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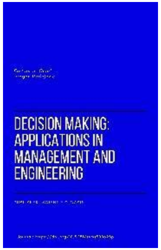

Fuzzy Decision Support for Sustainable Dance Heritage Preservation Using AI-Driven Narrative Modelling

Lu Zhang[1], Ting Yu[2], Yuxia Kong[3], Ying Fu[4*]

1 College of Arts, Shinawatra University, Thailand. Email: 413323869@qq.com
2 College of Arts, Shinawatra University, Thailand. Email: ting.y@siu.ac.th
3 International college, Phetchabun Rajabhat University, Thailand. Email: yuxiakong1030@gmail.com
4 Faculty of Technical Education, Rajamangala University of Technology Thanyaburi, Thailand. Email: ying_f@mail.rmutt.ac.th

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ABSTRACT

The preservation of intangible cultural heritage (ICH) is becoming progressively more difficult due to environmental disruptions and the intricate nature of recording historical performance traditions. Conventional preservation approaches remain constrained by the absence of scalable mechanisms capable of ensuring reliable decision-making within uncertain environments. This study introduces a fuzzy-based decision support architecture integrated with Artificial Intelligence (AI)-oriented narrative modelling to facilitate the sustainable preservation of dance heritage. Initially, a systematically organised representation of Chinese Lion Dance movements is developed to capture both the foundational motion patterns and the expressive attributes embedded within this traditional performance practice. The proposed framework is subsequently connected to sensor-generated data streams, thereby establishing a computationally executable platform for automated motion acquisition and transcription. The Dance Preservation Dataset (400k), obtained from Kaggle, undergoes pre-processing through Z-score normalisation, after which Principal Component Analysis (PCA) is employed for feature extraction to minimise dimensional complexity while preserving the most influential movement-related attributes. The recorded performances are then transformed into Labanotation, enabling structured archival documentation and facilitating the synthesis of new performances without compromising the authenticity and structural integrity of traditional dance expressions. To accomplish this objective, a hybrid neuro-fuzzy model is designed by integrating Sugeno-type fuzzy-mutated Enhanced Recurrent Neural Networks (STFuzzy-ERNN) with Sugeno-type fuzzy inference systems (SFIS). The STFuzzy-ERNN component performs movement pattern identification, whereas the SFIS module delivers interpretable and transparent decision-making capabilities. The proposed framework assesses several preservation-oriented criteria, including movement intricacy, expressive richness, and historical relevance, thereby generating explainable recommendations for conservation prioritisation and archival management. Experimental outcomes demonstrate superior performance, achieving precision of 0.9892, recall of 0.9875, inference time of 6.4, and model size of 47.3. Furthermore, feature-importance evaluation identifies the most influential movement characteristics and sensor modalities contributing to preservation prioritisation. The findings establish an extensible and data-centric strategy for protecting intangible dance heritage. Through the integration of AI, fuzzy reasoning, and narrative modelling, the framework enhances long-term documentation, analytical interpretation, and intergenerational transmission of traditional dance practices for educators, performers, and cultural heritage organisations.

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[*] *Corresponding author.*
E-mail address: ying_f@mail.rmutt.ac.th

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1. Introduction

The preservation of dance heritage plays a fundamental role in sustaining cultural identity, artistic richness, and social continuity within an increasingly digitalised and globally interconnected society [15]. Dance functions as a multidimensional communicative medium that integrates bodily movement, rhythm, emotional expression, and symbolic representation to convey collective narratives, traditions, and societal values. It reflects historical transformation, communal interaction, and cultural plurality, thereby constituting a significant dimension of Intangible Cultural Heritage (ICH) [22]. Preserving these cultural expressions requires intelligent systems capable of systematically capturing both the expressive and contextual dimensions of dance in a structured and meaningful manner [13].

Artificial Intelligence (AI) has generated transformative opportunities for analysing, modelling, and reproducing complex cultural knowledge structures [28]. AI-oriented narrative modelling enables dance to be interpreted as an organised narrative framework in which movement sequences are interconnected with emotional themes, symbolic meanings, and cultural interpretations. Through this approach, dance performances can be transformed into structured digital narratives suitable for computational analysis, archival storage, and large-scale dissemination [23]. Such mechanisms improve the interpretability of cultural expressions while simultaneously supporting the preservation of evolving artistic practices through scalable and accessible knowledge repositories [16]. Hao and Miao [6] further proposed a neural-symbolic architecture integrating neural representation learning with symbolic reasoning and self-supervised semiotic alignment mechanisms to enhance contextual understanding and cultural representation.

Fuzzy decision support systems provide an effective mechanism for addressing the uncertainty and subjectivity associated with cultural heritage evaluation processes [18]. In dance heritage preservation, attributes such as aesthetic significance, emotional intensity, and cultural relevance cannot be measured precisely through conventional computational approaches. Fuzzy logic enables these abstract characteristics to be represented through linguistic variables, thereby facilitating adaptive reasoning and flexible evaluation procedures [10]. The integration of AI-driven narrative modelling with fuzzy-based decision-making frameworks creates intelligent preservation mechanisms capable of supporting sustainable, context-aware, and culturally sensitive dance heritage conservation strategies [2; 14].

Earlier investigations explored the application of AI and fuzzy systems for cultural heritage preservation; however, many of these approaches demonstrated limited adaptability, weak contextual generalisability, and inconsistent performance outcomes. Dragomir and Dragomir [4] introduced a hybrid neuro-fuzzy framework for cultural heritage conservation monitoring that combined Multi-Sensor Feedforward Neural Networks (FF-NN) with Mamdani Fuzzy Inference Systems (MFIS) using parameters such as temperature, vibration, and pressure. The framework achieved 94.3% accuracy, 92.3% precision, and 90.3% recall, while temperature contributed approximately 60.6% to the fault detection process. Nevertheless, the rigid structure of predefined fuzzy rules reduced recall performance in fault-dominant and borderline scenarios, thereby limiting overall adaptability and operational effectiveness. Similarly, [27] developed an advanced computational framework for the preservation and representation of ICH through a neural-symbolic architecture that merged neural representations with symbolic reasoning and self-supervised semiotic alignment techniques. Although the framework enabled adaptive modelling, contextual continuity, and interactive cultural representation, its applicability across diverse real-world cultural settings remained insufficiently validated [8].

The preservation of traditional dance heritage remains constrained by challenges associated with complex movement structures, inconsistent documentation practices, and ambiguous evaluation standards. Existing preservation approaches provide limited support for accurate decision-making concerning conservation priorities, analytical interpretation, and the responsible transmission of culturally significant dance traditions. This study addresses these limitations by integrating AI-driven narrative modelling with hybrid Sugeno-type fuzzy-mutated Enhanced Recurrent Neural Networks (STFuzzy-ERNN) to facilitate precise movement analysis alongside interpretable, data-oriented decision-making mechanisms for sustainable dance heritage preservation [3; 30].

1.1 Key Contributions of the Research

- The Dance Preservation Dataset comprising 400k movement records was obtained from Kaggle, where pre-processing was conducted through Z-score normalisation, followed by PCA-based dimensionality reduction to extract the most influential motion-related attributes.
- The STFuzzy-ERNN framework was developed through the integration of SFIS with Enhanced Recurrent Neural Networks (ERNN) to improve adaptive movement recognition and interpretable reasoning capabilities.
- The proposed framework enables efficient and explainable dance heritage preservation through sensor-driven movement analysis combined with transparent decision-making mechanisms.

2. Related Works

Existing investigations concerning sustainable heritage preservation using AI and fuzzy logic approaches demonstrated improved performance outcomes; however, several methodological and practical limitations remained unresolved. Wang et al. [24] introduced an accurate framework for reconstructing complex dance movements under nonlinear and incomplete motion conditions. The study proposed a Two-Dimensional Matrix Calculation (TDMC) model integrated with a Hybrid Genetic Algorithm-Fuzzy Logic Differential Evolution (HGA-FLDE) mechanism. Experimental findings achieved 0.95 accuracy with a minimum error rate of 0.39, outperforming comparative approaches, while rehabilitation-oriented scenarios attained 0.94 accuracy [11]. Despite these improvements, the framework depended heavily on sophisticated hybrid optimisation procedures and sensor-driven Inertial Measurement Unit (IMU) data, thereby restricting efficient real-time practical implementation.

Li [12] improved folk dance image recognition performance and enhanced instructional strategies through Deep Learning (DL)-based techniques. The study implemented an optimised Deep Neural Network (DNN) architecture and compared its performance against conventional classification approaches. The outcomes indicated a 14.7% improvement in recognition accuracy together with stronger robustness characteristics. Nevertheless, the framework lacked validation within large-scale real-time operational environments [9; 17]. Another investigation evaluated the influence of digital information technologies on architectural heritage preservation within uncertain decision environments. The study employed interval-valued q-rung orthopair fuzzy weighted average (IVq-ROFWA) and interval-valued q-rung orthopair fuzzy weighted geometric (IVq-ROFWG) aggregation operators to assess preservation alternatives. The findings identified augmented reality as the leading alternative according to IVq-ROFWA, whereas IVq-ROFWG ranked heritage building information modelling as the highest-performing option [19]. However, the assessment was conducted using a limited number of alternatives and lacked validation within real-world implementation settings.

A further study developed a framework for selecting and classifying dance styles within pretrained DL environments operating under uncertainty conditions. The approach utilised transfer learning-based pretrained models integrated with a compromise solution framework known as

CFFMARCOS, which incorporated circular Fermatean fuzzy sets for multi-criteria decision-making processes. The results demonstrated enhanced ranking reliability, stronger interpretability, and improved decision transparency. Nonetheless, the framework was not evaluated in large-scale real-world deployment scenarios [20]. Huang and Nguyen [7] identified an optimal cultural tourism model aimed at supporting Indigenous communities while simultaneously preserving cultural heritage. The investigation adopted the Fuzzy Analytic Hierarchy Process (FAHP) to assign weights and prioritise evaluation criteria. The outcomes revealed effective tourism model combinations with improved decision performance. However, the framework relied predominantly on subjective expert judgements and lacked practical implementation evidence capable of reflecting dynamic cultural environments [1; 26].

The digital preservation of folk sports culture was also improved through realistic generation of traditional movement imagery. The proposed framework introduced an enhanced Cycle-Consistent Generative Adversarial Network (CycleGAN) model integrated with pose consistency, identity preservation, appearance consistency mechanisms, and specialised loss functions. The findings enhanced image quality, producing a 1.49% improvement in inception score while achieving 58.25% realism during authenticity evaluations. Despite these advancements, the investigation focused mainly on image generation and did not validate real-time practical applications. Zhou and Sangsawang [29] proposed a data-driven blended learning framework for sustainable minority dance education. The framework combined motion capture technology with Artificial Gorilla Troop Optimized Conditional Variational Autoencoder (AGTO-CVAE) mechanisms and K-means clustering to characterise dance movements and learning patterns. The findings demonstrated high precision of 0.9875, reduced computational complexity, and improved learner analysis capabilities. Nevertheless, the framework remained specialised for small-scale minority dance programmes and required dedicated motion capture equipment, thereby limiting broader large-scale applicability [21].

2.1 Research Gap

Despite substantial progress in DL, fuzzy decision-making frameworks, and hybrid optimisation approaches for dance and heritage preservation, several critical research deficiencies remain unresolved. Existing investigations frequently rely on limited datasets and narrowly focused dance categories, thereby constraining the broader applicability, scalability, and generalisability of the developed frameworks [2; 28]. Furthermore, many existing approaches depend extensively on complex hybrid architectures or subjective expert-driven evaluations, which increase computational overhead while simultaneously introducing interpretational bias and inconsistency into preservation processes [7].

In addition, the integration of AI-driven narrative modelling, semantic representation of dance knowledge, real-time operational capability, and large-scale validation remains insufficiently explored within sustainable dance heritage preservation systems. Current frameworks often lack explainable reasoning mechanisms capable of supporting transparent preservation decisions under uncertain cultural and environmental conditions. This study addresses these limitations through the integration of interpretable fuzzy logic with an accurate AI-based architecture using STFuzzy-ERNN. The proposed framework facilitates scalable, explainable, and data-oriented preservation of complex dance heritage while effectively managing uncertainty and improving sustainable cultural conservation processes [5].

3. Methodology

This research develops a fuzzy AI-driven framework capable of accurately capturing, analysing, and preserving dance movements to support sustainable, interpretable, and data-oriented heritage documentation and transmission processes. The Dance Preservation Dataset was collected from Kaggle, while pre-processing procedures included Z-score standardisation followed by PCA-based dimensionality reduction to retain the most significant movement-related attributes. The STFuzzy-ERNN framework was employed to achieve precise dance movement recognition and facilitate interpretable, data-driven preservation decision-making. The complete methodological workflow adopted in this study is illustrated in Figure 1.

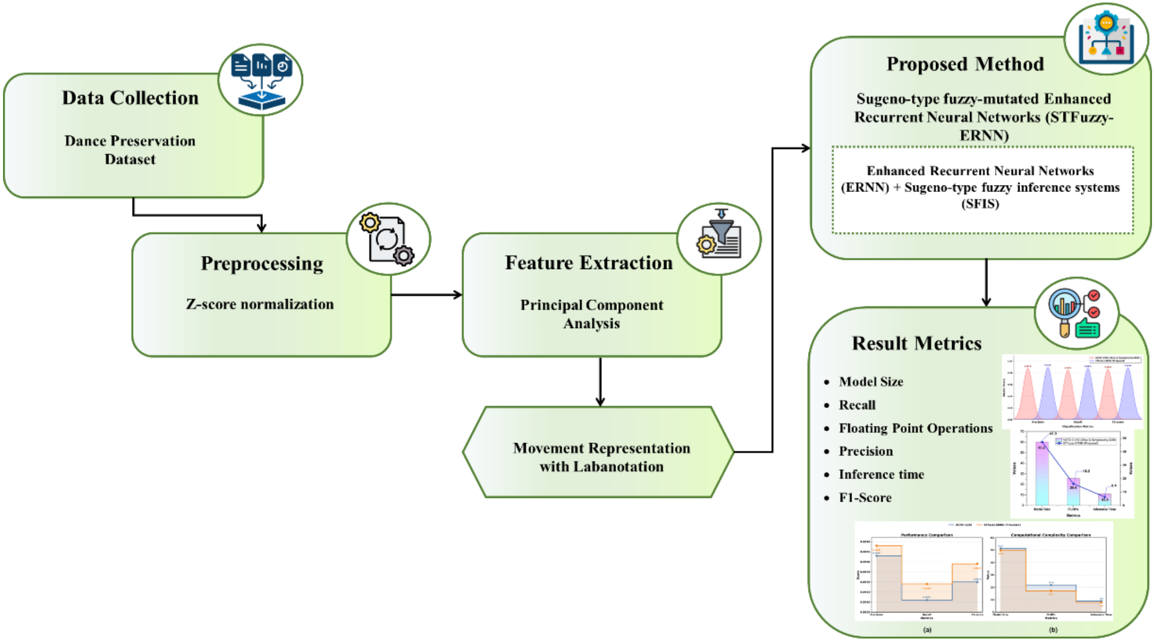


Fig.1: Pictorial Representation of Methodology Flow

3.1 Data Collection

The Dance Preservation Dataset (400k) was sourced from the open-access Kaggle platform. It is designed to support the preservation and analytical study of Intangible Cultural Heritage (ICH), with a particular focus on classical dance forms. The dataset integrates motion-related data, expressive characteristics, and cultural evaluation indicators, capturing dynamic variations in posture, intensity, and coordination. It further includes structured annotations such as movement complexity, expressive richness, cultural significance, and preservation priority levels. This well-organised dataset facilitates movement classification, sequential pattern analysis, and evidence-based decision-making, thereby supporting the sustainable documentation, conservation, and transmission of traditional dance knowledge systems. The dataset was validated with 70% for training and 30% for testing data. The data has been extracted from https://www.kaggle.com/datasets/ziya07/dance-preservation-dataset-mdhpd.

3.2 Z-Score Normalization using Standardized Data

To address scale variability and ensure a uniform feature distribution for extraction, Z-score normalisation is applied to sensor-based dance movement data. This transformation standardises each observation by centring it around the mean (μ) and rescaling it according to the standard deviation (σ), thereby enabling consistent comparative analysis across diverse sensor signals and movement intensity levels. This process enhances data comparability and stabilises subsequent analytical modelling. The standardisation process is formally expressed in Equation (1).

$$W_{new} = \frac{W-\mu}{\sigma} \tag{1}$$

Where, W_{new} is normalized feature value of W. It produces a normalised dataset with uniformly scaled feature values, thereby enhancing consistency, stability, and reliability for subsequent feature extraction and analytical processing.

3.3 Feature Extraction using PCA

PCA reduces the high dimensionality of multi-sensor dance movement data while preserving the most informative motion-related features. This transformation enables complex dance patterns to be represented using a smaller set of highly discriminative components that effectively capture movement dynamics and expressive characteristics. Let the pre-processed sensor data be represented as $\Gamma j; j = 1 \ldots N$, where each sample corresponds to a recorded dance movement segment.

Initially, the dataset mean vector is calculated as defined in Equation (2).

$$\Psi = \frac{1}{N}\sum_{j=1}^{N}\Gamma_j \qquad (2)$$

Where, Ψ is mean vector, N is total number of data samples. The data are then centered by subtracting the mean (Φ_j):

$$\Phi_j = \Gamma_j - \Psi \qquad (3)$$

Next, the covariance matrix (D) is calculated to capture the variance structure of the movement data using Equation (4).

$$D = \frac{1}{N}\sum_{j=1}^{N}\Phi_m\Phi_m^S \qquad (4)$$

Here, Φ_m^S denotes transpose of the mean-centred vector of Φ_m. Eigen decomposition is performed on the covariance matrix with Equation (5).

$$DU_j = v_jU_j \qquad (5)$$

Where U_j is eigenvector corresponding to jth principal component and v_j represents eigenvalue representing the variance captured by the corresponding eigenvector. The principal components associated with the highest eigenvalues are then selected to construct a reduced-dimensional feature space. Subsequently, each movement sample is projected into this reduced space as defined in Equation (6).

$$X_{jl} = V_l^S\Phi_j \qquad (6)$$

Here, X_{jl} is Projected feature value of sample j onto the lth principal component, V_l^S represents transpose of the selected eigenvector. This yields a compact feature set that effectively captures the key spatiotemporal characteristics of dance movements, thereby enabling accurate pattern recognition and supporting the preservation of cultural heritage.

3.4 Movement Representation with Labanotation

The movement representation stage transforms processed dance data into a structured symbolic format using Labanotation. In this stage, normalised and PCA-derived features are mapped into standardised symbols representing key body segments, including the shoulder, elbow, hip, knee, and ankle, alongside directional orientation, movement level, and temporal sequencing. This conversion ensures precise documentation of movement sequences, enabling computational interpretability and faithful reproduction of dance actions. Overall, it establishes a formalised digital archive that preserves movement structures for subsequent analysis, retrieval, and reconstruction of traditional dance heritage.

3.5 Sugeno-Type Fuzzy-Mutated Enhanced Recurrent Neural Networks (STFuzzy-ERNN) for Movement Pattern Recognition

The proposed STFuzzy-ERNN integrates ERNN with SFIS to effectively model and interpret sensor-driven dance sequences. ERNN captures complex temporal dependencies within movement data, while SFIS provides interpretable rule-based evaluation, enabling transparent reasoning alongside predictive modelling. This hybrid configuration supports accurate recognition, classification, and preservation of culturally significant Chinese Lion Dance movements, ensuring both precision and explainability in decision-making processes.

3.5.1 Enhanced Recurrent Neural Networks (ERNN) for Accurate Pattern Recognition

Recurrent Neural Networks (RNN) are DL models designed to process sequential sensor-based dance movement data for pattern recognition and movement sequence analysis. In this context, the forward propagation mechanism of a standard RNN for sequential dance modelling is formulated in Equations (7–10).

$$a_v = d + Wj_{v-1} + Uz_v \tag{7}$$

$$j_v = tan\,h(a_v) \tag{8}$$

$$o_v = c + Xj_v \tag{9}$$

$$\hat{y}_v = sigmoid\ (o_v) \tag{10}$$

Here, a_v is intermediate activation, d and c are bias vector for output and hidden layer, Wj_{v-1} represents Recurrent weight matrix connecting Hidden state from the previous time step, U denotes Weight matrix connecting input to hidden layer, z_v is input feature vector at time step v, j_v signifies Hidden state at time step v, o_v represents output layer activation before final prediction, Connecting the hidden layer to the output layer is the weight matrix X, $\hat{y}_v$ denotes predicted output at time step v and $tan\,h$ and $sigmoid$ are activation function for hidden state and output layer.

However, standard RNNs suffer from vanishing gradient issues, limited capability in capturing long-term dependencies, and increased computational burden, which reduces their effectiveness in modelling complex, high-dimensional sensor-based dance movements. To address these limitations, this study employs ERNN, which enhances learning efficiency and network stability through optimised parameter adaptation, improved temporal feature learning, and reduced errors in sequential movement recognition. ERNN extends conventional RNN functionality through adaptive learning mechanisms and integration with SFIS to model intricate temporal patterns in dance movement data. It processes sensor-derived sequences from Chinese Lion Dance performances, capturing both short-term motion transitions and long-range temporal dependencies across movement structures. The incorporation of fuzzy mutation within ERNN further improves robustness in handling uncertainty and variability inherent in expressive dance gestures.

In addition, the model supports interpretable decision-making by translating learned temporal representations into rule-based outputs. This enables the evaluation of key preservation criteria such as movement complexity, expressive richness, and cultural significance. ERNN extracts dynamic decision rules, while SFIS generates transparent and structured outputs that support explainable decision processes. Overall, ERNN contributes to a scalable, robust, and interpretable framework that enhances movement detection, structured documentation, and intelligent prioritisation for sustainable dance heritage preservation.

3.5.2 Sugeno-Type Fuzzy Inference Systems (SFIS) for Decision-Making

SFIS enables interpretable decision-making within dance heritage conservation by evaluating key attributes such as movement complexity, expressive richness, and cultural significance. It converts temporal features extracted by ERNN into structured, rule-based outputs, thereby ensuring transparent, consistent, and data-driven prioritisation in the documentation, archiving, and preservation of traditional dance forms.

In this research, let $V = \{v_1, v_2, v_3, \dots, v_m\}$ represent universe of discourse corresponding to Chinese Lion Dance movement features, and $\mathcal{F}(V)$ denote fuzzy subsets describing characteristics such as complexity, expressiveness, and cultural value. The input variables are linked to relevant evaluation criteria and are represented using linguistic terms to capture the inherent uncertainty and subjectivity in dance assessment processes. The fuzzy rule-based system (FRBS) constitutes the foundational structure of SFIS, where knowledge representation is formalised through IF–THEN rules, as defined in Equation (11).

$$IF \quad w_1 \ is \ B_1, w_2 \ is \ B_2, \dots, w_m \ is \ B_m \quad THEN \ z \ is \ A \tag{11}$$

Here, $w_1, w_2, \dots w_m$ are input variables, $B_1, B_2, \dots, B_m$ are fuzzy sets corresponding to each input variable, z is output variable with Fuzzy set (A). The fuzzy logical operations applied to rule evaluation are represented as in Equation (12&13):

$$B \cup A : (B \cup A)(w) = B(w) \vee A(w) \tag{12}$$

$$B \cap A : (B \cap A)(w) = B(w) \vee A(w) \tag{13}$$

Here, $B(w)$ and $A(w)$ are Membership functions, $B \cup A$ represents Fuzzy union, $B \cap A$ is Fuzzy intersection. Here, the consequent is represented as a linear function of inputs by Equation (14):

$$IF \quad w_1 \ is \ B_1, w_2 \ is \ B_2, \dots, w_m \ is \ B_m \quad THEN \ z = d_0 + \sum_{j=1}^{m} d_j w_j \tag{14}$$

Where d_0 is Bias term and d_j is coefficients representing the contribution weight of each dance feature w_j with m number of input features considered in the fuzzy inference system. In this model, SFIS utilises temporal features extracted by ERNN and maps them into quantifiable outputs. This facilitates systematic evaluation of dance performances, prioritisation of preservation efforts, and identification of culturally significant movement patterns, thereby enhancing transparency and explainability in the decision-making process. The STFuzzy-ERNN framework strengthens the learning of temporal dependencies while effectively handling uncertainty inherent in complex dance datasets. It improves recognition accuracy, ensures interpretability through rule-based reasoning, and supports robust decision-making processes. In addition, it enables scalable preservation of culturally significant movement patterns derived from sensor-based inputs. The overall research procedure is outlined in Algorithm 1.

3.5.3 Algorithm 1. Sugeno-Type Fuzzy-Mutated Enhanced Recurrent Neural Networks (STFuzzy-ERNN) for Movement Pattern Recognition

```
Input: Sensor sequence Z = {z1, z2…, zV}
Initialization:
  Initialize ERNN parameters: W, U, X, biases (d, c)
  Initialize hidden state j0 = 0
  Define fuzzy sets B and rule base R
  Set learning rate η and epochs E
For epoch = 1 to E do
    For each sequence step v = 1 to V do
      # ERNN Forward Pass
      a_v = d + W * j_(v-1) + U * z_v
      j_v = tanh(a_v)
      o_v = c + X * j_v
      y_hat_v = sigmoid(o_v)
      # Store temporal features
      T_v = j_v
    End For
```

```
    # SFIS Processing
    For each feature vector T_v do
      Fuzzify inputs into linguistic variables
      For each rule r in R do
        If (conditions satisfied) then
          Compute rule output using linear function
        Else
          Skip rule
        End If
      End For
      Aggregate rule outputs → Z_out_v
    End For
    # Loss Computation
    Compute error between y_hat and true label Y
    # Backpropagation
    Update W, U, X, d, c using gradients
  End For
Output:
  Final prediction Y = y_hat
  Fuzzy evaluation score Z_out
```

4. Result

In this study, an explainable AI-based fuzzy decision support system was developed to facilitate the sustainable preservation and maintenance of traditional dance heritage data. This section presents the outcomes of the experimental evaluation and comparative analysis. The software and hardware specifications used in this research are summarised in Table 1.

Table 1
Experimental Setup

Components	Details
RAM	32GB
Processor	Intel Core i7
Programming Language	Python
Operating System (OS)	Windows 11
Library	TensorFlow, Keras, NumPy, Pandas, Scikit-learn

4.1 Experimental Analysis

Figure 2 illustrates the PCA-transformed feature space, where dance samples are clustered into distinct groups representing high, medium, and low preservation priorities. It demonstrates the effectiveness of dimensionality reduction in isolating movement patterns, thereby supporting informed decision-making within the fuzzy-based heritage preservation framework.

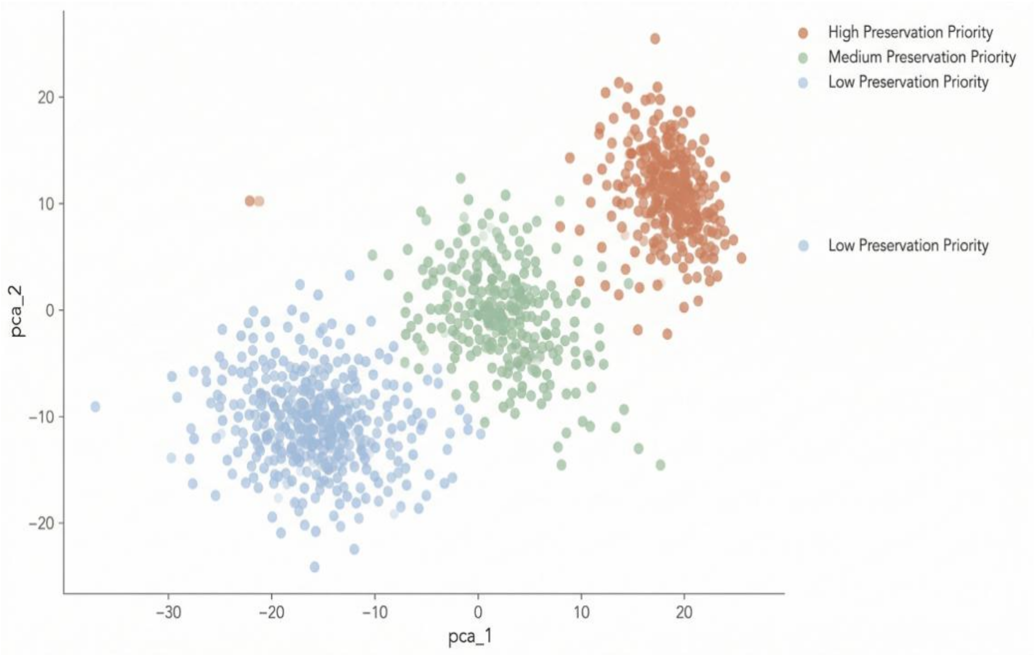


Fig.2: PCA-Based Clustering with Clear Groups of Preservation Priorities Based on the Extracted Features of the Dance Motions

Figure 3 illustrates the correlation between sensor-derived motion features and energy-related measures with respect to fuzzy variables. The presence of strong positive and negative relationships highlights key interdependencies that are essential for feature selection, thereby improving model interpretability and enhancing the accuracy of the neuro-fuzzy decision support system.

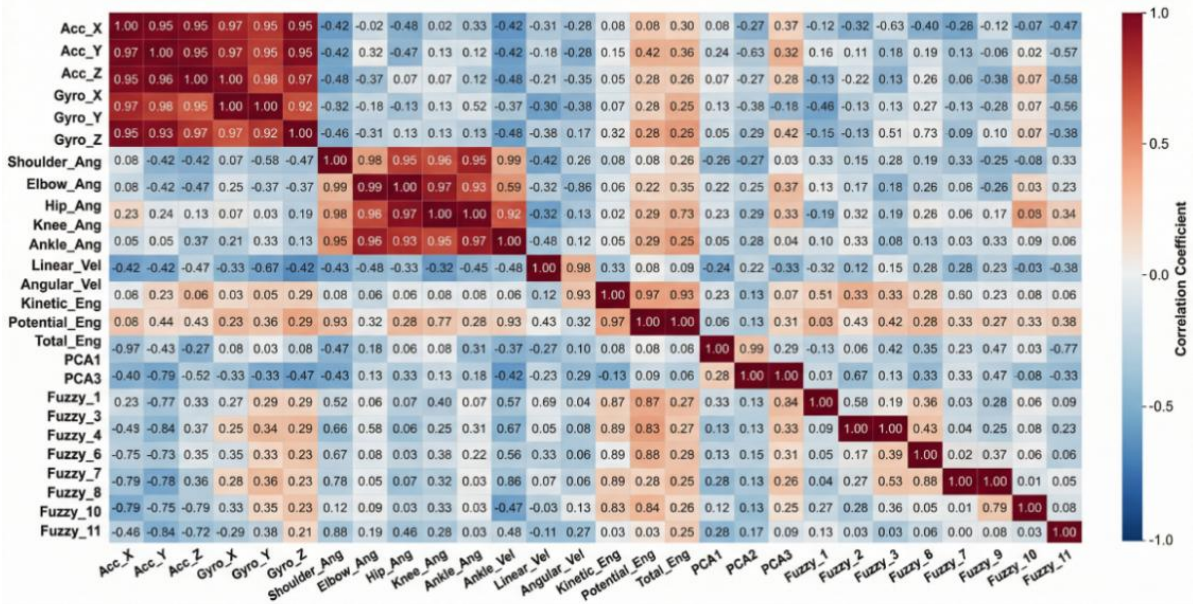


Fig.3: Correlation Indicating Relationship Between Motion, Energy and Fuzzy Decision Variables

Figure 4 presents a visual representation of the PCA projection integrated with kernel density estimation and fuzzy score-based colour mapping. It highlights regions of data concentration along with varying levels of preservation importance. The visualization demonstrates the alignment between fuzzy intensity values and spatial clustering patterns, thereby supporting interpretable, data-driven prioritisation in heritage preservation decision-making.

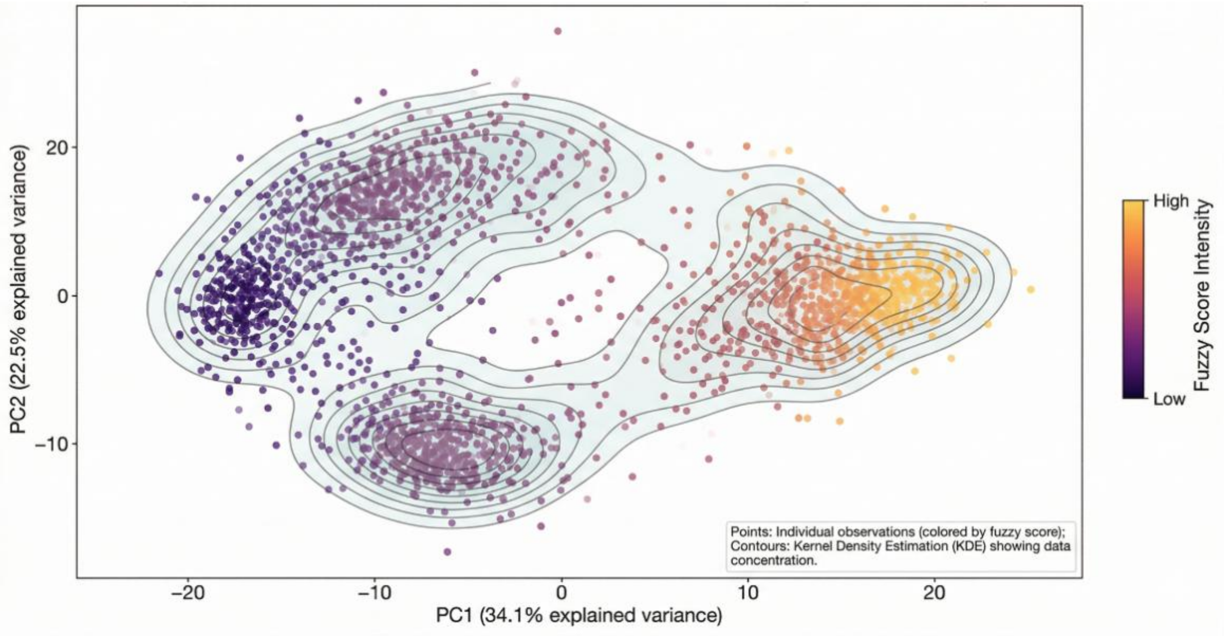


Fig.4: Hybrid PCA Visualization Between Data Density Contours and Fuzzy Score Intensity Distribution

Figure 5 illustrates the temporal evolution of multiple dance samples projected within the PCA feature space. The resulting trajectories capture changes in movement patterns over time and reveal underlying dynamic behavioural structures. These temporal pathways are essential for training ERNN, as they enable effective learning of sequential dependencies and motion evolution. Overall, this representation supports the analysis of dance dynamics for accurate modelling, preservation, and potential regeneration of traditional dance behaviours.

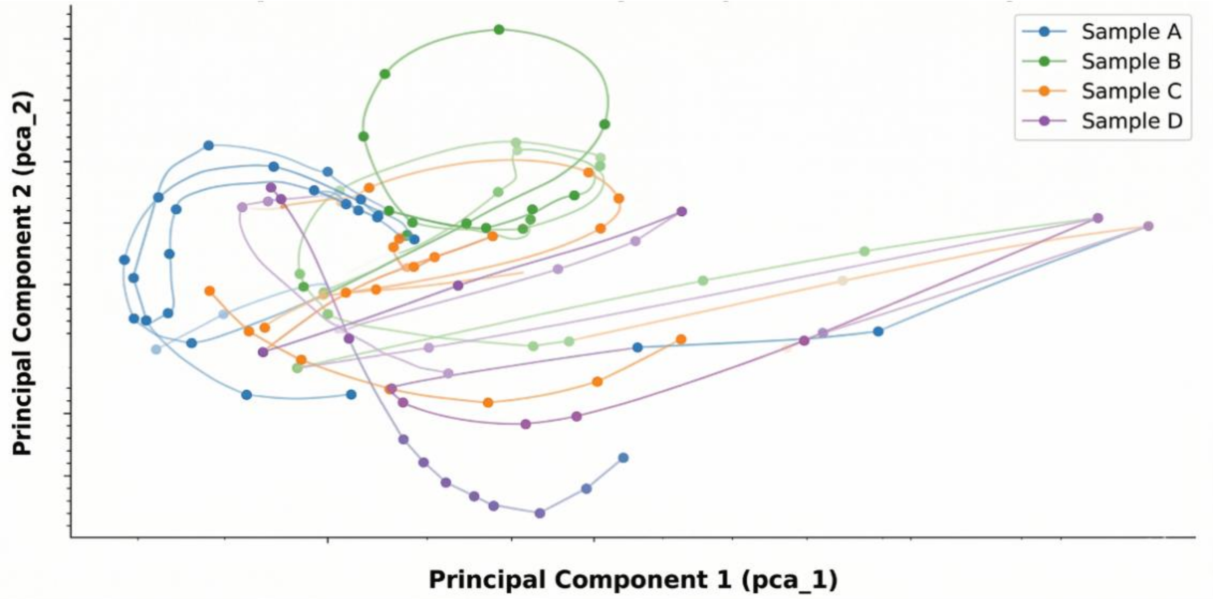


Fig.5: Temporal Patterns of Dance Samples of Dynamic Development in Reduced Feature Space of PCA

Figure 6 illustrates the synchronised temporal patterns of joint angles, velocity, and normalised energy across multiple dance samples. It captures both rhythmic consistency and variability in movement execution, reflecting key structural characteristics of dance dynamics. This representation is essential for feature extraction, motion analysis, and accurate modelling within the AI-driven preservation framework.

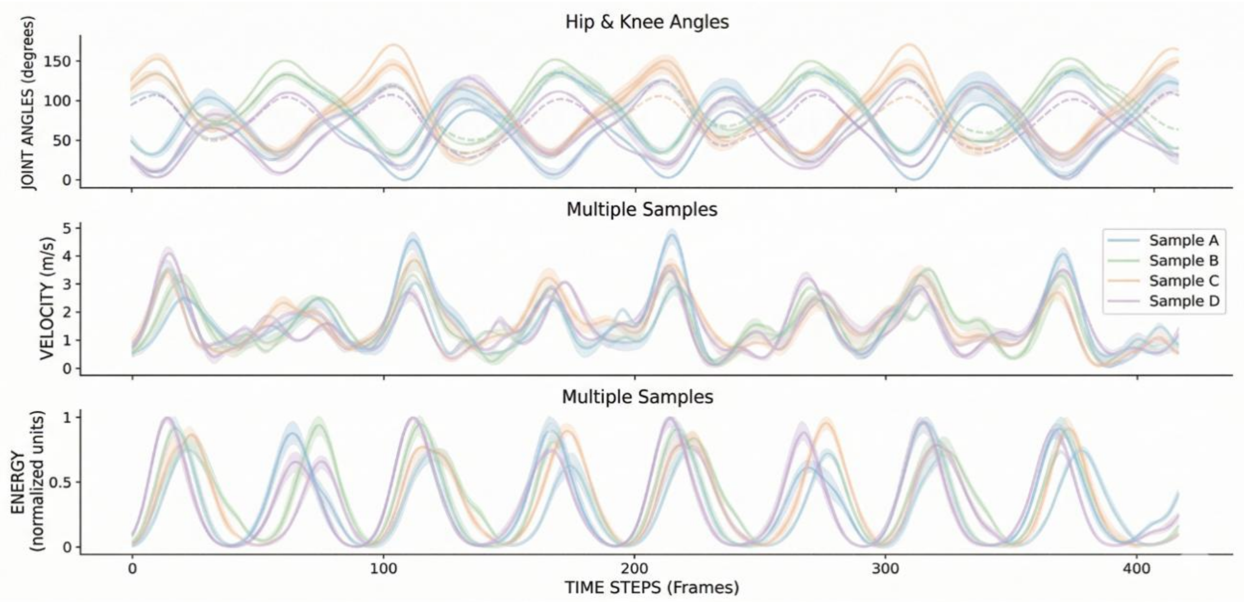


Fig.6: Patterns of Dance Movements with the Angles of Joints, Speed and Energy Changes Over Time

Figure 7 presents the normalised feature importance scores corresponding to key movement parameters, including PCA components, joint angles, and energy-based measures, used for prioritising dance preservation. The results highlight which motion characteristics exert the greatest influence on decision-making, thereby supporting informed and sustainable archival strategies within the AI-driven dance heritage documentation framework.

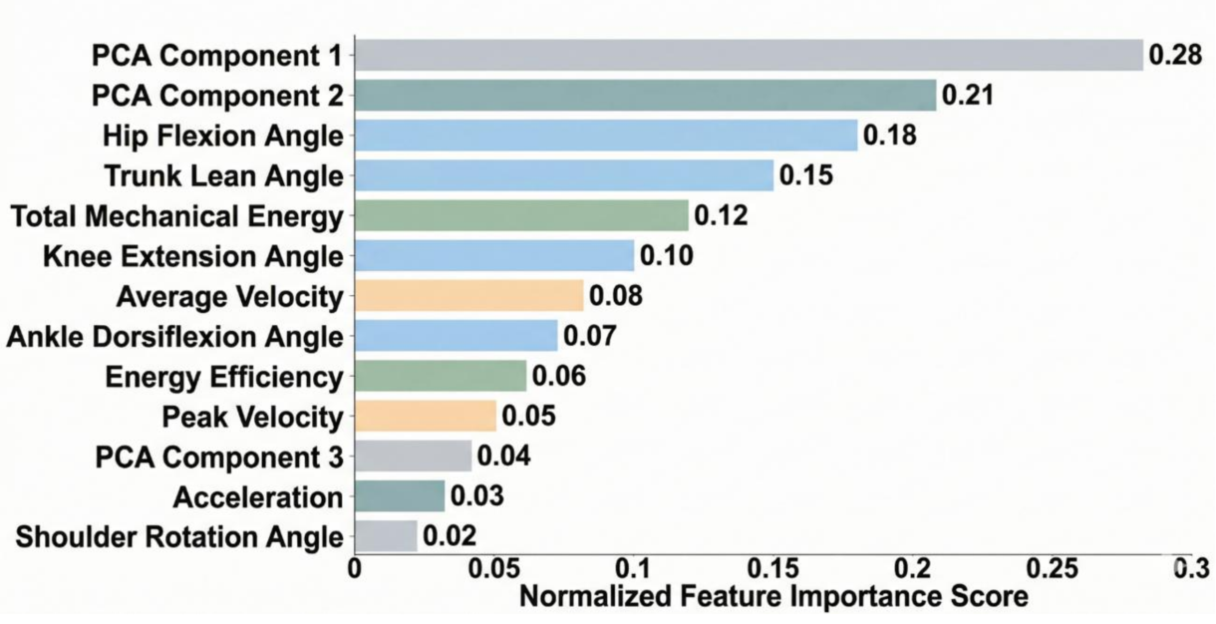


Fig.7: Feature Importance of Dance Movement Parameters for Preservation Prioritization through PCA Analysis

Figure 8 presents the velocity and energy trajectories of a contemporary dance sample, illustrating rhythmic accumulation, peak exertion phases, and subsequent deceleration patterns. By emphasising time-dependent motion dynamics, this visualisation enhances the understanding of high-energy movement segments and expressive performance characteristics that are critical for heritage documentation. Consequently, it supports preservation objectives by highlighting motion features essential for accurately capturing and conserving traditional dance forms.

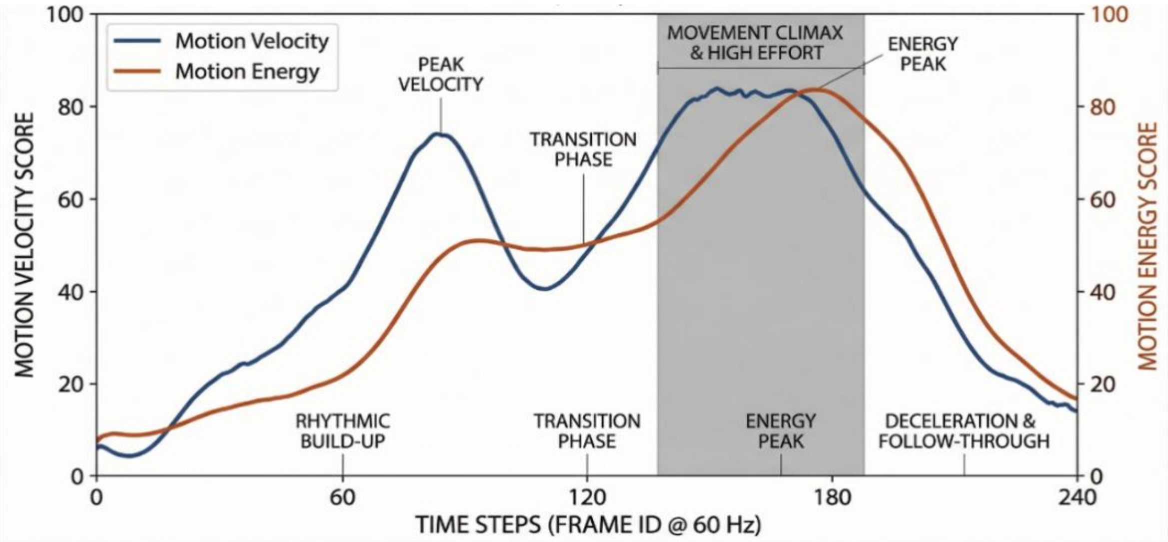


Fig.8: Temporal Variation of Motion Velocity and Energy in a Selected Dance Performance

4.2 Comparative Analysis

The proposed STFuzzy-ERNN is compared with existing model such as AGTO-CVAE (Zhou & Sangsawang 2026) in terms of metrics provided in Table 2.

Table 2
Performance Metrics

Metrics	**Definition**
Model Size (MB)	Refers to total memory footprint of the trained model, including weights, biases, and architecture parameters, determining storage requirements and deployment feasibility.
Recall	This metric reflects the model's capacity to identify significant dance movement patterns by measuring the proportion of positively detected cases out of all actual positives.
Floating Point Operations (FLOPs)	Represents the total number of arithmetic operations (additions, multiplications) performed during model inference, indicating computational complexity and efficiency.
Precision	Indicates the proportion of correctly predicted positive instances among all predicted positives, assessing accuracy in identifying true movement sequences without false alarms.
Inference Time (ms)	The time taken by the model to process input data and generate output predictions, reflecting system responsiveness for real-time or offline dance movement recognition.
F1-Score	The harmonic mean of precision and recall, providing a single metric to evaluate balance between correctly detecting movements and avoiding false positives.

The comparative performance of AGTO-CVAE (Zhou & Sangsawang, 2026) and the proposed STFuzzy-ERNN model is presented in Table 3. The STFuzzy-ERNN achieves superior results, with the highest recall of 0.9875, precision of 0.9892, and F1-score of 0.9886, indicating enhanced effectiveness in accurately recognising complex traditional dance movements.

Table 3
Comparison of Recall, Precision, and F1-Score for Dance Recognition Models

Method	**Dataset**	**Precision**	**Recall**	**F1-Score**
AGTO-CVAE (Zhou & Sangsawang, 2026)	Minority Dance Blended Learning Dataset	0.9875	0.9845	0.9859
STFuzzy-ERNN (Proposed)	Dance Preservation Dataset	0.9892	0.9875	0.9886

Figure 9 presents the comparative performance of AGTO-CVAE and the proposed STFuzzy-ERNN model in terms of precision, recall, and F1-score. The STFuzzy-ERNN demonstrates superior performance, achieving a precision of 0.9892, recall of 0.9875, and F1-score of 0.9886. These results indicate its greater capability in accurately identifying complex dance movement patterns and improving the reliability of decision-making within the preservation framework.

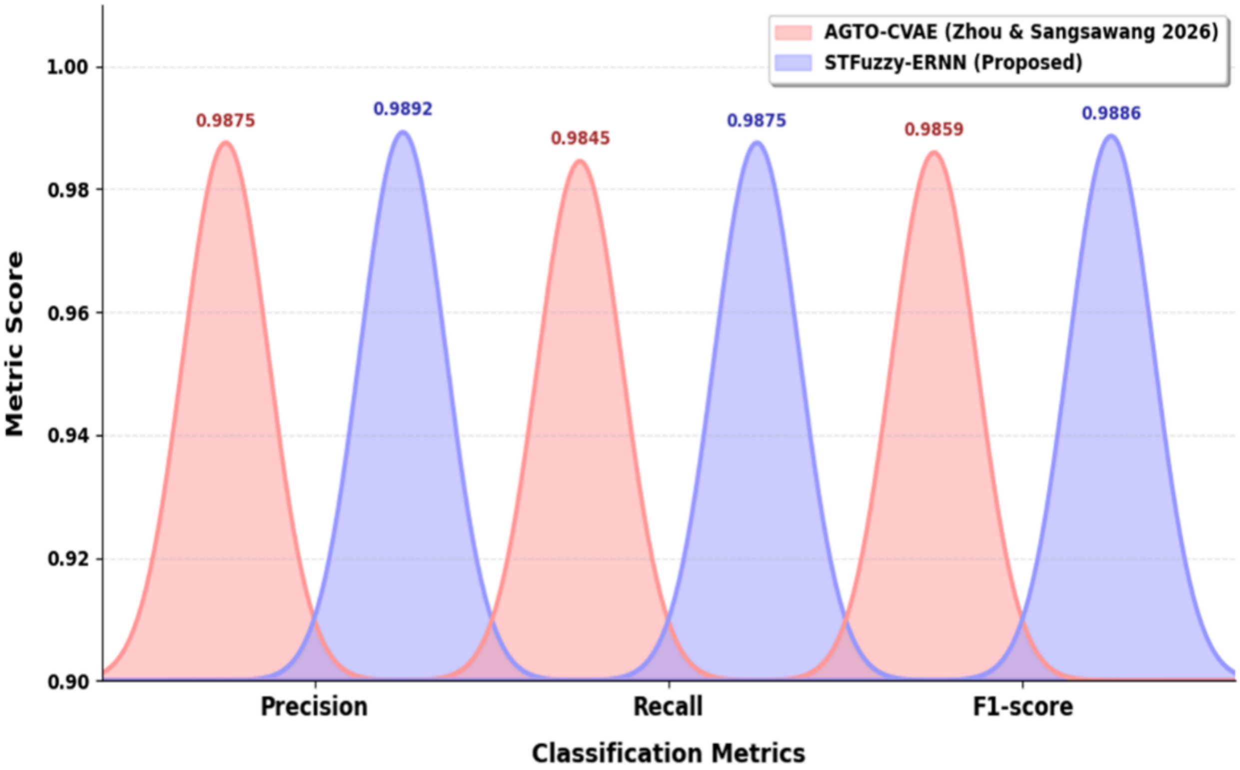


Fig.9: Comparison of Classification Performance Metrics Between AGTO-CVAE and STFuzzy-ERNN Models

Table 4 presents a comparative analysis of computational efficiency between existing methods and the proposed STFuzzy-ERNN model. The results demonstrate that STFuzzy-ERNN significantly improves efficiency by reducing model size to 47.3 MB, lowering FLOPs to 16.2, and achieving an inference time of 6.4 ms. These improvements indicate a faster, more lightweight, and computationally efficient framework, making it well-suited for real-time dance movement recognition and sustainable heritage preservation applications.

Table 4

Comparison of Model Size, FLOPs, and Inference Time for Dance Models

Method	Dataset	Model Size	FLOPs	Inference Time
AGTO-CVAE (Zhou & Sangsawang, 2026)	Minority Dance Blended Learning Dataset	60.2	25.6	10.9
STFuzzy-ERNN (Proposed)	Dance Preservation Dataset	47.3	16.2	6.4

Figure 10 compares the existing approaches with the proposed STFuzzy-ERNN model in terms of model size, FLOPs, and inference time. The results show that STFuzzy-ERNN achieves a significant reduction in computational cost, with a model size of 47.3 MB, FLOPs of 16.2, and an inference time of 6.4 ms. These improvements demonstrate its superior efficiency and suitability for real-time and resource-efficient dance heritage preservation systems.

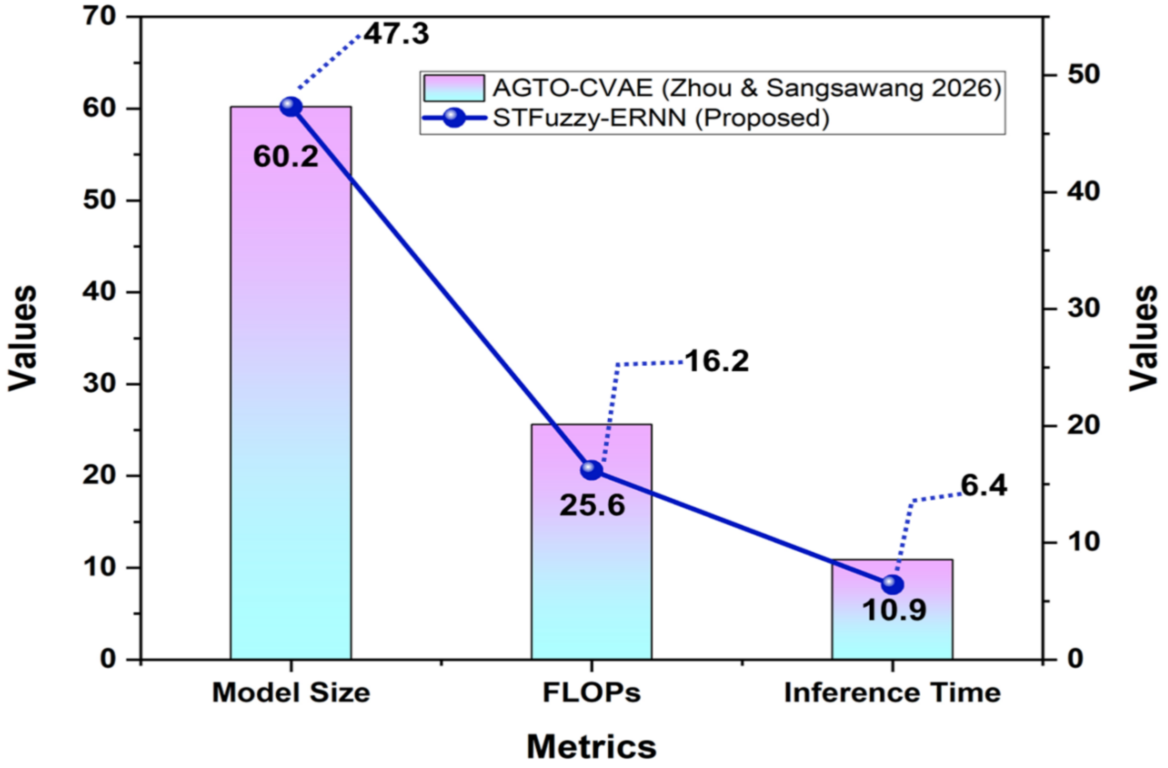


Fig.10: Computational Efficiency Comparison of Models Based on Size, FLOPs, and Inference Time

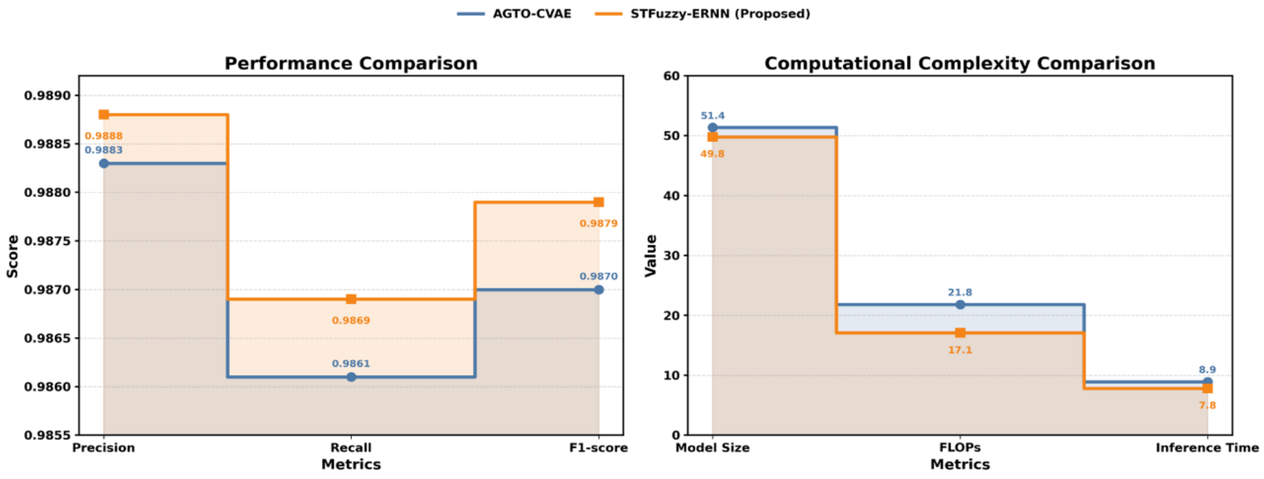
Table 5 presents a combined evaluation of accuracy and computational efficiency for existing methods and the proposed STFuzzy-ERNN, trained on the Dance Preservation Dataset. The results indicate that STFuzzy-ERNN achieves slightly improved performance, with a precision of 0.9888, recall of 0.9869, and F1-score of 0.9879. At the same time, it demonstrates reduced computational requirements, including a model size of 49.8 MB, FLOPs of 17.1, and an inference time of 7.8 ms. These findings highlight a balanced trade-off between high predictive performance and computational efficiency, confirming the suitability of the proposed model for scalable and real-time dance heritage preservation applications.

Table 5

Overall Performance and Efficiency Comparison of Dance Recognition Models

Method	Precision	Recall	F1-score	Model Size	FLOPs	Inference Time
AGTO-CVAE	0.9883	0.9861	0.9870	51.4	21.8	8.9
STFuzzy-ERNN (Proposed)	0.9888	0.9869	0.9879	49.8	17.1	7.8

Figure 11 compares the performance and computational complexity of the existing model with the proposed STFuzzy-ERNN. In Figure 11(a), the proposed model demonstrates a marginal improvement in performance metrics, achieving a precision of 0.9888, an F1-score of 0.9879, and a recall of 0.9869. In contrast, Figure 11(b) highlights a significant reduction in computational requirements, with a smaller model size (49.8 MB), lower FLOPs (17.1), and reduced inference time (7.8 ms). Overall, these results indicate that the STFuzzy-ERNN achieves both high predictive performance and efficient computation, ensuring its suitability for scalable deployment in dance heritage preservation systems.



(a) (b)

Fig.11: Integrated (a) Performance and (b) Computational Complexity Comparison Between Baseline and Proposed Models

5. Discussion

This study developed an AI-driven fuzzy decision support framework that integrates narrative modelling with sensor-based data to examine, document, and prioritise the sustainable conservation of traditional dance heritage [25]. Conventional approaches such as AGTO-CVAE Zhou and Sangsawang [29] are constrained by high computational complexity and limited capability in effectively capturing intricate temporal and structural dependencies within sequential dance data. In contrast, STFuzzy-ERNN delivers high-quality and interpretable preservation of traditional dance by integrating AI-based narrative modelling with fuzzy logic. This enables effective movement capture, dimensionality reduction, structured documentation, and systematic decision-making processes. Consequently, the framework supports educators, performers, and cultural institutions in achieving sustainable, scalable, and explainable heritage conservation. In practical terms, this approach enables accurate documentation, analysis, and preservation of traditional dance forms, thereby facilitating their sustainable transmission and supporting informed, data-driven heritage conservation decisions.

6. Conclusion

This study presents an explainable fuzzy decision-making system integrated with AI-driven modelling to enable accurate, interpretable, and scalable preservation of complex dance movements under uncertainty. The Dance Preservation Dataset was sourced from Kaggle. Data pre-processing was carried out using Z-score normalisation, while feature extraction was performed through PCA. The STFuzzy-ERNN model effectively captures temporal patterns in dance movements and supports reliable, explainable, and evidence-based decision-making for the sustainable preservation of complex cultural heritage expressions. The proposed model demonstrates strong performance, achieving a precision of 0.9892, recall of 0.9875, and F1-score of 0.9886, alongside improved computational efficiency with a model size of 47.3 MB, FLOPs of 16.2, and an inference time of 6.4 ms. However, the framework is limited by dataset diversity constraints, dependence on sensor-based inputs, challenges in ontology scalability, potential bias in fuzzy rule design, and reduced robustness in real-time deployment scenarios. Future work will focus on expanding datasets, integrating multimodal sensing systems, enhancing real-time processing capabilities, and extending applicability to a wider range of dance forms.

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