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Research on Intelligent Diagnosis of Motion System Injuries Based on Gait and Kinematic Parameters of Multimodal Data

Dangwei Cheng [1], Guangping Zhuo [1], Xinpeng Miao [1], Pengyuan Ma [1], Fei Ma [2]

[1] School of Computer Science and Technology, Taiyuan Normal University, Jinzhong, Shanxi 030619, China

[2] Department of Computer Science, Taiyuan University, Taiyuan, Shanxi 030032, China

ABSTRACT

This study aims to explore the use of the Transformer model for analyzing multimodal and multidimensional gait data, validating the effectiveness of the multi-head attention mechanism in case summarization and disease diagnosis. A retrospective case series design was adopted, involving 1200 samples collected from the Gait Laboratory of the Second Affiliated Hospital of Shanxi Medical University. The data include gait information from patients with osteoarthritis, anterior cruciate ligament injuries, and meniscus injuries, as well as healthy volunteers. Each sample encompasses foot pressure distribution, pressure intensity distribution, and motion data of the ankle, knee, and hip joints, along with labeled disease categories for model training and testing. Key data of clinical interest were curated into datasets to compare the performance of the Transformer model, based on the multi-head attention mechanism, with conventional convolutional neural networks in training and diagnosing conditions from gait data. The results demonstrate that the Transformer model achieves high diagnostic accuracy in gait analysis, with precision reaching approximately 95%. This study proves the feasibility of AI-based gait diagnosis using the Transformer model, providing valuable diagnostic references for orthopedic clinicians.

KEYWORDS

Gait Detection; Transformer Model; Multi-Head Attention Mechanism; Deep Learning

1. INTRODUCTION

Gait refers to an individual's posture, stride, and movement patterns during walking, reflecting their physiological state and overall health. It is influenced not only by the nervous and musculoskeletal systems but also by factors such as emotions, fatigue, and environmental conditions. Gait analysis plays a crucial role in identifying health issues, with significant applications in disease diagnosis, performance evaluation in sports, and health monitoring for the elderly.

Gait analysis involves several key elements, including the gait cycle (stance phase and swing phase), stride length, cadence, walking speed, symmetry, and stability. The gait cycle refers to the full process from when one foot contacts the ground to when the same foot contacts the ground again. Stride length and cadence measure the distance and frequency of each step, respectively, while gait symmetry and stability reflect coordination and steadiness during walking.

Abnormal gait is often associated with specific diseases, such as Parkinson's disease, stroke, and joint disorders. Common gait abnormalities include shortened strides, unsteady gait, and limping, which may indicate neurological or musculoskeletal issues. By analyzing gait, medical professionals can detect health problems early and intervene accordingly.

The applications of gait analysis are extensive. In disease diagnosis, gait abnormalities can serve as early warning signals for neurological disorders like Parkinson's disease. In rehabilitation assessment, changes in gait reflect a patient's recovery status, such as improvements in gait patterns post-stroke. Gait analysis is also vital in elderly health monitoring, as it can effectively predict the risk of falls. In the sports domain, gait analysis is utilized to evaluate athletes' techniques, performance, and potential injuries.

Gait data collection methods include video analysis, wearable sensors, and force sensors. Video analysis leverages computer vision to extract gait features, while wearable devices such as accelerometers and gyroscopes enable real-time gait monitoring. Force sensors, on the other hand, assess step stability through plantar pressure measurements.

Gait data typically comprises multi-dimensional information, such as video data, sensor data, and biological signals, each varying in significance for disease diagnosis. Effectively integrating and analyzing these dimensions poses a significant challenge in gait analysis. To address this, Transformer models, particularly with their multi-head attention mechanism, have demonstrated remarkable advantages in processing gait data.

Through self-attention mechanisms, Transformer models can dynamically focus on different features within multi-dimensional information, capturing complex relationships between various data dimensions and thereby improving the accuracy of gait analysis. The multi-head attention mechanism allows the model to process different features of gait data, such as stride movements in video data and stride length variations in sensor data, assigning varying attention weights based on their importance. Furthermore, Transformers effectively model the temporal characteristics of gait data, overcoming the gradient vanishing or exploding issues often encountered with traditional RNNs or LSTMs when handling long sequences.

The application scenarios for Transformers are diverse. For example, in gait analysis for Parkinson's disease, they can identify features such as reduced stride length and unsteady steps. In stroke rehabilitation assessment, they analyze gait symmetry and stability. In elderly health monitoring, they can detect fall risks in real time.

In summary, Transformer models, with their robust capabilities for multi-dimensional information integration and temporal modeling, hold great promise for gait analysis. They can contribute to early disease diagnosis, personalized treatment, and comprehensive health monitoring.

2. OBJECTIVES AND METHODS

2.1. Objectives

This study is a retrospective case series. Data were collected from 1,200 patients and healthy individuals at the Gait Laboratory of the Second Affiliated Hospital of Shanxi Medical University. The dataset includes patients diagnosed with osteoarthritis, anterior cruciate ligament injuries, and meniscal injuries, as well as data from healthy volunteers. The collected data encompass plantar pressure-related information and joint angle deviation data. All data exclude any patient-identifiable information, and informed consent was obtained from all patients and their families. The study was approved by the hospital's ethics committee.

2.2. Methods

2.2.1. Gait Data Collection

Gait plantar data and lower limb joint data were collected using the Footscan 2m HE plantar pressure distribution testing system and the Codamotion 2CX1 three-dimensional joint motion capture system. For each test, plantar measurement data were exported as 17 xls files, while lower limb joint data were exported as 6 xls files. A total of 1,200 measurement sessions were conducted, and after data cleaning, 800 valid samples were retained for analysis.

For this study, 70% of the dataset was used as the training set, 15% as the validation set, and 15% as the test set. All measurements were conducted in the Gait Laboratory of the Second Affiliated Hospital of Shanxi Medical University under standardized conditions using the same equipment, operated by professional physicians. The measurement results are shown in Figure 1.

Figure 1. Gait detection plantar data and joint data metadata

2.2.2. Data Preprocessing

After data cleaning, patient data in the database were grouped according to different conditions (e.g., healthy, knee joint injuries, ligament injuries, meniscal injuries, etc.). Each group was labeled based on its symptomatic characteristics, and the labels were used as folder names for storage. Key data relevant to physicians, such as plantar pressure distribution, were extracted from the gait metadata. Distribution analysis of plantar pressure data showed significant differences across conditions, as illustrated in Table 2. Similarly, the distribution analysis of joint range of motion data revealed that joint mobility was severely restricted by different conditions, as shown in Table 3. Additional features, including stride length, cadence, and gait cycle parameters, were also incorporated.

To prevent excessively large data values from impacting model performance, normalization was applied to the data, accelerating model convergence.

Table 1. Summary table of plantar pressure distribution

Range / Condition	MI	ACL	OA	Nomal
Right Forefoot Pressure	16.3%±4.3%	17.8%±3.78%	18.8%±3.7%	17.4%±3.5%
Right Hindfoot Pressure	29.3%±6.0%	30.0%±7.26%	28.1%±6.0%	29.3%±3.5%
Left Forefoot Pressure	20.7%±4.5%	20.9%±4.63%	22.2%±4.0%	21.2%±3.5%
Left Hindfoot Pressure	33.5%±5.5%	31.2%±6.5%	30.8%±6.1%	31.9%±4.0%

Table 2. Summary table of maximum joint range of motion

Range / Condition	MI	ACL	OA	Nomal
Right Ankle Joint Range of Motion	25.5°±5.5°	23.7°±6.0°	21.2°±4.5°	27.4°±4.5°
Left Ankle Joint Range of Motion	31.2°±6.5°	26.3°±6.0°	25.8°±5.5°	30.4°±5.5°
Right Knee Joint Range of Motion	51.7°±11.7°	48.4°±12.7°	39.2°±14.7°	61.4°±4.5°
Left Knee Joint Range of Motion	54.0°±13°	48.5°±14°	39.7°±13°	62.9°±4.5°
Right Hip Joint Range of Motion	32.2°±5.5°	29.3°±6.0°	28.5°±6.0°	35.6°±4.0°
Left Hip Joint Range of Motion	34.6°±6.0°	29.6°±8.0°	28.5°±6.0°	36.7°±3.5°

2.3. Model Construction

In this study, a Transformer model was employed, leveraging the self-attention mechanism to train and analyze the multi-dimensional data collected from the gait laboratory. Gait data consists of multiple related features with varying weights and importance, making it necessary to effectively assign appropriate weights to each data dimension through the self-attention mechanism. The Transformer model, with its powerful self-attention capability, can automatically identify and capture long-range dependencies and complex patterns within the data, thereby enhancing its ability to process gait data, as shown in Figure 2.

In practical application, gait data is first converted into vector representations through input embeddings. The self-attention mechanism is then applied to compute the relationships among the features within the input data, adjusting the importance of each dimension. During training, the feature weights for each dimension are learned dynamically, enabling the model to focus on the most critical features while ignoring irrelevant ones. This mechanism significantly improves the model's adaptability and accuracy in handling multi-dimensional data.

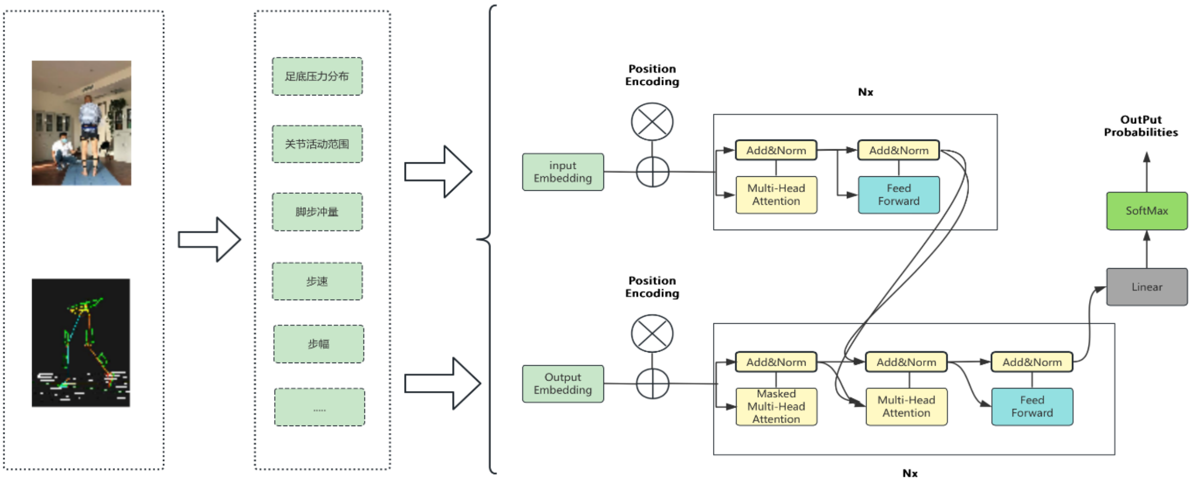

Figure 2. Multimodal gait analysis diagnostic model diagram

2.4. Experimental Environment

The experiments in this study were conducted on a Linux operating system. The hardware configuration for training included eight GeForce RTX 3090 GPUs. The software environment comprised Python 3.10.18 and the PyTorch 1.10 framework, with the Transformer model employed for classification tasks.

2.5. Evaluation Metrics

This study used Recall, Precision, F1-score, and Accuracy as metrics to evaluate the performance of different classification models.

Recall measures the proportion of actual positive samples correctly predicted as positive by the model. A high recall indicates the model can identify more positive samples, reducing missed detections. The formula for recall is as follows:

$$Recall = \frac{TP}{TP+FN} \tag{1}$$

Precision measures the proportion of correctly predicted positive samples among all samples predicted as positive. High precision indicates fewer false positives, reducing unnecessary medical interventions, particularly in diagnosing arthritis. The formula for precision is as follows:

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

F1-score is the harmonic mean of precision and recall, combining the effects of false positives and false negatives. It provides a comprehensive performance evaluation by balancing precision and recall. The formula for F1-score is:

$$F1 = \frac{2TP}{2TP+FP+FN} \tag{3}$$

Accuracy measures the proportion of correctly classified samples among all samples. It offers an overview of the model's overall performance. However, in cases of class imbalance, it should be used alongside other metrics like precision and recall. The formula for accuracy is:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

TP (True Positives): The number of correctly classified positive samples.

FP (False Positives): The number of negative samples incorrectly classified as positive.

TN (True Negatives): The number of correctly classified negative samples.

FN (False Negatives): The number of positive samples incorrectly classified as negative.

3. RESULTS

This study aims to validate the effectiveness of the Transformer model in gait analysis and diagnosis, while exploring the characteristics of multi-dimensional gait data and their impact on model performance. Through a series of experiments, the results, as shown in Table 3, indicate that the Transformer model demonstrates excellent diagnostic prediction performance in gait analysis tasks, achieving an accuracy of approximately 95%. Notably, its self-attention mechanism proves more efficient than traditional models, particularly in handling multi-dimensional data with long-term dependencies.

3.1. Model Comparison and Controlled Experiments

Table 3. The results of a classification experiment conducted by Transformer in gait analysis

Model	Recall	Precision	F1-Score	Accuracy
CNN	0.935	0.937	0.935	0.936
RNN	0.932	0.933	0.931	0.932
Transformer	0.951	0.951	0.945	0.955

To evaluate the advantages of the Transformer model, this study compared it with CNN and RNN models. CNN and RNN are classic deep learning architectures, excelling at extracting local features and processing sequential dependencies, respectively. However, gait analysis data often contains multiple dimensions and exhibits long-term dependencies. The self-attention mechanism in Transformer models better captures long-range dependencies and relationships among different features.

As shown in Table 3, experiments demonstrated that the Transformer model outperformed CNN and RNN across several metrics, including accuracy and recall. Notably, it exhibited significant advantages in recognizing complex patterns and weighting multi-dimensional features.

3.2. Ablation Experiments and Key Feature Analysis

Table 4. Relevant experimental indexes after the change of ablation characteristics

Feature	Recall	Precision	F1-Score	Accuracy
All	0.951	0.951	0.945	0.955
Joint Data	0.929	0.931	0.928	0.929
Plantar Pressure	0.934	0.936	0.933	0.934
Other	0.871	0.873	0.871	0.871

To further validate the effectiveness of the Transformer model and analyze the critical features in gait data, ablation experiments were conducted in this study. The results showed that joint data and dynamic information are the most influential features for gait diagnosis outcomes. These biomechanical features play a crucial role in gait analysis and are directly linked to the identification of gait abnormalities. For instance, joint data reflects gait stability and coordination, while dynamic information captures mechanical characteristics during gait, such as balance and naturalness of steps. These two factors provide essential insights for distinguishing normal gait from abnormal gait.

Through ablation experiments, we further confirmed the contribution of these two types of features to the gait analysis model. Removing these features led to a significant decline in the model's predictive accuracy, highlighting their importance in gait diagnosis. This finding provides a strong basis for feature selection in future gait analysis systems and underscores the core role of joint data and dynamic information in identifying gait abnormalities.

4. DISCUSSION

Gait analysis, as a non-invasive and easy-to-operate biomechanical evaluation method, holds broad application prospects. By analyzing gait, it is possible not only to effectively evaluate and diagnose issues such as movement disorders and neurological diseases but also to provide valuable reference data for rehabilitation training. Gait abnormalities are often early symptoms of various diseases, particularly in fields like Parkinson's disease, Alzheimer's disease, and post-stroke rehabilitation, where gait analysis has become an important auxiliary tool for clinical diagnosis.

With technological advancements, gait analysis can provide more precise evaluations for physicians through digital methods, aiding in the development of personalized treatment plans. Furthermore, gait analysis finds applications in areas such as optimizing athletic performance for athletes and predicting falls among the elderly, showcasing its immense clinical and research value. Therefore, in-depth exploration of gait analysis techniques, especially when combined with modern deep learning methods, can drive progress in fields like medicine and rehabilitation, leading to significant societal and health impacts.

Deep learning methods, particularly models based on convolutional neural networks (CNNs), recurrent neural networks (RNNs), and Transformers, have achieved remarkable advancements in gait analysis in recent years. Deep learning can automatically extract high-dimensional features from raw data without relying on manual feature extraction, significantly improving the efficiency and accuracy of gait analysis. In gait detection tasks, deep learning models can handle complex sequential data, capture subtle features in gait variations, and effectively distinguish between normal and abnormal gait.

CNNs excel at extracting local features, while RNNs are adept at capturing sequential relationships in gait data. However, Transformer models outperform these due to their self-attention mechanism, which enhances performance in weighting multi-dimensional data and capturing long-range dependencies. Through deep learning modeling of gait data, precise recognition of gait patterns can be achieved, providing robust support for early diagnosis of gait abnormalities and personalized treatment.

Gait data typically includes multiple dimensions, such as plantar pressure distribution, joint data, and dynamic information, each carrying different types of information for gait analysis. Consequently, their weight in diagnosis varies. By leveraging the self-attention mechanism, Transformer models can automatically identify the importance of each dimension and assign appropriate weights, thereby improving diagnostic accuracy.

In this study, ablation experiments revealed that joint data and dynamic information significantly impact gait analysis diagnosis outcomes, underscoring their critical role in identifying gait abnormalities. However, feature selection and weighting in gait analysis require further exploration. Future research can investigate additional biomechanical features and their relationships with diseases to further enhance diagnostic capabilities. Additionally, maximizing the potential of multi-dimensional data to extract valuable information remains a key direction for future research.

Despite achieving promising results, this study faces the challenge of a relatively small dataset. Gait analysis, as a highly individualized task, exhibits significant variations in gait patterns across individuals, age groups, and pathological conditions. Therefore, the diversity and scale of datasets are critical for model training effectiveness. A smaller dataset may lead to overfitting, limiting the model's generalization capability.

Future research should focus on expanding datasets by collecting gait data from diverse populations, such as the elderly, patients, and athletes, to enrich data diversity. This will not only improve model accuracy and robustness but also enable better adaptability and practical application in various clinical scenarios. Additionally, training models on diverse datasets will enhance their ability to capture subtle differences between various gait characteristics, providing a stronger foundation for accurately identifying gait abnormalities.

Through the adoption of the Transformer model for gait analysis, this study validated the significant potential of deep learning in detecting gait abnormalities. Experimental results demonstrated that the Transformer model effectively captures critical features in multi-dimensional data, with joint data and dynamic information showing significant influence in predicting gait abnormalities. Moreover, the model's efficiency and accuracy in diagnostic predictions provide essential decision-making support for physicians.

The integration of gait analysis techniques with deep learning models offers reliable tools for early diagnosis of gait abnormalities and data support for developing personalized rehabilitation treatment plans. In summary, this study provides a strong theoretical foundation for the application and development of gait analysis, offering important references for clinical diagnosis and treatment decisions. In the future, with the expansion of datasets and model optimization, gait analysis technologies are expected to play an increasingly significant role in clinical medicine.

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REFERENCES

[1] ZOU B, HAN J, WANG Y, et al. Semi-structural interview-based Chinese multimodal depression corpus towards automatic preliminary screening of depressive disorders [J]. IEEE Transactions on Affective Computing, 2022.

[2] LIU H, ZHANG S, LIANG X, et al. Transformer-based gait recognition for person identification [J]. Journal of Visual Communication and Image Representation, 2022.

[3] SUN J, LIU Z, XU Q, et al. Gait recognition using Transformer networks for enhanced security [J]. IEEE Access, 2023.

[4] WANG X, ZHANG J, WANG S, et al. A novel Transformer-based gait classification method for early detection of Parkinson's disease [J]. IEEE Transactions on Biomedical Engineering, 2023.

[5] LIU Y, ZHOU H, ZHU L, et al. Transformer and deep learning models for gait biometrics recognition [J]. Neurocomputing, 2023.

[6] CHEN X, ZHANG R, ZHANG X, et al. Gait analysis and recognition based on Transformer architecture [J]. Pattern Recognition Letters, 2022.

[7] LI J, LIU Y, LIU Z, et al. Gait recognition using Transformer models for healthcare applications [J]. Journal of Healthcare Engineering, 2023.

[8] MA Y, LI X, JIN D, et al. Transformer-based fusion model for gait-based person authentication [J]. Ieee Transactions on Systems, Man, and Cybernetics: Systems, 2023.

[9] ZHANG J, YU H, LI B, et al. Transformer-based model for human gait recognition in surveillance systems [J]. International Journal of Computer Vision, 2022.

[10] LI X, LIU S, WANG J, et al. Multi-view gait recognition using Transformer networks [J]. Computer Vision and Image Understanding, 2022.

[11] JIANG T, LI B, YU W, et al. A Transformer-based framework for gait recognition with sequence learning [J]. Neurocomputing, 2022.

[12] LIU D, ZHANG L, FANG Y, et al. Gait recognition with Transformer for elderly monitoring system [J]. Journal of Ambient Intelligence and Humanized Computing, 2023.

[13] WANG Z, LIU M, ZHOU W, et al. Deep Transformer networks for gait-based person verification [J]. IEEE Transactions on Information Forensics and Security, 2022.

[14] XU H, LIANG Q, CHEN Y, et al. Gait recognition using a deep learning Transformer model for medical diagnosis [J]. Biomedical Signal Processing and Control, 2022.

[15] WANG J, LI H, LI Y, et al. An end-to-end Transformer model for gait recognition in surveillance systems [J]. Computer Vision and Image Understanding, 2023.

[16] ZHANG X, WANG H, LI Y, et al. Transformer-based deep learning model for gait analysis in rehabilitation medicine [J]. IEEE Transactions on Medical Imaging, 2023.

[17] XU Y, ZHANG D, WANG S, et al. A novel Transformer-based model for human gait classification and analysis [J]. Pattern Recognition, 2023.

[18] sFENG Y, ZHANG J, WANG S, et al. Transformer-based gait recognition model for biometric security [J]. Journal of Biometrics and Biostatistics, 2023.

[19] HU J, LI J, LI Q, et al. Gait pattern recognition based on Transformer models for fall detection [J]. IEEE Journal of Biomedical and Health Informatics, 2022.

[20] YANG Z, ZHAO W, XU C, et al. Transformer-based approach for gait-based human action recognition [J]. Journal of Machine Learning Research, 2023.

[21] ZHANG M, LI Z, WANG X, et al. Transformer and deep neural network-based gait recognition for health monitoring [J]. Journal of Neural Engineering, 2023.

[22] LI B, YU Q, LIU Z, et al. A new Transformer model for gait recognition in multi-task learning scenarios [J]. Cognitive Computation, 2022.

[23] ZHANG Y, LIU T, MA Y, et al. Robust gait recognition with Transformer networks for security applications [J]. Security and Privacy, 2023.

[24] LU X, WANG X, YAN Z, et al. Transformer-based spatiotemporal modeling for gait recognition in video surveillance [J]. IEEE Transactions on Circuits and Systems for Video Technology, 2023.

[25] LI Y, FENG W, LI H, et al. Gait-based human authentication using Transformer models [J]. Journal of Applied Research and Technology, 2023.

[26] LI Z, ZHANG Q, LI J, et al. Transformer-based fusion model for gait analysis in medical applications [J]. Journal of Medical Systems, 2023.

[27] LIU Q, WANG Y, LI L, et al. A Transformer-based system for gait-based recognition of individuals in smart environments [J]. Smart Health, 2023.

[28] ZHAO T, ZHU J, LUO Z, et al. A Transformer-based deep learning method for human gait recognition [J]. Multimedia Tools and Applications, 2022.

[29] ZHAO Z, LI Y, FANG J, et al. Transformer-based model for gait anomaly detection in healthcare systems [J]. IEEE Transactions on Biomedical Engineering, 2023.