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DEEP RESIDUAL NETWORK FOR USER IDENTIFICATION BASED ON STAIR AND LIFT USAGE USING SMARTWATCH SENSOR AND BAROMETER DATA

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Abstract. *This research proposes a new technique for recognizing individual users based on their unique stair and elevator usage behaviors, captured using wearable sensor systems and atmospheric pressure measurements. A specialized deep residual network, following the ResNeXt paradigm, is developed to analyze personal movement signatures observed during stair climbing, stair descent, and elevator travel. The proposed model extracts temporal features from multimodal sensory streams, combining accelerometer outputs with barometric pressure variations. These inputs provide insight into both kinetic activity and fine-grained elevation changes. Utilizing the publicly available Stair and Lift Taking dataset, our approach achieves a user identification accuracy of 95.34% across a cohort of 20 individuals. This performance significantly exceeds traditional machine learning algorithms and standard deep learning models. Incorporating barometric pressure readings into the model boosts recognition accuracy by an additional 13.84% points compared to using accelerometer data alone. The results underscore that vertical displacement patterns contain distinctive biometric information, which can be effectively harnessed for personal identification. By demonstrating the viability of using everyday locomotion behaviors as implicit biometric traits, this study contributes to biometric security and context-aware systems, offering promising avenues for seamless, non-intrusive authentication in innovative settings and wearable computing platforms.*

Keywords: User identification, Deep learning, ResNeXt, Wearable sensors, Barometer, Stair and lift usage

1. **Introduction.** Patterns of human movement serve as a valuable source of behavioral biometric data for user identification and authentication [1, 2]. Although considerable research has been directed toward gait analysis and the classification of general activities

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using wearable sensing technologies, less attention has been given to the biometric potential of vertical movements, such as stair climbing and elevator rides [3]. These forms of vertical mobility are common in everyday life and incorporate both physiological traits – including muscle coordination, postural control, and strength – and individual movement habits, which may offer distinctive user-specific signatures [4].

With recent advances in wearable sensor systems, it is now feasible to perform continuous activity monitoring using compact, embedded devices found in consumer electronics such as smartwatches and fitness bands [5]. Among embedded sensors, accelerometers are commonly used to measure dynamic motion, while barometric pressure sensors detect altitude changes. Together, these sensors provide complementary data streams that accurately characterize vertical movements with fine detail [6, 7]. This fusion of modalities enables the detection of individual differences in motion execution that may not be discernible using acceleration data alone.

Several properties make stair and elevator behavior promising for biometric applications [8]. First, these activities involve coordinated motor actions that differ based on personal attributes such as body composition, fitness level, and posture control [9]. Second, individuals often develop routine movement strategies – for instance, some ascend stairs quickly in enormous strides, while others adopt a consistent, deliberate pace [10]. Third, the dual nature of vertical mobility – dynamic motion during stair ascent and relatively static posture during elevator use – provides varied behavioral contexts for distinguishing users.

Recent developments in deep learning, especially the use of deep residual networks (ResNets), have shown considerable effectiveness in capturing complex patterns in time-series sensor data [11]. The residual architecture mitigates the vanishing gradient problem, a common challenge in deep neural networks, thereby enabling deeper model construction [12]. These deeper networks can better represent the temporal hierarchies and structural dependencies inherent in human movement data.

This study presents a novel user identification framework that leverages vertical mobility behavior captured by wearable sensors to characterize activity patterns associated with stair use and elevator transitions. To model these behavioral traits, we develop a ResNet-based deep learning architecture that processes multimodal sensor inputs and extracts distinctive user-specific signatures. Experimental evaluation demonstrates that the proposed approach attains an identification accuracy of 95.34% across a cohort of 20 participants, substantially outperforming conventional machine learning techniques and standard deep learning baselines. These findings underscore the potential of routine physical activities as reliable, non-intrusive biometric indicators, advancing behavioral biometrics and facilitating seamless user authentication in bright environments and wearable computing applications.

The paper's structure is as follows. Section 2 reviews the existing literature on deep learning approaches for user identification. Section 3 introduces the proposed 1D-ResNeXt architecture and explains the dataset comprising stair and elevator activities, as well as the evaluation criteria used. Section 4 describes the experimental design and presents the performance outcomes. Section 5 provides an in-depth discussion of the findings, concludes the study, and outlines potential directions for future research.

2. **Related Work.** This section presents a comprehensive review of the relevant literature, encompassing prior studies on activity recognition using wearable sensors, sensor-based biometric identification methods, and the application of deep learning techniques for user recognition from sensor data.

2.1. **Activity recognition with wearable sensors.** The use of wearable sensors for human activity recognition (HAR) has received significant attention in recent years [13, 14]. Bulling et al. [15] provided a detailed tutorial on using body-worn inertial sensors for HAR, outlining key challenges and promising directions in this area. Similarly, Valli and Amutha [16] surveyed existing methodologies, categorizing them by sensor type, recognition strategy, and application domain.

Focusing more narrowly on vertical mobility detection, Karande et al. [17] proposed the Stair and Lift Taking dataset, designed to differentiate between stair usage and elevator rides. They demonstrated that Random Forest classifiers trained on a combination of accelerometer and barometric pressure data achieved 87.61% classification accuracy. Their findings highlighted the critical role of barometric pressure sensors in detecting altitude-related changes. Notably, the model's performance declined to 68% accuracy when only inertial measurement unit (IMU) data was used, underscoring the limitations of relying solely on inertial features for vertical activity classification.

2.2. **Sensor-based biometric identification.** The use of sensor data for biometric identification has gained traction as an effective, non-intrusive solution for user authentication. Foundational research [18] demonstrated the viability of gait-based authentication using accelerometer signals, showing that individuals possess distinctive motion signatures that can serve as biometric traits. Building on this premise, Lu et al. [4] developed gait verification techniques tailored for mobile devices, enabling continuous and unobtrusive identity verification in everyday scenarios.

Further contributions by Ailisto et al. [19] examined the use of accelerometer-derived gait data for identifying individuals and reported favorable outcomes, particularly within small-scale participant groups. Expanding the research landscape, Ngo et al. [20] compiled what was, at the time, the largest dataset of gait recordings collected from inertial sensors. They also conducted comprehensive evaluations of multiple personal authentication algorithms based on walking patterns.

Despite these advancements, most prior studies have focused on horizontal locomotion, such as walking or running. In contrast, the potential of vertical mobility behaviors – notably stair ascent/descent and elevator use – as sources of biometric information has mainly remained underexplored. This gap persists even though such activities inherently involve rich physiological and behavioral features, offering untapped opportunities for user identification.

2.3. **Deep learning for sensor data analysis.** Deep learning techniques have significantly transformed the processing and interpretation of sensor data for both activity recognition and biometric user identification. In their comprehensive survey, Wang et al. [21] reviewed deep learning strategies for recognizing human activities using sensor inputs, emphasizing their notable superiority over conventional machine learning algorithms, especially in modeling complex activity patterns.

Of particular relevance to this study, Ordóñez and Roggen [22] illustrated the advantages of integrating convolutional neural networks (CNNs) with long short-term memory (LSTM) architectures for multimodal activity classification using wearable devices. Complementing this work, Hammerla et al. [23] conducted a comparative analysis of various deep learning models applied to wearable-based activity recognition, offering essential guidance on selecting appropriate architectures for different activity categories.

The ResNet [24] has emerged as a powerful model for analyzing time-series sensor data. Its architecture addresses the vanishing gradient problem by incorporating skip connections, enabling the learning of deeper, more complex temporal relationships. Li et al. [25] evaluated multiple feature extraction methods for activity classification and concluded that deep residual networks achieved superior performance, particularly for fine-grained recognition tasks involving high intra-class variability.

While deep residual networks have shown promise in activity recognition, their application to user authentication via patterns derived from vertical mobility, such as stair usage and elevator behavior, remains relatively unexplored. This research contributes a novel perspective by leveraging ResNet-based architectures for biometric identification, effectively bridging the domains of activity recognition and behavioral biometrics through the lens of vertical movement analysis.

3. **The Proposed Framework.** This section outlines the methodological approach adopted in our study to assess the significance of physical activity data in user identification. The proposed framework for identifying users is depicted in Figure 1, providing a visual representation of the overall system architecture.

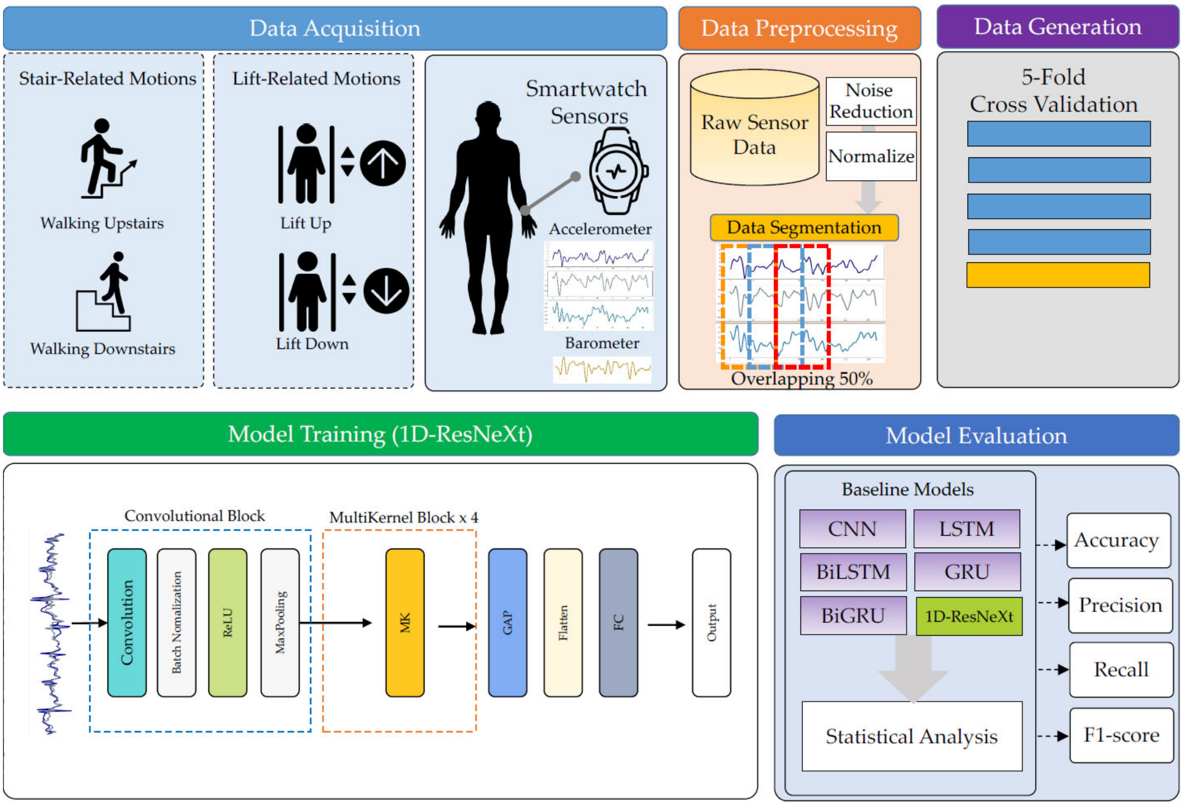

FIGURE 1. The user identification workflow used in this work

Figure 1 illustrates the complete user identification pipeline employed in this study, presenting a step-by-step breakdown of the system's operations, from initial data collection to the final classification stage. The framework is structured into four core phases, each representing a key component of the data processing and model development workflow.

The process begins with the data acquisition phase, during which motion data is recorded as participants engage in vertical mobility activities, including stair traversal (ascending and descending stairs) and elevator use (moving up and down via lifts). This data is captured using smartwatch-integrated sensors, specifically the accelerometer, which tracks movement dynamics, and the barometric pressure sensor, which measures altitude variations.

The second phase involves data preprocessing, where raw sensor outputs are systematically refined. This step includes noise filtering to remove extraneous fluctuations, normalization to standardize data across sensor modalities, and segmentation using a sliding-window approach with 50% overlap. This overlapping strategy ensures temporal coherence while producing fixed-length segments suitable for deep learning models.

In the third phase, the data generation process focuses on producing reliable, representative samples for model training and testing. A 5-fold cross-validation scheme is adopted, ensuring that the dataset – collected from 20 individual participants – is evenly partitioned while maintaining the distribution of activities within each fold.

The fourth phase focuses on model training, wherein the proposed 1D-ResNeXt deep learning architecture is employed. This model features a series of multi-kernel convolutional blocks that extract temporal features at multiple resolutions. Each convolutional layer is followed by batch normalization and ReLU activation, which support stable training and nonlinear transformations. The architecture concludes with global average pooling and fully connected layers to perform the final classification task.

Finally, the model evaluation phase assesses the system's generalization and robustness. Using the same 5-fold cross-validation protocol, the model's performance is quantified through standard evaluation metrics: accuracy, precision, recall, and F1-score. Comparative analysis is conducted against baseline models, including CNN, LSTM, BiLSTM, GRU, and BiGRU, to validate the effectiveness of the proposed 1D-ResNeXt model.

3.1. **Stair and Lift Taking dataset.** The Stair and Lift Taking dataset was created at the University of Siegen, Germany, to facilitate distinguishing between stair use and elevator (lift) movements using wearable sensor recordings. This dataset comprises information from 20 participants with diverse profiles (10 males and 10 females, mean age 26.0 $\pm$ 10.75 years), aiming to capture a wide range of movement behaviors across different demographic groups.

Sensor data was acquired from Bangle.js 2 smartwatches equipped with accelerometers and barometric pressure sensors, both operating at 50 Hz. The experiments took place within an eight-floor university building, where participants were asked to move between floors using either stairs or elevators. The mode of travel was assigned randomly to eliminate potential bias in data collection. Participants were instructed to move naturally, sometimes carrying bags or using mobile phones, to ensure the data reflected realistic daily behaviors.

The resulting dataset consists of approximately 525 minutes (equivalent to 8 hours and 45 minutes) of labeled sensor data, categorized into five distinct activity classes:

- Null: Intervals where no stair or elevator activities occurred (52.0% of the data),
- Lift Up: Ascending to higher floors via elevator (14.4%),
- Lift Down: Descending to lower floors via elevator (14.8%),
- Stairs Up: Climbing stairs to ascend floors (7.6%),
- Stairs Down: Descending stairs to lower floors (11.2%).

Each recorded instance includes timestamps, three-axis accelerometer readings (X, Y, Z), acceleration magnitudes, barometric pressure values, and corresponding ground-truth activity labels.

This dataset holds a distinctive position as the only publicly available activity recognition dataset that explicitly incorporates elevator usage as a classified activity. Furthermore, it uniquely leverages barometric pressure sensing to differentiate between methods of vertical mobility effectively.

3.2. **Data preprocessing.** Preprocessing sensor data is a vital step in preparing it for user identification tasks, as it directly affects the quality, consistency, and model-readiness of the input signals. In this study, we designed a dedicated data preprocessing pipeline to convert the raw signals from the Stair and Lift Taking dataset into a structured format optimized for deep learning-based analysis. The pipeline comprises several critical stages aimed at improving signal fidelity, ensuring data uniformity, and segmenting continuous sensor streams into analyzable segments.

The initial stage involves data cleaning, which addresses issues such as missing values and anomalous readings. Missing samples, often caused by brief sensor interruptions or signal degradation, are handled differently depending on their duration. Short-term gaps (less than 100 milliseconds) are interpolated using linear methods, while longer gaps are excluded from further processing to avoid introducing unreliable data.

To remove high-frequency noise, particularly in accelerometer signals, a Butterworth low-pass filter with a cutoff frequency of 20 Hz is applied. This denoising step plays a crucial role in eliminating unwanted motion artifacts – especially those caused by hand gestures or extraneous body movements – without distorting the meaningful signal components related to stair and elevator activity.

Next, we apply Min-Max normalization to rescaling all sensor readings to a standard range between 0 and 1. This scaling is performed independently for each accelerometer axis (x, y, z) and for barometric pressure data. By standardizing the input features, we prevent any individual dimension from disproportionately influencing the model during training, ensuring balanced feature contribution and improved convergence.

The segmentation phase divides the continuous time series into 4-second windows with 50% overlap between consecutive segments. This overlapping windowing strategy is designed to retain temporal continuity and reduce the risk of missing transitional movements between activities. Empirical tuning revealed that a 4-second window offers an effective trade-off between computational efficiency and the temporal resolution required to capture activity-specific patterns.

Subsequently, we extract features from each segmented window. This includes both time-domain metrics – such as mean, standard deviation, minimum, maximum, range, kurtosis, and skewness – and frequency-domain attributes, including dominant frequency, spectral energy, and spectral entropy. Additionally, we compute the rate of change in barometric pressure within each window, which serves as an informative feature for detecting vertical movement trends and estimating ascent or descent speed.

The output of this preprocessing pipeline is a set of structured feature vectors, each labeled with the corresponding user identity. These refined inputs are then fed into our deep learning model. Experimental results confirm that this preprocessing strategy significantly improves the system's ability to differentiate users based on their unique vertical mobility patterns, particularly during stair and elevator interactions.

3.3. **The proposed 1D-ResNeXt.** In this study, we introduced a deep residual learning framework, 1D-ResNeXt, to enhance the accuracy of sensor-based HAR. The proposed architecture draws on the design principles of the ResNeXt model. Unlike InceptionNet, which merges feature maps through concatenation, 1D-ResNeXt employs element-wise addition of feature maps from kernels of varying sizes. This architectural decision significantly reduces the total number of parameters, making the model particularly well-suited for low-latency applications and resource-constrained environments such as edge computing platforms.

Figure 2 presents the configuration of the multi-kernel module, which functions as the core component of the proposed 1D-ResNeXt architecture. The module receives raw sensor inputs and routes them through three independent convolutional streams, where each branch applies filters with distinct temporal receptive fields – specifically 1×3, 1×5, and 1×7. Before these multi-scale convolutions are performed, every branch first applies a 1×1 convolution to compressing feature dimensions, thereby lowering computational overhead. This bottleneck strategy reduces the total number of learnable parameters while retaining sufficient expressive power within the network.

Instead of concatenating the branch outputs, the module integrates the results from the three streams element-wise. This choice differentiates the design from Inception-based architectures and further limits parameter growth. After the addition step, the merged representation is refined through another 1×1 convolution layer. A subsequent element-wise addition introduces a skip connection from the module's input, thereby

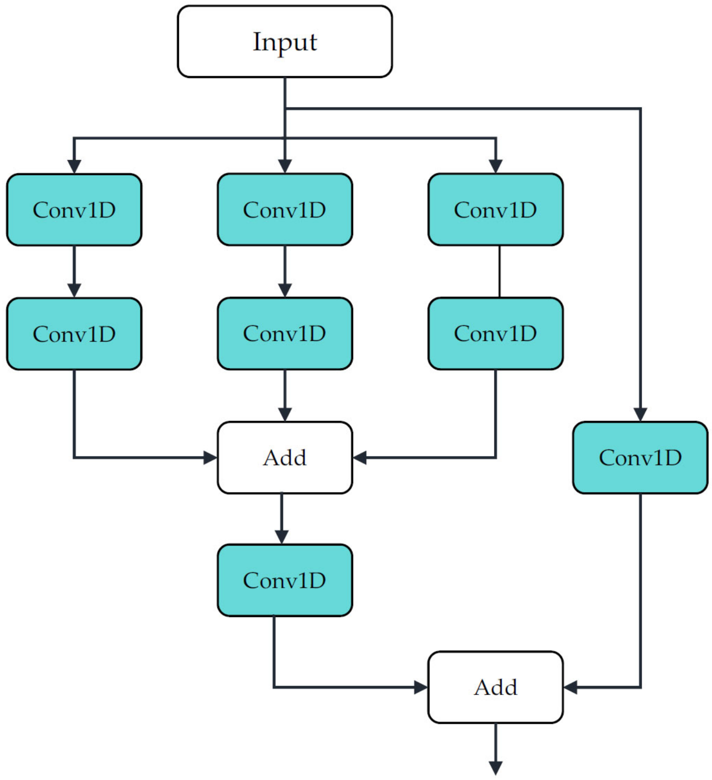

FIGURE 2. The multi-kernel module presented in this work

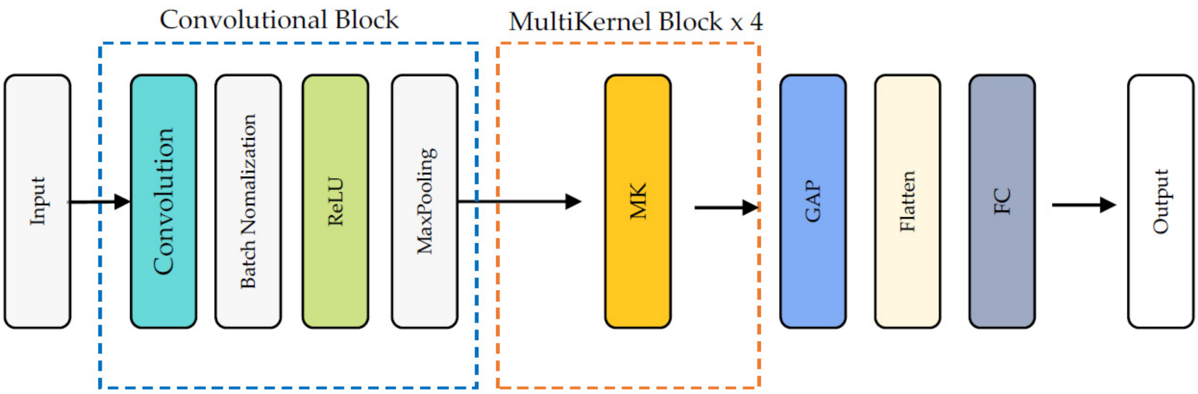

FIGURE 3. The 1D-ResNeXt model

implementing the residual learning mechanism that supports stable gradient propagation during training.

Through this multi-kernel arrangement, the model learns temporal dependencies across multiple time scales simultaneously, a capability that is especially important for capturing the diverse movement rhythms and cadence variations characteristic of human stair-climbing and elevator-usage behaviors.

Figure 3 depicts the overall structure of the proposed 1D-ResNeXt network designed for user identification based on vertical mobility behavior. The architecture starts with an input layer that receives the preprocessed accelerometer and barometric pressure signals. An initial feature-extraction block follows, consisting of a standard 1D convolution, batch normalization, and a ReLU activation function, which together extract preliminary patterns from the incoming sensor streams.

The central component of the model is composed of four multi-kernel blocks arranged sequentially, corresponding to the module described earlier in Figure 2. These blocks progressively learn temporal representations at multiple resolutions. The earlier MK layers focus on capturing fine-grained motion cues, while the deeper layers encode more abstract behavioral characteristics that differentiate users.

After passing through the multi-kernel stages, a max-pooling layer performs downsampling to reduce computational complexity while preserving the most informative responses. The network then applies a global average pooling layer, which condenses the temporal feature maps into a fixed-length vector, ensuring consistent dimensionality across varying input durations. A subsequent flattening operation prepares this output for the classification stage.

The final prediction is generated by a fully connected layer equipped with a softmax function, which assigns the extracted feature vector to one of the 20 user categories in the dataset. Overall, this end-to-end configuration enables the model to automatically derive discriminative representations directly from raw sensor measurements, eliminating the need for hand-crafted feature engineering.

3.4. **Performance measurement criteria.** Four standard performance indicators were employed to assess the effectiveness of deep learning algorithms in sensor-driven user identification. The evaluation was conducted using a 5-fold cross-validation scheme to ensure robust, reliable results. The formal definitions and mathematical formulations of these four evaluation metrics are presented in the following equations.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

These metrics are widely adopted in HAR research. A true positive (TP) occurs when an activity is correctly classified. In contrast, a true negative (TN) refers to correctly identifying non-target classes, and misclassifying an activity as a different class results in a false positive (FP), whereas incorrectly labeling an instance from another class as the target class leads to a false negative (FN).

4. **Experiments and Results.** This part of the study provides an in-depth assessment of the 1D-ResNeXt model, developed to recognize individual users based on their movement behaviors involving stairs and elevators. A series of detailed experimental evaluations were conducted to examine how the model performs under varied sensor setups, with direct comparisons against leading-edge deep learning techniques.

The section begins by outlining the experimental design, specifying details such as software implementation, hardware environment, and the methodology used for performance evaluation. Following this, we discuss the outcomes obtained from two distinct experimental frameworks, each aimed at analyzing how sensor variations influence identification effectiveness.

In the first setup (Scenario I), the model's accuracy was tested using accelerometer data alone. In contrast, the second setup (Scenario II) involved integrating barometric pressure data to assess its influence on recognition performance. Across both conditions, standard evaluation metrics – namely, accuracy, precision, recall, and the F1-score – were calculated for all models.

The findings underscore the robustness of the proposed 1D-ResNeXt framework in discerning unique vertical locomotion signatures. It consistently outperformed traditional deep learning architectures and hybrid systems across all experimental contexts, demonstrating superior capability for modeling vertical movement characteristics for user authentication.

4.1. **Experimental setting.** All experimental procedures in this work were performed in the Google Colab Pro environment, which provides computational resources via an NVIDIA Tesla V100 GPU. Model development and testing were implemented in Python (version 3.6.9) using well-established libraries, including TensorFlow 2.2.0, Keras 2.3.1, Scikit-Learn, Numpy 1.18.5, and Pandas 1.0.5.

The research was structured around two distinct experimental setups to examine how different types of input data influence the effectiveness of user authentication. Each configuration involved a unique dataset split for training and validation of the proposed 1D-ResNeXt framework, as shown in Table 1. The primary objective of these scenarios was to assess how integrating multiple sensor modalities could enhance the accuracy of user identification.

Table 1. List of experiments conducted in this study

Scenario	**Description**
I	Using only accelerometer data
II	Using accelerometer data and barometer data

4.2. **Experimental results.** In each experimental setup, the Stair and Lift Taking dataset was utilized to train and evaluate the deep learning models. Model performance was assessed using a 5-fold cross-validation strategy to ensure robustness and generalizability. The evaluation focused on measuring the identification accuracy of the proposed 1D-ResNeXt architecture under the two experimental conditions specified in Table 1.

Table 2 presents a comparative evaluation of the model's effectiveness across the two defined scenarios. In Scenario I, only accelerometer data was employed, whereas Scenario II incorporated both accelerometer and barometric pressure data. The inclusion of barometric information led to a substantial performance boost, with identification accuracy increasing from 81.50% to 95.34%, marking an improvement of 13.84 percentage points.

Table 2. Evaluation metrics of the 1D-ResNeXt architecture across multiple sensor-based experimental scenarios

Scenario	**Recognition performance**			
	Accuracy	**Precision**	**Recall**	**F1-score**
I	81.50%(±0.41%)	82.09%(±0.44%)	81.55%(±0.39%)	81.62%(±0.42%)
II	95.34%(±0.67%)	95.54%(±0.62%)	95.40%(±0.63%)	95.41%(±0.65%)

Similar improvements were observed across all performance indicators. Precision, recall, and F1-score each rose by approximately 13-14 percentage points, highlighting the consistent benefit of integrating altitude-sensitive data. These results strongly support the hypothesis that barometric pressure readings provide critical discriminative features, enabling more accurate identification of individuals based on vertical mobility behaviors.

Tables 3 and 4 offer a detailed comparative analysis of various deep learning models applied to Scenarios I and II. In Scenario I, which utilizes only accelerometer readings, the proposed 1D-ResNeXt framework demonstrates a clear performance advantage. It achieves an accuracy of 81.50%, significantly surpassing the CNN model – the next-highest performer – which records just 53.78%. In contrast, conventional sequence-based architectures such as LSTM, BiLSTM, GRU, and BiGRU deliver substantially lower accuracy, ranging

Table 3. Evaluation metrics of deep learning models trained and validated on sensor data in Scenario I

Model	Recognition performance			
	Accuracy	Precision	Recall	F1-score
CNN	53.78%(±0.75%)	54.65%(±0.39%)	53.54%(±0.71%)	52.80%(±0.58%)
LSTM	37.37%(±1.64%)	37.70%(±1.62%)	36.23%(±1.67%)	35.39%(±1.69%)
BiLSTM	39.19%(±1.03%)	39.31%(±1.88%)	38.07%(±1.23%)	37.33%(±1.75%)
GRU	29.80%(±1.47%)	28.89%(±1.93%)	28.06%(±1.32%)	26.51%(±1.91%)
BiGRU	43.80%(±0.64%)	43.39%(±0.54%)	42.63%(±0.57%)	42.10%(±0.50%)
1D-ResNeXt	**81.50%(±0.41%)**	**82.09%(±0.44%)**	**81.55%(±0.39%)**	**81.62%(±0.42%)**

Table 4. Evaluation metrics of deep learning models trained and validated on sensor data in Scenario II

Model	Recognition performance			
	Accuracy	Precision	Recall	F1-score
CNN	74.11%(±1.04%)	74.76%(±0.43%)	73.87%(±0.79%)	73.33%(±0.97%)
LSTM	59.29%(±2.61%)	59.41%(±3.50%)	57.68%(±2.92%)	56.60%(±2.40%)
BiLSTM	64.13%(±2.94%)	65.34%(±2.27%)	62.81%(±2.81%)	62.49%(±3.00%)
GRU	47.42%(±1.68%)	43.99%(±2.14%)	45.67%(±1.78%)	42.09%(±1.81%)
BiGRU	70.51%(±1.94%)	71.10%(±2.23%)	69.60%(±1.92%)	69.74%(±2.06%)
1D-ResNeXt	**95.34%(±0.67%)**	**95.54%(±0.62%)**	**95.99%(±0.63%)**	**95.40%(±0.65%)**

from 29.80% to 43.80%. These results indicate that such recurrent structures are less effective in capturing discriminative temporal patterns when relying solely on accelerometer data.

Scenario II (refer to Table 4) incorporates barometric pressure measurements alongside accelerometer signals. This addition leads to an overall performance improvement across all evaluated models, demonstrating the utility of multimodal sensor integration. Notably, the superiority of the 1D-ResNeXt model becomes even more evident under these conditions. It achieves a peak accuracy of 95.34%, while the CNN model – again the second-best – reaches only 74.11%. This considerable margin, exceeding 21 percentage points, reinforces the efficacy of the 1D-ResNeXt architecture in fusing heterogeneous sensor modalities and learning complex interdependencies within multimodal time-series data.

The findings underscore three significant insights. First, incorporating barometric pressure measurements improves the precision of user recognition when analyzing vertical motion behaviors. Second, the 1D-ResNeXt model consistently outperforms traditional deep learning methods tailored for this application. Third, integrating a refined model architecture with diverse sensor modalities enables the system to achieve exact user identification, making it suitable for practical authentication scenarios.

5. **Conclusion and Future Works.** This research introduced a novel deep learning framework, 1D-ResNeXt, tailored for user identification by analyzing vertical mobility behaviors – specifically stair climbing and elevator usage – captured via wearable sensors and barometric pressure data. The proposed architecture effectively models complex, user-specific movement patterns by leveraging residual learning and cardinality-based convolution modules optimized for one-dimensional temporal signals. Extensive empirical evaluations demonstrated the model's clear superiority over conventional deep learning methods, achieving peak identification accuracy of 95.34% when both accelerometer and barometric pressure inputs were utilized. This performance highlights the architectural efficiency of 1D-ResNeXt in extracting hierarchical spatial-temporal features and reinforces the importance of multimodal sensor fusion in biometric applications.

The experimental results yielded several significant insights that further advance the field of behavioral biometrics. The inclusion of barometric pressure data led to a substantial gain in accuracy – from 81.50% to 95.34% – confirming the richness of vertical motion cues in user authentication tasks. Comparative evaluations revealed that existing models enhanced with multimodal data could not match the precision of the proposed approach, underscoring the need for architecture-level innovations tailored to vertical mobility patterns. To build upon these findings, future work should explore cross-environment generalization, longitudinal stability, integration with complementary biometrics, and privacy-preserving mechanisms such as federated learning. Additionally, improving adversarial robustness and optimizing the model for deployment on low-power wearable devices remain critical for real-world implementation. Ultimately, this study establishes vertical mobility sensing as a practical and effective biometric modality, offering a foundation for seamless, unobtrusive authentication in pervasive computing environments.

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