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Innovative Visualization Approach for Biomechanical Time Series in Stroke Diagnosis Using Explainable Machine Learning Methods: A Proof-of-Concept Study

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Abstract: Stroke remains a predominant cause of mortality and disability worldwide. The endeavor to diagnose stroke through biomechanical time-series data coupled with Artificial Intelligence (AI) poses a formidable challenge, especially amidst constrained participant numbers. The challenge escalates when dealing with small datasets, a common scenario in preliminary medical research. While recent advances have ushered in few-shot learning algorithms adept at handling sparse data, this paper pioneers a distinctive methodology involving a visualization-centric approach to navigating the small-data challenge in diagnosing stroke survivors based on gait-analysis-derived biomechanical data. Employing Siamese neural networks (SNNs), our method transforms a biomechanical time series into visually intuitive images, facilitating a unique analytical lens. The kinematic data encapsulated comprise a spectrum of gait metrics, including movements of the ankle, knee, hip, and center of mass in three dimensions for both paretic and non-paretic legs. Following the visual transformation, the SNN serves as a potent feature extractor, mapping the data into a high-dimensional feature space conducive to classification. The extracted features are subsequently fed into various machine learning (ML) models like support vector machines (SVMs), Random Forest (RF), or neural networks (NN) for classification. In pursuit of heightened interpretability, a cornerstone in medical AI applications, we employ the Grad-CAM (Class Activation Map) tool to visually highlight the critical regions influencing the model's decision. Our methodology, though exploratory, showcases a promising avenue for leveraging visualized biomechanical data in stroke diagnosis, achieving a perfect classification rate in our preliminary dataset. The visual inspection of generated images elucidates a clear separation of classes (100%), underscoring the potential of this visualization-driven approach in the realm of small data. This proof-of-concept study accentuates the novelty of visual data transformation in enhancing both interpretability and performance in stroke diagnosis using limited data, laying a robust foundation for future research in larger-scale evaluations.

Keywords: gait analysis; Siamese neural network; stroke survivors; interpretation

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1. Introduction

Stroke is a common cause of gait abnormalities in older adults [1]. Depending on the location and severity of the stroke, it can affect the motor pathways in the brain that control movement, coordination, and balance [2]. This can result in various gait abnormalities, such as foot drop, spasticity, and hemiplegia. Foot drop is a condition where the foot cannot be lifted properly, resulting in a dragging gait [3]. Spasticity is a condition where there is increased muscle tone, causing stiffness and difficulty with movement [4]. Hemiplegia is severe weakness on one side of the body, which can result in an uneven gait [5]. Additionally, stroke survivors may also experience fear of falling, decreased confidence in their gait, and reduced physical activity levels. Rehabilitation programs, such as occupational therapy, physical therapy, and exercise, can help stroke survivors improve their gait and reduce the risk of falls [6].

However, these individuals need personalized intervention programs that must be based on quantitative assessments of movement. Gait analysis is the process of evaluating the way a person walks, with the aim of identifying abnormalities or changes in their gait pattern [7]. This type of analysis is commonly used in the assessment of various conditions affecting mobility, including aging, neurological disorders, and musculoskeletal injuries. Accurate and reliable gait analysis is essential for the diagnosis, treatment, and management of these conditions. Utilizing laboratory techniques for gait analysis can be time-intensive and necessitate a dedicated environment with specialized equipment, resulting in high costs and limited accessibility. Although quantitative motion analysis provides reliable and repeatable measurements, as documented by Mohan et al., these approaches are now being enhanced through the integration of wearable sensors and artificial intelligence (AI) methodologies to address these constraints [7].

Nevertheless, regardless of the chosen analytical approach, a fundamental challenge remains: effectively leveraging the quantitative insights obtained from gait analysis to diagnose movement problems' nature and severity [8], decipher the underlying mechanisms of motor disorders, and gauge the impact of interventions aimed at their rehabilitation. Such decisions are pivotal in enhancing patients' mobility, thereby influencing their overall functionality and quality of life. However, given the substantial amount of data generated by contemporary gait analysis, arriving at these decisions has proven to be an intricate, resource-intensive, and time-demanding process. In this context, artificial intelligence emerges as a promising avenue for aiding in and augmenting such clinical decision making.

Using these techniques can provide a more efficient and cost-effective means of gait analysis that can be more widely accessible. The ability of CNNs to learn and extract features from complex visual data such as gait patterns makes them particularly suited to gait analysis. Furthermore, SNNs allow for more robust comparisons between gait patterns, accounting for individual variations in appearance and movement that traditional gait analysis methods may miss. Hence, the primary scope and contributions of this work encompass several significant aspects in the field of stroke diagnosis and personalized treatment strategies: (i) The innovative visual representation of biomechanical time series: Our work introduces a pioneering approach to the visual representation of biomechanical time series data related to stroke diagnosis. By leveraging advanced visualization techniques, we offer a more intuitive and informative way to analyze and interpret complex temporal data patterns. (ii) Addressing data limitations using Siamese neural networks (SNNs): We tackle a prevalent challenge in the medical domain—limited data availability. To overcome this hurdle, we employ state-of-the-art Siamese neural networks (SNNs) that excel in learning from small datasets. Our SNN-based framework demonstrates its capability to extract meaningful information from sparse data, enhancing the accuracy and reliability of stroke diagnosis. (iii) Facilitating knowledge extraction through visual explanations: In addition to accurate diagnosis, our work places a strong emphasis on knowledge extraction. We harness the power of visual explanations to elucidate the decision-making process of our model. By providing transparent and interpretable insights into the features and factors contributing to stroke diagnosis, we empower clinicians with a deeper understanding of the underlying mechanisms. This knowledge, in turn, facilitates the development of personalized treatment strategies tailored to individual patient profiles. In summary, this study has the potential to revolutionize gait analysis and stroke diagnosis by leveraging advanced neural network techniques; improving the accessibility, accuracy, and personalization of analyses; and potentially leading to more effective treatment strategies. The integration of CNNs and SNNs, along with the focus on visualization and knowledge extraction, could bring about significant advancements in the medical field.

State of the Art

According to the literature, various studies have explored the use of deep learning (DL) techniques for the evaluation of gait patterns [7,9]. Lau et al. conducted a study where they employed support vector machines (SVMs), artificial neural networks (ANNs), and radial basis function neural networks (RBFs) as classifiers to categorize five different walking conditions (stair ascent, stair descent, level ground, upslope, and downslope) for hemiparetic post-stroke survivors [10]. The results showed that the SVM-based classifier performed better than the ANN and RBF methods, achieving an overall classification accuracy of 97.5%. In a separate study, Kaczmarczyk et al. utilized an ANN for the classification of gait patterns in post-stroke survivors [11]. Convolutional neural networks (CNNs) are a type of deep learning algorithm that has shown promise in stroke, particularly in the development of Siamese neural networks (SNNs). SNNs use a pair of identical CNNs that learn to extract features from two input images, and then, compare them to identify similarities or differences. Fan et al. utilized an SNN based on inertial sensor-based signals for automatic fall risk assessment for stroke survivors [12]. In another study, Vieira et al. used an SNN for the detection of ischemic stroke in computed tomography (CT) scans [13]. In the context of gait analysis, SNNs can be used to compare gait patterns between individuals or to analyze changes in gait patterns over time or in response to interventions. Zhang et al. [14] presents a gait recognition method using Siamese Neural Networks for human identification. It improves gait feature extraction with gait energy images, outperforming traditional approaches on a large gait database. Liu et al. [15] combines bioinformatics and AI for human identification through gait recognition. It uses deep learning and a Siamese network for spatial and temporal gait features, enhancing distance metric learning. The results on a significant gait database show superior performance to existing methods.

Hayashi et al. [16] investigate the significance of prehospital stroke diagnosis, emphasizing the need for precision, especially in identifying large vessel occlusions. Using machine learning, the researchers assessed five diagnostic algorithms and found that Extreme Gradient Boosting-based models achieved the highest diagnostic value, with impressive results across stroke subcategories. Yang et al. [17] address the rising global burden of ischemic stroke (IS) by employing machine learning. It identifies 69 differentially expressed genes associated with IS and reveals immune and inflammatory pathways. Machine learning techniques, including LASSO, SVM-RFE, and Random Forest, achieve impressive diagnostic accuracy with AUC values up to 1.000. However, the ANN model, while effective with positive samples, faces challenges in classifying negatives. Badriyah et al. [18] enhances CT scan image quality for stroke patients and uses machine learning, including Random Forest, to classify stroke sub-types with impressive 95.97% accuracy. An interesting study by Horst et al. [19] addresses the 'black box' challenge in machine learning, focusing on individual gait patterns in clinical biomechanics. Using Layer-Wise Relevance Propagation (LRP), their research unveils the significance of input variables like ground reaction forces and joint angles at different gait cycle phases. This innovative approach sheds light on complex ML methods, making them more interpretable in gait analysis and enhancing their potential for diagnosis and treatment.

After conducting a thorough examination of the current literature, it becomes clear that the use of gait analysis data for diagnosing stroke is an area that has not been extensively studied using AI. Additionally, there is a lack of comprehensive surveys that aim to visually present biomechanical and gait data. It is important to note that our study is groundbreaking as it introduces the innovative concept of visualizing biomechanical data, transforming them into image-based representations. This pioneering effort explores previously uncharted territory in this specific field.

2. Materials and Methods

In this section, we delineate the materials and methodologies employed in our study to investigate the efficacy of the proposed visualization technique.

2.1. Participants

This study included a total of 34 chronic stroke survivors and 30 healthy older adults. The non-stroke group consisted of healthy individuals over 55 years of age who had not sustained any injuries in the last year and were living independently in the community. The stroke survivors group consisted of chronic subjects over 55 years of age without severe motor impairments. All individuals were informed about the study and provided their consent before participating. The Research Ethics Committee of Democritus University of Thrace (ΔΠΘ/ΕΗΔΕ/28061/165/20.01.2023) approved this research.

2.2. Data Collection Procedure

When the subjects entered the gait laboratory, they were given instructions on the testing procedure and familiarized with the walking task. Anthropometric measurements were taken, and 57 spherical retroreflective markers were placed on anatomic landmarks and specific locations of the head, thorax, pelvis, and upper and lower limbs, following a marker set described in the literature [20]. Afterward, the subjects walked barefoot along a 10 m walkway in the laboratory at a speed within $\pm 5\%$ of their individual self-selected walking speed (SWS), which was determined during the familiarization session using infrared timing gates and maintained throughout data collection via metronome. Trials were conducted until at least 10 complete gait cycles were recorded for each foot (left and right side) landing on the force platform, with a trial considered valid only if the foot of the side being tested made clean contact with the force platform and the walking speed was within $\pm 5\%$ of the individual SWS. Kinematic data were collected at 100 Hz using 10 optoelectronic cameras (Vicon T-series, Oxford, UK), and kinetic data were collected at 1000 Hz via a force platform (Bertec 4060–10, OH) embedded in the floor, which were synchronized with the kinematic data.

2.3. Data Analysis

In this study, 5 trials (complete gait cycles for each foot) per subject were employed. The vertical ground reaction force (GRF) was used to identify the initial contact and toe-off events of the stance phase, with a threshold of 20 N. The ipsilateral initial contact was determined using motion data and Vicon Nexus 2.14 software. The kinematic data were filtered using an MSE Woltring filter at 10 Hz, and the conventional Gait Model 2 (CGM2.4) was used to generate motion features (Nexus 2.14, Oxford, UK). For each trial of each subject, selected time series were extracted, with a total of 170 trials analyzed for the stroke group and 150 trials for the non-stroke group. Figure 1 presents the kinematic data utilized in this study, including measurements of ankle plantarflexion/dorsiflexion, knee flexion/extension, hip flexion/extension, hip abduction/adduction, and hip internal and external rotation for the paretic and non-paretic legs, along with the three-dimensional center of mass position. Each time series was resized to 101 time points using cubic spline interpolation. Once the gait cycles were properly interpolated, the data were normalized to a common range, allowing for easy comparisons across different subjects. By grouping together all the gait cycles of the corresponding signals and using their global extrema to scale the data to a range of [0, 1], it was ensured that the data were consistent and comparable, which can also help to identify any meaningful differences or trends that might exist between different groups.

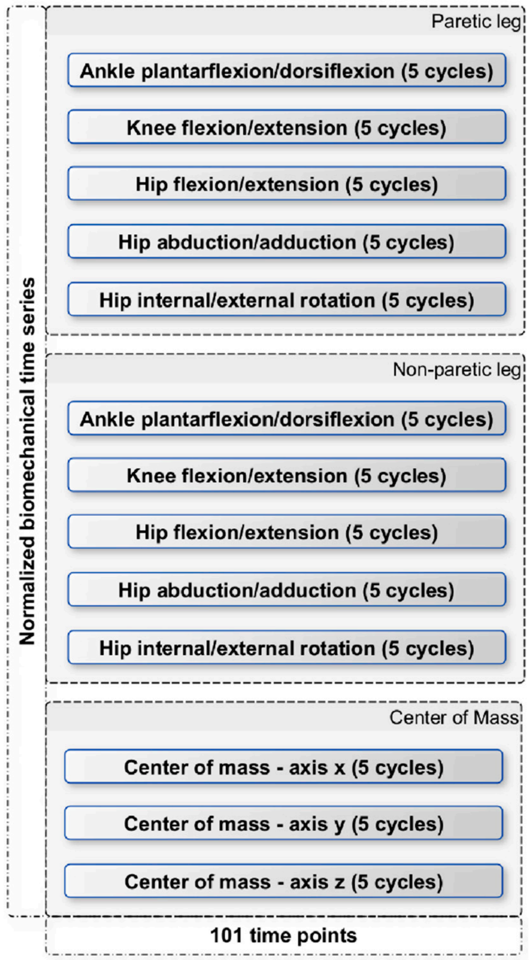


Figure 1. Visual representation of image construction.

2.4. Feature Engineering—Image Construction

After splitting and normalizing the selected signals, a 2D matrix was constructed by concatenating the corresponding gait cycles originating from the same signal in chronological order. Each row of the matrix represented a particular cycle, and each column represented the time axis expressed as a cycle percentage. The i-th element of a given row represented the corresponding percentage from the start of the cycle, providing a way to track the motion over time. The matrix allowed for point-by-point cycle correspondence, which is particularly useful in comparing cycles and identifying any patterns or differences between subjects.

Finally, all the matrices were concatenated vertically. The end result was one 2D matrix per subject (or c3d file) with elements values in the range [0, 1]. These matrices combined subjects' motion data that had been transformed into the same scale and can help extract meaningful insights regarding the subjects' mobility. This feature engineering technique is particularly useful in comparing the mobility of healthy subjects and stroke survivors and identifying any differences that may exist between the two groups.

2.5. Learning Methodology

In this section, the proposed methodology is presented in Figure 2.

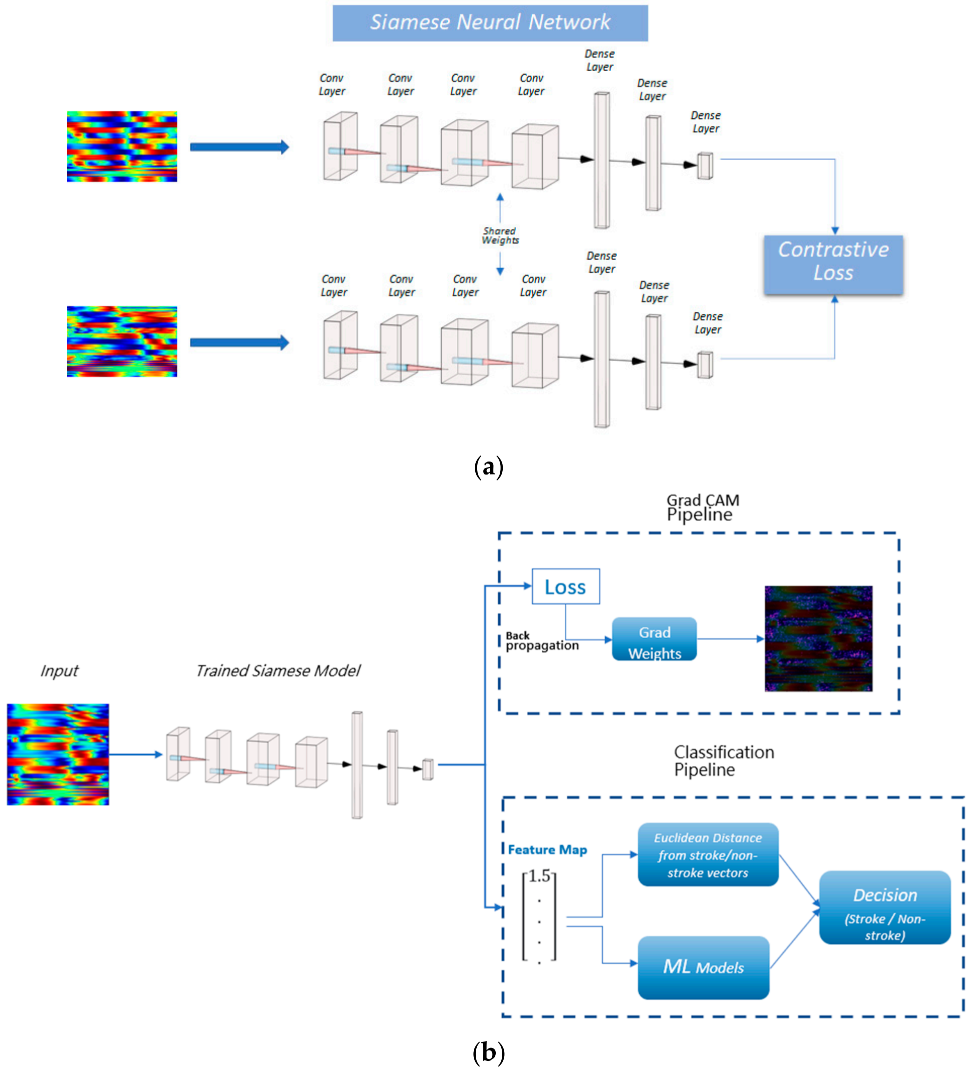


Figure 2. (**a**) The concept of the Siamese neural network. (**b**) The proposed pipeline to classify and interpret the images.

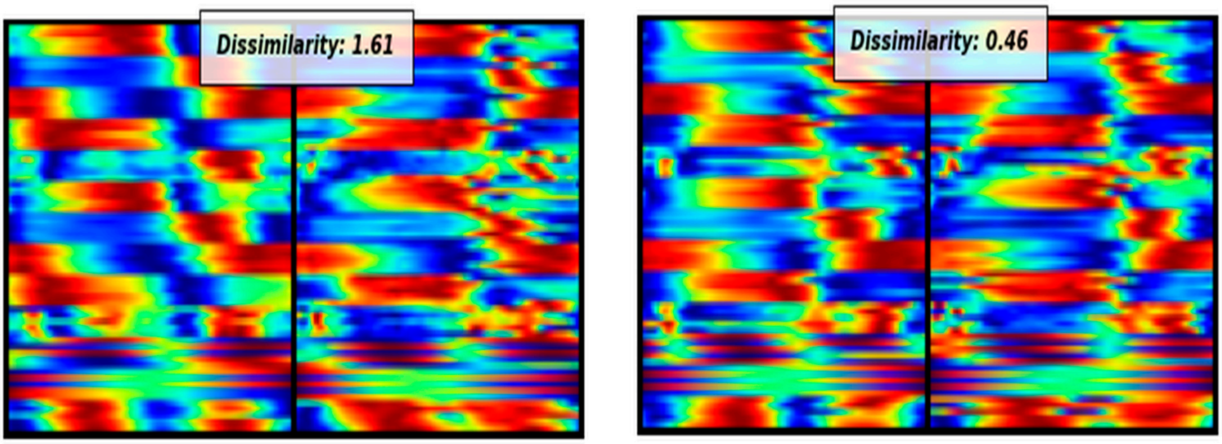
A Siamese neural network (SNN) is a popular neural network architecture, especially when dealing with limited amounts of data. SNNs were introduced by Bromley et al. [21] Some of the most popular applications that use SNNs are face recognition [22] and signature verification [23]. An SNN usually consists of two identical neural networks sharing the same weights and architecture (Figure 2a). This way, the model is trained based on a similarity function that measures the distance between the feature vectors of two images. We trained the model with contrastive loss [24], which is a distance-based loss function that aims to minimize the Euclidean distance between similar feature vectors and is described as follows:

$$L = (1 - Y)\frac{1}{2}(Dw)^2 + \frac{1}{2}\{\max\,(0, m - Dw)\}^2$$

where Y represents the vectors' similarity, which is 0 if the vectors are similar and 1 for dissimilar vectors, while Dw is the Euclidean distance between the vectors. For the evaluation of the model, we used an accuracy metric, which is defined as follows.

$$\frac{TP + TN}{TP + TN + FP + FN}$$

For our experiments, we used a small model with three convolutional blocks where each block consists of a convolutional layer, a dropout, and a batch normalization. Finally, the model results in a feature vector with 5 values. This way, each image that enters the model ends up in a vector with size 5 that describes the image. After the training, the feature vectors from images of the same class should have minimal Euclidean distance. An example is presented in Figure 3, where images from the same class have a small dissimilarity distance, whereas images from different classes have a big dissimilarity distance.



(**a**) (**b**)

Figure 3. Image (**a**) depicts the dissimilarity distance between a stroke and a non-stroke image, while image (**b**) provides the dissimilarity distance between two normal images.

To classify a new image, the average distance of the image from each class is calculated and the image is classified in the class with the smaller distance. In addition, we deployed two powerful machine learning, support vector machines [25] and Random Forests [26], which were trained on the feature vectors resulting from the SNN.

We also studied the explainability of our method by applying Grad-CAM (Gradient-weighted Class Activation Mapping) [27] in test images (Figure 2b). In medical problems, it is crucial for deep learning models to be explainable to enhance trust and acceptance, resolve legal and ethical issues, detect errors and failures, enhance the model's performance, and ensure patient safety. It is imperative that medical professionals comprehend the DL model's decision-making process to make well-informed decisions for their patients. Grad-CAM serves as an explainability tool that aids in comprehending the decision-making process of convolutional neural networks (CNNs) in computer vision tasks. It facilitates the identification of areas within an input image that had the most significant influence on the CNN's final prediction, achieved by generating a heatmap that highlights the regions the CNN emphasized. Researchers and developers use Grad-CAM to gain an understanding of why a particular prediction was made, pinpoint and rectify errors, enhance the model's performance, and elevate trust and transparency in the model's decision-making process. Grad-CAM computes a class activation map for a specific input image by analyzing the gradients flowing into the final convolutional layer of a CNN. Here, we describe the basic steps of the Grad-CAM computation:

1. The input image is fed through the CNN, and the output feature maps are generated.
2. The gradient of the predicted class score with respect to the feature maps of the last convolutional layer is calculated.
3. The gradients obtained in step 2 are averaged globally to obtain a set of weights, which represent the importance of each feature map in the final prediction.
4. The feature maps of the last convolutional layer are linearly combined using the weights obtained in step 3 to produce the class activation map.
5. The class activation map is then passed through a Rectified Linear Unit (ReLU) function, which sets negative values to zero and keeps positive values the same. This

thresholding step results in a heatmap that highlights the regions of the input image that are most significant for the predicted class.

2.6. Validation

The dataset utilized in our study comprises a total of 64 images, distributed as follows: 34 images representing stroke survivors and 30 images representing individuals without a history of stroke incidence. In order to facilitate the fair and unbiased allocation of data, we employed a stochastic validation strategy of 70% training/30% testing. Specifically, we applied 10-time random splitting of 70%/30%. As is standard practice, the data in the test set comprised new, unknown subjects that were not included in the training set. This approach was meticulously implemented to ensure that each subset accurately reflected the overall distribution of data. Furthermore, the SVM model was trained with RBF kernel and C = 1.0, while the RF was trained with 50 trees. The NN consisted of two hidden layers and was trained for 10 epochs and with cross entropy loss and the Adam optimization algorithm.

3. Results

In this section, we present the outcomes of our study, providing a detailed account of the findings in a clear and organized manner.

3.1. Performance

In order to investigate the performance of the proposed SNN, it was trained with Adam optimizer with a learning rate of 0.0005 for 5 epochs, achieving a loss of 0.004. All methods, SVM, RF, NN, and Euclidean distance, are able to classify the images into stroke and non-stroke with 100% accuracy. The findings are shown in Table 1, illustrating the efficacy of the suggested visual representation approach. The transformation of biomechanical signals into images offers a concise means of conveying information, which accounts for the remarkable accuracy achieved by the Euclidean distance classifier in accurately categorizing samples at a rate of 100%. However, due to the odd shape of the image in conjunction with the small size of the dataset, the training phase is sensitive as it is prone to overfitting.

Table 1. Performance in stroke and non-stroke classification.

Method	Accuracy (%)
Euclidean Distance	100
SVM	100
RF	100
NN	100

Furthermore, Figure 4 illustrates the progression of error propagation in relation to the number of iterations during the training phase. As depicted, the model demonstrates rapid convergence towards a plateau accompanied by a significant reduction in loss. This is the reason that the model was trained only for five epochs.

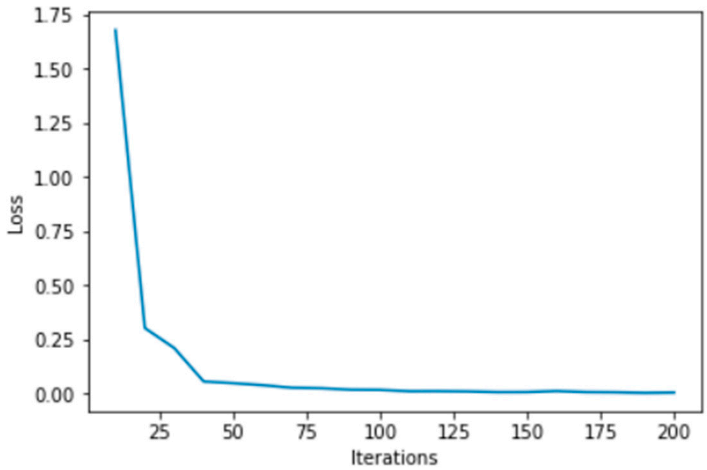


Figure 4. Loss function through iterations during training.

Figure 5 demonstrates the statistical summaries of Euclidean distances for stroke and non-stroke samples. When classifying an image with the Euclidean distance, its distance from train stroke and train non-stroke was measured. Whichever set had the shortest distance was classified into that category. This is how the statistics of the graph below arose. Specifically, A represents the Euclidean distances of test stroke samples from train stroke survivors, while B represents the Euclidean distances of test stroke samples from train non-stroke survivors. Conversely, C and D correspond to the Euclidean distances of test non-stroke samples from train non-stroke and train stroke samples, respectively.

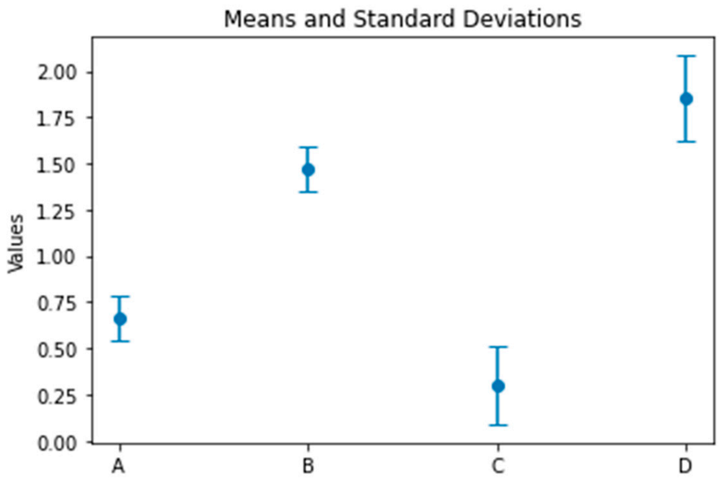


Figure 5. Mean and standard deviations of Euclidean distance between stroke and non-stroke samples.

Figures 6 and 7 demonstrate the Confidence Intervals (CIs) of SVM and RF. CIs are statistical measures used to quantify the uncertainty or variability in an estimate or prediction made by a machine learning model, including SVM and RF.

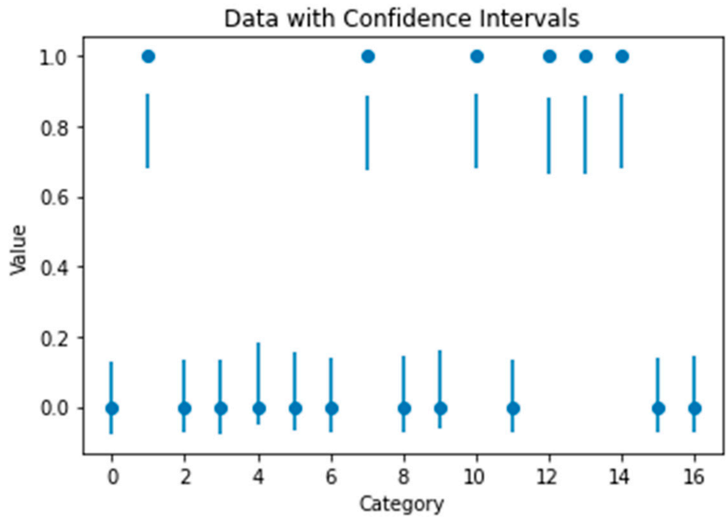


Figure 6. CIs of SVM decisions.

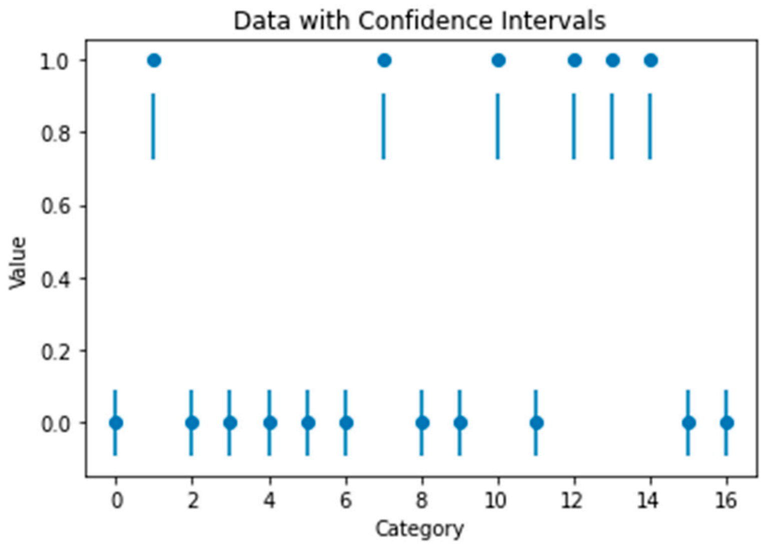


Figure 7. CIs of RF decisions.

After the examination of the presented figures, a remarkable observation emerges: both SVM and RF classifiers show an increased level of confidence when categorizing a subject as a stroke case. This distinct trend is particularly encouraging in the context of medical applications, where the imperative to minimize false negatives is a priority. Another notable observation is the comparative stability of the CI associated with RF in contrast to SVM. This disparity in the stability of CI values suggests that RF may offer more consistent and reliable performance across different scenarios or datasets.

3.2. Interpretation

The novelty of this work lies in the extraction of informative features, which is based on the Grad-CAM algorithm, since the task of diagnosis described above is easy, as shown by the 100% accuracy of our models. Figures 8 and 9 present two cases of using Grad-CAM on stroke and non-stroke images. The bright regions show where the model is looking to extract the corresponding feature vector. Specifically, Figures 3 and 4 demonstrate that the Grad-CAM algorithm effectively identifies and highlights dissimilar regions between stroke and non-stroke samples. Particularly, the most pronounced disparities are concentrated in the legs, particularly in the paretic leg. These areas exhibit the highest intensity discrepancies. Notably, specific movements such as knee flexion/extension and hip flexion/extension (indicated by red boxes in the interpretation image and points (20, 10) and (40, 20) in both images) exhibit more consistent values in non-stroke samples, whereas stroke samples display fluctuations. Another example pertains to hip abduction/adduction and hip internal/external rotation (represented by green boxes in the interpretation image and points (0, 25) and (25, 35) in both images). In stroke samples, hip abduction/adduction initially remains at zero, whereas it maintains a non-zero value in non-stroke samples. Additionally, within the Grad-CAM images, the highlighted yellow box region indicates activation associated with knee flexion/extension and hip flexion/extension of the non-paretic leg. This activation signifies the areas of interest that contribute significantly to the model's decision-making process. Furthermore, the presence of white boxes draws attention to the fact that the center of mass (axis-z) also plays a role in the model's decision, as highlighted by these regions. These examples exemplify significant disparities between stroke and non-stroke samples, and the utilization of the Grad-CAM algorithm verifies that the model takes these differences into consideration.

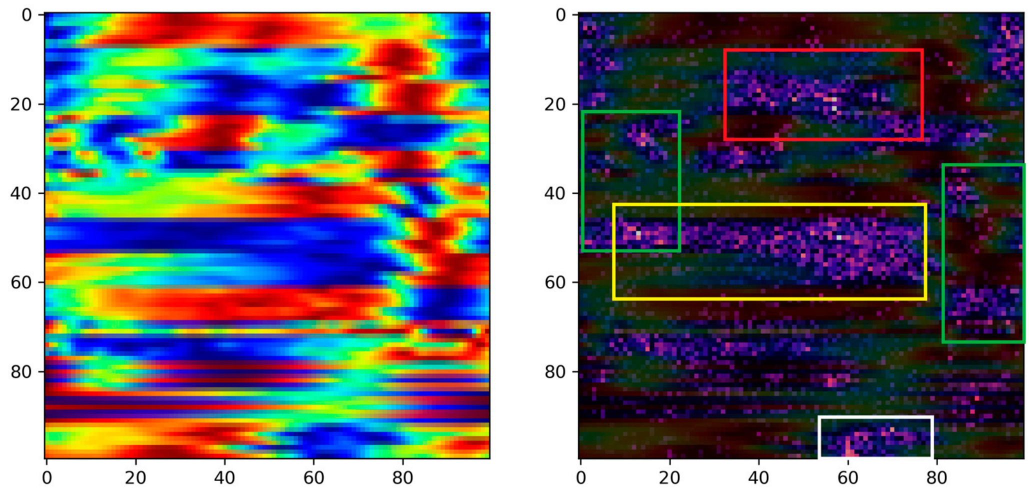


Figure 8. Grad-CAM in a stroke survivor. Boxes highlight the critical points according to Grad-CAM algorithm.

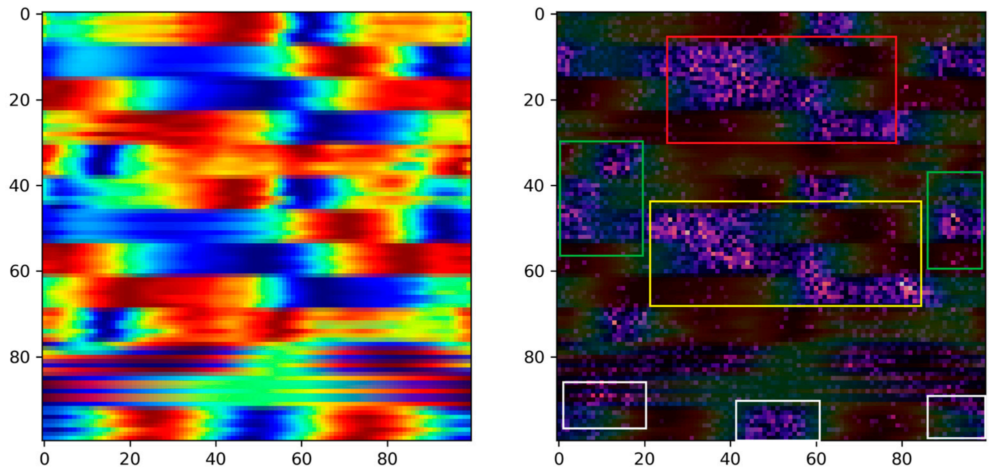


Figure 9. Grad-CAM in a non-stroke survivor. Boxes highlight the critical points according to Grad-CAM algorithm.

To make sure the proposed algorithm works properly, we created a mask consisting of the sum of all stroke Grad-CAM masks and a mask that consists of all non-stroke Grad-CAM masks in order to investigate whether the SNN is always 'looking' in the same regions to classify a new sample. In Figure 10a,b we present the resulting masks, which prove that the model is consistent in the areas it considers for its decisions.

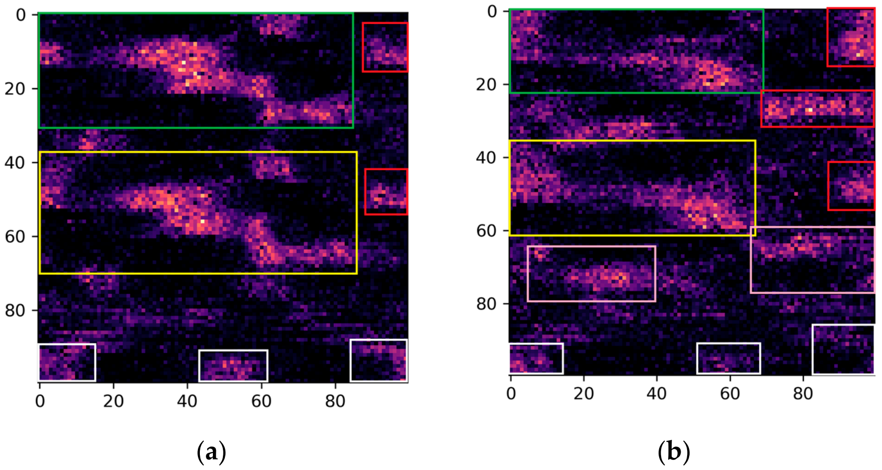


Figure 10. Mean Grad-CAM masks for testing group of the employed stroke and non-stroke survivors. Specifically, (**a**) presents non-stroke participants and (**b**) stroke survivors. Boxes highlight the critical points according to Grad-CAM algorithm.

4. Discussion

The primary objective of this research paper is to introduce a pioneering approach that merges the visual representation technique of biomechanical time series with an explainable machine learning methodology. This combined framework aims to effectively identify and analyze crucial parameters related to stroke. By integrating visual representations with explainable ML techniques, this novel approach offers a comprehensive and interpretable means of studying stroke-related factors and their impact. As a "Proof of Concept Study," this initiative underscores the novelty of melding visual representation techniques with explainable machine learning methodologies, serving as a preliminary yet promising step towards a more comprehensive and interpretable analysis of stroke-related biomechanical data.

Additionally, due to the limited biomechanical motion analysis data, this study addresses this challenge by using Siamese Neural Networks. Siamese neural networks have proven their effectiveness when dealing with limited amounts of data. In this study, due to the small number of stroke survivors, we converted the biomechanical signals into images by using the aforementioned visual representation technique in order to harness the power of the convolutional SNN. As observed, despite the small amount of data, the proposed methodology presents encouraging outcomes, providing 100% accuracy. The crux of the novelty in this study does not reside in the classification models employed, but significantly in the feature extraction approach orchestrated by the Siamese neural networks and the unique visualization technique. This distinct approach of converting biomechanical data into a visual format, coupled with the adept feature extraction capability of the SNN, lays the foundation for the encouraging results observed. However, it is crucial to gather more data and samples to draw safer conclusions. Conducting further investigations with a larger and more diverse dataset will help us obtain more reliable results and strengthen the validity and generalizability of our findings.

Moreover, in the pursuit of identifying critical biomechanical parameters associated with stroke, we employed the Grad-CAM technique with the primary objective of interpreting the decision-making process of the proposed model. The rationale behind this approach stems from the essential need for explanatory insights into AI-based decision making in medical contexts. Specifically, by interpreting the regions within images that activate the model's output, we can potentially offer fresh perspectives to clinicians, providing them with valuable information for improved understanding and decision making in stroke-related cases. Based on the activated regions identified by the Grad-CAM algorithm, several key biomedical parameters emerge as significant. These include ankle plantarflexion/dorsiflexion, knee flexion/extension, and hip flexion/extension in both the paretic and non-paretic legs. Additionally, hip abduction/adduction and hip internal/external rotation play a noteworthy role, specifically in the paretic leg. Furthermore, the center of mass (axis-z) is also identified as an influential factor in the model's decision-making process. Overall, between the two groups, we see obvious differences in the activation areas during the swing phase. These findings highlight the importance of these specific parameters in understanding the underlying factors driving the model's predictions. This nuanced understanding paves the way for developing more targeted rehabilitation strategies, reinforcing the substantial potential of the visualization and explanatory techniques employed in this study.

Specifically, ankle plantarflexion/dorsiflexion, knee flexion/extension, and hip flexion/extension are fundamental to the normal locomotion process, contributing to the smoothness and efficiency of movement. In stroke survivors, impairments in these parameters can disrupt the coordination and range of motion during the gait cycle [28]. Deviations from the expected patterns could indicate muscular weaknesses, spasticity, or compensatory movements that are common after stroke [29,30]. Moreover, hip abduction and adduction are important for maintaining stability during the gait cycle, and deficits in these motions could affect balance and overall gait symmetry [31]. Likewise, limitations in hip internal and external rotation might indicate muscular control imbalances or joint stiffness. Consequently, the emphasis on these parameters is in accordance with the challenges in controlling the lateral and rotational movements of the hip joint post-stroke [5]. In addition, the engagement of the center of mass, particularly on the vertical (z) axis, indicates issues of balance and weight distribution [32]. Stroke survivors often show alterations in weight-bearing capacity and balance control, which may affect their overall gait pattern. Finally, the observed differences in the activation regions during the swing phase suggest that this phase is particularly sensitive to the identified parameters. The swing phase involves lifting the foot off the ground and moving it forward for the next step. It requires a precise sequence of joint movements and muscle contractions. Differences in activation patterns during this phase could reflect adaptations made by stroke survivors to compensate for deficits in motor control and strength.

The above identified parameters highlight potential areas of dysfunction, providing clinicians with a clearer understanding of the underlying biomechanical issues. By leveraging these insights, tailored rehabilitation approaches can be developed to improve post-stroke gait patterns and enhance overall mobility and quality of life. However, it is important to note that the specific biomechanical differences can vary depending on the severity of the stroke, the location of the brain damage, and individual factors. The elucidation of these biomechanical parameters through the innovative visualization and explainable machine learning methodologies deployed in this study illuminates a pathway for a more informed, personalized rehabilitation planning, potentially leading to better patient outcomes and an enriched understanding of post-stroke locomotor dynamics.

This study presents certain limitations that chiefly stem from the constrained sample size and the single-source nature of the biomechanical data, which was garnered from one gait analysis laboratory. This scenario potentially narrows the generalizability of the proposed model, thus necessitating caution in extrapolating the findings across a broader spectrum. Moreover, the uniqueness of the visualization technique employed, while innovative, requires further validation to establish its efficacy and versatility in different contexts or with varied datasets. Looking ahead, the roadmap for future work is outlined with several pivotal directions. Foremost among these is the acquisition of more data and the external validation of the model, which entails engaging with diverse datasets potentially sourced from different gait analysis laboratories. This step is crucial to foster a more robust and generalized model capable of handling varied biomechanical data. Moreover, we have outlined a strategic roadmap that involves the integration of wearable sensors, specifically Inertial Measurement Units (IMUs), to capture comprehensive kinematic data. This forward-looking approach aims to further enrich our analysis and strengthen the applicability of our methodology in real-world scenarios, offering the potential to advance the field of biomechanical data utilization in medical diagnosis. Additionally, the exploration of newly derived signals holds promise in enriching the model's input and, consequently, its predictive prowess. Furthermore, the amalgamation of explanatory techniques like Grad-CAM with Shapley Additive Explanations (SHAP) [33] is envisioned to provide a more nuanced understanding of the model's decision-making process. This blend of techniques aims to not only enhance the interpretability of the model, but also foster more coherent communication of its findings to clinicians, thereby bridging the gap between complex machine learning models and practical clinical application.

5. Conclusions

The analysis of data plays a pivotal role in comprehending human motion, particularly in the context of examining the walking patterns of individuals who have experienced a stroke. The suggested approach has the capacity to propel our comprehension of gait patterns to new heights and enhance the diagnosis and treatment of mobility-related conditions. In particular, the previously mentioned visual representation of time series data introduces an inventive technique that enables the simultaneous presentation of diverse biomechanical information encompassing the entire movement being analyzed. By acting as tools for extracting knowledge, these visual representations equip clinicians with valuable insights, allowing them to tailor personalized interventions based on specific moments within the gait cycle.

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