Person Identification using Gait Recognition

Challenge by Simi Reality Motion Systems

The “One-Size-Fits-All” Problem

Our Goal: A Truly Personalized World

Barrier 1: The “Setup” Wall

- Not Cost-Effective: Slow and expensive to deploy
- Prone to Mistakes: Manual data entries are unreliable and expensive

Barrier 2: The “Integration” Wall

- Not "Real-time": The delay breaks immersion
- Not fast adapting: The interaction feels clunky and unnatural

Use Cases

01
Real-Time Personalized Interactions
Robot Interactions

02
Access Restriction
Elevator in this building

03
Customizable Environments
Smart Home Control

Bio-Inspired Perception Engine

Personalized

Highly accurate
identification

Lightweight

Portable
Low Energy Consumption

Real-Time

Neuromorphic approach
for real-time inference

Secure

Less personal data
Local

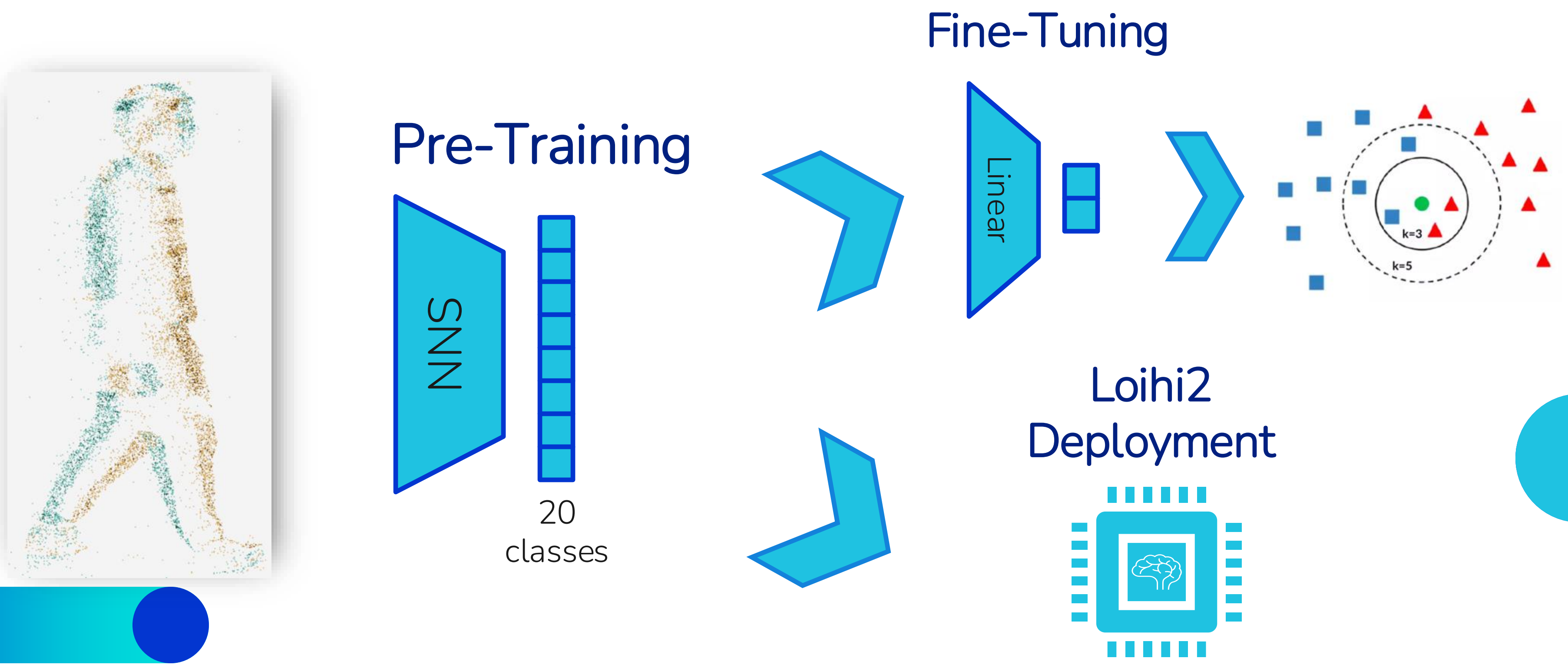
Capturing the Event Stream

Events

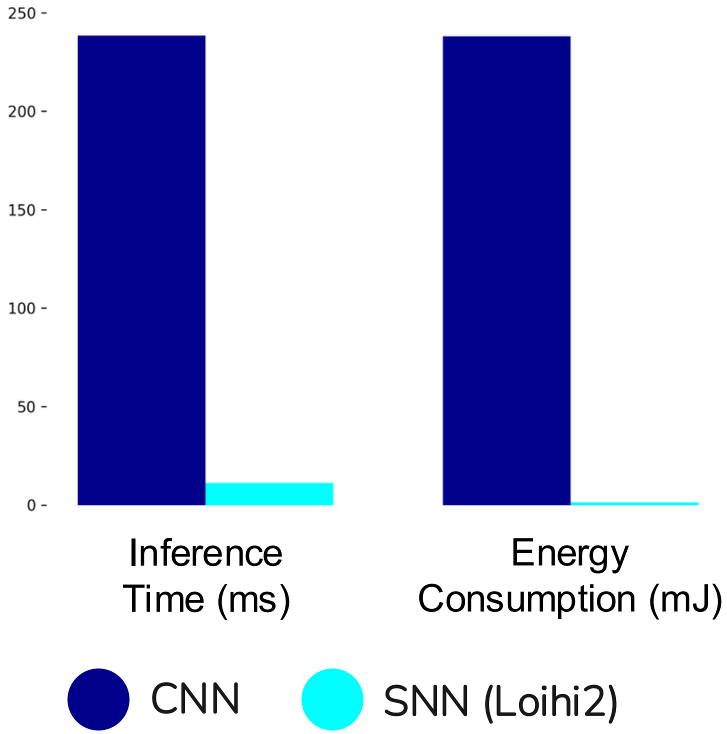
More privacy by less personal features

Less data enabling real-time implementation

Technical Details



Impact



~98%
Accuracy

21x
Faster Inference Time

180x
Energy Efficient

Future Directions

01
Continual Learning
Open Set Classification

02
Network Architecture
GRU and Noise Reduction

03
Loihi2 Live Deployment
Loihi2 for Live Inference

04
Different Modalities
Sports and Drone Detection

Thank you for your attention!

Our team

Paul Ungermann

Live Inference Coding
Data Acquisition

Simon Appoltshauser

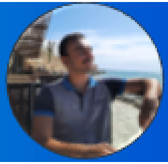
Live Inference
Data Acquisition

Fauzi Sholichin

SNN Ensamble Optimization

Eraraya Morenzo Muten

SNN Development
Loihi2 Inference

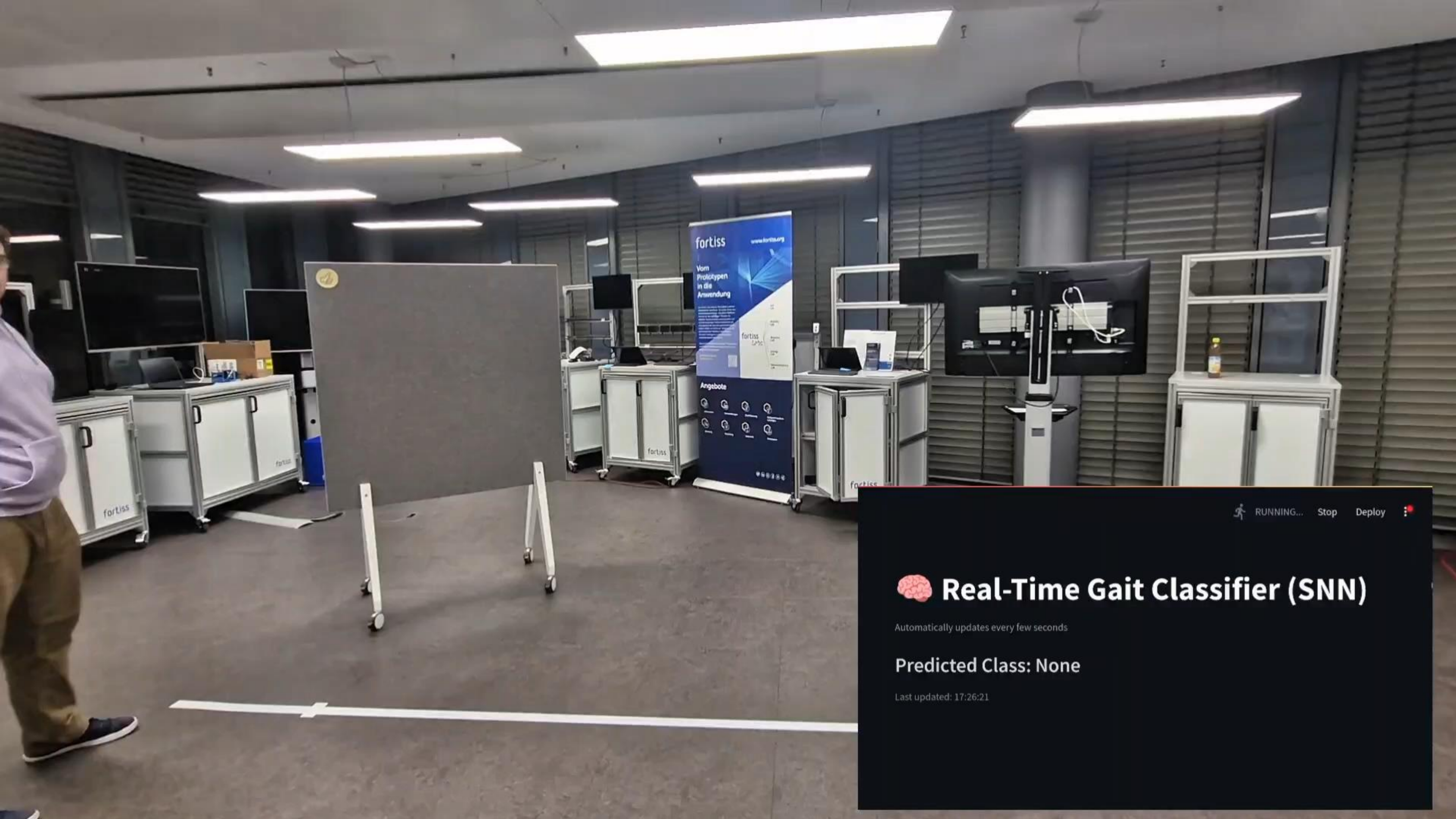


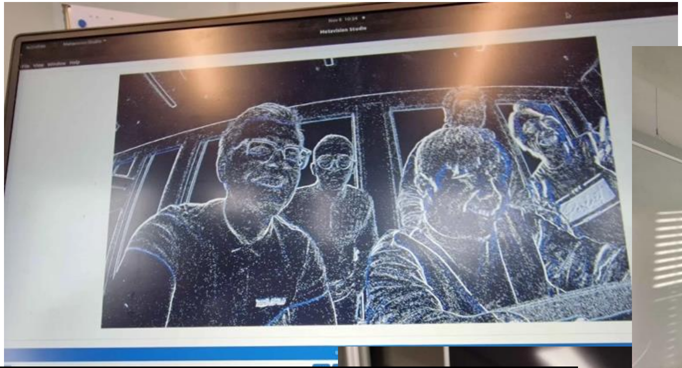
Mohamed Moez Abid

Modelling, Noise Cancellation

Michael Neumeier

Mentor

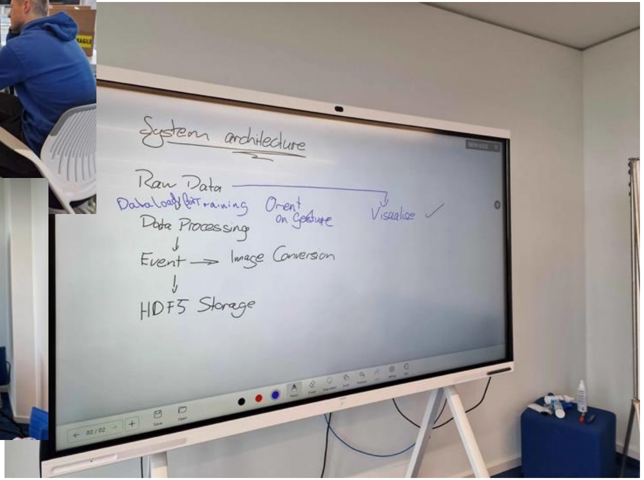

fortiss
www.fortiss.org
Vom Prototypen in die Anwendung
Angebote
fortiss
RUNNING...
Stop
Deploy
🧠 Real-Time Gait Classifier (SNN)
Automatically updates every few seconds
Predicted Class: None
Last updated: 17:26:21



Per core utilization:

AxonIn	NeuronGr	Neurons	Synapses	AxonMap	AxonMem	Total	Cores	
3.20%	12.50%	0.49%	22.40%	0.12%	0.00%	20.68%	1	
12.80%	12.50%	0.24%	51.20%	0.06%	0.00%	51.30%	52	
0.01%	12.50%	50.01%	46.80%	12.80%	0.00%	57.93%	1	Conv(4, 4, 128)
0.01%	12.50%	50.01%	12.60%	0.20%	0.05%	20.53%	2	Conv(4, 8, 64)
0.01%	12.50%	50.01%	3.60%	0.40%	0.20%	13.61%	4	Conv(8, 8, 32)
0.01%	12.50%	50.01%	1.35%	0.80%	0.40%	12.29%	8	Conv(8, 16, 16)
0.01%	12.50%	50.01%	0.23%	1.60%	0.80%	12.35%	16	Conv(16, 16, 8)
0.01%	12.50%	71.68%	0.00%	6.40%	6.40%	81.93%	16	Conv(32, 32, 2)
Total							100	

Thank You ☺



Benchmarking CNN vs SNN vs Ensemble (SNN + minEGRU) Models

Model Name	Model Size and Performance			Computation Cost	
	Parameter	Memory	Accuracy	Inference (ms)	Energy (mj)
EV-Gait-CNN	$47.\ 10^7$	180 MB 🔴	84%	± 2268	0,1 🔴
EV-Gait-SNN (PLIF)	$2{,}1.10^7$	**8.5 MB** 🟢	**98%**	**± 20**	0,011
EV-Gait-SNN (PLIF + EGRU)	$3{,}7.10^7$	14.15 MB 🔴	95%	±157,7	0,028
EV-Gait-SNN (PLIF + minEGRU)	$\mathbf{2{,}6.10^7}$	**10.14 MB** 🟢	**96%**	**±150,9**	0,028

SNN Computation Cost Based on Sparsity Metrics energy per inference[3]

- Short temporal windows (<50-100 timesteps), **PLIFSNN** with proper tuning is **sufficient.**
- Medium Long temporal windows -> EV-Gait-SNN (PLIF + **minEGRU**)
looks promising since better then PLIF**EGRU**, future work need to test with different size dataset to validate.

1) Yik, Jason, et al. "The neurobench framework for **benchmarking neuromorphic computing algorithms** and systems." *Nature communications* 16.1 (**2025**): 1545.
2) DATTA, Gourav, et al. "In-sensor & neuromorphic computing are all you need for **energy efficient computer vision**". In: IEEE, **2023**. p. 1-5.
3) Feng, L., Tung, F., Ahmed, M. O., **Bengio, Y.**, & Hajimirsadeghi, H. (**2024**). Were RNNs all we needed?. *arXiv preprint arXiv:2410.01201*.