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Multi-Scale Temporal Analysis With a Dual-Branch Attention Network for Interpretable Gait-Based Classification of Neurodegenerative Diseases

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S1. Related Work

To contextualize our proposed DAERN model, we review previous work in the areas of gait analysis for neurodegenerative disease diagnosis, deep learning methods for temporal feature extraction, interpretability techniques in AI for healthcare, and gait signal processing. This section highlights the limitations of existing methods and the specific research gaps addressed by our approach.

A. Gait analysis for NDDs diagnosis

Gait abnormalities are widely recognized as clinical biomarkers in the diagnosis of NDDs such as ALS, HD, and PD. Previous research has shown that each of these diseases is associated with distinct gait patterns; for example, PD patients often exhibit shuffling steps and reduced stride length [10], while HD is characterized by irregular gait rhythms and balance issues [11]. Traditional gait analysis for NDDs diagnosis often involves manual observation and assessment by clinicians, which is subjective and may overlook subtle temporal patterns indicative of early disease stages.

To address this limitation, various computational approaches have been developed to automate gait analysis. Classical machine learning methods, including Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN), have been applied to extract gait features such as step length, cadence, and gait velocity [5]. While these methods provide some diagnostic capability, they typically rely on handcrafted features, which may not fully capture the complex temporal dependencies of gait data. Moreover, these traditional approaches struggle with generalizability, especially in distinguishing between subtle gait differences among NDDs. Deep learning, particularly CNNs and RNNs, has emerged as a powerful tool in this field due to its ability to automatically extract relevant features from raw gait data [12]. However, existing deep learning approaches have limitations in their ability to model both short- and long-term dependencies simultaneously, an essential aspect for capturing multi-scale temporal features in gait signals. The ability to capture both local and long-term temporal dependencies is essential for gait-based classification of NDDs. Local gait variations (e.g., stride-to-stride irregularities) provide crucial indicators for distinguishing diseases such as PD and HD, where short-term motor fluctuations are clinically significant. Meanwhile, long-term dependencies (e.g., multi-cycle gait deterioration) are critical for recognizing progressive impairments in ALS and advanced PD. To effectively model these patterns, DAERN integrates DCCBlock for short-term gait analysis, MHSA for long-range dependencies, and Cross-Attention Fusion to jointly learn both local and global gait disruptions. This architecture enables a comprehensive understanding of gait abnormalities across different neurodegenerative conditions, improving classification accuracy and clinical relevance. While previous studies, such as Mengarelli et al. [13], have achieved strong performance on the Gait in Neurodegenerative Disease (Gait-NDD) dataset using traditional machine learning techniques, our study explores the advantages of a deep learning-based approach (DAERN) for automatic feature learning, multi-scale temporal modeling, and improved interpretability. Unlike handcrafted feature extraction, DAERN learns hierarchical gait representations through DCCBlock and MHSA, enabling superior generalization across varying noise levels and gait conditions. Furthermore, DAERN enhances model explainability through SHAP and Grad-CAM, providing clinical insights beyond feature ranking used in traditional machine learning models. Experimental results show that DAERN outperforms machine learning classifiers under real-world gait variability, confirming the potential of deep learning for robust gait-based neurodegenerative disease classification.

B. Deep learning for multi-scale temporal feature extraction

Deep learning models, including CNNs, RNNs, and their variants, have shown promise in temporal sequence modeling, which is essential for analyzing gait data with multi-scale dependencies. CNN-based architectures, such as ResNets and DenseNets, are effective in capturing local features through convolutional layers but generally lack the capacity to model long-term dependencies due to their limited receptive field [14]. Dilated Convolutions have been introduced in recent studies to expand the receptive field without increasing computational cost, making them a suitable choice for capturing local temporal patterns in sequential data [15]. Models such as Temporal Convolutional Networks (TCNs) have used dilated convolutions for time-series classification, demonstrating superior performance in tasks requiring short-term dependency modeling [16]. However, these models still face challenges in capturing global dependencies, particularly in long time-series data like gait signals in NDDs.

On the other hand, RNN-based architectures, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), are capable of capturing long-term dependencies by maintaining memory states over time [17]. These models have been widely applied to medical time-series data, including electrocardiogram (ECG) and electroencephalogram (EEG) signals, due to their temporal modeling capabilities. However, RNNs are prone to vanishing or exploding gradient problems, which can hinder training efficiency, especially on large datasets with high temporal resolution [18]. Moreover, they tend to be computationally intensive, making them less suitable for applications requiring real-time or low-latency processing. To overcome these challenges, recent research has explored hybrid approaches that combine CNNs with attention mechanisms to capture both local and global dependencies.

Attention mechanisms, particularly self-attention and multi-head self-attention, have gained traction for their ability to model long-range dependencies in sequential data [19]. The transformer architecture, which leverages self-attention, has revolutionized sequence modeling in natural language processing and has shown potential in medical time-series analysis [20]. However, few studies have applied self-attention mechanisms in the context of gait analysis for NDDs, where both short-term and long-term dependencies are critical. Our DAERN model builds upon this concept by integrating a DCCBlock for local feature extraction and a multi-head self-attention branch for global feature extraction, thus enabling comprehensive multi-scale temporal analysis.

C. Interpretability in AI for medical applications

Interpretability is a crucial component in AI applications for healthcare, as it helps clinicians understand and trust the model's predictions. While deep learning models often outperform traditional methods in classification tasks, their "black box" nature limits their adoption in clinical practice, where transparency and accountability are paramount [21]. In recent years, various interpretability techniques have been developed to shed light on the inner workings of deep learning models. Model-agnostic methods like Local Interpretable Model-agnostic Explanations (LIME) and SHAP have been widely adopted to explain feature contributions for specific predictions [22], [23].

In the context of temporal data, gradient-based methods such as Grad-CAM and IG have been adapted to visualize the contribution of temporal segments to the final prediction [24], [25]. These methods have shown promise in applications like ECG and EEG signal classification, where understanding the temporal regions contributing to the diagnosis is critical. However, there has been limited research on applying interpretability techniques to gait data for NDDs diagnosis. In this study, we employ SHAP and IG to provide interpretable insights into the DAERN model's predictions, allowing clinicians to identify specific gait features associated with each NDDs, thus enhancing the model's clinical applicability.

D. Gait signal processing techniques

The analysis of gait signals for disease classification often involves preprocessing techniques aimed at enhancing the quality of the data and extracting meaningful features. Signal preprocessing steps such as filtering, normalization, and segmentation are commonly used to remove noise and improve signal clarity [26]. Feature extraction methods like Principal Component Analysis (PCA) and Wavelet Transform have been explored to reduce dimensionality and identify relevant temporal features [27]. However, these handcrafted features may not capture the full spectrum of temporal patterns needed for accurate NDDs classification.

With the advent of deep learning, researchers have shifted towards end-to-end learning, where raw gait signals are directly inputted into neural networks that automatically learn feature representations [28]. However, few models account for the unique temporal structures in gait data specific to NDDs. In recent studies, multi-scale feature extraction has emerged as a promising approach to handle the diverse temporal characteristics of gait data. For example, recurrence plots and Gramian Angular Fields have been used to transform gait signals into images, allowing for spatial analysis through CNNs [29]. However, this transformation approach may result in information loss and computational overhead. Our DAERN model avoids these pitfalls by directly processing raw gait signals while capturing multi-scale dependencies through its dual-branch architecture.

S2. Data preprocessing and augmentation

To prepare the GaitNDD data for deep learning analysis, we applied a series of preprocessing steps aimed at enhancing data quality and ensuring consistency across recordings. Key preprocessing steps included as follows.

A. Preprocessing steps

1. Z-Score Normalization

Z-score normalization is applied to each gait signal to standardize it, transforming the data to have a mean of 0 and a standard deviation of 1:

$$x_{\text{normalized}} = \frac{x-\mu}{\sigma} \tag{S1}$$

where x is the original gait signal, μ represents the mean of x, σ represents the standard deviation of x.

To ensure no data leakage or overoptimistic performance estimation, z-score normalization was applied separately for each fold during cross-validation, where the mean and variance were computed using only the training set and then applied to the corresponding test set. This ensures that test data remains unseen during normalization, preventing any bias in model evaluation.

While force platform data can be normalized relative to body weight, we opted against this approach to preserve critical gait characteristics associated with neurodegenerative diseases. Disease-specific gait features, such as force variability in ALS and inconsistent weight distribution in HD, could be artificially suppressed by weight-based normalization. Additionally, our data collection protocol ensures that inter-subject variability does not introduce bias, as confirmed by prior studies using raw VGRF signals for gait-based classification.

2. Gait Cycle Segmentation

To segment each recording into individual gait cycles, heel strikes are detected in the vertical acceleration signal, denoted by $a_v(t)$. A heel strike at time t_i is identified as a local maximum in $a_v(t)$, satisfying:

$$a_v(t_i) > a_v(t_{i-1}) \quad \text{and} \quad a_v(t_i) > a_v(t_{i+1}) \tag{S2}$$

where $a_v(t)$ represents the vertical acceleration signal at time t, t_i denotes the time of a detected heel strike.

Gait signals were segmented into individual gait cycles, ensuring that each sample corresponds to a complete heel strike-to-heel strike sequence. To minimize segmentation inconsistencies, dynamic time warping (DTW) alignment was applied to synchronize gait phases across samples before resampling all cycles to a fixed length (256 time steps). Additionally, time normalization (0-100% phase scaling) and augmentation techniques (stride-length scaling, random shifting) were used to mitigate discrepancies arising from inter-subject gait variability. Empirical evaluations confirmed that these strategies significantly improved segmentation consistency, leading to more robust classification performance.

3. Noise Reduction

A low-pass filter is applied to each signal to reduce high-frequency noise, resulting in a filtered signal $y(t)$. The convolution of the input signal $x(t)$ with the filter impulse response $h(t)$ is defined as:

$$y(t) = \int_{-\infty}^{\infty} x(\tau)h(t-\tau)\, d\tau \tag{S3}$$

where $y(t)$ is the filtered signal at time t, $x(t)$ is the original signal, $h(t)$ is the impulse response of the low-pass filter.

4. Handling Missing Data

Missing data points are imputed using linear interpolation. For a missing data point at time t, the imputed value $x_{\text{interpolated}}(t)$ is calculated as:

$$x_{\text{interpolated}}(t) = x(t_{-1}) + \frac{x(t_{+1}) - x(t_{-1})}{t_{+1} - t_{-1}} \times (t - t_{-1}) \tag{S4}$$

where t_{-1} and t_{+1} are the closest observed timestamps before and after t, $x(t_{-1})$ and $x(t_{+1})$ are the values at times t_{-1} and t_{+1}, respectively.

B. Data Augmentation Techniques

CutMix is applied by combining portions of two gait cycles from different classes [31]. For two signals $x_1(t)$ and $x_2(t)$, a new signal $x_{\text{CutMix}}(t)$ is generated by replacing a segment of $x_1(t)$ with the corresponding segment from $x_2(t)$:

$$x_{\text{CutMix}}(t) = \begin{cases} x_1(t) & \text{if } t \notin \text{cut region} \\ x_2(t) & \text{if } t \in \text{cut region} \end{cases} \tag{S5}$$

S3. Discussion

A. Comparison with state-of-the-art methods

The proposed DAERN model demonstrates superior classification performance on the GaitNDD dataset, achieving state-of-the-art results through hierarchical deep feature extraction. Compared to prior work by Mengarelli et al. [13], which utilized handcrafted time-domain and spectral features with traditional machine learning classifiers (e.g., SVM, RF, k-NN), DAERN automatically learns discriminative gait representations through DCCBlock and MHSA. This eliminates the need for manual feature engineering while enabling the model to capture both short- and long-term gait dependencies. However, it is important to acknowledge that traditional machine learning models, such as those used by Mengarelli et al. [13], offer advantages in interpretability and feature transparency, as they allow for explicit ranking of gait descriptors based on their contribution to classification. In contrast, DAERN relies on explainable AI (SHAP, IG and UMAP) to visualize its decision-making process. Future research could explore hybrid approaches, integrating handcrafted biomechanical descriptors with deep learning-based feature extraction, potentially improving both interpretability and generalization across diverse patient populations.

While AlexNet and LSTM have demonstrated success in prior gait classification studies, their limitations hinder their effectiveness in neurodegenerative disease classification. AlexNet, as a CNN-based model, lacks the ability to capture temporal dependencies, relying solely on spatial feature extraction from time-frequency representations. Additionally, its fixed receptive field restricts its ability to analyze long-range gait dynamics. LSTM, on the other hand, processes sequential data effectively but suffer from vanishing gradient issues when dealing with long gait sequences. Furthermore, their recurrent nature results in computational inefficiencies and limits multi-scale feature extraction. In contrast, DAERN addresses these challenges through its dual-branch architecture, which combines DCCBlock for local dependency modeling and multi-head self-attention for long-term dependency learning. This design enables DAERN to extract both short- and long-range gait features in a computationally efficient manner. Moreover, the integration of BottleDrop regularization enhances model generalization, while interpretability techniques (SHAP and IG) provide clinically relevant insights into feature importance. These advantages collectively enable DAERN to outperform traditional CNN and RNN-based approaches, establishing a more robust framework for gait-based neurodegenerative disease classification.

Compared to earlier works, the proposed method not only establishes a new benchmark for NDD classification but also provides interpretable results, aligning with the need for trustworthy AI in healthcare. Its robustness, scalability, and superior performance metrics make it a promising tool for real-world deployment in clinical diagnostics.

The computational complexity of DAERN arises primarily from its dual-branch architecture, integrating DCCBlock and multi-head self-attention, which enables multi-scale temporal modeling of gait signals. While training is resource-intensive, requiring ≈6.2 hours on an NVIDIA 4090 GPU, inference is significantly more efficient, with a processing time of 2.678 ms per sample on a GPU and 16.599 ms per sample on a CPU. These inference speeds make DAERN feasible for deployment in standard clinical environments. However, real-time applications on resource-constrained devices may face challenges due to memory and computational demands. To address this, future work will explore model pruning, quantization, knowledge distillation, and cloud-based inference strategies to enhance efficiency. These optimizations will ensure that DAERN remains suitable for both high-performance clinical workstations and portable, real-time gait analysis systems.

To assess DAERN's feasibility for deployment, we measured inference latency across three additional hardware platforms. On a high-performance hospital server (NVIDIA A100 GPU), DAERN achieves 1.4 ms per sample, while on an edge computing device (Jetson Xavier NX), latency increases to 8.9 ms, still maintaining real-time performance. However, on a mobile processor (Snapdragon 8 Gen 2), inference latency reaches 15.7 ms, indicating the need for further optimization to enable efficient deployment in low-power environments. To enable real-time deployment on resource-constrained devices, DAERN can be optimized using pruning, quantization, and knowledge distillation. Pruning removes redundant parameters in MHSA layers, reducing computational complexity without significant accuracy loss. Quantization converts floating-point parameters to INT8 precision, accelerating inference on edge devices and mobile processors. Additionally, knowledge distillation can train a lightweight student model, preserving DAERN's accuracy while reducing inference time. Future work will explore these techniques to enhance DAERN's efficiency for real-world clinical applications.

B. Limitations and future work

1) Dataset Limitations and Generalization Challenges

One key limitation of this study is the relatively small and demographically homogeneous GaitNDD dataset, which may limit the generalizability of DAERN to broader clinical populations. To address this, future work will prioritize multi-center collaborations aimed at collecting gait data from diverse institutions, patient groups, and acquisition environments. This will enable robust external validation and support generalization across varied demographic and sensor conditions. Additionally, we will explore the use of generative adversarial networks (GANs) to synthesize realistic gait signals that augment underrepresented classes and simulate variations in stride length, noise conditions, and disease stages. These synthetic samples, coupled with domain adaptation techniques, will help improve the model's robustness and adaptability in real-world clinical settings.

In future work, we aim to enhance the generalizability of the proposed DAERN model beyond the controlled conditions of the GaitNDD dataset by implementing several key strategies. First, cross-dataset validation will be conducted using publicly available gait datasets collected in naturalistic environments to assess model robustness under real-world conditions. Second, domain adaptation techniques, such as adversarial training and feature alignment, will be explored to mitigate distribution shifts between controlled and real-world gait data, while transfer learning will be employed to fine-tune the model on diverse datasets. Third, data augmentation methods incorporating synthetic perturbations, such as stride length variations, sensor noise, and surface irregularities, will be applied to improve robustness against environmental variability. Fourth, we plan to extend data collection to wearable sensor-based gait recordings captured in daily-life settings, ensuring a more ecologically valid representation of gait patterns in individuals with NDDs. Finally, personalized and adaptive modeling approaches, including meta-learning and few-shot learning techniques, will be investigated to tailor the model to individual gait characteristics, accommodating inter-subject variability and disease progression. These future directions will strengthen the practical applicability of DAERN, facilitating its potential deployment in real-world clinical and ambulatory monitoring scenarios.

2) Intra-Class Variability and Adaptive Learning

Gait patterns within each NDD category exhibit significant intra-class variability due to disease progression, comorbidities, and individual biomechanical differences. For example, early-stage PD may present with mild gait disturbances, whereas advanced PD is characterized by severe shuffling and postural instability. Similarly, gait alterations in ALS vary depending on motor neuron degeneration patterns. While DAERN effectively captures key gait features, its performance could be further improved through personalized and adaptive learning strategies.

Future research will explore transfer learning and meta-learning to fine-tune the model for individual patients, improving adaptability across diverse gait profiles. Additionally, demographic-aware modeling will be investigated to account for age- and gender-related gait variations, while progression-aware learning will incorporate disease severity labels to refine DAERN's ability to track gradual gait deterioration. Finally, data augmentation techniques simulating progressive gait alterations will be employed to enhance model robustness across different disease stages.

3) Multi-Modal Data Fusion for Enhanced Classification

A key limitation of this study is that the GaitNDD dataset provides only VGRF signals, lacking critical spatial gait parameters such as step length, step width, and stride length, which are essential for identifying Parkinsonian gait disturbances. While DAERN compensates by leveraging temporal gait features (e.g., stance time variability, swing asymmetry), future work will explore multi-modal gait analysis by integrating VGRF with kinematic parameters, inertial sensor data, and spatiotemporal gait metrics.

Beyond gait data, integrating MRI-based neuroimaging, biosensor data, and speech analysis could significantly enhance classification accuracy by providing complementary disease biomarkers. Structural brain abnormalities from MRI scans could reveal neurodegenerative patterns associated with different NDDs, while biosensors tracking muscle activity (EMG), EEG, heart rate variability (HRV), and hand tremors could aid in distinguishing ALS from PD. Additionally, speech biomarkers (e.g., dysarthria in ALS, hypophonia in PD, erratic articulation in HD) could provide further discriminatory power. However, the integration of multi-modal data presents challenges such as data synchronization, computational complexity, and interpretability, which future research will address through efficient feature fusion architectures and cross-modal alignment techniques.

4) Real-World Applicability and Longitudinal Analysis

While DAERN has demonstrated efficacy in cross-sectional gait classification, real-world applications require models capable of monitoring disease progression over time. Future work will explore longitudinal gait modeling, leveraging sequential learning techniques to capture gradual gait deterioration. Additionally, integrating DAERN's predictions with clinical progression scales (e.g., the Unified Parkinson's Disease Rating Scale for PD) could enhance its utility for tracking neurodegenerative disease trajectories.

To improve real-world applicability, adaptive modeling approaches will be explored, including few-shot learning and self-supervised learning (SSL) to reduce reliance on large labeled datasets. Furthermore, future research will focus on wearable sensor-based gait monitoring in real-life settings, ensuring ecological validity and robustness against environmental variability.

Another limitation of the current study lies in the absence of clinician-verified interpretation of the feature attribution maps generated by SHAP and IG. While these methods provide valuable insights into the temporal regions and gait features influencing the model's decisions, their clinical validity remains to be formally assessed. In future work, we plan to collaborate with neurologists and movement disorder specialists to evaluate whether the highlighted features correspond to clinically recognized gait abnormalities associated with specific neurodegenerative diseases. Such expert validation will not only improve interpretability and trust in the model's outputs but also guide refinements in the feature attribution process to ensure alignment with pathophysiological mechanisms. This clinician-in-the-loop approach will be crucial for translating DAERN into a trustworthy and actionable tool for clinical decision support.

By addressing these limitations through cross-dataset validation, multi-modal data fusion, adaptive learning, and longitudinal modeling, future iterations of DAERN will be better positioned for real-world clinical deployment and ambulatory disease monitoring.

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