# Edge-Based Anomaly Detection and SMS Alerting in a Low-Cost Wearable Health Monitor for Rural Communities

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# Statement of the Problem

## Failures of Existing Solutions

01

### Latency & Reliability

Cloud-centric systems depend on uninterrupted connectivity **(Rancea et al., 2024).**

02

### Hardware Constraints

Heavyweight deep learning models consume gigabytes of memory and power rendering them unfit for embedded platforms **(Aung et al., 2024).**

03

### Harsh Environments

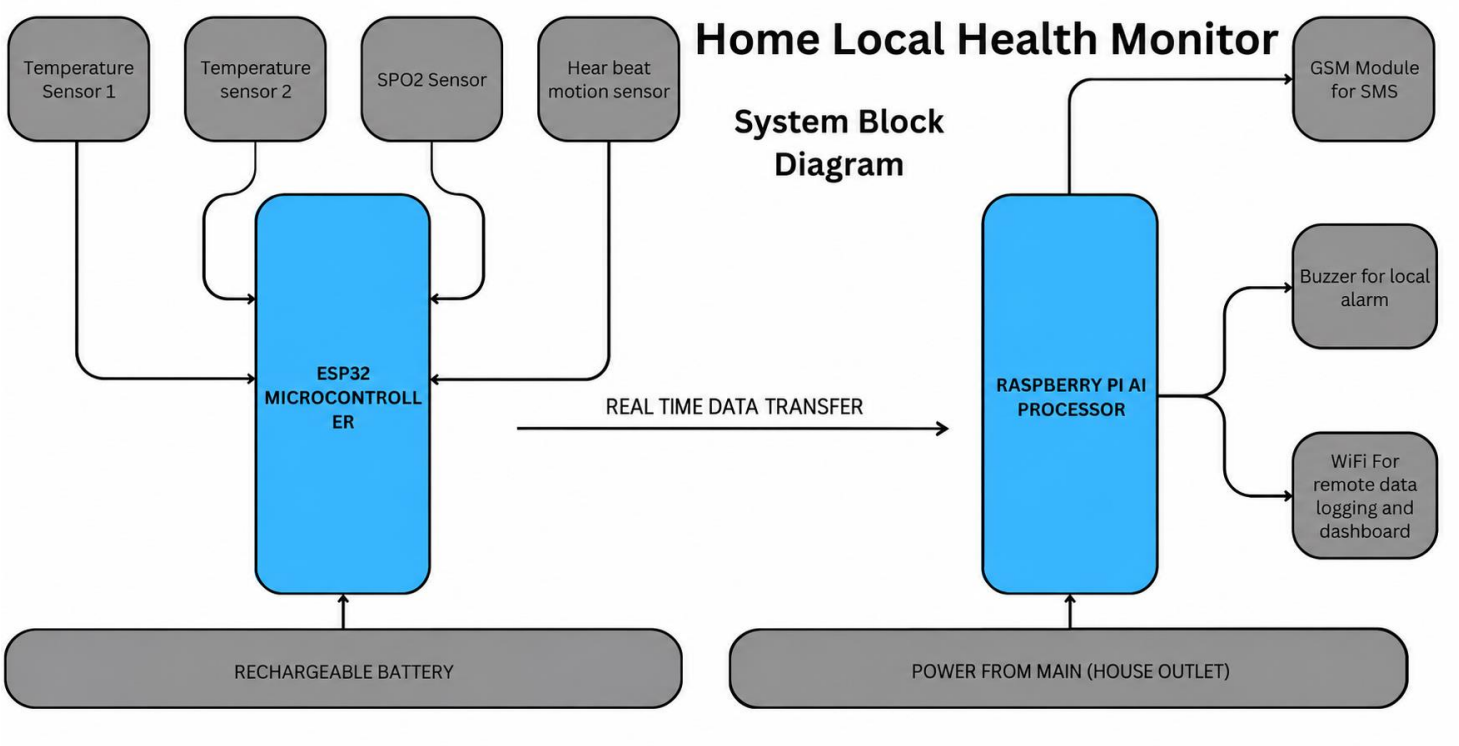
Laboratory-trained models fail in rural contexts due to temperature extremes, dust and motion artifacts **(Zhang et al., 2024).**

04

### Power Inefficiency & Short Device Lifetime

Existing wearables exhaust batteries within hours under continuous sensing and inference making it unsustainable **(Khosh manesh et al., 2021).**

# System Architecture



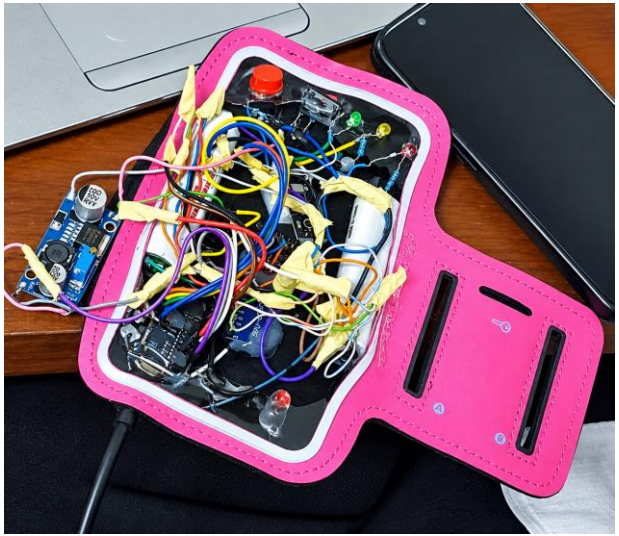

As built: the local Wi-Fi the wearable joins is published by a handset, not by the gateway (a three-device arrangement, not two).

# Designed, built, validated

| Stage | Designed | Built | Validated | Evidence here |
|---|---|---|---|---|
| PPG beat detection → heart rate | ✓ | ✓ | ✓ | vs ECG reference, MAE 1.81 bpm |
| Ratio-of-ratios $SpO_2$ | ✓ | ✓ | ✗ | Uncalibrated, serves as an optical proxy |
| Butterworth 8 Hz + NLMS filter | ✓ | ✗ | ✗ | Not in the firmware |
| Welford detector (wearable) | ✓ | ✓ | ✗ | Scored on device, not evaluated |
| Quantised autoencoder (gateway) | ✓ | ✓ | ✓ | Both corpora |
| Store-and-forward GSM queue | ✓ | ✓ | part | 10 trials, 1 simulated outage |
| Deep-sleep duty cycling | ✓ | ✗ | ✗ | 3 h measured vs 2-day target |
| Gateway hosts the local Wi-Fi | ✓ | ✗ | n/a | A handset supplied it |

WHAT WAS BUILT

# The wearable node



Four sensors on one shared $I^2C$ bus: **MAX30102** (PPG → heart rate and an uncalibrated $SpO_2$ proxy), **AHT25** (temperature), **MPU-6050** (3-axis motion).

- Built on an **ESP32-S3** Super Mini, powered by 2× parallel **18650 Li-ion cells (3000 mAh)** with a **TP4056 BMS**.
- **In the build:** Runs a statistical Welford's algorithm to score personalized z-scores.
- Flags anomalies with reason codes (e.g. **spo2_drop**), sounds a buzzer, and streams a feature packet to the gateway every **3 seconds** over local Wi-Fi.

DETECTION · TIER 1

# On the body: a personal statistical detector

- **Personal Baseline:** Continuously learns each wearer's own normal vitals (via Welford's running statistics)

- **Clinically Weighted Score:** Prioritizes vital signs in order of clinical urgency: blood oxygen (**0.45**), heart rate (**0.35**), temperature (**15%**), and motion (**0.05**).

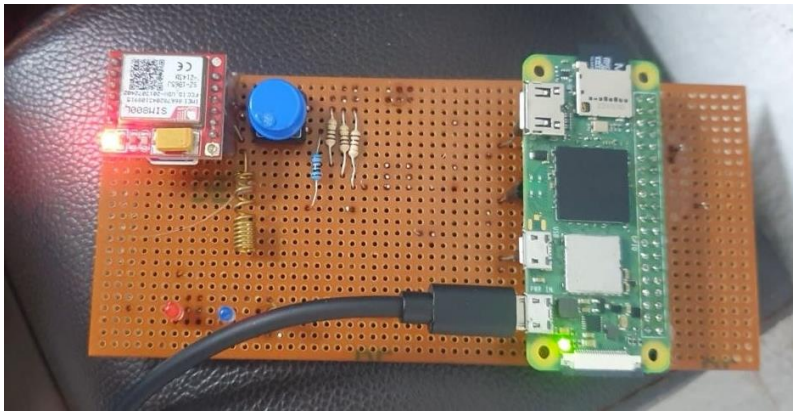
- Accounts for physical movement so a faster heartbeat during activity won't trigger a false alarm, while any blood oxygen level below 90% triggers an immediate emergency alert **(directional $SpO_2$ weighting**)

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- Statistical, therefore requires no neural network runtime on the node for real time anomaly detection.

WHAT WAS BUILT

# The Home Gateway



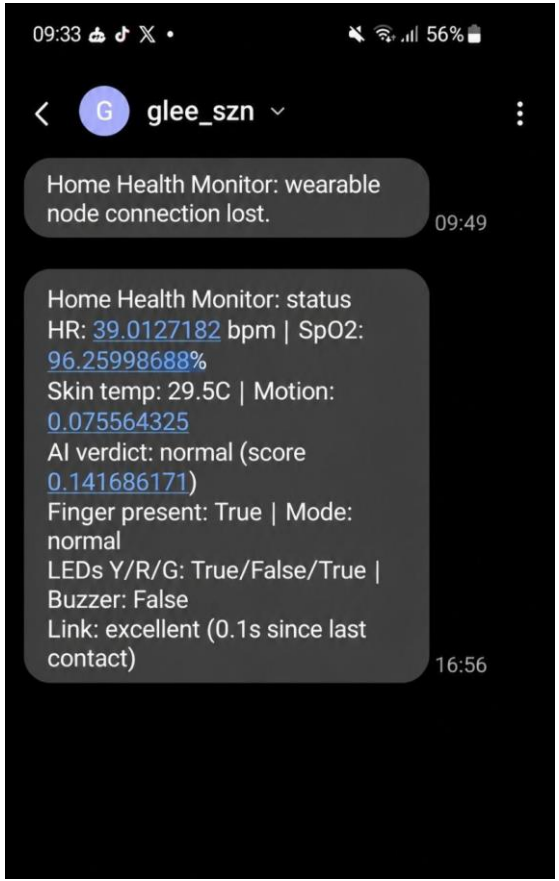
- Built on a **Raspberry Pi Zero 2W**, interfaced over UART to a **SIM800L 2G GSM module** for SMS dispatch.
- Discards readings below a **0.80** quality score via binary masks, compressing valid packets into 5-minute bins across a **24-hour rolling 288 × 16 tensor**.
- Runs a compressed **18 KiB int8 autoencoder** over that tensor every 15 minutes, catching gradual drift by reconstruction error.
- Receives wearable data over local Wi-Fi with no internet required, logs 12 months of history in SQLite, and serves a live caregiver dashboard.
- Uses a logical OR rule converting the anomaly score to a binary decision.

$$D_t^{GW} = \begin{cases} 1, & A_t^{GW} > \theta_{GW} \\ 0, & A_t^{GW} \leq \theta_{GW} \end{cases}$$

ALERTING

# GSM Machine

- Routine status message/ping, so the verdict reads normal because nothing was wrong.
- When the wearable drops off the local network the gateway sends a “connection lost” sms
- **Outages are survivable.** Undelivered alerts sit in a store-and-forward queue on the gateway and are re-sent once the network returns.
- **Delivery is measured, not assumed.** Ten end-to-end trials: mean 29 s against a 30 s goal, slowest 48 s. The 95% interval runs 22 to 35 s



# Dataset, Composition & Training

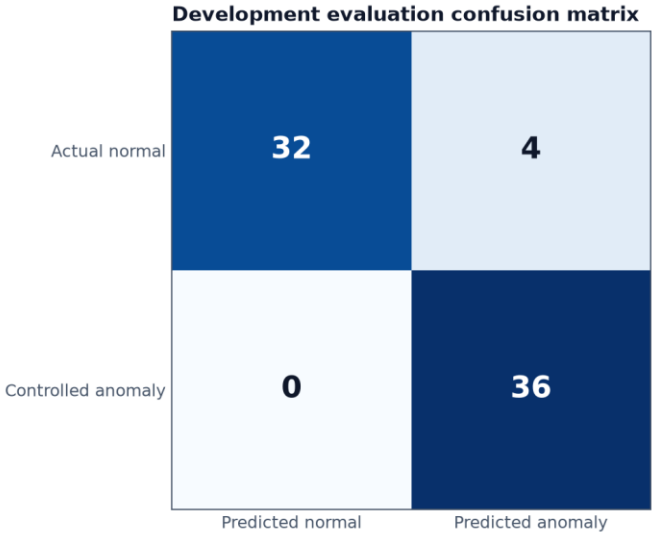
## DEVELOPMENT CORPUS (PROVENANCE)

- 612 raw rows in the supplied home-monitoring CSV
- 36 structurally distinct rows; **11 of them labelled Normal**
- Those 11 rows set the range and covariance of a deterministic generator
- 60 virtual subjects × 4 × 24-h windows = 240 windows
- 42 / 9 / 9 subjects, split at subject level **(train / validation / test subjects).**
- 168 / 36 / 36 corresponding windows

## WHAT IT DOES & DOES NOT PROVE

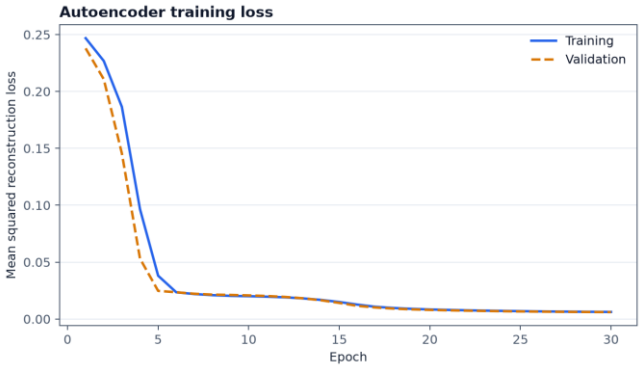
- **Proves:** the (training → quantisation → deployment) path works end to end.
- **Proves nothing about physiology.** You cannot train a field model on eleven rows.
- Tagged **development-only** in the repository, so it cannot later be mistaken for a field model.
- Every detection figure on the next slide inherits this limit.
- **Training setup:** $\theta_GW$ 0.01429 (P99 of validation error). Adam, lr $1\times10^{-3}$, batch 16, 30 epochs, seed 42.

# Detection Performance



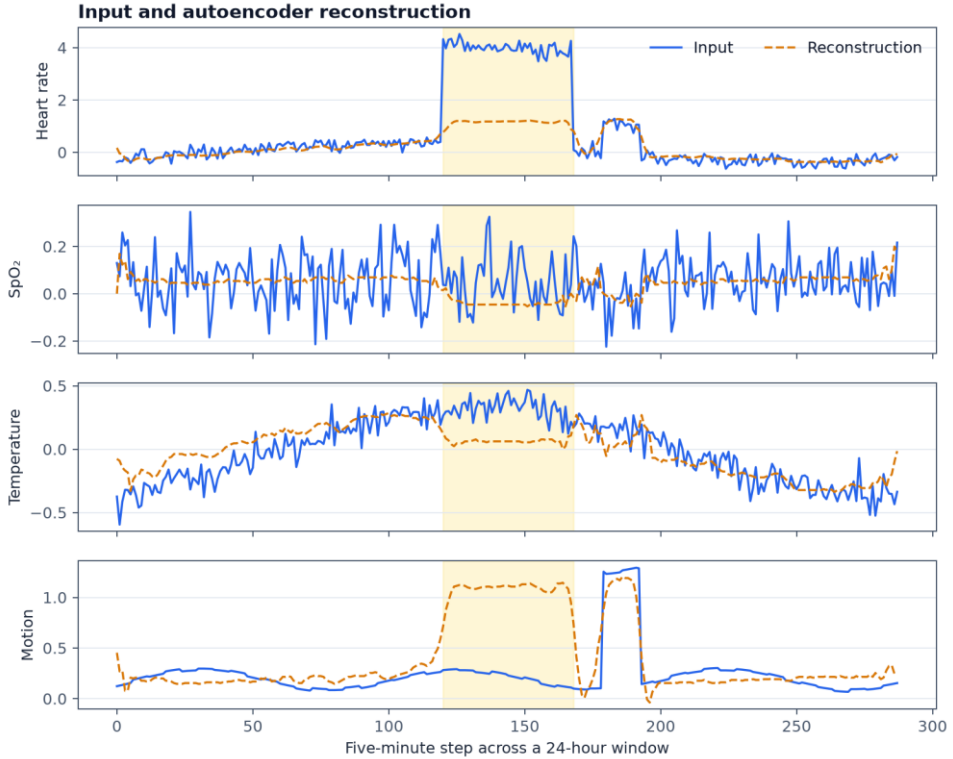

- Accuracy **94.44%** (95% Wilson Interval 86.57 – 97.82)
- Recall **100%** (90.36 – 100) Not a clinical miss rate.
- Specificity **88.89%** (74.68 – 95.59)
- Precision **90.00%** (76.95 – 96.04)
- F1 **94.74%**
- **72 windows.** The 36 anomaly windows are scripted perturbations of the 36 held-out normal windows, from the same generator. **They are anomaly-like deviations, not diagnosed clinical events.**

# Training Behaviour & Reconstruction Fidelity




**Training / validation loss curve**

- Loss: **0.24 to 0.006** across 30 epochs (seed 42)
- Validation tracks training with no divergence

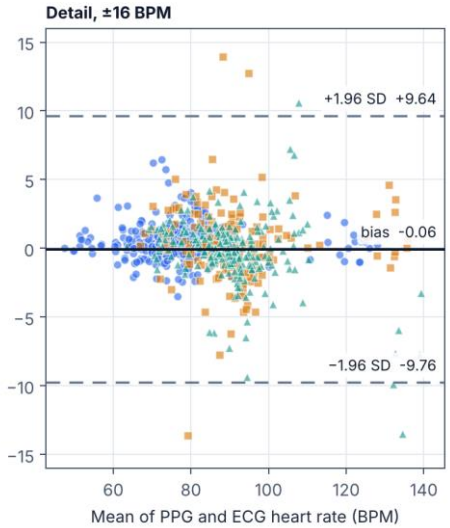


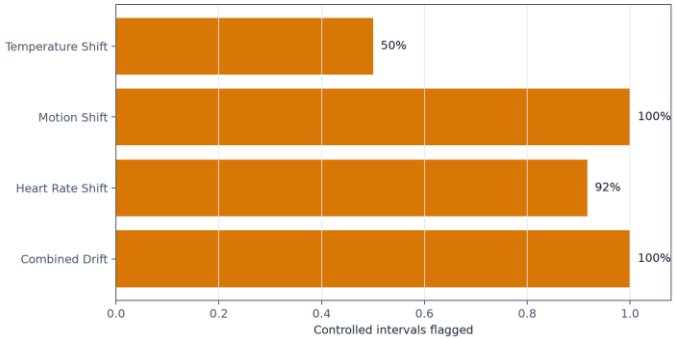

**Input vs reconstruction on a normal 24-hour window,**

# Real Corpus Validation (22 Adults, 66 Recordings)

**Pulse Transit Time PPG corpus: 22 adults, 66 recordings, simultaneous PPG and ECG under structured activity.**

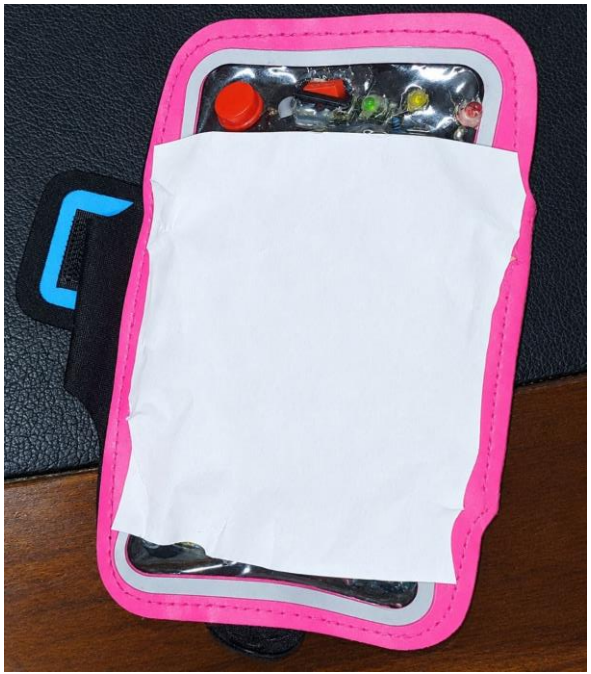
- Evaluated a **4.2 KiB int8 model** on **66 paired PPG/ECG recordings from 22 adults**, keeping 4 participants completely locked out for unbiased testing.
- Virtually zero average error (**-0.06 bpm bias**), staying within **±6 bpm while sitting** but widening to **±16 bpm while walking** (due to the unbuilt NLMS motion filter)




Triggered **0 false alarms on 12 healthy test intervals** catching **100%** of combined drift and motion shifts, **92%** of heart-rate shifts, and **50%** of temperature shifts..

# Device-level performance



## Power & Battery Runtime:

Draws **1.0 A continuously** at 3.3 V, yielding **3.0 hours** of runtime (2.1 hours derated) compared to the **2-day** design target.

Driven by two firmware gaps: no deep-sleep mode and energy aware duty cycling

## SMS Alert delivery

Averaged **28.7 seconds** across 10 end-to-end trials (median 26.1 s, range 16.3–48.3 s), right around the **30-second** design goal (95% CI: 22.4–35.0 s).

Tested on a single cellular network in urban Lagos.

# How far this is from deployable

LIMITATIONS & FUTURE WORK

- **Accuracy criterion not met.** Design target >95%; measured 94.44 and the model has not yet been tested on real, clinically diagnosed patient deterioration.
- **The oxygen channel is uncalibrated** and carries the heaviest weight in the composite score requiring a paired calibration study against a medical-grade pulse oximeter.
- **Power:** 3 hours device lifetime. Needs firmware updates to enable deep-sleep mode and lower active power consumption.
- **The 72-hour field-like run** was configured and never executed and no measurements were taken in rural “field like” settings
- **Completing the Signal-Conditioning Chain** by implementing a Butterworth low-pass and the NLMS adaptive filter to cancel motion artifact at its source rather than adjusting for it later

# Questions

Thank You.
Questions & Discussion

# Aim & Objectives of the Study

**AIM: To develop and evaluate a low-cost wearable and home-based health monitoring system that uses lightweight AI for real-time anomaly detection and GSM emergency alerting in rural communities.**

1. Conduct a comprehensive state-of-the-art review on TinyML, GSM telehealth and rural monitoring.
2. Design and prototype a cost-effective wearable system integrating PPG/$SpO_2$, temperature, and motion sensors with low-power microcontrollers.
3. Develop lightweight on-device AI for real-time anomaly detection using TinyML and robust signal processing methods
4. Implement a resilient GSM/SMS emergency alerting pipeline with store-and-forward logic
5. Experimentally evaluate detection accuracy, alert latency, power consumption & reliability under bench and field-like conditions.

# Mathematical Models I : Signal Acquisition, Processing, Inference, Compression

- Raw signals contain noise from motion and sensor drift.

$$x(t) = s(t) + n(t)$$

- NLMS adaptive filtering is **specified** to suppress motion artifacts; the evaluated build discounts heart rate by measured motion instead.

$$e(n) = d(n) - \mathbf{w}^{\top}(n)\mathbf{x}(n)$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \frac{\mu}{\varepsilon + \mathbf{x}^{\top}(n)\mathbf{x}(n)} \cdot e(n) \cdot \mathbf{x}(n)$$

- SpO2 is estimated via the ratio-of-ratios method.

$$R = \frac{AC_{\text{red}}/DC_{\text{red}}}{AC_{\text{ir}}/DC_{\text{ir}}} \quad ; \quad SpO_2 = a - bR$$

- Heart rate is derived from the average inter beat interval.

$$HR_t = \frac{60}{IBI}$$

- A threshold rule **(Gateway)** converts the anomaly score into a binary decision. Overall system decision follows a **logic OR rule**

$$D_t^{GW} = \begin{cases} 1, & A_t^{GW} > \theta_{GW} \\ 0, & A_t^{GW} \leq \theta_{GW} \end{cases}$$

$$D_t = D_t^{W} \vee D_t^{GW} \vee D_t^{PB} \vee D_t^{SQ}$$

- Post-training quantisation reduces memory and compute cost.

$$q = \text{round}\left(\frac{W}{S}\right) + Z$$

# Recommendations

- **Integrate into CHW Workflows:** Embed this technology directly into Community Health Worker programs, linking the SMS alerting subsystem to localized triage protocols for pre-emptive intervention
- **Hardware Iteration for Manufacturing:** Transition the prototype from project boards to flexible printed circuits and moulded Li-Po packs to maximize comfort for elderly demographics.
- **Decentralized Telehealth Policy:** LMIC health ministries must invest in edge-based, GSM-reliant monitoring systems immediately rather than waiting years for universal broadband coverage.

# Future Work

- AES Encryption for Data Security, Adaptive personalized baseline learning, hybrid communication fallbacks as 2G GSM Networks are phased out over time