Deep Learning Analysis on Wearable Devices

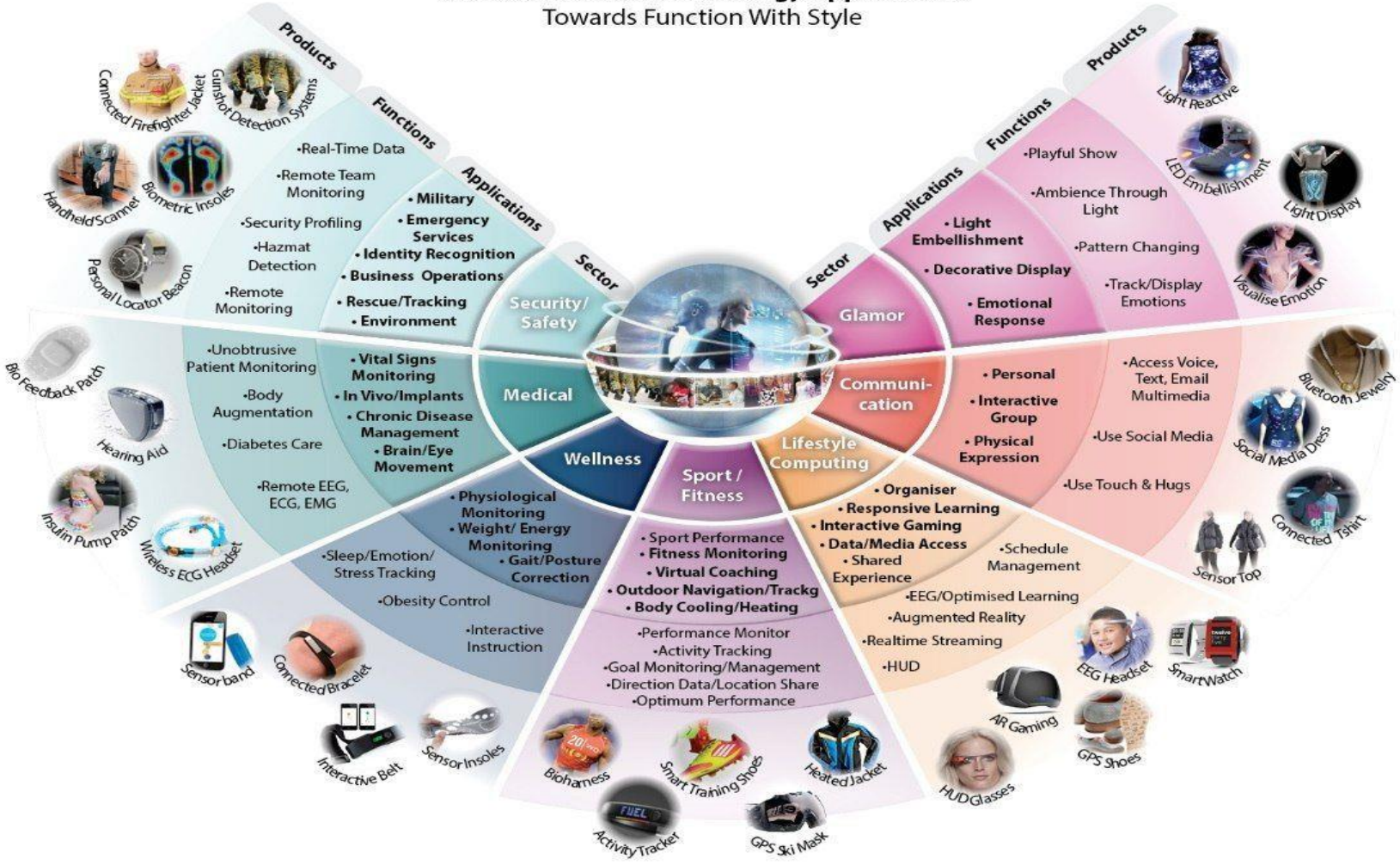
CERN openlab Technical Workshop 2020

Anna Ferrari, Daniela Micucci, Marco Mobilio, Paolo Napoletano, Sofia Vallecorsa

23/01/2020

a.ferrari34@campus.unimib.it

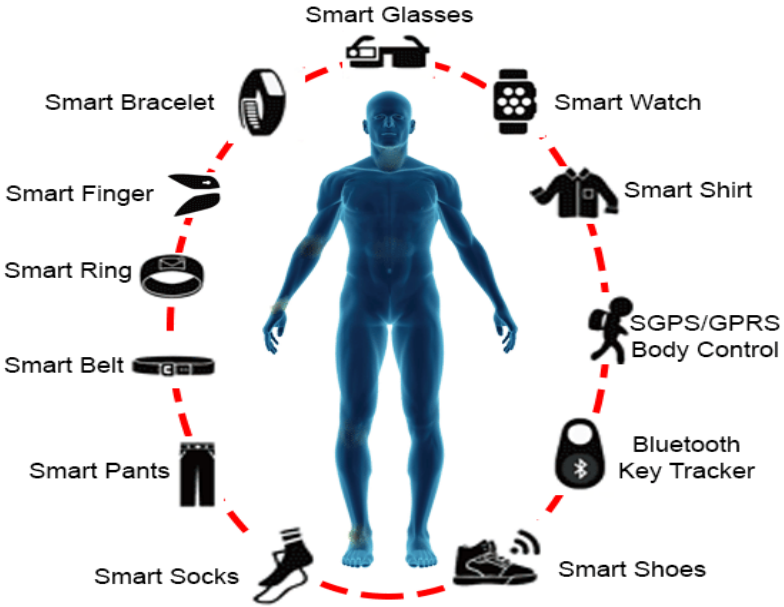
World of Wearable Technology Applications:
Towards Function With Style



Research Focus - Devices

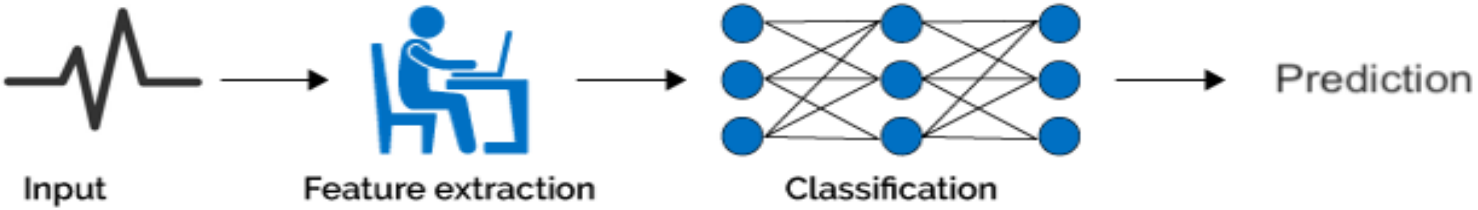
Wearable Devices

- ***Heterogeneous data** acquisition*
- ***Sensors embedded** in devices are more and more accurate*
- *Possible to use **outdoor***
- *Part of everyday life*
- *Not invasive*

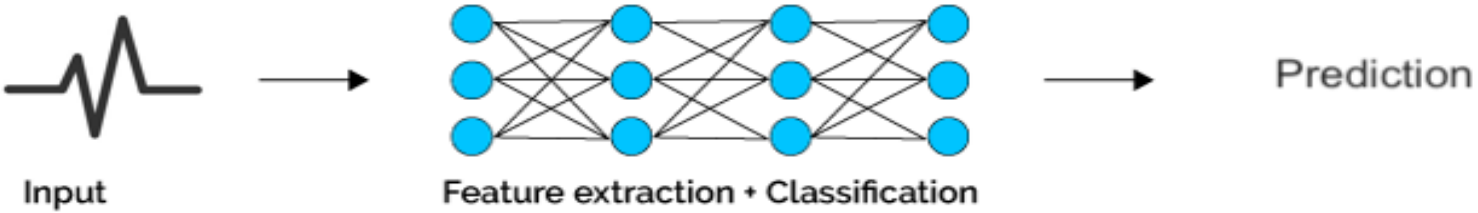


Research Focus - Techniques

Traditional Learning



Deep Learning



Research Focus – Medical

Neurological disorder detection

Parkinson Monitoring

Remote assistance

Strocke Detection

Life style monitoring

Falls Detection

Sport tracking

Heart attack Detection

Stress monitoring

Well-being

Healthcare

Personal Monitoring

e-Health

Alzheimer detection

Sleep tracking

Calories burning

Dementia monitoring

Early Diagnosis

Patient Monitoring

CERN openlab

UNIVERSITÀ DEGLI STUDI DI MILANO BICOCCA

Research Focus – Medical

Neurological disorder detection

Remote assistance

Parkinson Monitoring

Strocke Detection

Life style monitoring

Falls Detection

Sport tracking

Heart attack Detection

Stress monitoring

Well-being

Healthcare

Personal Monitoring

e-Health

Alzheimer detection

Sleep tracking

Calories burning

Dementia monitoring

Early Diagnosis

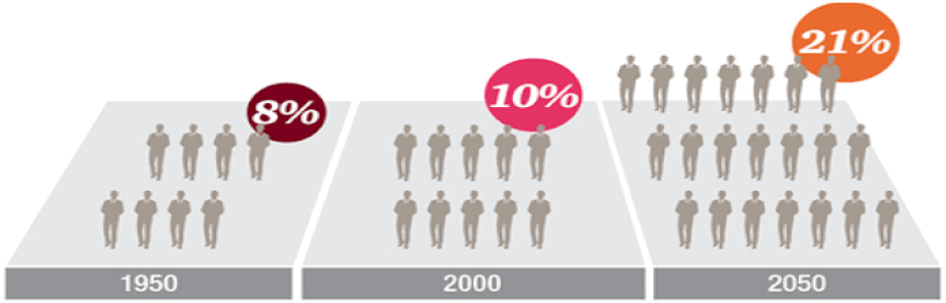
Patient Monitoring

CERN openlab

UNIVERSITÀ DEGLI STUDI DI MILANO BICOCCA

Falls Detection - Motivation

Proportion of the word population aged 60+ years



Source: UN report World Population Ageing 1950-2050

Falls are a major health risk that impacts the quality of life of elderly people.
The 30 % of the over 60 population **falls at least once per year**.

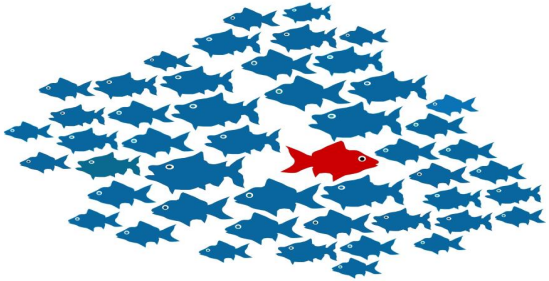
A **prompt notification** would help in reducing the injuries that the fall could cause.

Goal: Automatic Fall detection through wearables devices

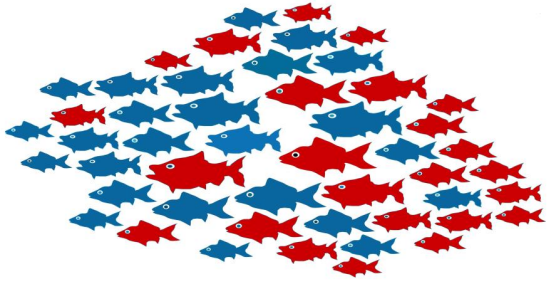
Falls Detection - Methods

Methods for Falls detection

Unsupervised Anomaly Detection



Supervised Classification



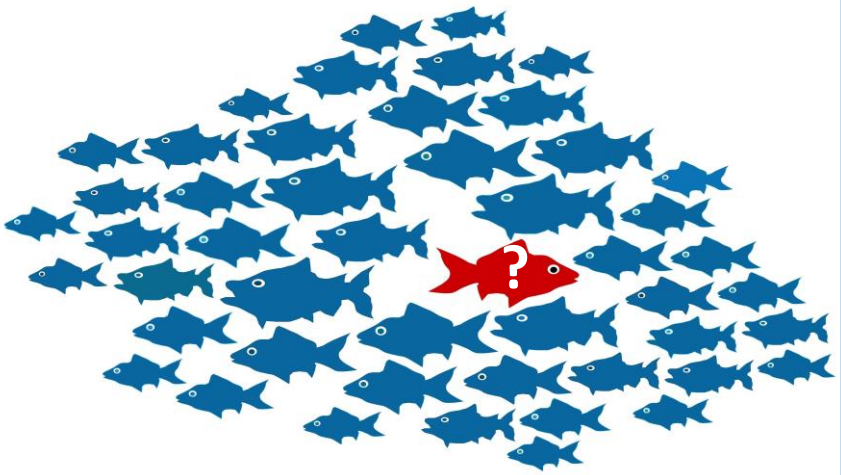
Falls Detection - Methods

Deep Learning on Wearable Devices

Anomaly detection

Anomalies *are patterns in data that do not conform to a well defined notion of normal behavior*

Anomaly Detection *refers to the problem of finding patterns in data that do not conform to expected behavior*

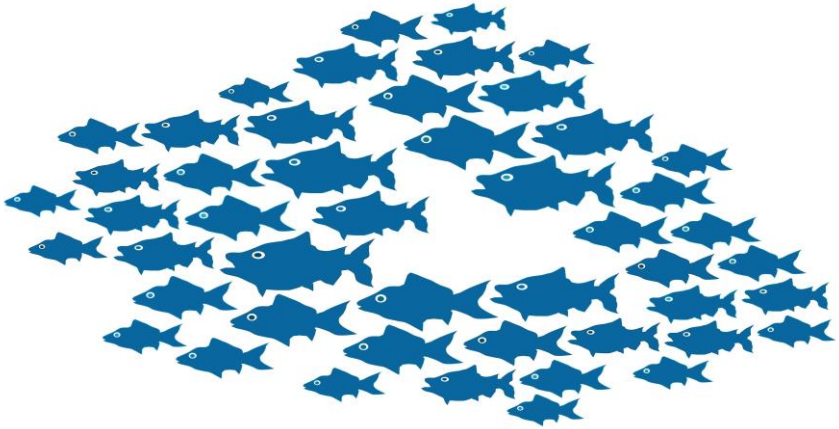


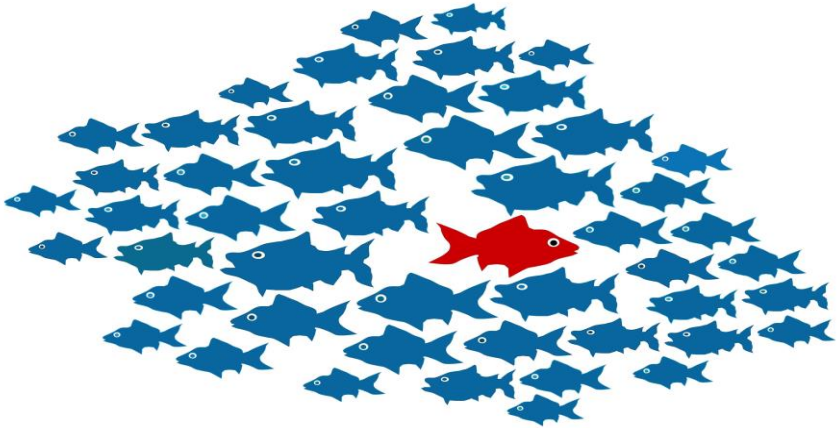
Falls Detection - Methods

Deep Learning on Wearable Devices

Anomaly detection

*The algorithm is **unsupervised:** it is **trained on one class** (the normal class) and the new instance is classified as anomaly if its features are too different to those belonging to the normal class.*

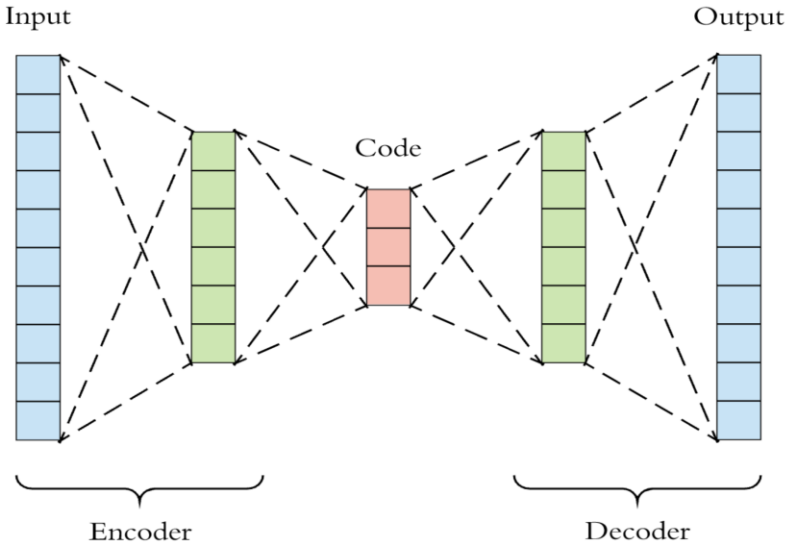




Falls Detection - Methods

Deep Learning on Wearable Devices

Anomaly detection – Variational Autoencoder (VAE)



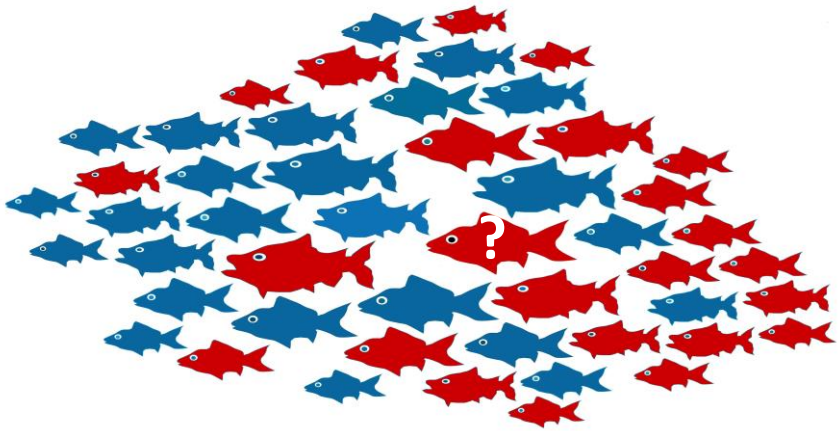
	Hidden Layers	Encoder	Decoder
VAE 1	convolutional	{1x3} x 64	{1x32} x 64
	convolutional	{1x3} x 64	{1x3} x 64
	3 residual block	convolutional {1x3} x 32	convolutional {1x3} x 32
VAE 2	3 residual block	convolutional {1x3} x 32	convolutional {1x3} x 32

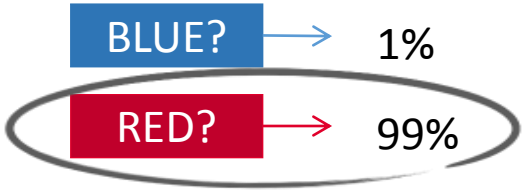
Falls Detection - Methods

Deep Learning on Wearable Devices

Classification

*The algorithm **is trained** overall population and the new instance is classified to the most **likely class**.*



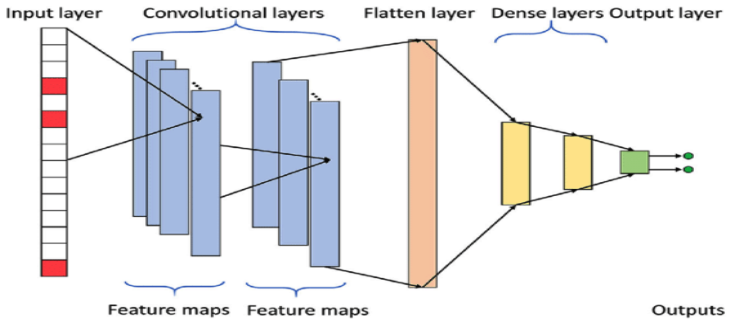


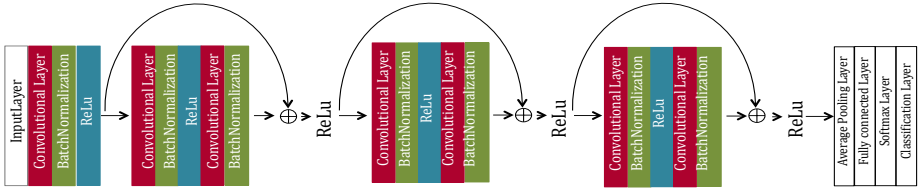
Falls Detection - Methods

Deep Learning on Wearable Devices

Classification

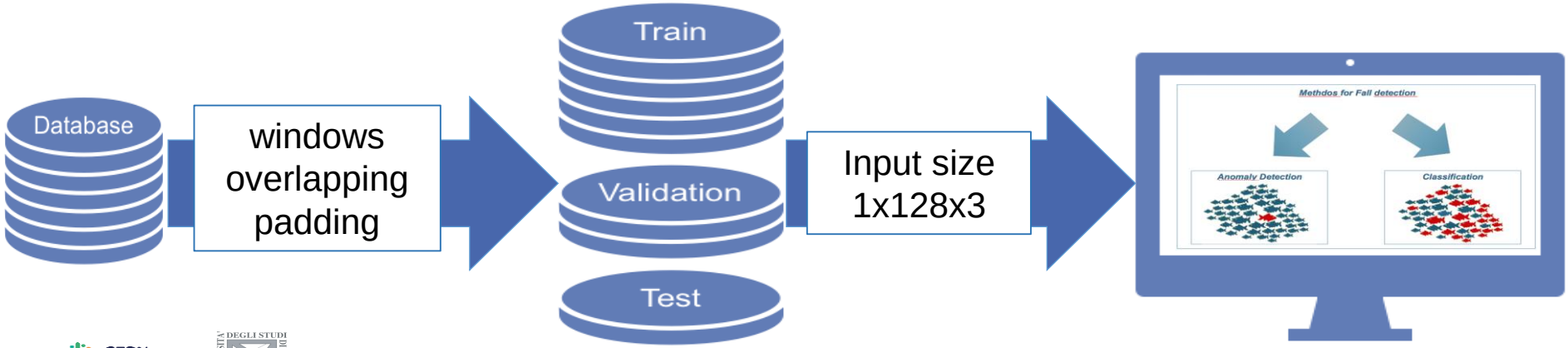
	Layers name	Shape
CNN	conv 1	{1x3} x 90
	conv 2	{1x3} x 90
RestNet	Res block 1 Res block 2 Res block 3	Convolutional, Batch normalization, ReLu, Convolutional Batch normalization





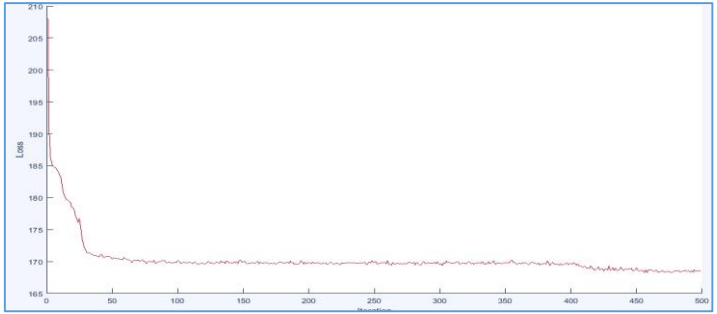
Falls Detection - Dataset

Dataset	Dataset Size	Sensor	Classes
UMAFall [4]	ca 6000 Train ca 2000 Validaiton ca 1000 Test	xyz - Acc	Actvity Label = 0 Fall Label = 1

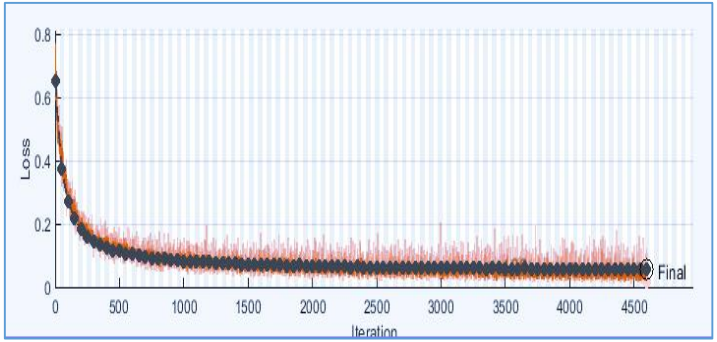


Falls Detection - Results

Methods	Techniques	Accuracy
Falls as Anomalies	VAE - 2 Conv layers	73.24%
Falls as Anomalies	VAE – 3 blocks Residual	70.03%



Methods	Techniques	Accuracy
Falls Classification	CNN – 2 Conv layers	98.47%
Falls Classification	ResNet – 3 blocks	99.69%



Falls Detection - Conclusions

The propose of the project is to create a **classifier able to predict whether a fall event** is occured. The **promising preliminary results** incourages us to

- **further investigate and improve** results;
- **extend** to other anomaly detection and classification research fields.

Questions?

Remote Assistance
Facial Recognition
Dementia Monitorning
Sleep Quality Monitoring
Remote Monitoring
Object Recognition
CNN & ResNet
Disease Prevention
Climate
Human Activity Recognition
lifestyle Monitoring
Sport Tracking
Stress Monitoring
Calories Burning
Portfolio Construction
Financial sentiment
Flame Monitoring
Hurricanes Intensity Analysis
Energy, Position & Particles ID

CMS Trigger Rate Monitoring
Physics Mining Detection
Graphs Generator
Music Generator
Vehicle detection
Extreme Events Detection
Avalanche Deposit Detection
Tissue Abnormalities
Tissue Abnormalities
Abnormal Event Detection
Parkinson Detection
Fake News Detection
VAE
Falls Detection
Autonomous Driving
Heart attack Detection
Cancer Diagnosis
Diagnostic imaging

a.ferrari34@campus.unimib.it

References

[1] A. Ferrari, D. Micucci, M. Mobilio, and P. Napoletano. "Human Activities Recognition Using Accelerometer and Gyroscope." *European Conference on Ambient Intelligence*. Springer, Cham, 2019.

[2] D. Micucci, M. Mobilio, P. Napoletano, and F. Tisato, “Falls as anomalies? an experimental evaluation using smartphone accelerometer data,” Journal of Ambient Intelligence and Humanized Computing, vol. 8, no. 1, pp. 87–99, 2017.

[3] A. Jinwon, and Sungzoon Cho. "Variational autoencoder based anomaly detection using reconstruction probability." *Special Lecture on IE* 2.1, 2015.

[4] E. Casilari, J. A. Santoyo-Ramón, and J. M. Cano-García."UMAFall: A Multisensor Dataset for the Research on Automatic Fall Detection." Procedia Computer Science 110: 32-39, 2017.

[5] S. Abbate, M. Avvenuti, F. Bonatesta, G. Cola, P. Corsini, A. Vecchio. “A smartphone-based fall detection system.” Pervasive Mob Comput 8(6):883–899, 2012.