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Beyond Context: Identifying Individuals from Physiological Signals Across Experiments

Pedro Rodrigues*

Laboratory for Instrumentation, Biomedical Engineering and Radiation Physics (LIBPhys), NOVA School of Science and Technology, Caparica 2829-516, Portugal
Email: pme.rodrigues@campus.ft.unl.pt

Abstract

This study evaluates the feasibility of using ECG and EDA signals for biometric identification in diverse VR contexts. Participants were first assessed in a controlled puzzle-based VR game and later in a dynamic exergame, separated by a two-year temporal gap. The proposed CNN model achieved 98.9% accuracy in the controlled environment, confirming the reliability of physiological signals for biometric identification. However, a 24% performance decline was observed in the dynamic exergame setting, highlighting the critical challenge of contextual dependence in biometric systems. Unlike most existing studies, which examine time spans of no more than a week, this work provides new insights into the impact of long-term variability and task-induced changes on identification performance. The findings underscore the importance of addressing contextual and temporal variability to improve the robustness and adaptability of biometric models.

Keywords: Biometric Systems; User-Dependent; Signal Processing; Electrocardiography (ECG); Electrodermal Activity (EDA)

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* Corresponding author. Email address: pme.rodrigues@campus.fct.unl.pt

1. Introduction

The rapid expansion of physiological data collection in research and industry has heightened concerns regarding privacy and data security [1]. Although anonymization techniques are standard, the unique patterns embedded in physiological signals pose challenges to fully preserving anonymity [2]. This issue is especially pertinent for biometric data, which the General Data Protection Regulation (GDPR) classifies as sensitive personal information requiring stringent safeguards [1, 3]. Yet, the potential to re-identify individuals from anonymized physiological data – particularly when collected across multiple experimental contexts – remains underexamined. Physiological signals such as electrocardiography (ECG) and electrodermal activity (EDA) often carry individual-specific features that can inadvertently act as identifiers [2] with recent machine-learning advances further amplifying worries about the limits of anonymization by revealing how these subtle signal features can be used for re-identification [4, 5]. While prior studies have explored identification within a single context, the degree to which models generalize across varying tasks or temporal gaps is less understood, underscoring the need for further investigation in scenarios with repeated or sequential experiments [2].

Virtual reality (VR) offers a balanced platform for ecological validity and experimental control, enabling researchers to design engaging, highly reproducible scenarios that still capture a wide range of participant movements. In contrast to a real setting – where behaviors may be restricted [6] – VR allows the introduction of more dynamic tasks that generate richer physiological responses [6]. Through precise design and calibration of each context and stimuli, researchers can systematically manipulate environmental variables without sacrificing standardization, thus minimizing external confounders. This makes VR an ideal setting for testing whether physiological data recorded under varying conditions still serve as robust identifiers. Moreover, VR scenarios can closely replicate real-world contexts while maintaining sufficient experimental control, thereby providing a more comprehensive perspective on how different operational scenarios impact biometric recognition performance [6].

To explore this, we conducted a VR-based study which was divided into two phases. During the first phase, we collected physiological data from 30 participants playing a VR game. In the second phase, conducted after a 2-year temporal gap, a subset of 5 participants returned to play a different exergame. This experimental design uses VR's capacity for both standardization and variability, while minimizing the game setup and movements as possible confounding factors and offering an evaluation of whether a model trained on physiological data from the first game can reliably identify individuals during the second game. By focusing solely on physiological signals, it isolates their potential as unique identifiers, independent of variations between the two experiments.

We believe our findings have important implications for the study of biometric recognition using physiological signals over extended timelines, addressing a gap in current studies, which typically consider time spans of no more than a week [2]. Additionally, our results may contribute to advancements in data privacy and anonymization practices, particularly considering GDPR's requirements for safeguarding biometric data. If physiological signals enable cross-context identification, existing anonymization methods may need to be reevaluated, raising critical

ethical and regulatory concerns regarding the use of such data in research settings.

2. Related Work

The biometric identification of individuals has long been a focus in both academic research and commercial applications, driven by the need for automatic recognition and authentication in real-world settings. Biometric modalities are commonly categorized into physiological and behavioral traits [7]. Physiological traits include observable and measurable physical characteristics such as fingerprints, palm geometry, ear shape, facial patterns, retina, etc. [7]. These traits are often favored because they exhibit uniqueness, permanence, and relative ease of collection, making them well-suited for reliable identification and verification [7].

In contrast, behavioral traits pertain to patterns in human actions, such as gait, keystroke dynamics, handwriting, and speech behavior [7-9]. While potentially more variable over time than physiological traits, they can still be distinctive enough for identity recognition in certain contexts. The two categories – physiological and behavioral – sometimes overlap, as behaviors can be partially influenced by underlying physiology and vice versa [10].

Recent advances in sensor technology and data analytics have spurred interest in novel physiological signals for biometric identification [4]. Modalities such as electrocardiogram (ECG) [11], electroencephalogram (EEG) [12], heart rate (HR) [13], heart rate variability (HRV) [14], respiration (RSP) [15] and electrodermal activity (EDA) [4] have all been investigated either individually or in combination within multimodal biometric frameworks. These signals offer additional dimensions of individuality – beyond traditional fingerprints or facial recognition – by capturing real-time physiological states that are more difficult to counterfeit [2].

For the purposes of this study, ECG and EDA were selected to represent distinct facets of human physiology.

- ECG is a periodic signal generated by the heart's electrical activity during contraction and relaxation cycles [16]. Its morphology varies between individuals due to anatomical and physiological factors, such as heart size [17], position [18], and fitness level [19], making it a promising candidate for biometric identification through machine-learning-based feature extraction and classification. For example, in [5], various time-frequency representations (e.g., MFCC, spectrogram, mel spectrogram) and deep CNN architectures (e.g., VGGNet, ResNet, DenseNet) were explored for ECG classification across multiple datasets, achieving a Correct Identification Rate (CIR) of 98.99%. Similarly, [20] introduced a Cascaded CNN method using two CNNs: F-CNN for feature extraction and M-CNN for biometric comparison. This approach, tested on five PhysioNet datasets, demonstrated strong generalization with an average identification rate of 94.3%.

- EDA, in contrast, is a non-periodic, event-driven signal that reflects changes in the skin's electrical conductance [21], often triggered by stimuli, stress, or emotional states [22]. While less predictable than ECG, EDA still exhibits user-specific patterns shaped by individual physiological and

psychological conditions, making it suitable for biometric recognition [23-25]. For example, [25] proposed a multimodal biometric recognition method using ECG, PPG, and EDA, employing Gaussian models to accurately identify 25 participants. Similarly, [24] utilized ECG, EDA, and EMG data from 68 participants during a driving simulation [26], testing four architectures – KNN, SVM, ANN, and an ensemble of these models – achieving accuracies of 94.8%, 97.07%, 98.24%, and 98.2%, respectively.

While much of the existing literature focuses on biometric identification within a single, controlled context – such as continuous ECG monitoring or standardized EDA measurements – relatively few studies have examined cross-context identification where individuals are recognized across different tasks, environments, or time periods [2]. This gap is particularly relevant when physiological signals are collected repeatedly in longitudinal studies or across multiple settings, posing new challenges and opportunities for re-identification. The possibility of reliably identifying individuals based on ECG or EDA, even when experimental conditions change, also underscores the need to reevaluate current anonymization strategies and raises critical questions about privacy and data protection in compliance with regulations like the GDPR.

This particularly concerning towards pseudo-anonymization strategies, which involves replacing personally identifiable information with coded references or pseudonyms, yet it remains possible to re-link the data to individuals if certain keys or contextual cues become available [27, 28]. Although pseudo-anonymization offers some level of security by obfuscating direct identifiers (e.g., names, ID numbers), it does not irreversibly break the link to the data subject in the way true anonymization does [27]. This challenge is amplified in the context of physiological data, were even without explicit identifiers, unique signal features (e.g., ECG waveform morphology) can inadvertently reveal an individual's identity.

If these features remain stable across different tasks or recording sessions, pseudo-anonymization alone may fail to prevent re-identification. A model trained on an individual's ECG or EDA data in one setting may successfully recognize the same person in another setting, illustrating a lack of "contextual variability" that would otherwise help mask identity. This persistence of signal-specific traits poses significant privacy risks, since an adversary with access to pseudo-anonymized physiological data and a re-identification model could match signals across different databases or experiments. Such scenarios highlight the limitations of pseudo-anonymization for sensitive biometric data and emphasize the need for stronger anonymization techniques, particularly when working with repeated or longitudinal measurements.

3. Materials and Methods

This paper proposes a biometric recognition pipeline encompassing data acquisition, signal processing and classification. For classification, this paper proposes the use of a convolutional neural network. The Following subsections will address the various steps in the pipeline.

3.1. Data Acquisition and Description

First Experiment

The dataset from the first experiment, originally collected in 2022 by Rodrigues et al., [29] contains electrocardiogram (ECG), electrodermal activity (EDA), and respiration signals. Participants in this experiment engaged in a puzzle-based VR game requiring them to connect dots in a prescribed order. The game featured three difficulty levels, each comprising multiple sequences. Difficulty was modulated by (i) adjusting the time limit, (ii) increasing the number of dots to connect, and (iii) introducing more complex sequences, thereby inducing varying stress levels. Figure 1 illustrates an example of the data acquisition setup.

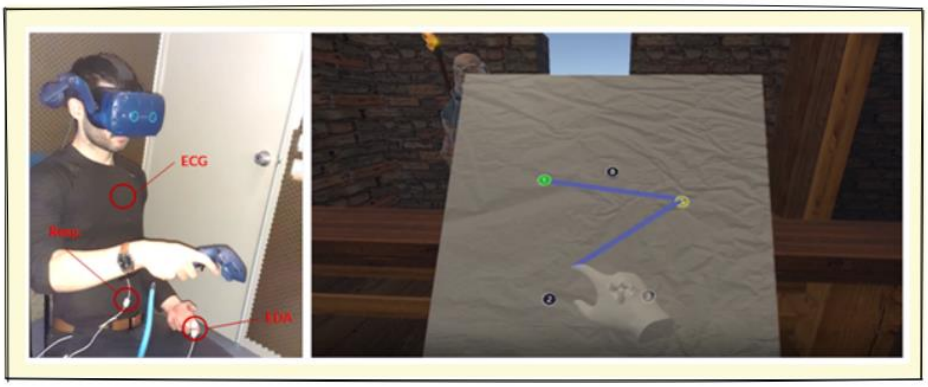


Figure 1: Experimental setup used for data acquisition in experiment 1. The left side of the figure depicts the experimental setup adopted in [29] to record the physiological data during gameplay. The right-side figure shows a screenshot of the VR puzzle game.

For the present study, only ECG and EDA are used because the respiration sensor malfunctioned during the second experiment. Both signals were recorded at 1,000 Hz using a Plux biosignal system[a]. ECG electrodes were positioned on the chest using a standard derivation, and EDA electrodes were placed on the left palm. To minimize motion artifacts, participants were asked to limit movement of the left arm. All participants were seated in a soundproof, temperature-controlled environment to reduce noise and maintain consistent conditions. Each recording lasted an average of 25 minutes, and 30 participants contributed data.

Second Experiment

The second experiment recruited a convenience sample of participants from the first study. This experiment utilized a VR exergame designed to present a notably different context, featuring four levels (Figure 2):

- **Level 1 (Passive):** Participants press trackpad buttons on the right (R) or left (L) controllers according to on-screen prompts. Approaching buttons must be pressed the specified number of times before they reach the player. Although minimal movement is required, the speed increases as the level progresses. Correct presses boost the score, while missed presses result in penalties.
- **Level 2 (Medium):** Expands on Level 1 by introducing targets to shoot. Participants press a trigger button to fire projectiles at targets located at various distances; some targets require simultaneous actions, adding complexity.

[a] https://www.pluxbiosignals.com/

- **Level 3 (Action):** Adds moving walls that approach at escalating speeds, requiring players to dodge by moving left, right, or ducking while still performing the tasks from previous levels.
- **Level 4 (Mega):** Places walls on three sides (front, left, right), with a randomly appearing green button that demands quick reflexes and body movement to press within a limited time.

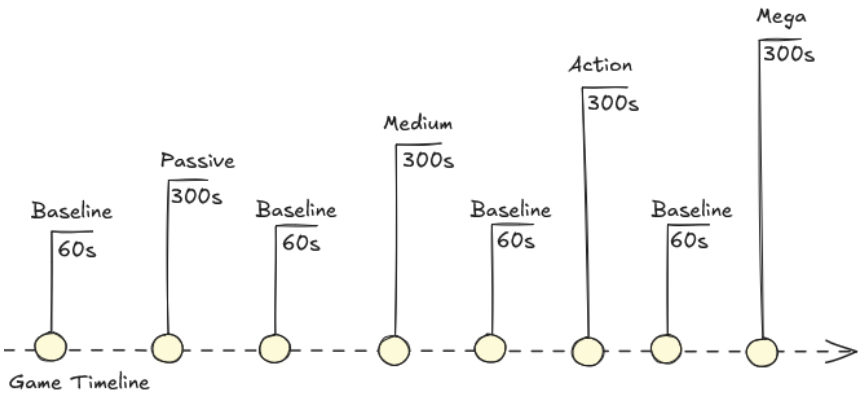
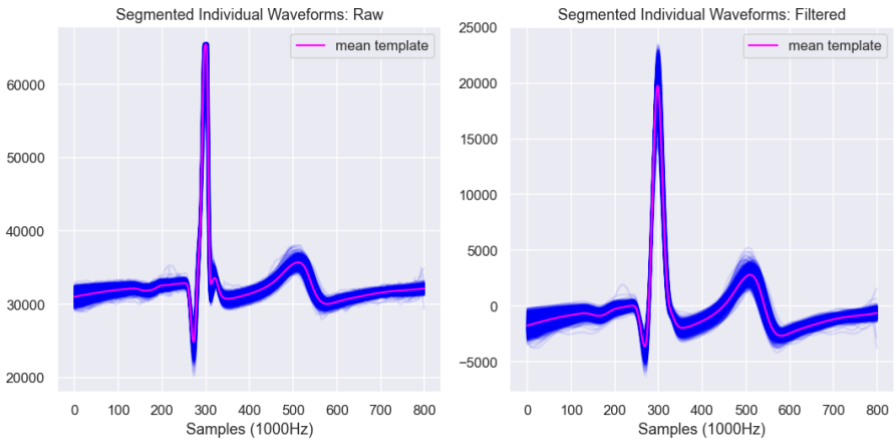


Figure 2: Visual representation illustrating the sequence of activities and their duration.

This design introduced new movements, events, and stimuli, creating a substantially different physiological context compared to the first experiment. Data were recorded for an average of 28 minutes, and 5 participants – who had also taken part in the first experiment – were included in this second study.

3.2. Data Cleaning and Segmentation

All signals were initially subjected to a cleaning procedure that involved removing any missing values. Subsequently, each signal was filtered according to its specific characteristics. For the ECG signal, a fifth-order Butterworth high-pass filter with a 0.5 Hz cutoff frequency was applied, followed by powerline filtering at 50 Hz (see Figure 3 – top) [30]. In the case of EDA, a 1024-point boxcar convolution was employed to attenuate ECG interference and motion artifacts (Figure 3 – bottom). The EDA signal was not decomposed into the separate skin conductance level (SCL) and skin conductance response (SCR) components.



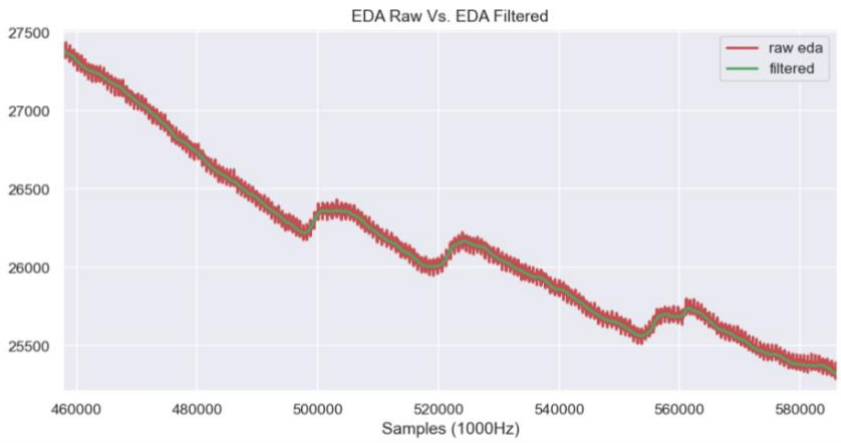


Figure 3: Comparison of ECG (top) and EDA (bottom) waveforms before and after filtering. In the top panel, each blue waveform corresponds to an 800-ms segment centered on the R-peak, and the magenta curve represents their average template. The panel on the left shows the unfiltered ECG, while the panel on the right shows the filtered signal. In the bottom panel, the red curve shows the raw EDA signal, visibly contaminated by ECG noise, while the green curve represents the filtered version.

After filtering, both ECG and EDA signals were downsampled to 100 Hz and then segmented using a sliding window of length equal to 10 seconds, with an overlap of 5 seconds (50%). This window size was determined to best capture key features in both EDA and ECG. Smaller windows risked losing essential EDA dynamics, while larger windows decreased the number of segments per participant, thus reducing the overall sampling of the analysis.

3.3. Training and Test Sets

The final segmented data from experiment 1 included a total of 30 classes each with an average of 235 samples per participant. The dataset from experiment 2 included a total of 5 classes each with 346 samples per participant. This increase in sample size between the two experiments is due to the difference in time needed to complete both experiments which differed by 3 minutes. Nevertheless, this imbalance has no expected effect on the final output, since data is segmented using the same time window configuration. For training and testing the first dataset was divided with a ratio of 90:10 respectively.

For model development and evaluation, the Experiment 1 dataset was randomly split into training and testing subsets using a 90:10 ratio. This split was chosen to maximize the training pool while still reserving a representative sample for unbiased performance assessment.

3.4. Model Architecture

The baseline model proposed in this study is a one-dimensional, 9-layer convolutional neural network (CNN) designed to classify 30 subclasses of participant identities. The architecture is relatively shallow due to the limited number of samples per class. It begins with a two-channel input layer that accepts one-dimensional ECG and EDA

signal segments of fixed length (10 seconds). These inputs undergo preprocessing to improve signal clarity, as described in Section 3.2. Following the input layer, the network comprises two one-dimensional convolutional layers, two max pooling layers, one dropout layer, two fully connected layers, and a SoftMax output layer with 30 nodes representing the identity classes. A summary of the network structure is provided in Table 1.

Table 1: Summary of CNN Architecture.

Layer	Output	Kernel size	Stride	Trainable Param.
Conv1D (Layer 1)	996 × 32	5	1	352
Max Pooling (Layer 2)	497 × 32	3	2	0
Conv1D (Layer 13)	493 × 30	5	1	4,830
Max Pooling (Layer 4)	246 × 30	3	2	0
Dropout (Layer 5)	1 × 7380	-	-	0
FC (Layer 6)	1 × 120	-	-	885,720
FC (Layer 7)	1 × 30	-	-	3,630
SoftMax (Layer 8)	1 × 30	-	-	0
Total Param.			**894,532**	

The first convolutional layer (Layer 1) has a kernel size of 5 and 32 filters to process the input data, with no padding. It is followed by a max pooling layer (Layer 2) with a pooling size of 3, reducing the output dimensions to 497 × 32. The second convolutional layer (Layer 3) also has a kernel size of 5 but uses 30 filters, further refining the feature map from Layer 2. Another max pooling operation (Layer 4), with a pooling size of 3, compresses the feature map dimensions from 493 × 30 to 246 × 30. The resulting output is then flattened, and a dropout layer (Layer 5) with a rate of 50% is applied to reduce overfitting by randomly deactivating neurons during training. The first fully connected layer (Layer 6) maps the flattened output to 120 neurons, followed by a second fully connected layer (Layer 7) that reduces the number of neurons to 30, which connects to the SoftMax output layer. The SoftMax layer generates a probability distribution across the 30 identity classes. A rectified linear unit (ReLU) activation function is applied after each convolutional and pooling layer. Additionally, an L2 regularization factor

of 0.0001 is incorporated into the fully connected layers to improve generalization and mitigate overfitting. Figure 4 illustrates an overview of this CNN architecture.

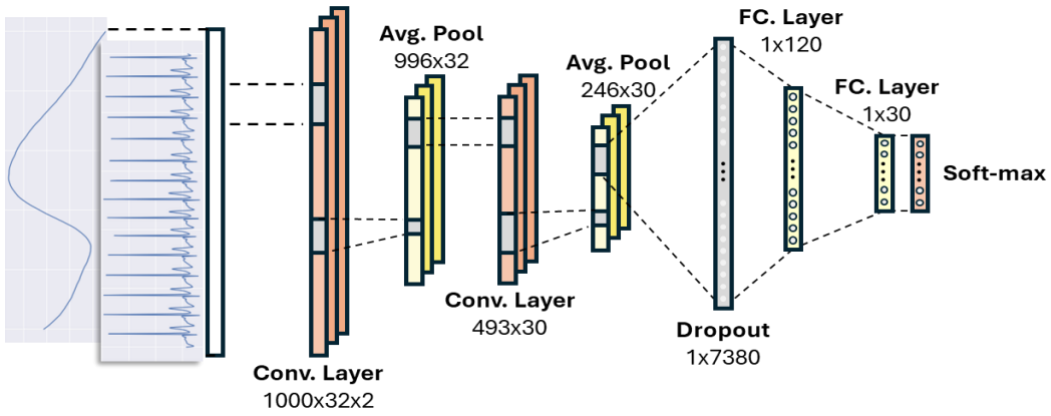


Figure 4: The architecture for the baseline CNN model.

4. Experimental Results

As outlined in Section 3, the experimental setup was designed in two workflows. The first workflow focuses on training and validating the proposed CNN model using data exclusively from the first experiment. The second workflow evaluates how well the trained model generalizes to a different context (i.e., the second experiment), thereby assessing whether the learned features remain robust under altered conditions. This section is therefore divided into two subsections, each corresponding to one of these workflows.

4.1. Model Training and Testing

The 9-layer 1D-CNN described in Section 3.4 was trained on data from Experiment 1 over 75 epochs with a batch size of 75. Figure 4 presents the training and test loss curves, as well as the accuracy curves.

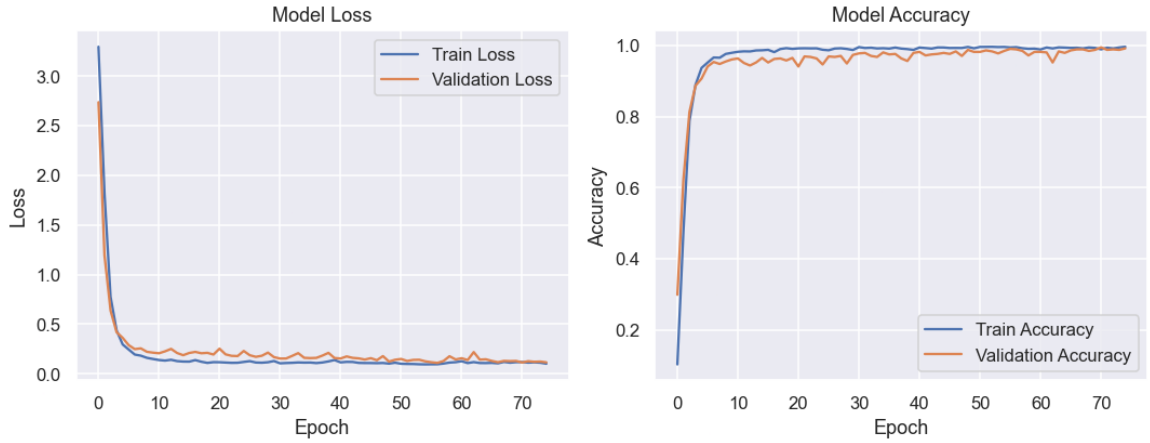


Figure 4: Training and validation performance of the model over 75 epochs. The left plot shows the loss (final

test value: 0.12), and the right plot shows the accuracy (final test value: 98,9%).

Upon completion of training, the model achieved a final test accuracy of 98.9% (95% CI: [98.4%, 99.7%]). The high accuracy suggests that the CNN successfully captured distinctive features of each participant's ECG and EDA signals. The confidence interval was computed via bootstrapping on the test set over 1,000 iterations. Figure 5 shows the confusion matrix for the 30 identity classes in the test set.

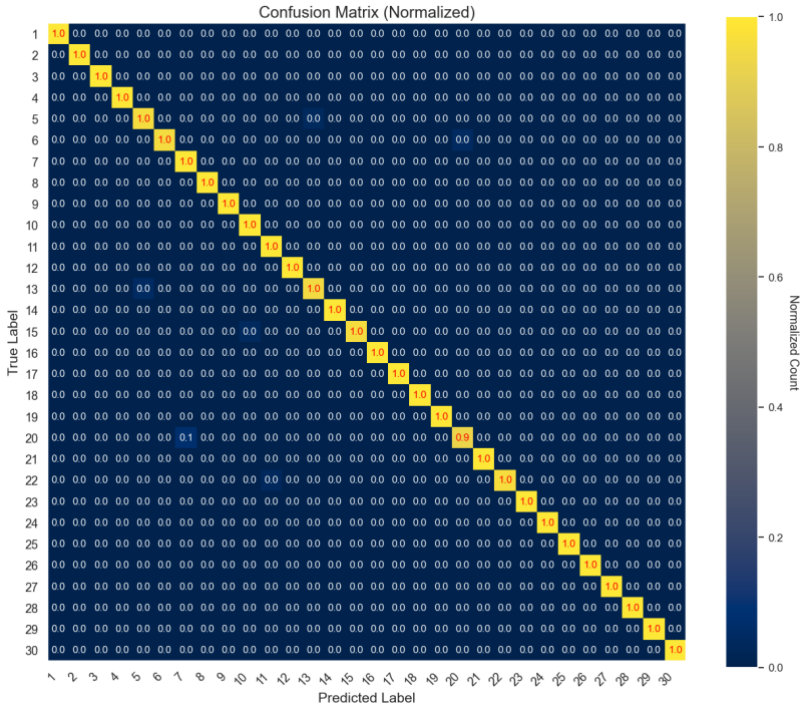


Figure 5: Confusion matrix illustrating the performance of the model on the test data. Misclassifications are sparse and do not indicate any systematic bias toward specific classes.

4.2. Model Contextual Validation

To evaluate how well the trained CNN generalizes to a new context, we tested it on data from the second experiment. As detailed in Section 3, this second experiment involved a VR exergame setting, which is substantially different from the puzzle-based VR activity used in the first experiment. A total of five participants (drawn from the initial 30) contributed data to Experiment 2, allowing a direct comparison of classification performance across two distinct contexts.

Table 2 summarizes the recognition accuracy for each of the five participants. While participant **2** retained perfect classification accuracy (100%) in both experiments, four participants experienced varying degrees of performance decline – as much as 30%. Notably, participant **3** showed the largest drop (from 100% down to 48.5%), suggesting that their physiological signals exhibited greater context-dependent variability. This decline

raises potential limitations of the model's ability to generalize across different tasks, movement patterns, and environmental stimuli.

Table 2: Comparison of classification accuracy across Experiment 1 and Experiment 2 for the subset of five participants. Each row shows the participant's accuracy in the controlled puzzle-based VR task (Experiment 1) and the exergame VR task (Experiment 2).

Participant	Acc. Experiment 1	Acc. Experiment 2
2	100 %	100 %
3	100 %	48,5 %
4	100 %	59,1 %
8	100 %	95,1 %
19	100 %	76,2 %

5. Discussion

The results presented in section 4 highlight both the potential and the limitations of using ECG and EDA signals for biometric identification across varying contexts. In the first experiment – a relatively controlled puzzle-based VR environment – the proposed CNN architecture achieved near-perfect accuracy, underscoring its capacity to learn distinctive features of each participant's physiological signals. A finding consistent with existing literature under controlled conditions [4, 5, 12]. However, the second experiment introduced a markedly different context featuring a dynamic exergame with additional movements and stimuli, an aspect less explored in similar studies. Under these new conditions, most participants demonstrated a notable decline in recognition performance, suggesting that physiological-based biometric models may be highly context-dependent.

These observations underscore the importance of evaluating biometric models in realistic, context-shift scenarios. While high accuracy in controlled conditions validates the model's core capacity for identity recognition, the reduced performance in a substantially different VR setting suggests that additional measures may be needed to ensure robust cross-context generalization. Approaches such as domain adaptation, data augmentation, or more sophisticated feature extraction methods could help address changes in physiological signals induced by variations in movement, stress levels, or environmental conditions.

Moreover, physiological signals like ECG and EDA are inherently sensitive to individual health statuses and daily habits. Diet, physical exercise, sleep quality, and stress are all known to influence autonomic responses, potentially altering signal patterns in ways that can degrade model accuracy over time or in different contexts [2]. Participants who undergo significant lifestyle changes between experiments – such as increased physical activity or dietary modifications – may exhibit altered cardiovascular or electrodermal responses, compromising the stability of their biometric signatures [17-19]. This study lacked a verbal questionnaire that could identify potentially confounding variables such as health conditions or recent lifestyle changes, factors which likely

contributed to the observed accuracy drop in the second experiment.

Despite these constraints, the strong performance in Experiment 1 illustrates that physiological signals can serve as reliable biometric identifiers under consistent recording conditions. The challenge lies in preserving that reliability across contexts and time. Future work could build upon these findings by including a broader participant pool, which would strengthen the model's capacity to generalize across a wider range of physiological profiles. Additionally, longitudinal monitoring – repeated measurements taken over extended periods – may capture gradual physiological changes and clarify how lifestyle habits or evolving health conditions affect biometric consistency. Incorporating supplementary physiological or behavioral modalities could further bolster robustness; if one modality becomes less reliable under certain tasks or conditions, another may compensate. This redundancy is particularly valuable given the potential impact of individual variability.

Ultimately, these results highlight the feasibility of ECG- and EDA-based identification, while also revealing vulnerabilities when transitioning to more complex or physically demanding environments, over an extended timeline. Addressing these vulnerabilities will be crucial for real-world applications, particularly where users may perform diverse activities. By integrating adaptive machine learning techniques and carefully controlling or monitoring lifestyle-related confounders, future biometric systems can aim to achieve stable, high-accuracy performance across heterogeneous conditions and time.

6. Conclusion

This study investigated the feasibility of using ECG and EDA signals for biometric identification across two distinct VR contexts: a controlled puzzle-based environment and a dynamic exergame, separated by a two-year temporal gap. While the high recognition accuracy in the controlled setting (98.9%) highlights the potential of physiological signals as biometric identifiers, the significant performance decline (24%) in the exergame scenario underscores the critical challenge of contextual dependence. This decline reflects the sensitivity of these signals to variations in task complexity, movement patterns, and environmental factors – an underexplored area in the field, where most studies focus on short-term intervals, often no more than a week.

By demonstrating the impact of both temporal and contextual variability, this work opens avenues for future research to address these challenges. Longitudinal studies with diverse and larger participant cohorts, combined with advanced modeling approaches such as domain adaptation and multimodal integration, are essential to better understand and mitigate context-induced variability. Additionally, while this study does not explicitly address anonymization, the findings suggest opportunities for future investigations into how context-dependent signal changes might influence data privacy frameworks. Advancing this line of inquiry will be crucial for developing robust, adaptable, and ethically sound biometric systems based on physiological signals.

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