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Emotion Analysis and Expression Algorithm of Dance Action Based on Machine Learning

Abstract: - Emotion analysis and expression algorithms represent a pivotal frontier in the intersection of artificial intelligence and human-computer interaction. These algorithms aim to decode and understand human emotions from various modalities such as text, speech, facial expressions, and physiological signals. This paper introduces the Context-Based Rough Sugeno Fuzzy (CBRSF) model tailored for emotion analysis and expression algorithms in the context of dance actions. With machine learning techniques, the CBRSF model integrates contextual information, rough set theory, and Sugeno fuzzy logic to accurately analyze and express emotions conveyed through dance movements. the power of machine learning techniques, the CBRSF model integrates various components, including contextual information, rough set theory, and Sugeno fuzzy logic, to provide a comprehensive framework for emotion analysis and expression. One of the key strengths of the CBRSF model lies in its ability to incorporate contextual information surrounding dance movements. Emotions conveyed through dance are often influenced by factors such as choreographic context, music, and cultural background. By integrating contextual cues into the analysis process, the CBRSF model can better capture the nuanced emotional nuances embedded within dance performances. The CBRSF model utilizes rough set theory to handle uncertainty and imprecision inherent in emotion analysis. Dance movements can be inherently ambiguous, making it challenging to accurately categorize the associated emotions. Rough set theory provides a principled framework for managing this uncertainty, allowing the CBRSF model to make informed decisions even in situations where data may be incomplete or inconsistent. Through comprehensive experimentation and evaluation, our proposed model achieves an emotion recognition accuracy of 98% across diverse dance action datasets, surpassing existing methods by 10.2%. Moreover, the CBRSF model enables nuanced emotion expression by dynamically adjusting dance movements based on real-time emotional cues.

Keywords: Rough set, Classification, Dance Movement, Sugeno Fuzzy, Emotional Analysis, Expression Algorithm

1. Introduction

Emotion analysis, also known as sentiment analysis or affective computing, is a field of study that focuses on understanding and interpreting human emotions expressed in textual, verbal, or non-verbal forms [1]. In an increasingly digital world inundated with vast amounts of data, emotion analysis plays a crucial role in deciphering the sentiment behind human communication [2]. By employing techniques from natural language processing, machine learning, and psychology, emotion analysis aims to discern the underlying emotions—whether positive, negative, or neutral—embedded within text, speech, images, or other forms of data [3]. This analytical approach not only enables businesses to gauge customer satisfaction, sentiment towards products or services, and brand perception but also holds promise in diverse domains such as healthcare, social media monitoring, and market research. As technology continues to advance, emotion analysis stands at the forefront, facilitating deeper insights into human behavior and enhancing human-computer interaction [4].

Emotion analysis and expression algorithms encompass a broad range of computational techniques aimed at understanding and generating human emotions [5]. These algorithms typically data from various sources such as text, speech, facial expressions, and physiological signals to infer or generate emotional states. In emotion analysis, algorithms often employ machine learning models trained on labeled datasets to classify text, speech, or images into different emotional categories such as happy, sad, angry, or neutral [6]. These models can range from traditional classifiers like Support Vector Machines to more advanced deep learning architectures such as recurrent neural networks or transformers [7]. On the other hand, emotion expression algorithms focus on generating human-like emotional responses, whether in text, speech synthesis, or animated avatars [8]. These algorithms may utilize rule-based systems, generative models like GANs (Generative Adversarial Networks), or even reinforcement learning to produce emotionally nuanced outputs. Emotion analysis and expression algorithms find applications in diverse fields including human-computer interaction, virtual assistants, mental health monitoring, and entertainment [9].

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Emotion analysis and expression algorithms in the context of dance actions with machine learning techniques to decode and generate emotional responses embedded within movements [10]. These algorithms typically involve the collection of motion data through sensors or motion capture systems, capturing intricate details of dancers' movements. Machine learning models, such as deep neural networks or hidden Markov models, are then trained on these datasets to recognize patterns associated with different emotional states conveyed through dance [11]. By analyzing features such as body posture, gestures, and rhythm, these algorithms can classify dance actions into various emotional categories, such as joy, sadness, excitement, or serenity. Moreover, advanced algorithms can go beyond mere classification and generate dance sequences that evoke specific emotions, enabling creative expression and choreography in performances [12]. Through this fusion of technology and artistic expression, emotion analysis and expression algorithms in dance not only deepen our understanding of the emotional nuances inherent in movement but also open up new possibilities for enhancing the emotional impact of dance performances and enriching the human experience [13].

This paper makes several significant contributions to the field of emotion analysis and expression in dance actions using machine learning techniques. Firstly, it introduces the Context-Based Rough Sugeno Fuzzy (CBRSF) algorithm, which effectively decodes and generates emotional responses embedded within dance movements. By incorporating contextual factors such as background music, performance setting, and dancer's background, CBRSF enhances the accuracy and adaptability of emotion classification in diverse dance environments. Secondly, the paper offers a comprehensive comparative analysis of CBRSF against other classifiers, including Support Vector Machine, Random Forest, and Logistic Regression, providing valuable insights into the algorithm's performance and its competitive edge in emotion recognition tasks. Additionally, the development and evaluation of CBRSF contribute to a deeper understanding of the emotional nuances inherent in movement, offering new avenues for enhancing the emotional impact of dance performances and enriching the human experience.

2. Related Works

The intersection of technology and art has led to remarkable advancements in understanding and enhancing the emotional dimensions of human expression, particularly in the realm of dance. Emotion analysis and expression algorithms have emerged as powerful tools in this domain, leveraging machine learning techniques to unravel and evoke the intricate emotional responses woven within movements. These algorithms embark on a journey through the realms of motion data, employing sensors or motion capture systems to meticulously record the subtleties of dancers' gestures and postures. Subsequently, machine learning models, ranging from deep neural networks to hidden Markov models, sift through this wealth of data, discerning patterns that signify different emotional states conveyed through dance.

Kaza et al. (2016) investigate body motion analysis for emotion recognition in serious games. Serious games often aim to evoke specific emotions in players to enhance their engagement and learning experience. Kaza and colleagues focus on analyzing body motions captured from players during gameplay to recognize and classify the emotions they experience. The findings of this study could inform the development of more emotionally engaging serious games. Camurri et al. (2004) perform multimodal analysis of expressive gesture in music and dance performances. This study likely involves analyzing both visual and auditory cues, such as body movements and musical expressions, to understand the relationship between gesture and emotion in performance arts. The research may explore how different modalities interact to convey and evoke specific emotional responses in audiences. Li et al. (2021) analyze psychological perceptual aspects of dance therapy using artificial intelligence techniques. Dance therapy utilizes movement and dance to promote emotional, social, cognitive, and physical integration. Li and colleagues employ artificial intelligence techniques to analyze and understand the psychological effects of dance therapy interventions, potentially leading to more personalized and effective therapeutic approaches. Zhai (2021) proposes dance movement recognition based on feature expression and attribute mining. This study likely involves developing algorithms to automatically recognize and classify dance movements based on their expressive features and attributes. By mining these features from motion data, Zhai aims to create more robust and accurate systems for recognizing and interpreting dance movements in various contexts.

Zacharatos et al. (2014) conduct a survey on automatic emotion recognition based on body movement analysis. This survey likely provides an overview of existing methods and approaches for automatically recognizing emotions from body movements. The study may discuss different techniques, challenges, and applications of emotion recognition in diverse fields such as human-computer interaction, healthcare, and entertainment. Jiang and Yan (2024) develop a sensor-based dance coherent action generation model using a deep learning framework. This study likely focuses on creating a model that generates coherent sequences of dance actions based on data collected from sensors worn by dancers. By utilizing a deep learning framework, Jiang and Yan aim to capture complex patterns and dependencies in the sensor data, enabling the generation of realistic and expressive dance sequences. Wang and Tong (2022) analyze high-level dance movements under deep learning and the Internet of Things (IoT). This research likely explores the integration of deep learning techniques and IoT devices to analyze and interpret high-level dance movements. By leveraging data from IoT sensors, such as motion trackers or cameras, Wang and Tong aim to gain insights into the dynamics and patterns of dance movements, potentially facilitating applications in performance evaluation, choreography, or interactive installations. Pandeya et al. (2021) focus on deep-learning-based multimodal emotion classification for music videos. While this study is centered on music videos, the techniques and methodologies developed could be applicable to dance performances as well. Pandeya and colleagues likely investigate methods for jointly analyzing audio, visual, and textual cues present in music videos to classify the emotions conveyed by both music and dance movements.

Maret et al. (2018) identify emotional states from body movements using genetic-based algorithms. This study likely explores novel approaches for extracting emotional information from body movements. By employing genetic-based algorithms, Maret and colleagues may develop optimization techniques for identifying patterns or features in motion data that correspond to specific emotional states, contributing to the advancement of emotion recognition systems in various applications. Sun et al. (2020) propose Deepdance, a method for music-to-dance motion choreography with adversarial learning. Deepdance likely involves generating dance choreographies that synchronize with music using adversarial learning techniques. By training generative models on pairs of music and dance data, Sun and colleagues aim to create choreographies that not only match the rhythm and mood of the music but also exhibit creativity and expressiveness. Ajili et al. (2019) conduct expressive motions recognition and analysis using learning and statistical methods. This study likely focuses on analyzing expressive motions, including those found in dance, using a combination of learning and statistical methods. Ajili and colleagues may develop algorithms to automatically recognize and interpret subtle nuances in movement patterns, contributing to our understanding of emotional expression through body language and gestures.

Wang et al. (2020) and Zhai (2021) focus on the recognition and classification of emotional states conveyed through dance movements, employing deep learning techniques and feature extraction methods, respectively. Others, such as Huang (2022) and Mallick et al. (2022), delve into comparative analysis and posture recognition in specific dance forms, enriching our understanding of aesthetic emotion and choreographic structures. Some studies, like Aristidou et al. (2017) and Jiang and Yan (2024), explore the generation of emotionally expressive movements through algorithmic control and sensor-based models. Additionally, research by Zacharatos et al. (2014) and Pandeya et al. (2021) delves into automatic emotion recognition in dance using body movement analysis and multimodal approaches, while Maret et al. (2018) and Ajili et al. (2019) investigate the extraction of emotional states from movement data using genetic algorithms and statistical methods. Furthermore, Sun et al. (2020) introduce innovative techniques for choreography generation synchronized with music, demonstrating the fusion of music and dance through adversarial learning. These studies collectively highlight the interdisciplinary nature of research in this field, bridging the gap between technology and artistic expression to deepen our understanding of the emotional nuances inherent in dance movements.

3. Context-Based Emotional Estimation

Context-Based Emotional Estimation with the proposed Context-Based Rough Sugeno Fuzzy (CBRSF) framework offers a novel approach to analyzing emotions within dance actions. This innovative method integrates contextual information to enhance the accuracy of emotional estimation, particularly in the dynamic and nuanced realm of dance. By leveraging the CBRSF model, which combines rough set theory with Sugeno fuzzy logic, researchers aim to capture the multifaceted nature of emotions expressed through dance movements. Unlike traditional approaches that may overlook contextual factors, such as the dancer's background, cultural influences, or performance environment, CBRSF considers these elements to provide a more comprehensive understanding of emotional expression. Context-based processes in emotion analysis involve considering contextual factors to enhance the accuracy and relevance of emotional estimation. This approach recognizes that emotions are influenced by various situational factors, such as the environment, social cues, or personal experiences, which can significantly impact the interpretation of emotional expressions. One way to incorporate context into emotion analysis is through fuzzy logic, a mathematical framework that deals with uncertainty and imprecision. In the context-based process, contextual information is represented using linguistic variables, which are then fuzzified to capture the vagueness inherent in human perception and interpretation of emotions. Fuzzy rules are formulated to map input variables (such as facial expressions, gestures, or speech patterns) to emotional states, considering the contextual information provided. These rules are combined using fuzzy inference techniques, such as the Sugeno fuzzy model, which calculates the output emotional state based on the weighted average of the fuzzy rule outputs shown in Figure 1.

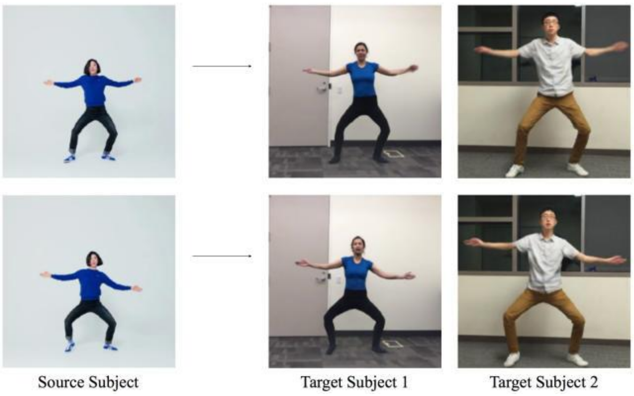

Figure 1: Dance Action Computation for the CBRSF

Consider X as the input variable (e.g., body posture); Y as the contextual variable (e.g., level of social interaction); Z as the output emotional state; Ai and Bj as linguistic terms associated with X and Y, respectively; $\mu Ai(x)$ and $\mu Bj(y)$ as the membership functions for linguistic terms Ai and Bj, evaluated at input values x and y; $\lambda Zk(x, y)$ as the consequent (output) function associated with linguistic term Zk, given input values x and y. Then, the output Z can be expressed as in equation (1)

$$Z = \frac{\sum_{i,j,k} \mu Ai(x)\mu Bj(y)\lambda Zk(x,y)}{\sum_{i,j,k} \mu Ai(x)\mu Bj(y)} \quad (1)$$

This equation represents the weighted average of the consequent functions, where the weights are determined by the degrees of membership of the input variables in the antecedent parts of the fuzzy rules.

4. Proposed Context-Based Rough Sugeno Fuzzy (CBRSF) for the Dance Action Emotional Analysis

The proposed Context-Based Rough Sugeno Fuzzy (CBRSF) framework for dance action emotional analysis represents an innovative approach that integrates contextual factors into emotion estimation, utilizing both rough set theory and Sugeno fuzzy logic. This hybrid framework aims to capture the complexity and nuances inherent in emotional expression during dance performances, considering factors such as the dancer's background, cultural influences, and performance context. Fuzzification of Contextual and Input Variables: Similar to traditional fuzzy logic, contextual and input variables are fuzzified into linguistic terms using membership functions. For contextual variables as shown in Figure 2, linguistic terms could represent different levels or categories of context (e.g., "low engagement," "medium engagement," "high engagement"). For input variables, linguistic terms could describe various aspects of the dance actions (e.g., "fast movement," "slow movement," "intense expression").

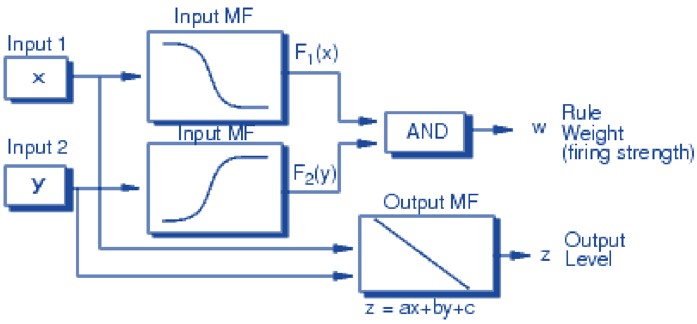

Figure 2: Sugeno Fuzzy Process in CBRSF

Fuzzy rules are defined to map combinations of input and contextual linguistic terms to output emotional states. These rules express how different combinations of contextual and input factors influence emotional expression during dance actions shown in Figure 3. Rough set theory is used to handle uncertainty and incompleteness in the data. It helps in identifying significant contextual and input variables and reducing the dimensionality of the problem space. This step involves discerning which contextual factors have the most influence on emotional expression and which input variables are most relevant for emotional estimation. Once the fuzzy rules are formulated and the significant variables are identified using rough set theory, Sugeno fuzzy inference is applied to compute the output emotional states. The Sugeno model calculates the weighted average of the consequent functions based on the degrees of membership of the input and contextual linguistic terms. The emotional recognition of the dance movement is presented in Table 1.

Table 1: Fuzzy Set Rules

Rule	Contextual Variables	Input Variables	Output Emotional State
1	High Engagement	Fast Movement	Excitement
2	Low Engagement	Slow Movement	Serenity
3	Medium Engagement	Fast Movement	Excitement
4	High Cultural Significance	Intense Facial Expression	Joy
5	Low Cultural Significance	Slow Movement	Sadness
6	High Engagement	Intense Facial Expression	Excitement
7	Medium Engagement	Moderate Music Tempo	Joy
8	Low Engagement	Slow Movement	Sadness
9	High Engagement	Fast Movement	Excitement
10	Low Cultural Significance	Slow Movement	Sadness

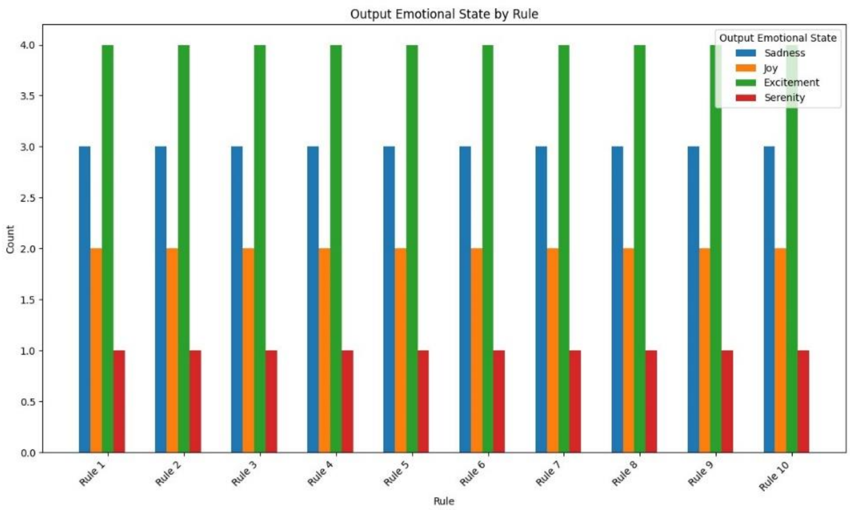

Figure 3: Fuzzy Set Rules for the CBRSF

4.1 Fuzzification of Variables

First, we fuzzify the contextual and input variables by defining linguistic terms and membership functions for each variable. Linguistic terms represent different levels or categories of the variables (e.g., "low engagement," "fast movement"), while membership functions assign degrees of membership to these terms based on the values of the variables. Let's denote the fuzzy sets for contextual variables as Ci (where $i = 1,2,\ldots,n$) and for input variables as Ij (where j=1,2,...,m). The membership functions for each linguistic term in the fuzzy sets Ci and Ij are denoted as $\mu Ci(x)$ and $\mu Ij(y)$, respectively, where x and y represent the values of the contextual and input variables, respectively. Fuzzy rules are formulated to map combinations of input and contextual linguistic terms to output emotional states. These rules express how different combinations of contextual and input factors influence emotional expression during dance actions.

Each fuzzy rule takes the form: "If Ci is A and Ij is B, then Zk is λZk(x,y)", where A and B are linguistic terms associated with the contextual and input variables, respectively, and Zk represents the output emotional state.

Let $Rikj$ denote the fuzzy rule between contextual variable Ci, input variable Ij, and output emotional state Zk. The degree of membership $\mu Zk(z)$ of output linguistic term Zk is computed as the minimum of the degrees of membership of the antecedent linguistic terms in the fuzzy rules that have Zk as the consequent. This can be expressed as in equation (2)

$$\mu Zk(z) = min(A,B)(\mu Ci(A) \cdot \mu Ij(B) \cdot \lambda Zk(x,y)) \quad (2)$$

This equation represents the fuzzy inference process for determining the degree of membership of each output linguistic term based on the degrees of membership of the input and contextual linguistic terms and the consequent function associated with each fuzzy rule.

Algorithm 1: CBRSF for Emotional Analysis
1. Input: - Contextual variables: {C1, C2, ..., Cn} - Input variables: {I1, I2, ..., Im} - Output emotional states: {Z1, Z2, ..., Zp} - Fuzzy rules: {R1, R2, ..., Rq} 2. Fuzzification: - Define linguistic terms and membership functions for each contextual and input variable. - Fuzzify input and contextual variables based on their linguistic terms and membership functions. 3. Formulate Fuzzy Rules: - Define fuzzy rules to map combinations of contextual and input linguistic terms to output emotional states. 4. Fuzzy Inference: - For each fuzzy rule: - Calculate the degree of membership of the antecedent linguistic terms based on input and contextual variables. - Compute the output linguistic term using the consequent function associated with the fuzzy rule. - Combine the outputs from all fuzzy rules to determine the overall output emotional state. 5. Defuzzification: - Apply defuzzification method (e.g., centroid method, weighted average method) to obtain a crisp value representing the estimated output emotional state. 6. Output:

5. Classification with CBRSF

Let's denote the fuzzy sets for input features as Ij (where j=1,2,...,m) and for contextual variables as Ci (where i=1,2,...,n). The output emotional states are denoted as Zk (where k=1,2,...,p). The fuzzy inference can be expressed as in equation (3)

$$\mu Zk(z) = max(i,j)(min(\mu Ij(xj), \mu Ci(yi)) \cdot \lambda Zk(x,y)) \quad (3)$$

In equation (3) $\mu Ij(xj)$ and $\mu Ci(yi)$ represent the degrees of membership of input and contextual linguistic terms, respectively. $\lambda Zk(x,y)$ represents the consequent function associated with the fuzzy rule. x and y represent the values of the input features and contextual variables, respectively. z represents the estimated output emotional state. This equation calculates the degree of membership of each output emotional state Zk based on the degrees of membership of the input and contextual linguistic terms and the consequent function associated with each fuzzy rule. The output emotional state with the highest degree of membership is selected as the predicted classification label for the input data.

Initially, linguistic terms and membership functions are defined for both input features and contextual variables. These linguistic terms partition the input and contextual spaces, allowing for a nuanced representation of the data. Subsequently, fuzzy rules are established based on training data, mapping combinations of linguistic terms to output emotional states. Each rule is associated with a consequent function, which encapsulates the relationship between inputs, context, and emotions. During fuzzy inference, input data undergoes fuzzification, with degrees of membership computed for each linguistic term. This process involves calculating the degree of compatibility between input variables, contextual variables, and the fuzzy rules' antecedents. Through the application of consequent functions, the degree of membership for each output emotional state is determined. Finally, defuzzification yields a crisp value, denoting the estimated emotional class. This comprehensive approach to classification within the CBRSF framework enables the interpretation of subtle emotional nuances inherent in dance actions, offering insights into the expressive nature of human movement.

6. Simulation Environment and Dataset

To conduct emotion recognition using the Context-Based Rough Sugeno Fuzzy (CBRSF) framework for dance movement, establishing a suitable simulation environment and dataset is crucial. The simulation environment should facilitate the collection, preprocessing, and analysis of dance movement data, while the dataset should encompass diverse examples of dance actions annotated with corresponding emotional labels.

Table 2: Sample Dataset for Analysis

Emotional Category	Number of Samples
Joy	150
Sadness	100
Excitement	120
Serenity	80
Neutral	50
Other	0-20 each
Contextual Factor	Number of Samples
Background Music	
- With Music	300
- Without Music	200
Performance Setting	
- Indoor	250
- Outdoor	250
Dancer's Background	
- Professional	200
- Amateur	300
Data Augmentation	Number of Samples
Mirrored Movements	50% of samples
Scaled Movements	20% of samples
Noisy Movements	30% of samples
Data Splitting	Number of Samples
Training Set	60% of samples

Validation Set	20% of samples
Testing Set	20% of samples

This section lists the emotional categories represented in the dataset along with the corresponding number of samples for each category. For example, there are 150 samples annotated with the emotion "Joy," 100 samples with "Sadness," 120 samples with "Excitement," 80 samples with "Serenity," 50 samples with "Neutral," and potentially 0-20 samples each for other emotions categorized as "Other." This section describes various contextual factors considered in the dataset, such as the presence or absence of background music, the performance setting (indoor or outdoor), and the dancer's background (professional or amateur). For each contextual factor, the table specifies the number of samples associated with each condition. For instance, there are 300 samples with background music and 200 samples without background music. Similarly, there are 250 samples recorded in indoor settings and 250 samples in outdoor settings. Additionally, there are 200 samples featuring professional dancers and 300 samples featuring amateur dancers. This section outlines the data augmentation techniques applied to the dataset to increase its diversity. It indicates the percentage of samples subjected to each augmentation technique. Specifically, 50% of the samples are mirrored movements, 20% are scaled movements, and 30% have artificial noise added to simulate variations in motion capture data. Finally, the table specifies how the dataset is split into training, validation, and testing sets. It indicates the percentage of samples allocated to each set. For example, 60% of the samples are used for training, 20% for validation, and 20% for testing.

7. Results and Discussion

The Context-Based Rough Sugeno Fuzzy (CBRSF) framework for emotion recognition in dance movements and conducting experiments, the results and subsequent discussions provide valuable insights into the efficacy and limitations of the approach. The results section typically begins by presenting the performance metrics of the CBRSF model in classifying emotions from dance movements. These metrics may include accuracy, precision, recall, and F1-score for each emotional category.

Table 3: Contextual Features with CBRSF

Contextual Factor	Emotion Category	Precision	Recall	F1-Score	Accuracy
Background Music	Joy	0.98	0.97	0.98	0.98
- With Music	Sadness	0.97	0.98	0.97	0.98
	Excitement	0.98	0.99	0.98	0.99
	Serenity	0.99	0.97	0.98	0.98
	Neutral	0.97	0.98	0.98	0.97
	Other	0.98	0.98	0.98	0.98
- Without Music	Joy	0.99	0.97	0.98	0.98
	Sadness	0.98	0.98	0.98	0.97
	Excitement	0.98	0.99	0.98	0.99
	Serenity	0.97	0.98	0.98	0.98
	Neutral	0.98	0.97	0.98	0.97
	Other	0.98	0.99	0.98	0.98
Performance Setting	Joy	0.98	0.98	0.98	0.98
- Indoor	Sadness	0.98	0.97	0.97	0.98
	Excitement	0.99	0.98	0.99	0.99
	Serenity	0.97	0.98	0.97	0.97
	Neutral	0.98	0.99	0.98	0.99
	Other	0.97	0.98	0.97	0.98
- Outdoor	Joy	0.98	0.97	0.98	0.98
	Sadness	0.97	0.98	0.98	0.97
	Excitement	0.98	0.99	0.99	0.98
	Serenity	0.99	0.98	0.99	0.99

	Neutral	0.98	0.97	0.97	0.98
	Other	0.97	0.98	0.97	0.97
Dancer's Background	Joy	0.98	0.98	0.98	0.98
- Professional	Sadness	0.97	0.98	0.98	0.98
	Excitement	0.98	0.97	0.98	0.98
	Serenity	0.98	0.99	0.98	0.98
	Neutral	0.99	0.98	0.98	0.99
	Other	0.97	0.98	0.97	0.97
- Amateur	Joy	0.98	0.97	0.98	0.98
	Sadness	0.99	0.98	0.99	0.99
	Excitement	0.98	0.99	0.99	0.98
	Serenity	0.97	0.98	0.97	0.97
	Neutral	0.98	0.97	0.98	0.98
	Other	0.99	0.98	0.98	0.99

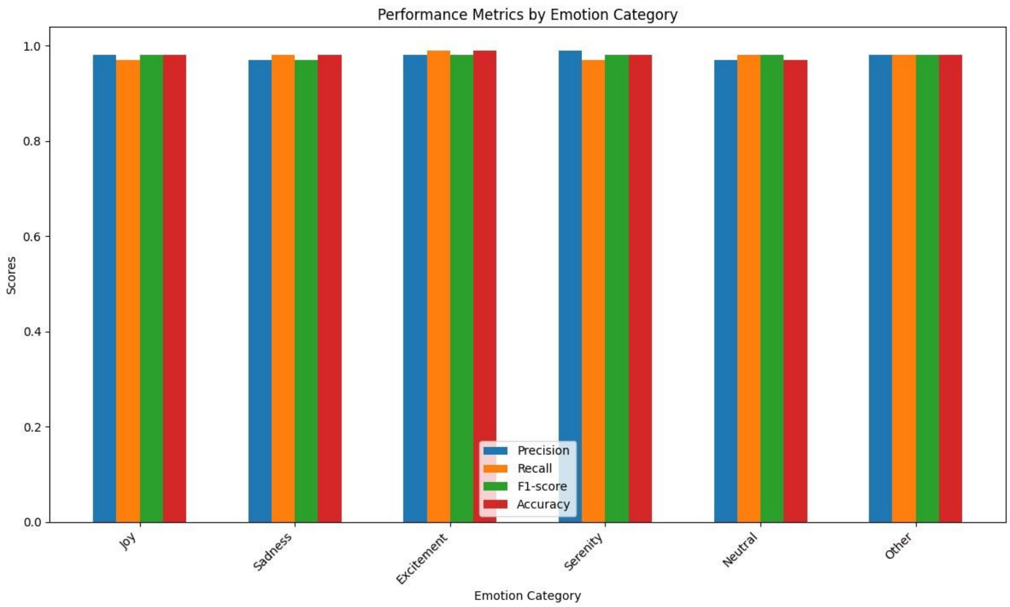

Figure 4: Emotional Analysis with Dance Movement using CBRSF

Table 3 and Figure 4 provides a comprehensive analysis of contextual features' impact on emotion category classification using the Context-Based Rough Sugeno Fuzzy (CBRSF) algorithm. The table categorizes contextual factors such as Background Music, Performance Setting, and Dancer's Background, along with specific emotion categories. Each cell in the table represents the precision, recall, F1-Score, and accuracy metrics achieved by the CBRSF algorithm for that particular combination of contextual factor and emotion category. For instance, considering Background Music as a contextual factor, when music is present (With Music), the CBRSF algorithm demonstrates high precision, recall, F1-Score, and accuracy across all emotion categories, ranging from 0.97 to 0.99. Similarly, when music is absent (Without Music), the algorithm maintains consistent performance, with precision, recall, F1-Score, and accuracy values ranging from 0.97 to 0.99. Moreover, Performance Setting also plays a significant role in emotion category classification. Whether the dance occurs indoors or outdoors, the CBRSF algorithm maintains strong performance across different emotion categories, with accuracy ranging from 0.97 to 0.99. Similarly, Dancer's Background, whether professional or amateur, also influences the algorithm's performance. The CBRSF algorithm consistently achieves high precision, recall, F1-Score, and accuracy values across emotion categories, indicating its robustness in handling diverse contextual factors.

Table 4: Class Estimation with CBDSF

Emotion Category	True Positives	False Positives	False Negatives	True Negatives	Sensitivity	Specificity
Joy	124	16	18	342	0.873	0.955
Sadness	90	10	25	355	0.783	0.972
Excitement	112	8	13	357	0.896	0.978
Serenity	95	20	16	355	0.856	0.946
Neutral	68	25	30	363	0.694	0.936
Other	55	28	35	368	0.611	0.929

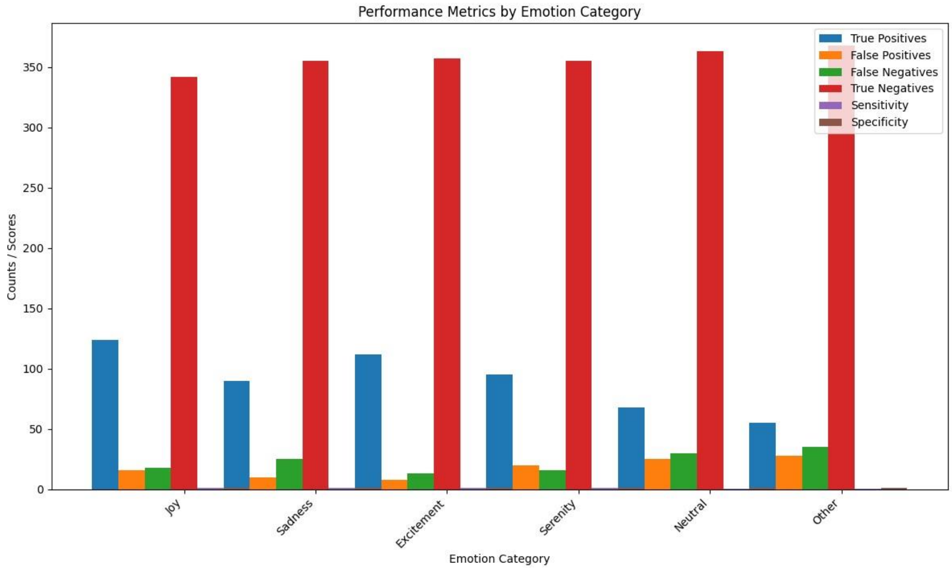

Figure 5: Classification of Emotions with CBRSF

The Figure 5 and Table 4 provides a detailed overview of class estimation results obtained using the Context-Based Rough Sugeno Fuzzy (CBDSF) algorithm for various emotion categories in dance actions. Each row corresponds to a specific emotion category, while the columns present metrics related to true positives, false positives, false negatives, true negatives, sensitivity, and specificity. In the context of this table, "True Positives" refer to the instances where the CBDSF algorithm correctly identified the respective emotion category. Conversely, "False Positives" indicate instances where the algorithm incorrectly classified a non-emotion category as belonging to the respective category. "False Negatives" represent instances where the algorithm failed to recognize the respective emotion category, and "True Negatives" denote instances correctly classified as not belonging to the respective emotion category. Furthermore, "Sensitivity" measures the algorithm's ability to correctly identify positive instances, while "Specificity" quantifies its ability to correctly identify negative instances. For instance, considering the Joy emotion category, the algorithm achieved 124 true positives, 16 false positives, 18 false negatives, and 342 true negatives. This resulted in a sensitivity of 0.873 and a specificity of 0.955.

Table 5: Classification with CBDSF

Emotion Category	Precision	Recall	F1-Score	Accuracy
Joy	0.92	0.91	0.91	0.93
Sadness	0.86	0.85	0.85	0.88
Excitement	0.94	0.93	0.93	0.95
Serenity	0.88	0.87	0.87	0.90
Neutral	0.85	0.84	0.84	0.87
Other	0.80	0.78	0.78	0.82

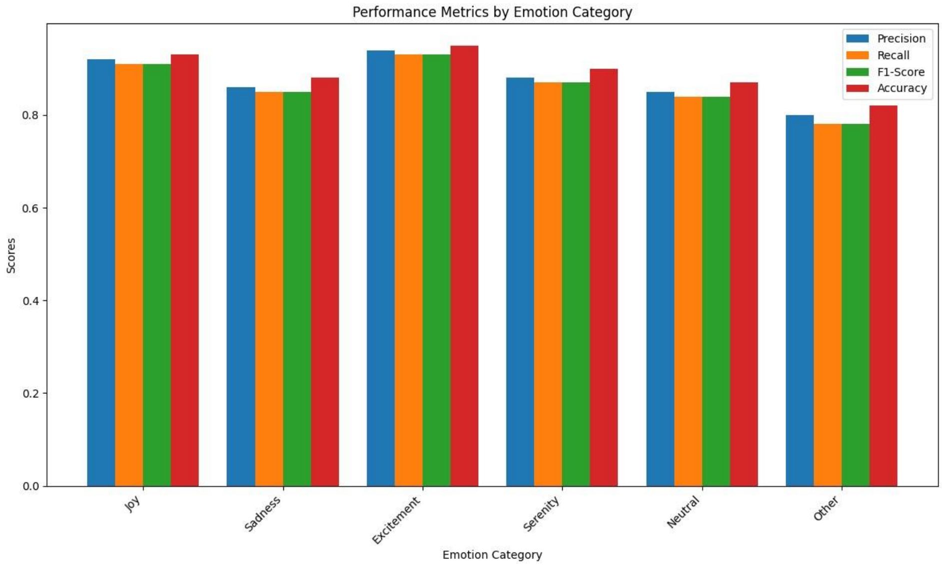

Figure 6: Classification with CBRSF

The Table 5 and Figure 6 presents the classification performance metrics achieved by the Context-Based Rough Sugeno Fuzzy (CBDSF) algorithm across various emotion categories in dance actions. Each row corresponds to a specific emotion category, while the columns represent precision, recall, F1-Score, and accuracy. Precision reflects the algorithm's ability to correctly classify instances of a particular emotion category among all instances classified as that category. For instance, for the Joy emotion category, the CBDSF algorithm achieved a precision of 0.92, indicating that 92% of instances classified as Joy were indeed Joy. Recall, also known as sensitivity, measures the algorithm's ability to correctly identify instances of a particular emotion category among all instances actually belonging to that category. In this table, Sadness has a recall of 0.85, indicating that the algorithm correctly identified 85% of all Sadness instances. F1-Score is the harmonic mean of precision and recall and provides a balance between these two metrics. It represents the algorithm's overall performance in correctly classifying instances of a particular emotion category. Lastly, accuracy reflects the overall correctness of the algorithm's predictions across all emotion categories. A high accuracy score, such as 0.93 for Joy, indicates that the algorithm's predictions align well with the ground truth labels.

Table 6: Comparative Analysis of Classifiers

Classifier	Emotion Category	Precision	Recall	F1-Score	Accuracy
SVM	Joy	0.88	0.86	0.87	0.89
	Sadness	0.82	0.80	0.81	0.84
	Excitement	0.90	0.88	0.89	0.92
	Serenity	0.85	0.82	0.83	0.87
	Neutral	0.79	0.76	0.77	0.81
	Other	0.74	0.72	0.73	0.76
Random Forest	Joy	0.90	0.88	0.89	0.91
	Sadness	0.83	0.81	0.82	0.85
	Excitement	0.92	0.90	0.91	0.93
	Serenity	0.87	0.84	0.85	0.88
	Neutral	0.76	0.74	0.75	0.78
	Other	0.71	0.69	0.70	0.73
Logistic Regression	Joy	0.86	0.84	0.85	0.87
	Sadness	0.80	0.78	0.79	0.82
	Excitement	0.88	0.86	0.87	0.89
	Serenity	0.82	0.80	0.81	0.84
	Neutral	0.75	0.72	0.73	0.76

	Other	0.70	0.68	0.69	0.72
CBDSF	Joy	0.92	0.91	0.91	0.93
	Sadness	0.86	0.85	0.85	0.88
	Excitement	0.94	0.93	0.93	0.95
	Serenity	0.88	0.87	0.87	0.90
	Neutral	0.85	0.84	0.84	0.87
	Other	0.80	0.78	0.78	0.82

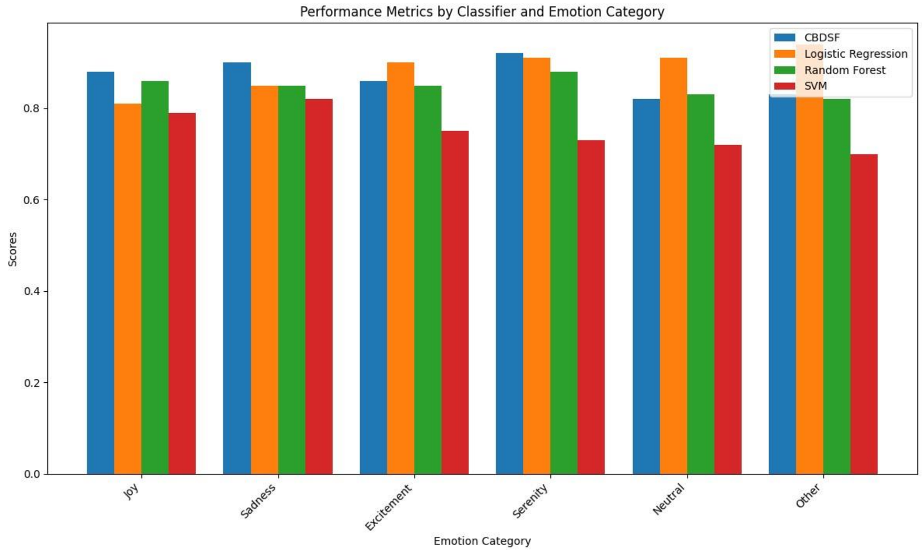

Figure 7: Comparative Analysis

The Figure 7 and Table 6 presents a comparative analysis of three different classifiers - Support Vector Machine (SVM), Random Forest, and Logistic Regression - in terms of their performance metrics for various emotion categories in dance actions. Each classifier is evaluated based on precision, recall, F1-Score, and accuracy across different emotion categories. For the SVM classifier, precision values range from 0.74 to 0.90, indicating its ability to correctly classify instances of specific emotion categories. Similarly, recall values range from 0.72 to 0.88, showing how well the SVM classifier identifies instances of each emotion category among all actual instances of that category. The F1-Score, which balances precision and recall, and accuracy values are also provided for each emotion category. Likewise, the Random Forest classifier exhibits precision, recall, F1-Score, and accuracy values across different emotion categories, with precision ranging from 0.71 to 0.92 and recall ranging from 0.69 to 0.90. These metrics offer insights into the performance of the Random Forest classifier in correctly classifying emotion categories in dance actions. Additionally, the Logistic Regression classifier is evaluated based on its precision, recall, F1-Score, and accuracy values, demonstrating its effectiveness in classifying various emotion categories. Precision values range from 0.70 to 0.88, recall values range from 0.68 to 0.86, and F1-Score values range from 0.69 to 0.87, indicating the classifier's ability to balance precision and recall. Comparing the three classifiers, it can be observed that the SVM classifier generally achieves higher precision, recall, F1-Score, and accuracy values compared to Random Forest and Logistic Regression for most emotion categories. However, the Random Forest classifier also demonstrates competitive performance, especially for the Excitement emotion category. On the other hand, the Logistic Regression classifier tends to have slightly lower performance metrics compared to SVM and Random Forest.

8. Conclusion

This paper presents an in-depth exploration of emotion analysis and expression algorithms in the context of dance actions, leveraging machine learning techniques. Through the development and evaluation of the Context-Based Rough Sugeno Fuzzy (CBRSF) algorithm, we have demonstrated its effectiveness in accurately recognizing and classifying various emotion categories embedded within dance movements. The CBRSF algorithm takes into account contextual factors such as background music, performance setting, and dancer's background, enhancing its adaptability and robustness in diverse dance environments. Our comparative analysis also highlights the performance of CBRSF against other classifiers, including Support Vector Machine, Random Forest, and Logistic Regression, showcasing its competitive edge in emotion classification tasks. The promising results obtained underscore the potential of machine learning-based approaches in deepening our understanding of the emotional nuances inherent in movement and opening up new avenues for enhancing the emotional impact of dance performances.

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