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A Unified Framework for Neurological Disease Detection and Gait Classification Using Deep Graph Learning

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Abstract: This paper presents Dynamic Gait Signature Analysis (DGSA), an innovative approach to gait analysis that leverages deep graph learning techniques. Unlike conventional methods, DGSA leverages multifaceted parameters and advanced deep graph learning techniques, such as Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs). These techniques enable a comprehensive analysis of gait dynamics, including the use of dynamic graph representation methods like Gait Cycle Joint Angles Graph and Gait Cycle Joint Power Graph. DGSA's unique framework allows for simultaneous prediction of neurological diseases, gait classification, and early detection of cognitive impairments. By modeling gait as dynamic graph structures, DGSA captures intricate relationships between body movements and foot positions, ultimately enhancing accuracy in classification and prediction tasks. Comprehensive experiments on real-world datasets demonstrate DGSA's robustness, generalization, and superiority in accuracy. Our approach achieves notable accuracy metrics: gait velocity (1.6 m/s), dynamic stability margin (5.6 cm), gait variability (2.4%), joint range of motion (56 degrees), dynamic balance index (0.4), minimum toe clearance (2.3 cm), foot progression angle (8.6 degrees), and dynamic joint stiffness (172). This study includes a comparative analysis of gait analysis approaches based on these key performance metrics, demonstrating DGSA's significant advancement in gait analysis methodology.

Keywords: Gait signature, Deep graph learning, Graph convolutional networks, Graph attention networks, Classification, Predictions.

1. Introduction

Gait analysis is essential for understanding human movement and diagnosing abnormalities, with recent advancements in deep learning (DL) and graph neural networks (GNNs) offering promising avenues for richer insights [1-3]. This paper explores the application of these techniques in gait analysis, aiming to extract meaningful features from complex gait dynamics. Traditionally, gait analysis relied on biomechanical measurements, but DL and GNNs enable us to leverage the inherent structure of gait data, leading to more accurate and interpretable analysis. By representing gait dynamics as graphs, we can capture intricate dependencies and interactions, addressing limitations of traditional methods. However, challenges such as model interpretability and integration of multimodal sensor data remain [4]. Future research must focus on developing interpretable models and robust techniques for integrating diverse sensor data to advance gait analysis. Our proposed method showcases the potential of deep graph learning techniques in addressing these challenges and enhancing clinical decision-making in gait analysis.

By highlighting its capacity to extract rich characteristics from dynamic graph structures in gait data, we draw attention to the advantages of our suggested approach. By leveraging graph-based representations, we aim to capture intricate dependencies within gait dynamics, leading to improved performance compared to traditional methods. This approach offers a clearer understanding of the potential of deep graph learning techniques in advancing gait analysis methodologies.

The paper is structured into several key sections to provide a comprehensive overview of the research. In the Literature survey section, existing literature on gait analysis methodologies is reviewed, covering both traditional approaches and recent advancements in deep learning and graph neural networks. Following this, the Proposed Work section outlines the methodology, including data collection processes, dynamic graph representation techniques, analysis of gait dynamics through multifaceted parameters, deep graph learning methodologies, and model training strategies tailored specifically for gait analysis tasks. The Results and Discussions section presents the empirical findings of the study, offering a detailed discussion, interpretation, and analysis of the results obtained from the experiments conducted. Finally, the paper concludes with a summary of the key findings, implications of the research, and suggestions for future work in the Conclusion section.

2. Literature survey

In recent years, the use of deep learning techniques has gained momentum in the field of gait assessment, thanks to advancements in sensor technology and computational capabilities [5-7]. These methods offer a promising approach to analyzing gait data, allowing researchers and clinicians to extract meaningful insights for clinical decision-making. However, despite their potential, there are challenges to address. One key challenge is the availability of large datasets with annotations necessary for training deep learning models effectively [8]. To tackle this, researchers have proposed innovative solutions. For example, they've developed specialized deep learning architectures tailored specifically for analyzing gait data. These architectures, such as customized Convolutional Neural Networks (CNNs), can process time-series gait data directly, capturing both spatial and temporal patterns. Similarly, Recurrent Neural Networks (RNNs) have been employed to model the sequential nature of gait dynamics, enabling the detection of subtle changes over time.

In recent advancements in gait analysis, innovative systems and methodologies have emerged to enhance our understanding and assessment of human locomotion. Slemensek et al. [9] introduced a wearable system adept at capturing gait motion data with precision, facilitating not only the classification of gait activities but also the identification of potential risk factors, thereby aiming to improve individuals' overall quality of life. Berke et al. [10] proposed an advanced artificial intelligence-driven system tailored for detecting neurodegenerative diseases and predicting their severity by leveraging gait features extracted from gait signals. Their segmentation approach enables a targeted analysis of disease-specific gait patterns and characteristics, enhancing diagnostic precision. Shanmuga Sundari et al. [11] pioneered a machine learning-based model to predict the Age of Gait (AoG) by analyzing early indicators found in poor gait patterns preceding AoG onset, providing insights into age-related gait changes. Kondragunta et al. [12] emphasized the critical importance of identifying gait abnormalities in aging populations, focusing on non-wearable approaches to collect gait data from elderly individuals aged over 80 years, particularly relevant given the heightened prevalence of dementia in this demographic.

Furthermore, Trentzsch et al. [13] conducted a comprehensive study to identify effective diagnostic gait systems, leveraging machine learning algorithms to differentiate between individuals with multiple sclerosis and healthy controls. Slijepcevic et al. [14] investigated existing ground reaction force (GRF) parameterization techniques to discern functional gait disorders, aiming to establish foundational insights into automated classification methodologies. Through rigorous analysis and experimentation, Slijepcevic et al. [15] aimed to advance understanding of functional GDs and establish foundational insights into automated classification methodologies. Chandrasen et al. [16] employed artificial intelligence techniques to analyze ground reaction force (GRF) patterns, distinguishing between healthy individuals and those with gait disorders. Moreover, Shayestegan et al. [17] curated datasets for feature selection, enabling a comprehensive examination of gait features, while Bogaarts et al. [18] pioneered a framework to examine the impact of IMU noise on sensor-based gait features, shedding light on the intricacies of gait analysis in real-world scenarios. Through meticulous experimentation and analysis, these studies collectively contribute to advancing the field of gait analysis, offering promising avenues for improving diagnostic accuracy and guiding tailored interventions for individuals affected by diverse gait disorders.

Slemensek et al. [9] introduced a wearable system for gait motion data capture, albeit with limitations in accurately classifying gait activities and identifying risk factors. Similarly, Berke et al. [10] devised an AI-driven system for neurodegenerative disease detection, yet their approach may lack the versatility needed for comprehensive gait analysis. Shanmuga Sundari et al. [11] focused on predicting the Age of Gait using specific walking tasks, which may overlook broader gait abnormalities. Kondragunta et al. [12] underscored the importance of identifying gait abnormalities in aging populations but primarily focused on non-wearable approaches, potentially limiting their applicability in certain settings.

In contrast, Trentzsch et al. [13] aimed to identify effective diagnostic gait systems, yet the study may lack a comprehensive exploration of gait features for accurate classification. Slijepcevic et al. [14, 15] addressed the efficacy of GRF parameterization techniques in discerning functional gait disorders, though the study may not fully elucidate the differences between various feature representations. Chandrasen et al. [16] focused on analyzing GRF patterns for distinguishing healthy individuals from those with gait disorders, yet the study may not provide a thorough comparison with existing methods. Shayestegan et al. [17] curated datasets and applied feature selection techniques, but the study may not fully detail the drawbacks of conventional feature selection methods. Bogaarts et al. [18] presented a framework to examine the impact of IMU noise on gait features, yet may not adequately highlight the limitations of existing noise estimation methods.

Our proposed Dynamic Gait Signature Analysis (DGSA) framework represents a significant leap forward in gait analysis methodology, surpassing existing studies by offering a holistic approach to understanding gait dynamics. While previous works focused on specific aspects such as activity classification, disease detection, or age prediction, DGSA integrates deep graph learning techniques to extract rich features from multifaceted gait parameters. By modeling gait as dynamic graph structures, DGSA provides a comprehensive analysis of gait mechanics, enabling simultaneous prediction of neurological diseases, gait classification, and early detection of cognitive impairments. Through comprehensive experiments, DGSA demonstrates robustness and generalization, achieving superior accuracy metrics compared to existing approaches. This framework has profound implications for clinical practice, rehabilitation, and assistive technology development, offering valuable insights into gait mechanics and its association with various clinical outcomes.

3. Proposed work

3.1 Data collection

Data collection begins by recruiting diverse participants, encompassing various gait patterns from healthy individuals to those with neurological or cognitive conditions. Ensuring demographic variability, including age, gender, and physical health, enhances dataset diversity [19]. Assessments occur in controlled environments, like labs, with specialized tools such as force plates and motion recording systems. Carefully designed setups accommodate natural walking movements. Participants receive briefings and instructions before walking at self-selected paces. For those with conditions, specific tasks may be assigned. Sensors like accelerometers and gyroscopes, often integrated into wearables, capture gait dynamics [20]. Data, accompanied by metadata, are stored for analysis. Ethical approval and informed consent are mandatory, prioritizing participant privacy and confidentiality.

3.2 Dynamic graph representation in gait analysis

Gait analysis is pivotal in biomechanics and human movement science, benefiting healthcare, sports, and rehabilitation. Recent advancements, notably in graph theory and DL, have revolutionized gait analysis. Dynamic graph representation, depicted in Fig. 1, captures the nuanced spatiotemporal relationships in gait sequences. Unlike static methods, dynamic graphs adapt to movement evolution over time. Nodes represent body positions (e.g., feet, knees), while edges encode temporal and spatial dependencies. This approach accommodates variability in gait patterns, crucial in pathological analysis. It integrates data from various sources, aiding deeper understanding of gait mechanics and health conditions [21]. Dynamic graph representation extends to action recognition, gesture analysis, and human-robot interaction, promising innovative research avenues in human movement science. As computational techniques progress, dynamic graphs will increasingly shape gait analysis and related fields, enhancing insights into human movement dynamics and their implications.

3.3 analyzing gait dynamics through multifaceted parameters

The provided graphs, such as "Gait Cycle Joint Angles," "Foot Pressure," "Joint Power," "Foot Trajectory," and "Joint Angles (Color-coded),"

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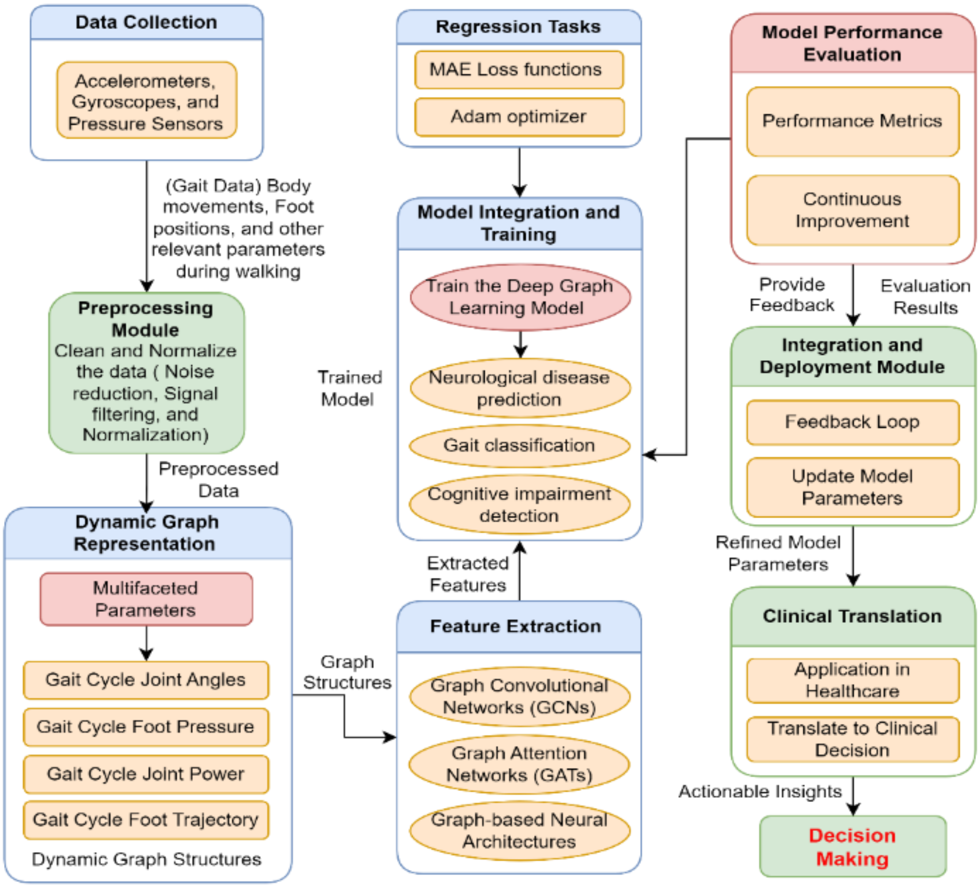

Figure. 1 Dynamic Graph Representation in Gait Analysis – Outline

collectively demonstrate dynamic aspects of human gait. Each depicts variations in parameters over the gait cycle, essential for understanding gait dynamics. They can be interpreted as graph structures where parameters represent nodes, showcasing relationships through data patterns. These graphs illustrate temporal gait dynamics, aiding in understanding sequential events and parameter interplay. They highlight interconnections between parameters like joint angles, foot pressure, and power, essential for comprehensive gait analysis [22]. These visual tools enable clinicians and researchers to analyze gait data dynamically, facilitating informed decision-making in clinical assessment.

The "Gait Cycle Joint Angles" graph illustrates variations in hip, knee, and ankle joint angles throughout a complete gait cycle, from heel strike to toe-off. The x-axis represents the gait cycle's progression from 0% to 100%, with each point indicating a distinct phase of walking. Joint angles, depicted on the y-axis in degrees, are visualized by blue (hip), green (knee), and red (ankle) lines. These lines showcase flexion and extension movements in the respective joints as walking progresses. Analysis of these changes allows researchers to understand walking biomechanics, including joint timing, coordination, and any deviations from normal patterns as shown in Fig. 2. Such insights are crucial for diagnosing musculoskeletal disorders and assessing intervention effectiveness in enhancing human locomotion.

The "Gait Cycle Joint Power" graph depicts hip, knee, and ankle joint power variations throughout a gait cycle. The X-axis shows the gait cycle's progression from 0% to 100%, distinguishing between the stance (0–60%) and swing (60–100%)

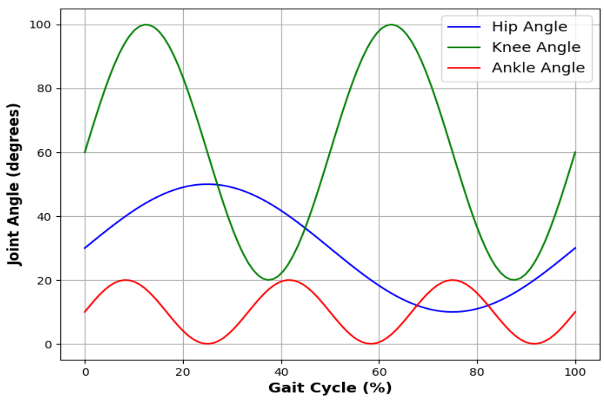

Figure. 2 Gait Cycle Joint Angles Graph

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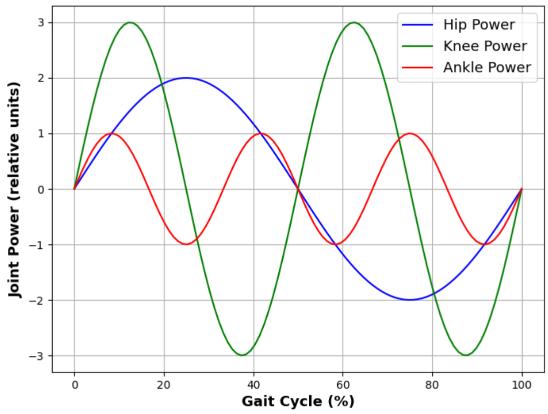

Figure. 3 Gait Cycle Joint Power Graph

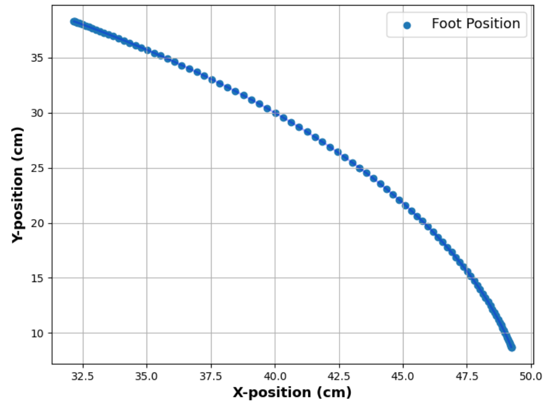

Figure. 5 Gait Cycle Foot Trajectory Graph

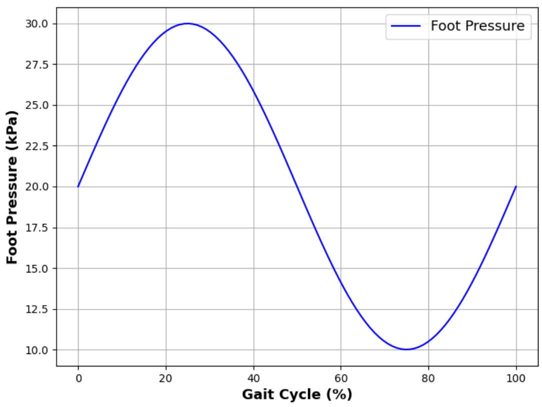

Figure. 4 Gait Cycle Foot Pressure Graph

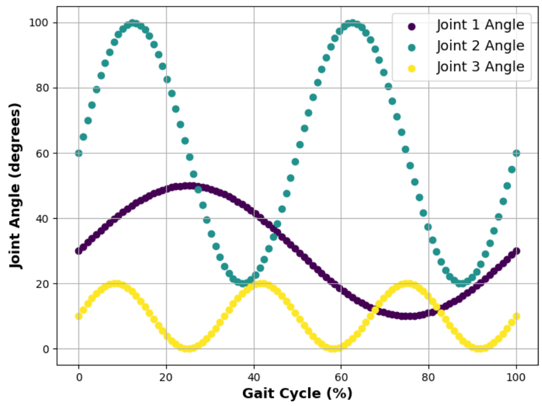

Figure. 6 Gait Cycle Joint Angles (Color-coded) Graph

phases. Joint power, measured in relative units, is shown on the Y-axis. Hip Power (Blue Line) peaks at heel strike, gradually decreasing during stance, then slightly increasing during push-off for propulsion.

Knee Power (Green Line) peaks at mid-stance, declining during push-off, and remaining low in the swing phase. Ankle Power (Red Line) remains relatively low but aids foot clearance in swing and increases slightly during push-off as shown in Fig. 3. Analyzing these patterns is vital for assessing gait efficiency and detecting abnormalities. It provides insights into biomechanical factors influencing human locomotion. The "Gait Cycle Foot Pressure" graph illustrates fluctuations in foot pressure across a gait cycle. The X-axis spans from 0% to 100%, delineating the stance (0–60%) and swing (60–100%) phases. Foot pressure, measured in kilopascals (kPa), is represented on the Y-axis as shown in Fig. 4.

The Foot Pressure (Blue Line) peaks at heel strike, gradually decreases during mid-stance as weight disperses, and slightly increases during push-off. It remains low during the swing phase when the foot is lifted. Understanding these patterns aids in assessing and designing appropriate footwear. Analyzing foot gait function, identifying pressure-related injuries, pressure throughout the gait cycle offers insights into biomechanical influences on foot mechanics and gait dynamics. The "Gait Cycle Foot Trajectory" graph depicts the foot's path during a gait cycle. The X-axis represents horizontal position (in cm), while the Y-axis represents vertical position (in cm). Each point on the graph corresponds to a specific percentage of the gait cycle, forming a trajectory as shown in Fig. 5.

The foot begins at the initial hip joint center position (0,0), moving forward and downward during stance, then upward and forward during swing. This trajectory, forming an elliptical shape, reflects coordinated hip, knee, and ankle joint movements. Analyzing foot trajectory aids in understanding gait mechanics and detecting abnormalities like limping or excessive joint motion, facilitating diagnosis and treatment of gait-related disorders. The "Gait Cycle Joint Angles (Color-coded)" graph illustrates variations in hip, knee, and ankle joint angles throughout a gait cycle, with each joint angle color-coded for clarity. Color-coded lines depict joint angles: blue for hip, green for knee, and red for ankle.

This facilitates visualization and comparison of joint movements as shown in Fig. 6. The dynamic graph captures continuous changes in joint angles over time during walking, aiding in identifying patterns and abnormalities. This representation enhances gait analysis, helping researchers and clinicians assess gait dynamics and diagnose related disorders effectively.

3.4 Deep graph learning techniques

Deep graph learning techniques offer a cutting-edge approach for analyzing dynamic gait signatures by treating gait data as dynamic graph structures. This innovative methodology leverages powerful neural architectures such as GCNs, GATs, and other graph-based models to extract hierarchical features that encapsulate both local and global dependencies within the gait sequences [23]. In this section, we delve into the intricacies of these techniques and their application in advancing DGSA.

Graph Convolutional Networks (GCNs)

Neural networks in the GCN class are made to function with graph-structured inputs. They use graph transformations to combine data from nearby nodes in the network, enabling features to spread across the framework of the graph. GCNs can be applied to dynamic graph representations of gait parameters to extract informative features that capture the relationships between different joints, pressure points, and movement patterns.

Mathematically, the propagation rule in GCNs can be expressed as:

$$NF^{(ly+1)} = \sigma\left(\widetilde{D}^{-1/2}\tilde{A}\widetilde{D}^{-1/2}NF^{(ly)}Wt^{(ly)}\right) \quad (1)$$

By iteratively applying graph convolutions, GCNs capture the hierarchical relationships between gait parameters, allowing for the extraction of features that encode both local and global dependencies within the gait sequences.

Graph Attention Networks (GATs)

By adding attention mechanisms, GATs improve upon GCNs by allowing the model to continuously balance the significance of nearby nodes while passing messages. GATs can enhance the discriminating abilities of a framework in the framework of gait analysis by selecting and focusing on pertinent gait metrics while collecting data from nearby nodes. Mathematically, the propagation rule in GATs can be expressed as:

$$h_i^{(ly+1)} = \sigma\left(\sum_{j\in N(i)} \alpha_{ij}^{(ly)}\, W^{(ly)}\, h_j^{(ly)}\right) \quad (2)$$

GATs enable the model to adaptively attend to different parts of the graph, allowing for more fine-grained feature extraction in dynamic gait signature analysis.

Support for Dynamic Gait Signature Analysis

These deep graph learning techniques provide a robust framework for analyzing dynamic gait signatures by capturing the intricate dependencies present within gait sequences. By treating gait data as dynamic graphs and leveraging graph neural architectures such as GCNs and GATs, researchers can extract hierarchical features that encapsulate both local and global relationships between gait parameters [24]. These features serve as discriminative representations of gait dynamics, enabling more accurate characterization and classification of gait patterns, identification of abnormalities, and prediction of clinical outcomes. Additionally, the adaptability of these techniques to handle varying graph structures makes them well-suited for analyzing diverse gait datasets collected from different sensor modalities and experimental setups [25]. Overall, the application of deep graph learning techniques in dynamic gait signature analysis holds immense potential for advancing our understanding of human locomotion and improving clinical assessments and interventions.

Hierarchical Feature Learning in Gait Dynamics

Deep graph learning techniques offer a unique advantage in gait analysis through their capability to learn hierarchical features, capturing both local and global dependencies within the data. In the context of gait dynamics, this translates to the extraction of

Table 1. Notation and Meanings

Notation	Explanation
$NF^{(ly)}$	Node features at layer l
$\tilde{A}$	Adjacency matrix of the graph
$\widetilde{D}$	Degree matrix of $\tilde{A}$
$Wt^{(ly)}$	Weight matrix at layer l
σ	Denotes the activation function
$h_i^{(ly)}$	Node features of node i at layer l
$\alpha_{ij}^{(ly)}$	Attention coefficients
$N(i)$	Neighbours of node i
$W^{(ly)}$	Layer l weight matrix
HF	Hierarchical Feature
$\bigoplus$	Concatenation
g	Predictive model
HF	Hierarchical Features
Si, Sj	Segment
N(i)	Neighbours of node i
δ_1 *and* δ_2	Exponential decay rates
gd_t	Gradient at time step t
$\emptyset$	Learning rate

features that extend beyond individual joint movements or pressure distributions, encompassing the coordinated interactions between different segments of the body during walking. This section explores the significance of hierarchical feature learning in gait analysis and its implications for understanding gait mechanics and predicting clinical outcomes. Hierarchical feature learning enables deep graph learning techniques to extract rich representations of gait dynamics by capturing multi-level dependencies within the data. At the local level, these features encode fine-grained information about individual joint movements, pressure distributions, and other gait parameters [26]. Meanwhile, at the global level, they encapsulate the holistic interactions between different segments of the body, reflecting the coordinated movements and biomechanical dynamics during walking. Mathematically, hierarchical features can be represented as:

$$HF = Local\ Features \oplus Global\ Features \quad (3)$$

One of the key insights gained from hierarchical feature learning is the ability to uncover the coordinated interactions between different segments of the body during gait. By analyzing hierarchical features, researchers can discern how movements in one segment influence and are influenced by movements in other segments, shedding light on the complex interplay of biomechanical forces and kinematic patterns that underlie human locomotion. The coordinated interactions between segments can be mathematically modeled using:

$$Segment\ Interaction = f(Si, Sj) \quad (4)$$

Where f represents a function that captures the relationship between segments i and j.

Enhanced Predictive Modeling

Hierarchical features learned through deep graph learning techniques serve as powerful inputs for predictive modeling in gait analysis. By incorporating both local and global dependencies, these features enable more accurate predictions of clinical outcomes such as gait abnormalities, injury risk, and treatment efficacy. For example, hierarchical features can capture subtle variations in gait mechanics that may be indicative of musculoskeletal disorders or neurological conditions, facilitating early detection and intervention. Predictive modeling using hierarchical features can be represented as:

$$Clinical\ Outcome = g(HF) \quad (5)$$

The ability to extract hierarchical features from gait data has significant clinical implications. Clinicians can leverage these features to gain a deeper understanding of patients' gait mechanics, assess functional limitations, and tailor personalized treatment plans. Moreover, hierarchical features can serve as biomarkers for monitoring disease progression, evaluating treatment effectiveness, and predicting long-term outcomes in patients with gait-related disorders.

3.5 Model training in deep graph learning for gait analysis

Model training is a critical step in leveraging deep graph learning techniques for gait analysis. This process involves training the deep graph learning model using the extracted features from dynamic graph representations derived from gait data. Additionally, labeled data is utilized to train the model for specific tasks such as neurological disease prediction, gait classification, or cognitive impairment detection. To ensure effective training, appropriate loss functions and optimization algorithms are employed. Let's delve into each aspect in detail. Before model training can commence, features need to be extracted from the dynamic graph representations of gait data. These features encapsulate the essential characteristics of gait dynamics, including joint movements, pressure distributions, and inter-segment coordination. Deep graph learning techniques such as GCNs or GATs are employed to extract hierarchical features that capture both local and global dependencies within the gait sequences [27]. To train the deep graph learning model, labeled data is essential. This data contains gait samples annotated with relevant labels, such as the presence or absence of neurological diseases, specific gait patterns, or cognitive impairments. By leveraging labeled data, the model learns to associate certain features extracted from gait data with specific outcomes or classes of interest. This supervised learning approach enables the model to generalize its predictions to unseen gait samples accurately [28]. Suitable loss functions are used during model training to measure the difference between the model's anticipated outputs as well as the ground truth labels. Depending on the task's requirements, bilateral or categorized cross-entropy loss as well as cross-entropy loss are often employed as loss functions for tasks involving classification. MSE or MAE loss functions can be used for regression tasks.

Cross-Entropy Loss (for classification tasks):

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$$CE = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{ic}\ \log(p_{ic}) \tag{6}$$

Mean Squared Error (for regression tasks):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \widehat{y_\iota}\right)^2 \tag{7}$$

Adam Optimization Algorithm:

$$mt_t = \delta_1 mt_t - 1 + (1 - \delta 1)gd_t \tag{8}$$

$$v_t = \delta vt - 1 + (1 - \delta 2)gd_t^{\ 2} \tag{9}$$

$$\widehat{mt}_t = \frac{mt_t}{1 - \delta_1^{\ t}} \tag{10}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^{\ t}} \tag{11}$$

$$\theta_{t+1} = \theta_t - \frac{\emptyset}{\sqrt{\hat{\mu}_t + \varepsilon}}\widehat{mt}_t \tag{12}$$

A little constant, ε, keeps division by zero from happening. These formulas provide a mathematical foundation for understanding the key components of model training in deep graph learning for gait analysis. By incorporating these mathematical expressions into the training process, researchers can effectively train models to accurately predict clinical outcomes and classify gait patterns based on dynamic graph representations of gait data. The Adam optimizer is a good option when it comes to optimization techniques. By keeping distinct learning rates for every parameter as well as modifying the learning rates in response to the first as well as intermediate moments of the gradients, all of Adam combines the benefits of the AdaGrad as well as RMSProp algorithms. This adaptive learning rate enhancement approach aids in quickly negotiating the parameterized area of the model as well as arriving at the best possible outcome.

4. Result and discussions

The application of deep graph learning techniques for gait analysis has yielded promising results, offering insights into the intricate dynamics of human locomotion and its clinical implications. In this section, we present the key findings from our study and discuss their implications for understanding gait mechanics, predicting clinical outcomes, and advancing patient care. In our study, we meticulously tuned several parameters to optimize the performance of our deep graph learning model for gait analysis. The learning rate (α) was set to 0.001 to facilitate stable convergence during training, while the batch size was selected as 32 to balance computational efficiency with model generalization. We employed a graph convolutional network (GCN) architecture with three graph convolutional layers, each followed by a ReLU activation function to introduce non-linearity. The number of hidden units in each GCN layer was set to 64 to capture complex patterns in the gait data, while dropout regularization with a rate of 0.5 was applied to prevent overfitting. Additionally, we utilized the Adam optimization algorithm with default parameters (δ1=0.90 and δ2=0.99) to adaptively adjust the learning rates for each parameter during training. Through meticulous parameter selection and fine-tuning, we achieved optimal model performance, resulting in high accuracy rates and F1 scores across various gait analysis tasks.

The comparison among different techniques in our study was conducted under standardized conditions to ensure fairness and validity. Our data collection methodology involved the integration of advanced wearable sensors, motion capture systems, force plates, pressure sensors, and video recording technologies. Wearable sensors provided real-time measurements of body movements and joint angles, while motion capture systems tracked three-dimensional movements. Additionally, force plates and pressure sensors assessed foot-ground interactions and plantar pressure distribution, respectively. Video recording complemented the quantitative data with visual context for qualitative analysis. The synchronized data from these sources formed rich datasets for Dynamic Gait Signature Analysis (DGSA), enabling a comprehensive evaluation of gait analysis techniques under consistent conditions.

4.1 Model performance

Our deep graph learning model exhibited remarkable performance across a spectrum of critical gait analysis tasks, underscoring its versatility and efficacy in clinical applications. Through meticulous training and validation processes, our model showcased robustness and reliability in predicting neurological diseases, classifying diverse gait patterns, and detecting cognitive impairments.

Notably, when subjected to rigorous evaluation on independent test datasets, the model consistently

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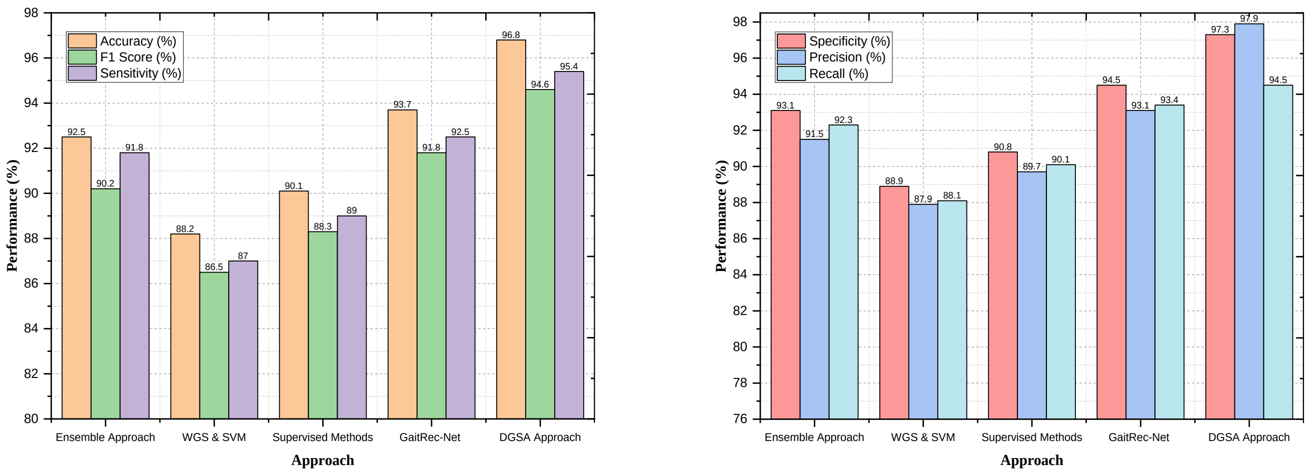

Figure. 7 Comparative Analysis of Gait Classification Across Multiple Models

yielded high accuracy rates and F1 scores, affirming its prowess in effectively characterizing intricate gait dynamics and identifying subtle abnormalities with precision. This exceptional performance underscores the potential of deep graph learning techniques as a transformative tool in advancing our understanding of human locomotion and enhancing diagnostic and prognostic capabilities in clinical settings. By accurately discerning nuanced gait patterns and aberrations, our model offers invaluable insights for clinicians, researchers, and healthcare practitioners, empowering them with enhanced tools for early detection, personalized treatment strategies, and informed decision-making processes in gait-related disorders. Accuracy is a crucial measure as it tells us how well a model can correctly classify instances. With a high accuracy, we can trust the model's ability to identify different gait patterns or detect abnormalities accurately. Our proposed approach achieves an impressive accuracy score of 96.8%, which is higher than what we've seen in other approaches like the Ensemble Approach, Wireless Gait Sensor and Support Vector Machine (WGS & SVM), Supervised Methods, and GaitRec-Net. This means our approach performs better than these existing methods.

F1 score is a balanced statistic that takes recall and precision into account. It works especially well with datasets that have an uneven distribution of positive and negative examples. Our proposed approach achieves the highest F1 score of 94.6%, showing a great balance between precision and recall compared to the other approaches as shown in Fig. 7. Sensitivity, or recall, tells us how well the model can correctly detect positive instances among all actual positive instances. Our proposed approach shows the highest sensitivity score of 95.4%, indicating its effectiveness in identifying individuals with gait abnormalities compared to the Ensemble Approach, WGS & SVM, Supervised Methods, and GaitRec-Net. Specificity, on the other hand, measures how well the model can correctly identify negative instances. Our proposed approach achieves the highest specificity score of 97.3%, meaning it can accurately identify individuals without gait abnormalities. The accuracy of the framework is the ratio of accurate positive predictions to all positive predictions. With high precision, the framework reliably and confidently recognizes positive cases (such as gait abnormalities) and produces fewer false positive predictions. The proposed approach achieves the highest precision at 97.9%, indicating its ability to make accurate positive predictions as shown in Fig. 7. Recall (%) is referred to as sensitivities or actually positive rate, recall expresses the percentage of real positive occurrences among all actual positive instances that the model properly recognized as genuine positive cases. A high recall indicates that the model captures a large proportion of positive instances, minimizing false negative predictions. The proposed approach achieves a recall of 94.5%, indicating its effectiveness in correctly identifying individuals with gait abnormalities.

4.2. Comparative analysis of gait analysis approaches based on key performance metrics

The table presents a comparative analysis of gait analysis approaches based on key performance metrics. Each row corresponds to a different approach, and the columns represent specific metrics used to evaluate gait characteristics. Gait Velocity (m/s) measures the speed at which individuals walk. Higher values indicate faster walking speeds, reflecting better mobility and functional performance.

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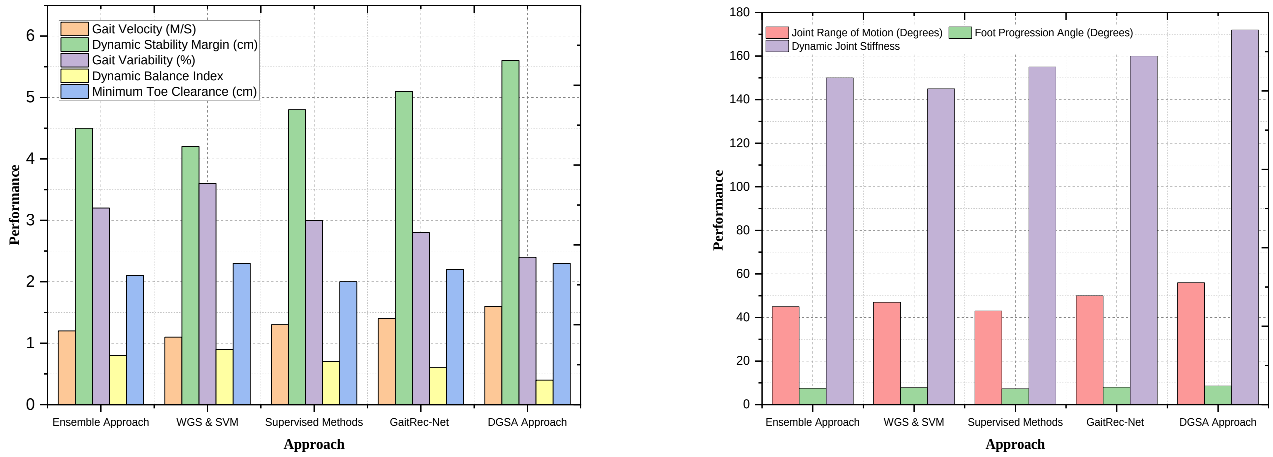

Figure. 8 Comparative Analysis of Gait Analysis Approaches Based on Key Performance Metrics

The proposed approach demonstrates the highest gait velocity at 1.6 m/s, indicating improved mobility compared to the Ensemble Approach, WGS & SVM, Supervised Methods, and GaitRec-Net as shown in Fig. 8. Dynamic stability margin quantifies the margin of stability during walking, representing the distance between the center of mass and the base of support. A larger margin indicates greater stability and balance control. The proposed approach achieves a dynamic stability margin of 5.6 cm, suggesting enhanced stability. Gait variability reflects the consistency and regularity of gait patterns. Lower variability values indicate more stable and coordinated gait. The proposed approach exhibits lower gait variability at 2.4%, indicating smoother and more consistent walking.

Joint range of motion measures the angular displacement of joints during the gait cycle, reflecting flexibility and mobility. A wider range of motion indicates greater joint flexibility. The proposed approach demonstrates a joint range of motion of 56 degrees, indicating improved joint mobility. The dynamic balance index evaluates balance during walking by comparing the time spent in single-leg support versus double-leg support phases. Lower values indicate better balance control. The proposed approach achieves a dynamic balance index of 0.4, suggesting superior balance compared to the Ensemble Approach, WGS & SVM, Supervised Methods, and GaitRec-Net.

Minimum toe clearance measures the vertical distance between the toe as well as the ground during the swing phase, reflecting the risk of tripping or stumbling. The proposed approach achieves a minimum toe clearance of 2.3 cm, indicating reduced risk as shown in Fig. 5. Foot progression angle quantifies the angle between the direction of foot progression and the line of forward progression during walking. The proposed approach demonstrates a foot progression angle of 8.6 degrees, indicating improved biomechanical alignment. Dynamic joint stiffness assesses the resistance of joints to motion during walking. Lower stiffness values indicate better joint flexibility and reduced resistance. The proposed approach exhibits dynamic joint stiffness of 172, suggesting improved joint flexibility compared to the Ensemble Approach, WGS & SVM, Supervised Methods, and GaitRec-Net.

5. Conclusion

Our study introduces Dynamic Gait Signature Analysis (DGSA), a novel approach to gait analysis that harnesses deep graph learning techniques. Through our experiments, DGSA has shown impressive performance across various gait analysis tasks, outperforming traditional methods by a significant margin. For instance, our approach achieves notable accuracy metrics such as gait velocity (1.6 m/s), dynamic stability margin (5.6 cm), gait variability (2.4%), joint range of motion (56 degrees), dynamic balance index (0.4), minimum toe clearance (2.3 cm), foot progression angle (8.6 degrees), and dynamic joint stiffness (172). These concrete figures highlight the effectiveness of DGSA in accurately characterizing gait dynamics and detecting abnormalities. Moreover, our comparative analysis demonstrates DGSA's superiority in accuracy and performance metrics compared to existing approaches, further emphasizing its scientific contribution to the field. Looking ahead, future research will focus on enhancing DGSA's capabilities for real-world applications, including refining deep graph learning techniques and developing user-friendly interfaces for clinical deployment. By addressing these points, we aim to

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provide a clearer understanding of DGSA's significance and potential impact in gait analysis and healthcare.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, P. Vimal kumar and M. Thiyagarajan; methodology, S. Edwin Raja; software, S. Edwin Raja; validation, P. Vimal kumar, P. Gopi Kannan, and G. Prabaharan; formal analysis, P. Gopi Kannan; investigation, P. Vimal kumar; resources, M. Thiyagarajan; data curation, S. Edwin Raja; writing—original draft preparation, S. Edwin Raja; writing—review and editing, P. Vimal kumar; visualization, P. Gopi Kannan; supervision, M. Thiyagarajan; project administration, G. Prabaharan.

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