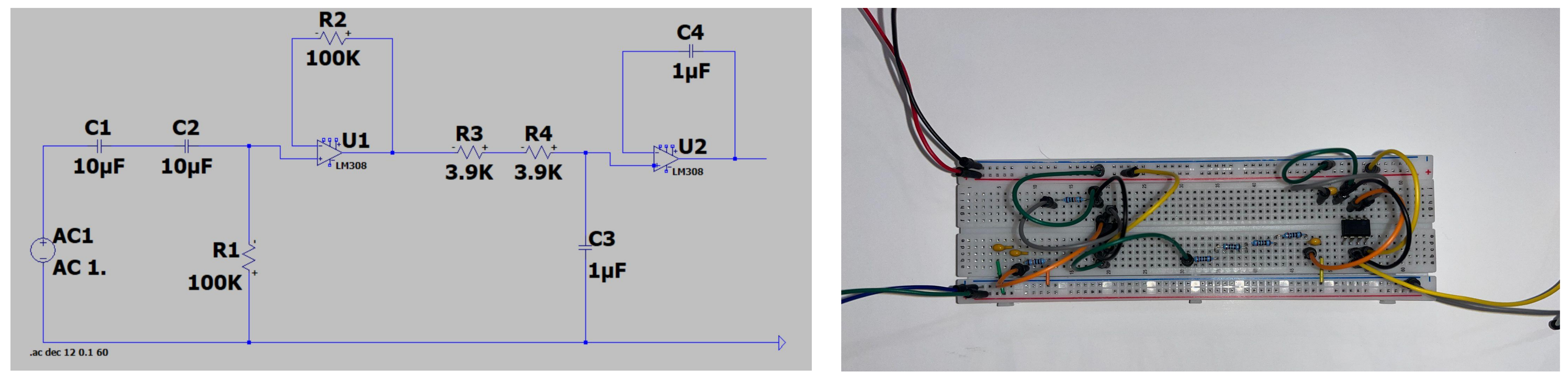

Figure 2. Final Hardware Prototype. A visual representation of the filter scemating made in LTSPice along with the physical build, designed to filter out any potential noise sources while letting maternal ECG (HR), EMG (contractions), & fetal ECG (FHR) signals pass.

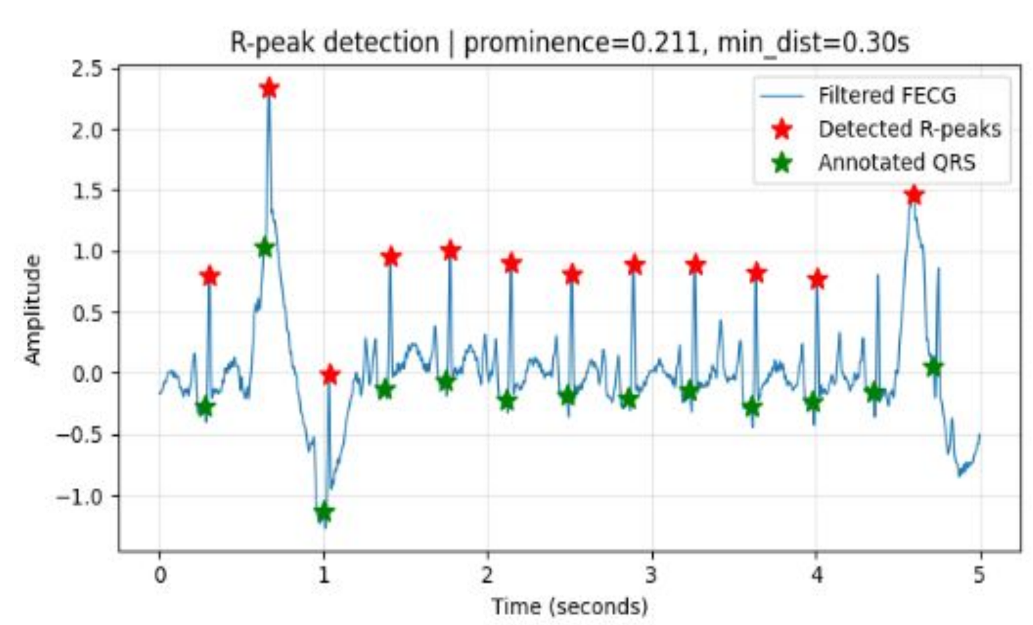

Figure 3a. Filtered FECG Signal with Algorithm-detected R-peaks (Red) Compared to Annotated QRS events (Green). The algorithm correctly identified 89.66% of true beats, while 90.98% of detected beats were accurate (**false positive rate** ≈ 9.0%; **F1** = 90.31%). **Mean absolute timing error** between detected and annotated beats was 27.05 ms.

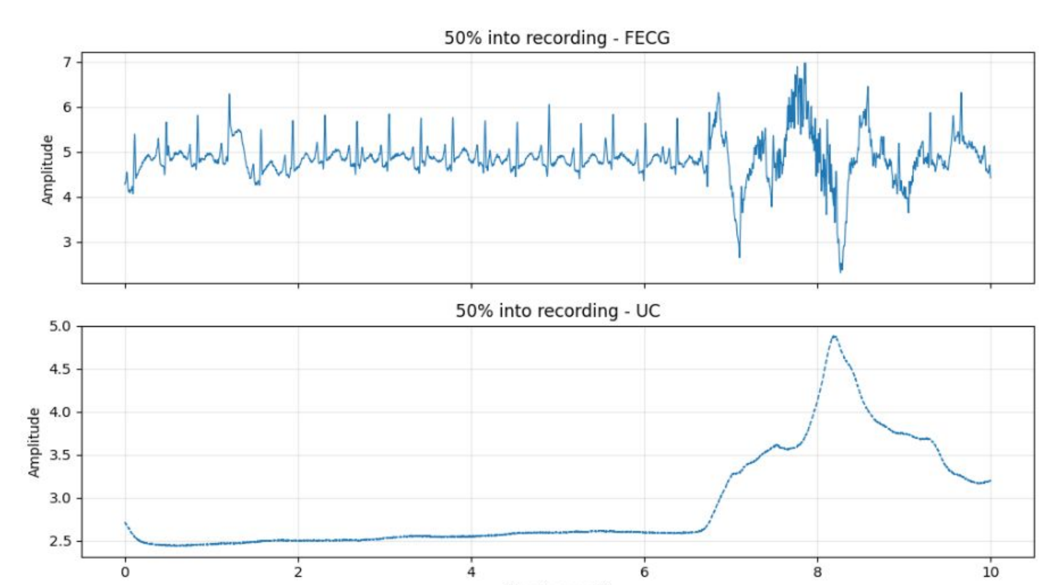

Figure3b. Incident Visualization. A representative segment showing filtered fetal ECG **(fECG)** and uterine contraction **(UC)** signals. Fetal heart rate **(FHR)** trends were aligned with UC activity to qualitatively assess potential deceleration patterns relative to contraction peaks and compared with **established clinical patterns** reported in the medical literature.[4]

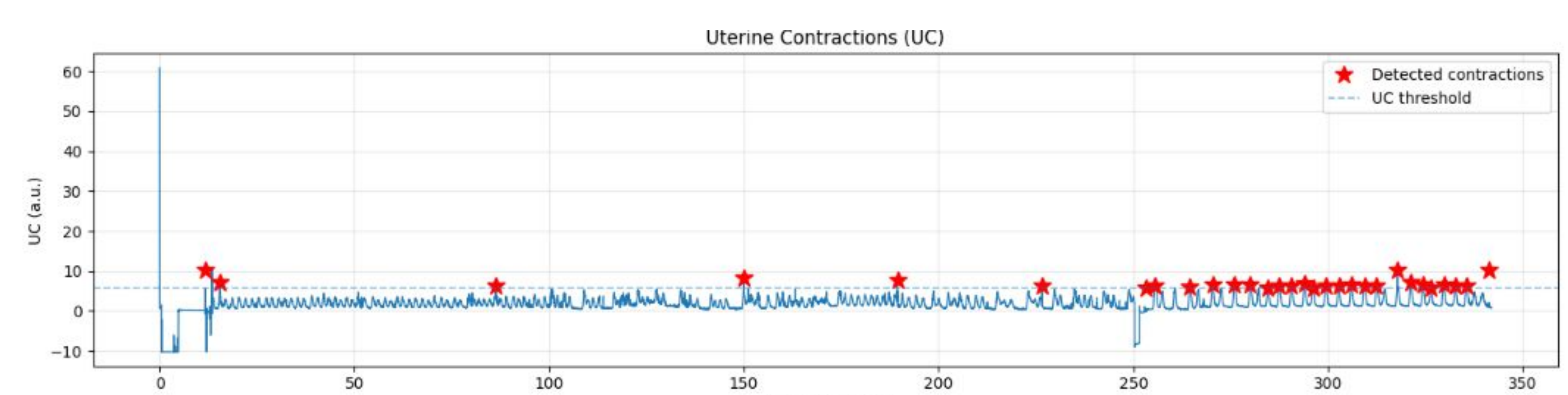

Figure 3c. Uterine Contraction (UC) Signal with Detected Contraction Peaks Identified. Threshold-based peak detection **(mean + 1.2σ,** with minimum spacing).A total of 30 contractions were identified, with 24 occurring in the final ~100 minutes (250 min to end). **Mean interval:** 3.83 ± 1.51 min, consistent with reported active labor frequencies[5] (every 3-5 mins lasting 45-60 seconds each). No ground-truth annotation was available; results represent a plausibility assessment rather than validated performance.

Manufacturing Costs

Op-amp……………….$40	Arduino board………..….$28
Resistors……………..….$8	Wires……………………..…$13
Capacitors…………….$10	Cloud Storage……………$0.40/GB
Breadboard…………….$10	

Table 2. Project Cost Breakdown. The estimated cost of an advanced prototype would total $109 for the hardware filtering module, while the main cost for the machine learning module stems from cloud storage needs, running at $0.40/GB

Verification Results

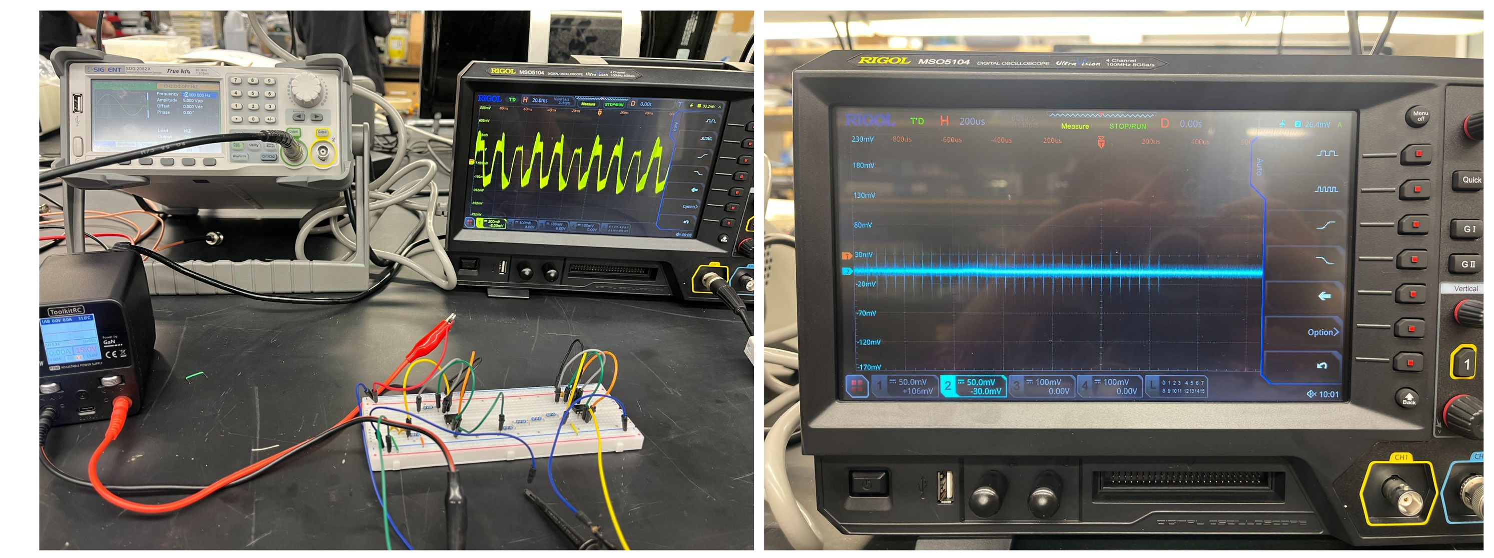

Figure 3. Hardware Filter Testing Results. Oscilloscope outputs during hardware testing procedures

Our **filter design** performed well in simulations, but practical testing did not produce the expected verification results. A test was considered a pass when all in-band frequencies appeared as clean, unaltered sine waves on the oscilloscope. Instead, the final filter output was dominated by noise from operational-amplifier oscillations, obscuring the desired signals. As a result, this hardware filter iteration failed verification.

FHR detection was validated against annotated QRS data (~90% precision/recall, ~27 ms timing error). UC detection showed physiologically plausible patterns but lacked ground-truth validation. Deceleration analysis was computationally tested; 3 parameter versions produced inconsistent results.

Design Status

Hardware Filter

During testing we found that the chosen op-amp, limited the filter's performance. Future iterations will have a gain stage within the circuit and use an alternative op-amp type such as an LM358, OPA2134, or T1074.

Machine Learning Model

Data tested on single channel PhysioNet p10143 (48,143 beats vs. 48,854 annotated). In future iterations, a multi-lead input would increase cross-channel confidence. Additionally, labeled training data of ~500–1,000 clinically labeled contraction + deceleration events across ≥50 diverse patients including varied gestational age, fetal position, and motion artifact conditions is needed for further V&V.

Acknowledgements

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Gantt Chart

References