Intelligent Diagnosis of Gait Disorders Using Video-Based 3D Motion Analysis

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***Abstract*—This experiment proposed an intelligent disease diagnosis method based on gait video analysis. Gait videos were analyzed using OpenPose for 2D pose estimation, and a Temporal Convolutional Network (TCN) was employed to predict 3D poses, obtaining 3D gait motion data of the target. After extracting motion features, a knowledge base and inference rules for gait abnormalities and diseases were constructed within the framework of the Open Semantic Technology Intelligent System (OSTIS). The gait features were semantically processed accordingly. Finally, a classification model was used to diagnose potential diseases and provide interpretable diagnostic recommendations. Experimental results demonstrated that this method effectively integrates 3D motion features with semantic reasoning, achieving accurate disease classification and diagnosis, thus offering a novel technological approach to intelligent medical diagnosis.**

***Keywords*—Gait Analysis, OpenPose, 3D Motion Features, OSTIS, Intelligent Medical Diagnosis**

I. Introduction

Gait analysis, as an important means of studying human motor functions, has significant value in the early screening and diagnosis of neurological diseases, skeletal disorders, and movement-related diseases [3], [12]. Gait features can reflect human movement patterns and functional states, as different diseases are often accompanied by specific gait abnormalities, such as shortened stride length, imbalanced gait cycle, and restricted joint mobility [8], [20]. Therefore, precise analysis and pattern recognition of gait data provide critical evidence for disease diagnosis. However, traditional gait analysis often relies on complex equipment in laboratory environments, such as motion capture systems or pressure sensor floors [6]. These methods are not only costly and challenging to popularize but are also limited by experimental conditions, resulting in a lack of flexibility in the data acquisition process.

In recent years, the rapid development of computer vision and deep learning technologies has provided new approaches to gait analysis. From Fig 1 video-based gait analysis methods enable the efficient and low-cost acquisition of human motion data using standard video equipment [11]. The emergence of pose estimation technologies like OpenPose [1] makes it possible to extract human 2D keypoints from video data, while deep learning models such as Temporal Convolutional Networks (TCN) [2], [19]further allow for high-precision 3D pose prediction from 2D keypoints. This technical framework provides powerful tools for gait analysis, enabling the efficient extraction and analysis of gait data under non-contact conditions.

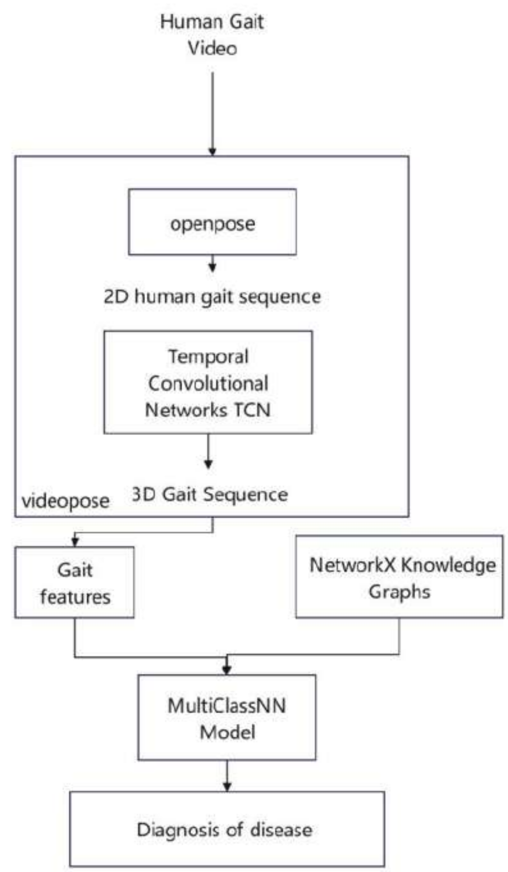

Figure 1. Gait diagnostic network composition.

At the same time, with advancements in intelligent medical technologies, semantic reasoning and knowledge representation are increasingly being applied in the field of disease diagnosis. The Open Semantic Technology for Intelligent Systems (OSTIS) provides strong support for the structured representation of medical knowledge and logical reasoning. By constructing a knowledge base related to gait abnormalities and combining it with inference rules for semantic processing of gait features, it is possible to perform logical deduction from gait features to disease diagnosis, thereby improving the accuracy and interpretability of diagnostic results [18].

II. Related work

A. Data preparation

The analysis and research of gait data require high-quality annotated datasets as a foundation. This study utilized two types of gait data: healthy gait samples and pathological gait samples. The healthy gait data were obtained from the publicly available Human3.6 dataset, which contains rich 3D human motion data and is well-suited for the extraction and analysis of gait features [7]. The pathological gait data were collected from online videos of patients with Parkinson's disease and other gait abnormalities. Keypoint information was extracted from these videos using video analysis techniques, and 3D gait data were subsequently generated [?] These data samples encompass various gait features and abnormal patterns, providing ample data support for model training and evaluation. Additionally, to enhance the model's generalization capability, the dataset was augmented with gait data from different patients, ensuring coverage of a broader range of gait abnormality types [13].

B. Extraction of gait features

Gait features are critical representations of human movement patterns, as different diseases are often associated with specific gait abnormalities [4]. This study extracted 10 key features from 3D gait data, including stride-related metrics $stride\_ratio$, big_gait, $small\_gait$, speed $speed$, gait cycle characteristics $mean\_gait\_cycle\_time$, $mean\_swing\_phase\_time$, step width $mean\_step\_width$, and joint range of motion $right\_ankle\_angle\_range$, $left\_ankle\_angle\_range$, $knee\_angle\_range$. These features provide a comprehensive description of individual gait patterns and form a foundation for disease identification. Patients with Parkinson's disease often exhibit reduced stride length, asymmetric gait, and slower movement, while stroke patients may present with prolonged gait cycles or abnormal swing phase durations. Limited joint motion, such as restricted ankle or knee movement, can also indicate specific gait disorders.

III. Material and Methods

A. openpose predicts 2D sequences

The core of gait analysis lies in extracting key features of human motion. This paper utilizes the OpenPose framework to estimate 2D keypoint sequences of human gait from videos. OpenPose is a deep learning-based multi-person pose estimation method that can locate 17 keypoints of the human body including the nose, neck, shoulders, elbows, wrists, hips, knees, and ankles and outputs the 2D coordinates of each keypoint in the image.

The core optimization objective of OpenPose is to accurately locate human body keypoints and model the connections between keypoints by jointly optimizing keypoint heatmaps and part affinity fields . Its optimization objective is defined by the following loss function:

$$\mathcal{L} = \sum_{k=1}^{K} \left\| \mathbf{H}_k - \hat{\mathbf{H}}_k \right\|^2 + \sum_{c=1}^{C} \left\| \mathbf{L}_c - \hat{\mathbf{L}}_c \right\|^2 \tag{1}$$

From the formula, the first part represents the loss of the keypoint heatmaps, while the second part represents the loss of the part affinity fields. By jointly optimizing, the loss function $\mathcal{L}$ simultaneously constrains the accuracy of the keypoints optimized through $\mathbf{H}_k$ and $\hat{\mathbf{H}}_k$ and the connections between the keypoints optimized through $\mathbf{L}_c$ and $\hat{\mathbf{L}}_c$. This joint modeling enables OpenPose to achieve high-precision estimation of keypoint detection and human skeleton connections in complex scenarios.

B. Temporal Convolutional Network module predicts 3D sequences

This paper utilizes 2D skeleton data extracted by OpenPose to predict 3D pose sequences from 2D keypoint sequences using a Temporal Convolutional Network . Convolution is the core module of the Temporal Convolutional Network and is used to preserve contextual information in temporal sequence modeling. Its design incorporates a temporal causality constraint into the receptive field of the convolution kernel [15]. To capture long-term dependencies in the temporal sequence, Temporal Convolutional Network introduces dilated convolutions within the convolution layers, enabling deep networks to extract features across different time scales. To enhance the training stability of deep networks, residual connection modules are added. Residual connections allow the input to be directly passed to the output, alleviating the problem of vanishing gradients. The formula for dilated convolution is:

$$\mathbf{y}_t = \sum_{i=0}^{k-1} \mathbf{W}_i \cdot \mathbf{x}_{t-i \cdot d} \tag{2}$$

In the formula, k represents the length of the convolution kernel, and d is the dilation rate, which controls the expansion speed of the receptive field. $\mathbf{x}$ represents the input data of the temporal sequence, and $\mathbf{W}$ is used to extract features from the input data and learn the weight relationships across different time steps. By expanding the receptive field, the model can better capture contextual information from the sequence, enabling more accurate estimation of 3D pose sequences.

The input 2D gait sequence joint trajectories is fed into the model as a temporal sequence. The model utilizes multiple layers of causal dilated convolutions to capture both short-term and long-term dependencies in the temporal sequence, thereby learning the mapping relationship between the input data and the corresponding 3D motion patterns. The network outputs the 3D joint coordinate sequence for each time step.

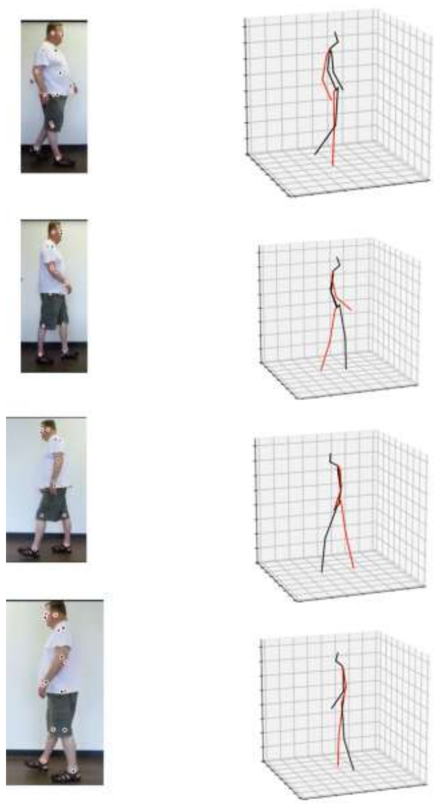

Figure 2. 3D Gait Prediction Gait.

The Fig 2 illustrates the workflow of gait sequence analysis for patients with gait disorders. The left-side image shows the extraction of 17 2D keypoints of the human body using OpenPose, which are annotated on the original image to describe the patient's gait features. Subsequently, deep learning models such as Temporal Convolutional Networks are used to predict these 2D keypoint sequences into the 3D skeletal gait sequence on the right. The 3D skeletal diagram demonstrates the patient's motion trajectory and posture features in three-dimensional space, with red and black skeletons representing dynamic changes at different time steps. This clearly highlights the characteristic changes associated with gait disorders, providing a reliable basis for gait analysis and disease diagnosis.

C. Analysing gait and feature extraction

This graph shows the complete gait cycle phase dynamics, and extracting gait characterisation information from the graph can help diagnose possible gait disorders.

Through the gait analysis shown in the Fig 3, gait features such as gait cycle time, swing phase duration, step length, step width, and joint range of motion (ROM) can be extracted. These features are used to evaluate gait symmetry, stability, and movement efficiency, aiding in the diagnosis of gait abnormalities hemiplegic gait or neurological impairments. This provides a basis for rehabilitation training and disease screening [16].

Normal gait and pathological gait can be distinguished through joint motion patterns. The Fig 4 below illustrates the temporal variation curves of the left knee joints in three-dimensional space X, Y, Z coordinates across different gait categories normal, Parkinson's, stroke, and other pathological gaits. The curves for each category reflect the motion trajectories of the knee joints throughout the gait cycle.

Green is normal gait, the key characteristics of healthy gait include left-right symmetry, smoothness of the knee joint trajectories, and periodic changes.

Purple is Parkinsonian gait is characterized by stiffness in joint motion, reduced range of motion, and less distinct trajectory changes. The restricted knee joint motion trajectories can effectively differentiate Parkinson's disease from normal gait.

Blue is Stroke The most notable feature of stroke gait is the asymmetry in the motion trajectories of the left and right knee joints.

Other pathological gaits is red curve, Other pathological gaits are characterized by irregularity and instability in knee joint trajectories, which may be caused by arthritis, spastic gait, or other lower-limb functional impairments.

To diagnose diseases based on gait characteristics, I extracted 10 features from the gait cycle. Here, I will use two representative features as an example. The formula for the range of motion (ROM) is as follows:

$$\text{Angle} = \arccos\left(\frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \cdot \|\mathbf{B}\|}\right) \tag{3}$$

Joint angle is an important feature in gait analysis for assessing joint flexibility and range of motion (ROM). It plays a significant role in diagnosing and distinguishing Parkinson's disease, stroke, and other gait abnormalities. In Parkinson's patients, the ROM of the knee and hip joints is significantly reduced.

Stride ratio is a key quantitative metric in gait analysis, used to evaluate the relationship between stride length and body dimensions (typically measured by lower limb length or other body reference dimensions). It provides a standardized measure of stride length relative to body proportions, eliminating the influence of height or body size differences on the comparison of absolute stride lengths. The formula is as follows:

$$\text{Stride Ratio} = \frac{\text{Mean Stride Length}}{\text{Mean Body Size}} \tag{4}$$

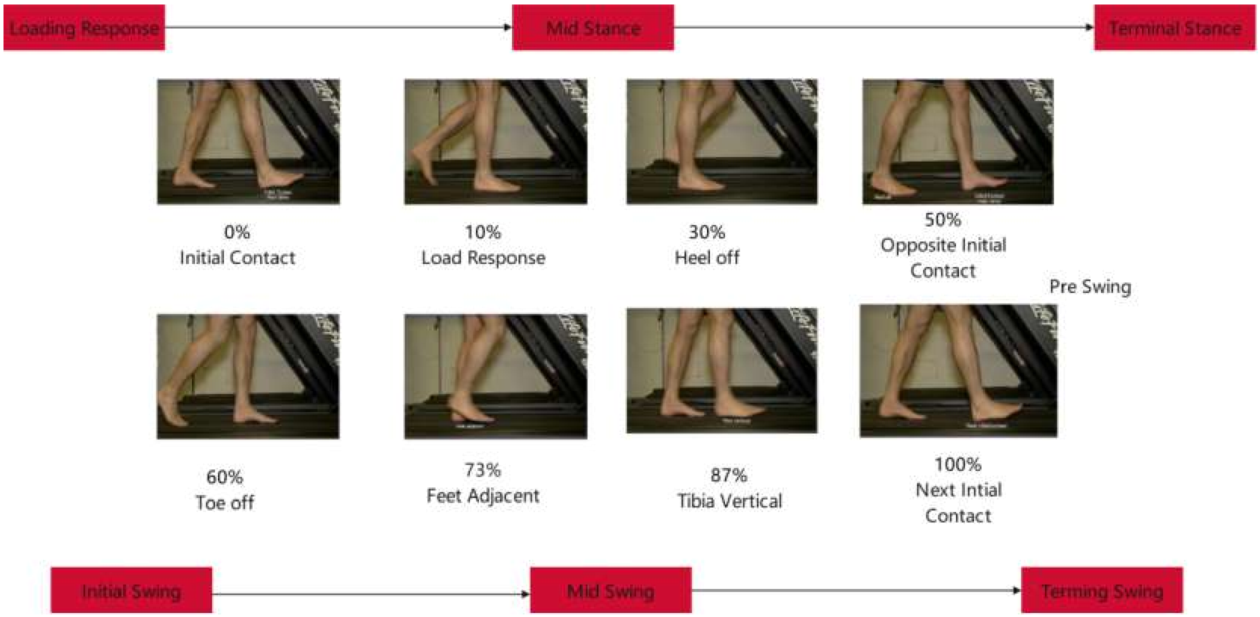

Figure 3. Illustration of the gait cycle.

By calculating the horizontal displacement of the same foot making ground contact twice during the gait cycle, the stride length for each step is determined, and the average stride length is obtained. The average body size is then calculated using the anatomical coordinates of key points hips, knees, and ankles. Dividing the average stride length by the average body size yields the stride ratio [17].

The stride ratio standardizes the relationship between stride length and body size, eliminating the influence of individual body dimensions. It is a crucial indicator for assessing gait symmetry, coordination, and disease screening. By combining the absolute stride length and the body reference length, a more comprehensive analysis of gait abnormalities Parkinsonian gait or stroke gait can be performed.

D. OSTIS-based diagnostic knowledge graph construction

OSTIS relies on semantic networks, so the first step is designing an ontology that maps relationships between gait parameters, diseases, and symptoms. We define the following class for Gait based on parameters: $step\_length$, $speed$, $movement\_symmetry$, $rhythm$, $knee\_flexion\_angle$, $torso\_tilt$, and metrics such as $asymmetry > 15\%$, $speed < 0.8\,m/s$. As a result, it is possible to define classes for diseases, for example: $Parkinson's\_Disease$, $Arthritis$, $Multiple\_Sclerosis$, $Ankle\_Injury$. In this case, there are properties such as $associated\_symptoms$, and $prevalence\_statistics$. This allows the definition of classes for symptoms, for example: $resting\_tremor$, $joint\_pain$, $muscle\_weakness$.

For OSTIS systems, Gait analysis is based on the following relationships:

- $hasSymptom$ (Disease $\rightarrow$ Symptom)
- $hasGaitParameter$ (Disease $\rightarrow$ Gait)
- $correlatesWith$ (Parameter $\rightarrow$ Disease)

OSTIS supports rule-based inference using semantic relationships. An example of diagnostic rules is shown in the following script:

```
If movement asymmetry > 20% and speed<0.6
m/s → suggest Multiple_Sclerosis
rule:
   (gait: movement_asymmetry > 20%) &
   (gait: speed < 0.6)
->(diagnosis: Multiple_Sclerosis,
  probability: 0.75);
If knee flexion angle < 30°and joint_pain
→ suggest Arthritis
rule:
   (gait: knee_flexion_angle < 30) &
   (symptom: joint_pain)
->(diagnosis: Arthritis,probability: 0.85)
```

The advantages of OSTIS technology include Interpretability, Flexibility, and Knowledge Integration. This results in a common ontology that can be expanded with new disease parameters and combines data from diverse sources, such as research and clinical guidelines.

This architecture enables an intelligent system for automated diagnosis and clinical decision support. Implementation requires ontology refinement and collaboration with medical experts. To establish a semantic association between gait features and disease diagnosis, this study utilized the OSTIS platform to construct a three-layer diagnostic knowledge graph, which includes gait features, gait abnormalities, and disease types. OSTIS is an open

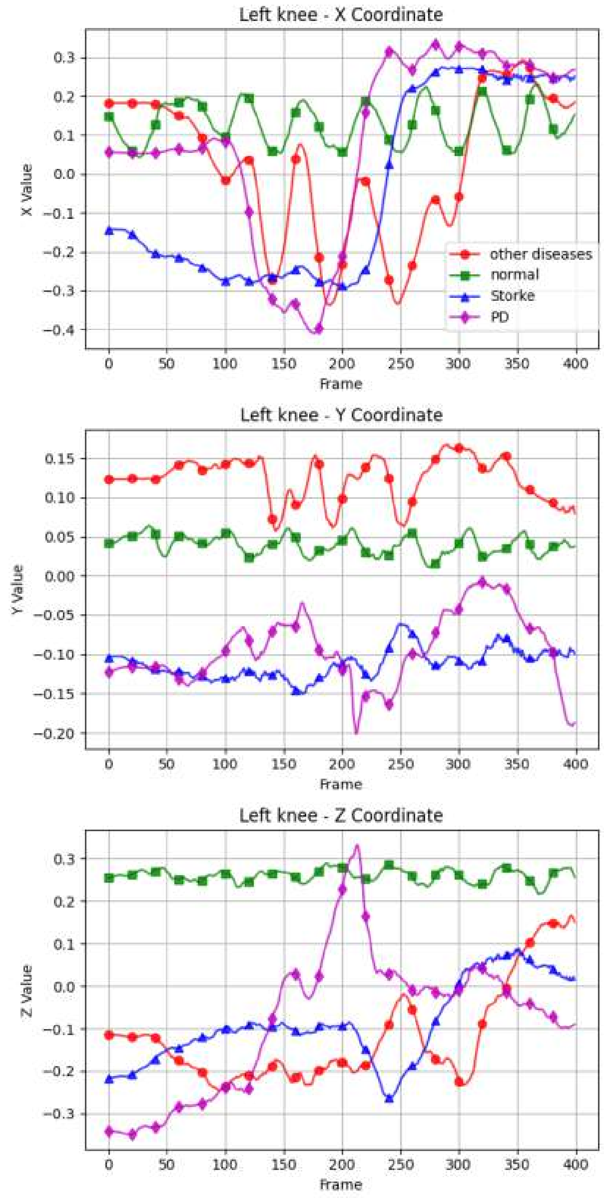

Figure 4. Four categories of knee coordinate change.

semantic technology intelligent system that can model and infer complex semantic relationships through the structured representation and logical reasoning capabilities of its knowledge base [14]. To integrate the semantic information from the OSTIS knowledge graph into the diagnostic model, this study employed the Node2Vec embedding method to represent the nodes in the knowledge graph as low-dimensional vectors. These embedding vectors preserve the semantic structural information of the knowledge graph, enabling the model to utilize the semantic associations of gait features for classification and reasoning [9].

Random walks were performed on the nodes in the knowledge graph gait features, gait abnormalities, and diseases to generate node sequences. Node2Vec was then used to train these sequences and generate vector representations 128 dimensions for each node [10]. The embedding vectors of the gait feature nodes were fused with the actual extracted gait feature data to form semantically enhanced representations of gait features.

E. *MulticlassNN model diagnostics*

The MulticlassNN model integrates gait features and knowledge graph embeddings to construct a neural network-based classification model for gait-related diseases [5]. The model performs four-class classification, distinguishing among “No Disease,” “Parkinson’s Disease,” “Stroke,” and “Other Gait Disorders.”

The input to the model consists of two components: 10 gait features such as stride ratio, speed, joint angle range and a 128-dimensional embedding vector generated from the knowledge graph. The knowledge graph embeddings, created using the Node2Vec algorithm, encode the semantic relationships among gait features, gait abnormalities, and disease nodes into a high-dimensional space, thereby enhancing the feature representation capability.

From the Fig 5, it can be observed that different gait features exhibit significant variations in their distributions across the four classes (Normal, Parkinson’s Disease, Stroke, and Other Gait Disorders). These distribution patterns reflect the characteristic differences in gait abnormalities, providing crucial evidence for disease classification.

From the Fig. 5, it is evident that the feature distributions corresponding to different diseases exhibit significant differences.

Parkinson’s Disease: Characterized by small stride lengths, prolonged gait cycles, and reduced ranges of motion in the ankle and knee joints. Stroke: Features a dispersed distribution, with manifestations such as gait asymmetry, prolonged cycle time, and abnormal swing phase time. Other Gait Disorders: Displays a broader distribution, potentially exhibiting compensatory gait characteristics (e.g., increased stride length and step width). These distribution patterns provide critical evidence for the classification model. By capturing these patterns, the model can effectively distinguish between the gait characteristics of different diseases.

The role of the MulticlassNN model is to combine the physical significance of gait features with the semantic relationships in the knowledge graph to achieve efficient classification of disease-related gaits. Knowledge graph embeddings compensate for the limitations of standalone gait features, enhancing the model’s ability to recognize gait abnormalities such as Parkinson’s disease and stroke. Ultimately, through quantitative analysis of gait features and automated classification, the model provides an accurate tool for early disease screening and diagnosis.

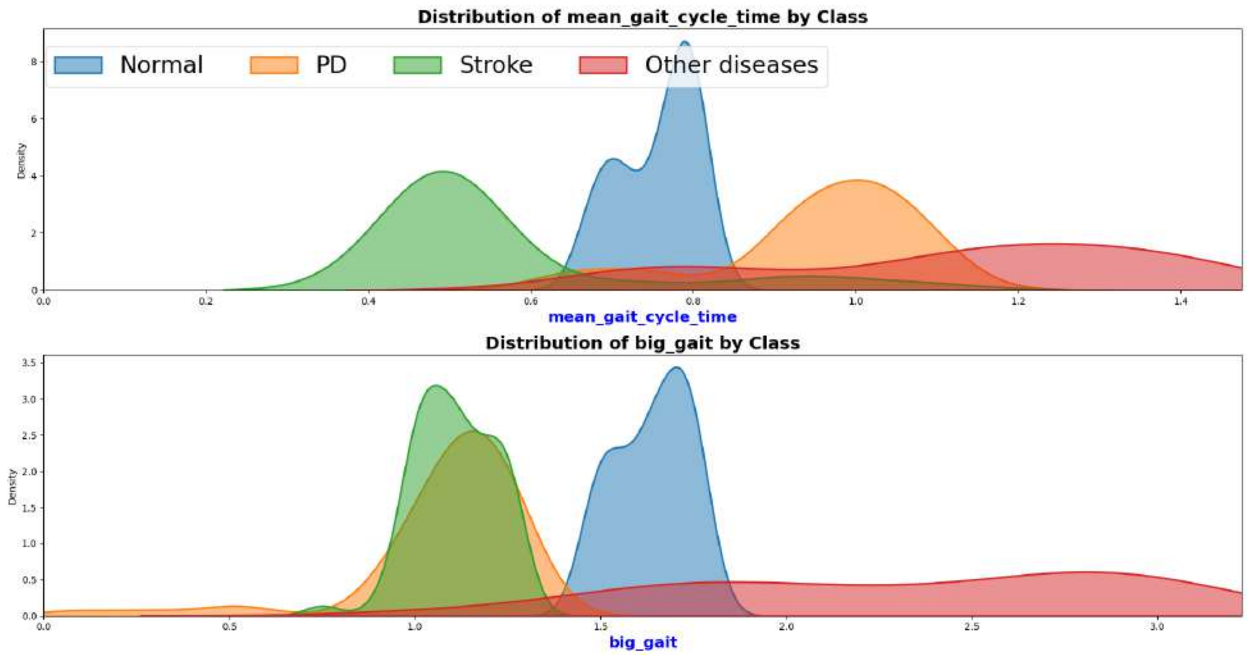

Figure 5. Distribution of values for gait features.

IV. Experimental Results

From Fig. 6 an intelligent disease diagnosis method based on gait video in a four-classification task normal, Parkinson's disease, stroke, and other gait disorders

The loss curve during training indicates that the model converges well within 500 iterations, with the validation loss stabilizing at 0.39 and the training loss decreasing to 0.17. This demonstrates that the model exhibits good fitting performance during both the training and validation phases.

From the Fig 7 report, it can be observed that the Macro Average and Weighted Average F1 scores are both close to 0.93-0.94, further validating the robustness of the model in the overall classification task.

On the test set, the overall accuracy of the model reached 91.8%. From the classification report, it can be observed that the performance metrics across different categories are excellent. Specifically, the "Normal" and "Other Gait Disorders" categories achieved a precision, recall, and F1-score of 1.0.

The recall for Parkinson's Disease is the highest (1.0), but the precision is 0.77, indicating a small number of misclassifications in this category. For the Stroke category, the precision is 1.0, while the recall is 0.74, which may be attributed to the complexity of its feature distribution.

V. Conclusion

This paper proposes an intelligent disease diagnosis method based on gait videos, integrating 3D gait feature extraction, knowledge graph construction, and a deep learning classification model to accurately diagnose four gait states: "Normal," "Parkinson's Disease," "Stroke," and "Other Gait Disorders." Using OpenPose for 2D pose estimation on gait video data and a Temporal Convolutional Network (TCN) to predict 3D poses, ten gait features were extracted, including stride length, gait speed, gait cycle, step width, and joint range of motion. These features comprehensively describe gait patterns and provide critical data support for disease classification.

Additionally, by combining the knowledge graph constructed with the Open Semantic Technology Intelligent System (OSTIS) and the Node2Vec embedding method, the semantic relationships among gait features, gait abnormalities, and diseases were embedded into a high-dimensional space. This enhanced the feature representation capability, providing semantically enriched feature inputs for the model.

The loss curve during training shows that the model converged well within 500 iterations, with the validation loss stabilizing at 0.39 and the training loss decreasing to 0.17. Experimental results indicate that the proposed method achieved a classification accuracy of 91.8% on the test set and demonstrated excellent robustness across multiple classification performance metrics. This indicates that the model effectively captures the characteristic information of the respective categories. The model exhibited good fitting performance during both training and validation phases.

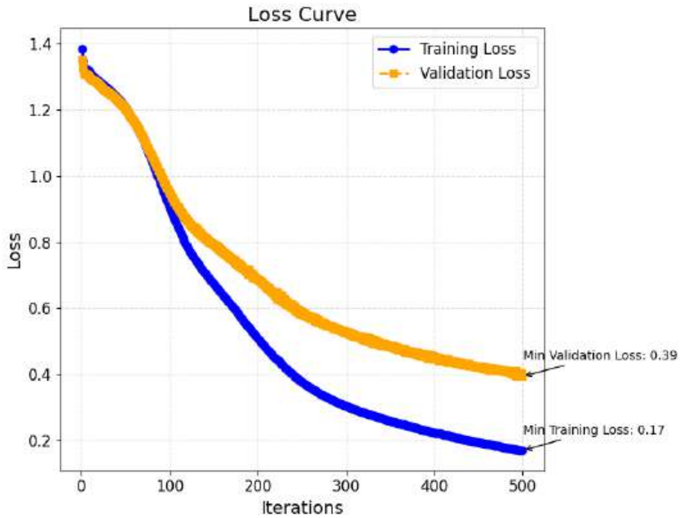

Figure 6. Model losses and classification results.

Accuracy: 0.9180327868852459
Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	9
1	0.77	1.00	0.87	17
2	1.00	0.74	0.85	19
3	1.00	1.00	1.00	16
accuracy			0.92	61
macro avg	0.94	0.93	0.93	61
weighted avg	0.94	0.92	0.92	61

Figure 7. Classification Report and Metrics Overview.

By combining the semantic reasoning capability of the knowledge graph with the precise representation of 3D gait features, this method not only achieves efficient disease classification but also provides semantic interpretability for the diagnostic process, enhancing the explainability of diagnostic results.

This study achieves intelligent and efficient diagnosis of gait abnormalities and diseases through the organic integration of gait feature extraction, semantic reasoning, and classification models. It provides a novel technological approach to intelligent medical diagnosis based on gait analysis. This method holds significant application value in fields such as early disease screening, rehabilitation assessment, and intelligent medical auxiliary diagnosis. Furthermore, it offers theoretical and practical support for the development of future intelligent and contactless medical technologies.

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ИНТЕЛЛЕКТУАЛЬНАЯ ДИАГНОСТИКА ЗАБОЛЕВАНИЙ ПОХОДКИ С ИСПОЛЬЗОВАНИЕМ ВИДЕОАНАЛИЗОВ 3D-ДВИЖЕНИЯ

Аоди Дин, Александр Недзьведь, Хунлинь Цзя, Дзжийдян Го

В данном эксперименте предложен метод интеллектуальной диагностики заболеваний на основе анализа видео походки. Видео походки анализировались с использованием OpenPose для 2D-оценки позы, а для предсказания 3D-поз использовалась временная сверточная сеть (TCN), что позволило получить 3D-данные о движении походки целевого объекта. После извлечения движенческих признаков была построена база знаний и правила вывода для нарушений походки и заболеваний в рамках системы интеллектуальных технологий Open Semantic Technology Intelligent System (OSTIS). Признаки походки были соответственно семантически обработаны. В завершение использовалась модель классификации для диагностики потенциальных заболеваний и предоставления интерпретируемых диагностических рекомендаций. Экспериментальные результаты продемонстрировали, что данный метод эффективно интегрирует 3D-движенческие признаки с семантическим выводом, достигая точной классификации и диагностики заболеваний, тем самым предлагая новый технологический подход к интеллектуальной медицинской диагностике.

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