



## AN EFFICIENT MACHINE LEARNING APPROACH TO RECOGNIZE GAIT COMPONENT

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**Abstract:** Human motion is an important spatio-temporal pattern since it can be a powerful indicator of human well-being and identity. Many authentication techniques were developed over the years. Human gait recognition is one of these techniques. It involves the coordination of several parts of the human body: the brain, the spinal cord, the peripheral nerves, muscles, bones, and joints. Gait analysis has been widely studied for a variety of applications including healthcare, biometrics, sports and many more. The activities recorded in this dataset are walking, running, sitting and standing. In the new space, the spatial-temporal features are sufficiently combined with distance metric learning to drive the similarity metric to be small for pairs of gait from the same person, and large for pairs from different persons. In particular, human gait offers a unique motion pattern of the individual. Gait refers to the study of locomotion in humans and animals. This article explores machine learning techniques for user authentication on database which is a human gait data collection for analysis and activity recognition. Consequently, the experiments on the world's largest gait database show our framework impressively outperforms state-of-the-art methods.

**Index Terms** – Machine Learning, Gait Components, Security, Spatio-Temporal, Recognition, Neural Network.

### I. INTRODUCTION

Identification is one of the most important aspects in security. Biometrics is one of the techniques that can be used to identify an individual. For example, fingerprint recognition is used for identifying people from each other by using their fingerprints. In addition to fingerprint recognition, other biometrics include ear, vein, retina and gait recognition. Gait recognition, identifying a person's body movement, is also a technique of biometrics. In gait analysis, a person's movement describes personal way of walking and that means it could be used for identifying a person. Gait recognition is a biometric technique that is used for identifying biological and behavioral specification. Gait recognition technology methods divide into two; first one is holistic-based method and the second one is model-based method. Holistic based approach relies on extracting statistical features of motion based while model-based method identifies body parts to create a 3D gait model.

Gait plays a major role in health care applications to identify the walking style of the person and movements of the human, the normal gait refers to the correct walking style stance (pattern), swing phases and sequence of the person, the abnormal gait refers to irregular pattern of a person walking style stance, swing phases and sequence of the person, in different situations. Several research has been done on human gait analysis, while human walking spending some energy conserved from the different parts of the body, some energy distributed from the body that depends on different parts of the body. The analysis of the body can be identified by the walking movements of the lean angle and ramp angle.

As shown in Fig. 1, gait is the walking posture of a person, comprising a regular movement trend and variations present at joints of the upper limbs and lower limbs during walking. Gait recognition is a recognition technology based on biometrics, and is intended to identify a person according to the walking posture of the person. With the gait analysis, we can accurately detect many biomedical information, such as gender, age, race and the like, of a person to whom the gait belongs can be obtained. Moreover, the gait information can also be utilized to diagnose and cure many diseases, such as Neurodegenerative Diseases, Parkinson's disease, Huntington's Disease and so on. For the field of recognition technology, gait is biometrics of great potential, which mainly manifests in the following three aspects:

- 1) **Remotely Accessible:** surveillant can obtain gait information of a specific subject from a distance, and collect it secretly in a contactless manner. Differently, the biometrics such as iris and fingerprint are collected with the need of a person's cooperation. The remote access is very important in intelligent video surveillance.

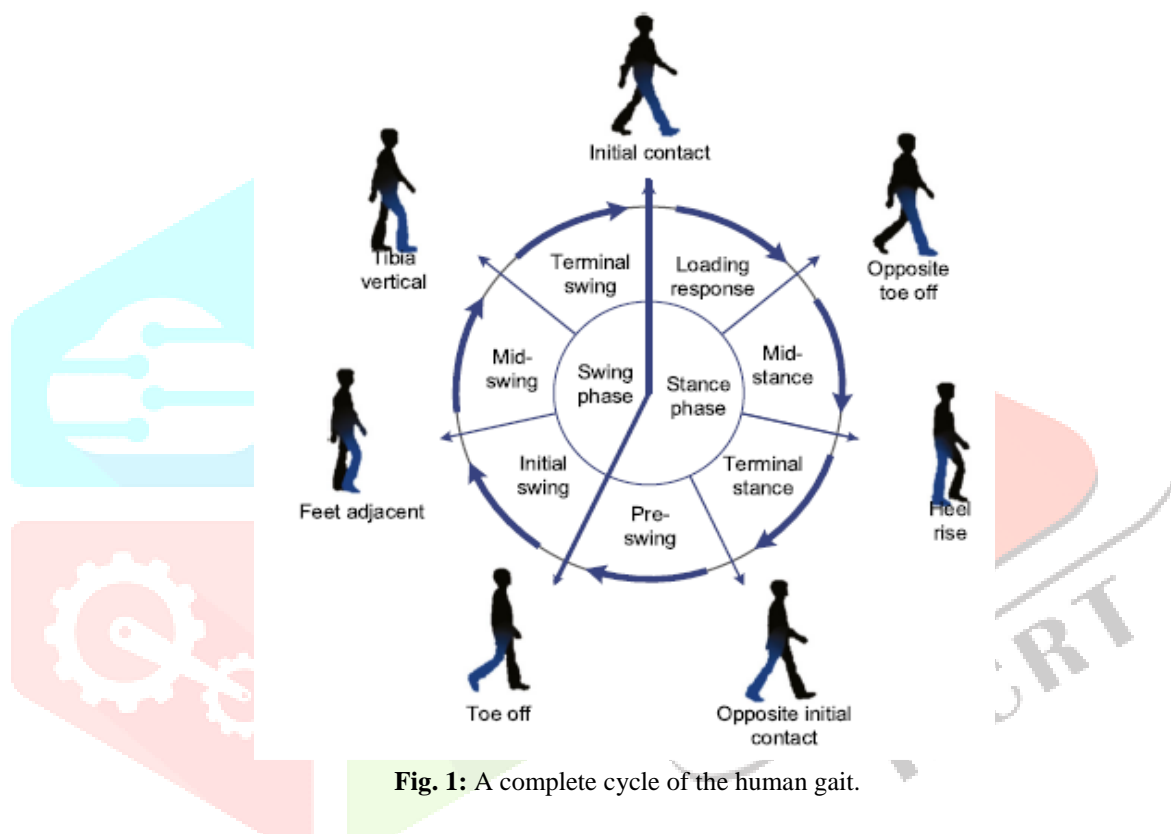
- 2) **Robustness:** even in low resolution videos, a gait feature still works well. In contrast, an accurate face recognition and vocal print recognition impose relatively high requirements on the quality of data resources.
- 3) **Security:** it is difficult to imitate or camouflage human gait. If a person changes his/her gait in public deliberately, he/she would become more suspicious and gain attention.

However, accurate gait recognition is still a challenging work as

- 1) The unobvious inter-class differences from different people; and
- 2) The large intra-class variations from the same person as the different walking speeds, viewpoints, clothing, and belongings.

The detail challenges can be summarized as:

- 1) Complexity surveillance environments— the human gait identification is very sensitive to cluttered environments, illumination changes, partial occlusions, and crowded people.
- 2) Diverse subject-related factors — the different walking speed, dressing, and carrying conditions. all seriously influence the human gait and automatic identification.
- 3) The cross-view variance — the crossview variance leads to the appearances of human gait be substantially altered, which will increase the intra-class variations and decrease the inter-class variations.



**Fig. 1:** A complete cycle of the human gait.

Gait analysis has been widely studied for a variety of applications including healthcare, biometrics, sports, and many more. Classification of a person's given its emotional state has also been explored. A person's pride, happiness, neutral emotion, fear, and anger has been classified with high statistical confidence given only its gait pattern. Generally, three types of gait monitoring systems exist, namely: cameras using image processing, floor sensors and wearable sensors. The use of cameras for gait is vulnerable to details in the environment such as levels of lighting. Besides that, use of cameras is considered an invasion of privacy in living environments, e.g. for healthcare. Because of disadvantageous parallels to video surveillance. The disadvantage of wearable sensors is that the sensors need to be attached to the body, may be uncomfortable to wear, as well as require assistance to attach correctly. On the other hand, floor sensor systems have the advantage of being non-invasive and even unobtrusive, less prone to environmental noise and undemanding the subject's attention, which affects the data quality positively. Among humans, the term gait refers to the study of locomotion. Gait occurs due to a cooperation of several parts of the human body including the brain, spinal cord, nerves, muscles, bones, and joints. Within a walking sequence, gait can be understood as a translation of human brain activity to the patterns of muscle contractions. The command is generated by the human brain which is transmitted to initiate the neural centers through spinal cord which eventually results in patterns of muscle contractions supported by the feedback from muscles, joint, and the receptors. This will result in the movement of the trunk and lower limbs in a connected way whilst the feet recursively touching ground surface and the change center-of-mass of the human body. Gait can be defined as repetitive cycles for each foot resulting in a sequence of periodic events. Each cycle can be divided into phases as shown in Figure 1. Gait can be perceived as a transformation of brain activity to muscle contraction patterns resulting in a walking sequence. It is a command generated in the brain and transmitted through the spinal cord to activate the lower neural centers, which will consequently result in muscle contraction patterns assisted by sensory feedback from joints, muscles and other receptors to control the movements. This will result in the feet recurrently contacting the ground surface to move the trunk and

lower limbs in a coordinated way, delivering a change in the body center-of-mass position. Gait is a sequence of periodic events characterized as repetitive cycles for each foot. Each cycle is divided into two phases stance and swing.

## II. RELATED WORK

- (i) Jie Yin et.al proposed a support vector machine (SVM) classification for detecting the gait based activities, it is the problem of anomalies detection in training data, sensors are attached to the human body that identified the abnormal detection, the feedback-based mechanism is not encompassed the proposed model.
- (ii) The feedback-based mechanism is most required to solve for the gait. Ahmed et.al proposed for abnormal gait detection technique the joining the human body parts by using Fourier transformation method. Faezeh et.al proposed a different approach for a model-based approach for analysing the leg and arm movements and shoulders in human gait recognition, this problem is not solve the neuropathic gait. A model is constructed using active contour models (ACM) this model is incorporated with a feedback-based approach.
- (iii) K-nearest neighbour problem and classification problem is quite similar to the feedback-based approach. From the previous works, feedback-based approach is quite suitable to the machine learning algorithms, SVM, FFT, MSE, DFT, KNN[12]. All machine learning problems arises due to dataset of training video sequences that provides the comparison between the normal gait and abnormal gait, but feedback-based approach is appropriate. Parkinson gait have high false rate detection occurs.
- (iv) Zheng et al used Random Forests (RF) and KStar to discriminate between neuro-degenerative diseases. The maximum accuracy reported was 94.02%. Yang et al.6 use SVM to classify a number of neurodegenerative diseases based on gait. The reported maximum accuracy is 93.96%. SVM was also used by Begg et al. for automated recognition of young-old gait types with a reported average success rate of 83.3%. Finally, Chan et al. employed Multilayer Perceptron (MLP), KStar and Support Vector Machines (SVM) to distinguish between walking up or down stairs and between younger and older adults. They reported accuracy of 95.7% in determining the former and 80.6% in determining the latter.

**Gait Recognition Using Inertial Sensors** Sensor-based gait recognition can be performed in three main ways: by sensors in the floor, by sensors in the shoes, and by sensors on the body. Among these methods and their variations, inertia-sensor based methods are the most attractive. This is because that the inertial sensors can be easily placed on the body to capture the details of the movement characteristics, and the captured time-series gait data are effective for person identification and authentication. In early research of inertia-based gait recognition, Ail is to et al. proposed a signal-correlation method, where the recognition was performed in the means of template matching and cross-correlation computation. Following this work, Gafurov et al. made many significant improvements. In they analyzed the minimal effort impersonation attack and the closest person attack on gait biometrics. In they collected 300 gait sequences from 50 subjects by placing an accelerometer sensor in the user's pocket, and achieved an equal error rate (EER) of 7.3%. In they tried foot-, pocket-, arm- and hip-based user authentication and found that a sideways motion of the foot provides the most discrimination, and a different segment of the gait cycle often leads to a different level of discrimination.

**Deep Learning for Gait Recognition** Gait biometrics have been widely studied for authentication and access control. In recent years, deep learning has achieved great success in the field of secure computing and activity recognition. Deep learning-based gait recognition methods also demonstrated boosted performance over the traditional machine learningbased methods, e.g., SVMs. Various deep neural networks can be used to extract the motion characteristics from the image sequences or the inertial time series. Considering the outstanding ability of CNN in image-feature abstraction, many researchers employed CNNs for gait or activity recognition. In three deep CNNs were constructed for gait recognition, using the users' gait energy images as input. Feature maps at different convolutional stages were fused to improve the classification accuracy. In deep CNNs with contrastive loss and triplet ranking loss were proposed for cross-view gait recognition, and high performances were obtained in person authentication and identification. In based on the gait data extracted by a periodogram-based gait separation algorithm, deep CNNs were constructed for gait classification.

## III. MACHINE LEARNING

With the increased of the usage of technology, data collection has been easier in different disciplines including medicine, business, education, security and so on. Automatic visual surveillance is of paramount importance due to security problems in recent years. Cameras provide potential sources for capturing data useful for gait recognition. Gait recognition is among the most appropriate biometric methods. Moreover, the development of open source and commercial machine learning and data mining tools enabled experts to employ systems to support decisions on these data collected in different fields. Machine learning is a way of automation that studies the structure and function of algorithms that can learn and make estimations based on the given data. Such algorithms work by constructing a model to perform data-driven estimates and decisions from sample inputs. In this work, machine learning of particular interest to us is required to discover spatial patterns in sensor data. To this end, we are using the

two basic types of machine learning supervised and unsupervised. In this research, we have a feature vector of biometric measurements (gait data) and we aim to explore whether they are informative enough to identify a specific person. In order to make the identification either the biometric is sufficiently unique that clustering (distance calculation) relative to the original feature space will be sufficient, or a mapping from feature to label space is necessary (classification). In the following, we discuss the machine learning algorithms used in this research.

### 3.1 Deep Learning for Gait Recognition

We begin with going through the entire process of the gait feature learning framework. As illustrated in Fig. 2, the proposed approach for gait recognition consists following components. Firstly, we combine the raw sequence of surveillance images into GEIs, which are exploited as the input of the deep neural network. Instead of the conventional CNN, we use Siamese network, which can simultaneously minimize the distance between similar subjects and maximize the distance between dissimilar pairs, to learn sufficient spatial feature representations of gait for human identification. Secondly, the original walking sequences in one gait period are fed into the fine-tuned C3D architecture to extract discriminative periodic temporal feature. Similarly, the Siamese neural network is utilized to learn sufficient temporal feature representations of human gait based on pairwise gait sequential frames. After that, the well-learned GEI-based spatial feature and C3D-based temporal feature are combined as the joint feature to represent human gait. Lastly, the concatenated spatiotemporal gait features are fused by NFST to be embedded into a discriminative latent null space. Finally, the final human recognition is made by comparing the Euclidean distances (i.e., matching scores) between the feature vectors of gallery and probe gait sequences in the null space.

### 3.2 Inertial Sensors in Smartphones

Accelerometers and gyroscopes are typical inertial sensors that are equipped by most smartphones. Accelerometers and gyroscopes measure inertial dynamics in three directions, namely, along the X, Y and Z axes. The three-axis accelerometer is based on the basic principle of acceleration and is used to measure a smartphone's acceleration (including gravity) in the X, Y and Z directions. The accelerations in the three directions reflect the changes in the smartphone's linear velocity in 3D space and, hence, reflect the movement of smartphone users. The three-axis gyroscope captures the angular velocity of a smartphone during its rotation in space, which can also be used to describe the movement pattern of a user. The smartphones used in our work are manufactured by Samsung, Xiaomi and Huawei, all of which run the Android operating system. When a user is walking, the smartphone accelerates and rotates according to the movements of the user. These data are assumed to be individually unique, so we can collect them as the source data for gait dynamics. The smartphone itself can provide hardware synchronization for the accelerometer and the gyroscope. When the inertial data is recorded through the Android interface, the synchronization may be slightly affected. However, this is tolerable and only has little effect on our gait recognition method.

### 3.3 Gait Data Extraction

When using smartphones to collect the inertial data in the wild, we do not know when, where and how the smartphones will be used. Consequently, the captured data consist of walking sessions and nonwalking sessions, but only walking data are of interest to gait feature extraction and person identification. Thus, the continuous inertial sequence collected by smartphones in the wild must be partitioned. Considering that walking data and nonwalking data are semantically different and that inertial time series are continuous in both the space and time domains, we model the partitioning problem as a time-series segmentation problem. Inspired by U-Net [94], we build a semantic segmentation algorithm with a one-dimensional DCNN. The architecture of the proposed network is shown in Figure 1, and the details are listed in Table I. In order to improve the segmentation accuracy, we fuse hierarchical convolutional features from multiple stages in the network.

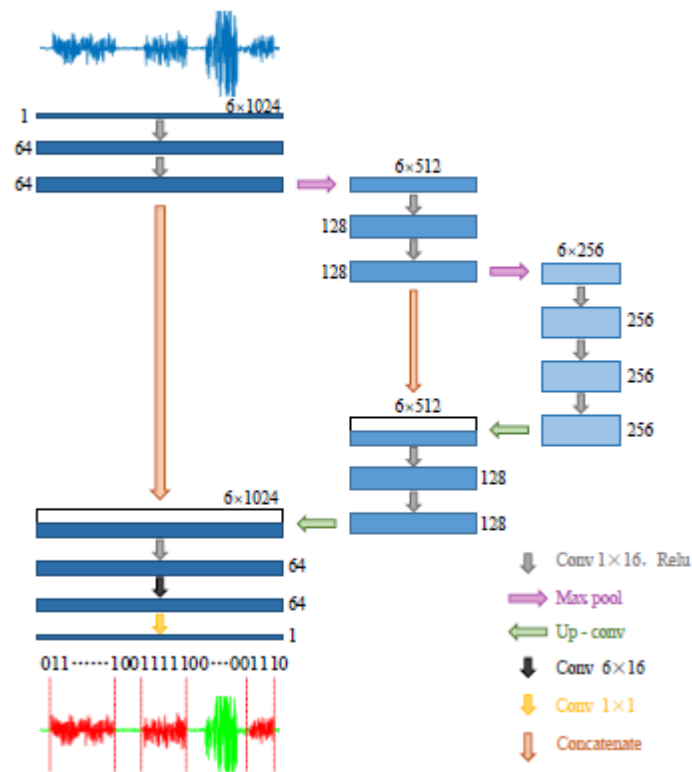


Fig.2: Architecture of the network for gait data extraction.

### 3.4 Floor sensor systems and datasets for gait analysis

Cameras, inertial sensors or floor sensor systems have been used to analyze gait. Floor sensor systems have the advantage of being unobtrusive and resistant to surrounding noise; in comparison, camera systems require adequate illumination while wearable inertial sensors require daily placement and maintenance. A floor sensor system can be inconspicuous in a home environment allowing the acquisition of natural gait signals over large periods of time. While floor sensor systems have been built for automatic gait analysis applications, they have relied heavily on physiologically defined, man-made and complex features such as the body's center of pressure, stride length, and cadence, rather than using raw sensor signals, to construct gait classifier models. An example of gait recognition system using a switch sensor system is the UbiFloorII system developed by Jaeseok Yun. The switches in the Ubi Floor system are made of photo interrupters sensors. The switch sensor generates 0 V or 5 V (on-off) according to the pressure exerted on the floor sensor system. In the sensors used for gait analysis are three force plates to obtain the ground reaction force, perpendicular to the floor sensor system. Piezoelectric sensors are used as the sensing mechanism. The piezoelectric effect measures the accumulated charge in solid materials as a response to force stress. In this case, the measured pressure is the response to the pressure exerted by the weight of the subject walking on the floor. The change in pressure modifies the voltage level in the piezoelectric sensor output, to enable gait measurement. Gait analysis applications range from healthcare to provide insight into brain degenerative disease to security applications to build a biometric system for security clearance. Applications can also be found in gait analysis for sports. This research focuses on floor sensor technology due to its unobtrusiveness allowing natural gait signals to be captured over a large period of time. For the purpose of classification of human postural and gestural movements using floor sensor systems, Saripalle et al. employed force platforms to infer the center of pressure of individuals. 11 body movements by volunteers were classified with an accuracy ranging from 79% to 92% using linear and non-linear supervised machine learning models. Feature selection is emphasized as a critical step for obtaining reliable accuracy scores, but this approach is limited by the lack of a single classification model suitable for all types of movement. Floor sensors systems have been used to distinguish human movements. Headon and Curwen recognized movements undertaken by a single user. The recognition is achieved by analyzing the Ground Reaction Force (GRF) in a weight-sensitive floor. The changes in the GRF arise from activities performed at the same position, including jumping, sitting and rising. A hidden Markov model was used for human movement classification. The classification performance was close to 100%. One of the disadvantages of such study is that the postural activities were performed statically at the same position.

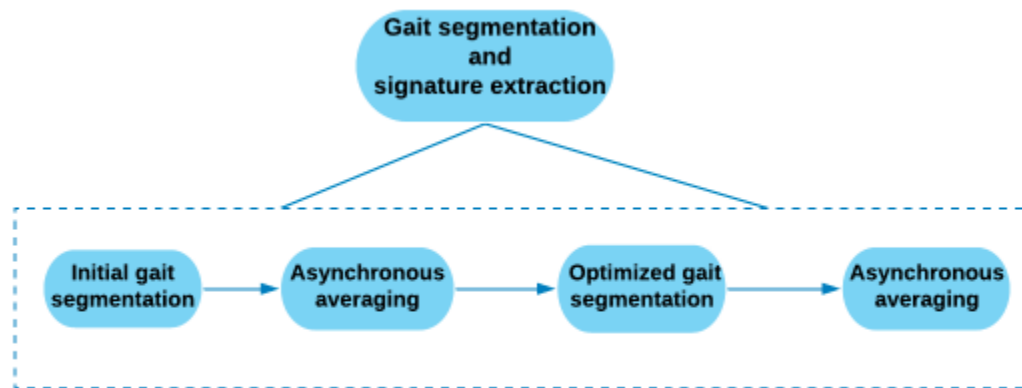
### 3.5 Asynchronous Averaging of Gait Cycles

Existing approaches for step detection and gait cycle segmentation, typically, rely on measurements collected from hand-held devices such as smartphones that are already equipped with imus. However, due to the large number of affecting factors on the sensor readings, such as the user's motion mode and the device mode, these methods suffer from robustness issues and might collapse if the underlying assumption is not satisfied. One solution to the problem is to classify the mode of the system and use the additional information obtained from this knowledge to robustify the algorithm. imu signals also contain what will be referred

to as the *gait signature* that is caused by the steps we make when moving. Examples include bio-mechanical analysis of limping patterns for diagnosis of certain diseases such as Parkinson's . An approach for computing a unique gait signature using measurements collected from imu is proposed in Chapter 6. The gait signature as observed by the imu depends on both gait and device modes and as such reveals a rich information source suitable for a variety of applications. Our key contribution is a proposed algorithm for off-line analysis of imu data during motion, with the following outline:

- (i) Gait segmentation using optimization to maximize similarity of the gait cycles. This step might need initialization, and here classical step detection algorithms can be used.
- (ii) Estimation of the gait signature by averaging over the segments. This is done on a normalized time scale, so small variations in step cycle times are handled by resampling techniques.
- (iii) Extraction of a low dimensional feature vector for the gait cycle using Fourier series analysis on the estimated gait signature. This feature vector includes physically explainable patterns.

Although the algorithm used for gait signature estimation is tailored for off-line applications, on-line extensions are also plausible. Thus, the gait signature estimation method can be used for either on-line classification, or off-line gait analysis.



**Fig.3:** The flow diagram of the gait signature extraction using norm of pre-processed imu signals.

#### IV. RESULTS AND DISCUSSION

In this paper, gait recognition using smartphones in the wild was studied. A hybrid method was proposed to seamlessly combine the DCNN and DRNN for robust inertial gait feature representation. During gait data collection, the smartphones were used under unconstrained conditions, and information about when, where, and how the user walks was totally unknown. A fully convolutional neural network was presented to partition the inertial data into walking and nonwalking sessions, and hierarchical convolutional features were fused for accurate semantic segmentation. In this chapter spatio-temporal gait and footstep representations have been studied with deep learning methodologies. In the healthcare theme, dual-task has been classified with robust classification performance by providing an F-score of 97.33% in the optimal case, while in the security theme, state-of-the-art footstep recognition performance has been obtained in a biometric verification scenario, obtaining an optimal EER of 0.7%. Therefore, robust pattern recognition in gait and footstep analysis have been provided with high statistical significance. The methodologies to obtain the optimal results used deep machine learning principles based on convolutional neural networks. In the healthcare theme, the link between cognitive activities and its effects on the changes in human gait patterns was investigated. The first set of experiments focused on the temporal analysis to distinguish 10 gait activities patterns. The following experiments focused on the spatio-temporal domain analysis of 13 gait activities. The research then moved on to the analysis of the effect of cognitive activities in gait patterns from healthy individuals. The methodology delivered results with a cohort of 69 participants performing dual-tasks experiments. In the optimal case scenario, an Fscore of 97% was obtained to identify dual-tasks patterns. The methodology clearly outperformed optimized classical machine learning models (non-deep learning) and was able to distinguish the gender of participants with an optimal F-score of 97.3%. Finally, a research project on improving human health in urban environments was presented. The methodology successfully detected rodent activity based on its urine spectra response with unsupervised machine learning techniques.

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