Heart Rate Prediction from Running Activity

Deep Learning Course Project - CentraleSupélec

From Challenging Public Data to Custom Solutions

Problem Statement

Goal: Predict heart rate time-series from running activity data

Inputs:

- Speed sequences (m/s)
- Altitude sequences (meters)
- User metadata (gender, userId)

Output: Heart rate predictions (BPM) over time

Target Performance: MAE < 10 BPM

Why? Health monitoring, fitness tracking, validate wearable sensors

Dataset: Endomondo Challenge

Initial Dataset: FitRec (Endomondo)

- Total available: 260,000 workouts with HR data

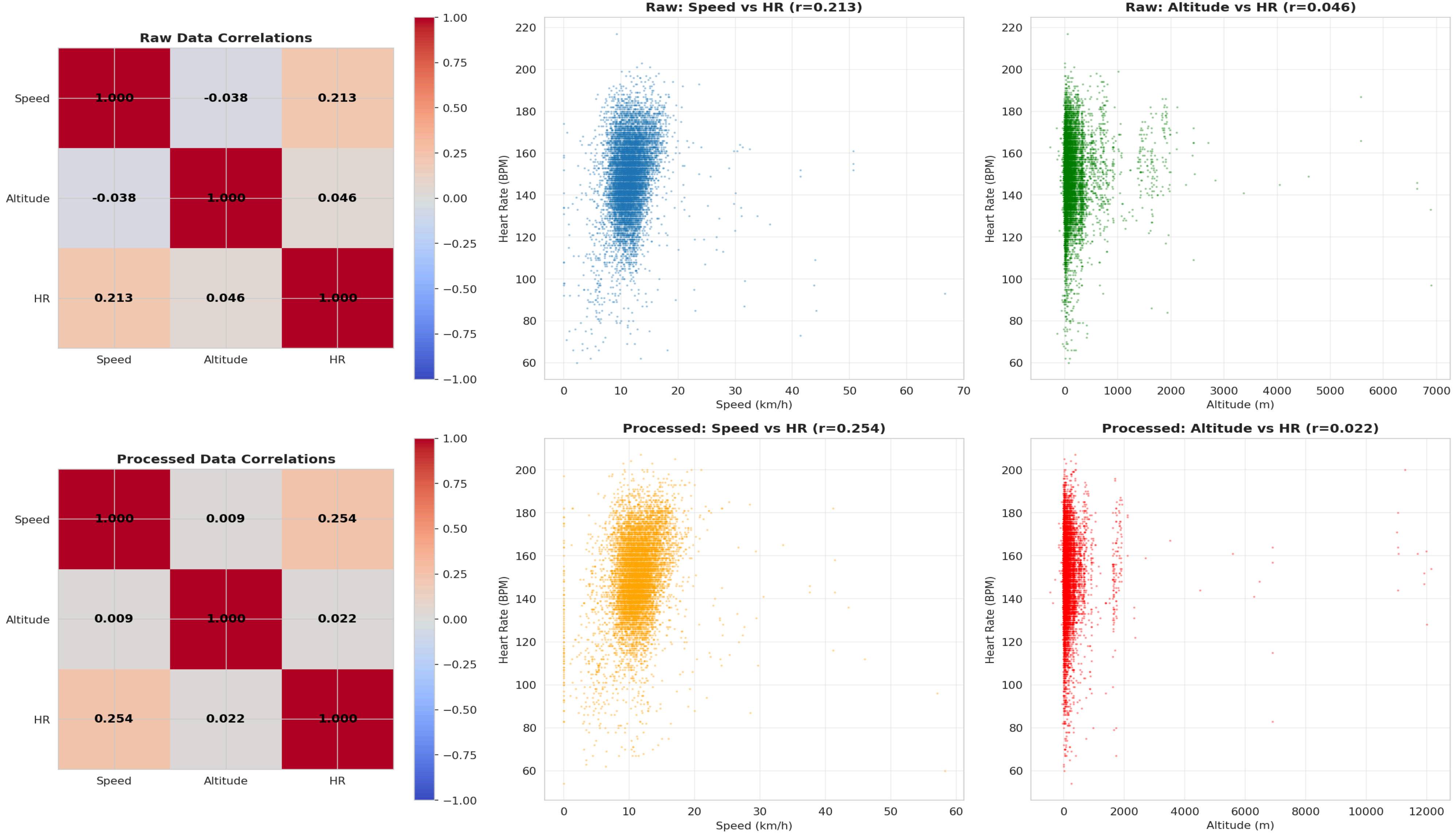
Major Problem: Data Quality

- Applied 7 quality filters (valid sport, complete HR, GPS quality, etc.)
- **Result: Only 13,000 usable workouts (5% of total!)**

Key Finding: Low Correlation

- **Correlation Problem**

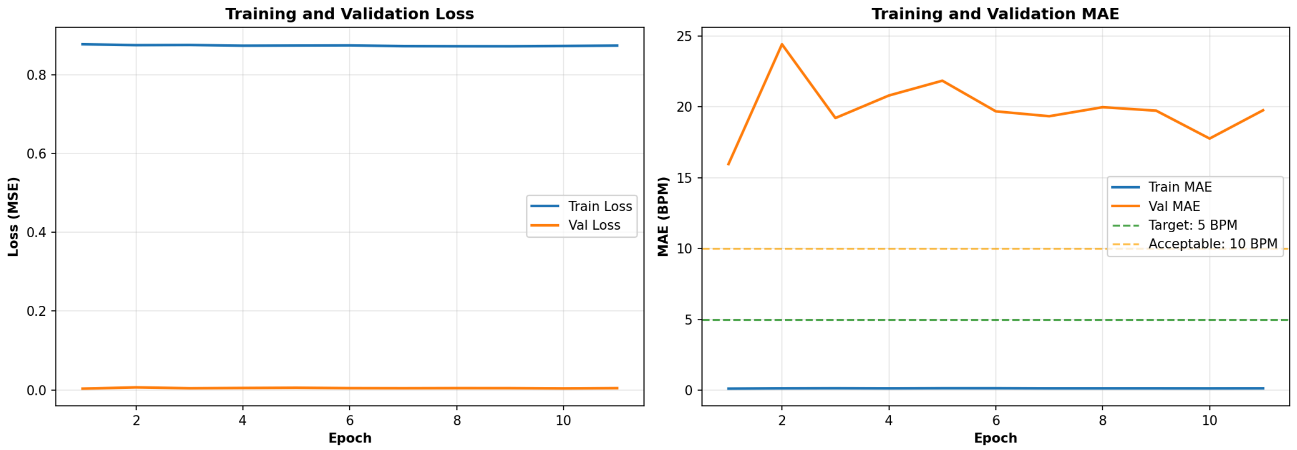
RAW vs PROCESSED DATA CORRELATION COMPARISON



First Models: LSTM and GRU

Strategy: Max out VRAM for fast training

- Basic LSTM: Batch size 128, 2 layers, 64 hidden units
- Result: MAE ~15 BPM



Also tried GRU: Similar performance (~15 BPM)

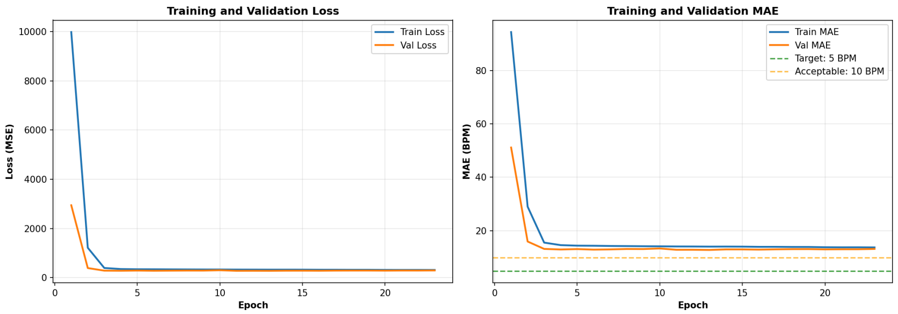
Conclusion: Architecture wasn't the problem, data quality was!

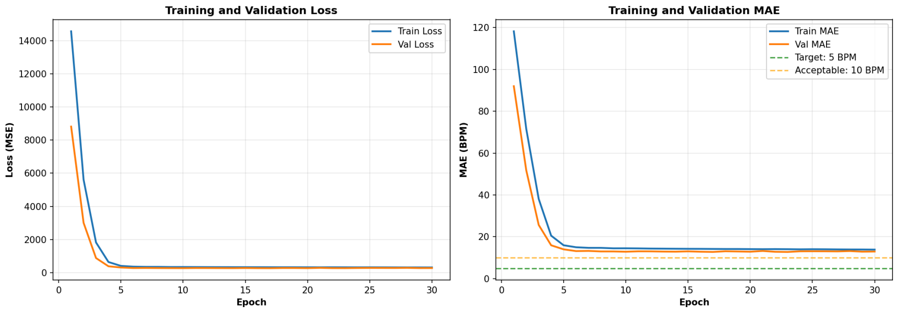
Batch Size Experiment

Hypothesis: Smaller batches might help with noisy data

Experiment: Tested batch sizes 8, 16, 32, 64

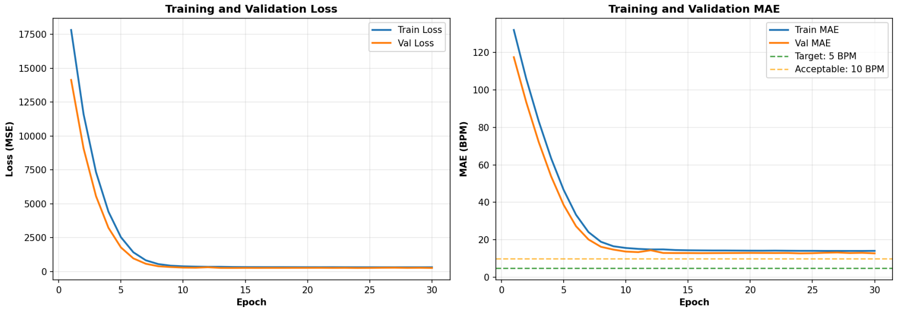
- Same architecture (LSTM, 64 hidden, 2 layers)
- Same learning rate (0.001), 30 epochs each

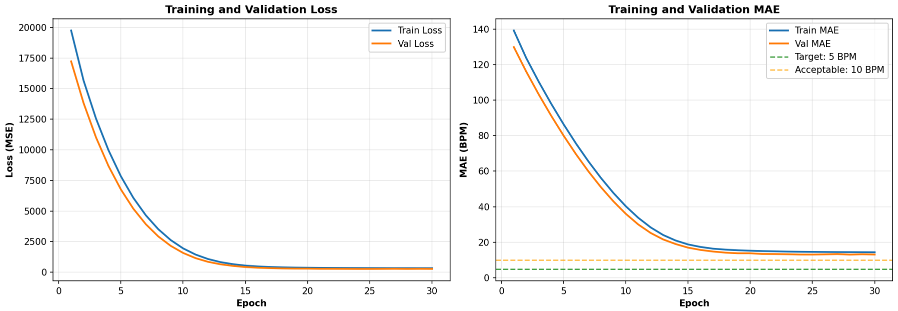




BS=8: Noisy | **BS=16: BEST (but slowest)**

Batch Size Results





BS=32: Slightly worse | **BS=64: Fast but generalizes poorly**

Key Finding: BS=16 optimal - we chose quality over speed

Also tried: Lag-Llama transfer learning (didn't help much with low correlations)

The Breakthrough: Apple Watch Data

New Approach: Collect our own high-quality data!

Custom Dataset:

- 285 running workouts from us and friends (2019-2025)
- 6 years of training history
- Apple Watch sensors (consistent, high quality)

Quality Comparison:

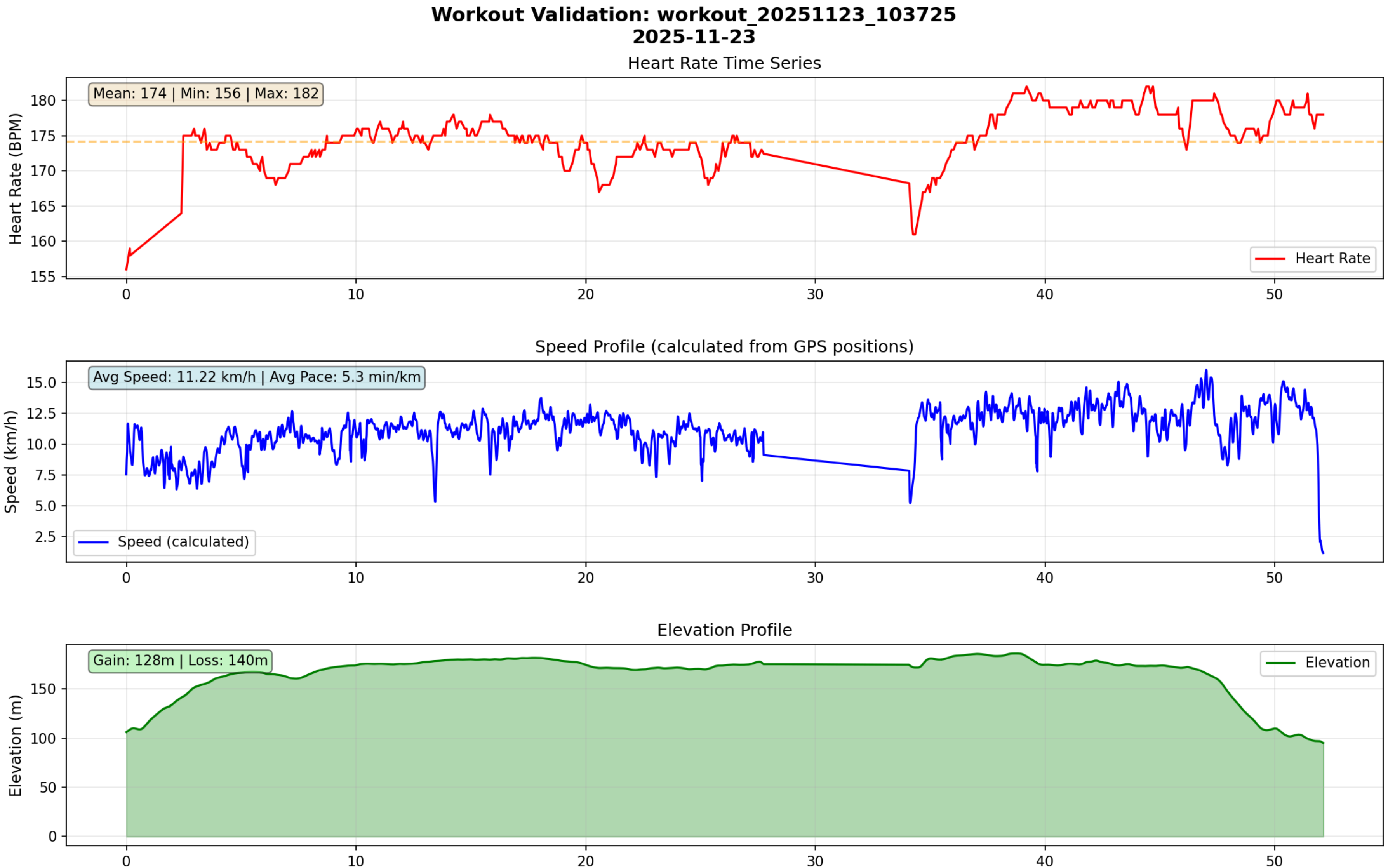
- **Endomondo:** r ≈ 0.3 (weak)
- **Apple Watch:** r ≈ 0.68 (strong!)

Data Evolution: 17x more HR samples in 2025 vs 2019

- 2019: 0.7 HR samples/min (sparse)
- 2025: 12 HR samples/min (rich detail)

Apple Watch Data Quality

2025 Workout: High Quality (12 HR samples/min)



Next Steps: Fine-Tuning Strategy

Proposed Two-Stage Training:

Stage 1: Pre-train on Endomondo

- Learn general speed-to-HR patterns from 13K workouts
- Capture population-level relationships

Stage 2: Fine-tune on Apple Watch

- Adapt to individual physiology using 285 high-quality workouts
- Leverage strong correlations (r=0.68)

Expected Benefit: Best of both worlds

- General knowledge from diverse users
- Personalization from high-quality individual data
- Target: MAE < 10 BPM

Summary

Key Insights:

1. **Data Quality > Model Complexity** - 260K → 13K workouts (5% usable)
2. **Systematic Experiments** - Batch size search found BS=16 optimal
3. **Custom Data Collection** - Apple Watch: 17x better sampling, r=0.3 → 0.68
4. **Two-Stage Training** - Pre-train general + fine-tune personal

Contributions:

- Comprehensive data pipeline (Endomondo + Apple Watch)
- Systematic hyperparameter experiments
- Identified temporal distribution shift (2019 vs 2025 fitness evolution)

Questions?