# Fall Detection by Human Pose Estimation and Kinematic Theory

Dr. Vincenzo Dentamaro
Prof. Donato Impedovo
Prof. Giuseppe Pirlo

UNIVERSITÀ DEGLI STUDI DI BARI ALDO MORO

# Objectives of the work

In a society with increasing age detecting falls in time is of a paramount importance. The hypothesis is that the Kinematic theory of rapid human movements, originally developed to describe handwriting patterns, and used in conjunction with other features such as spatio-temporal features, can help detecting falls with 2D rgb camera:

- Modeling the human falls movement pattern by using the kinematic theory of rapid human movements and its sigma-lognormal model;
- Understand body parts that play a major role in fall detection trough computer vision.

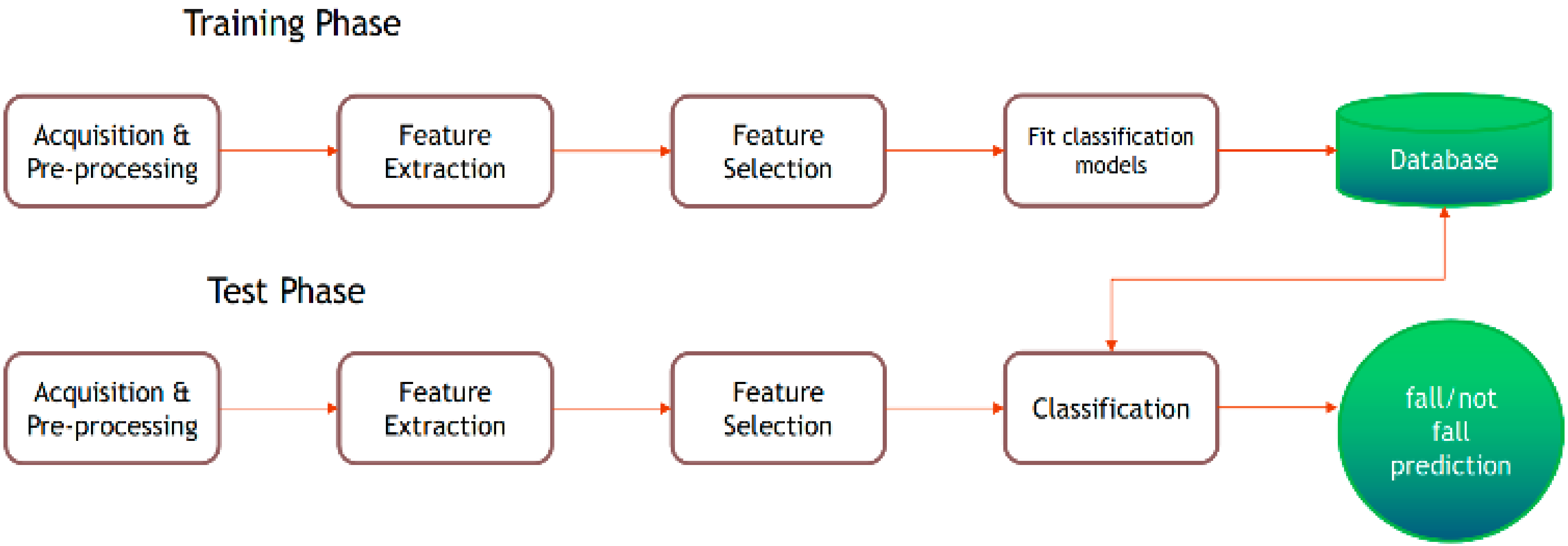
UNIVERSITÀ DEGLI STUDI DI BARI ALDO MORO

# Datasets

1. The first dataset used for experiments is the Le2i. It contains 192 fall videos and 57 non fall (also called of activity daily life) videos shot with a single off the shelf RGB camera with duration ranging from 10 to 45 seconds. The framerate is 25 FPS with 320x240 as resolution

2. The additional dataset used for experiments is the URFD. This dataset contains 70 (30 falls + 40 activities of daily living) sequences

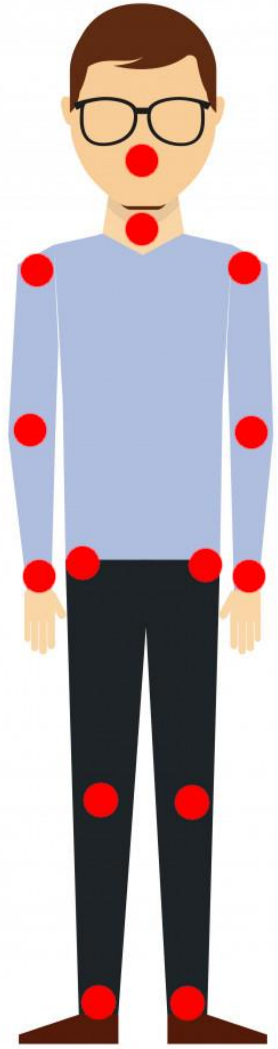
# The classification pipeline



# Pose Estimtion

All videos belonging to the dataset were processed through the Openpose 1.6.1 program, which allowed to:

- Split the video into frames;
- Extrapolate the skeleton of the person present in each frame;
- Extract the spatial coordinates of all the joints of each skeleton.



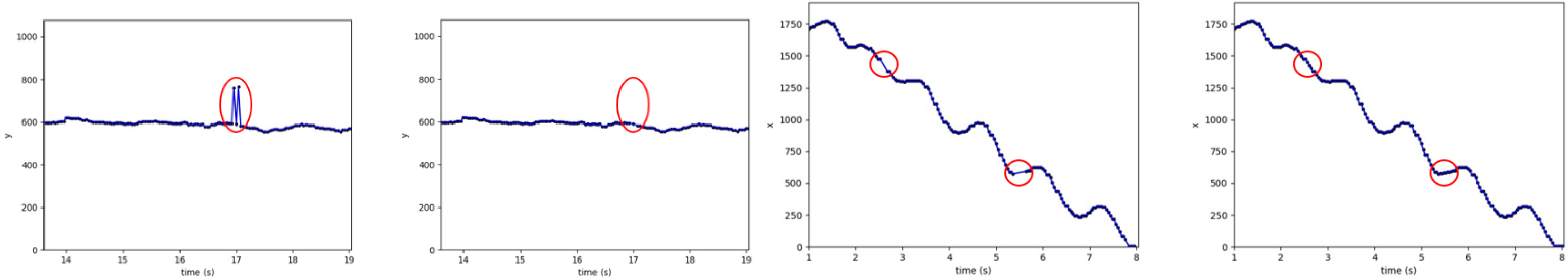
# Issues

The data acquisition techniques that have been used have highlighted the occurrence of small errors:

In some cases Openpose was unable to correctly locate the position of one or more joints;

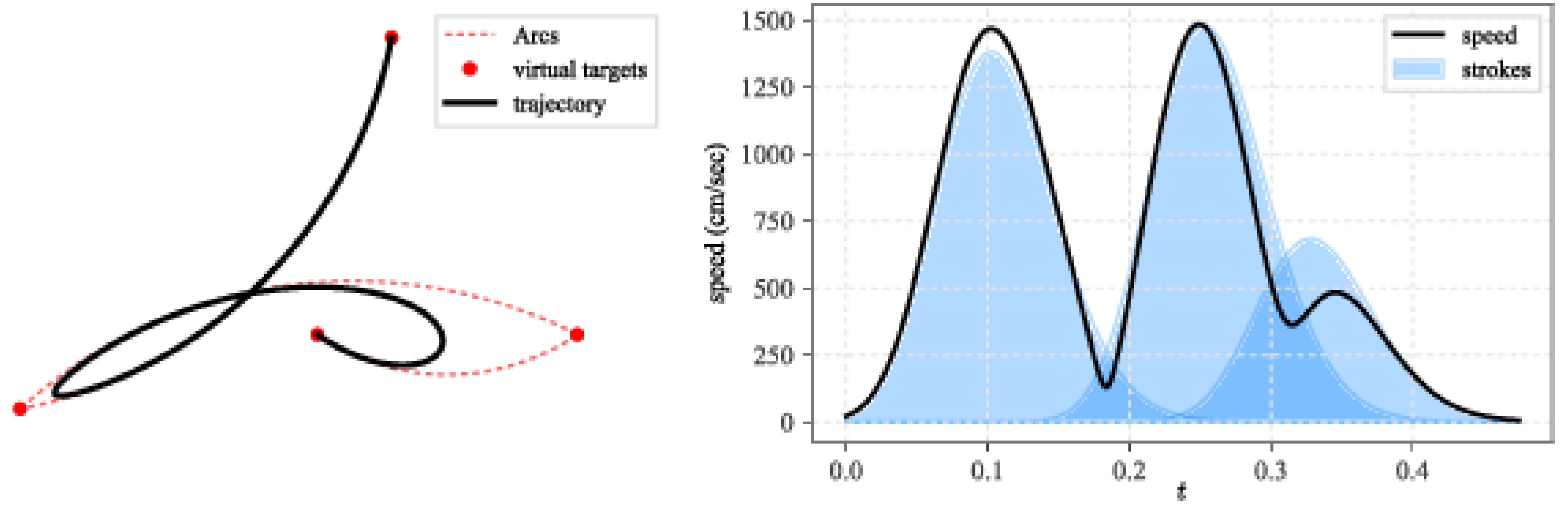
# Elimination of peaks along the y axis

since human movement is a continuous and harmonious, it is unthinkable that the extracted data will report sharp jumps forward or backward. Therefore, having established a threshold equal to 50 pixels and considering the position of each part of the body in correspondence with the first frame of each walk, all those measurements whose ordinate component y go out of the interval defined by the threshold [y-50, y + 50 ] were removed and later linearly interpolated.



# The sigma-lognormal model

$$\left|\vec{v}_j(t;P_j)\right| = D_j \Lambda(t - t_{0j}; \mu_j, \sigma_j^2) = \frac{D_j}{\sigma(t - t_{0j})\sqrt{2\pi}} \exp\left\{\frac{\left[\ln(t - t_{0j}) - \mu_j\right]^2}{-2\sigma_j^2}\right\}$$

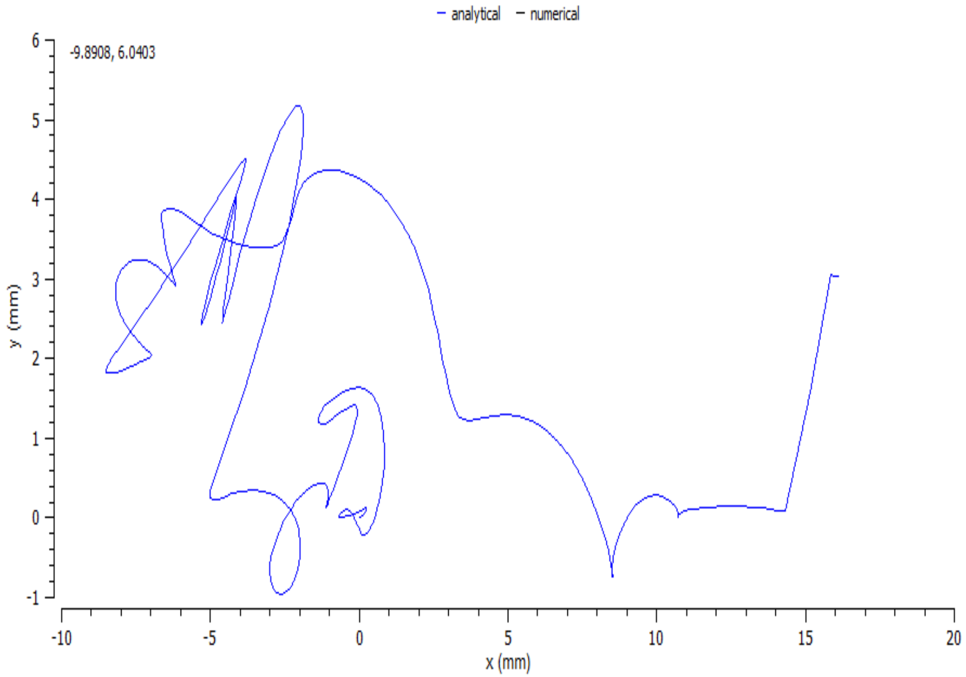



ΣΛ trajectory (left) with the corresponding action plan and the lognormal components (right).

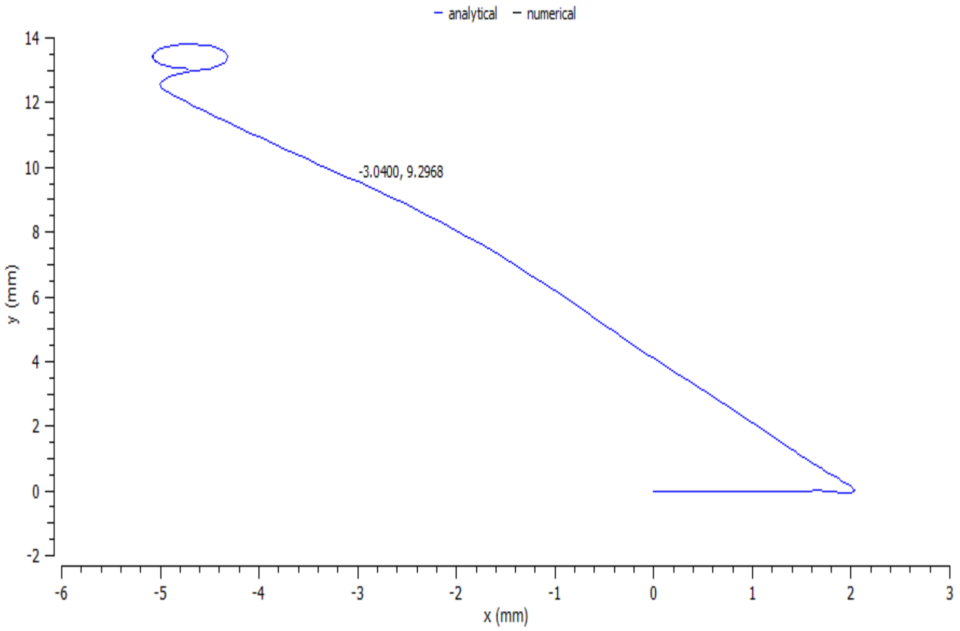
# The sigma-lognormal model

## Movement profile and lognormal sigma profile

Nose acceleration profile of person non falling




Nose acceleration profile of person when falling



# Spatio-Temporal Features

| | |
|---|---|
| Displacement | $d_i = \sqrt{\Delta x_i^2 + \Delta y_i^2}$ |
| Displacement x | $\Delta x_i = x_{i+1} - x_i$ |
| Displacement y | $\Delta y_i = y_{i+1} - y_i$ |
| Velocity | $v_i = d_i / \Delta t_i$ |
| Velocity x | $v_{x,i} = \Delta x_i / \Delta t_i$ |
| Velocity y | $v_{y,i} = \Delta y_i / \Delta t_i$ |
| Acceleration | $a = v_i / \Delta t_i$ |
| Acceleration x | $a_{x,i} = v_{x,i} / \Delta t_i$ |
| Acceleration y | $a_{y,i} = v_{y,i} / \Delta t_i$ |
| Tangent angle | $\rho_i = \tan^{-1}(\Delta y_i / \Delta x_i)$ |

UNIVERSITÀ DEGLI STUDI DI BARI ALDO MORO

# Sigma-lognormal Features

| Feature name | Description |
|---|---|
| Lognormal stroke number | Number of lognormal strokes |
| D parameter | D parameter for all lognormal strokes |
| μ parameter | μ parameter for all lognormal strokes |
| σ parameter | σ parameter for all lognormal strokes |
| $\theta_s$ parameter | $\theta_s$ parameter for all lognormal strokes |
| $\theta_e$ parameter | $\theta_e$ parameter for all lognormal strokes |

# Statistical Features

| Feature name | Formulation |
|---|---|
| Mean | $\bar{x} = \dfrac{x_1 + x_2 + .. + x_n}{n}$ |
| Median | given $x = [x_1, x_2, .., x_n]$<br>thus $\mu = x[\frac{n}{2}]$ |
| Standard Deviation | $\sigma_X = \sqrt{\dfrac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N}}$<br>where $\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$ |
| 1 and 99 percentile | $n = [\dfrac{P}{100} \times N]$ |

# Classification

After extracting the features from each single step of each individual patient, the classification is proceeded through the use of 2 distinct classification algorithms:

1. K-Nearest Neighbour
2. Random ForestSupport Vector Machine non linear with RBF kernel

**10-Fold cross validation accuracy**

# Accuracy on Le2i dataset

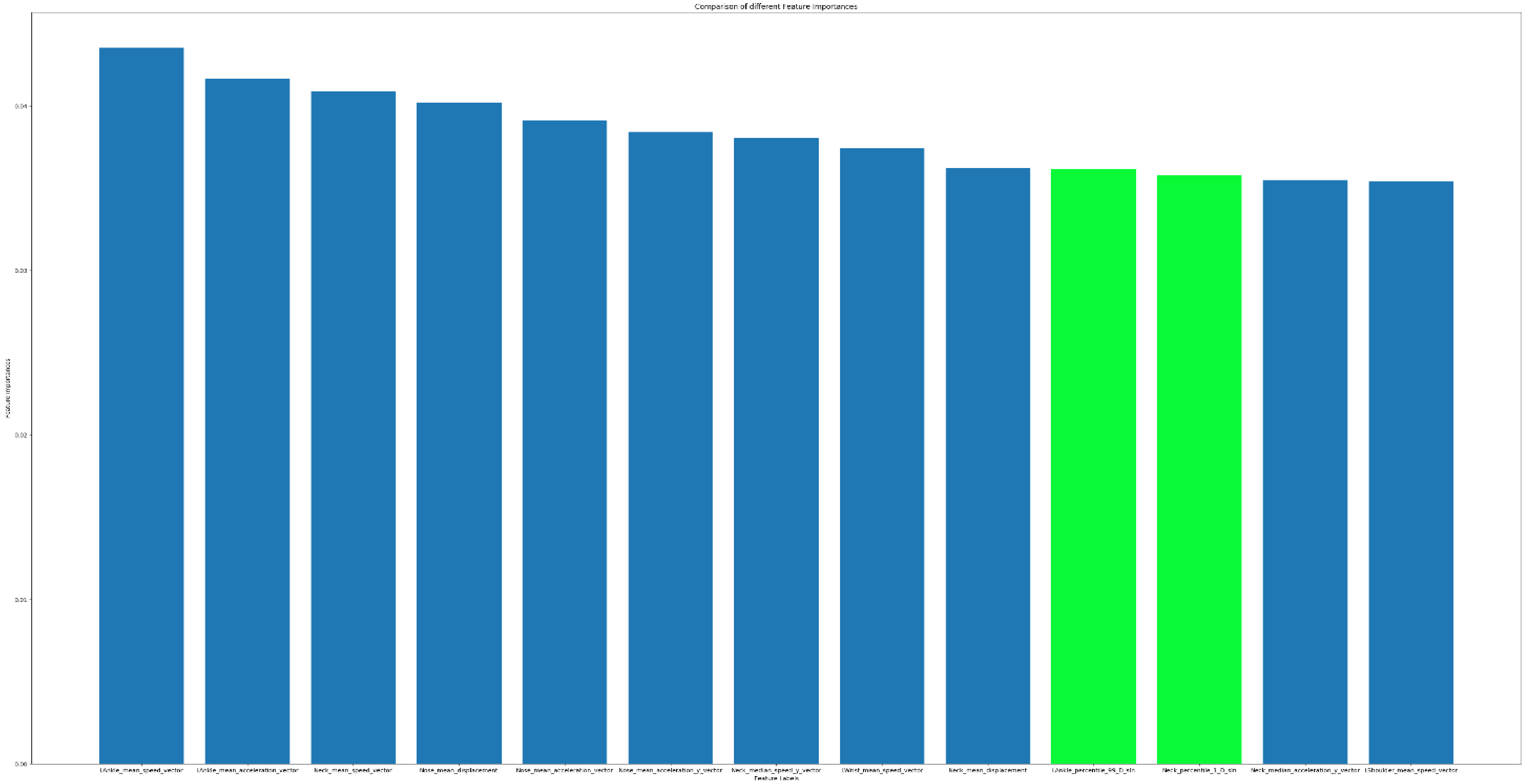
UNIVERSITÀ DEGLI STUDI DI BARI ALDO MORO

| Work in | Accuracy |
|---|---|
| [10] and [11] | 86.21% |
| [12] | 79.31% |
| [13] | 85.4% |
| [14] | 86.14% with SVM 97.52% with SVDD |
| [15] | 96% |
| [16] | 86.84%. |
| **This Work** | **98%** |

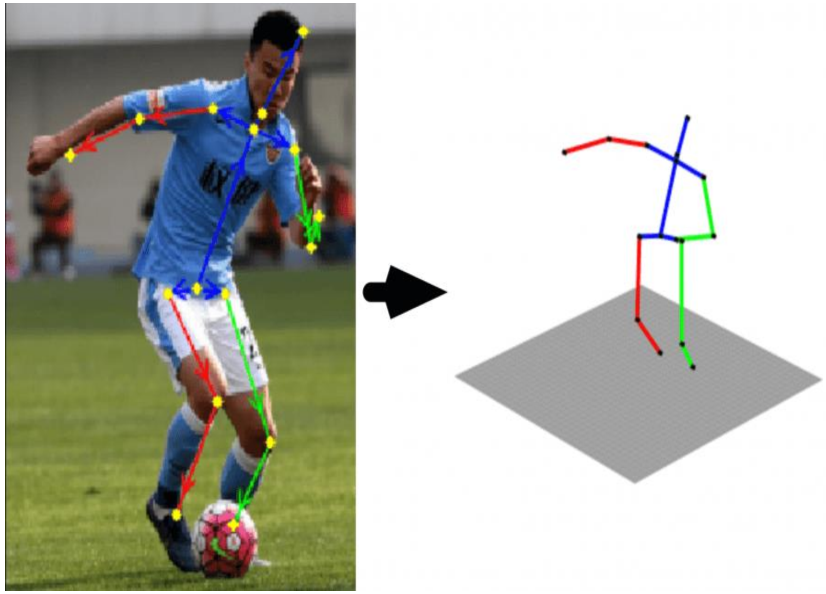
# Accuracy on URFD dataset

| Work in | Accuracy |
|---|---|
| [29] | 89% |
| [31] | 98.57% LSTM on Accelerometer<br>92.86% RGBD data |
| [32] | 90.53% |
| [33] | 82.85% |
| **This Work** | **99%** |

# Features Ranking



# Future Work



In future 3D Pose Estimation and the use of advanced deep learning techniques will be used and compared with the shallow learning approach presented in this work.

# THANK YOU FOR WATCHING

UNIVERSITÀ DEGLI STUDI DI BARI ALDO MORO