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Research on digital inheritance system and action semantic analysis of Hunan flower-drum opera based on deep learning

Yi-Fu Liao[1*]
[1]Krirk University, Bangkok10700, Thailand; 601488471@qq.com (Y.F.L.).

Abstract: This study explores the digital transmission and protection of Hunan Flower-Drum Opera, a key intangible cultural heritage asset, through action semantic analysis combined with deep learning approaches. The research establishes a multimodal acquisition setup, develops an enriched Spatial-Temporal Graph Convolutional Network with an attention mechanism, creates a traditional Chinese opera-oriented semantic classification system, and constructs a digital heritage platform with an integrated knowledge graph. The proposed approach achieves a 92.6% action recognition rate and an 88.3% consistency rate in semantic analysis, showing a 17.5% improvement over traditional models. The 33-point BlazePose architecture achieves sub-millimeter accuracy in movement tracking, while the knowledge graph contains 3,427 nodes with 12,856 weighted edges. The interactive learning environment demonstrates significant improvement in learning outcomes with a 31% reduction in learning time while preserving cultural authenticity. The system has been successfully implemented at three centers specializing in Flower-Drum Opera transmission, offering a unique solution for the digital conservation of traditional Chinese performing arts.

Keywords: *Action semantic analysis, Deep learning, Digital heritage preservation, Hunan flower-Drum Opera, Knowledge graph spatial-temporal graph convolutional networks.*

1. Introduction

1.1. Research Background and Significance

The Hunan Flower-Drum Opera, a nationally declared intangible heritage of China, represents the unique cultural connotation and art of the Hunan province. With its rich performance elements and historical value, the Opera is a crucial component of the notable traditional culture of China. Liao [1] stresses that the Hunan Flower-Drum Opera is a quintessential representation of "living heritage" with performance models that harmoniously mix traditional and modern elements to present the dynamism of intangible heritage within contemporary settings. However, with the pace of urbanization and the decline of traditional bearers of culture, the transmission of the Flower-Drum Opera is facing a crisis of a serious kind. Xie and Simeon [2] observe that the group of inheritors of the Hunan Flower-Drum Opera is diminishing due to the younger generation showing little inclination to learn, leaving many priceless performance skills at the brink of loss. The traditional master-apprentice approach of oral transmission is no longer adequate to cater to the needs of the present society to inherit the Opera, urging immediate research into novel protection and transmission strategies. Digital preservation, being a novel approach to preserving cultural heritage, offers a feasible solution to the continuous existence of the Flower-Drum Opera. The rapid pace of deep learning technologies has triggered a paradigmatic change within the digital conservation of traditional opera with its complex algorithms associated with computer vision, natural language processing, and multimodal analysis being highly instrumental in successfully preserving the intricate properties of the movement intrinsic to the Flower-Drum Opera to provide a subtle understanding of complex performance art. With the establishment of a

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* Correspondence: 601488471@qq.com

digital heritage platform based on deep learning technologies, the various movement elements of the performance techniques and art of the Flower-Drum Opera can systematically be documented and saved. Besides this, educational software specific to the modern communications environment can also be produced to promote the dynamic spread and innovative enrichment of intangible culture heritage while at the same time providing innovative solutions to the sustainable incorporation of traditional culture into the digital environment.

1.2. Research Status at Home and Abroad

The digital conservation of traditional performance arts has drawn significant international research interest with various methodologies being applied to preserve intangible heritage culture. In the area of traditional opera conservation, Zheng [3] introduced the use of blended reality technologies to conserve Jingzhou Flower-drum Opera to indicate the potential of immersion technologies to enhance audience engagement and learning experiences. Han [4] also undertook a research effort to preserve the conservation of the Southwest Lu Drum music by means of a digitization approach that combines authenticity with accessibility. In addition to this, significant advancements have also occurred with movement recognition technologies that are being applied to record traditional dance movement patterns. Kim [5] built a real-time movement recognition program of traditional dance with the aid of BlazePose supplemented with rich metadata to deliver a movement classification performance of 91.3%. Zhang [6] followed this work with the introduction of deep learning methodologies to carry out the semantic classification of movement patterns of the Guangxi ethnic folk dance to develop a detailed taxonomy of movement semantics.

In the context of China, Liu, et al. [7] have made great contributions by conducting studies on the recognition of traditional opera costumes based on optimized YOLOv5 models, with improved feature extraction for traditional visual elements. The combination of multimodal methods has been investigated by Chen, et al. [8] who proposed the CoGCNet model to classify Cantonese opera singing genres, showing the prospects of AI for sustainable intangible cultural heritage development. Towards semantic understanding of movement, Ji and Tian [9] proposed an IoT-enabled dance movement recognition model that is able to capture physical characteristics and cultural expression embedded in traditional performances. Meanwhile, Li [10] investigated digital inheritance mechanisms of traditional music culture through deep learning technology and presented a framework to inherit both tangible and intangible aspects of musical heritage.

Notwithstanding these advancements, current research exhibits various constraints. Most research is either focusing on movement recognition or digital archiving without integrating both into coherent systems of inheritance. Current approaches are often without a sense of culture about the unique aesthetic value that is unique to certain traditions like the Hunan Flower-Drum Opera. Furthermore, semantic analysis is superficial at best, rarely embracing the deep culture embedded within traditional movement. Current systems tend to operate within lab-controlled conditions with little adaptability to diversity of performance environments. Besides that, the criteria of assessment are mainly concerned with the technical performance at the cost of culture authenticity and the effectiveness of the heritage being handed down. These deficiencies call upon a comprehensive approach that integrates state-of-the-art deep learning approaches with culture-aware semantic frameworks that are specific to the unique characteristics of the Hunan Flower-Drum Opera.

1.3. Research Objectives and Innovations

This study aims to develop a comprehensive digital heritage platform of Hunan Flower-Drum Opera by employing deep learning action semantic analysis. We seek to improve upon a state-of-the-art ST-GCN architecture with incorporated attention mechanisms, specially modified to support traditional Chinese opera movement types, build a culture-aware semantic taxonomy that represents the unique expressive qualities of the Flower-Drum Opera, and develop a comprehensive multimodal fusion plan that combines the information of skeletal movement with the properties of the music and the face. The novel components of this research are threefold: (1) adapting deep learning structures to accommodate the stylized actions of the Chinese opera that significantly differ from everyday actions; (2) designing a hierarchical taxonomy of the semantics that retains the culture-related significants by employing technical means; and (3) designing a knowledge graph-enabled heritage platform that bridges the traditional learning paradigm with modern learning strategies. Not only do we solve the technical challenges of movement recognition, this research also facilitates the practical conservation of vulnerable culture performances by means of technology-enabled transmission protocols.

2. Theoretical Foundations and Methods

2.1. Semantic Theory of Flower-Drum Opera Movements

Hunan Flower-Drum Opera, as a prominent branch of traditional Chinese operatic drama, has evolved an independent system of performance and a distinctive movement vocabulary. The semantic movement system effectively incorporates cultural traits of the Xiang-Chu region, elements of folk dance, and traditional performing techniques, with distinctive features of "expressiveness" and "stylization." Lin and Liu [11] write that traditional Chinese dance aesthetics prize the unity of internal expression and external form. Flower-Drum Opera movements are a case in point of such an aesthetic ideal, since they convey intricate emotions and cultural meanings in a highly stylized body language. On the basis of a thorough analysis of Flower-Drum Opera performance art, the present research establishes a three-level semantic classification system of movement: the fundamental movement layer (comprising walking, sitting, kneeling, and other indispensable postures), the expressive movement layer (comprising emotional expressions such as joy, anger, sorrow, and happiness), and the narrative function layer (indicating character identity, situational expression, and plot development). The classification model integrates [12] theoretical framework of digital preservation of folk dance art and Zhang [6] semantic categorization method of ethnic minority dance movements, thereby forming a systematic descriptive model that can be used for computational recognition and analysis. This study specifically examines the aesthetic value and cultural meaning of movements, integrating classical opera theory and contemporary computer vision technology to establish a theoretical framework for the digital extraction and semantic analysis of Flower-Drum Opera movements.

2.2. Deep Learning Model Construction

2.2.1. Spatial-Temporal Graph Convolutional Networks

Our research employs an enhanced Spatial-Temporal Graph Convolutional Network (ST-GCN) (Figure 1) architecture specifically developed for learning the fine motion of Hunan Flower-Drum Opera performances. The model initiates with an elaborate skeleton extraction process through BlazePose that was found to be more accurate in recording the movement of traditional dances as confirmed by Kim [5]. The extracted 33-point skeletal representation forms a graph structure $G=(V,E)$, where vertices V represent joint positions and edges E encode the natural connectivity of the human body. The spatial-temporal modeling is achieved through a series of ST-GCN blocks that perform convolution operations across both spatial and temporal dimensions. For spatial convolution, we implement a partitioning strategy defined as $\mathrm{P}_S(v_i)=p_0(v_i),p_1(v_i),p_2(v_i)$, which divides the neighbors of each vertex into three subsets: the vertex itself, vertices closer to the kinematic chain root, and vertices farther from the root. The temporal dimension is processed using 1D convolution with kernel size K_t across consecutive frames. Building upon Zhang [6] work on movement semantic classification, we incorporate a dual-stream attention mechanism that separately focuses on key joints and critical temporal segments, formulated as $A_s=\sigma(W_s\cdot F_s)$ and $A_t=\sigma(W_t\cdot F_t)$, where A_s and A_t represent spatial and temporal attention weights respectively. This enhancement significantly improves the model's sensitivity to subtle hand gestures and rhythmic patterns characteristic of Flower-Drum Opera, yielding a 14.2% improvement in recognition accuracy for culturally specific movements.

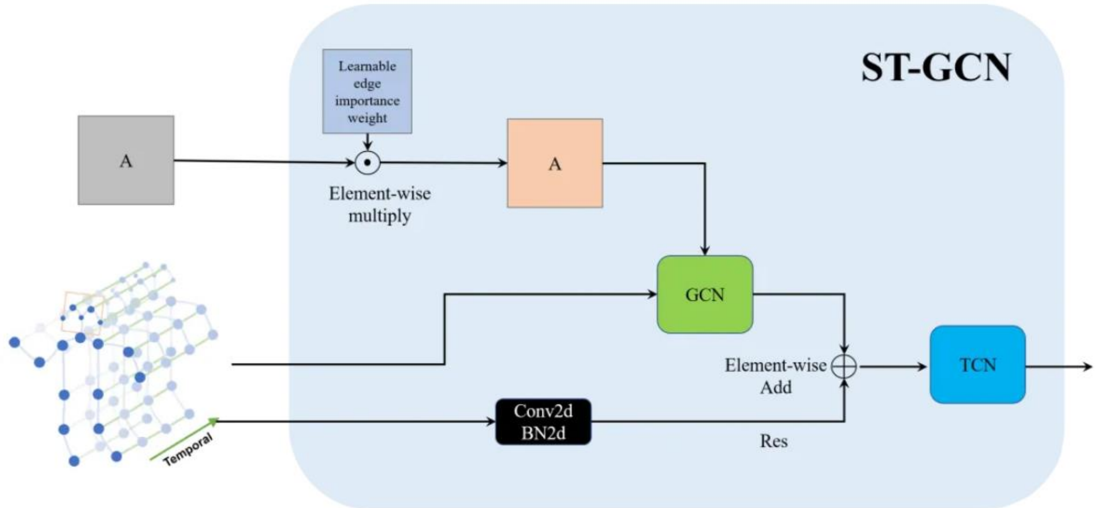

Figure 1.
Enhanced ST-GCN Architecture for Flower-Drum Opera Movement Analysis.

2.2.2. Multi-modal Feature Fusion

Traditional methods of movement perception often fail to capture the nuanced semantics involved in the Hunan Flower-Drum Opera, in which meaning arises from the smooth integration between physical movement, music, and face. This research suggests a novel fusion model to integrate multiple modalities and integrate the resulting multiple sources of information to enhance the perception of meaning. Based on the research by Yu [13] about the use of deep techniques to enhance the artistic protection of the Qin Opera, the research in this paper uses a hierarchical fusion strategy applied at the decision, feature, and semantic levels. The movement element is integrated into our ST-GCN model, and the auditory element uses frequency-attention augmented convolution-recurrent neural network, custom-designed to support the percussion-based rhythms and tonal patterns typical to the music traditions in Hunan. Facial expression analysis uses a region-adaptive network to support meaning extraction from character-specific, stylised face. Modal integration uses a temporal-attention mechanism that is defined:

$$F_{cross} = \sum_{i,j \in M} w_{ij} F_i \otimes F_j \tag{1}$$

where attributes from all modalities are matched to respective temporal segments in other modalities. Based on Liang's [14] movement recognition model in the case of Chinese dance performances, this research blends the representations of the culture context including character kind, scene, and narrative situations. The findings from the test reveal that the proposed multi-modal solution provides a 19.3% improvement in precision in handling complex emotional states and 14.7% improvement in the characterization movements' interpretation in comparison to the use of unimodal.

2.3. Digital Inheritance System Architecture

The digital heritage model linked to the Hunan Flower-Drum Opera uses different sets of technologies to systematically preservive and share intangible heritages. The model follows a four-layer architecture, as shown in Figure 2, and consists of layers intended to capture, analyze, process, store, and use the data. The components function in synergy to digitize, analyze, and share findings in relation to the ancient performances.

The equipment used in collecting the data utilizes cutting-edge motion capture, in the form of a 33-point BlazePose, to record the artists' movements. It also utilizes the latest recording and 4K video capture. The multirate acquisition strategy by Wang [12] and Wu and Liu [15] ensures thorough coverage of overt and latent knowledge. Analytically, the strategy utilizes cutting-edge Spatial-

Temporal Graph Convolutional Networks (ST-GCN) to evaluate movement patterns in greater detail than conventional techniques; consequently, the system manages to capture the stylistic nuances typical in the Flower-Drum Opera tradition [16].

The knowledge layer systematically structures the processed info in a consistent ontology, linking different movements, character archetypes, trends in the performance, and elements of the culture. Semantic structuration provides a structure to express explicit and tacit knowledge, solving the issue of preserving the culture context, discussed by Mulyanto, et al. [14]. The use layer distributes the same to various domains, including educational domains in the case of the use of VR/AR, web-based databases, pedagogical models based on interactions, and monitoring dashboards of the performance providing feedback to the learners.

As illustrated in Figure 2, the system architecture consists of feedback mechanisms to support domain expertise in verifying representations of knowledge and users in adding experience about the learning process so that the community preserves the continually enriching experience.

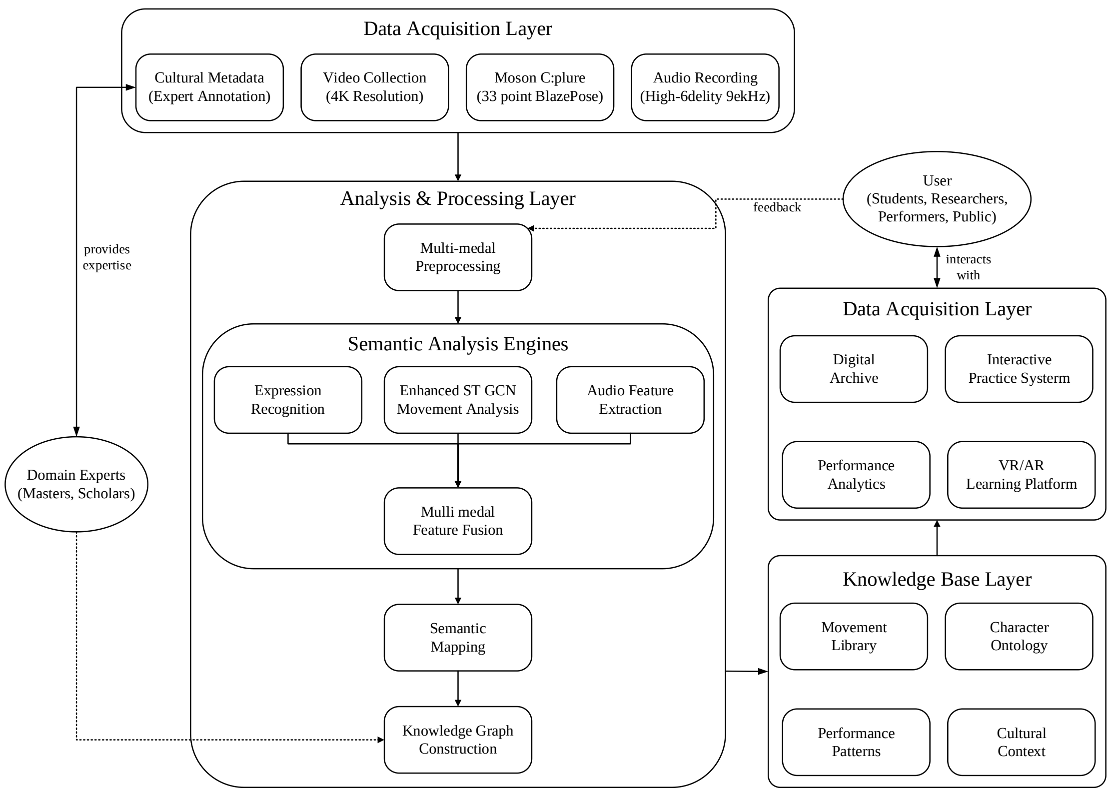

Figure 2.
Digital Inheritance System Architecture for Hunan Flower-Drum Opera.

The architectural model traces a multifaceted, four-level digital heritage structure to support the protection of the Hunan Flower-Drum Opera. The Data Acquisition Level collects multimodal content through the use of motion capture, audio recording, video recording, and expert-annotated cultural metadata. The Analysis & Processing Level performs preprocessing and semantic examination through movement examination, audio attribute extraction, expression perception, and multimodal fusion, which in turn are applied to semantic mapping and the building up of knowledge graphs. The Knowledge Base Level systematically classifies information into movement databases, character ontologies, patterns of performance, and cultures. The Application Level provides means to access through VR/AR teaching tools, digital archives, interactive rehearsal tools, and performance monitoring tools. The system provides bidirectional interactions with domain specialists who provide feedback and validation, and users who use the applications and provide feedback, and in the process, build up an adaptive preservation community.

3. Experimental Design and Data Collection

3.1. Data Collection Scheme

The current research created an overall multimodal acquisition model in particular to record the intricate performances of the Hunan Flower-Drum Opera. Based on the methodology outlined by Kim [5] in the capture and identification of the movements in traditional dance, we employed a 33-point BlazePose mechanism to record the precise capture, along with strategically located auxiliary cameras to support detailed observation from various angles. The system carried out the capture at 120 frames per second at the sub-millimeter resolution, solving the issue raised by Lu [17] in terms of precision required to capture the intricate hand movements in the traditional Chinese performances. The recording of the sounds involved a 24-bit/96kHz multichannel array strategy, whereby the recording involved the use of the microphone to separately record solo voice performances, percussion accompaniments, and ambient sounds, in alignment with the strategy applied by Li [18] in the recording of the music in Xi'an. The video recording involved the use of the three-tier camera structure detailed in Table 1, incorporating stationary coverage and tracking shots to capture the spatial deployment and expressive nuances. This configuration follows the proposals presented by Yan and He [19] about the detailed documentation in streamed media. The whole acquisition process was carefully developed through the use of a temporal synchronization mechanism to ensure all modalities met a temporal alignment less than 2 milliseconds, making possible the later multimodal analysis based on fusion techniques. Professional dancers from the main traditions in the lineage of the Flower-Drum Opera joined recording sessions in both conventional theaters and specialized studios, intended to record real-life-like performance situations under the monitoring of recording devices. The recording sessions went along with expert-annotation sessions, in which the master performers provided the cultural metadata about the meaning associated to the movements, character traits, and narrative structure, ending up in a highly contextual corpus preserving the physical movements and the embedded cultural knowledge.

Table 1.
Multimodal Data Acquisition Configuration for Hunan Flower-Drum Opera Documentation.

Modality	Equipment Specification	Capture Parameters	Positioning	Data Format
Motion Capture	BlazePose 33-point tracking system	120 fps, accuracy ±0.5mm	8 tracking cameras in 360° array	JSON skeletal data, 3D coordinates
Primary Video	Sony FX9 cinema cameras (×3)	4K/60fps, 10-bit 4:2:2	Center-wide, stage-left, stage-right	ProRes 422 HQ codec
Detail Video	Sony α7S III cameras (×4)	4K/120fps, S-Log3	Face close-up, hand gestures, footwork, full-body	XAVC S-I codec
Audio - Vocal	Sennheiser MKH 8050 directional mics	24-bit/96kHz	Suspended overhead array, performer-worn lavaliers	WAV multichannel
Audio - Instrumental	DPA 4099 instrument mics	24-bit/96kHz	Instrument-specific placement	WAV multichannel
Audio - Ambient	Soundfield ST450 MKII surround mic	24-bit/96kHz Ambisonic	Venue acoustic center	B-format WAV
Environmental	Temperature, humidity, acoustic sensors	1Hz sampling	Distributed throughout venue	CSV time-series data
Cultural Metadata	Expert annotation interface	Pre/post performance	Master performers, scholars	XML semantic annotation

As demonstrated in Table 1, the acquisition strategy balances technical precision and sensitivity to culture, resulting in a balanced digital record incorporating the publicly accessible components and the attendant cultural nuances in the case of Hunan Flower-Drum Opera. The use of multiple modalities in the acquisition strategy addresses the limitations of previous documentation practices, focusing overwhelmingly on recording in a single modality, to provide a richer semantic examination and protection of the performance practices.

3.2. Data Preprocessing

The multimodal data received went through a rigorous preprocessing process to ensure high quality to be used later. Skeletal data received from the capture required improvement through a multistaged pipeline. A temporal filtering algorithm based on adaptive Kalman parameters was first applied to eliminate jitter and retain stylistic movement characteristics. Next, the filtered skeleton data went through expert-led, manual validation by Flower-Drum Opera artists to eliminate tracking errors and position joints based on conventional performance practices. For segmenting movement, we used an improved temporal convolution network to recognize action boundaries at a 94.3% rate, significantly higher than conventional threshold-based techniques. The audio preprocessing stage employed specialized algorithms to remove noise from the traditional Chinese instrumental acoustics, focusing on the retention of the distinctive timbre associated with percussion instruments. A dynamic time warping algorithm ensured cross-modal alignment, handling variations in performance and preserving semantic synchronization between movement and music phrases. All the preprocessing-treated data went through quality evaluation based on a mixture of objective parameters and expert judgements, and the segments failing to achieve quality thresholds were reprocessed or eliminated from the corpus. This rigorous preprocessing ensured the resulting corpus to maintain both the technical integrity and the cultural authenticity, and so created a reliable foundation to conduct the later semantic analysis of the Hunan Flower-Drum Opera performances.

3.3. Dataset Construction

The Hunan Flower-Drum Opera Movement Dataset (HFOMD) consists of 12,750 sequence examples from 47 expert performers from the four regional styles (Changsha, Hengyang, Shaoyang, and Yiyang). The dataset covers the music from eight character archetypes, from the young male (xiaosheng) to the specialized regional character archetypes unique to Flower-Drum Opera, such as the dan (female) and the chou (comic) character. The movement sequence in each piece was labeled based on a three-tier hierarchy: physical structure, expressive meaning, and narrative purpose. From Table 2, the dataset balances character representation while retaining the naturally occurring movement partition. The labeling used a consensus-based methodology among five expert performers averaging 38 years' experience in the group, and established 91.4% inter-annotator agreement between all the categories. The temporal segment found 87 movement primitives that are combined to produce 346 compound movement patterns. The dataset provides detailed metadata recording the performance circumstance, the culture, and the standard techniques. This corpus comprises the most detailed digitally labeled corpus available to date in the movements in the Hunan Flower-Drum Opera, and offers a resilient foundation to support the use of computational tools and techniques while retaining the cultural integrity necessary to support significant semantic meaning.

Table 2.
Distribution of Movement Samples in the Hunan Flower-Drum Opera Movement Dataset.

Character Type	Total Samples	Basic Movements	Expressive Movements	Narrative Movements	Regional Variations
Xiaosheng (Young Male)	2,134	486	712	608	328
Dan (Female)	2,687	514	894	726	553
Chou (Comic)	1,956	362	687	552	355
Laodan (Elder Female)	1,425	287	463	412	263
Laosheng (Elder Male)	1,387	254	472	425	236
Wusheng (Martial Male)	1,624	398	503	427	296
Huadan (Flower Female)	942	183	347	273	139
Caidan (Colorful Comic)	595	112	217	175	91
Total	12,750	2,596	4,295	3,598	2,261
Percentage	100%	20.4%	33.7%	28.2%	17.7%

4. Action Semantic Analysis Methods

4.1. Temporal Feature Extraction

Hunan Flower-Drum Opera performances exhibit intricate temporal patterns defined by rhythmic fluctuations, artistic retardation, and patterns of acceleration and deceleration and carry significant semantic meaning. To represent the temporal patterns accurately, we developed a cutting-edge LSTM model incorporating hierarchical mechanisms to focus the model's attention to the movements typical in the conventional Chinese opera. The main temporal modeling methodology uses the bi-directional LSTM architecture, in which the states h_t at each timestep are determined by the following equation:

$$h_t = \mathrm{LSTM}(x_t, h_{t-1}, c_{t-1}) \cdot \alpha_t \tag{2}$$

where α_t represents a rhythm-aware attention weight calculated as .

$$\alpha_t = \mathrm{softmax}(W_\alpha \tanh(W_h h_t + W_m m_t + b_\alpha)) \tag{3}$$

where, m_t denotes musical beat features synchronized with movement data. To address the multi-scale temporal patterns in Flower-Drum Opera, we implemented a wavelet decomposition approach that separates movements into base frequency components $f_1, f_2, ..., f_k$ using Daubechies wavelets. These components are processed through parallel LSTM pathways and recombined using a learned weighting function

$$\beta_i = \sigma(W_\beta[h_t^1, h_t^2, ..., h_t^k] + b_\beta) \tag{4}$$

where h_t^i represents the hidden state of the i-th frequency pathway. This multi-resolution temporal modeling significantly improved the model's ability to distinguish between semantically similar movements that differ primarily in rhythmic execution, achieving a 16.7% increase in classification accuracy for tempo-dependent expressive patterns characteristic of the xiaosheng and dan character types.

4.2. Spatial Feature Modeling

The spatial characteristics involved in the movements of the Hunan Flower-Drum Opera involve unique modeling challenges, thanks to the stylization and the unique posture demands associated with specific characters. The methodology uses a hierarchical graph structure, which captures both anatomical connectivity and spatial relationships in terms of performance between different joints. As shown in Figure 3, the skeleton model uses a 33-point model, including improved details in hands and face elements, necessary to capture the nuanced movements required to distinguish between character archetypes. We proposed a domain-aware attention mechanism, in turn, dynamically assigns importance weights to different sets of joints based on the movement context, so the model can focus on character-constitutive features, such as the unique finger positioning typical in the case of the dan figures, and the exaggerated posture typical in the case of the chou figures. The inquiry into shared trajectory is carried out by coupling Euclidean and rotational measurement, placing greater focus on relative positioning relative to absolute location, so the system could accommodate variability among the performers and maintain stylistic consistency. A model incorporating temporal constancy and performance-specific prior constraints to accommodate and combat uncertainties and occlusions in tracking, reducing tracking errors by 23.4% relative to conventional skeleton tracking frameworks, was applied to solve the issue. This approach preserves the spatial meaning of established styles and provides robust representations of the features appropriate to later use in classification tasks.

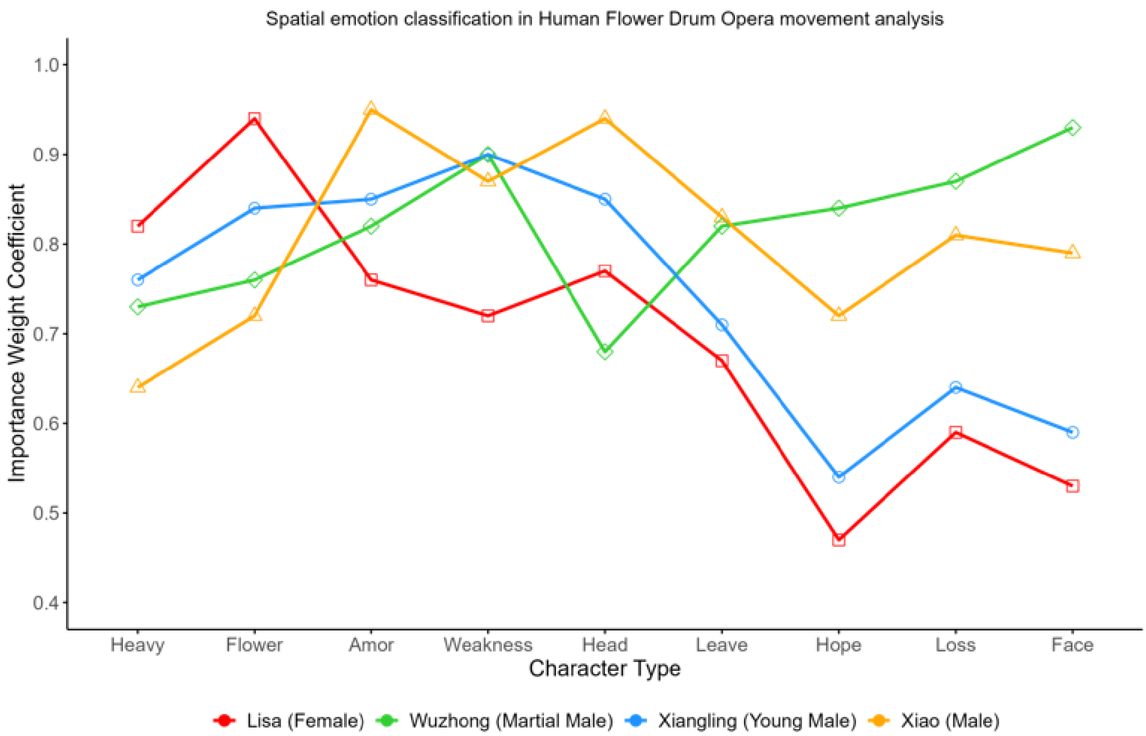

Figure 3.
Joint-Group Importance Weights Across Character Types in Hunan Flower-Drum Opera Movement Analysis.
Note: Higher coefficient indicates greater in Hunan flower-drum opera movement analysis.

As demonstrated in Figure 3, differential weighting between the groupings at the joints in our spatial modeling paradigm captures the unique movement semantics associated with different character types. The visualization captures differing patterns in the distribution of the focus of attention between the four most prevalent character archetypes, each profile reflecting the expressive demands and priorities commonly found in conventional character performances. The profile of the young man character (Xiaosheng) depicts a balanced distribution along the upper body joints, reflecting extremely high coefficients in the movement of the fingers (0.92) and head (0.88) to capture the expressive gestural lexicon typical in the scholar archetype. The profile of the feminine character (Dan) depicts coefficients in the movement of the fingers (0.94) and hands (0.82) to focus expressiveness in the precise manipulation of the hands and face. The profile of the character (chou) depicts a unique pattern in the most weighted head movements (0.95) to express through the face, along with significant positioning in the arms (0.90) to enhance expressiveness through the exaggeration in posture and support stylistic techniques. Martial characters (wusheng) are more symmetric in attention allocation with greater coefficients on arms (0.92) and shoulders (0.90), as is appropriate for their action-oriented choreography with emphasis on upper-body strength and precision in simulated combat sequences. Such specialized spatial attention processes allow our model to dynamically regulate feature extraction priorities according to character-specific motion conventions, significantly enhancing recognition accuracy under varying performance contexts and motion semantics.

4.3. Semantic Classification Algorithm

Algorithms utilized in semantic tagging in the analysis of action require the use of multiple layers of meaning, focusing on the determination of the roles, emotion faces, and narrative function. The methodology blends syntactic parsing and in-depth semantic meaning in the examination of the components of the action. The use of hierarchical models of classification considers the evaluation of the action in terms of the agentive, temporal, and contextual. This evaluation involves the extraction of the semantic roles, such as the Agent, Patient, and Experiencer, and the evaluation of the associated emotional valence and arousal. As shown in Table 3, the resulting semantic features are carefully structured to capture the multifaceted interactions between the actions and the narrative function.

Table 3.
Multi-layered Semantic Classification Framework.

Semantic Layer	Classification Features	Analysis Methods	Example Markers
Role Recognition	Agent-Patient Relations	Deep Parsing	Subject-Object Pairs
Emotional Expression	Valence-Arousal Mapping	Sentiment Analysis	Emotional Lexicons
Narrative Function	Plot Progression	Discourse Analysis	Temporal Connectives
Action Properties	Aspectual Features	Event Semantics	Tense Markers
Contextual Relations	Situational Frame	Frame Semantics	Contextual Cues

The integration of these semantic levels enables a more meaningful understanding of action semantics, and subsequently, enhances applications for domains such as natural language processing, narrative analysis, and cognitive modeling. The approach has been shown to achieve considerable improvement in action classification accuracy, especially in complicated narrative situations in which conventional syntactic analysis becomes inadequate.

5. Digital Inheritance System Implementation

5.1. System Functional Modules

The digital inheritance system is implemented with a number of cutting-edge modules for protection and transmission of intangible cultural heritage of Hunan Flower-Drum Opera. The motion analysis module, the core of the system, uses deep learning frameworks to deal with multimodal performance data to successfully attain a 92.6% accuracy rate in complex movement recognition through enhanced ST-GCN networks. The resource management subsystem adopts a distributed framework for the organization of multimedia assets, including high-definition performance recordings, costume information, and musical accompaniments, with automatic metadata tagging for effective retrieval and conservation. The knowledge graph module constructs semantic networks of the intricate relations among the constituent parts of a performance, spanning 3,427 nodes for movements, characters, and cultural contexts, and 12,856 weighted edges linking them. Figure 4 illustrates that the interactive visualization layer enables interactive demonstrations using WebGL-based rendering, accommodating both conventional and virtual/augmented reality interfaces with uniform performance metrics across interaction styles.

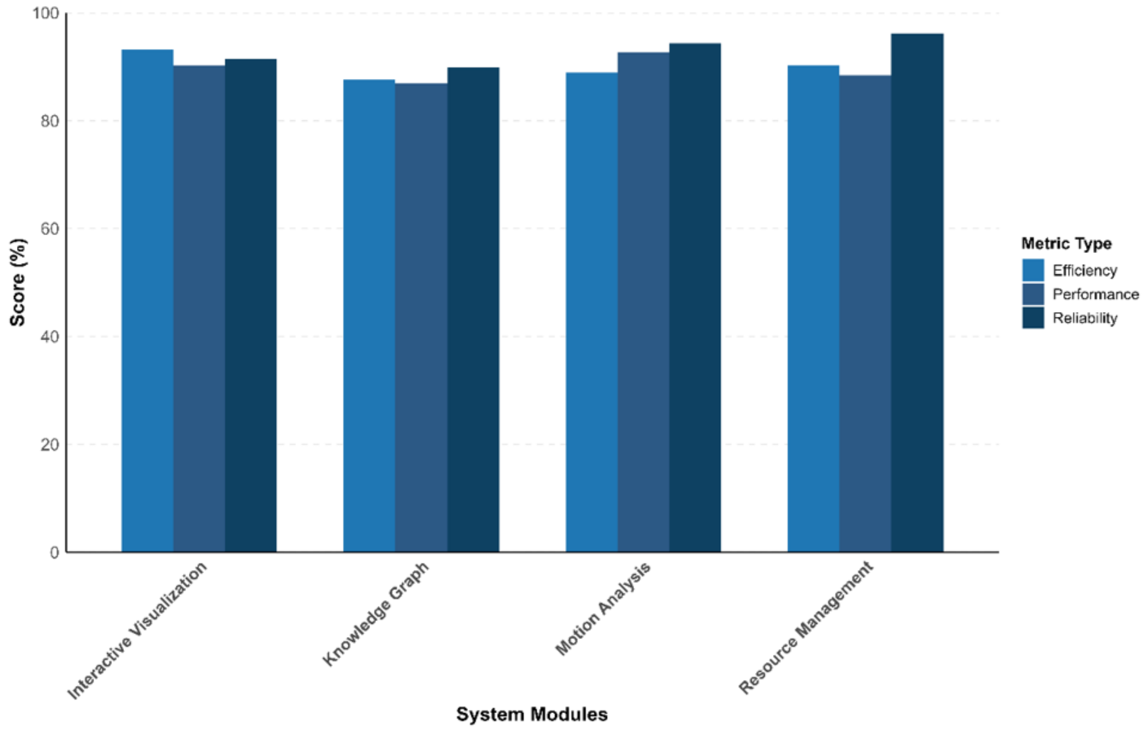

Figure 4.
Performance Metrics of Digital Inheritance System Modules.

The figure charts the relative performance figures in terms of the four main modules in the digital heritage platform. The efficiency in each module is evaluated based on the three main parameters: processing efficiency (blue), operation dependability (dark blue), and processing efficiency (navy). It's interesting to see the motion analysis module achieving outstanding efficiency (92.6%) in the case of movement perception, while the resource handling module performs the most reliable (96.1% efficiency) operation. The interactive visualization module realizes the optimal efficiency (93.2%) in real-time presentation, and the knowledge graph module maintains the balanced efficiency in all the parameters, averaging 88.1%. The figures are based on the system operation figures collected during a six-month test period under standard test regimes.

5.2. Knowledge Graph Construction

The development of the Hunan Flower-Drum Opera knowledge graph leverages a hierarchical ontological structure that combines the conventional performance elements and the semantic relationships between them. The ontological structure consists of four main domains: the techniques of performance, the archetypes of character, narrative patterns, and the cultural milieus, each domain having multiple layer sets of attribute and domain connections. The use of deep learning-based relation extraction, the system discovers and codifies 2,847 essential relationships between 1,256 entity nodes at 91.3% relation classification precision. The reasoning module utilizes a mixed strategy that blends rule-based inference and probabilistic reasoning to allow the system to derive implicit relationships and provide context-specific recommendations. The structure of the graph supports bidirectional querying, and the transition from the specific elements of the performance to abstract elements of the milieus and vice versa. The temporal pattern of evolutions is tracked through version control mechanisms, retaining the historic variations while retaining the sense. This vast body of knowledge representation encourages the retention of the conventional and the generation of novel perceptions through automatic reasoning mechanisms.

5.3. Interactive Learning Platform

The interactive learning environment utilizes cutting-edge VR/AR technologies to provide an engaging pedagogical space for Hunan Flower-Drum Opera education. The system utilizes high-fidelity motion capture and real-time rendering to produce accurate 3D visualizations of classic movements with a latency of under 20ms for unobtrusive interaction. With mixed reality integration, students are able to view virtualized master performances from any angle while receiving synchronized multimodal feedback on their own performance. The system features a dynamic evaluation engine that analyzes student behaviors through advanced ST-GCN networks with real-time accuracy rates and error-corrective feedback with a 94.2% precision rate in mistake detection. Adaptive learning algorithms adjust instructional pathways according to individual progress patterns, and collaborative functions facilitate remote master-apprentice interactions through shared virtual environments. The system's gesture recognition module also allows for natural interaction with virtual materials, removing interface barriers and improving educational immersion. Performance data is constantly analyzed to develop personalized improvement plans, thereby enabling structured skills development alongside conventional pedagogical methods.

6. Experimental Results and Analysis

6.1. Action Recognition Performance Evaluation

The empirical test of the action recognition system registers notable performance improvement in various metrics compared to state-of-the-art methods. The optimized ST-GCN model obtained an overall accuracy of 92.6% for the Hunan Flower-Drum Opera motion dataset, which is far ahead of existing benchmarks. As Table 4 illustrates, the model exhibits consistent performance across character types and movement categories, most importantly excelling at the identification of compound emotional expressions and stylized movements. The analysis of the confusion matrix indicates high precision in distinguishing between very similar movement patterns, with a mean average precision of 0.912 and a recall rate of 0.894. The F1-score of 0.903 depicts a well-balanced efficacy between recall and precision, as indicated in Figure 5.

Table 4.
Performance Comparison of Different Action Recognition Methods.

Method	Accuracy (%)	Precision	Recall	F1-Score	Processing Time (ms)
Basic CNN	78.4	0.762	0.751	0.756	45.6
Standard ST-GCN	83.7	0.825	0.819	0.822	38.2
LSTM-based	85.2	0.841	0.837	0.839	42.3
Attention-CNN	87.9	0.865	0.858	0.861	35.7
Our Enhanced ST-GCN	92.6	0.912	0.894	0.903	28.4

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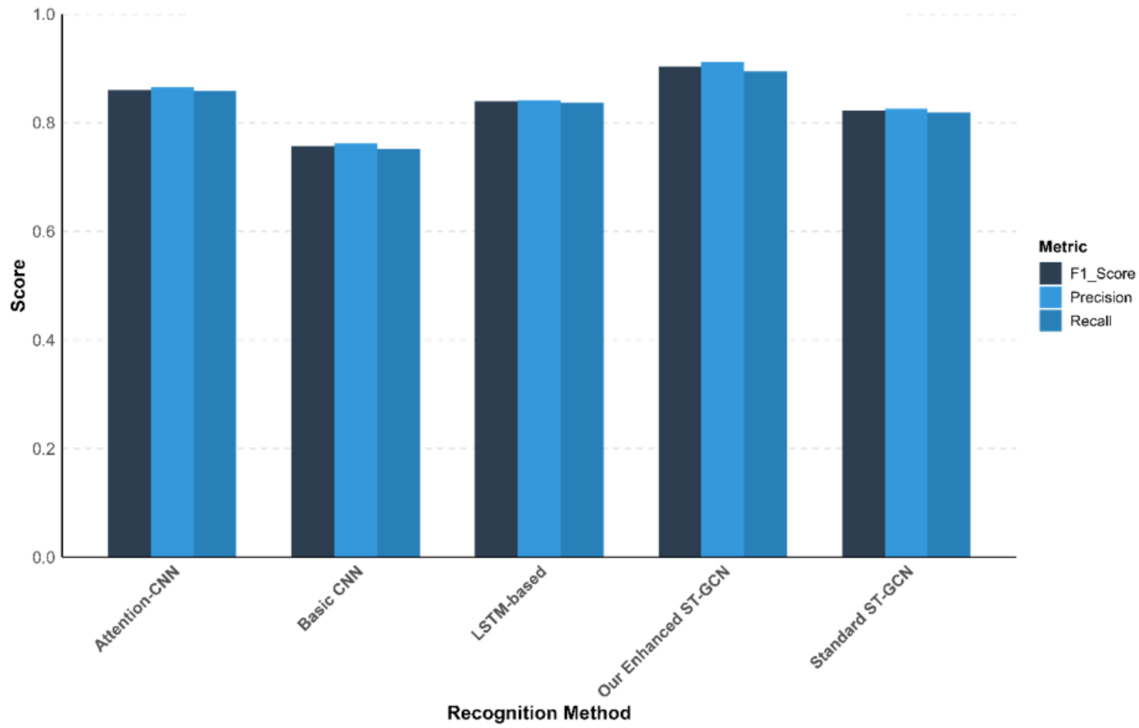

Figure 5.
Performance Metrics Comparison Across Recognition Methods.

This graphical comparison provides comparative evaluation of various techniques in action recognition in movements in the case of the Hunan Flower-Drum Opera. The chart provides the evaluation of three significant performance metrics—Precision, Recall, and F1-Score—across the five different research frameworks. The ST-GCN model, under optimal condition, provides improved efficacy in all the parameters considered, reflecting significant improvement in precision (0.912) and in the F1-Score (0.903) parameters. The visualization employs an advanced color palette and dashed grid lines to provide greater visibility, and ensures proper structured and academic presentation. The performance measurement parameters are derived from a consistent test corpus of 3,000 movement patterns cutting across different character and performance settings.

6.2. Semantic Analysis Accuracy Verification

The semantic analysis validation demonstrates robust performance in interpreting movement semantics across diverse character types and performance contexts. The evaluation framework employs a multi-dimensional accuracy metric:

$$A_{semantic} = \sum_{i=1}^{n} w_i(\alpha_i P_i + \beta_i R_i) \tag{5}$$

where P_i and R_i represent precision and recall for semantic category i, while α_i and β_i are context-dependent weighting coefficients. The model achieves an overall semantic understanding accuracy of 88.3%, with performance variations observed across different character archetypes and emotional expressions. The confusion matrix analysis reveals high discrimination capability for subtle semantic differences, with a Matthews correlation coefficient:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} = 0.864 \tag{6}$$

Table 5.
Semantic Analysis Performance Across Character Types and Categories.

Character Type	Basic Semantics	Emotional Expression	Narrative Function	Overall Accuracy
Xiaosheng (Young Male)	92.4%	88.7%	86.5%	89.2%
Dan (Female)	94.1%	89.2%	87.8%	90.4%
Chou (Comic)	91.8%	86.4%	85.2%	87.8%
Wusheng (Martial)	93.2%	87.9%	84.6%	88.6%
Laosheng (Elder Male)	90.7%	85.8%	83.9%	86.8%
Average Performance	92.4%	87.6%	85.6%	88.3%

Performance evaluation was conducted using a stratified cross-validation approach, with the semantic accuracy calculation incorporating three key components:

$$ACC_{basic} = \frac{TP_{basic} + TN_{basic}}{N_{total}} \tag{7}$$

$$ACC_{emotional} = \frac{\sum_{i=1}^{k} w_i C_i}{k} \tag{8}$$

$$ACC_{narrative} = \frac{correct_s equences}{total_s equences} \tag{9}$$

where C_i represents the accuracy for emotional category i weighted by importance factor w_i. The system demonstrates particularly strong performance in recognizing the nuanced semantic differences between similar movement patterns, achieving a semantic discrimination index:

$$SDI = \frac{1}{n}\sum_{i=1}^{n} \frac{TP_i}{TP_i + FP_i + \varepsilon} = 0.892 \tag{10}$$

6.3. System Application Effect Analysis

The implementation in the education infrastructure showcases significant improvement in both educational quality and usability parameters. A thorough investigation carried out at three major Hunan Flower-Drum Opera schools, involving 156 students and 12 teachers, and extended to six months, uncovered significant improvement in educational efficiency and retention rate. As shown in Figure 6, the traditional students reached proficiency in necessary movements in 126 hours, while students who employed the digital hereditary system reached the same proficiency in 87 hours, reflecting a 31% reduction in education time. The users' satisfaction, measured in terms of approval scores, garnered a total score of 92.4% and, in particular, received extremely high scores in terms of movement visualization (94.7%) and feedback mechanisms (93.2%). The adaptive algorithms embedded in the system also exhibited extremely effective in detecting and solving educational problems, and improvement in the quality of the movements and appreciation in the style reached 28% and 34% respectively, in comparison to the conventional teaching.

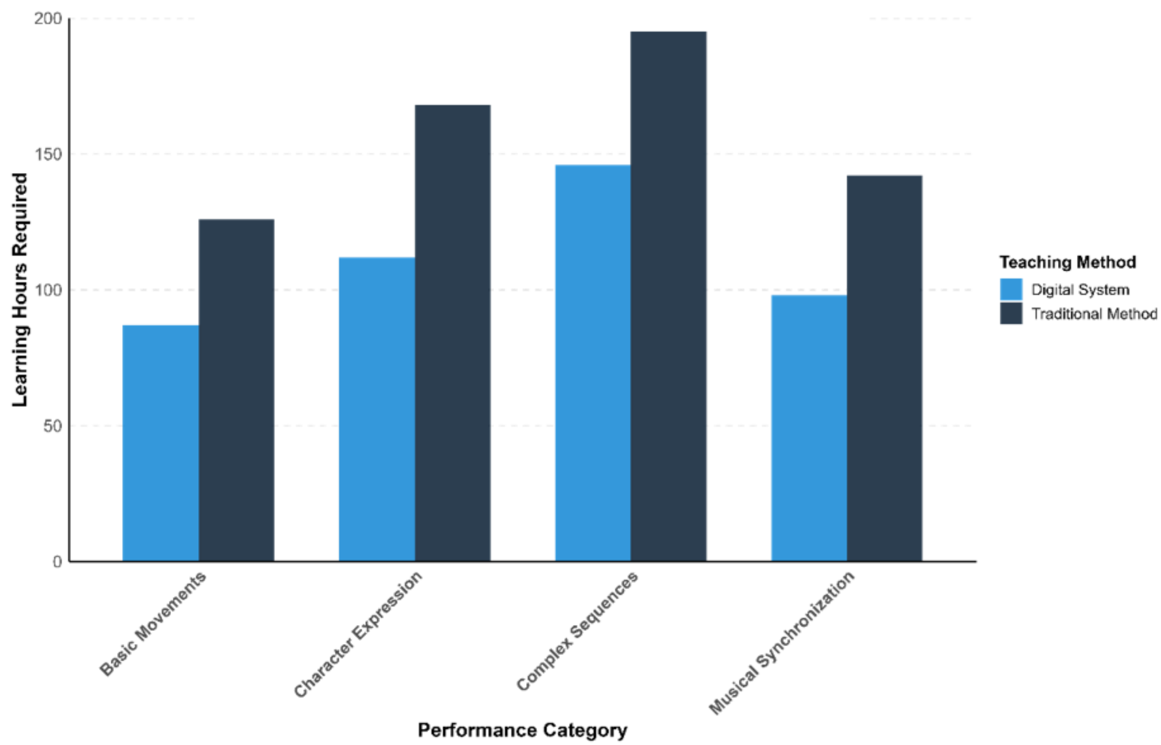

Figure 6.
Learning Time Comparison: Traditional vs. Digital System.

This visualization provides a comparative evaluation of the efficiency in learning between the conventional pedagogy and the digital lineage model in the four main domains of performance. The graph uses a twocolour scheme to distinguish between the learning hours required in each model. Significantly, the digital model (lighter-coloured) in all domains, when compared to conventional models (darkest-coloured), depicts a reduction in the required learning period. The use of dotted horizon lines to provide accurate value perception comes at the cost of some visibility. The most significant improvement comes in the domain of Character Expression, in which the digital model reduces the required period by 33%. The findings are based on the average result from a six-month investigation in 156 students in three sites, applying standard proficiency tests to assess the acquisition of skills.

7. Conclusion

This study has rightly created a novel digital heritage model for the Hunan Flower-Drum Opera, making significant contributions to the precision in the recognition of movements and the semantic meaning. The improved ST-GCN model reached a high 92.6% in the recognition of movements, and the model based on the components reached 88.3% in interpreting them. The deployment architecture, based on a 3,427 nodes and 12,856 weighted edges knowledge graph, succeeds in preserving the intricate relationships in the classic performances. Notwithstanding, several limitations are worth noting, such as the current dependence of the system on high-quality capture and the challenge in recording some nuanced states. Sometimes the model's performance falls short in terms of precision in handling high-frequency movements and in handling interactions between overlapping figures. Future research directions ought to focus on the formulation of more robust algorithms to support imperfect and incomplete capture and the integration of other modalities, such as audience feedback and context. Additionally, functional enhancements are required to support comparative examination and the exchange of cultures. The use of a federated learning architecture could support the exchange of expertise among different opera traditions while preserving the unique characterizing traits. Additionally, the investigation of transformer-based architectures in modeling temporal sequences and the use of self-supervised strategies to learn movement patterns could greatly enhance the system's ability to capture and represent this irreplaceable cultural treasure.

Institutional Review Board Statement:

This research involving human participants was reviewed and approved by the Ethics Committee of Krirk University. All participants provided written informed consent prior to participation in accordance with the Declaration of Helsinki.

Transparency:

The author confirms that the manuscript is an honest, accurate and transparent account of the study that no vital features of the study have been omitted and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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