PACE: Providing Authentication through Computational Gait Evaluation with Deep learning

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ABSTRACT

This research presents PACE (Providing Authentication through Computational Gait Evaluation), a novel methodology for gait-based authentication leveraging the power of deep learning algorithms. The primary objective of PACE is to enhance the security and efficiency of user authentication mechanisms by capitalizing on the unique gait patterns exhibited by individuals.This study delineates the development and implementation of a deep learning model, which was trained on a set of extracted features. These features, including mean, variance, standard deviation, kurtosis, and skewness, were derived from accelerometer and gyroscope data, serving as descriptors of users' gait patterns for the deep learning model.The model's performance was evaluated based on its ability to classify and authenticate users accurately using these features. For the purpose of this study, twelve participants were enlisted, with sensors affixed to their back hip and right ankle to collect the requisite accelerometer and gyroscope data.The experimental results were highly promising, with the model achieving an exceptional accuracy rate of 99% in authenticating users. These findings underscore the potential of PACE as a viable alternative to conventional machine learning methods for gait authentication. The implications of this research are far-reaching, with potential applications spanning a multitude of scenarios where security is of paramount importance.

CCS CONCEPTS

• **Security and privacy → Biometrics**.

KEYWORDS

Gait Authentication, Deep Learning, Biometric Identifier, IoT Devices, User Verification , User Authentication Mechanisms, PACE Methodology , Wearable Sensors , Security Enhancement

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1 INTRODUCTION

In the era of digital transformation, the proliferation of Internet of Things (IoT) devices has necessitated the development of robust and efficient user authentication mechanisms. Traditional methods, such as passwords and biometrics, while widely used, are not without their limitations. Consequently, the exploration of innovative and non-intrusive means of authentication has gained momentum, with gait-based authentication emerging as a promising alternative. Gait, the unique pattern of an individual's walk, serves as a reliable biometric identifier. Recent advancements in technology have enabled the capture and analysis of gait patterns using devices such as smartphones and wearable sensors. For instance, Musale, Baek, and Choi (2018) proposed a lightweight user authentication technique for IoT systems, called Li-GAT, which exploits various information collected from IoT devices, including the subconscious level of user activities, to effectively authenticate users [1]. Similarly, Muaaz and Mayrhofer (2017) evaluated the robustness of a smartphone-based gait recognition system against zero-effort and live minimal-effort impersonation attacks under realistic scenarios [2].

Gait authentication transcends the unidimensional nature of traditional authentication methods due to its autonomous characteristics. Its potential applications extend beyond device access, marking its versatility. In the healthcare sector, for instance, gait authentication can serve as a critical tool for detecting incidents such as falls or identifying injuries that manifest in irregular gait patterns. Furthermore, gait authentication can significantly augment an individual's quality of life through its integration with other intelligent systems. In the context of smart homes and smart vehicles, gait recognition can facilitate anticipatory actions, enabling these systems to respond to the user's needs even before they are explicitly communicated.

This research presents PACE (Providing Authentication through Computational Gait Evaluation), a novel methodology for gait-based authentication leveraging the power of deep learning algorithms. The primary objective of PACE is to enhance the security and efficiency of user authentication mechanisms by capitalizing on the unique gait patterns exhibited by individuals. The implications of this research are far-reaching, with potential applications spanning a multitude of scenarios where security is of paramount importance.

2 RELATED WORKS

The field of user authentication leveraging gait patterns has seen significant advancements in recent years, with various innovative approaches being proposed.

Musale, Baek, and Choi (2018) introduced a lightweight user authentication technique for IoT systems, known as Li-GAT (Lightweight Gait Authentication Technique) [1]. This technique utilizes various information collected from IoT devices, particularly subconscious user activities, to authenticate users effectively. The approach not only achieves high accuracy but also reduces resource consumption, making it a promising solution for IoT devices with limited computational and communication resources.

In another study, Muaaz and Mayrhofer (2017) evaluated the robustness of a smartphone-based gait recognition system against zero-effort and live minimal-effort impersonation attacks under realistic scenarios [2]. This work underscores the importance of considering potential security threats in the design and implementation of gait recognition systems. Their findings suggest that gait recognition systems can be robust against impersonation attacks, further strengthening the case for gait-based authentication.

Mufandaidza, Ramotsoela, and Hancke (2018) developed a smartphone user authentication system that uses a user's gait pattern as a biometric feature [3]. The system is designed to continue the authentication process in the background if the outcome is positive. If authentication fails, the device's location information is sent to a predetermined email address, thereby alerting the authorized user about the device's location. This approach demonstrates the potential for integrating gait-based authentication with other security measures to enhance overall system security.

Lastly, Lee, Lee, Park, Lee, and Kim (2022) proposed a sensor compensation algorithm to overcome various real-world factors that could potentially affect gait-based authentication [4]. They also introduced new 2D cyclogram features to enhance user authentication performance. This work highlights the importance of addressing real-world challenges to improve the reliability and effectiveness of gait-based authentication systems.

These studies collectively highlight the potential of gait-based authentication as a robust and reliable user authentication method. They also underscore the need for ongoing research to address potential challenges and enhance system performance.

3 METHODOLOGY

3.1 Overview

In this section of the research paper, we will discuss the comprehensive approach that was devised to accomplish our primary goals. These goals include developing a deep learning model capable of distinguishing between multiple users based on their gait, achieving the highest level of accuracy by integrating data from all 12 participants into the model, and determining the optimal location and instrument (gyroscope or accelerometer) for data collection. To evaluate the performance of our model, we will analyze various metrics such as the learning curve for accuracy, highest accuracy, macro precision, macro recall, and F1 score. Additionally, we aim to identify the combinations of data location and features that yield the highest possible

3.2 Data Set

The data set utilized for our model was generously provided by Professor Dr. Jong-Hoon Youn from the University of Nebraska. This data had already undergone substantial preprocessing, leaving feature extraction as the primary task for model preparation, which we will elaborate on in the feature extraction section of the methodology. The dataset comprises both accelerometer and gyroscope readings from the hip and right ankle of all 12 participants. The accelerometer data, represented in XYZ coordinates, indicates the direction and position of device acceleration.In contrast, the gyroscope data measures angular velocity across the x, y, and z axes. Data points were collected approximately every 10 milliseconds, equating to a gait cycle duration of 1 second in the context of our project. Consequently, each gait cycle encompasses 100 data points for each x, y, and z dimension. Each data set comprised approximately 40,000 data points, which corresponds to an estimated 400 seconds of walking per individual. This substantial volume of data provided a robust basis for our deep learning model to discern and learn from the unique gait patterns of each participant. When incorporating a second data set for a different location into the model, there are two methods to consider for inputting the data.

The first method, vertical concatenation, is advantageous due to its simplicity and efficiency. This approach does not require any additional hyperparameter input features for the models to process, which simplifies the model and reduces computational requirements. However, it may not be the most optimal choice for deep learning algorithms as it does not consider the potential relationships between data from different locations [1].

On the other hand, horizontal concatenation involves creating additional features that have the potential to enhance model performance by capturing more complex patterns in the data. However, this approach may require more processing time due to the increased complexity of the model. Additionally, the introduction of more features could potentially lead to overfitting if not properly managed [2].

3.3 Feature extraction

In the initial stages of implementing our deep learning model, we input preprocessed data without any feature extraction. However, as the number of users and data points increased, this approach proved to be insufficient in terms of generating high accuracy and time efficiency. To enhance the performance of our model in these aspects, we further processed the data in two crucial ways. The first of these involved the integration of the following five features:

- **Mean:** Mean measures the typical steps of a person.
- **Variance:** Variance tells us how much those strides change in length.
- **Standard deviation:** Standard deviation would tell us how similar or different each step is from their average step.
- **Kurtosis:** Kurtosis measures if the person has many strides that are very different from the average stride length.
- **Skewness:** Skewness tells us if there's a tendency for the person to take steps that are mostly longer or shorter than average

The selection of these features was based on previous studies that utilized machine learning algorithms and recommendations from the project mentor. In study [1], the mean, standard deviation, and skew were examined. Initially, only the mean feature was used, but after showing promising results, variance and standard deviation were incorporated. The inclusion of these three features significantly enhanced the model's performance. Consequently, it was decided to include kurtosis and skew as the final two features, which further improved the model's accuracy. It is important to note that the effectiveness of these features was influenced by the adjustment in the number of data points compared to the participants' data used for feature calculation. However, as additional locations and gyroscope data were introduced, the impact of this adjustment seemed to diminish. The reasons behind this phenomenon will be discussed in detail in the results section of the paper.

The second approach to data processing involved the use of a sliding window technique. This method was employed in the computation of the five features, and its effectiveness appeared to be influenced by the volume of data utilized in the feature calculations. A unique aspect of this method was that the function's output was capable of generating a larger overall number of data points for the model's computations, attributable to the retracement window size.

However, a limitation of the sliding window technique was its need for continual adjustment based on the volume of user data being utilized. Generally, an increase in user data necessitated an expansion in the window size and a corresponding adjustment to the ratio of retracement to new user data calculation.

It is noteworthy that prior to the incorporation of any additional instruments or locations into the right ankle accelerometer user data, the window size appeared to be most optimal when utilizing 0.66% of a single user's overall data and a retracement of 75

3.4 Model Design and Implementation

The specific type of model utilized in this study was a Deep Forward Feed neural network. The model itself was relatively simple, consisting of a ReLu activation function and 2 hidden layers. Initially, the hyperparameters were set as follows: a learning rate of 0.1, 8 hidden units, 15 input features, and an 80:20 train-test split. However, in order to optimize performance, we conducted experiments with different numbers of hidden units and found that the model achieved the best results with 64 hidden units.

Regarding the learning rate, we based our decision on what is typically considered a default setting. We initially selected the higher end of the default range but then decided to experiment with lower values, specifically 0.01 and 0.001. After careful analysis, we concluded that a learning rate of 0.01 would be most suitable due to its reduced volatility in accuracy percentage from epoch to epoch during both testing and training. Additionally, this learning rate maintained a better learning curve compared to the lower rates.

It is important to note that the input features remained unchanged throughout the research period, except when multiple accelerometer and gyroscope data sets were incorporated into the model. However, the training and test split was consistently maintained at the 80:20 ratio and was not altered.

Furthermore, we conducted tests with additional hidden layers, but these did not result in a significant increase in accuracy. Instead, the model experienced a substantial increase in the time required to complete all epochs.

3.5 Model Training and Evaluation

During the model's training and evaluation phase, we undertook several critical steps to achieve our final results. The evaluation metrics employed in this phase included:

- **Accuracy:** This metric quantifies the proportion of correct predictions made by the model across all predictions.
- **Macro-averaged Precision:** This measure calculates the precision for each individual's gait independently and then averages them, thereby assigning equal weight to each class, irrespective of its size.
- **Macro-averaged Recall:** This metric quantifies how many actual instances of each individual's gait the model correctly identified.
- **Macro-averaged F1-score:** This measure determines the model's average performance across all classes in terms of both precision and recall

These metrics were selected based on the specific requirements of the project and the nature of the model used.

In the process of training our model, we employed a variety of data combinations. Initially, the model was trained independently on each data set, which included data from both the gyroscope and accelerometer located at the back hip and right ankle. Following this, we proceeded to train the model using combinations of these data sets.

As for the training epochs, we ultimately utilized 60,000 epochs. However, this figure was not arbitrarily chosen. Instead, we adopted an iterative approach, progressively increasing the number of epochs in increments of 10,000. This decision was guided by careful observation of the model's performance and learning curve, allowing us to optimize the number of epochs for our specific model and data.

4 RESULTS

4.1 Overview

The analysis of our research results yields a multitude of conclusions, each influenced by various factors such as the number of features, the implementation of the sliding window, the hyperparameters, the number of data sets incorporated, and the method of their concatenation. Our examination of the results commences with the discussion of the model's performance when each data set is input individually. Subsequently, we progress to the evaluation of the model when two data sets are input, and finally, when three data sets are incorporated. Throughout this process, we will compare the distinct aspects of the results derived from each additional data set and discuss the necessary modifications at each stage. Additionally, we aim to identify the combinations of data location and features that yield the highest possible

4.2 Single Data Sets

In our study, we utilized two distinct instruments at two separate locations: the right ankle and the back hip. At each location, we collected data from both an accelerometer and a gyroscope. Initially, the experiments were conducted by processing the raw data, comprising only the x, y, and z values, without the application of a sliding window or any additional features.

To mitigate the computational burden associated with processing large quantities of data, we strategically selected 18,000 data points from each user. This decision was informed by the observation that increasing the volume of data led to a substantial increase in processing time. In the absence of additional features, the model's performance was evaluated solely on the basis of accuracy, with the rankings for each dataset determined accordingly. The following section delineates the specific outcomes and insights derived from this approach.

- **Back hip accelerometer: accuracy was 43.17%**
- **Right ankle accelerometer: accuracy was 38.9%**
- **Right ankle gyroscope: accuracy was 37.59%**
- **Back hip gyroscope: accuracy was 35.82%**

After adding all the features and the sliding window this is how the model performed again with only accuracy.

- **Back hip accelerometer: accuracy was 95.12%**
- **Right ankle accelerometer: accuracy was 94.72%**
- **Right ankle gyroscope: accuracy was 94.5%**
- **Back hip gyroscope: accuracy was 94.21%**

4.3 Two Data Sets

Following the analysis of individual data sets, we proceeded to explore the integration of a second data set into our model. The experiment was conducted using various combinations of data, including the back hip gyroscope and accelerometer, right ankle gyroscope and accelerometer, and back hip gyroscope and right ankle accelerometer.

Two distinct methods were employed in the initial stages of data deployment. The first approach involved concatenating the gyroscope data to the accelerometer data collected from the right ankle, followed by the extraction of the previously mentioned features. Subsequently, the data was concatenated again, this time horizontally, and input into the model as supplementary features.

Upon examination and comparison of the outcomes from this segment of the experiment, we observed minimal variation in the final accuracy rate of the model's predictions between the two methods. Both approaches yielded an approximate accuracy of 98% with 10,000 data points from each instrument and 60,000 epochs. However, a notable difference emerged in the learning rate of the model. When the data was concatenated horizontally, the model reached an accuracy rate of 90% around 5,000 epochs, whereas vertical concatenation required approximately 10,000 epochs to achieve the same accuracy. It is pertinent to highlight that the horizontal concatenation necessitated a longer computation time for feature extraction.

Ultimately, the decision was made to proceed with horizontal concatenation, despite the increased time requirement. Utilizing the same extracted features as the single data sets, along with 18,000 data points and 60,000 epochs, the following results were obtained:

- **Right ankle accelerometer and gyroscope: accuracy was 98.83%**
- **Back hip accelerometer and gyroscope: accuracy was 98.64%**
- **Back hip gyroscope and Right ankle accelerometer: accuracy was 98.12%**

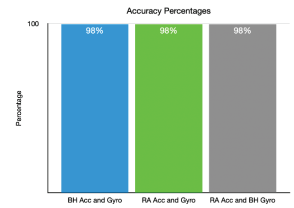

Figure 1: side by side comparison of the models accuracy with all the data sets

4.4 Three Data Sets

The final experiment consisted of three data sets: right ankle and back hip accelerometer and right ankle gyroscope. At first we didn't think there would be any improvement in accuracy due to the amount of data we have, but we were still surprised to see our models' accuracy improved to 99.14%. From here we evaluated the other metrics noted earlier in the paper along with the learning curve which are shown in the figures. Thew first two images are a projection of the accuracy of the model.The following two figures below demonstrate how fast the model learns over 20,000 epochs. One demonstrates the learning curve for the loss of the model. While the other is for the learning curve for accuracy.

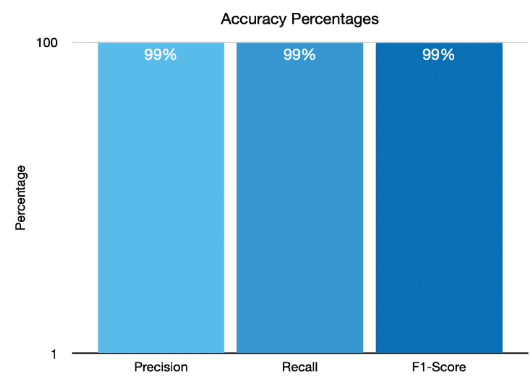

Figure 2: Three metrics of evaluation for the final combination of data

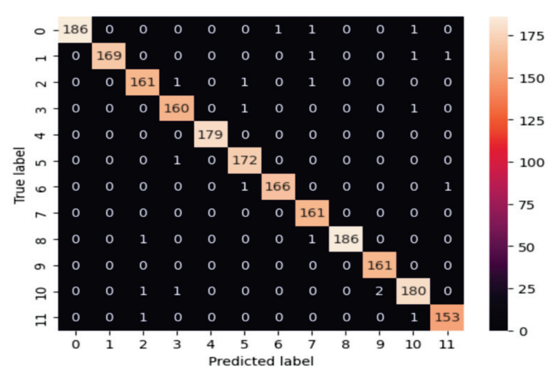

Figure 3: show the model prediction for each user

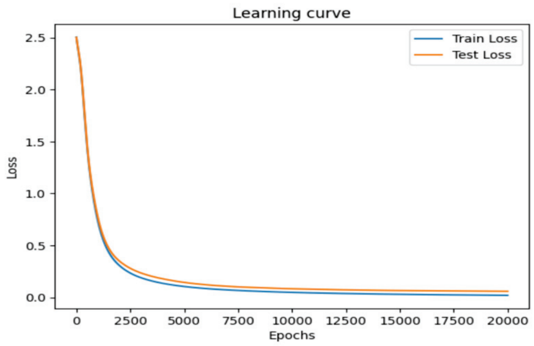

Figure 4: This figure shows the learning curve for loss

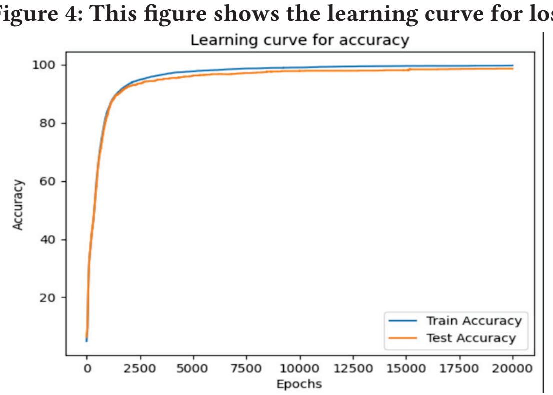

Figure 5: This figure shows the learning curve for accuracy

FUTURE WORK

In order to obtain a more extensive and accurate understanding, we plan to collect additional data from diverse users and delve deeper into the impact of certain features that only marginally improved accuracy. These features were not fully explored due to the already high accuracy rate and diminishing returns associated with adding more features. Additionally, an alternative direction for future work could involve concentrating on authenticating a single individual, rather than solely differentiating between users.

CONCLUSION

The research paper introduces PACE, a novel method for gait-based authentication using deep learning. Through careful experimentation with data sets and feature extraction, the study achieved an impressive accuracy rate of 99.14%. The success of PACE demonstrates the viability of gait-based authentication as a robust alternative to traditional methods. Its applications are vast, with potential to enhance security across various domains. The findings mark a significant advancement in user authentication, opening new avenues for more secure and efficient systems.

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REFERENCES

[1] Prashant Musale, Deokjai Baek, and Byung-Jae Choi. 2018. Lightweight gait based authentication technique for IoT using subconscious level activities. In *2018 IEEE 4th World Forum on Internet of Things (WF-IoT)*. IEEE, 564-567. https://doi.org/10.1109/WF-IoT.2018.8355210

[2] Muhammad Muaaz and René Mayrhofer. 2017. Smartphone-Based Gait Recognition: From Authentication to Imitation. *IEEE Transactions on Mobile Computing* 16, 11 (Nov. 2017), 3209-3221. https://doi.org/10.1109/TMC.2017.2686855

[3] Mpho P. Mufandaidza, Tshepiso D. Ramotsoela, and Gerhard P. Hancke. 2018. Continuous User Authentication in Smartphones Using Gait Analysis. In *IECON 2018 - 44th Annual Conference of the IEEE Industrial Electronics Society*. IEEE, 4656-4661. https://doi.org/10.1109/IECON.2018.8591193

[4] Seungho Lee, Seungho Lee, Eunbi Park, Joonki Lee, and In Young Kim. 2022. Gait-Based Continuous Authentication Using a Novel Sensor Compensation Algorithm and Geometric Features Extracted From Wearable Sensors. *IEEE Access* 10 (2022), 120122-120135. https://doi.org/10.1109/ACCESS.2022.3221813

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