Deep Learning-Based Gait Recognition Using Smartphones in the Wild [1]

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Introduction

- **Problem Statement:** Using deep learning methods to identify and authenticate a person by their gait data provided by an application on their smartphones.

- **The project comprises three subparts:** Gait data extraction, Gait Identification, and Authentication.

- The motive of the paper is to propose an effective and seamless combination of DCNN and DRNN for robust inertial gait feature representation.
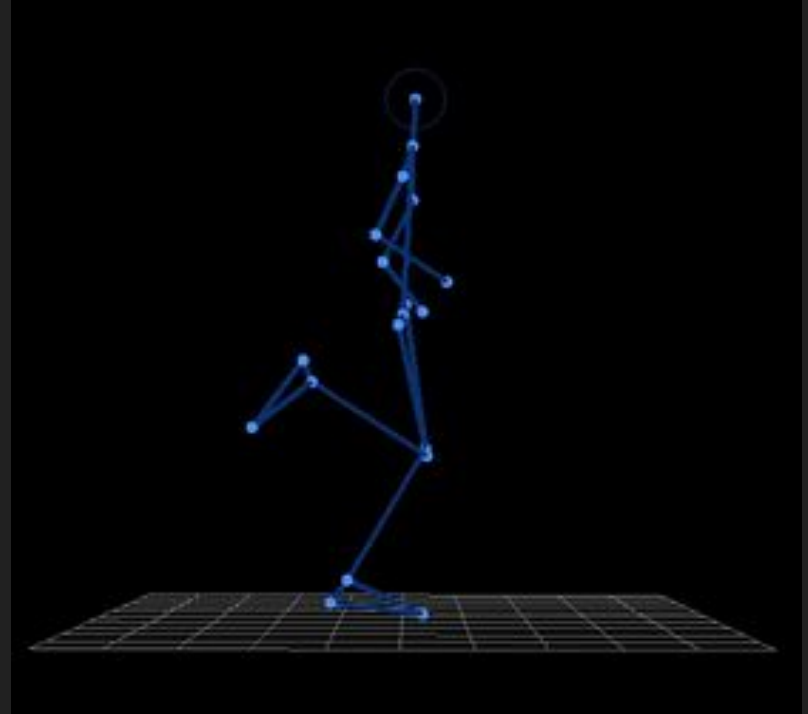
Datasets

WhuGAIT Dataset: 3-axis accelerometer and 3 axis gyroscope data, collected at a sampling rate of 50 Hz using an Android application. All data is pre-processed using Gait Segmentation algorithm. Train/Test split of 90%-10%. Length of each sample is 128. Comprises of the following datasets:

- Dataset 1 (Identification): 118 subjects. 33,104 Training samples, 3740 Testing samples.

- Dataset 2 (Identification): 44,339 samples are used for training, and the rest 4,936 for testing.

- Dataset 3 (Identification): 26,283 samples are used for training, and the rest 2,991 for testing.

- Dataset 4 (Identification): 35,373 samples are used for training, and the rest 3,941 for test.

- Dataset 5 (Authentication): There are 66,542 samples and 7,600 samples for training and test, respectively. Horizontally aligned data.

- Dataset 6 (Authentication): Contains same data as dataset 5. Vertically aligned data.

- Dataset 7 (Segmentation): 577 samples from 10 subjects, with data shape of 6×1024. 519 of them were used for training and 58 were used for testing.

- Dataset 8 (Segmentation): We took 1,354 samples from 118 subjects, with data shape of 6×1024. 1022 samples from 20 subjects as training data and 332 samples from other 98 subjects for testing.

Data Extraction

- Smartphones to collect the inertial data
- Walking sessions and non-walking sessions
- Partitioning problem as a time-series segmentation problem
- Inspired by U-Net
- Semantic segmentation algorithm with a one-dimensional DCNN
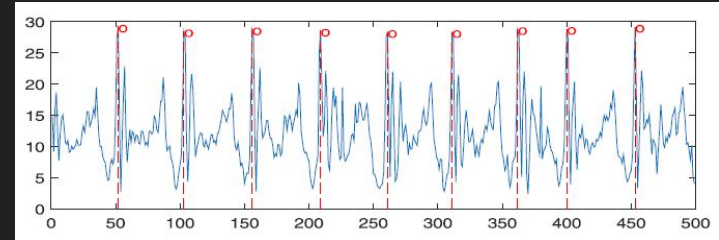

Fig. 1: Data Extraction Network Architecture

Fig. 2: An example of step segmentation. (a) The gait curve ACCo, calculated on the three components as shown in Figure 2. (b) The segmentation results, where the red dots denote the local maximums and divide the steps.
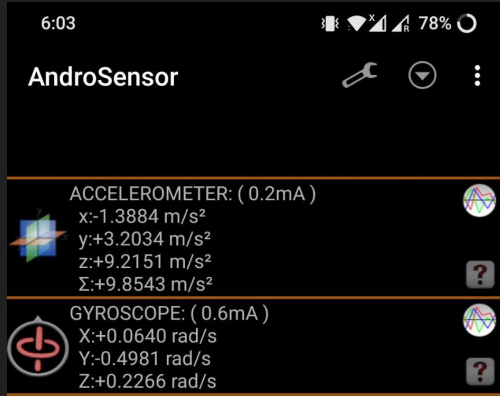
Data Extraction Implementation
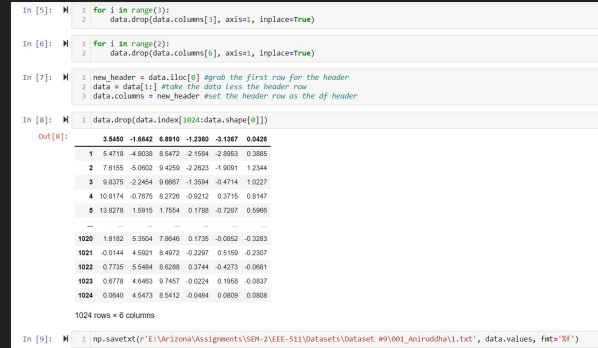

Fig. 3: AndroSensor Android Application

Fig. 4: Data Formatting

Fig. 5: Data Collected from Smartphone

- **Dataset #7:** 577 samples of 10 subjects, with data shaped as 6 × 1,024. Among these samples, 519 are used for training and 58 are for test. Both the training and test samples are from the 10 subjects.

- **Dataset #8:** 1,354 samples of 118 subjects, with data shaped as 6×1,024. Among these data, 1,022 samples from 20 subjects are used for training, and 332 samples from the other 98 subjects are used for test.

Learning Rate: 0.0001
Epochs: 150

Data Extraction Results

- '1' as the walking data, and '0' as the non-walking data. The labels are manually annotated.

- **Dataset #7:** The training data and test data have no overlap but are all from the same 10 subjects, the proposed method achieves an accuracy of 90.22%, which shows the effectiveness of the proposed method in separating walking data from non-walking data.

- **Dataset #8:** The training data and the test data are from different subjects, an accuracy of 85.57% is obtained, which indicates that the proposed method has high generalization ability.
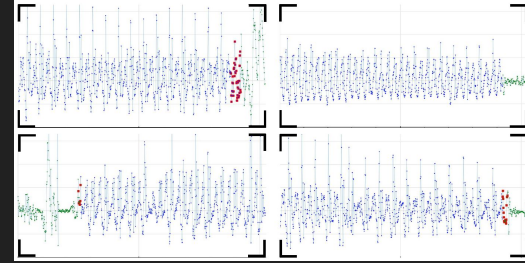
Fig. 6: Four examples of walking data extraction using the proposed method. Note that, the blue points denote the walking data, green points denote the non-walking data, and the red denotes the false classified.

Fig. 7: Accelerometer and Gyroscope data extracted from one of our peer's data

Identification

Input - Inertial gait curve:

$$\mathbf{x} = (x_1, x_2, \ldots, x_T),$$

$$\text{w.r.t.,}\, x_t = (acc_x^t, acc_y^t, acc_z^t, gyr_x^t, gyr_y^t, gyr_z^t)^\top$$

Output vector:

$$\mathcal{O} = (o_1, o_2, \ldots, o_n)$$

Fig. 8: Network Architecture for Gait Identification.

Identification Implementation

LSTM Network: Each hidden layer in the LSTM has N = 1024 hidden nodes, the learning rate is set to 0.0025, and the number of epochs for training is 200.

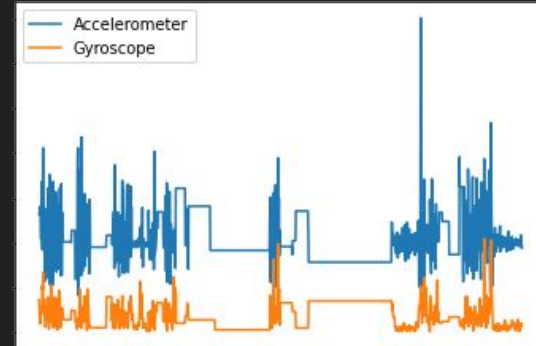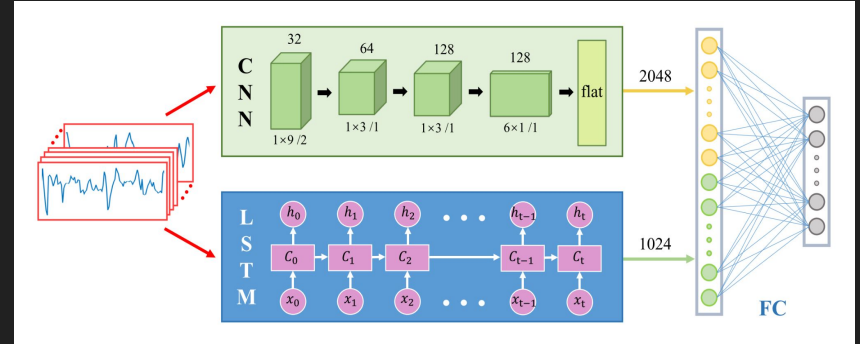State for each layer at time 't':

$$\mathbf{h}_t^l = \sigma\,(W_{xh}^l x_t + \mathbf{h}_{t-1}^l W_{hh}^{tl} + \mathbf{h}_t^{l-1} W_{hh}^{ll} + \mathbf{b}_h^l)$$

Updating state:

$$\mathbf{i}_t = \sigma_i\,(W_{xi} x_t + W_{hi}^t \mathbf{h}_{t-1}^l + W_{hi}^l \mathbf{h}_t^{l-1} + W_{ci} \mathbf{c}_{t-1} + \mathbf{b}_i)$$
$$\mathbf{f}_t = \sigma_f\,(W_{xf} x_t + W_{hf}^t \mathbf{h}_{t-1}^l + W_{hf}^l \mathbf{h}_t^{l-1} + W_{cf} \mathbf{c}_{t-1} + \mathbf{b}_f)$$
$$\mathbf{c}_t = \mathbf{f}_t + \mathbf{c}_{t-1} \sigma_i\,(W_{xc} x_t + W_{hc}^t \mathbf{h}_{t-1}^l + W_{hc}^l \mathbf{h}_t^{l-1} + \mathbf{b}_c)$$
$$\mathbf{o}_t = \sigma_o\,(W_{xo} x_t + W_{ho}^t \mathbf{h}_{t-1}^l + W_{ho}^l \mathbf{h}_t^{l-1} + W_{co} \mathbf{c}_{t-1} + \mathbf{b}_o)$$
$$\mathbf{h}_t^l = \mathbf{o}_t \sigma_h\,(\mathbf{c}_t)$$

Output Feature:

$$feat_{lstm} = \mathbf{h}_T^L$$
$$= (f_1, f_2, \ldots, f_N)$$

CNN Network: Six-axis accelerometer / gyroscope data shaped as 6 × 128. The learning rate is 0.0025, and the number of epochs for training is 200.

Layer Name	Kernel Size	Number of features	Stride	Feature Map
Conv1_1	1 x 9	32	2	6 x 64 x 32
pool1	1 x 2	/	2	6 x 32 x 32
conv2_1	1 x 3	64	1	6 x 32 x 64
conv2_2	1 x 3	128	1	6 x 32 x 128
pool2	1 x 2	/	2	6 x 16 x 128
conv3_1	6 x 1	128	1	1 x 16 x 128

Table 1: Details of the CNN structure

Identification Implementation (Continued)

Fully Connected Layer: Concatenation of the features extracted by LSTM and CNN, i.e.,

$feat_{full} = feat_{LSTM} + feat_{CNN}$

Classification Output:

$$\mathbf{o} = \mathbf{Softmax}(feat_{full} * W_o + \mathbf{b}_o)$$

Obtained Class Label:

$$\mathbf{o}' = (o'_1, o'_2, \dots, o'_n)$$

$$o'_i = \begin{cases} 1 & \mathbf{x} \in s_i, \\ 0 & other. \end{cases}$$

Cross-Entropy Loss Function:

$$\mathcal{L}(\mathbf{o}, \mathbf{o}') = \sum_i^n o'_i \ln o_i + (1 - o'_i)\ln(1 - o_i)$$

Identification Results

Classification Methods	Dataset #1	Dataset #2
CNN	92.54%	95.10%
CNN+LSTM	91.42%	95.67%
CNN+LSTM$_{fix}$	**93.43%**	**98.43%**

Table 2: Classification Performance Of Deep Learning-Based Methods

- The two Dataset #1, Dataset #2, are used to evaluate the following deep learning-based methods: CNN, CNN+LSTM, and CNN+LSTM.

- The classification results are shown in Table. All the methods achieve greater than 90% accuracy on both datasets. Dataset #1 contains 118 subjects, and Dataset #2 consists of the gait data of 20 subjects.

- Comparison Methods: To evaluate the proposed methods for person identification, we are planning on using the following method:
  - Fourier

Authentication

- Two sequences of gait data x_a and x_b:

$$\mathbf{x_a} = (x_{a,1}, x_{a,2}, \ldots, x_{a,T})$$
$$\mathbf{x_b} = (x_{b,1}, x_{b,2}, \ldots, x_{b,T})$$

- Authentication is formulated as a binary classification problem

- The output of the network is set as two dimensions. We use 'True' and 'False' to denote that the input data are from the same subject and different subjects, respectively

Authentication Implementation

- CNN is a feature extractor to map input inertial signals into lower-dimensional abstractions

- CNN trained on 98 subjects and tested on 20 subjects that have no overlap.

- CNN is fixed as feature extractor

- I/p gait signal is 6x128, O/p of CNN is 1x16x128

- rearrange the CNN features into 16 × 256 for a pair of inputs

- Features fed into double-layer LSTM for training and prediction
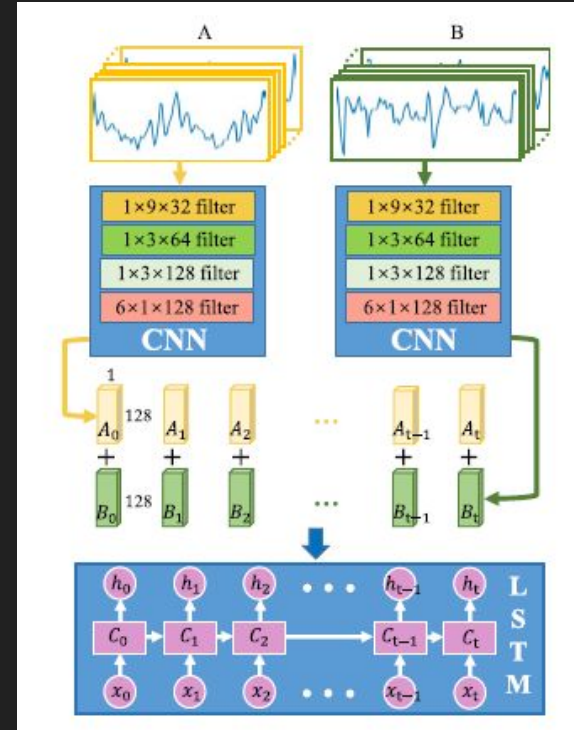
Fig. 9: The network architecture for gait authentication

Authentication Results

- On Implementing the CNN and CNNfix+LSTM architectures on dataset 5 and 6, we have received the adjacent performance table (testing accuracies)

- According to these results, CNNfix+LSTM performs more effectively on the vertical dataset (Dataset #6).

Authentication Methods	Dataset #5 (Horizontal)	Dataset #6 (Vertical)
CNN	78.3%	86.96%
CNN_{fix}+LSTM	85.48%	93.7%

Table 3: Authentication performance based on training accuracy of models

Conclusion

- For robust inertial gait feature representation, a hybrid technique was presented that smoothly combined the DCNN and DRNN.

- The smartphones were used in unrestricted conditions during gait data collection, and no information regarding when, where, or how the user walks was available.

- The suggested hybrid network outperformed the standalone networks by a wide margin.

- We got the opportunity to dive deep into machine learning frameworks such as Tensorflow, and development environments such as Jupyter Notebook and Google Colab.

- We were able to better understand many ideas related to the CNN and LSTM models.

- We discovered the many hyperparameters that have a direct impact on our model's accuracy.

System Specification & References

Systems Used:

- **HP Omen 15: Identification**
  - CPU: Intel i7-7700-HQ 7th Gen 3.02GHz Quad core
  - GPU: Nvidia GEFORCE GTX 1050ti 4GB
  - Ram: 16GB DDR4

- **Dell G3: Authentication**
  - CPU: Intel i7-8750-H8th Gen 2.2GHz Quad core
  - GPU: Nvidia GEFORCE GTX 1050ti 4GB
  - Ram: 16GB DDR4

- **HP 15 bs180: Data Extraction**
  - CPU: Intel i5-8250U 8th Gen 1.8GHz Quad core
  - GPU: AMD Radeon Adrenaline 2GB
  - RAM: 8GB DDR4

Software Used:

- Jupyter Notebook
- Google Colab
- Tensorflow-gpu v1.8.0

References:

[1] Q. Zou, Y. Wang, Q. Wang, Y. Zhao, and Q. Li, "Deep Learning-Based Gait Recognition Using Smartphones in the Wild," *IEEE Transactions on Information Forensics and Security*, vol. 15. pp. 3197–3212, 2020 [Online]. Available: http://dx.doi.org/10.1109/tifs.2020.2985628

Team Assignment 4 - Team final project - Final Presentation

Team #18

Student name: Aniruddha Anand Damle	worked on literature	worked on implementation (data, platform, test run, debug, compatibility...)	generated results (run results, result data processing, presenting results	wrote report (Intro, method, result, discussions, ...)	other significant contributions	peer approval 1	peer approval 2	peer approval 3
specific & detailed evidence is required to support claims of contributions (make reference to specific paragrphs, equation #, figure #, code line #'s sections, etc...)	N/A	N/A	N/A	1. Data Extraction 2. Data Extraction implementation 3. Data Extraction Results 4. System requirements and references	1. Worked on Formatting 2. Worked on presentation structure 3. Formatting images and tables 4. Wrote corresponding speaker notes	N/A	Approved	Approved

Student name: Prakriti Biswas	worked on literature	worked on implementation (data, platform, test run, debug, compatibility...)	generated results (run results, result data processing, presenting results	wrote report (Intro, method, result, discussions, ...)	other significant contributions	peer approval 1	peer approval 2	peer approval 3
specific & detailed evidence is required to support claims of contributions (make reference to specific paragrphs, equation #, figure #, code line #'s sections, etc...)	N/A	N/A	N/A	1. Introduction 2. Authentication 3. Authentication Implementation 4. Authentication Results 5. Conclusion	1. Wrote corresponding speaker notes	Approved	N/A	Approved

Student name: Aditya Kaduskar	worked on literature	worked on implementation (data, platform, test run, debug, compatibility...)	generated results (run results, result data processing, presenting results	wrote report (Intro, method, result, discussions, ...)	other significant contributions	peer approval 1	peer approval 2	peer approval 3
specific & detailed evidence is required to support claims of contributions (make reference to specific paragrphs, equation #, figure #, code line #'s sections, etc...)	N/A	N/A	N/A	1. Datasets 2. Identification 3. Identification Implementation 4. Identification Implementation (contd.) 5. Identification Results	1. Wrote corresponding speaker notes	Approved	Approved	N/A