ECE445
Fall 2025
SENIOR DESIGN LAB
PROJECT PROPOSAL

Insight: Cardiovascular Screening Device

Team 32:
Jay Nathan (jayrn2)
Rishab Iyer (riyer20)
Ethan Pereira (ethanrp2)

TA: Weiman Yang
Professor: Arne Fliflet, Rakesh Kumar
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1. Introduction

1.1. Problem

Cardiovascular disease (CVD) is the leading cause of death worldwide, responsible for nearly 20 million deaths annually, about one in three deaths overall. A significant share of these fatalities occur without prior diagnosis: approximately 45% of sudden cardiac deaths happen in individuals with no previously recognized heart disease, while nearly 20% of adults with hypertension and up to 23% of those with atrial fibrillation remain undiagnosed. These silent conditions, such as hypertension, arrhythmias, and sinus bradycardia risk factors, drive the majority of preventable CVDs.

Current solutions remain fragmented, while comprehensive screening still requires multiple expensive clinical visits, such as blood pressure measurement, lipid panels, ECGs, and rhythm monitoring, creating barriers for uninsured or underserved populations. The impact is most severe in rural communities, where mortality rates are 20% higher than in urban areas due to limited access to screening. Yet the challenge extends to cities as well, where preventive tests are often costly, not covered by insurance, and therefore underutilized. Consumer devices like blood pressure cuffs, smartwatches, and single-lead ECGs are disjointed, expensive, and difficult to interpret. Critically, there is no affordable, comprehensive, and user-friendly at-home screening solution that can detect CVD risks early.

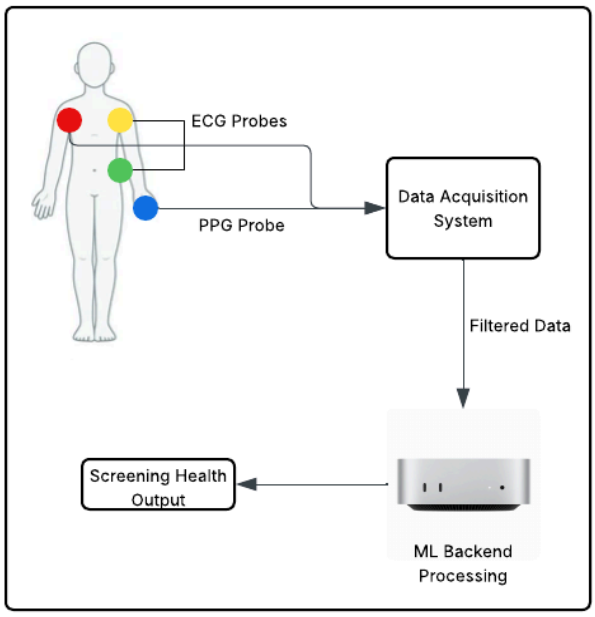
1.2. Solution

We propose a low-cost at-home device that serves as a screening tool for three hidden but common drivers of cardiovascular disease: arrhythmias (like atrial fibrillation), hypertension, and sinus bradycardia. By making early checks simple and affordable, the

device empowers people to detect risks before symptoms appear, reducing the likelihood of sudden, unexpected cardiac events. Unlike fragmented consumer devices or expensive clinical visits, this all-in-one tool allows anyone to perform a one-minute screening at home, with clear results that indicate whether a possible condition has been detected and if follow-up with a doctor is recommended.

The system is designed for ease of use. A user places their fingers on PPG sensors and 3 patches on the chest for ECG measurement. These signals feed into a compact board with an Atmega microcontroller, which sends the data to a computer via USB. Machine learning algorithms analyze the data to classify hypertension, sinus bradycardia, or arrhythmias, with results shown on a simple dashboard. This keeps the device affordable, portable, and easy to use.

1.3. Visual Aid (Insert Here)

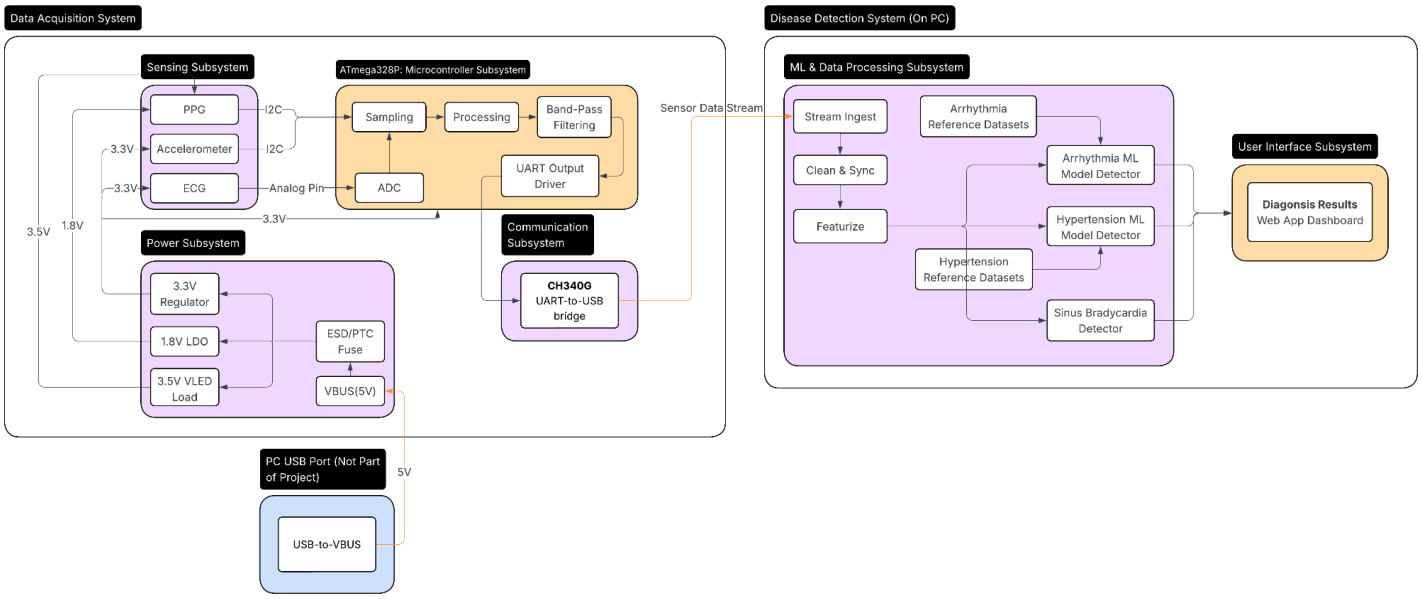


1.4. High-Level Requirements

1. The machine learning pipeline must achieve a minimum classification accuracy of 90% when detecting atrial fibrillation, sinus bradycardia, and hypertension on certified validation datasets, with results reported only when model confidence exceeds 90%.
2. The system must consistently reproduce the same classification result (arrhythmia, hypertension, or sinus bradycardia) in five consecutive trials on the same subject, demonstrating repeatability and reliability of the screening process.
3. The device must capture ECG- and PPG-derived heart rate values that agree within ±5 beats per minute in at least 80% of measurement windows, ensuring physiological accuracy sufficient for reliable screening.

2. Design

2.1 Block Diagram



2.2 System 1: Data Acquisition System (DAS)

The DAS captures ECG, PPG, and motion signals from the sensor pad and streams them to the host PC for analysis. It integrates the analog AD8232 ECG sensor, MAX30102 PPG sensor, and LIS3DH accelerometer, all managed by the ATmega328P microcontroller. The microcontroller samples the sensors, converts analog ECG to digital, packages the data, and transfers it over USB through a CH340G bridge to the host PC. This system is the hardware foundation of the entire pipeline and directly connects to the disease detection system.

2.2.1 Subsystem 1: Sensing

Overview: This block will have the analog ECG sensor (AD8232), the PPG module (MAX30102), and the 3-axis accelerometer (LIS3DH). The ECG outputs a formatted analog waveform to the ATmega's ADC; the PPG and accelerometer communicate over

I²C, and all three feed into the microcontroller for synced acquisition & streaming to the host.

Requirements: The subsystem must deliver ECG suitable for 250–500 Hz sampling without clipping or baseline saturation, provide PPG frames at 100–200 Hz with LED currents set to avoid photodiode saturation, and supply accelerometer samples at 100 Hz for motion gating. Interfaces must meet I²C timing, and the ECG analog output must remain within the MCU ADC input range with ≥9 ENOB preserved.

2.2.2 Subsystem 2: Microcontroller (ATmega328P)

Overview: The MCU schedules sampling, performs preprocessing (removal/scaling), timestamps all streams with a shared timer, applies band-pass filters to de-noise data, and prepares packetized data streams for output over UART.

Requirements: The MCU must maintain ECG readings at 250–500 Hz, PPG at 100–200 Hz, and accelerometer data at 100 Hz with inter-sensor skew kept to a few milliseconds. Besides these rates, it must align samples with a shared timer, attach sequence numbers over USB so that the data arrives in near real-time. The ADC chain must also keep at least eight bits of res on ECG without clipping, and the firmware must recover automatically from sensor disconnects or pad to prevent data loss.

2.2.3 Subsystem 3: Communication

Overview: This block bridges the MCU UART to the host over USB and shares the same connector that powers the board. It carries newline-delimited CSV records and simple status messages to the laptop. In addition, the same USB connector provides the VBUS 5V line, which is connected to the Power Subsystem to generate the board's supply rails.

Requirements: The USB link must run at ≥ 230,400 bps (preferably 460,800 bps) to send ~22-6 kB/s of CSV data without buffer overflow, and deliver data within 150 ms of being generated. Also, the VBUS 5V supply must remain stable during USB enumeration, so the board doesn't reset when the CH340G connects.

2.2.4 Subsystem 4: Power

Overview: A single laptop USB port powers the DAS and provides data. The 5 V input passes ESD, then generates 3.3 V for the MCU/ECG/ACC, 1.8 V for the MAX30102 logic, and a switched 5 V “VLED” rail for PPG LED drivers, with grounding to keep LED return currents away from the ECG analog sensor.

Requirements: The subsystem must continuously supply at least 500 mA at 5 V ±0.1 V to the board, keep 3.3 V and 1.8 V, and keep ripple on the ECG analog rail under 1 mV.

2.2.5 Tolerance Analysis:

The main risk is keeping the ECG signal clean while the PPG LEDs pulse and the user moves. The AD8232 produces about 1 Vpp into the ATmega328P’s 10-bit ADC, so noise must stay under 1 mV RMS. The MAX30102 can draw up to 50 mA LED pulses, which may cause ground bounce. By isolating the LED, adding bulk and and tying grounds at a single point, the ripple should stay within a normal range even at high LED duty cycles so the ECG channel keeps its quality.

ECG Path (AD8232): Output swing 0.1–3.2 V @ VS=3.3 V; mapped to ~1.0 Vpp at the ATmega328P 10-bit ADC ≈ 310 LSB per QRS. Noise must stay <1 mV RMS to preserve R-peak & PTT.

PPG Path (MAX30102): LED pulses up to 50 mA on 3.1–5.0 V VLED rail; logic 1.7–2.0 V. Using star-grounding and dedicated LED return limits ground bounce to ≈ 0.5 mV ($V=L\Delta I/\Delta t$, L=10 nH, ΔI=50 mA, Δt=1 μs).

VLED Containment: A 47 μF bulk + 0.1 μF local cap per LED limits VLED drop to ~5 mV during 50 μs pulses, separate from the 3.3 V ECG rail.

Feasibility: Even under the worst-case LED duty cycle and motion, ripple on the ECG analog rail remains <1 mV, so the ADC is stable and should meet pipeline targets.

2.3 System 2: Disease Detection System

The Disease Detection System is responsible for processing the incoming physiological data, extracting features, and running machine learning (ML) models to classify cardiovascular risk factors. It comprises two main subsystems: ML & Data Processing and the User Interface.

2.3.1 Subsystem 1: ML & Data Processing

Overview: The ML & Data Processing subsystem runs on the host PC and is responsible for ingesting the ECG, PPG, and accelerometer data streamed from the Data Acquisition System. It filters and synchronizes signals, extracts clinically relevant features such as heart rate variability (HRV), RR intervals, pulse transit time (PTT), and PPG morphology, and then applies machine learning models to classify arrhythmia, hypertension, and sinus bradycardia. This subsystem connects directly with the communication link from the microcontroller and provides structured JSON outputs to the User Interface subsystem for visualization.

Requirements:

- Arrhythmia and hypertension model classifiers must achieve ≥ 90% confidence before reporting results, and must achieve ≥ 90% accuracy on certified validation datasets
- Sinus bradycardia detection must correctly flag mean heart rates <60 bpm with accuracy ≥95% across at least 80% of test windows.
- JSON outputs for the User Interface subsystem must include 3 subfields, one for each disease including: condition labels, confidence scores, and timestamps each, and explanation of methods

2.3.2 Subsystem 2: User Interface

Overview: The User Interface subsystem provides the end user with a clear, real-time display of the screening results. Hosted on a laptop dashboard, it visualizes whether arrhythmia, hypertension, or sinus bradycardia has been detected, along with confidence scores, disclaimers, and explanations of methods for how results were achieved. It receives structured JSON messages from the ML & Data Processing subsystem and translates them into human-readable outputs.

Requirements:

- From ML JSON output receipt to on-screen update ≤500 ms for labels, metrics, and explanations
- UI must suppress disease labels unless reported confidence ≥90% and display “insufficient confidence” otherwise.
- For data privacy purposes, UI must store data locally only and all session data must be cleared from RAM either when a new ML output receipt is received or within 3 seconds of session end.

2.3.3 Tolerance Analysis

The main tolerance risk in the disease detection system is timing skew between ECG and PPG when calculating pulse transit time (PTT) for hypertension detection. At a nominal PTT of 200 ms, a 10 ms skew represents a 5% error. Literature shows Systolic Blood Pressure (SBP) estimates vary about 20–30 mmHg per log change in PTT, so this worst-case skew corresponds to only ~1–1.5 mmHg error—well below clinical thresholds such as the 10 mmHg increments used for diagnosis.

Our design mitigates this further by sampling ECG at 250 Hz (4 ms resolution) and PPG at 100 Hz (10 ms resolution). With interpolation and shared-timer synchronization, the effective skew drops to ~5 ms, reducing the expected error to <1 mmHg. This demonstrates mathematically that even under worst-case timing misalignment, the hypertension detector remains accurate and feasible.

3. Ethics and Safety

3.1. Ethics

Our project raises important ethical considerations as outlined by the IEEE and ACM Codes of Ethics, which emphasize honesty, safety, and fairness. Since the device is a *screening tool* rather than a diagnostic medical device, it is very crucial to communicate this distinction clearly to avoid misleading users. To reduce potential harm, the interface will display results as indicators with confidence levels and include disclaimers encouraging follow-up with medical professionals. Additionally, user privacy will be protected by limiting data storage to publicly available datasets.

3.2. Safety

From a safety perspective, the device presents minimal direct physical risks, as it operates at low voltage (<5V) and uses non-invasive sensors such as electrodes for ECGs and PPGs. However, there are indirect risks if results are misinterpreted. False negatives could lead to delayed care, while false positives could cause unnecessary anxiety. We will mitigate this through careful algorithm validation using certified datasets (e.g., MIT-BIH, PPG-DaLiA), consistency testing using the mentioned datasets, and clear transparency and honesty regarding system limitations. Having clear usage instructions, particularly for ECG electrode placement, will help further reduce the chances of accidental misuse.

4. References

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