1* Jing Wang

Research on dance teaching methods based on emotion recognition and emotion analysis

Journal of Electrical Systems

Abstract: - In sports dance (SPD) education, it is common to give excessive value on technique while ignoring emotion. This issue causes emotions and motion to be poorly integrated, which negatively impacts the educational result. As a result, this study employs a sensor to gather video data from SPD performers and then extracts the crucial characteristic spots to estimate their poses. This study proposes unique capuchin search-driven bi-directional tuned recurrent network (CS-BRN) architecture to efficiently categorize dancers' emotions. Additionally, the arousal value can be used to categorize the arousal valence (AV) emotional paradigm into various parts. The AV paradigm performs superior in high and low fields, which correlate to exciting, nervous and mild feelings, respectively. We employed metrics to evaluate this study's performance like precision (90%,) accuracy (96%), F1-score (92%), recall (91%), The findings of the trial demonstrate that the suggested method has a high degree of emotional recognition accuracy and can precisely identify the crucial moments in the performers' technical motions. This study significantly aided in the emotional identification and alleviation of SPD participants during the education procedure by precisely identifying the crucial parts of their technical motion presentations.

Keywords: Sports Dance (SPD), Dance Teaching, Emotion Recognition, Sensor, Capuchin Search-Driven Bi-Directional Tuned Recurrent Network (CS-BRN)

I. INTRODUCTION

Emotion recognition technology has enormous possibilities to enhance teaching approaches in the field of dance instruction. A personalized approach to teaching and dancing might be enabled possible by integrating emotion detection into dance education. It allows instructors to get important insights into students' emotional states. Technology and teaching combined with dance education are transforming conventional teaching approaches and providing new ways to improve student learning. Enhanced instructors appreciate their students' emotional states and address their requirements by integrating emotion analysis into their instruction. This invention promotes a caring and sympathetic learning environment by enabling instructors to modify their teaching tactics appropriately. By using this method, students improve their technical proficiency among their emotional intelligence, which enhances their whole dancing experience and gets students prepared for a variety of creative activities [1]. The modern techniques improve students' understanding of dance as significant medium by using developments in emotion-detection technology and cognitive science. The teacher might modify the curriculum to assist the dancer learn more than technical proficiency, however, interpersonal skills and imaginative thinking are developed through the use of real-time emotional data. Teachers can create a more holistic learning environment that enhances the connection among movement, emotion and increases students' general engagement along with the appreciation of performing arts [2]. Emotion recognition technology powered by artificial intelligence (AI) has completely altered how humans recognize and understand human emotions. Through the evaluation of various clues, includes body language, speech signals and facial expressions, the skill is capable to, by design, identify and classify different emotional states. More accurate and multifarious emotional assessment is making possible by the use of modern techniques to recognize miniature variation in tone, gesture and facial movements. Enhancing to enable is modified and empathetic experience, this skill finds applications in a wide range of industries, including education, healthcare and customer service [3]. Technology provides a great toolkit for dance instructors to assess the emotional dynamics of the student. Teachers might employ statistical techniques and sensors to analyze physiological indicators such as conductivity of the skin, variability in heart rate and smiles. The observations offer invaluable feedback that enables educators to modify their approaches, generate specialized assistance and create a more understanding as well as supportive learning environment, all of which enhance student achievement and general experience [4]. Sustaining an invisible emotional differentiation entail trying to interpret the intricate dancer's internal signals. Teachers with this ability perform more than teach they shift into emotional translators, taking each dancer on a unique developmental path. Teachers should modify the instruction by gaining insight in advance regarding the dancer's inner world by identifying tiny indications. When individuals navigate the complexities of their emotional landscape within the framework of dance, the profound insight fosters an

1 *Corresponding author: Jing Wang, 18631477708@163.com
HeBei Minzu Normal University, Chengde, 067000, China

environment of compassion in which dancers are acknowledged and valued, leading to substantial progress [5]. Emotion analysis algorithms change the way dance is taught by examining the psychological side of dance and exposing the inner motivations, tales and desires hidden in each movement. Such algorithms provide educators an effective instrument for analyzing dance's emotional intricacies, facilitating a deeper understanding of the various ways in which movement transmits the human experience. Teachers to assets students' express conversations and improve their technical skill as well as emotional resonance in dance by teaching students to recognize the intents and feelings that motivate dance sequences [6]. Teachers are important for supporting student generate dance performance to effectively express preferred theme, emotion, or messages. The assessment of moving appearance model in an assortment of choreographic situation, teachers enable student to appreciate the subtlety concerned in expressing emotion by dance. Encouragement student understands, interpersonal skills and self-awareness is also very important. Promote insightful conversations around the emotional aspect of dance fosters a greater knowledge of human expression and connection within the art form in addition to improving the creative growth of the participants [7]. To emphasize the equally useful communication among emotion and movement, the cutting-edge techniques of teaching dance extend transcends conservative models. The methods provide equivalent weight to the emotional expression that dances expresses, compare to technological skill. Figure 1 depicts the sports dance performance. It develops an extensive understanding of dance as a form of creative expression and interpersonal connection by encouraging students to feel significantly and communicate the emotions through movement [8].

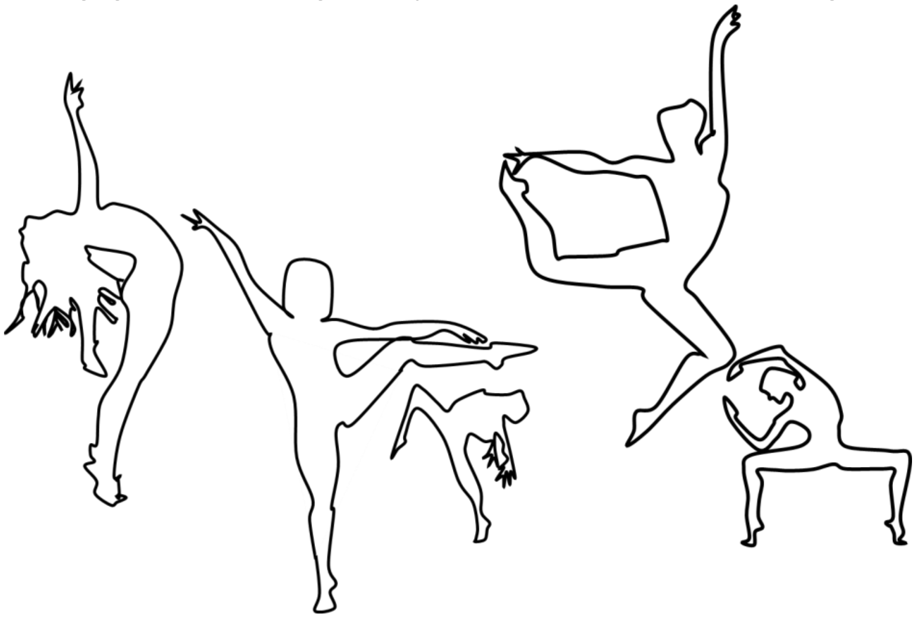

Figure 1: Sports dance performance

Dancing training approaches that include emotion detection and analysis provide a comprehensive approach to education. By supporting students in recognizing and expressing their emotions through movement, teachers help students obtain an improved understanding of the cognitive and emotional components of dance. This immersive approach not only increases technical skill but also cultivates self-worth, compassion and empathy. Students' comprehension of the expressive potential of movement is enhanced by the supervised exploration of emotions in choreography. This enhances their innovative interpretations and assists to develop greater intimacy with dance as an instrument of self-expression [9]. Teachers might effectively integrate technology in dance instruction to expand their students' options for creative and musical exploration. Students that use technology might employ it as an instrument for transformational expression and explore their emotional authenticity higher. Dancers are able to explore new avenues for movement and self-expression through technology, the way it is through interactive applications, digital designs and experiences. Such enhances their creative practice and assist to develop greater connections with their profession [10-11]. Dancing instruction might be revolutionized by including emotion detection into the curriculum. An innovative method has the impending to change education as a whole. Educators might employ technology to assist students better understand the emotional implications of dance moves, which can assist to produce a new generation of technically proficient as well as highly compassionate and sensitive dancers. Both instructors and students stand to gain significantly from this inventive combination [12]. Regarding people's consent and privacy when it comes to the emotions are being studied. The aim of this study of improving students' emotional intelligence, creative interpretation and technical competency through individualized feedback and customized training, this study explores the implementation of emotion identification and analysis into dance methods of instruction.

A. Motivation of the study

The study integrates emotion detection and examination technology in an effort to investigate novel method in dance instruction. To develop an extensive knowledge of the way emotions, affect learning and performance, teachers can improve how to teach and enhance student involvement, expressiveness and the entire dance experience. By exploring the distinction among creativity and the internet, the initiative aims to provide insights into customized and effective dance education.

B. Key contribution

1. Video dataset is collected and utilizing a CS-BRN approach is used to develop dance teaching strategies which make use of emotion detection technologies, improve interaction and efficacy by customizing training to the emotional states of students.
2. To detecting student emotions during dancing practice using face recognition technology.
3. Teachers may use this data to adjust their teaching strategies based on their understanding of students' emotional involvement integration also makes it possible to record physiological reactions and physical actions which help to comprehend emotional states.

The following parts: A summary of the literature review is given in part 2, a more detailed description of the techniques is given in part 3 as well a discussion and analysis are presented in part 4. Part 5 provides a conclusion.

II. RELATED WORK

Study found that automatically identifying emotions from body movement was a two-layer feature selection paradigm. It surpasses current techniques in identifying happy, sadness, fear, rage and neutral emotions with high accuracy. Analyzing variance (ANOVA) [13] in the first layer and using a genetic algorithm in the second layer, the lack of labeled data with 3D skeletal data, a personality concentration augmented spatial-temporal graph convolutional network for gesture support emotion identification. It extracted 3D skeleton coordinates from the machine learning (ML) [14] by using posture estimation, surpassing previous models and improving multimodal emotion identification. Research [15] addressed the problem of labeled data scarcity in healthcare by examining self-supervised learning (SSL) in emotion identification. The effective SSL was learning from unlabeled data and improving data efficiency, it contrasted SSL with supervised learning while training convolutional neural networks (CNN) for emotion identification. The increasing accessibility of physiological data via wearable technologies, a recommender system for tourist experiences (TERS) [16] based on user's emotional states were suggested. It tackled problems with recognizing emotions from heart rate data in day to day living. The technique consisted of TERS design deep learning (DL) based emotion recognition and data gathering. The Dancing Coach (DC) [17], a method that helps with practicing dance steps basic salsa was the main emphasis of the proposed. It presented the results of the initial user assessment, which included 25 participants. It included ideas for future improvements as well as good comments on coordination, rhythm and learning stages. The research [18] proposed a prediction system called Dance Trend, which used color space information and body movement data to predict the popularity of dance videos on user-generated content (UGC) platforms. Dance Trend illustrated the critical significance that body movement characteristics has in forecasting the popularity of dance videos by combining human motion analysis with machine learning approaches and table 1 shows that methods, findings and limitations in related work.

Table 1: Outcomes of related works

Reference No.	Methods	Findings	Limitations
[19]	Histogram of oriented gradient-ensembles with shared representation (HOG-ESR), a novel algorithm, combine HOG and ESRs for face expression identification.	HOG-ESRs improve face emotion identification on the FER2013 dataset by reducing mistakes, increasing accuracy and increasing endurance.	The FER2013 dataset was used to evaluate the study's efficacy, which can limit its application to other datasets or real-world situations.
[20]	A four-module model for minyan song emotion categorization that combines the use of CNN and attention-based	The suggested model outperformed the others, obtaining ideal parameters and	The research ignored to investigate possible biases in emotion categorization and

	long short-term memory (LSTM) with audio data and lyrics.	p>0.80 precision, recall and accuracy.	the generalizability of the algorithm outside songs.
[21]	Developed an emotional system that used video, audio and face signals to optimize audio-visual interaction and save expenses.	Optimizing multimodal inputs reduces computing costs. Improved sharing techniques increased the classifier's accuracy to 74%.	The efficiency of the system varies with music, video and cultural context, which could restrict its generalizability even in the face of effectiveness.
[22]	Study contrasts teaching styles (TS), command and problem solving, in physical education, surveyed 50 students through interviews.	An ANOVA indicated that there were cognitive gaps ($p \leq 0.01$) favoring problem solving TS, which 76.47% of students preferred. A focus of the qualitative study was the fostering of dynamism, collaboration and innovation.	Due to the study emphasis on self-reporting, student's opinions on teaching approaches might be biased.
[23]	Three workshops worth of learning data from dancers: instructor vs. personal techniques, Move On tech and self-structured learning.	Dancers use diverse techniques, guided by teachers or preference, affecting novice versus expert learning.	The study workshop emphasis could have ignored individual variations and real-world dance learning circumstances.
[24]	Examines Norwegian physical education (PE) practicum, concentrating on teacher students' creative dancing experiences via reflections and interviews.	In dance education, student teaching has changed from using strict movements to combining words, emotion and movement.	The limited period and emphasis on the Norwegian setting could limit the extent of generalizability.

A. Problem statement

There are a number of difficulties in developing efficient dance instruction strategies that make use of emotion detection technologies. The reliability of emotion recognition algorithms is an important concern that might vary based on particular traits and lighting circumstances, among other factors. Integrating emotion detection into dance education also prompts worries about data security and privacy. To guarantee that the integration of technology does not compromise the interpersonal bond between the teacher and students, since that's essential for effective teaching in the field of dance education. To overcome this problem, we proposed CS-BRN architecture to efficiently categorize dancers' emotions.

III. Methods and Materials

The purpose of CS-BRN is used to develop dance teaching strategies which make use of emotion detection technologies, improve interaction and efficacy by customizing training to the emotional states of students. In this section first we have collected the video data set our proposed CS-BRN was executed and explained in detail.

A. Data collection

This study employs a sensor to gather video data from https://google.github.io/aistplusplus_dataset/factsfigures.html SPD performers.

B. Human pose estimation

The primary factor considered for evaluating the training action standard is the SPD trainer's position assessment. The trainer and training scenario for SP are included in the initial image data produced by Kinect. Finding the target is a prerequisite for extracting the SPD trainer's purpose in Figure 2. The key goal in this article is extracted using the inter-frame difference approach.

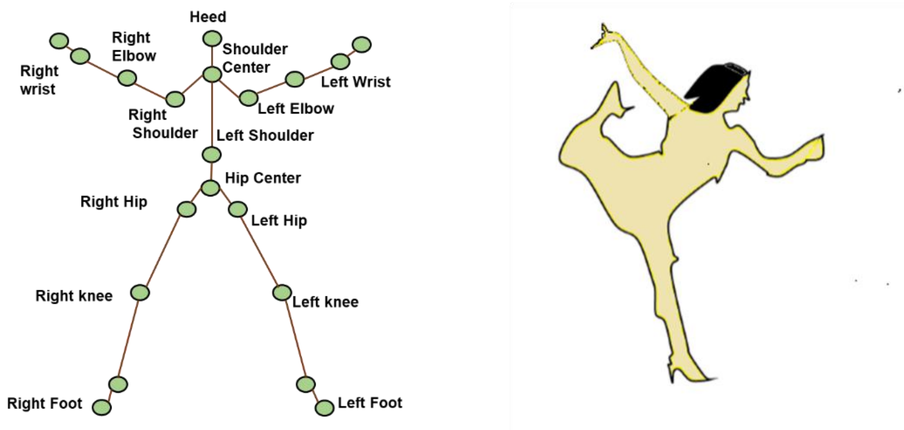

Figure 2: key Points of sports dance

C. Emotional classification model in SPD

1) AV emotional model

The arousal-valence (AV) emotion model is used in this experiment due to the fuzziness of emotion categorization, as shown in Figure 3. The distribution of various emotions as well as the correlations between them from the following figure 3 offers a visual depiction of different emotions and how each is distributed, revealing data regarding the connections and intensities between emotions. Positioning emotions closer to each other might suggest greater connection and even stronger emotional bonds. The figure tool facilitates comprehension of emotional dynamics and interaction within the represented environment by enabling people naturally views the emotional landscape.

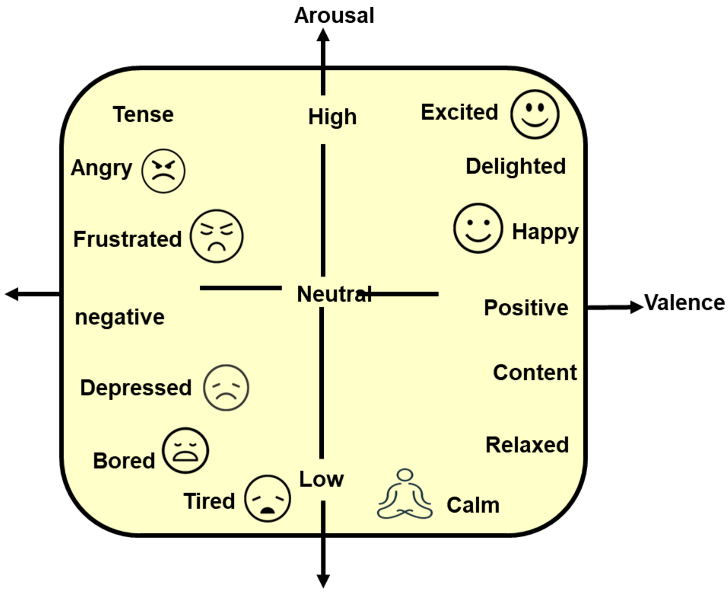

Figure 3: AV emotion model

D. Sports dance (SPD) emotional classification model based on capuchin search-driven bi-directional tuned recurrent network (CS-BRN)

A CS-BRN is used by the SPD emotional categorization model for in depth analysis. This advanced design combines BRN with optimization for CS, allowing for strong emotional categorization in sports dancing performances. By constantly modifying network characteristics, the CS-BRN improves flexibility to a wide range of emotional responses. It collects environment information and temporal relationships via iterative learning, allowing for accurate emotional identification. Through deeper insights into player expression and improved performance assessment, this novel technique provides a comprehensive framework for emotional dynamic within sports dance.

1) Bi-directional tuned recurrent network (BRN)

Recurrent networks (RNs) provide a very efficient method of time-based sequence management by highlighting relationships between closely related data components in the sequence. Time-varying memory cell and current unit output are equally contributed by the previous BRN units in equation (1).

$$\overleftarrow{d^s} = \tanh\left(\vec{X}_{db}.\vec{b}^{s-1} + \vec{X}_{dw}.w^s + \vec{a}_d\right) \tag{1}$$

Within BRN, the standard one-way model limits the output of the current unit to data from previous units alone. But in other cases, good estimates require taking into account both past and future units. To improve the model's understanding of dance's sequential structure, it first uses a bi-directional design that enables it to record both past and future context while analyzing motions. This assists in recognizing nuanced sentiments that are included into the dancing expressed as equation (2).

$$\overleftarrow{d^s} = \tanh\left(\vec{X}_{db}.\overleftarrow{b}^{s-1} + \vec{X}_{dw}.w^s + \vec{a}_d\right) \tag{2}$$

By using one that operates forwards and the other backwards, the BRN architecture makes this possible. Both units process the inputs concurrently and their outputs are fused according to the hidden state. In this work, we take use of this structure to build a BRN that combines the outputs at the end of each network. BRN is essential for identifying small emotional changes throughout the course of a dance performance because they can remember previous inputs in equation (3).

$$\vec{\Gamma}_v = \sigma\left(\vec{X}_{vb}.\vec{b}^{s-1} + \vec{X}_{vw}.w^s + \vec{X}_{vd}.\vec{d}^{s-1} + \vec{a}_v\right) \tag{3}$$

There are many approaches available for combining outputs, but since networks trained on the same set of data are interdependent, it continues to be hard to identify which is best. Below are the basic equations that control the BRN unit at time t provided in equations (4) and (5).

$$\overleftarrow{\Gamma}_v = \sigma\left(\overleftarrow{X}_{vb}.\overleftarrow{b}^{s-1} + \overleftarrow{X}_{vw}.w^s + \overleftarrow{X}_{vd}.\overleftarrow{d}^{s-1} + \overleftarrow{a}_v\right) \tag{4}$$

$$\overleftarrow{\Gamma}_e = \sigma\left(\overleftarrow{X}_{eb}.\overleftarrow{b}^{s-1} + \overleftarrow{X}_{ew}.w^s + \overleftarrow{X}_{ed}.\overleftarrow{d}^{s-1} + \overleftarrow{a}_e\right) \tag{5}$$

Moreover, the model is modified, which suggests that training has optimized its parameters to better match the specifics of sports dance emotional expression as in equation (6).

$$\overrightarrow{d^s} = \vec{\Gamma}_v \odot \overrightarrow{d^s} + \vec{\Gamma}_e \odot \vec{b}^{s-1} \tag{6}$$

The SPD emotional classification model, which is based on these components, can effectively identify the range of emotions shown in SPD performances. This makes it easier to analyze and comprehend the emotional stories that are connected with the choreography in equations (7) and (8). This methodology has the potential to improve participation of audiences, choreographic creation and coaching in the SPD industry.

$$\overleftarrow{d^s} = \overleftarrow{\Gamma}_v \odot \overleftarrow{d^s} + \overleftarrow{\Gamma}_e \odot \overleftarrow{b}^{s-1} \tag{7}$$

$$\vec{\Gamma}_p = \sigma\left(\vec{X}_{pb}.\vec{b}^{s-1} + \vec{X}_{pw}.w^s + \vec{X}_{pb}.\overrightarrow{d^s} + \vec{a}_p\right) \tag{8}$$

The BRN's output is described as follows in equation (9):

$$\hat{z} = softmax\left(\vec{X}_z.\sum_{s=1}^{S}\vec{b}^s + \overleftarrow{X}_z.\sum_{s=1}^{S}\overleftarrow{b}^s + a_z\right) \tag{9}$$

Where ← denotes the backward RN and → the forward BRN,

By evaluating movement sequences, improving prediction and identifying relationships between previous and subsequent steps, BRNs, find uses in sports dancing. Figure 4 illustrates the structure of BRN.

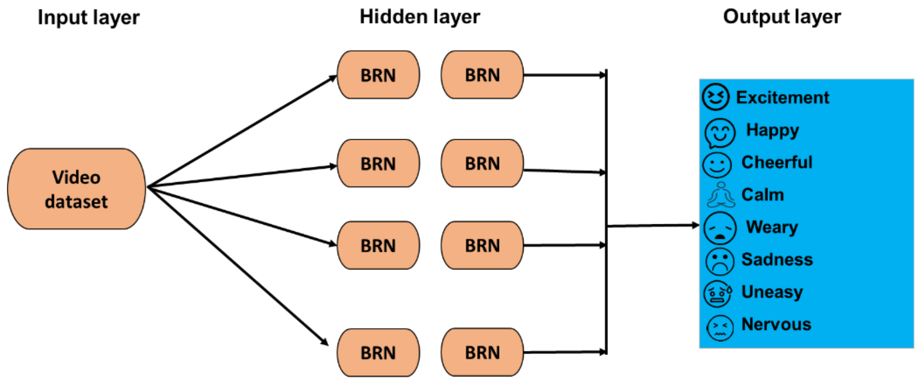

Figure 4: Structure of BRN

2) Capuchin search (CS)

The SPD emotional classification model classifies emotional expressions in sports dance performances using an optimization approach inspired by nature called CS. By searching for the best answers inside a problem space, CS imitates the foraging habits of capuchin monkeys. To improve the classification model's accuracy in identifying different emotional states expressed by dance movements, CS is used in the SPD context to optimize the model's parameters.

a) Global search: leaping motion

The emphasis of a Global Search-based Emotional Classification Model for SPD is jumping action. With data-driven methods, it classifies jumps' emotional responses. With the help of this model, athletes and dancers can develop performances that are more expressive by better understanding the emotional dynamics of sports dance. The horizontal distance, w between the source and destination tree branches is implemented by the capuchin's actual movement. The third law of motion can be used to represent w_0 as it is shown below equation (10).

$$w = w_0 + u_0 s + \frac{1}{2} b s^2 \tag{10}$$

Where u is the capuchin's new location, u_0 denotes its starting position, s denotes its acceleration. Equation (11) illustrates how the first law of motion can be used to determine the capuchin's velocity, or s, during the leaping action.

$$u = u_0 + bs \tag{11}$$

In the motion model, the, w and θ_0 components of the capuchin's starting velocity are specified as follows:

$$u_{0w} = u_0 \cos(\theta_0) \tag{12}$$

The angles measured from the positive x-direction are denoted by u_w while the beginning velocities in the, w and s directions are represented by u_{0w}, respectively. Following the steps listed in equations (12) and (13), the horizontal velocity, $u_w$could be obtained:

$$u_w = u_{0w} + b_w s \tag{13}$$

When set to zero, axe represents the horizontal acceleration. This makes it possible to reduce the capuchin's distance, w is equation (14):

$$w = w_0 + u_0 \, cos(\theta_0) s \tag{14}$$

Therefore, the vertical displacement, $z$obtained as follows equation (15):

$$z = z_0 + u_0 \sin(\theta_0) + \frac{1}{2} b_z s^2 \tag{15}$$

Where z_0 is the starting position, z is the capuchin's vertical acceleration, which denotes a g-like downward acceleration brought by gravity. When the height z equals the launch height $z_{0,}$ s may be found by solving SPD as follows in equation (16):

$$s = \frac{2u_0 \sin(\theta_0)}{h} \tag{16}$$

Equation (17) could be obtained by substituting equation (16) and using

$$s = 2u_0 + \frac{u_0^2 \sin(2\theta_0)}{h} \tag{17}$$

Here $2u_0$ is the jumping angle, h is the gravitational acceleration, u_0 is the starting location, $2\theta_0$ is the initial velocity and h is the capuchin's new position.

b) Local search: Swinging motion

Local search algorithms might make the method better by refining the rotating approach. The system initially evaluated the dancers' emotional expressions in real time to detect hidden signals such as body language and facial expressions. It proceeded to continuously modify the swaying parameters using local search approaches based on the detected emotions. To intensify that feeling of excitement when a dancer is expressing happiness, the algorithm might increase the amplitude and fluidity of the swinging movement. If a dancer seems melancholy, they might change their movement to something more subdued and delicate. The relationship between mood and movement is strengthened when dancers get specific guidance based on their emotional states via continuous feedback loops. This method provides a comprehensive approach to studying and performance, improving technical proficiency while enhancing emotional expression in dance. The capuchin at position y is exposed to two forces, which are as follows:

1. The mass y acting in a downward vertical direction
2. The tail's tension L which operates in the tail's direction.

The mass mg could be divided into:

1. The weight along the backward direction is shown by $y = L \, sin\theta$

2. $sin\theta$, which indicates the weight along the arc in the capuchin movement's direction.

These method fundamentals allow to describe the location, y throughout the capuchin's swinging action as,

$$y = Lsin\theta \tag{18}$$

The angle at which the capuchin is shifted from position θ is represented by the initial y. Algorithm 1 illustrates the pseudo-code for CS-BRN.

Algorithm 1: CS-BRN

Initialize CS-BRN parameters
Initialize bidirectional recurrent network parameters
Initialize tuning mechanisms parameters
Function capuchin_search(data):
Initialize CS parameters
While not converged:
For each candidate solution:
Evaluate solution using fitness function
Update solution using Capuchin search algorithm
Return best solution found
Function train_CS_BRN (data):
Initialize CS-BRN parameters
Initialize BRN parameters
Initialize tuning mechanism parameters
For each epoch:
For each data point in dataset:
Forward pass through bidirectional recurrent network
Compute loss
Backward pass through bidirectional recurrent network
Apply optimization algorithm to update BRN parameters
Apply tuning mechanisms to update CS-BRN parameters
    return trained CS-BRN model
    function predict_CS_BRN (input_data):
output = []
    for each data point in input_data:
    forward pass through trained CS-BRN model
obtain prediction
append prediction to output
return output
 # Main program
input_data = load_data()
CS_BRN_model = train_CS_BRN(input_data)
predictions = predict_CS_BRN(input_data)

IV. RESULT

The protocol evolution setup that complies with Python 3.11.4 was used to examine suggested optimization potential. Using a Windows 11 laptop with 32 GB of RAM was required for this research. Employing these requirements ensured reliability and consistency in evaluating of enhancements in performance through the assessment process. There are several performance indicators utilized to calculate the precision, accuracy, recall and f1-score, some of the metrics used for CS-BRN. To compare the suggested technique to other existing methods such as Hand-over-Face Gesture based Facial Emotion Recognition Method (HFG-FERM) [25], Multi-Modal Fusion Approach (MMFA) [25], Emotion Recognition through Facial Gestures (ERTFG) [25].

A. Accuracy

The degree of accuracy in a measurement, computation, or observation is referred as accuracy. When there is absence of error or deviations, it demonstrates that an amount or outcome matches the actual or predicted value. Dance teaching that takes into account students' emotional states improves accuracy through the use of emotion detection. To better engage students and create a good learning environment, teachers might change their strategy by recognizing emotions that include delight in equation (19).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{19}$$

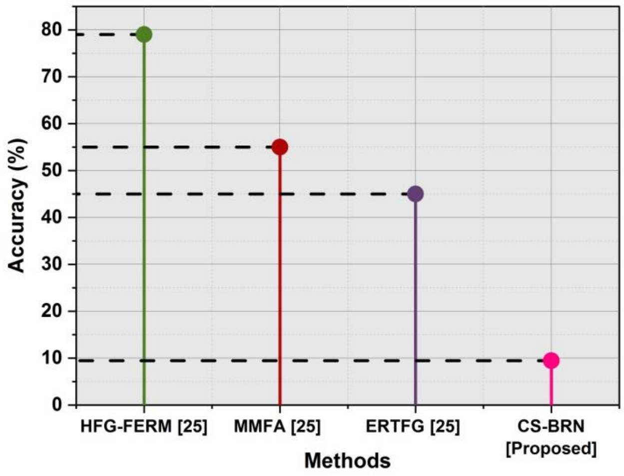

Figure 5: Evaluation of accuracy

Table 2: Numerical outcomes of accuracy

Methods	Accuracy (%)
HFG-FERM [25]	79
MMFA [25]	55
ERTFG [25]	45
CS-BRN [Proposed]	96

The comparative examination of the accuracy with existing and proposed method is shown in Figure 5 and Table 2 denotes the numerical outcomes of accuracy o recognize the dance performance. When we compared to other existing methods, our proposed CS-BRN method achieves 96% and existing methods such as HFG-FERM attains 79%, MMFA attains 55% and ERTFG attains 45%. It shows that the proposed technique is more efficient than other existing method.

B. Precision

The term precision describes the level of reliability or fineness in an amount or description. It emphasizes limited variation or departure from a standard and represents the precision and consistency of repeated measurements or the degree of information in a description. Emotion recognition is included into precision dance instruction techniques to improve comprehension and feedback. Teachers use technology or specialized methods to reduce break emotions and refine their methods to connect with students better and produce expressive performances in equation (20).

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{20}$$

The comparative analysis of the precision with proposed and existing method is shown in Figure 6 and Table 3 denotes the numerical outcomes of precision to recognize the dance performance. When we compared to other existing methods, the proposed method achieves 90% and existing methods such as HFG-FERM attains 85%, MMFA attains 69% and ERTFG attains 49%. It shows that our proposed technique is more efficient than other existing method.

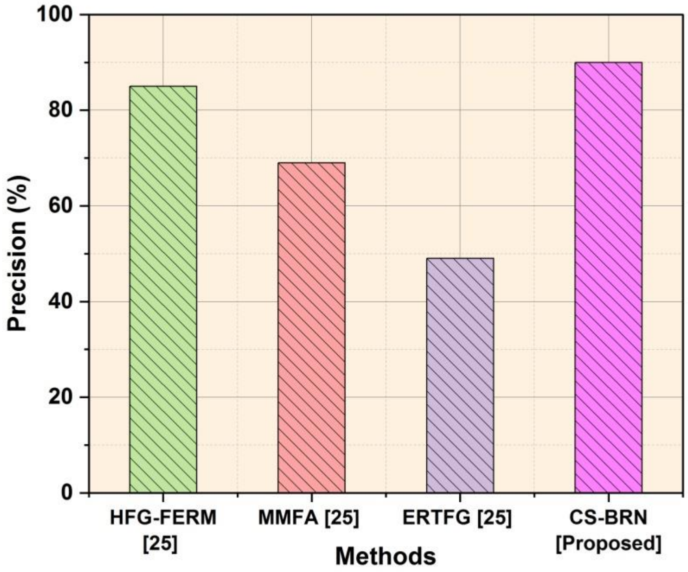

Figure 6: Evaluation of precision

Table 3: Numerical outcomes of precision

Methods	Precision (%)
HFG-FERM [25]	85
MMFA [25]	69
ERTFG [25]	49
CS-BRN [Proposed]	90

C. Recall

The term recall describes the capacity to recollect knowledge or experiences from memory. Integrating prior experiences or stored information into conscious consciousness is the process it entails. Effective recall is essential for learning, choice-making and solving issues in daily life as well as in psychological research. Recall criteria are used in dance teaching approaches that use emotion recognition to evaluate how well the system recognizes and recalls the feelings that dancers present during training. This is an important way to improve teaching effectiveness and refine algorithms that capture emotional subtleties in equation (21).

$$\text{Recall} = \frac{\text{FN}}{\text{FN} + \text{TP}} \tag{21}$$

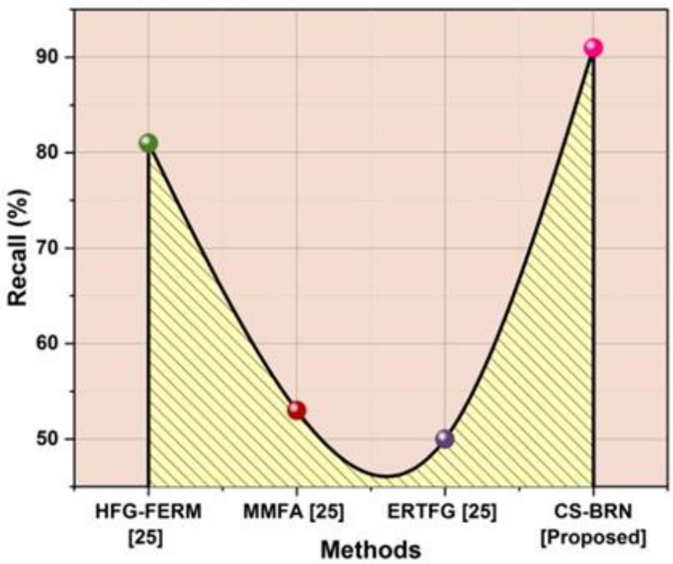

Figure 7: Evaluation of recall

Table 4: Numerical outcomes of recall

Methods	Recall (%)
HFG-FERM [25]	81
MMFA [25]	53
ERTFG [25]	50
CS-BRN [Proposed]	91

The comparative analysis of the recall with proposed and existing method is shown in Figure 7 and Table 4 denotes the numerical outcomes of recall to recognize the dance performance. When we compared to other existing methods, our proposed CS-BRN method achieves 91% and existing methods such as HFG-FERM attains 81%, MMFA attains 53% and ERTFG attains 50%. It shows that our proposed technique is more efficient than other existing method.

D. F1-score

Model performance for classification is assessed using a statistic called the F1 score. It provides balance to the two, taking account of both recall and accuracy. Better model performance is indicated by larger numbers. It is the harmonic mean of accuracy and recall, with values ranging from 0 to 1. F1 score is a statistic which is frequently utilized to assess how well models perform, particularly when it involves classification tasks. The system's ability to detect and react to students' emotional signals to be evaluated in the context of emotion-based dance instruction approaches is in equation (22).

$$\mathrm{F1-score} = \frac{(\mathrm{precision}) \times (\mathrm{recall}) \times 2}{\mathrm{precision} + \mathrm{recall}} \tag{22}$$

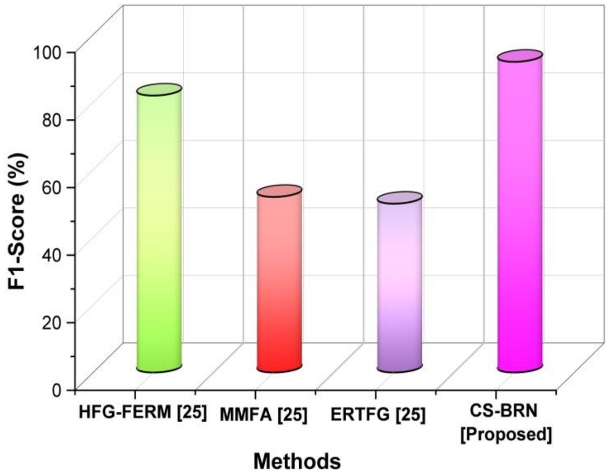

Figure 8: Evaluation of F1-score

Table 5: Numerical outcomes of F1-score

Methods	F1-Score (%)
HFG-FERM [25]	82
MMFA [25]	52
ERTFG [25]	50
CS-BRN [Proposed]	92

The comparative analysis of the f1-score with proposed and existing method is shown in Figure 8 and Table 5 denotes the numerical outcomes of f1-score to recognize the dance performance. When we compared to other existing methods, our proposed CS-BRN method achieves 92% and existing methods such as HFG-FERM attains 82%, MMFA attains 52% and ERTFG attains 50%. It shows that our proposed technique is more efficient than other existing method.

E. Emotional recognition

Employing technology to assess students' emotional states through speech, body language and facial expressions is known as "emotional recognition in dance education." It provides teachers the ability to modify their approaches and create an empowering atmosphere where developing one's emotional health and technical skills is valued equally, enhancing the learning process as a whole. The Figure 9 and Table 6 illustrates emotional excitement 95%, happy 95%, cheerful 94%, calm 93%, weary 93%, sadness 95%, uneasy 92%, nervous 91%.

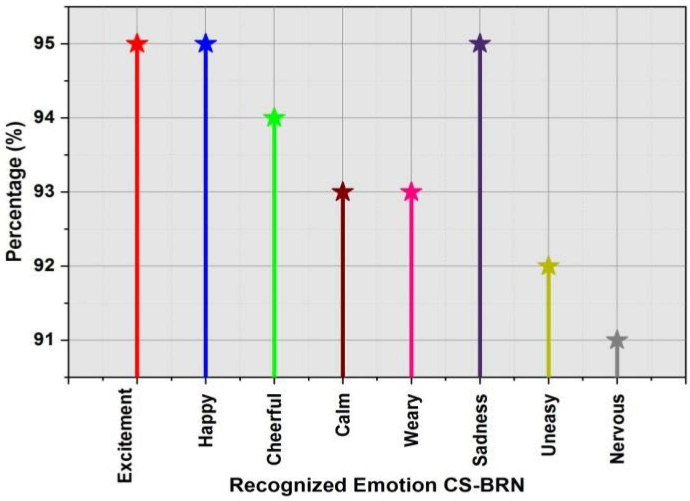

Figure 9: Emotional recognition

Table 6: Numerical values of emotional recognition

Recognized Emotion CS-BRN	Percentage (%)
Excitement	95
Happy	95
Cheerful	94
Calm	93
Weary	93
Sadness	95
Uneasy	92
Nervous	91

F. Discussion

The disadvantages of HFG-FERM [25], is intrinsically tough to describe emotion with accuracy. This issue stems beginning like relying to more the external fundamentals, includes light and obstacle, which might pretense important face clues requisite for perfect emotion recognition. The model requires of adaptability to various problems, particularly that observes to offer gesture and facial expressions and detracts from its overall usefulness. Under real applications, the model reliability is damaged by the concealment of significant features by supply cover the face, which additionally reduces accuracy. The changes in offer placement or occlusion patterns create unpredictability. The disadvantages make it most difficult for HFG-FERM to dependably and accurately recognize emotions.

The intricacies of MMFA [25] reside the ability to combine various data modality. It is difficult to achieve the ideal merger while maintaining the distinction of every modality. Its scalability can be limited to assure application difficulty, resulting in longer increase times and most computation overhead. Identify dances in the context of framework is difficult since several data modalities, such as text, images, to be efficiently integrated. To require complex algorithms and computational procedure to combine data while preserving the unique characteristics of each modality and model fusion, which hinders scalability and lead to longer growth cycles along with increased computing overhead. To assure the system's effectiveness in a variety of tasks and applications a balance must be established. To exploit the system's value while establishing the complexity of multi-modal data recognition, various elements must be balanced. The complexities in precisely classify dance performance by ERTFG [25] emphasize the impenetrability in decode person expressiveness. Emotions can provide important information about emotional states, but in many situations, it could be demanding to understand face expressions. Human’s capability to perceive facial movements can be impacted by environmental variations, individual variances and cultural influence, each of which might lead to misunderstandings. This emphasizes to require for a more thorough strategy that includes data stream and contextual awareness to improve the dependability of ERTFG systems. Through the integration of multiple data sources, such system might improve their overall efficacy and consistency by more precisely capturing the subtle emotions included in dance performances. By analyzing these drawbacks, the suggested method CS-BRN tends to overcome this issue and provide more efficient results.

V. CONCLUSION

Enhancing learning experience by the combination of emotion appreciation and assessment into dance teaching techniques is an impending appear. Instructors might modify their strategies to enhance engagement, motivation and retention by being aware of the emotional states of their students. This encompassing assist dancer to develop their emotional intelligence and self-awareness in addition to their technical proficiency. The techniques could impact dance instruction as technology develops, encouraging greater connections among movement, expression and personal growth. In dance education, emotion detection entails interpreting body language and facial emotions to customize training. The disadvantages include the possibility of oversimplifying dance training, problems with identifying emotions and cultural differences in how expressions are interpreted. To overcome this problem, we proposed CS-BRN approach is used to develop dance teaching strategies which make use of emotion detection technologies, improve interaction and efficacy by customizing training to the emotional states of students. The experiment results for F1-score (92%), precision (90 %,) accuracy (96%), recall (91%), which shows that proposed CS-BRN approach produces the accuracy is with superior results.

ACKNOWLEDGMENT

This research received no external funding.

REFERENCES

[1] Liu, S., 2022. An Adaptive Dance Motion Smart Detection Method Using BP Neural Network Model under Dance Health Teaching Scene. Journal of Environmental and Public Health, 2022.

[2] Huang, Y., 2022. Comparative analysis of aesthetic emotion of dance movement: a deep learning based approach. Computational Intelligence and Neuroscience, 2022.

[3] Zhai, X., 2021. Dance movement recognition based on feature expression and attribute mining. Complexity, 2021, pp.1-12.

[4] Yin, G. and Liu, J., 2022. Research on movement analysis and guidance in dance learning based on data mining. Computational Intelligence and Neuroscience, 2022.

[5] Zhang, Y., 2022. Application of Knowledge Model in Dance Teaching Based on Wearable Device Based on Deep Learning. Mobile Information Systems, 2022.

[6] Zeng, Z., 2022. Research on multimodal dance movement recognition based on artificial intelligence image technology. Computational Intelligence and Neuroscience, 2022.

[7] Li, N. and Boers, S., 2023. Human Motion Recognition in Dance Video Images Based on Attitude Estimation. Wireless Communications and Mobile Computing, 2023.

[8] Liu, X. and Hu, J., 2021. Dance movement recognition technology based on multifeature information fusion. Journal of Sensors, 2021, pp.1-11.

[9] Wang, S. and Yeon-hee, S., 2021. Role of ballet basic skills training based on multimedia video in international standard dance teaching. Journal of Sensors, 2021, pp.1-7.

[10] Fan, J., Yu, L. and Liu, J., 2022. Data Mining and Analysis of Management Theory on the Emotional Recognition of Students' Physical Fitness Improvement. Applied Bionics and Biomechanics, 2022

[11] Lu, R., 2022. Analysis of Main Movement Characteristics of Hip Hop Dance Based on Deep Learning of Dance Movements. Computational Intelligence and Neuroscience, 2022.

[12] Wang, Y., 2022. Research on Dance Movement Recognition Based on Multi-Source Information. Mathematical Problems in Engineering, 2022.

[13] Ahmed, F., Bari, A.H. and Gavrilova, M.L., 2019. Emotion recognition from body movement. IEEE Access, 8, pp.11761-11781.

[14] Shi, J., Liu, C., Ishi, C.T. and Ishiguro, H., 2020. Skeleton-based emotion recognition based on two-stream self-attention enhanced spatial-temporal graph convolutional network. Sensors, 21(1), p.205

[15] Montero Quispe, K.G., Utyiama, D.M., Dos Santos, E.M., Oliveira, H.A. and Souto, E.J., 2022. Applying self-supervised representation learning for emotion recognition using physiological signals. Sensors, 22(23), p.9102.

[16] Santamaria-Granados, L., Mendoza-Moreno, J.F., Chantre-Astaiza, A., Munoz-Organero, M. and Ramirez-Gonzalez, G., 2021. Tourist experiences recommender system based on emotion recognition with wearable data. Sensors, 21(23), p.7854.

[17] Romano, G., Schneider, J. and Drachsler, H., 2019. Dancing salsa with machines—filling the gap of dancing learning solutions. Sensors, 19(17), p.3661.

[18] Ding, S., Hou, X., Liu, Y., Zhu, W., Fang, D., Fan, Y., Li, K., Huang, L. and Zhou, F., 2023. DanceTrend: An Integration Framework of Video-Based Body Action Recognition and Color Space Features for Dance Popularity Prediction. Electronics, 12(22), p.4696.

[19] Zhong, Y., Sun, L., Ge, C. and Fan, H., 2021. HOG-ESRs face emotion recognition algorithm based on HOG feature and ESRs method. Symmetry, 13(2), p.228.

[20] Xiang, Z., Dong, X., Li, Y., Yu, F., Xu, X. and Wu, H., 2020. Bimodal emotion recognition model for minnan songs. Information, 11(3), p.145.

[21] Pandeya, Y.R., Bhattarai, B. and Lee, J., 2021. Deep-learning-based multimodal emotion classification for music videos. Sensors, 21(14), p.4927.

[22] Cuellar-Moreno, M. and Caballero-Juliá, D., 2019. Student perceptions regarding the command and problem solving teaching styles in the dance teaching and learning process. Research in Dance Education, 20(3), pp.297-310

[23] Rivière, J.P., Alaoui, S.F., Caramiaux, B. and Mackay, W.E., 2019. Capturing movement decomposition to support learning and teaching in contemporary dance. Proceedings of the ACM on Human-Computer Interaction, 3(CSCW), pp.1-22

[24] Ørbæk, T. and Engelsrud, G., 2021. Teaching creative dance in school–a case study from physical education in Norway. Research in dance education, 22(3), pp.321-335.

[25] Naik, N. and Mehta, M.A., 2020, July. An improved method to recognize hand-over-face gesture based facial emotion using convolutional neural network. In 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT) (pp. 1-6). IEEE.