

# GaitPrivacyON: Privacy-Preserving Mobile Gait Biometrics using Unsupervised Learning

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## ABSTRACT

Numerous studies in the literature have already shown the potential of biometrics on mobile devices for authentication purposes. However, it has been shown that, the learning processes associated to biometric systems might expose sensitive personal information about the subjects. This study proposes GaitPrivacyON, a novel mobile gait biometrics verification approach that provides accurate authentication results while preserving the sensitive information of the subject. It comprises two modules: *i*) a convolutional Autoencoder that transforms attributes of the biometric raw data, such as the gender or the activity being performed, into a new privacy-preserving representation; and *ii*) a mobile gait verification system based on the combination of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) with a Siamese architecture. The main advantage of GaitPrivacyON is that the first module (convolutional Autoencoder) is trained in an unsupervised way, without specifying the sensitive attributes of the subject to protect. The experimental results achieved using two popular databases (MotionSense and MobiAct) suggest the potential of GaitPrivacyON to significantly improve the privacy of the subject while keeping user authentication results higher than 99% Area Under the Curve (AUC). To the best of our knowledge, this is the first mobile gait verification approach that considers privacy-preserving methods trained in an unsupervised way.

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## 1. Introduction

The use of biometrics on mobile devices is currently one of the most popular authentication approaches [1; 2]. In particular, behavioural biometrics, which are based on the way subjects perform actions such as writing [3] and walking [4], allow the recognition in a passive and transparent way through wearables and smartphones, for example, using the accelerometer and gyroscope data [5; 6].

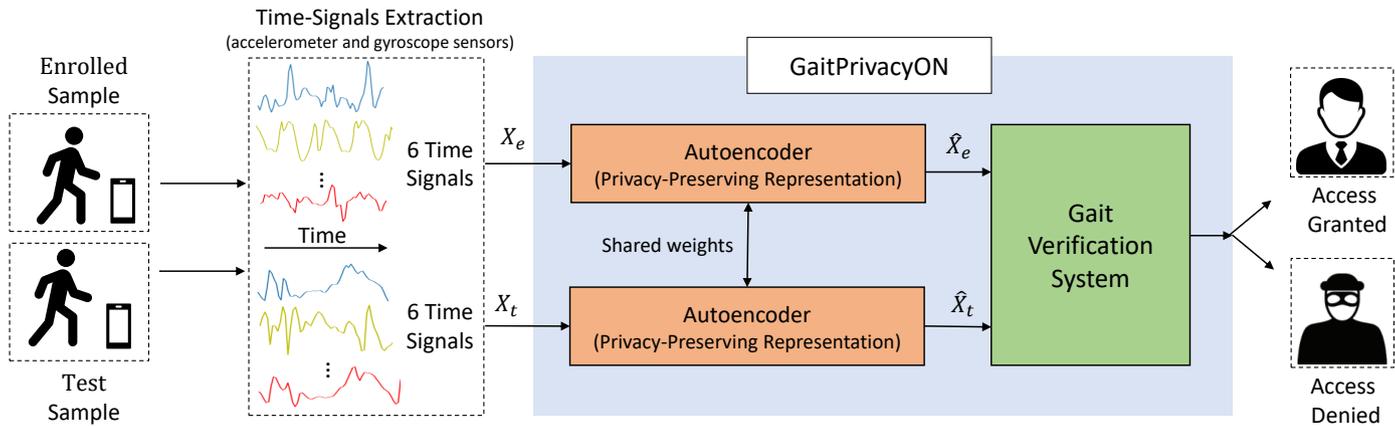
Despite the popularity of mobile behavioural biometrics, the data acquired can contain a large amount of personal and sensitive information such as demographics (e.g., gender, age, ethnicity, etc.) or the activity the subject is performing (e.g., walking, sitting, etc.) [7; 8; 9]. As a result, this technology might be considered as an invasion of personal privacy.

Privacy is a concept that has been defined in numerous ways [10], one example of which is the recent General Data Protection Regulation (GDPR) of the European Union [11]. This defines personal data as “any information relating to an identified

or identifiable natural person”. Within this set of data, there is a subgroup called sensitive data which includes “racial or ethnic origin, political opinions, religious or philosophical beliefs, trade union membership, genetic data, biometric data for the purpose of uniquely identifying a natural person, health data or data concerning the individual’s sex life or sexual orientation”. The automatic processing of such data without the explicit consent of the subject for any specific purpose is prohibited.

This study proposes GaitPrivacyON, a novel mobile gait biometrics verification approach that provides accurate authentication results while preserving the privacy of the subject. Fig. 1 provides a graphical representation of GaitPrivacyON. The main contributions of this study are:

- A novel mobile gait biometrics verification approach that provides accurate authentication results while preserving the privacy of the subject. It comprises two modules: *i*) a convolutional Autoencoder that transforms the biometric raw data into a new privacy-preserving represen-



**Fig. 1:** Diagram of GaitPrivacyON, which comprises two modules: *i*) an Autoencoder that is in charge of removing automatically the sensitive data; and *ii*) a gait verification system that is in charge of the gait verification task. Time signals extracted from the accelerometer and gyroscope sensors of the mobile devices are considered as input to GaitPrivacyON.  $X_e$ : Enrolled sample,  $X_t$ : Test sample,  $\hat{X}_e$ : Transformed enrolled sample,  $\hat{X}_t$ : Transformed test sample.

tation (e.g., gender or activity), and *ii*) a mobile gait verification system based on a combination of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) with a Siamese architecture.

- An in-depth quantitative analysis of GaitPrivacyON over two popular databases in the field of gait recognition, MotionSense [12] and MobiAct [13], achieving accurate verification results (higher than 99% Area Under the Curve, AUC) while reducing the recognition rate of sensitive data to  $\sim 50\%$  AUC.
- To the best of our knowledge, this is the first mobile gait verification approach that considers privacy-preserving methods trained in an unsupervised way.

## 2. Related Work

### 2.1. Mobile Gait Biometrics

Gait biometric recognition allows individuals to be authenticated based on the way they walk. It is a unique characteristic among individuals due to the specific arm swing amplitude, step frequency and length [14]. This characteristic can be easily detected in several ways. One of them is from Inertial Measurement Units (IMU), e.g., accelerometer and gyroscope [14], which enables gait biometrics authentication from mobile devices. An example of this was presented by Mantyjarvi *et al.* in [15]. Gait biometrics data captured by the accelerometer was used in a template matching and cross-correlation framework, achieving together, 7% of Equal Error Rate (EER). Many researchers followed this method, proposing new studies in the literature as described in the review of Sprager and Juric [16].

In recent years, Deep Learning (DL) approaches have dominated the field of gait recognition, being possible to extract more discriminative and robust features. Gadaleta and Rossi created in [17] one of the first systems based on DL (IDNet), specifically using CNNs. The authors used universal feature extractors for gait biometrics recognition with misclassification rates of less than 0.15%. Their results showed that CNN-based

systems learn more useful statistical features, achieving better performance than previous methods with pre-defined and often arbitrary features.

In addition, RNNs is one of the most powerful DL techniques for temporal sequences [18; 19]. Fernandez-Lopez *et al.* analysed accelerometer and gyroscope data to perform a subject recognition model [20]. A dataset with 774 subjects was used. The algorithm processed the signals by extracting the gait cycles and inputting them into an RNN, achieving an EER of 11.48%. However, the data used came from a sensor on a belt attached to the waist. That work did not present a natural situation of holding a phone. In order to have a more realistic scenario, Ackerson *et al.* proposed a new approach in which the OU-ISIR dataset was used [21]. This dataset comprises accelerometer and gyroscope data acquired from IMU sensors and accelerometer data from a smartphone. The authors developed one of the first approaches to use a type of RNN, Long Short-Term Memory (LSTM). The authors achieved an EER of 7.55%. Watanabe and Kimura collected mobile accelerometer data from 21 individuals in a more common scenario [22]. The subjects were carrying the device in their pocket or hand while walking. Following the DL advances, the authors proposed a LSTM framework, achieving an accuracy of 97%.

Another interesting approach was proposed by Zou *et al.* in [23]. The authors created a hybrid DL model combining CNNs and LSTM for more robust features. The proposed model brought together the advances of CNNs (extracting convolutional maps with more discriminative features) and RNNs (processing features as temporal sequences). The authors considered mobile devices in the wild, with 118 subjects and data extracted from the accelerometer and gyroscope, obtaining an accuracy of 93.7%.

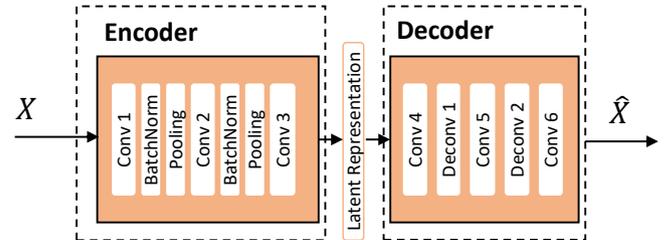
### 2.2. Privacy-Preserving Methods

Privacy-preserving concerns are becoming increasingly important nowadays due to the new privacy laws and regulations. Therefore, many researchers have extensively studied the field in the last decade [10].

In the human-activity recognition field, Iwasawa *et al.* proposed a model with an adversarial subject classifier and a regular activity-classifier based on CNNs [24]. The authors managed to privatise the subject’s discriminative information by 40% while keeping accurate activity recognition performances. Malekzadeh *et al.* in [12] presented a feature learning architecture that provides privacy-preserving data transmission and a new dataset for activity and attribute recognition collected from motion sensors. Their system was based on Generative Adversarial Networks (GANs), achieving a 45.8% reduction in accuracy in the gender classification task while the activity recognition task (e.g., downstairs, upstairs, jogging, and walking) only decreased by 1.37%. Osia *et al.* focused on activity recognition [25]. The authors developed a Siamese CNN split between an IoT device and the cloud so the IoT device had only the necessary information. The authors evaluated the model with the information exposed to the cloud service, managing to increase the EER in the gender classification task by 14%. Zhang *et al.* proposed a new framework for activity recognition and privacy-preserving of sensitive data [26]. The authors wanted to avoid the need for massive collection of sensitive data for model training. For this purpose, an unsupervised learning training for the privacy-preserving task was performed. The framework was treated by a transformation of the data together with a noise addition consisting of an Autoencoder and a CNN. Results of 56.79% accuracy was achieved for gender classification while the activity recognition task remained almost untouched.

In the gait biometrics verification field, Garofalo *et al.* developed a Siamese CNN framework [27]. In that work the authors managed to decrease the F1-score in the gender recognition task from 73% to 52% while loosing from 90.93% to 85.28% of accuracy in the task of gait verification. The authors used an adversarial learning technique.

Several techniques have also been applied to the image field but at the feature representation level. Therefore, these approaches could also be adapted and used for those tasks related to time domain signals. Terhörst *et al.* proposed an unsupervised approach based on similarity-sensitive noise transformations [28]. That approach added noise (Euclidean and cosine) to the feature representations. Experiments showed how attackers with prior knowledge about the privacy mechanism (added cosine noise) decreased the accuracy of gender estimation performance with logistic regression from ~90% to ~73%. Identity recognition performance only increased by ~5% EER. In [29] Incremental Variable Elimination (IVE) algorithm was proposed. The model was used to suppress binary and categorical attributes in biometric templates. The model, through decision tree training, managed to decrease the gender Correct Overall Classification Rate (COCR) by 20% but only increasing the EER in the identity recognition task by 1.4%. Instead of masking sensitive attributes, the authors in [30] presented an approach that tries to disentangle feature representations so sensitive information can be removed. That paper presented Privacy-Enhancing Face-Representation learning Network (PFRNet), an Autoencoder that achieved a latent representation in which increasing the EER in the identity recognition task by 2.7%, increases the Fraction of Incorrectly Classified images (FIC) in



**Fig. 2:** Autoencoder.  $X$ : Time signals,  $\hat{X}$ : Transformed time signals trained to maintain the performance on a primary task (e.g., user verification) and reduce the performance in a secondary task (e.g., sensitive attribute classification).

the gender recognition task to 43.5%. Morales *et al.* created SensitiveNets [31]. Its main purpose was to set aside sensitive information in decision making in order to ensure fairness and transparency. It was tested on feature representations of face images by defining and minimising its own loss function. SensitiveNets achieved representations that reduced the gender and ethnicity classification tasks to 54.6% and 53.5% respectively, decreasing recognition task accuracy only 2.6%.

The previous gait verification approaches presented in the literature can preserve specific sensitive attributes [27], but they require a large volume of labelled data for training. On the contrary, GaitPrivacyON considers unsupervised learning for the privacy preserving of the subjects without specifying the sensitive attributes to protect. Therefore, this avoids any model inference and provides greater protection than the models presented in the literature. Also, this approach allows the hiding of all sensitive attributes using a single transformation.

### 3. Proposed Approach: GaitPrivacyON

Fig. 1 shows the architecture of the proposed privacy-preserving approach. Six time signals are originally acquired from the mobile device as raw data comprising the three axes of the accelerometer and gyroscope. GaitPrivacyON considers a Siamese architecture that is used to learn the similarity between two different biometric templates from the same (genuine) or different (impostor) subject [32]. GaitPrivacyON comprises two modules: *i*) a convolutional Autoencoder that transforms the biometric raw data into a new privacy-preserving representation (Sec. 3.1); and *ii*) a mobile gait verification system based on the combination of CNNs and RNNs with a Siamese architecture (Sec. 3.2). For the training of GaitPrivacyON, we adapted the key aspects presented in the image style transformation field [26]. The details are explained in Sec. 3.3.

#### 3.1. Autoencoder

Fig. 2 provides a graphical representation of the proposed convolutional Autoencoder. A Siamese architecture with two inputs is considered as described in Fig. 1: enrolled sample ( $X_e$ ) and test sample ( $X_t$ ). The architecture is composed of a sequence of  $1 \times 3$  convolutional filters, coupled with ReLU activation functions. In the encoder, after each convolutional layer, batch normalization and  $1 \times 2$  max-pooling layers are used to decrease the size of the activation map. In the decoder, after

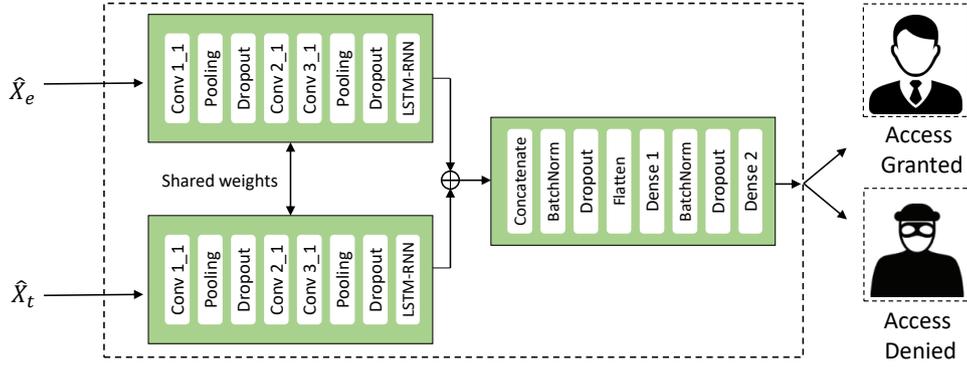


Fig. 3: Gait Verification System.  $\widehat{X}_e$ : Transformed enrolled sample,  $\widehat{X}_t$ : Transformed test sample.

each convolutional layer, a deconvolutional layer is used with  $1 \times 3$  strides of the convolution. The activation function of the last convolutional layer is linear. The Autoencoder allows the extraction of transformed data that retains the information for the verification task but protect the privacy of the subject, removing the sensitive information.

### 3.2. Gait Verification System

Fig. 3 provides a graphical representation of the architecture proposed for gait verification ( $\varphi$ ). In particular, we have adapted the approach originally presented by Zou *et al.* in [23] to our specific case (privacy-preserving gait verification). It is based on a novel Siamese architecture with two inputs: transformed enrolled sample ( $\widehat{X}_e$ ) and transformed test sample ( $\widehat{X}_t$ ). The inputs are reshaped including one new dimension. Unlike the method proposed in [23], the architecture is composed of a sequence of  $1 \times 3$  two-dimensional convolutional filters, coupled with ReLU activation functions. After 3 convolutional layers, batch normalization,  $1 \times 2$  max-pooling, and dropout with a probability of 0.5 are used. A reshaping layer is included to return to the shape of the time domain signals following by a bi-directional LSTM layer with 50 units. The dense layer has a size of 400 with a sigmoid activation function.

### 3.3. Training

GaitPrivacyON is trained following the idea proposed in the image style transformation field [33]. One image can be divided into two parts: *i*) the *content*, i.e., what is in the image, and *ii*) the *style*, i.e., how the image is illustrated. In our particular application of gait biometrics verification, the content is the unique information that allows to verify the identity of the subject whereas the style is the sensitive information of the subject that can be considered for other purposes not related to the authentication. This sensitive information may include the person's gender, age, ethnicity, or the activity the subject is performing while using mobile devices [24].

Following this idea, three different loss functions have been considered from the work presented in [26]: *task loss* ( $\mathcal{L}_t$ ), *content loss* ( $\mathcal{L}_c$ ), and *style loss* ( $\mathcal{L}_s$ )

The *task loss* ( $\mathcal{L}_t$ ) helps the system to maintain its usefulness in the main task of gait verification. We consider a categori-

cal cross entropy that compares the transformed data with the biometric raw data. Therefore, the *task loss* can be defined as:

$$\mathcal{L}_t(Y_a, \widehat{X}) = -Y_a \log(\varphi(\widehat{X})) \quad (1)$$

where  $Y_a$  and  $\varphi(\widehat{X})$  are the label and the predicted probability of the gait verification task, respectively.

The *content loss* ( $\mathcal{L}_c$ ) measures the content (i.e., the authentication information) that the transformed data ( $\widehat{X}$ ) and the biometric raw data ( $X$ ) have in common. For this purpose, we use the Euclidean distance to compare the feature maps provided by the  $i$ -layer of the  $\varphi$  network when using both the biometric raw data and the transformed data as input. In our case, we use the feature maps obtained behind *Conv3\_1* layer in Fig. 3. This was decided experimentally. The *content loss* is defined as:

$$\mathcal{L}_c^i(X, \widehat{X}) = \frac{1}{C_i H_i W_i} \left\| \varphi_i(\widehat{X}) - \varphi_i(X) \right\|_2^2 \quad (2)$$

where  $i$  is the layer and  $C_i \times H_i \times W_i$  is the shape of the feature map obtained after this layer. Comparing feature maps ensures that the content of the biometric raw data and the transformed data are similar but do not have to be identical.

The *style loss* ( $\mathcal{L}_s$ ) is responsible for maintaining the transformed data unstyled, thus avoiding the extraction of any sensitive information. For this purpose, we want to modify the style of the data by uniform random noise ( $N_s$ ) with range  $[-20, 20]$  as done by [26]. We consider the Gram matrix ( $G$ ) to measure the style differences between feature representations. Random noise is introduced as the new domain, avoiding using any information from the sensitive data for its protection, creating an unsupervised learning framework. For this purpose, both the transformed data and the random noise are fed into the trained gait verification system with the weights frozen. After that, the Gram Matrices of the feature maps obtained as output of the  $i$ -layer are compared. The Gram Matrix can be defined as:

$$G_i(X)_{c,c'} = \frac{1}{C_i H_i W_i} \sum_{h=1}^{H_i} \sum_{w=1}^{W_i} \varphi_i(X)_{h,w,c} \varphi_i(X)_{h,w,c'} \quad (3)$$

where the shape of  $\varphi_i(X)$  is  $C_i \times H_i \times W_i$  and the shape of its Gram matrix ( $G_i^{\varphi}$ ) is  $|C_i| \times |C_i|$ .  $\varphi_i(X)$  can be interpreted as  $C_i$  dimensional features for each  $H_i \times W_i$  point, where  $c$  and  $c'$  are two different dimensions.

**Table 1:** Architecture of the gender and activity inference systems. Prob- Probability. m- number of signals. SAC- Sensitive Attribute Classes.

Layer	Input Size ( $H \times W \times F$ )	Kernel ( $H \times W$ )	Padding	Activation	Prob
Conv1_1	m×100×1	1×3	Valid	Relu	-
Conv1_2	m×98×16	1×3	Valid	Relu	-
Batch_1	m×96×16	-	-	-	-
Pool_1	m×96×16	1×2	Valid	-	-
Drop_1	m×48×16	-	-	-	0.5
Conv2_1	m×48×16	1×5	Valid	Relu	-
Batch_2	m×44×32	-	-	-	-
Pool_2	m×22×32	1×2	Valid	-	-
Drop_2	m×22×32	-	-	-	0.5
Dense_1	m×100	-	-	-	-
Batch_3	m×100	-	-	-	-
Drop_3	m×100	-	-	-	0.5
Dense_2	m×SAC	-	-	-	-

The *style loss* measures the dissimilarity in style using the Frobenius squared norm of the difference of the Gram matrices of the transformed data  $\widehat{X}$  and the random noise  $N_s$ . In our case, we have decided experimentally to use the feature maps obtained behind *Conv2\_1* in Fig. 3. The *style loss* can be defined as:

$$\mathcal{L}_s^i(\widehat{X}, N_s) = \left\| G_i^e(\widehat{X}) - G_i^e(N_s) \right\|_F^2 \quad (4)$$

where  $F$  denotes the Frobenius squared norm. By using deeper layers, the extracted features will have a more similar appearance.

The final loss function of GaitPrivacyON ( $\mathcal{L}_t$ ) would be a weighted sum of the losses  $\mathcal{L}_t$ ,  $\mathcal{L}_c$ , and  $\mathcal{L}_s$ :

$$\mathcal{L}_t = \alpha \mathcal{L}_t + \beta \mathcal{L}_c + \gamma \mathcal{L}_s \quad (5)$$

where  $\alpha + \beta + \gamma = 1$ .

## 4. Experimental Setup

### 4.1. Datasets

Two popular databases are considered in this study: MotionSense database [12] and MobiAct database [13].

The MotionSense database comprises accelerometer and gyroscope data collected with an iPhone 6s. The dataset consists of 24 total subjects with information on gender, age, height, and weight. The data was acquired while the subjects performed 4 different activities (walking up and down stairs, jogging, and walking). All the subjects had the mobile phone fixed in the front pocket of the trouser.

The MobiAct database comprises accelerometer, gyroscope and magnetometer data collected using a Samsung Galaxy S3. A total of 56 subjects performing the same 4 activities (walking up and down stairs, jogging, and walking) were captured. Data on gender, age, height, and weight of the subjects were acquired. Unlike the previous dataset, subjects had a free choice of placement of their device, simulating a realistic scenario.

### 4.2. Experimental Protocol

The main goal behind the experimental protocol design is to analyse and prove the potential of the GaitPrivacyON approach for gait biometrics scenarios. Therefore, our approach is trained with accelerometer and gyroscope time domains signals from both MotionSense and MobiAct databases. A total of 80 subjects (i.e., 24 from MotionSense and 56 from MobiAct) performing 4 different activities (walking up and down stairs, jogging, and walking) are considered in the experimental framework. The total dataset consists of 55 males and 25 females. In both databases the frequency sampling has been normalised to mean 0 and standard deviation 1, with a sampling frequency of 50 Hz. Each time signal comprises 100 samples. Also, we consider time windows of 2 seconds with an overlapping ratio of 75%. The total dataset is divided into development and evaluation datasets, which contain different subjects with random selection. The development dataset, used for the training of GaitPrivacyON, has 70 subjects (85% of the subjects have been used for training and the remaining part for validation). After training, the remaining 10 unseen subjects are used for the final evaluation.

GaitPrivacyON considers two main tasks: *i*) gait biometrics verification, and *ii*) privacy-preserving information, for which auxiliary machine learning systems must be implemented to detect the subject sensitive information, in our case, the gender and activity of the subject while using the mobile device. The details of the architecture are included in Sec. 4.3.

GaitPrivacyON first trains only the gait verification system using the biometric raw data included in the development dataset. For this first stage, only binary cross-entropy is considered for the loss function. After this first stage, we train our proposed GaitPrivacyON approach (only the Autoencoder module, the weights of the gait verification system are frozen) using the same development dataset.

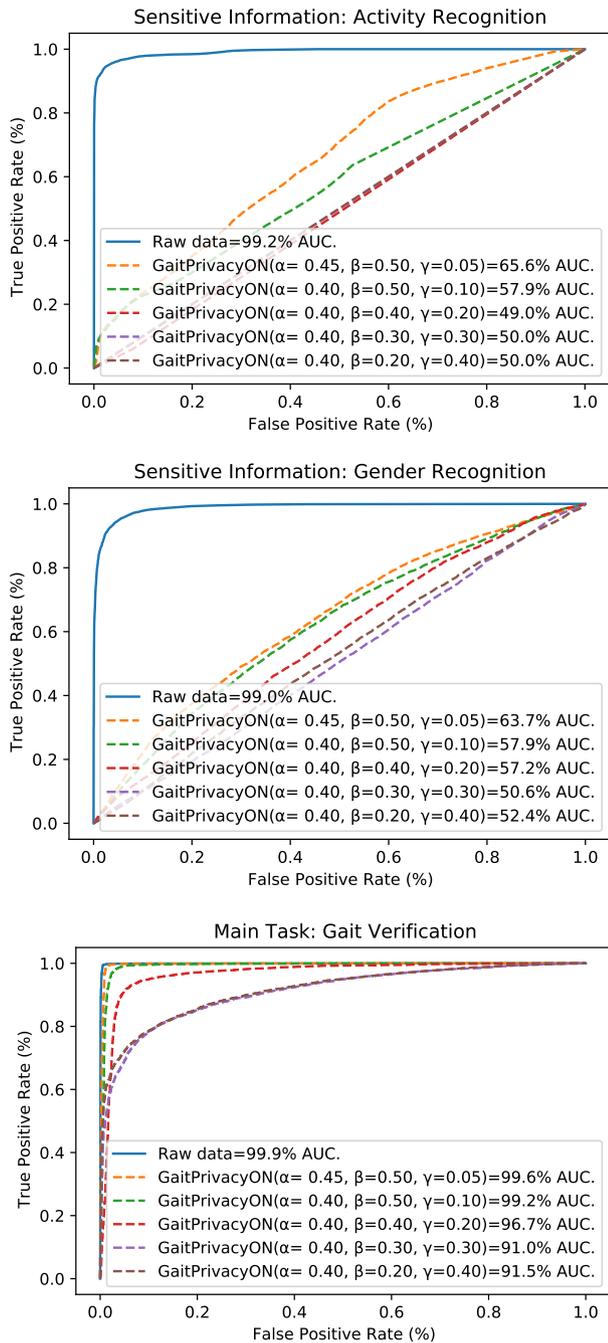
### 4.3. Gender and Activity Inference Systems

Table 1 shows the architecture of the proposed gender and activity inference systems. Six time domain signals are originally acquired from the mobile device as raw data, the three axes of the accelerometer and gyroscope. The input data is in the same shape as in GaitPrivacyON. The architecture is composed of a sequence of  $1 \times 3$  convolutional filters, coupled with ReLU activation functions. After some convolutional layers, batch normalization,  $1 \times 2$  max-pooling, and dropout with a probability of 0.5 are used. The dense layer has a size of 100. For the gender recognition system, a sigmoid activation function is considered whereas softmax is considered for the activity recognition system. Finally, cross entropy is used for the loss function.

## 5. Experimental Results

### 5.1. Gender and Activity Inference from Biometric Raw Data

In this first experiment we analyse the ability of machine learning systems to infer sensitive information of the user from the biometric raw data. Fig. 4 (top) shows the Receiver Operating Characteristic (ROC) curve together with the AUC of the



**Fig. 4:** ROC curves and AUC (%) results on the evaluation dataset for the two scenarios considered: *i*) Biometric raw data ( $X$ ), and *ii*) GaitPrivacyON ( $\widehat{X}$ ). Different parameters ( $\alpha, \beta, \gamma$ ) of GaitPrivacyON are tested in order to evaluate the results of the main task (gait verification) and the privacy-preserving information of the user (activity and gender recognition).

activity recognition system (solid curve). The proposed system achieves 99.2% AUC, differentiating the activity (walking up and down stairs, jogging, and walking) with precision.

Second, we analyse the results achieved by the proposed gender recognition system. The system has two classes: male and female. Fig. 4 (middle) shows the ROC curve together with the AUC achieved by the gender recognition system (solid curve). As in the case of the activity task, the gender recognition system is able to differentiate the gender with 99.0% AUC.

These baseline results prove the ability of machine learning systems to infer sensitive information of the user from the biometric raw data ( $X$ ), which might be considered as an invasion of the personal privacy. The next experiments analyse the results achieved by our proposed GaitPrivacyON approach and the proposed privacy-preserving domain  $\widehat{X}$ .

## 5.2. GaitPrivacyON

As indicated in Sec. 3.3, three different parameters can be configured in the training process of GaitPrivacyON to control the data transformation and the trade-off between the utility of the gait verification (main task) system and the sensitive information of the user (activity and gender):  $\alpha$  (*task loss* parameter),  $\beta$  (*content loss* parameter), and  $\gamma$  (*style loss* parameter).

We first analyse the results achieved in the main task, mobile gait verification. Fig. 4 (bottom) shows the ROC curves together with the AUC results of the gait biometrics verification system. Analysing the traditional approach, i.e., using the biometric raw data, the gait verification system is able to achieve accurate results with 99.9% AUC over the final evaluation dataset. However, as it was commented in Sec. 5.1, from this traditional approach it is also possible to extract sensitive user information, 99.2% AUC for activity recognition and 99.0% AUC for gender recognition.

The results achieved by GaitPrivacyON in the main task (gait verification) can be seen in Fig. 4 (bottom). In general, we can see different AUC results depending on the values of the training parameters (including symbols), ranging from 99.6% AUC to 91.0% AUC. The selection of these parameters affects in the extraction of the activity and gender sensitive information.

Fig. 4 (top) shows the ROC curves together with the AUC results achieved by GaitPrivacyON in the activity recognition task (dashed curves) when  $X$  is replaced by  $\widehat{X}$ . It can be seen how the AUC results decrease as  $\gamma$  increases, achieving a result close to random (49.02% AUC) when  $\gamma = 0.20$ .

A similar trend is also observed for the gender recognition task. Fig. 4 (middle) shows the ROC curves together with the AUC results achieved by GaitPrivacyON in the gender recognition task (dashed curves). It can be seen how the AUC results decrease as  $\gamma$  increases, achieving a result close to random (50.6% AUC) when  $\gamma = 0.30$ .

As a result, when the transformed data provided by GaitPrivacyON achieves AUC values close to random (50.0%) in the sensitive user information tasks, it will be assumed to achieve privacy-preserving results, as long as the AUC of the gait verification task hardly decreases. Therefore, we select as the optimal configuration parameters the  $\alpha = 0.40, \beta = 0.40, \gamma = 0.20$ , as the results in the gait biometrics verification task barely decrease (3.15 % AUC) while results close to random are achieved in both the activity (49.0% AUC) and gender (57.2% AUC).

GaitPrivacyON is able to decrease the AUC in the gender task from 99.0% to 57.2% while losing from 99.9% AUC to 96.7% AUC in the gait verification task. Compared to our work, Garofalo *et al.* in [27] decreased the F1-score in the gender recognition task from 73% to 52% while experiencing a degradation from 90.9% to 85.3% accuracy in the gait verification task. It is important to remark that in [27] the authors used

supervised learning. Nevertheless, GaitPrivacyON is based on unsupervised learning.

## 6. Conclusions

This study has presented GaitPrivacyON, a novel mobile gait biometrics verification approach that provides accurate authentication results while preserving the privacy of the subject. One of the main advantages of the approach is that the first module (convolutional Autoencoder) is trained in an unsupervised way, without specifying the sensitive attributes of the subject to protect. We have performed an in-depth quantitative analysis of GaitPrivacyON over two popular databases in the field of gait recognition, MotionSense [12] and MobiAct [13]. Our model is able to obtain good results, as the gait biometrics verification task barely decrease (3.2% AUC) while results close to random are achieved in both the activity (49.0% AUC) and gender (57.2% AUC) tasks. In conclusion, GaitPrivacyON increases the protection of the sensitive data (e.g., activity and gender) with unsupervised learning while being able to maintain the accuracy of the gait biometrics verification task.

## 7. Acknowledgements

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