FANNCortexM: An Open Source Toolkit for Deployment of Multi-layer Neural Networks on ARM Cortex-M Family Microcontrollers

Performance Analysis with Stress Detection

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IoT and Sensing Devices


Activity Trackers


Smartwatches

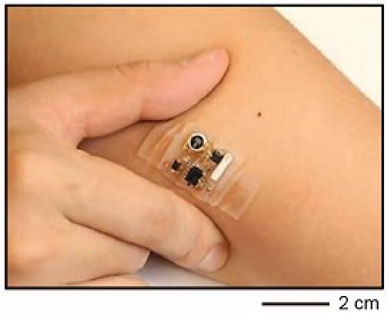

Smart eyewear


Smart footwear


Smart clothing


Motion capture clothing

Trend → Smaller, Smarter, Lifetime



Smart Patches


Skin patch sensors


Pressure sensor clothing


Healthcare

Wearable Device Limits and Challenges

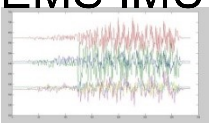
- Battery operated devices
  - Achieve long term monitoring
- Limited computational resources
  - Memory 1Mbyte range
  - Low power processing (i.e. Arm Cortex M4)
- On-board processing
  - Fast detection
  - No need for connectivity
  - Lower power consumption

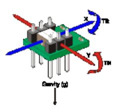
Source: planexta.com, artefactgroup.com, mimobaby.com

An IoT/Wearable System View

Sense

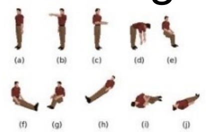
MEMS IMU



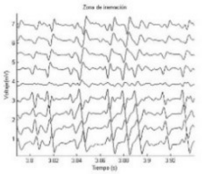


MEMS Microphone

ULP Imager



EMG/ECG/EIT



100 µW ÷ 2 mW

Analyze

Memory

e.g. Cortex-M

IOs

1 – 25 MOPS
1 – 10 mW

cm² Harvesting powered
→ mW (MaxP) + uW (AvgP)

Transmit

Short range, BW

Low rate (periodic) data

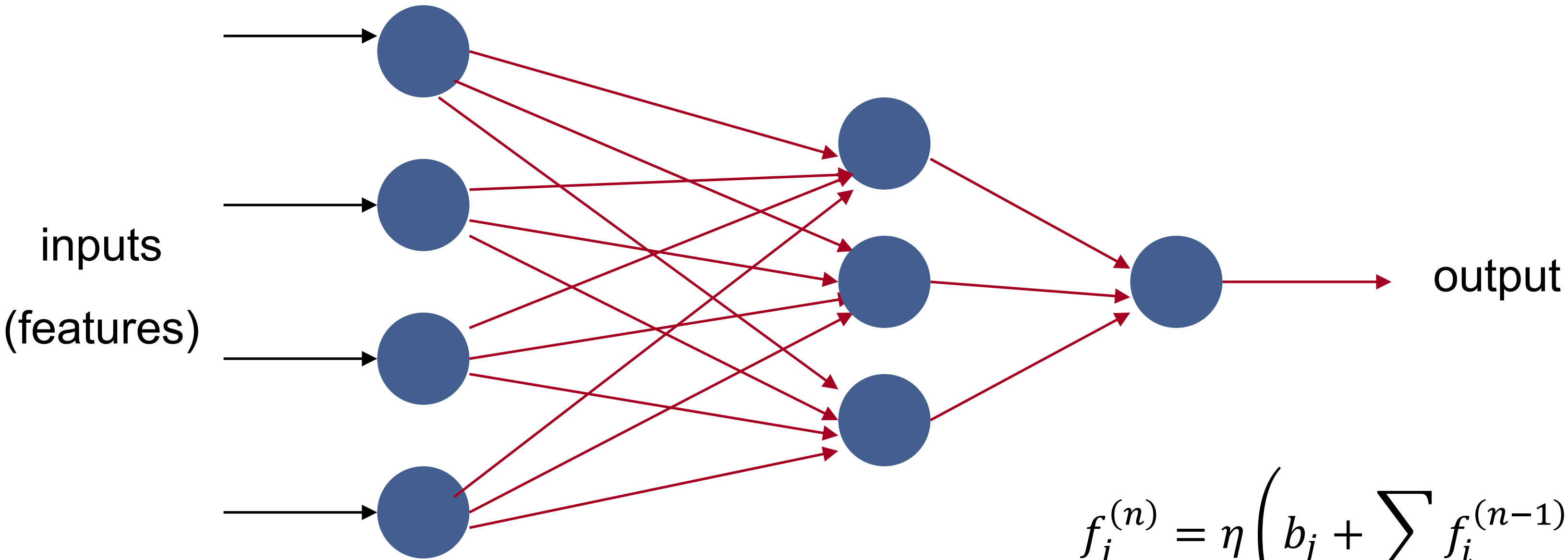
SW update, commands

Long range, low BW

LoRa SEMTECH

Idle: ~1µW
Active: ~ 10-100 mW

Artificial Neural Network



$$f_j^{(n)} = \eta\left(b_j + \sum_i f_i^{(n-1)} w_{j,i}^{(n)}\right)$$

classification

- marketing: consumer spending pattern
- defence: radar and sonar image analysis
- agriculture & fishing: fruit and catch grading
- medicine: ultrasound and ECG classification, EEGs, medical diagnosis

recognition and identification

- general computing and telecom: speech, vision and handwriting recognition
- finance: signature verification and bank note verification

Why now? – Platform and Data Availability

- Analysis in the cloud:
  - Energy hungry (data is local), privacy concerns, availability, cost
- Platforms are powerful enough

- sensor data + data analysis: use-cases
  - Fall detection for elderly
  - Health monitoring (livestock, pets)
  - Home security/control (motion detection, but not the cat)

- What is holding us back?
  - Cloud computing mindset
  - Complexity, availability of experts → simple tools needed!

Contributions

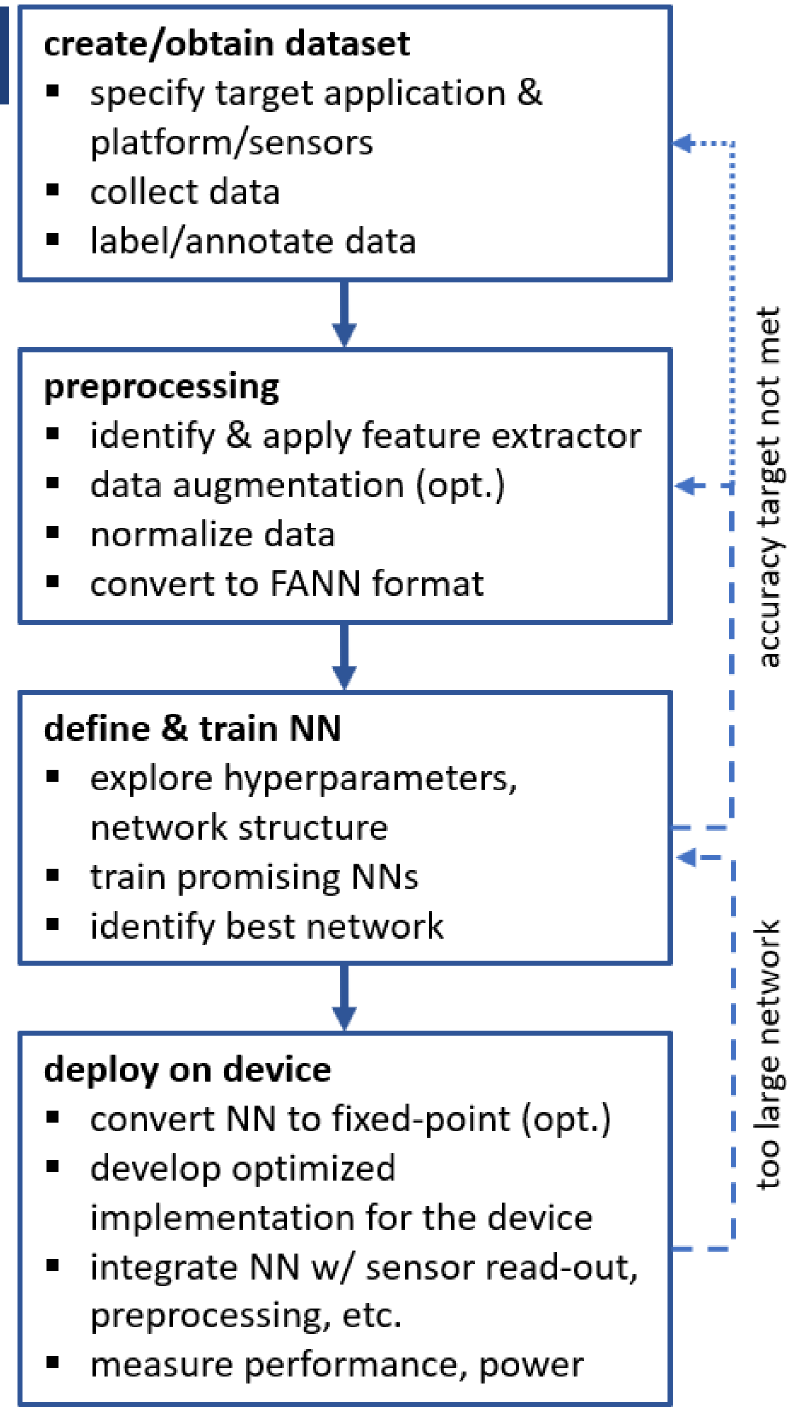
- Design of an optimized & easy-to-use framework for neural network inference on Cortex-M MCUs
  1. Acquire dataset
  2. Train NN with FANN [1] (easy: GUI, param search) – < 1h
  3. Deploy on MCU (w/o peripherals) – < 30 min.
- Evaluation with battery-operated low-power smart wearable device
  - Health monitor with the aim of emotion detection: ECG, Skin conductivity, temperature, IMU, microphone
  - Battery-powered, on-board processing, result communication
  - Performance, energy measurement on TI MSP432, Ambiq Apollo 2

[1] Nissen, S. (2003). Implementation of a fast artificial neural network library (fann). Technical Report.

Overview – Making It Easy

1. Creating dataset
   - Interface MCU to the sensors
   - Collect data samples & labels

2. Preprocessing/Augm.
   - Find good feature extractors (implementable on MCU)
   - (opt.) Data augmentation
   - Normalize data
   - Convert to FANN format (text file w/ input & output vals)

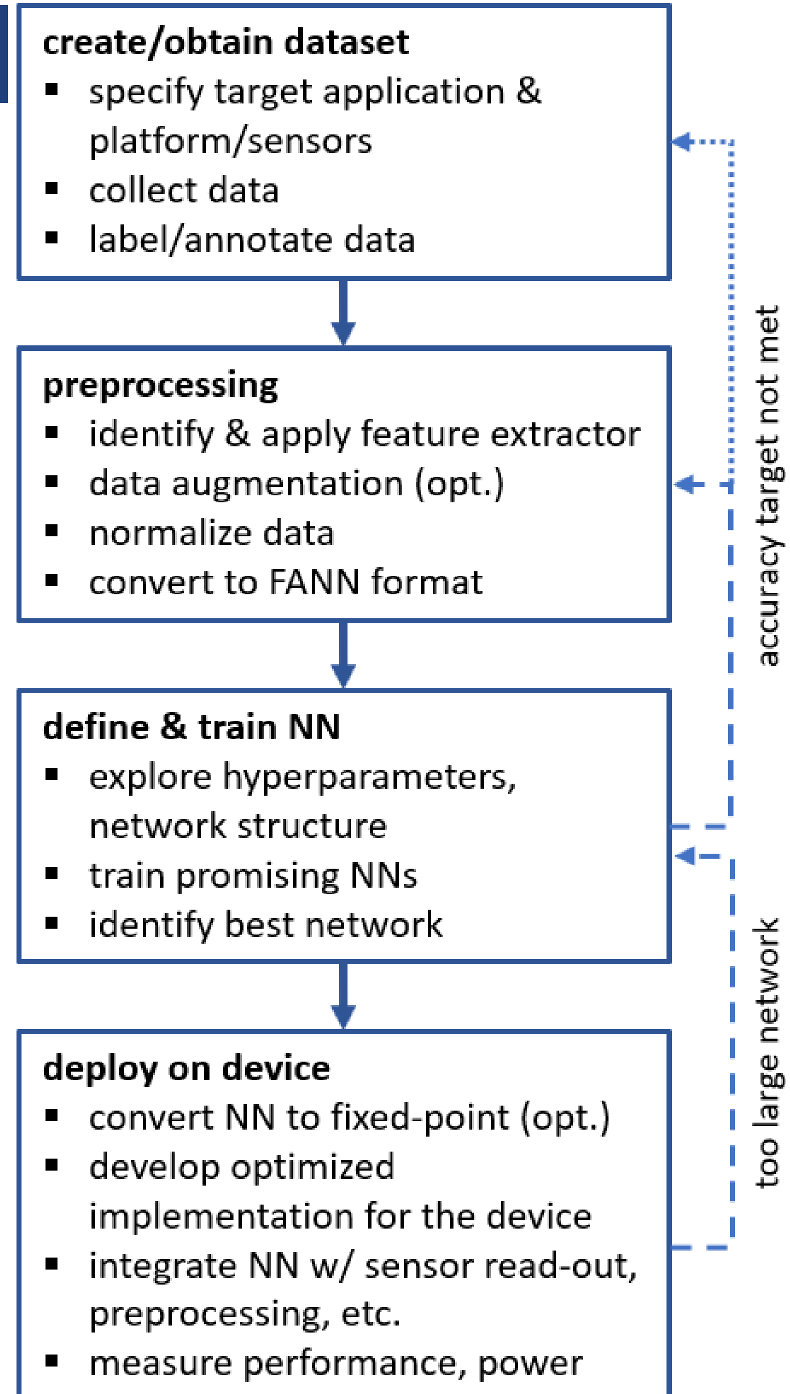


Overview – Making It Easy

3. Define & Train NN
   - Split dataset to train/val/test
   - Train NNs and adjust #layers, #hidden nodes, …
   - Select best network

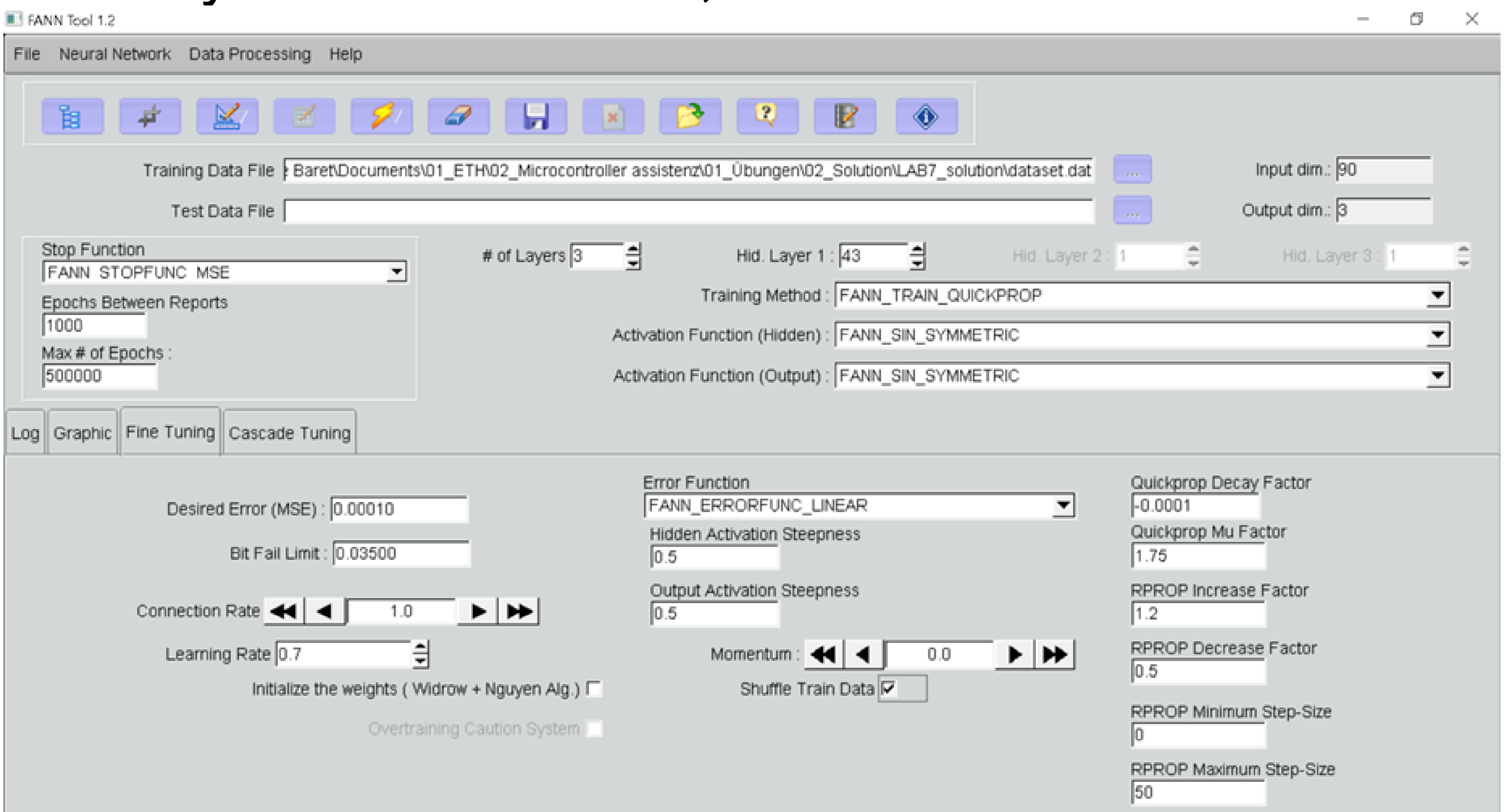
4. Deploy on Device
   - Run ‘generate.py’ to get ready-to-go C implementation

https://github.com/lukasc-ch/FANN-on-ARM



Fast Artificial Neural Network Library (FANN)

- Available in C, C++ PHP, Python, Delphi etc.
- Easy to learn and use; no GPU needed



FANN – Optimized Implementation for Cortex M

- 2x speed-up, smaller size (67 → 11 kB) v. non-opt. FANN
- Reduced code size
- Rely on CMSIS library for opt.
- Using FPU
- 50% energy savings

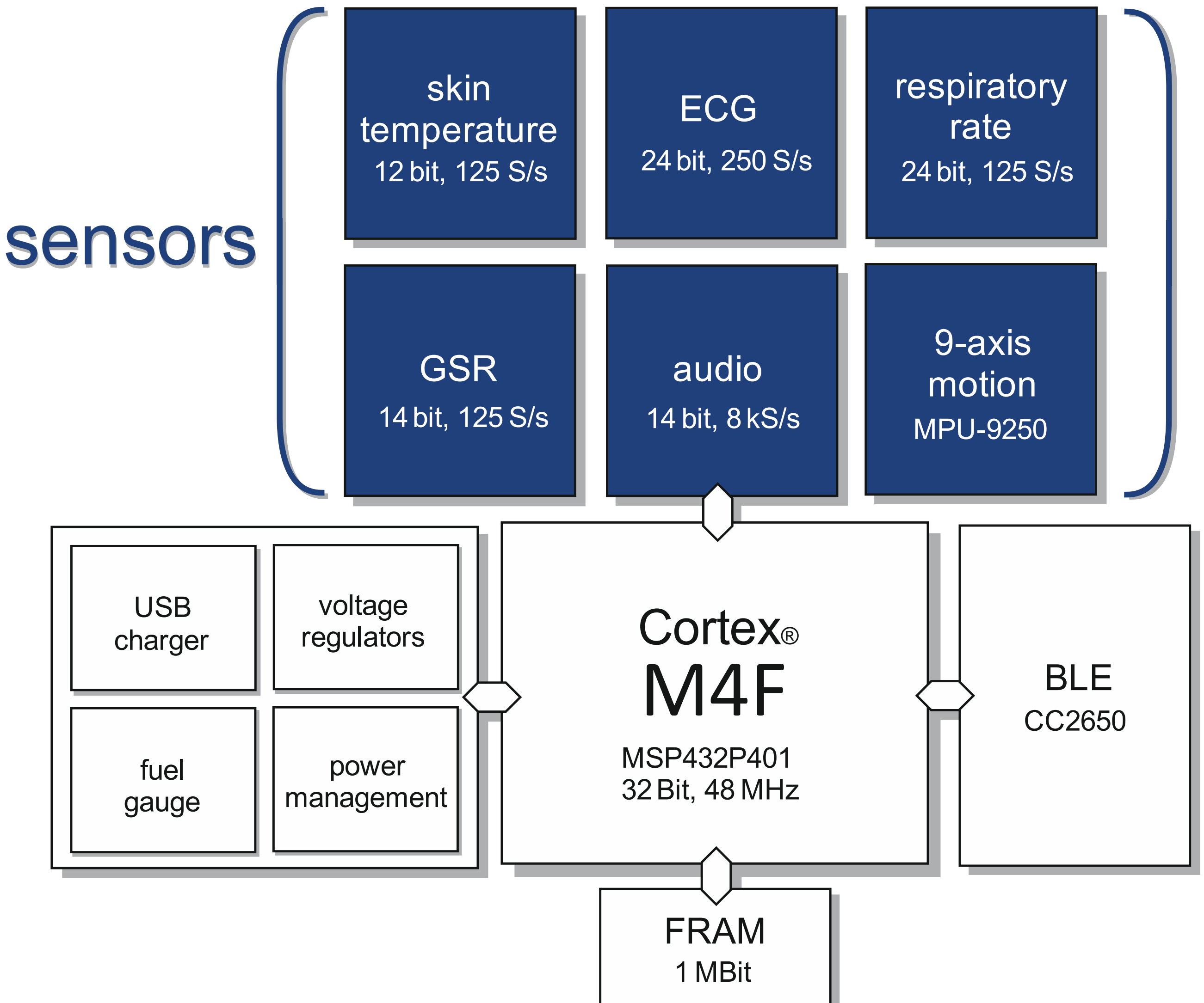
	12 MHz		24 MHz		48 MHz	
	T (ms)	E (µJ)	T (ms)	E (µJ)	T (ms)	E (µJ)
BASE	4.22	56.8	3.14	56.8	2.19	59.4
RAM	3.74	51.2	2.60	48.3	1.90	52.1
		−9.8%		−14.9%		−12.3%
RAMC	4.23	53.3	3.14	53.4	2.19	56.6
		−6.1%		−5.9%		−4.7%
RAMF	3.77	47.7	2.63	45.7	1.92	50.7
		−16.0%		−19.6%		−14.6%
OPT	3.53	46.8	2.55	45.1	1.78	48.2
		−17.7%		−20.5%		−18.8%
OPT + CMSIS	2.99	35.7	2.08	34.5	1.40	36.6
		−37.2%		−39.2%		−38.4%

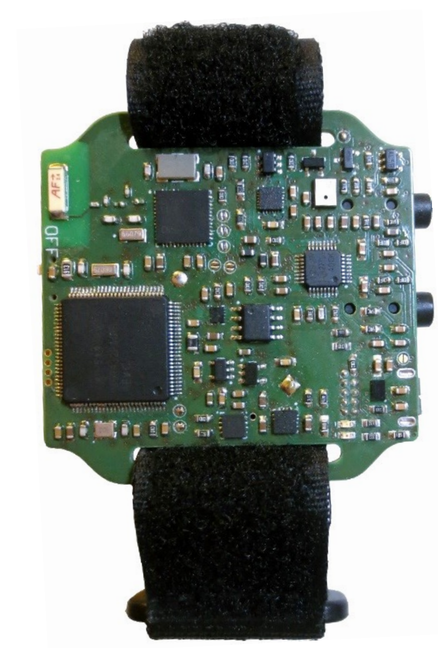
Case-study: Emotion Detection

- Training dataset: *Augsburg dataset*
  - Recorded ECG, EMG, GSR and respiration data of a subject in 4 emotional states on 25 different days
  - Classification into 3 stress levels

- Now go through the steps…
  - Step 1: data collection -- completed
  - Step 2: feature extraction, selection
  - Step 3: defining NN
  - Step 4: deployment & evaluation

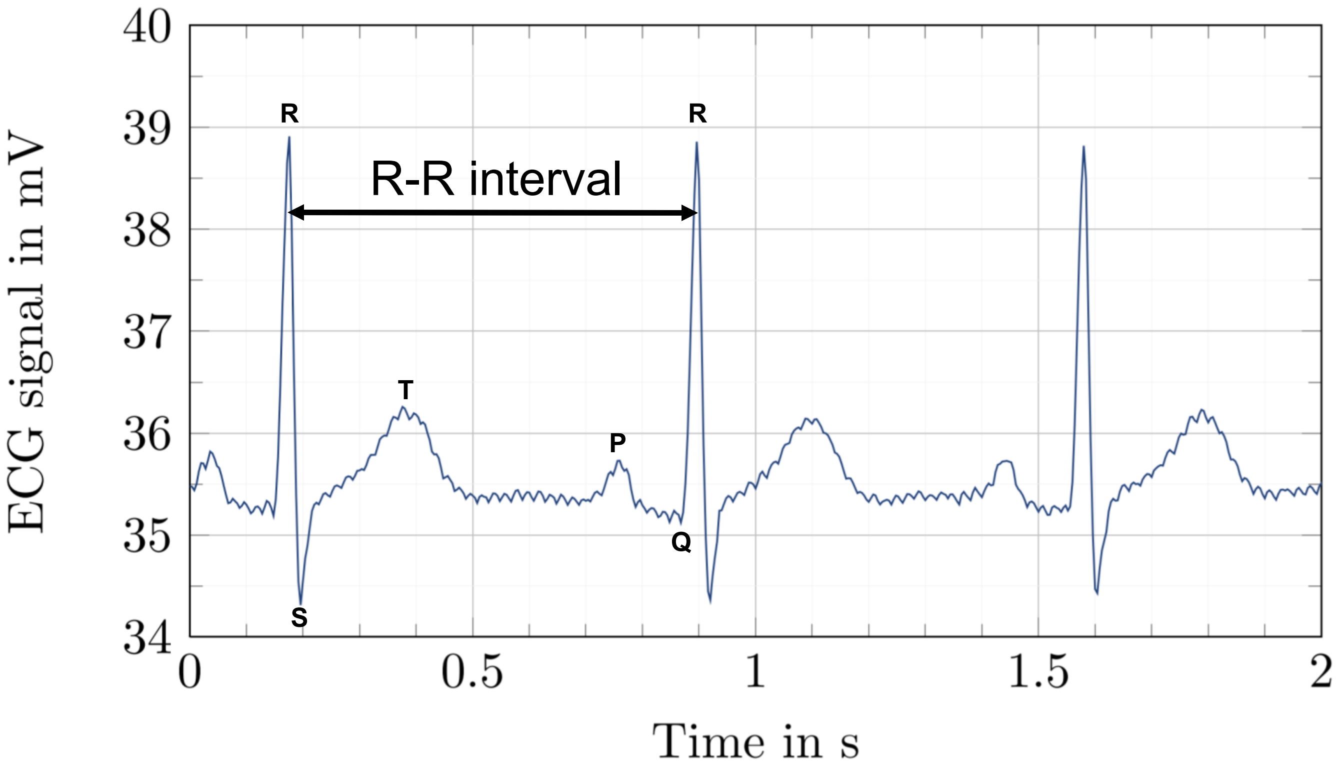
Hardware Overview



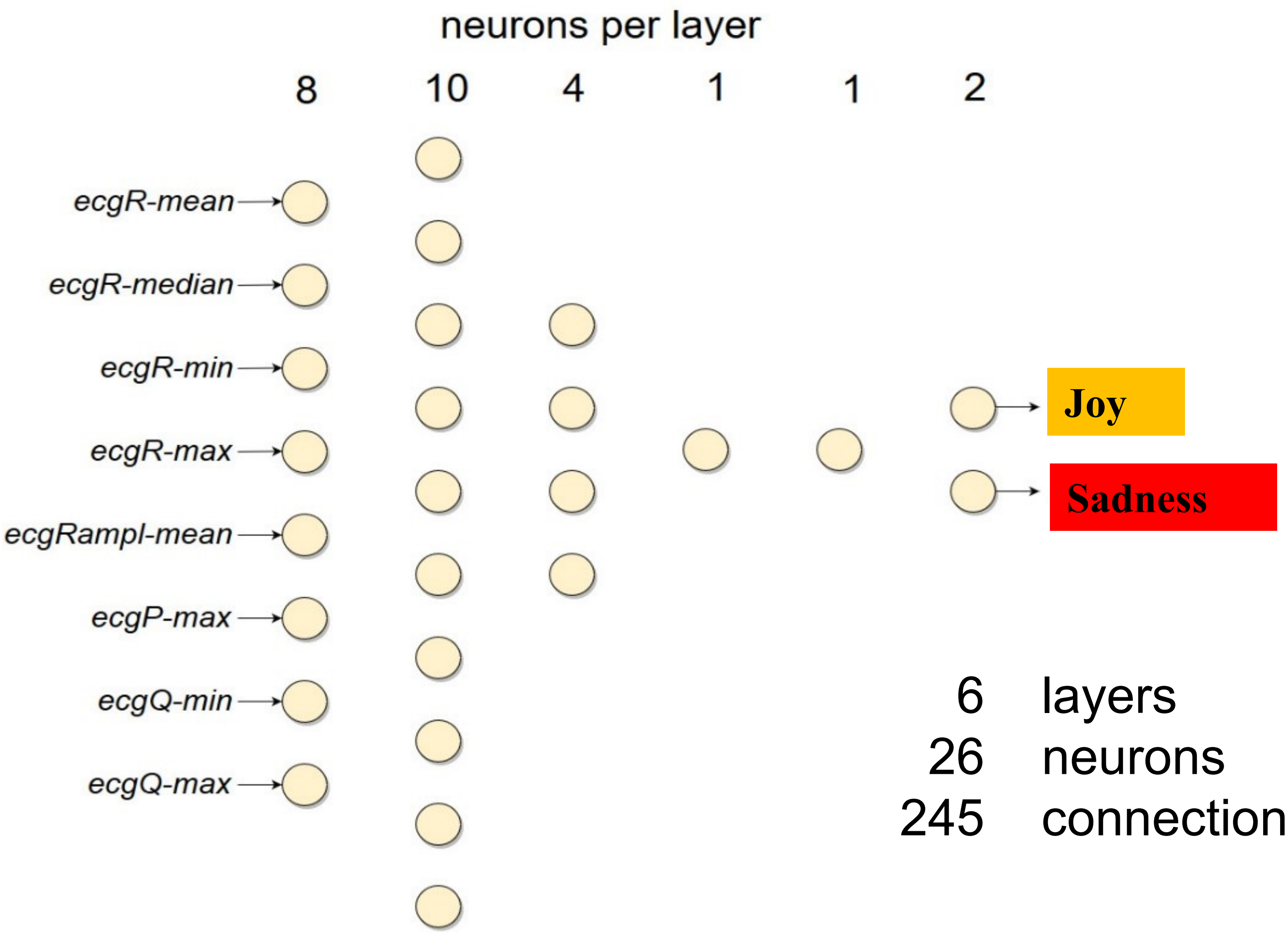


ECG Feature Extraction

Statistical features: mean, median, min, max of R-R interval etc.

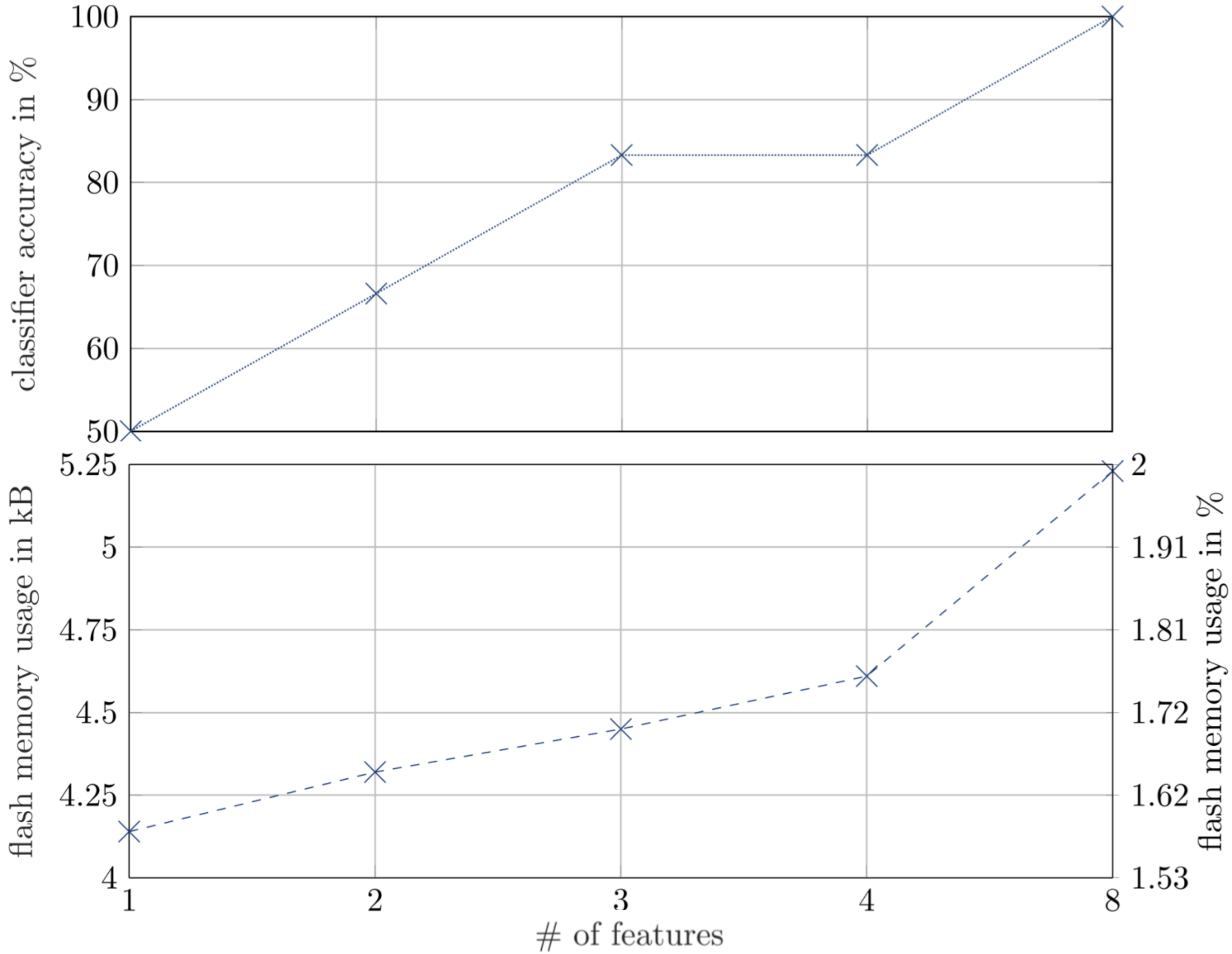


Network structure: Emotion Detection

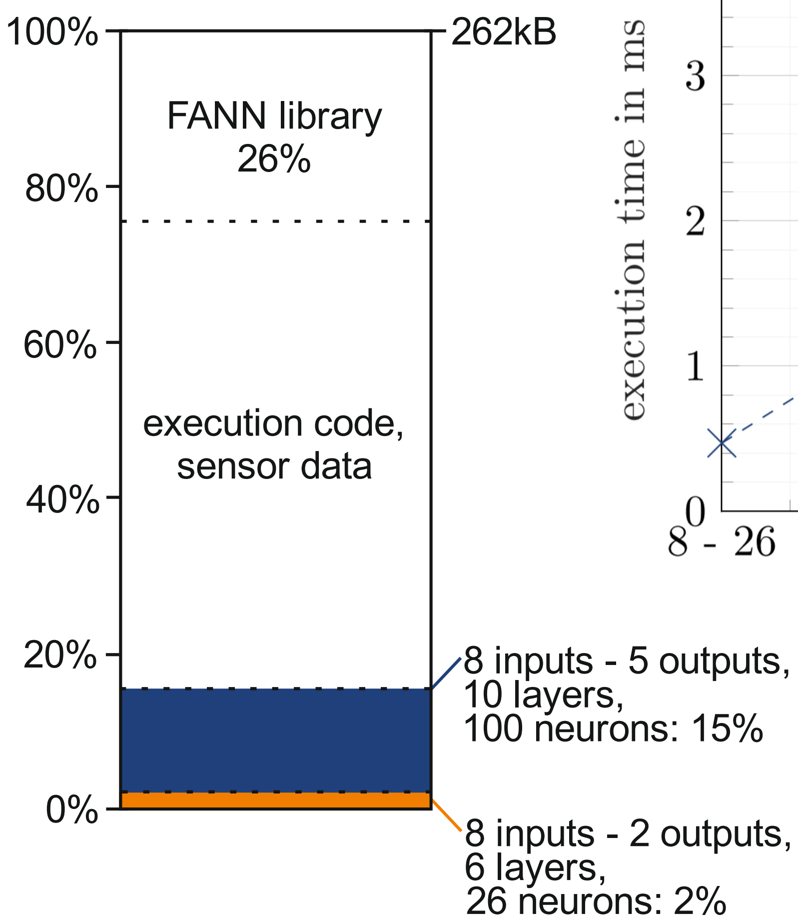


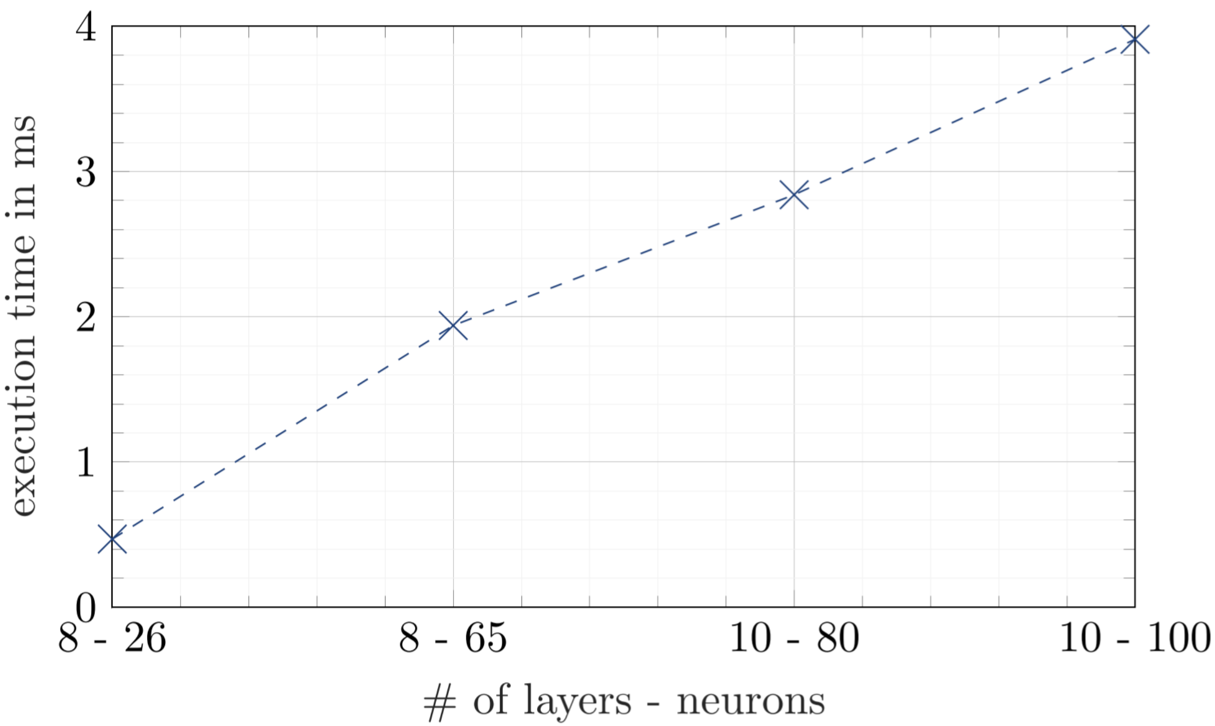
6	layers
26	neurons
245	connections

Feature Selection



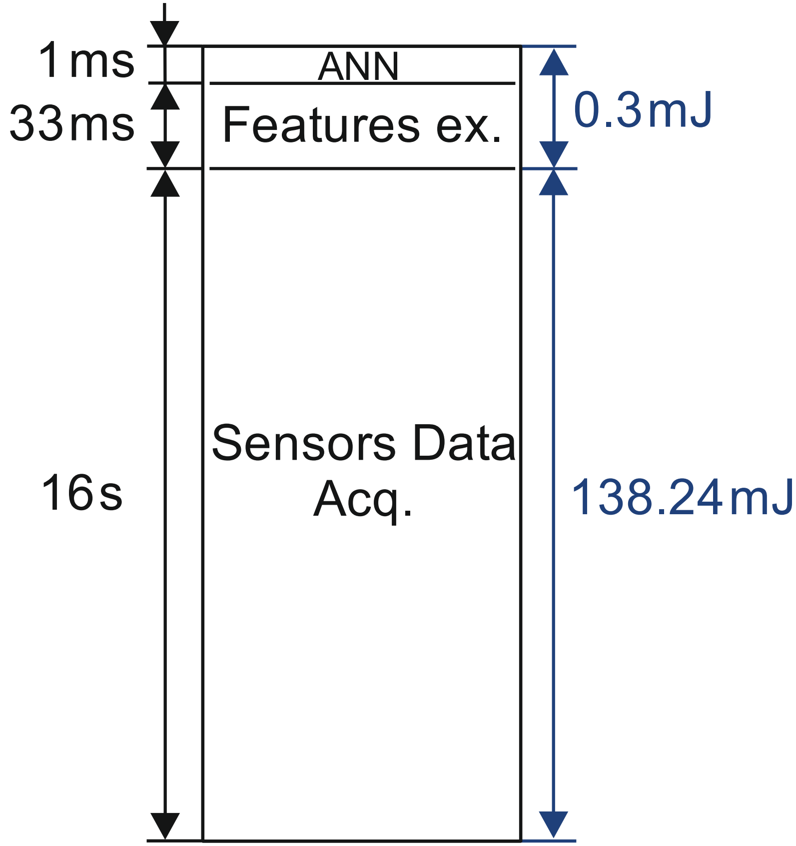
Results – Memory and Processing Load





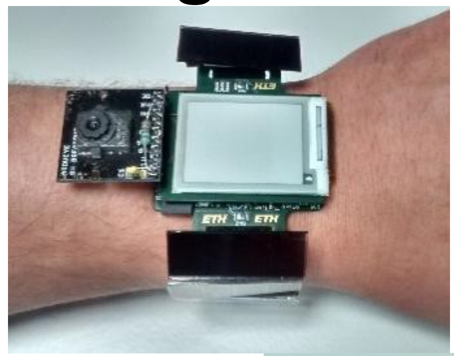
Results – Current & Energy Consumption

Component	Current (active)
Motion sensor	3.5 mA
ECG and respiration sensor	250 µA
Temperature sensor	20 µA
Audio sensor	1.65 mA
GSR	10 µA
Modes	**Drawn current**
Idle	229 µA
Classification	4.36 mA
Data streaming with BLE	16.56 mA



Toward Self-sustaining Smart Wearable

- 8 solar panels
  - Indoor: 600mJ
  - Outdoor: 9-17J

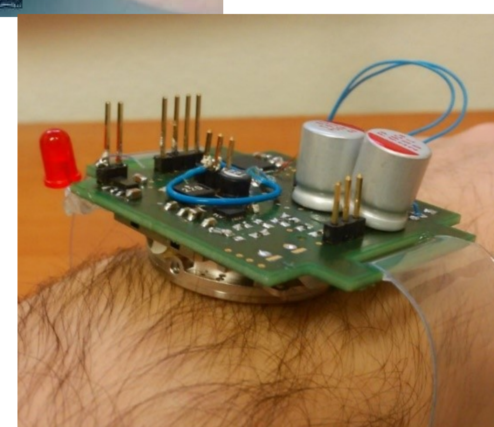


Up to 14 of detection per day
With kinetic harvester

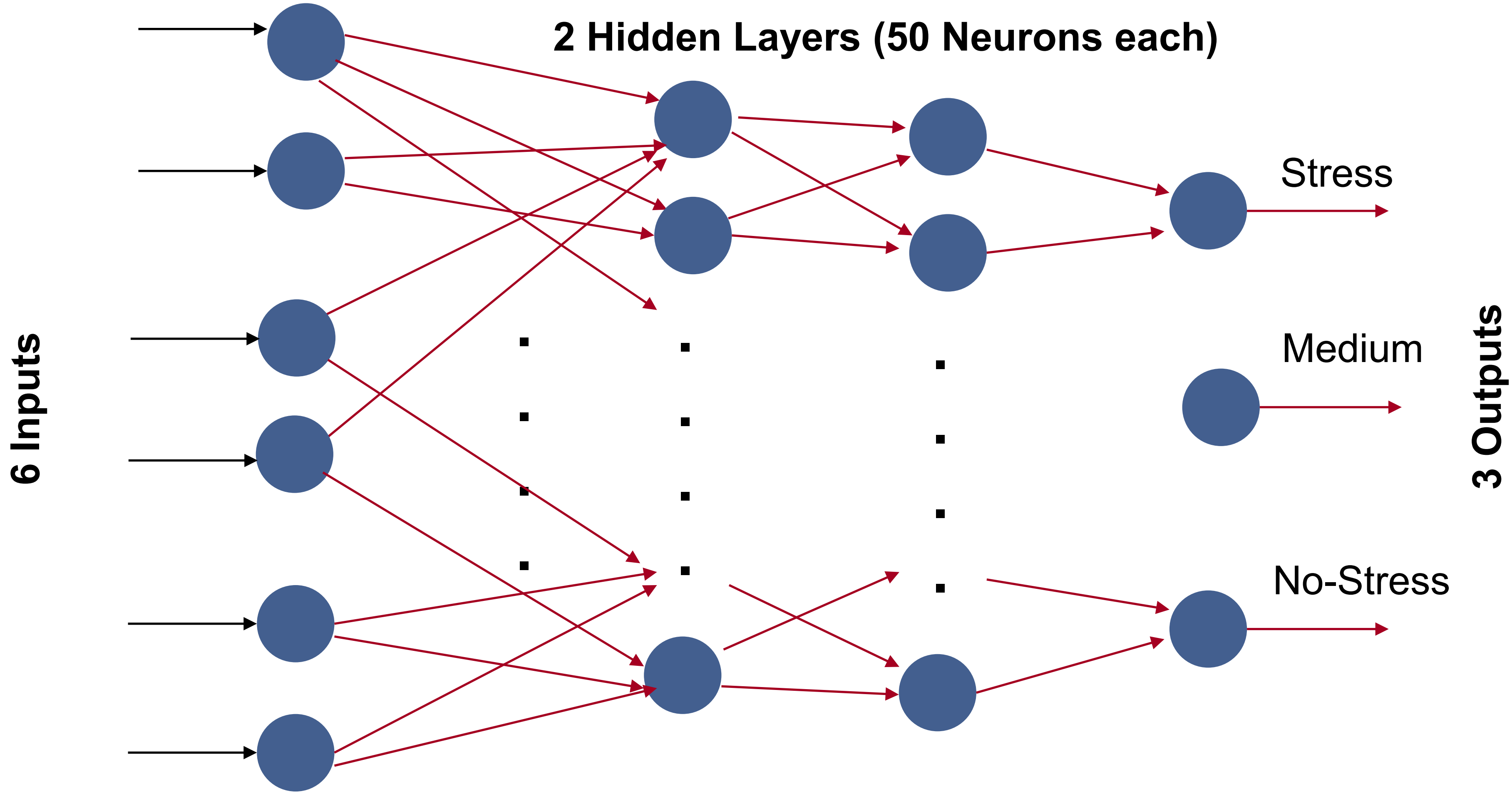
- 7 thermo-electric generators
  - **Indoors:** 0-2 mJ/d
  - **Outdoors:** 100-200 mJ/d

Up to of 10 days with a 600mAh battery.

- Kinetic harvester: 1800mJ/day (sporty person 30min run per day)
  - No occlusions,
  - No weather issue.



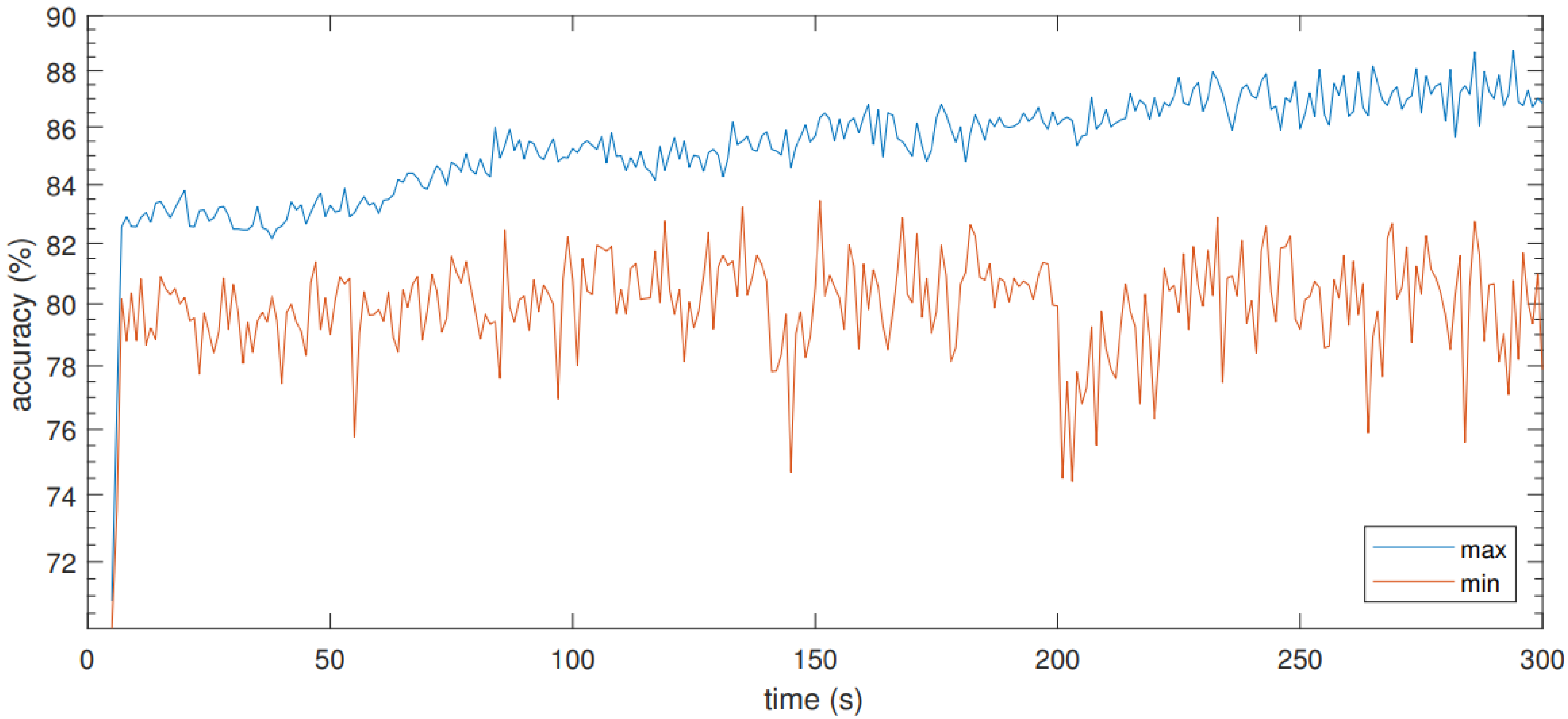
Stress Detection Neural Network – Scaling Up



- #operations: 300 + 2500 + 150 multiply-accumulate
- Memory: 1.2kB + 10kB + 0.6kB memory (weights)

Stress Detection Neural Network

- 2850 multiply-accum./classif., params: 12 kB
- Accuracy: 88% on three classes, 96% on two classes
- Time frame selection



Experimental results

- Stress Detection:
  - 2850 multiply-accum./classif., params: 12 kB
  - Accuracy: 88% on three classes, 96% on two classes
  - 4.5ms with 48MHz core speed -> ARM Cortex M4F (MSP 432)
  - Feature extraction in real time

Limitations to network size:

- 1030 neurons, 48903 weights and **22** layers
- One Classification takes 55ms! Flash is filled 90%, RAM is filled 17%!

Conclusion

- Evaluation/case-study on stress detection
  - Wearable device with Arm Cortex M4
  - 96% accuracy achievable, 4.5ms processing time, ~150mJ/classif.
  - Compute resources not the limitation!

- FANN-on-ARM
  - Enables rapid deployment of NNs on microcontrollers
  - Available online, try yourself!

https://github.com/lukasc-ch/FANN-on-ARM

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Questions

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