A Deep Learning Framework with Kinetic Chain Graphs for Sports Striking Motion Evaluation

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***Abstract*—Striking motion quality evaluation in sports is a core topic in intelligent motion analysis. Existing approaches often neglect kinetic chain sequencing and inter-segment force transfer that underpin efficient movement execution, leading to evaluations that are weakly grounded in biomechanics and insufficient to represent true motion quality. To address this limitation, we propose Kinetic Chain Graph Modeling for Striking Motion Evaluation (KCG-SME), a general deep learning framework that formulates the execution of striking motions as a chain-structured graph. In this formulation, nodes correspond to key body segments, while edges encode inter-segment interactions and force transmission along the kinetic chain. Temporal modeling is further incorporated over the entire motion cycle to capture long-range dependencies in motion execution. Although badminton striking motions are used as a representative case study, the proposed framework is general and applicable to a broad class of kinetic-chain-dominated movements, including tennis strokes and baseball pitching. Experimental results demonstrate that KCG-SME consistently outperforms baseline methods. On the forehand clear task, it achieves an absolute F1-score improvement of approximately 4.2%–15.7% compared with baselines. The source code is publicly available at https://github.com/fangluoning/KCG-SME.**

***Index Terms*—Human motion evaluation, Kinetic chain graphs, Graph modeling, Spatiotemporal learning, Motion representation, Striking motions.**

I. Introduction

Striking sports, including badminton, tennis, table tennis, and baseball, are widely practiced worldwide and involve a large and diverse participant population [1]–[4]. Striking motion quality in these sports depends on the coordinated execution of whole body movements, arising from the ordered activation and interaction of multiple body segments [5], [6]. In practice, motion quality evaluation has largely relied on expert judgement, which is inherently subjective and lacks consistency across evaluators and contexts, highlighting the need for intelligent motion evaluation methods that enable objective and reproducible assessment [7], [8].

Recently, wearable sensors have been widely adopted in sports motion analysis, as they can be directly attached to the human body or sporting equipment, enabling continuous acquisition of kinematic and physiological signals [9], [10]. Meanwhile, deep learning has emerged as an effective evaluation paradigm, significantly improving assessment performance compared with traditional handcrafted approaches. Together, wearable sensing technologies and deep learning constitute a central research direction for objective motion quality evaluation in sports motion analysis [11], [12]. For instance, Steels et al. [13] integrated inertial sensor data with angular velocity information to improve the characterization of stroke execution. Zheng et al. [14] incorporated pressure sensors into racket finger sleeves to quantify grip stability, enabling effective discrimination of players with different skill levels. Lin et al. [15] employed electromyography (EMG) to analyze muscle pre-activation patterns during jump smashes, revealing higher temporal synchronization at impact among elite athletes.

Despite significant progress on specific tasks, most existing methods represent human motion as independent signals or patterns, without explicitly modeling the biomechanical structure underlying coordinated movement. In striking actions, motion execution follows kinetic chain principles, where force generation and transfer depend on the ordered sequencing of body segments. Ignoring this structure leads to evaluations that are weakly grounded in biomechanics and less suitable for assessing the quality of kinetic chain dominated movements [16], [17].

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To address these limitations, we propose Kinetic Chain Graph Modeling for Striking Motion Evaluation (KCG-SME), a deep learning framework that incorporates kinetic chain structure into motion evaluation. Striking motions are modeled as chain-structured graphs, where body segments are represented as nodes and their coordinated force transmission is captured through structured connections, together with temporal modeling over the motion sequence. While badminton strokes are used as a case study, the proposed framework is general and applicable to a wide range of kinetic-chain-dominated striking movements.

The main contributions of this paper are as follows:

- We introduce a kinetic-chain-based graph representation that models the ordered force transmission among body segments and captures structural dependencies along the kinetic chain.
- We present a deep learning framework for striking motion quality evaluation, which combines kinetic-chain graph modeling with temporal modeling to improve evaluation accuracy.
- We evaluate the proposed method on real-world wearable sensor data, and experimental results show consistent improvements over baseline methods in motion quality assessment.

II. RELATED WORK

Research on striking sports motion analysis has increasingly focused on motion quality evaluation, aiming to assess execution proficiency using multimodal sensing data. Many existing studies employ data-driven models based on wearable sensors, such as inertial measurements, electromyography, and pressure signals, to infer skill level or performance quality through supervised learning frameworks trained on large-scale datasets [13], [18], [19]. These approaches demonstrate that wearable sensor data encode rich information related to execution quality, quality assessment is often derived implicitly from learned patterns.

Although vision-based methods have also been widely used for sports motion analysis [20]–[22], they are inherently limited by motion capture accuracy, occlusion, and the difficulty of capturing force-related information. In contrast, wearable sensors can be directly attached to the athlete or sporting equipment, providing continuous measurements of both movement and physiological states, which has motivated extensive research on sensor-based motion quality evaluation.

To obtain more objective evaluation cues, prior work has further explored kinematic and physiological indicators associated with striking performance, including joint angles, angular velocity, impact timing, and muscle activation patterns [23]–[25]. While such indicators offer interpretable measurements linked to motion execution, they are typically analyzed in isolation, with limited consideration of coordinated whole-body behavior.

Recent deep learning approaches further enhance motion quality evaluation by modeling complex spatiotemporal dependencies from multimodal sensor data [26], [27]. Nevertheless, most existing methods remain largely data-driven and do not explicitly encode biomechanical structure. In particular, the kinetic chain organization governing ordered force transmission across body segments during striking motions is rarely incorporated into the evaluation process, which constrains both interpretability and the ability to relate assessment outcomes to underlying execution mechanisms [28].

III. METHOD

A. Overall framework

Striking sports involve complex whole-body coordination, where motion quality is fundamentally governed by kinetic chain organization and sequential force transmission. Therefore, we propose KCG-SME, a deep learning framework that integrates kinetic chain structure into striking motion evaluation. As illustrated in Fig. 1, the proposed framework consists of three main stages:

1) Kinetic Chain Graph Construction, which organizes multimodal wearable signals into a chain-structured graph according to body segment connectivity.
2) Spatial GCN Encoder, which captures spatial dependencies and force propagation patterns along the kinetic chain.
3) Temporal Transformer Encoder, which models long-range temporal dynamics over the complete striking motion for quality assessment.

B. Kinetic Chain Graph Construction

Striking motion quality emerges from coordinated whole-body execution governed by kinetic chain mechanics, where mechanical energy is generated proximally and transmitted toward distal endpoints. Accordingly, we model striking motions as phase-indexed kinetic chain graph signals that explicitly encode segment representations and directed force transmission over time.

We define a kinetic chain consisting of N functional body segments ordered from proximal to distal, indexed by the node set $V = \{1, \ldots, N\}$. Each node represents a functional contributor to force generation or transmission. Given phase aligned multimodal observations $\{\hat{\mathbf{s}}_m(\tau_k)\}_{m=1}^{M}$ at phase τ_k, we construct a segment specific descriptor by aggregating modality information according to its biomechanical relevance:

$$\mathbf{x}_i(\tau_k) = \phi_i\big(\hat{\mathbf{s}}_1(\tau_k), \ldots, \hat{\mathbf{s}}_M(\tau_k)\big) \in \mathbb{R}^{d_i}, \tag{1}$$

where $\phi_i(\cdot)$ maps heterogeneous modality streams to the functional segment i. To obtain a unified representation amenable to graph based modeling, we project the heterogeneous segment descriptors into a shared latent space:

$$\mathbf{h}_i(\tau_k) = \mathbf{W}_i \mathbf{x}_i(\tau_k) + \mathbf{b}_i \in \mathbb{R}^{d}. \tag{2}$$

Stacking all node embeddings yields the kinetic chain state at phase τ_k,

$$\mathbf{H}(\tau_k) = \big[\mathbf{h}_1(\tau_k), \mathbf{h}_2(\tau_k), \ldots, \mathbf{h}_N(\tau_k)\big]^\top \in \mathbb{R}^{N \times d}. \tag{3}$$

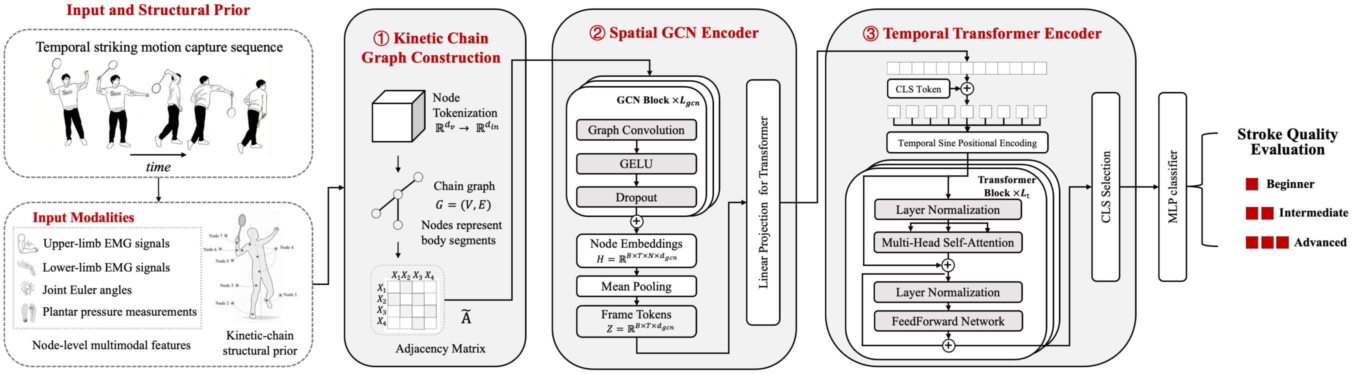


Fig. 1. Overall architecture of the proposed KCG-SME framework. The model takes node-wise multimodal wearable signals as input and incorporates a kinetic-chain structural prior. It consists of three main stages: 1) kinetic chain graph construction, 2) spatial GCN-based node representation learning, and 3) temporal Transformer encoding for stroke quality evaluation.

To instantiate the along chain coupling implied by the kinetic chain mechanism, we model the body as a directed chain graph $G = (V, E)$ with edges connecting adjacent segments,

$$E = \{(i, i+1) \mid i = 1, \dots, N-1\}. \tag{4}$$

Rather than using generic adjacency normalization, we introduce a directed incidence operator $\mathbf{B} \in \mathbb{R}^{(N-1)\times N}$ to encode the proximal to distal structure:

$$B_{e,i} = \begin{cases} -1, & \text{if edge } e = (i, i+1), \\ +1, & \text{if edge } e = (i-1, i), \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

Applying $\mathbf{B}$ to the node states induces an edge level transfer representation,

$$\mathbf{F}(\tau_k) = \mathbf{B}\mathbf{H}(\tau_k) \in \mathbb{R}^{(N-1)\times d}, \tag{6}$$

which captures directional differences between adjacent segments and serves as an explicit surrogate for inter segment force transfer and coordination along the kinetic chain.

The complete representation of a striking instance is given by the phase indexed sequence

$$\mathcal{G} = \{\mathbf{H}(\tau_k), \mathbf{F}(\tau_k)\}_{k=1}^{T}, \tag{7}$$

where $\mathbf{H}(\tau_k)$ characterizes segment states and $\mathbf{F}(\tau_k)$ characterizes along chain interactions at each phase. This construction embeds kinetic chain structure at the representation level, so that subsequent spatial modeling can operate on explicit inter segment coupling, while temporal modeling captures the evolution of both segment states and transfer patterns over the entire motion cycle.

C. Spatial GCN Encoder

Given the phase indexed kinetic chain representation, we aim to model spatial interactions among body segments in a manner consistent with force transmission along the chain. Unlike generic spatial encoders that aggregate arbitrary skeletal neighborhoods, striking motions require ordered and directed coupling between physically adjacent segments.

Let $\mathbf{H}(\tau_k) \in \mathbb{R}^{N\times d}$ denote the segment state matrix and $\mathbf{F}(\tau_k) \in \mathbb{R}^{(N-1)\times d}$ denote the corresponding along chain transfer representation at phase τ_k. We construct a chain aware spatial transformation that updates segment representations by jointly considering local segment states and adjacent transfer signals. Specifically, for each phase τ_k, we define the spatial encoding as

$$\tilde{\mathbf{H}}(\tau_k) = \sigma\Big(\mathbf{H}(\tau_k)\mathbf{W}_s + \mathbf{B}^\top \mathbf{F}(\tau_k)\mathbf{W}_f + \mathbf{1}\mathbf{b}^\top\Big), \tag{8}$$

where $\mathbf{W}_s \in \mathbb{R}^{d\times d'}$ and $\mathbf{W}_f \in \mathbb{R}^{d\times d'}$ are learnable projection matrices, $\mathbf{b} \in \mathbb{R}^{d'}$ is a bias term, $\mathbf{1}$ is an all ones vector, and $\sigma(\cdot)$ denotes a nonlinear activation function. The term $\mathbf{B}^\top\mathbf{F}(\tau_k)$ redistributes transfer information back to segment space, enabling each segment to incorporate influence from adjacent segments along the kinetic chain.

This formulation induces a structured message passing process that is inherently aligned with the kinetic chain. Segment updates are driven not only by their own states, but also by incoming and outgoing transfer patterns encoded in $\mathbf{F}(\tau_k)$. As a result, the spatial encoder captures coordination relationships that are directly tied to biomechanical force transmission, rather than arbitrary spatial proximity.

To increase representational capacity, multiple spatial encoding layers can be stacked, yielding a hierarchical abstraction of segment interactions along the chain. Let $\mathbf{H}^{(l)}(\tau_k)$ denote the segment representation at layer l, with $\mathbf{H}^{(0)}(\tau_k) = \mathbf{H}(\tau_k)$. The update rule is given by

$$\mathbf{H}^{(l+1)}(\tau_k) = \sigma\Big(\mathbf{H}^{(l)}(\tau_k)\mathbf{W}_s^{(l)} + \mathbf{B}^\top\mathbf{F}^{(l)}(\tau_k)\mathbf{W}_f^{(l)}\Big), \tag{9}$$

where $\mathbf{F}^{(l)}(\tau_k) = \mathbf{B}\mathbf{H}^{(l)}(\tau_k)$ is the induced transfer representation at layer l. This recursive formulation allows information to propagate progressively along the kinetic chain while maintaining a clear separation between segment states and inter segment transfer effects.

Compared with standard graph convolution on skeletal graphs, the proposed spatial encoding emphasizes along chain propagation and directionally structured interactions. By explicitly modeling transfer signals through the incidence operator, the encoder avoids blending unrelated segments and reduces ambiguity in learned spatial dependencies. The resulting spatially encoded representation provides a biomechanically grounded foundation for subsequent temporal modeling, which captures how these coordination patterns evolve across the striking motion cycle.

D. Temporal Transformer Encoder

Spatial encoding produces a sequence of phase indexed segment representations that capture inter segment coordination at each instant of the motion. However, striking quality is not determined by isolated phases, but by how coordination patterns evolve across the entire motion cycle. Temporal modeling is therefore required to capture long range dependencies among segment states and transfer patterns, and to aggregate them into a compact representation suitable for motion quality evaluation.

Let $\tilde{\mathbf{H}}(\tau_k) \in \mathbb{R}^{N \times d'}$ denote the spatially encoded kinetic chain representation at phase τ_k, obtained from the final spatial encoding layer. We first map each phase representation to a phase level embedding by aggregating over the chain dimension:

$$\mathbf{z}(\tau_k) = \rho\big(\tilde{\mathbf{H}}(\tau_k)\big) \in \mathbb{R}^{d'}, \tag{10}$$

where $\rho(\cdot)$ is a permutation invariant aggregation operator, such as averaging or weighted pooling along the chain. This operation preserves temporal ordering while compressing spatial structure into a phase consistent descriptor.

To model temporal dependencies across the motion cycle, we define a learnable temporal operator $\mathcal{T}(\cdot)$ that transforms the phase embedding sequence

$$\mathbf{Z} = \{\mathbf{z}(\tau_1), \mathbf{z}(\tau_2), \ldots, \mathbf{z}(\tau_T)\} \tag{11}$$

into a context enhanced sequence

$$\mathbf{Y} = \mathcal{T}(\mathbf{Z}), \tag{12}$$

where each $\mathbf{y}(\tau_k) \in \mathbb{R}^{d_t}$ integrates information from multiple phases. The operator $\mathcal{T}$ is designed to capture both local continuity and long range interactions along the normalized motion phase axis, enabling the model to encode phase dependent coordination patterns without assuming fixed execution speed.

The temporally encoded sequence $\mathbf{Y}$ is then summarized into a motion level representation through temporal aggregation:

$$\mathbf{g} = \psi\big(\mathbf{Y}\big) \in \mathbb{R}^{d_g}, \tag{13}$$

where $\psi(\cdot)$ denotes a learnable pooling function that emphasizes phases critical to motion quality. This representation compactly encodes the evolution of kinetic chain coordination over the full motion cycle.

Finally, motion quality evaluation is formulated as a mapping from the motion level embedding $\mathbf{g}$ to a task specific output:

$$\hat{\mathbf{y}} = f_{\text{eval}}(\mathbf{g}), \tag{14}$$

where $f_{\text{eval}}(\cdot)$ is a lightweight prediction head implemented as a multilayer perceptron. Depending on the evaluation task, $\hat{\mathbf{y}}$ may correspond to a quality score, a categorical label, or a distribution over quality levels.

By decoupling spatial coordination modeling from temporal dependency modeling, the proposed framework explicitly separates instantaneous inter segment interactions from their evolution across the motion cycle. This design allows the temporal module to focus on phase dependent dynamics and long range coordination patterns, yielding a compact and discriminative representation for striking motion quality evaluation.

IV. EXPERIMENTS

In this section, we take badminton as a representative example to evaluate the performance of KCG-SME in stroke motion assessment using a real-world dataset. The proposed method is compared with several state-of-the-art baseline models under the same experimental settings. The experiments address three questions: 1) the accuracy of KCG-SME relative to existing methods, 2) the necessity of different nodes in the kinetic chain, and 3) the contribution of individual model components.

A. Experimental Setup

Datasets. We conduct our experiments on the MultiSense-Badminton, which has been widely used in recent studies on badminton stroke analysis. The dataset comprises 7,763 stroke samples collected from 25 players spanning a broad range of skill levels. Data are acquired using synchronized multimodal wearable sensors, including motion capture, electromyography, plantar pressure sensing, and video streams. Each stroke is labeled with a stroke quality annotation for evaluation.

Node settings. Following the proximal-to-distal force transmission principle in striking biomechanics, we represent the human body as a seven-node kinetic chain, where each node corresponds to a functional segment responsible for force generation, transfer, or control during stroke execution. The chain starts from ground force input at the feet, propagates through lower-limb propulsion and trunk–shoulder energy coupling, and culminates in upper-limb acceleration and wrist-level distal control.

Each node is associated with sensing modalities that reflect its functional role, including plantar pressure measurements, joint Euler angles, and surface electromyography signals, as summarized in Table I. This seven-node configuration provides a compact yet complete representation of the force transmission pathway in striking motions and is adopted as the default setting in all experiments.

Baselines. We compare the proposed method with several recent and state-of-the-art baseline models that represent commonly adopted modeling paradigms in badminton stroke analysis, including Conv1D, LSTM, Transformer-based models, DeCoach, and a 2D-CNN. All baseline methods are evaluated under the same experimental settings to ensure a fair comparison.

Evaluation Metrics. We use standard metrics: Accuracy, Precision, Recall, and F_1-score. Additionally, we use the

TABLE I
SEVEN-NODE KINETIC CHAIN REPRESENTATION USED IN ALL EXPERIMENTS.

Node	Body Segment	Functional Role in Kinetic Chain
Node 1	Lead Foot	Ground force input and load distribution at stroke initiation
Node 2	Rear Foot	Bilateral support and weight transfer regulation
Node 3	Dominant Thigh	Lower-limb propulsion and energy generation
Node 4	Trunk–Shoulder	Energy transfer and coupling between lower and upper body
Node 5	Upper Arm	Proximal acceleration of the striking limb
Node 6	Forearm	Velocity amplification and swing regulation
Node 7	Wrist	Distal control affecting racket orientation and impact outcome

TABLE II
EXPERIMENTAL CONFIGURATION.

Setting	Configuration
Input Window	2.5 s (150 frames @ 60 Hz)
Feature Dimension	38
GCN Layers	3 (hidden dim: 64)
Transformer Encoder	3 layers, 4 heads
Transformer Dim	128
Feedforward Dim	512
Positional Encoding	Sine/cosine with learnable scale
CLS Token	One learnable global token
Classifier	LN $\rightarrow$ FC(128$\rightarrow$64) $\rightarrow$ GELU $\rightarrow$ Dropout(0.2) $\rightarrow$ FC(64$\rightarrow$3)
Dropout Rate	0.2
Batch Size	32
Optimizer	AdamW
Learning Rate	5×10^{-4}
Weight Decay	1×10^{-4}
Training Epochs	200 (early stopping, patience 20)
Random Seed	42
Data Split	70% / 20% / 10% (train/val/test)

Confusion Matrix to provide a clear summary of prediction outcomes. For model performance evaluation across various thresholds, the ROC (Receiver Operating Characteristic) curve is used. It plots the True Positive Rate (TPR) against the False Positive Rate (FPR), providing a visual representation of the trade-off between sensitivity and specificity. A higher curve indicates better model performance.

Hyperparameter Settings. We implement all models in PyTorch. The hyperparameter configurations of the proposed method are summarized in Table II. All baseline models follow the same data preprocessing, optimization, and training strategies as the proposed method. Specifically, the LSTM baseline employs two layers with a hidden size of 128; the Conv1D baseline uses a kernel size of 5 with channel dimensions of 64 and 128; and the Transformer baseline adopts an embedding size of 64 with two encoder layers.

B. *Striking Motion Quality Evaluation*

We evaluate striking motion quality assessment across different stroke types. Table III reports the performance of all methods on both the forehand clear and backhand drive tasks. KCG-SME achieves the highest performance across all evaluation metrics on both strokes, consistently outperforming all baselines.

For the forehand clear stroke, KCG-SME shows a clear performance advantage over all comparison methods, indicating its effectiveness in distinguishing stroke quality levels under a well-structured and temporally regular motion pattern. Notably, this performance gain is maintained on the backhand drive task, which involves different execution timing and motion characteristics. The consistent ranking across the two stroke types suggests that the proposed method remains stable under variations in striking patterns.

The confusion matrices in Fig.2 show that KCG-SME reduces misclassifications between neighboring quality classes compared with baseline models, particularly for samples with similar execution quality. The ROC curves in Fig.3 further confirm this observation by exhibiting higher class separability across both stroke types. Together, these results demonstrate that KCG-SME provides reliable and consistent stroke quality assessment across different striking motions.

C. *Module-Level Ablation Analysis*

We further analyze the contribution of individual architectural components through a module-level ablation study. Variants are constructed by removing the graph-based spatial modeling component (w/o GCN), the temporal sequence modeling component (w/o Temporal Transformer), or the positional encoding and classification head (w/o Positional Classifier), while keeping all other settings unchanged.

Table IV reports the quantitative results of different ablation variants. Removing the GCN results in a substantial accuracy drop from 0.9906 to 0.9279, showing that spatial modeling along the kinetic chain is critical for stroke quality assessment. When the temporal Transformer is removed, accuracy decreases to 0.9592, reflecting the importance of temporal dependency modeling for characterizing stroke execution patterns. In comparison, removing the positional classifier leads to a smaller but consistent performance degradation, with accuracy reduced to 0.9781, indicating that positional information and global aggregation contribute to performance but are not the dominant factors.

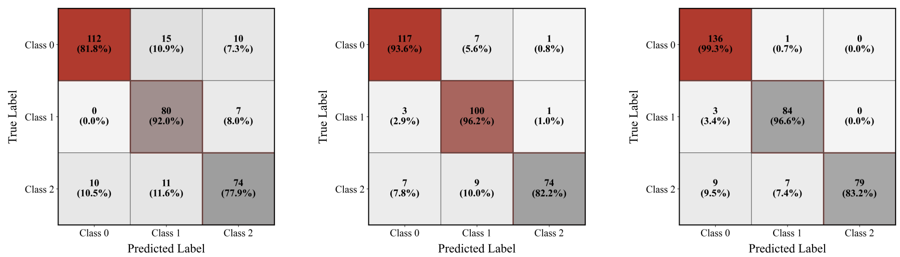
The full KCG-SME model achieves the highest accuracy (0.9906) and F1-score (0.9911) among all variants, indicating that spatial modeling, temporal modeling, and global representation learning jointly contribute to effective stroke quality assessment.

V. CONCLUSION

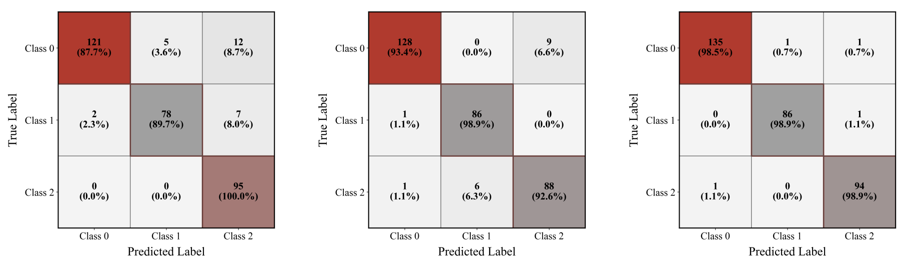
KCG-SME presents a general framework for striking motion quality evaluation by explicitly modeling kinetic-chain structure and inter-segment force transmission with a chain-structured graph, together with temporal modeling over the

TABLE III
STRIKING MOTION QUALITY EVALUATION PERFORMANCE ACROSS DIFFERENT METHODS.

Method	Forehand Clear				Backhand Drive			
	Accuracy	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score
Conv1D	0.8339	0.8286	0.8387	0.8299	0.7712	0.8301	0.7986	0.7709
LSTM	0.9122	0.9190	0.9066	0.9097	0.8621	0.8616	0.8592	0.8573
Transformer	0.9373	0.9440	0.9299	0.9337	0.8715	0.8928	0.8746	0.8730
DeCoach	0.9216	0.9228	0.9266	0.9210	0.9028	0.9033	0.9089	0.9019
2D-CNN	0.9467	0.9422	0.9497	0.9455	0.9279	0.9243	0.9261	0.9250
KCG-SME	**0.9875**	**0.9868**	**0.9878**	**0.9873**	**0.9687**	**0.9683**	**0.9696**	**0.9689**

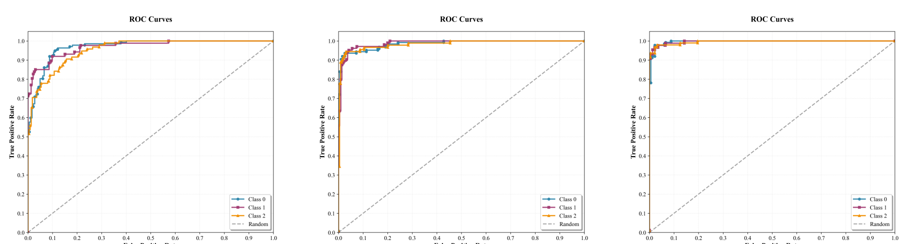


(a) Conv1D (b) LSTM (c) Transformer

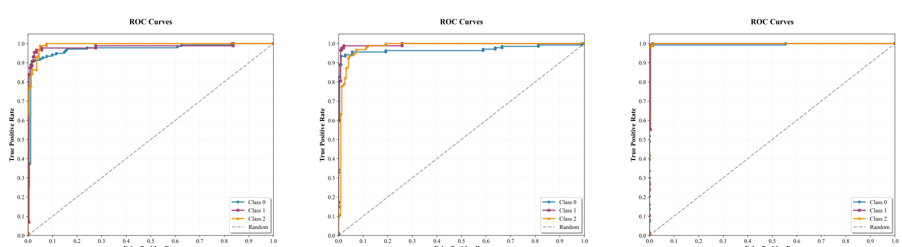


(d) DeCoach (e) 2D-CNN (f) KCG-SME

Fig. 2. Confusion matrices for forehand clear stroke quality classification across different methods.



(a) Conv1D (b) LSTM (c) Transformer



(d) DeCoach (e) 2D-CNN (f) KCG-SME

Fig. 3. ROC curves for the forehand clear stroke quality classification task across different methods.

TABLE IV
ABLATION STUDY OF KCG-SME COMPONENTS

Variant	Accuracy	Precision	Recall	F1-score
w/o GCN	0.9279	0.9255	0.9217	0.9221
w/o Temporal Transformer	0.9592	0.9544	0.9590	0.9541
w/o Positional Classifier	0.9781	0.9767	0.9763	0.9763
Full KCG-SME	**0.9906**	**0.9898**	**0.9927**	**0.9911**

motion cycle. By moving beyond independent joint-based representations, the framework enables accurate assessment of motion execution quality grounded in coordinated whole-body movement. Experimental results on real-world datasets demonstrate that KCG-SME consistently outperforms existing approaches in striking motion evaluation.

Future work will extend KCG-SME from motion quality assessment to explicit action guidance by formulating training recommendations in terms of kinetic-chain improvement. In particular, future studies will investigate how deviations in force transmission and segment coordination identified by the model can be translated into actionable guidance for technique correction, enabling systematic improvement of motion execution in kinetic-chain-dominated striking movements.

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