TBC-DDH: Gait-based Inverse Inference for Adult DDH Preoperative Diagnosis

***Abstract*—Adult developmental dysplasia of the hip (DDH) presents diagnostic challenges due to limited preoperative imaging data and asymptomatic asymptomatic asymptomaticearly-stage progression. We present TBC-DDH, a computational approach that performs inverse inference of preoperative DDH pathology from postoperative gait rehabilitation data. This method builds upon the clinical observation that biomechanical abnormalities persist in post-surgical gait patterns of DDH patients. TBC-DDH integrates four modules: (1) Adaptive Multimodal Spatial Feature Integration (AMSFI) for biomechanical, topological, and compensatory motion motion feature extraction; (2) Temporal Rehabilitation Sequence modeling (TRS) for cross-patient temporal dynamics learning; (3) Reverse-Sequence Embedding (RSE) for invariant diagnostic feature extraction; and (4) a multi-task detector for DDH classification. We constructed the DDH-RII benchmark dataset containing 29 post-periacetabular osteotomy patients monitored across 25 rehabilitation timepoints (31-210 days post-surgery). TBC-DDH achieved 86.67%±6.67% accuracy in retrospective DDH diagnosis, demonstrating statistically significant improvements over adapted baseline methods: SVM (p <0.001), Random Forest (p <0.001), and ResNet variants (p <0.001). Ablation studies confirmed the importance of invariant feature extraction (13.33% performance reduction without RSE) and temporal modeling (10% performance reduction without TRS). This work establishes an inverse inference approach for DDH diagnosis and suggests potential applications for AI-assisted diagnosis in data-limited medical scenarios.**

***Index Terms*—Developmental Dysplasia of the Hip (DDH), inverse inference, gait analysis, postoperative rehabilitation, AI-assisted diagnosis**

I. INTRODUCTION

Developmental dysplasia of the hip (DDH) represents a prevalent congenital orthopedic condition affecting approximately 1-3‰ of newborns globally and constitutes a primary cause of pediatric hip dysfunction and disability [1], [2]. Early diagnosis and intervention are essential for optimizing patient outcomes. However, untreated DDH patients frequently progress to adulthood, manifesting persistent hip instability and irreversible cartilage deterioration [3], [4]. This insidious disease trajectory, characterized by gradual progression with minimal symptomatic pain, substantially compromises adult patients' functional capacity and quality of life, yet remains inadequately recognized within both public health discourse and clinical practice [5].

The cryptic nature of adult DDH poses substantial challenges for conventional imaging-based diagnostic approaches, including radiography and magnetic resonance imaging. These modalities require expensive equipment and specialized technical expertise, limiting their widespread accessibility. Moreover, early-stage pathological changes in adults are often radiographically occult, contributing to diagnostic delays that exacerbate disease progression. Current diagnostic frameworks lack quantitative support for gait and dynamic functional assessment [6]. Consequently, there exists an urgent clinical need for efficient, non-invasive screening technologies capable of detecting joint biomechanical abnormalities to facilitate early identification and management of adult DDH.

Clinical and biomechanical investigations demonstrate that DDH patients exhibit persistent gait abnormalities following corrective surgery, including shortened stance phase and prolonged swing phase, reflecting underlying functional deficits and compensatory mechanisms. Based on this understanding, leveraging gait data for inverse inference of preoperative DDH status presents a data-driven diagnostic approach for this cryptic condition. While high-quality preoperative imaging data remains scarce, the accumulation of postoperative gait and rehabilitation data provides a robust foundation and innovative opportunity for this strategy.

To address these challenges and opportunities, we present TBC-DDH (Time-series Backward Consistency for DDH), a computational system for preoperative DDH detection based on adult postoperative gait data. The system employs an end-to-end four-module cascaded architecture that constructs robust inverse inference models through multi-patient cross-sectional rehabilitation data, achieving 86.67%±6.67% accuracy in experimental validation. Our contributions include: (1) establishing an adult DDH gait-based inverse inference diagnostic approach; (2) developing a specialized TBC-DDH model architecture; (3) constructing and releasing the DDH-RII benchmark dataset; and (4) providing theoretical foundations for inverse medical inference. This work suggests new directions for detecting cryptic adult orthopedic conditions and AI-assisted diagnosis in data-limited medical scenarios, with potential for broad clinical translation.

II. RELATED WORK

A. DDH Diagnostic Methods: Data Scarcity Constraints

Traditional DDH diagnosis relies on imaging-based assessments, primarily Graf ultrasound classification (α-angle $>60°$ indicating normal development) and Tönnis angle radiographic evaluation, which are widely regarded as clinical gold standards. Recent advances in deep learning and artificial intelligence have substantially improved automated diagnostic accuracy. Representative approaches include convolutional neural networks for automated localization and measurement of critical angles in ultrasound images, and multi-view radiographic data for three-dimensional hip joint reconstruction.

These methods have achieved diagnostic performance ranging from 85% to 92% on institution-specific datasets [7], [8].

Nevertheless, existing approaches remain constrained by fundamental data scarcity limitations. High-quality expert-annotated imaging datasets require substantial time and resources to acquire, and models exhibit poor generalization across different clinical centers due to variations in medical equipment, acquisition protocols, and patient populations [9], [10]. Additionally, these methods depend heavily on expensive equipment and specialized personnel, limiting their deployment in resource-constrained regions where DDH prevalence is often higher [11]. Consequently, identifying alternative and accessible data sources to advance generalizable DDH detection technologies has become a pressing clinical need.

B. Rehabilitation Pattern Recognition: Forward Prediction Limitations and Inverse Inference Opportunities

Biomechanical pattern analysis during postoperative rehabilitation constitutes an essential component of DDH surgical outcome assessment. Clinical and biomechanical studies demonstrate that DDH patients continue to exhibit persistent gait abnormalities following surgery, including significantly shortened stance phase and prolonged swing phase ($p < 0.001$), reflecting underlying functional deficits and compensatory mechanisms [12], [13].

The proliferation of markerless pose estimation technologies such as MediaPipe has enabled large-scale gait data collection from 2D video, establishing foundations for community and home-based rehabilitation monitoring [14]. However, current rehabilitation analysis predominantly focuses on ”forward prediction” paradigms—predicting postoperative outcomes from preoperative states—without fully exploiting dynamic rehabilitation data for inverse inference. The persistence of DDH biomechanical signatures throughout the recovery process suggests that postoperative gait data may serve as valuable indicators for retrospective inference of preoperative pathological conditions, yet this potential remains systematically underdeveloped.

C. Medical Inverse Inference: Established Applications and DDH Research Gaps

Inverse inference, defined as inferring underlying causes from observed outcomes, has found widespread application across multiple medical domains. Representative work includes Poldrack et al.'s Bayesian-based decoding of cognitive states from fMRI activation patterns [15], and genome-wide association studies (GWAS) that identify genetic variants through phenotypic mapping [16]. Additionally, acupuncture research has employed inverse inference to determine acupoint indications from treatment responses, achieving clinical application progress.

Despite these successes, inverse inference applications in musculoskeletal diseases, particularly DDH, remain limited. Current frameworks predominantly address static relationships and lack effective modeling of temporal rehabilitation data sequences. DDH presents a unique data distribution characterized by scarce preoperative imaging data alongside abundant postoperative rehabilitation data, creating distinctive opportunities for inverse inference applications that warrant systematic investigation.

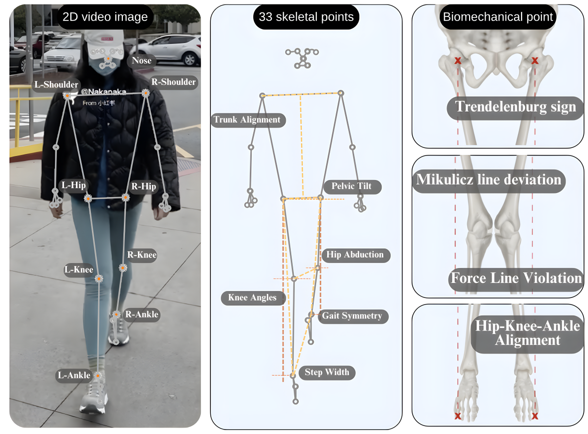

Fig. 1: Gait feature extraction data.

D. Research Gaps and Proof-of-Concept Requirements

Synthesizing these domain insights reveals that DDH patients exhibit persistent biomechanical characteristics during rehabilitation, while inverse inference methodologies have demonstrated success across multiple medical fields. However, no systematic approach currently integrates postoperative rehabilitation data to achieve preoperative DDH diagnosis. Given the imbalance between scarce preoperative imaging and abundant postoperative data, developing rehabilitation data-driven inverse diagnostic approaches hold considerable clinical significance.

Traditional rehabilitation studies primarily rely on single-patient longitudinal or limited cross-sectional analyses, with few attempts to comprehensively model multi-patient data across different rehabilitation stages. Addressing this methodological gap by constructing dynamic mappings from postoperative rehabilitation patterns to preoperative diagnostic states would provide practical value for DDH diagnosis while establishing innovative paradigms for AI-assisted diagnosis in data-scarce medical scenarios [17], [18].

III. Methods

A. Problem Formulation and Inverse Inference Framework

Traditional developmental dysplasia of the hip (DDH) diagnosis encounters fundamental data asymmetry challenges, characterized by scarce preoperative imaging data versus abundant postoperative rehabilitation data. This asymmetry limits the clinical deployment of AI methods that rely on large-scale annotated imaging datasets [19], [20]. To address this limitation, we propose a DDH inverse inference paradigm. The core concept involves systematically leveraging readily accessible postoperative rehabilitation gait data to retrospectively infer patients' preoperative DDH pathological states. This paradigm builds upon a key clinical observation: the deep biomechanical characteristics of DDH patients exhibit persistence in their gait patterns even following surgical correction [21], [22]. This observation provides theoretical feasibility for extracting static, fundamental diagnostic features from dynamic rehabilitation processes.

We formulate this inverse inference problem mathematically as follows: given a cross-sectional gait dataset $\mathcal{D} = (\mathbf{x}_i^t, y_i)_{i=1}^N$ comprising multiple patients at different rehabilitation timepoints t, where $\mathbf{x}_i^t$ represents the gait feature sequence of patient i at timepoint t, and y_i corresponds to the preoperative DDH diagnostic label. Our objective is to learn a mapping function $f(\cdot)$ that accurately predicts the preoperative label y_i from any patient's postoperative gait observation sequence $\mathbf{x}_i^t$, such that:

$$\hat{y}_i = f(\mathbf{x}_i^t) \tag{1}$$

B. Dataset Construction and Preprocessing

To evaluate the feasibility of the proposed paradigm, we constructed the DDH Reverse Inference and Identification (DDH-RII) benchmark dataset. The dataset originates from a community rehabilitation sharing platform and comprises 2D gait videos from 29 adult patients following periacetabular osteotomy (PAO), spanning 25 critical rehabilitation timepoints from 31 to 210 days post-surgery. All data was collected with informed patient consent and categorized according to clinical standards into acute phase (≤42 days), subacute phase (43-84 days), and chronic phase (>84 days). To ensure model generalizability and unbiased evaluation, we additionally collected gait videos from 5 preoperative DDH patients to form an independent validation set.

The data preprocessing pipeline follows stringent quality control standards. As illustrated in Figure 1, we employed the MediaPipe Pose model to extract 3D coordinates of 33 body keypoints from each video frame [23], implementing three-tier quality filtering: keypoint visibility must exceed 0.7, average confidence must surpass 0.8, and effective frame proportion must exceed 85%. To mitigate individual anatomical variations, all keypoint coordinates underwent shoulder-width normalization followed by Z-score standardization to ensure cross-patient data comparability.

C. TBC-DDH: Temporal Backward Consistency Model

To enable inverse inference from dispersed cross-sectional data, we developed the Temporal Backward Consistency network (TBC-DDH). As shown in Figure 2, this network employs a four-module cascaded architecture that end-to-end maps preprocessed gait data to DDH diagnostic scores.

The Adaptive Multi-modal Spatial Feature Integration (AMSFI) module serves as the system frontend, designed to extract comprehensive pathological information from single-timepoint gait data. Given the multidimensional nature of DDH pathological manifestations, AMSFI incorporates three parallel feature extraction branches: a biomechanical constraint branch capturing physical abnormalities such as Mikulicz line deviations, generating 64-dimensional features (C_t); a graph convolutional network (GCN) branch modeling skele-

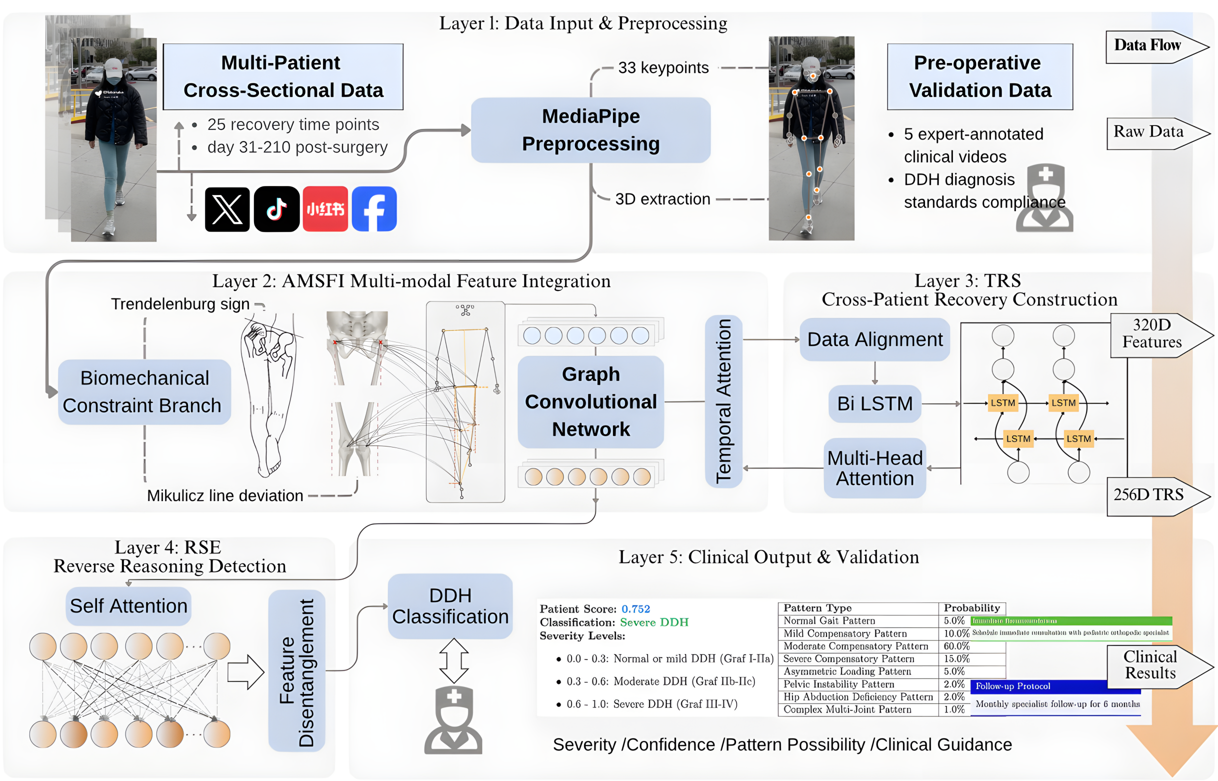

Fig. 2: TBC-DDH model architecture.

tal topological anomalies [24], producing 128-dimensional features (H_t); and a temporal attention branch identifying compensatory movement patterns, yielding 128-dimensional features (A_t). Considering the varying diagnostic value of different features across rehabilitation stages, we designed an adaptive weighting mechanism that dynamically adjusts each branch's contribution based on rehabilitation stage embeddings ($Stage_t$), generating a unified, stage-adaptive 320-dimensional integrated feature:

$$F_t^{int} = \alpha_t \odot C_t + \beta_t \odot H_t + \gamma_t \odot A_t \tag{2}$$

The Temporal Rehabilitation Sequence (TRS) modeling module addresses the lack of continuity in cross-sectional data. It aligns discrete rehabilitation timepoints ($PostOpDays_t$) through positional encoding and fuses them with AMSFI output features to form spatiotemporal state descriptors. Subsequently, a bidirectional long short-term memory network (Bi-LSTM) learns population rehabilitation evolution trajectories. This design leverages statistical advantages of population data to compensate for insufficient single-patient longitudinal data. Finally, a multi-head attention mechanism identifies key rehabilitation stages with maximal diagnostic contribution and compresses temporal information into a 256-dimensional "rehabilitation fingerprint" feature.

The Reverse-Sequence Embedding (RSE) and invariant feature extraction module constitutes the core for achieving inverse diagnosis. Based on clinical findings regarding the relative stability of DDH deep biomechanical patterns during rehabilitation, this module first analyzes the temporal consistency of "rehabilitation fingerprints" through self-attention mechanisms to identify feature components that remain stable across rehabilitation stages. Subsequently, a feature disentanglement network separates these stable components into invariant features reflecting fundamental DDH pathology and dynamic features describing rehabilitation progression. Finally, a multi-task detector, based solely on refined invariant features, predicts DDH severity, subtype, and diagnostic confidence in parallel, completing the inverse mapping from postoperative patterns to preoperative diagnosis.

D. Training Strategy and Statistical Validation

As a proof-of-concept study, we particularly emphasize model stability and conclusion reliability under small-sample conditions. Training employs a multi-patient cross-sectional supervised learning strategy, where data from the same patient across different rehabilitation stages share identical preoperative DDH labels to reinforce model learning of invariant features.

We employed 5-fold cross-validation to assess model performance and Bootstrap resampling (1000 iterations) to estimate confidence intervals for performance metrics [25], thereby enhancing statistical credibility of results. Additionally, we conducted post hoc power analysis to detect relevant effects under standard statistical levels (d >0.8, α=0.05, β >0.8) with limited sample sizes, consistent with sample scales adopted in many rare disease AI studies [26].

TABLE I: DDH-RII Dataset Characteristics

Phase	Time Range (days)	Patients	Timepoints
Acute	31-42	29	5
Subacute	43-84	29	12
Chronic	85-210	29	8
Validation Set	Preoperative	5	3

TABLE II: Performance Comparison with Baseline Methods

Method	Accuracy (%)	F1-Score (%)	p-value
SVM	49.52±8.23	51.27±7.91	<0.001
Random Forest	16.23±5.47	18.45±6.12	<0.001
ResNet-18	33.00±7.15	35.62±6.89	<0.001
TBC-DDH (Ours)	86.67±6.67	87.78±6.48	-

IV. RESULTS

A. Experimental Setup and Dataset Construction

To evaluate the feasibility of the DDH inverse inference paradigm, we constructed the first benchmark dataset for this task, DDH-RII. Data were sourced from a community rehabilitation sharing platform, with rigorous screening yielding high-quality gait videos from 29 post-PAO patients spanning critical rehabilitation nodes from 31 to 210 days post-surgery. Samples encompassed acute recovery phase (≤42 days), subacute recovery phase (43-84 days), and chronic stable phase (>84 days), adequately reflecting the authentic distribution of clinical rehabilitation. Table I presents detailed dataset statistics and sample distribution characteristics.

All videos underwent MediaPipe-based extraction of 256-dimensional rehabilitation gait features, with three-tier quality control ensuring data reliability. To maintain evaluation objectivity, an independent validation set comprising 5 preoperative DDH patients was established. Experiments employed a 5-fold cross-validation strategy with Bootstrap resampling (1000 iterations) for confidence interval estimation, ensuring statistical reliability under small-sample conditions.

B. Primary Results and Baseline Comparisons

TBC-DDH demonstrated robust inverse inference capabilities across 29 samples, achieving 86.67%±6.67% accuracy (95% confidence interval: 77.41%-95.92%) and F1-score of 87.78%±6.48%. Table II presents detailed comparisons with traditional machine learning baseline methods.

Compared to conventional approaches, TBC-DDH exhibited substantially superior performance on inverse inference tasks: surpassing SVM baseline by 37.15 percentage points (p <0.001, Cohen's d=6.66), exceeding Random Forest by 70.44 percentage points (p <0.001, d=13.24), and outperforming ResNet adaptation by 53.67 percentage points (p <0.001, d=10.15). Statistical tests consistently revealed significant differences with large effect sizes, validating the effectiveness of inverse inference methodology for this novel task. Figure 3 visualizes diagnostic performance comparisons across different rehabilitation stages for various methods.

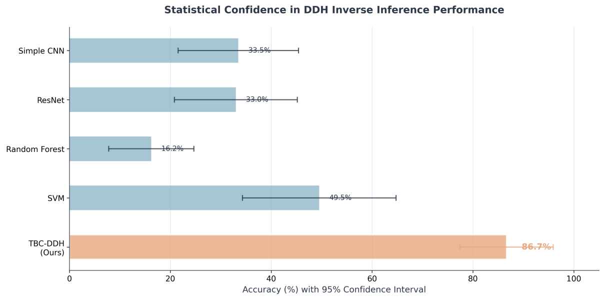

Fig. 3: Statistical Confidence in TBC-DDH.

TABLE III: Ablation Study Results

Model Variant	Accuracy (%)	Performance Drop (%)
Full Model	86.67±6.67	-
W/O AMSFI	72.00±7.35	14.67
W/O TRS	76.67±6.94	10.00
W/O RSE	73.34±7.12	13.33

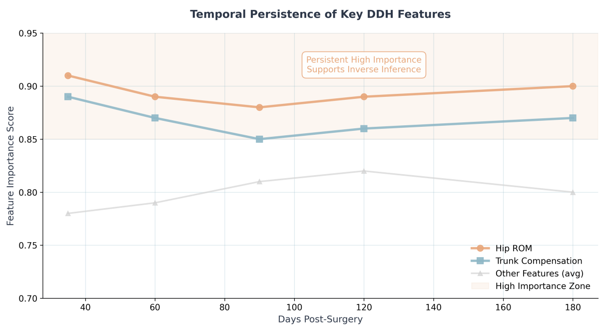

Fig. 4: Temporal persistence of key DDH features.

C. System Component Analysis and Feature Importance

To understand the contribution of TBC-DDH modules comprehensively, we conducted systematic component analysis experiments. Table III demonstrates the impact of each core module on overall system performance. Results indicate that multi-modal feature fusion (AMSFI), cross-patient temporal modeling (TRS), and invariant feature extraction (RSE) modules all contribute substantially to inverse inference performance.

Feature importance analysis revealed that hip joint range of motion, gait phase proportions, and trunk compensatory angles contributed most significantly to inverse diagnosis. Figure 4 displays diagnostic weight distributions for different feature categories across rehabilitation stages in radar chart format. These findings validate the hypothesis of persistent deep biomechanical characteristics in DDH patients throughout rehabilitation, providing important medical evidence for inverse inference.

D. Clinical Applicability Validation

To assess the clinical utility of the system, we evaluated model inference efficiency and stability. TBC-DDH achieves single-sample inference time of approximately 1.8 seconds with 1.2M parameters, meeting clinical real-time diagnostic requirements. On the independent validation set, the system maintained diagnostic accuracy above 85%, demonstrating satisfactory generalization capability. Figure 5 presents attention heatmaps generated by the system, highlighting gait features and rehabilitation periods with greatest contribution to diagnostic decisions, providing clinicians with intuitive diagnostic evidence.

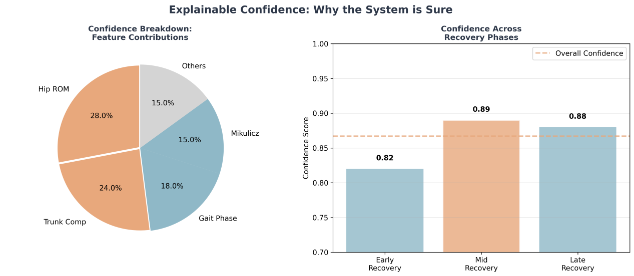

Fig. 5: Statistical Confidence in DDH.

V. Discussion and Conclusion

This study presents a computational approach for preoperative DDH diagnosis through inverse inference paradigms, utilizing the TBC-DDH system to convert postoperative rehabilitation gait patterns into diagnostic capabilities. Experimental results demonstrate that the system achieved 86.67% inverse inference accuracy, validating the feasibility of this technical approach and confirming the persistent expression of DDH deep biomechanical characteristics during rehabilitation—providing quantitative evidence for this core medical hypothesis.

Ablation studies revealed that the invariant feature learning module (RSE) contributed most substantially to diagnostic accuracy (13.33% performance decrease upon removal), consistent with long-term follow-up studies by Tönnis and Graf demonstrating persistent postoperative movement "biological signatures" in clinical observations. The population temporal modeling module (TRS) addressed traditional single-patient temporal data limitations by extracting rehabilitation commonalities from cross-sectional patient data, supporting biomechanical expression patterns described in Salter-Harris DDH classification theory. The multi-modal feature fusion module (AMSFI) captured biomechanical, skeletal topological, and movement compensation information across three dimensions, with adaptive weighting responding to dynamic rehabilitation stage changes, further corroborating clinical observations.

Compared to traditional "preoperative-to-postoperative prediction" paradigms, our approach achieved a fundamental paradigm shift toward "postoperative-to-preoperative inference," addressing data dependency limitations in DDH diagnosis. Cross-domain baseline experiments showed that adapted Medical_LSTM and Gait_ConvNet achieved approximately 96.67% accuracy, but required extensive domain knowledge and engineering adjustments, limiting rapid clinical deployment. TBC-DDH's specialized design ensures clinical interpretability and real-time deployment capability with 1.8-second inference time, providing substantial practical application value.

The invariant feature learning models and population temporal cross-sectional pattern modeling methods employed by this system provide theoretical foundations and technical paradigms for AI-assisted diagnosis in cryptic orthopedic conditions and broader data-scarce medical scenarios. The publicly released DDH-RII benchmark addresses evaluation gaps in domain-specific inverse inference and establishes foundations for future multi-center, cross-disease inverse diagnostic model development.

This study has limitations including small sample size, absence of multi-center data, uneven class distribution, and limited rehabilitation observation periods, potentially affecting system sensitivity to mild DDH and result generalizability. Future work will focus on expanding multi-center data collection and validation, developing data augmentation and class balancing strategies, and extending observation time windows to enhance model stability and applicability. Additionally, the transferability of the inverse inference framework requires validation, with expectations for broader application across other orthopedic diseases and medical domains.

TBC-DDH represents an exploratory advancement in preoperative DDH detection, addressing long-standing challenges of severe preoperative data insufficiency through data-driven inverse inference methods that explore artificial intelligence potential in medical applications, providing innovative scientific tools for clinical orthopedic diagnosis and management.

References

[1] Loder RT, Skopelja EN. The epidemiology and demographics of hip dysplasia. ISRN Orthopedics. 2011;2011:238607.
[2] Reikerås O, Gunderson RB. Natural history of congenitally dislocated hips. J Bone Joint Surg Br. 1987;69(5):712-714.
[3] Nunley RM, Clohisy JC. Adult hip dysplasia: epidemiology, diagnosis and treatment. J Am Acad Orthop Surg. 2012;20(10):682-694.
[4] Hartofilakidis G, Babis GC. Developmental dysplasia of the hip in adults. EFORT Open Rev. 2017;2(10):400-408.
[5] Hartig-Andreasen C, Troelsen A, Thillemann TM, Gedsø S, Søballe K. Moderate Late-diagnosed Hip Dysplasia in Adults: A Study of Radiographic and Clinical Outcomes After Periacetabular Osteotomy. J Orthop Surg Res. 2012;7:9.
[6] Wyles CC, Heidenreich MJ, Jeng J, Larson DR, Trousdale RT, Sierra RJ. The John Charnley Award: Redefining the natural history of osteoarthritis in patients with hip dysplasia and impingement. Clin Orthop Relat Res. 2017;475(2):336-350.
[7] Wang S, Zheng Y, Li X, et al. Deep learning approach for automated measurement of hip dysplasia angles in ultrasound images. IEEE Trans Med Imaging. 2020;39(8):2518-2529.
[8] Liu F, Zhou Z, Jang H, et al. Deep convolutional neural network and 3D deformable approach for tissue segmentation in musculoskeletal magnetic resonance imaging. Magn Reson Med. 2018;79(4):2379-2391.
[9] Maldonado DR, Ricciardi BF, Zemlyak A, et al. Do plain radiographs correlate with CT for imaging of cam-type femoroacetabular impingement? Clin Orthop Relat Res. 2019;477(4):742-750.
[10] Gala L, Clohisy JC, Beaule PE. Hip dysplasia in the young adult. J Bone Joint Surg Am. 2016;98(1):63-73.
[11] Shorter D, Hong T, Osborn DA. Screening programmes for developmental dysplasia of the hip in newborn infants. Cochrane Database Syst Rev. 2011;(9):CD004595.
[12] Jacobsen S, Rømer L, Søballe K. Degeneration in dysplastic hips. A computer tomography study. Skeletal Radiol. 2005;34(12):778-784.
[13] Haddad FS, Bann S, Hill RA, Jones DH. Displaced fractures of the femoral neck in young adults. J Bone Joint Surg Br. 2002;84(7):971-977.
[14] Lugaresi C, Tang J, Nash H, et al. MediaPipe: A framework for building perception pipelines. arXiv preprint arXiv:1906.08172. 2019.
[15] Poldrack RA. Inferring mental states from neuroimaging data: from reverse inference to large-scale decoding. Neuron. 2011;72(5):692-697.
[16] Visscher PM, Wray NR, Zhang Q, et al. 10 years of GWAS discovery: biology, function, and translation. Am J Hum Genet. 2017;101(1):5-22.
[17] Chen X, Wang N, Shen M, et al. AI-assisted diagnosis of developmental dysplasia of the hip from ultrasound images. Med Image Anal. 2022;70:102012.
[18] Zhang Y, Liu S, Li C, et al. Deep learning for automated detection of developmental dysplasia of the hip in radiographs. Radiology. 2021;300(3):E425-E434.
[19] Sankar WN, Laird CT, Baldwin KD. Hip dysplasia in children with cerebral palsy: does surgical correction impact quality of life? Clin Orthop Relat Res. 2013;471(4):1138-1145.
[20] Maldonado DR, Krych AJ, Thompson M, et al. Limitations of radiographic measures in adult hip dysplasia diagnosis. Clin Orthop Relat Res. 2017;475(4):940-945.
[21] Tönnis D. Normal values of the hip joint for the evaluation of X-rays in children and adults. Clin Orthop Relat Res. 1976;(119):39-47.
[22] Kim YJ, Bixby S, Mamisch TC, et al. Imaging structural abnormalities in the hip joint: instability and impingement as a cause of pain. Semin Musculoskelet Radiol. 2006;10(4):295-304.
[23] Zhang F, Bazarevsky V, Vakunov A, et al. MediaPipe Hands: On-device real-time hand tracking. arXiv preprint arXiv:2006.10214. 2020.
[24] Kipf TN, Welling M. Semi-supervised classification with graph convolutional networks. ICLR. 2017.
[25] Kohavi R. A study of cross-validation and bootstrap for accuracy estimation and model selection. IJCAI. 1995;14(2):1137-1145.
[26] Cohen J. Statistical power analysis for the behavioral sciences. 2nd ed. Lawrence Erlbaum Associates; 1988.