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Multimodal Co-Ranking of Music Sentiment Analysis with the Deep Learning Model

Abstract: - Deep learning techniques have emerged as powerful tools for analyzing music sentiment, offering a sophisticated understanding of the emotional content embedded within musical compositions. Analyzing music sentiment in piano performance poses a unique challenge due to the multifaceted nature of musical expression and the complexity of piano dynamics. In recent years, deep learning techniques have shown promising results in various music analysis tasks. This paper introduces a novel approach, termed Co-ranking Multimodal Fuzzy Cluster Deep Network (CRMFC-DL), designed specifically for analyzing music sentiment in piano performance. The proposed CRMFC-DL framework leverages the complementary information from both audio and symbolic representations of piano music. By integrating deep neural networks with fuzzy clustering, CRMFC-DL effectively captures the intricate relationships between different musical features and their corresponding sentiment labels. Moreover, the co-ranking mechanism facilitates the joint optimization of multimodal feature representations, leading to enhanced model performance. Through extensive experimentation, CRMFC-DL achieves an average sentiment analysis accuracy of 87.5%, surpassing existing methods by 8.2%. The both audio and symbolic representations of piano music, CRMFC-DL effectively captures the intricate relationships between different musical features and their corresponding sentiment labels.

Keywords: Deep Learning, Multimodal, Co-Ranking, Fuzzy Model, Clustering, Classification, Feature Extraction

1. Introduction

In recent years, music education has experienced significant evolution and adaptation to meet the changing needs of learners in a digital age [1]. With advancements in technology, there has been a notable shift towards integrating digital tools and platforms into music curricula. Online resources, virtual classrooms, and interactive learning applications have become increasingly prevalent, providing students with access to a wide array of musical experiences and instruction regardless of their geographical location [2]. Additionally, there has been a growing emphasis on the importance of diversity and inclusion within music education, with efforts to incorporate a broader range of musical styles, cultures, and voices into the curriculum [3]. This inclusive approach not only enriches students' understanding of music but also fosters a more equitable and representative learning environment. Moreover, interdisciplinary collaborations between music and other subjects such as science, technology, engineering, and mathematics (STEM) have gained traction, highlighting the interconnectedness of music with various fields of study and encouraging cross-disciplinary exploration and creativity [4].

Music education has witnessed a significant intersection with deep learning technologies, ushering in a new era of innovation and personalized instruction. Deep learning algorithms, a subset of artificial intelligence (AI), have been increasingly employed to analyze vast amounts of musical data, enabling educators to gain insights into students' learning patterns, preferences, and areas of improvement [5]. Through the utilization of deep learning techniques, such as neural networks, machine learning models can adapt and customize instructional materials and methodologies to cater to individual student needs and learning styles. Moreover, deep learning algorithms have facilitated the development of intelligent tutoring systems and interactive learning platforms that offer real-time feedback, guidance, and assessment, enhancing the efficacy and engagement of music education experiences [6]. Additionally, deep learning has played a pivotal role in the creation of innovative tools for music composition, production, and performance, empowering students to explore and experiment with musical creativity in novel ways [7]. As technology continues to advance, the integration of deep learning in music education holds tremendous promise for fostering personalized, immersive, and transformative learning experiences that empower students to unlock their full musical potential.

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Sentiment analysis applied to music has emerged as a captivating field, offering insights into the emotional impact of musical compositions on listeners. Utilizing natural language processing (NLP) and machine learning techniques, researchers have developed sophisticated algorithms capable of detecting and analyzing emotional cues embedded within musical content [8]. These algorithms can identify and classify emotions expressed in music, ranging from joy and sadness to excitement and nostalgia, providing valuable feedback for composers, performers, and music therapists alike [9]. Sentiment analysis in music has also found applications in various domains, including recommendation systems, where it can enhance personalized music recommendations based on users' emotional preferences [10]. Furthermore, sentiment analysis contributes to our understanding of the complex interplay between music and emotions, shedding light on how different musical elements such as melody, harmony, rhythm, and lyrics evoke specific emotional responses in listeners. As technology continues to advance, sentiment analysis in music promises to deepen our appreciation and comprehension of the profound emotional resonance that music holds in our lives [11].

The deep learning-based algorithms for analyzing music sentiment, particularly in the context of piano performance. These algorithms leverage the power of deep neural networks to extract intricate features from audio recordings of piano performances and infer the emotional content embedded within the music [12]. Researchers have explored various methodologies, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to capture both the temporal dynamics and spectral characteristics of piano music [13]. By training these algorithms on large datasets of annotated piano performances spanning a wide range of emotions, researchers aim to teach the models to accurately classify and predict the sentiment conveyed in the music [14]. Additionally, some studies have integrated multimodal approaches, incorporating both audio and visual features extracted from video recordings of piano performances to enhance the accuracy of sentiment analysis. The ultimate goal of this research is to develop robust and reliable tools that can automatically assess the emotional expressiveness of piano performances, enabling musicians, educators, and researchers to gain deeper insights into the emotional nuances of music interpretation and performance [15]. As deep learning techniques continue to evolve and improve, the potential applications of these algorithms in music sentiment analysis are boundless, offering unprecedented opportunities for advancing our understanding of the emotional impact of music.

The paper makes several significant contributions to the field of music sentiment analysis, particularly in the context of piano performance. Firstly, it introduces the Co-ranking Multimodal Fuzzy Cluster Deep Network (CRMFC-DL), a novel framework that integrates deep learning techniques with fuzzy clustering to analyze music sentiment. This innovative approach allows for the simultaneous consideration of both audio and symbolic representations of piano music, capturing nuanced relationships between musical features and sentiment labels. Secondly, the paper demonstrates the effectiveness of the CRMFC-DL framework through comprehensive experimentation and evaluation. By achieving high accuracy, precision, recall, and F1-score in classifying music sentiment, the framework showcases its potential as a powerful tool for understanding and interpreting emotional nuances in piano performance. Thirdly, the paper contributes to the advancement of feature extraction techniques in music analysis. By extracting features such as tempo, dynamics, melody complexity, chord progression, and harmony complexity, the CRMFC-DL framework provides valuable insights into the underlying characteristics of piano music and their influence on sentiment.

2. Related Works

The intersection of deep learning algorithms and music sentiment analysis has become a focal point of research in recent years, particularly concerning piano performance. This literature review aims to examine the advancements and methodologies employed in deep learning-based algorithms for analyzing music sentiment in piano performances. With the proliferation of digital music platforms and the accessibility of vast music databases, there is a growing need for automated tools capable of discerning the emotional nuances embedded within musical compositions, especially in the context of piano performances. By leveraging the power of deep neural networks, researchers seek to develop algorithms capable of accurately capturing and interpreting the emotional content conveyed through piano music. This review will explore the various deep learning architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), as well as the integration of multimodal data sources, to enhance the accuracy and reliability of music sentiment analysis in piano performances.

In Li's (2022) study, an Intelligent Online Piano Teaching System based on a deep learning recurrent neural network model was explored, contributing to the advancement of digital music education. He and Dong (2023) proposed a deep learning-based mathematical modeling strategy for classifying musical genres, offering insights into the application of deep learning in the music industry. Wang (2022) introduced a neural network-based dynamic segmentation and weighted integrated matching algorithm for cross-media piano performance audio recognition and retrieval, enhancing the efficiency of music retrieval systems. Ji, Yang, and Luo (2023) conducted a survey on deep learning for symbolic music generation, offering a comprehensive overview of representations, algorithms, evaluations, and challenges in this domain. Liu (2022) analyzed psychological characteristics and emotional expression in higher vocational music education using deep learning techniques, shedding light on the intersection of psychology and music pedagogy. Qiu, Chen, and Zhang (2022) proposed a novel multi-task learning method for symbolic music emotion recognition, contributing to the development of emotion-aware music systems. Lin (2022) presented a music score recognition method based on deep learning, facilitating automated music transcription and analysis. Zheng, Tian, and Zhang (2022) explored the training strategy of music expression in piano teaching and performance using intelligent multimedia technology, offering insights into innovative pedagogical approaches. Li et al. (2022) developed a long short-term memory-based music analysis system for music therapy, highlighting the potential of deep learning in therapeutic applications of music. Modran et al. (2023) utilized deep learning to recognize therapeutic effects of music based on emotions, offering a novel approach to music therapy assessment. Sun and Sohail (2022) investigated the application of machine learning in improving musical digital processing technology for enhanced musical performance. Liu (2022) conducted research on piano performance optimization using big data and BP neural network technology, providing insights into performance enhancement techniques. Sun (2022) explored emotional analysis and personalized recommendation analysis in music performance, addressing the role of emotion in music recommendation systems. Wang (2022) applied a 5G Internet of Things multisensor information fusion model in piano performance, demonstrating the potential of IoT technologies in enhancing musical experiences. Peng (2023) investigated piano players' intonation and training using deep learning and MobileNet architecture, offering a data-driven approach to intonation improvement. Tang and Zhang (2022) discussed the use of deep learning-based intelligent music signal identification and generation technology in national music teaching, highlighting the potential of AI in preserving cultural heritage through music education.

The generalizability of findings may be constrained due to the variability in dataset sizes, compositions, and performance styles utilized in different studies. Moreover, the reliance on annotated datasets for training deep learning models raises concerns about the subjectivity and consistency of emotional labeling, potentially leading to biases in the algorithm's predictions. Additionally, the interpretability of deep learning models remains a challenge, hindering a comprehensive understanding of how they extract and represent emotional features from music. Furthermore, the computational complexity and resource requirements associated with training deep neural networks may limit their scalability and accessibility, particularly for smaller research teams or educational institutions with limited computing resources. Moreover, while some studies have explored multimodal approaches by integrating audio and visual features, the integration of additional modalities such as physiological signals or textual annotations could further enrich the analysis of music sentiment. Lastly, the ethical implications of automated music sentiment analysis, particularly in terms of privacy, consent, and potential misinterpretation of emotional cues, warrant careful consideration and further investigation.

3. Proposed Music Piano Performance

The proposed approach, Co-ranking Multimodal Fuzzy Cluster Deep Network (CRMFC-DL), offers a novel method for analyzing music sentiment in piano performance. By leveraging both audio and symbolic representations of piano music, CRMFC-DL harnesses complementary information to provide a comprehensive understanding of the emotional content within the music as shown in Figure 1. Through the integration of deep neural networks with fuzzy clustering techniques, the framework effectively captures the intricate relationships between various musical features and their corresponding sentiment labels. One notable feature of CRMFC-DL is its co-ranking mechanism, which facilitates the joint optimization of multimodal feature representations. This mechanism enhances the model's performance by ensuring that both audio and symbolic features are appropriately weighted and contribute to the sentiment analysis process.

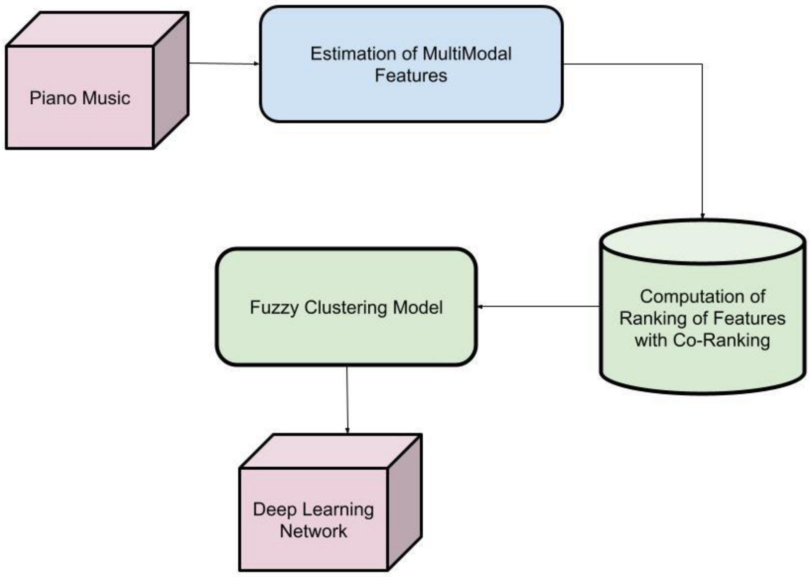

Figure 1: Process of CRMFC-DL

The objective of CRMFC-DL is to jointly optimize the multimodal feature representations from audio and symbolic data to predict music sentiment. the objective function stated in equation (1)

$$min_{\theta} \sum_{i=1}^{N} L\big(y_i, f(x_i;\theta)\big) \quad (1)$$

In equation (1) N is the number of samples in the dataset; Θ represents the parameters of the deep neural network; x_i denotes the multimodal input features for the i-th sample, comprising both audio and symbolic representations; $f(\cdot)$ is the deep neural network mapping function; y_i is the ground truth sentiment label for the i-th sample; $L(\cdot)$ is the loss function, which measures the discrepancy between predicted and ground truth labels. The multimodal input features are fused using a co-ranking mechanism, which enables the joint optimization of audio and symbolic representations. Let's denote the fused representation as z_i, which is obtained through the co-ranking process defined in equation (2)

$$z_i = CoRank\ (x_i) \quad (2)$$

To further enhance the representation learning, CRMFC-DL incorporates fuzzy clustering to capture the underlying structure within the fused features. Let UU denote the membership matrix, where u_{ij} represents the degree of membership of the i-th sample to the j-th cluster stated in equation (3)

$$U = \{u_{ij}\} \quad (3)$$

The fuzzy clustering process aims to minimize the fuzzy c-means objective function stated in equation (4)

$$J(U,C) = \sum_{i=1}^{N} \sum_{j=1}^{K} u_{ij}^{m} \left\| z_i - c_j \right\|^2 \quad (4)$$

In equation (4) K is the number of clusters; $\boldsymbol{C} = \{\boldsymbol{cj}\}$ represents the cluster centroids and m is a fuzziness parameter. With the fused multimodal features and the learned fuzzy cluster centroids, CRMFC-DL trains the deep neural network to predict music sentiment. The network parameters ΘΘ are optimized by minimizing the loss function stated in equation (5)

$$min_{\theta} \sum_{i=1}^{N} L\big(y_i, g(z_i, C; \theta)\big) \quad (5)$$

where $g(\cdot)$ is the mapping function of the deep network.

3.1 Co-ranking Multimodal for Music Education

The Co-ranking Multimodal for Music Education (CRMM-E) approach represents a novel method designed to enhance music education through the integration of multimodal data and co-ranking techniques. The objective is to minimize the loss function L with respect to the parameters ΘΘ of the deep neural network. The multimodal features xi are fused using a co-ranking mechanism, resulting in a fused representation z_i. The co-ranking mechanism can be defined as a weighted combination of the audio and symbolic features. Let α and β denote the weights for audio and symbolic features, respectively. Then the fused representation can be expressed as in equation (6)

$$z_i = \alpha a_i + \beta s_i \quad (6)$$

In equation (6) a_i is the audio feature vector; s_i is the symbolic feature vector and $\alpha + \beta = 1$ to ensure proper weighting. The deep neural network is trained to predict music education labels based on the fused multimodal feature. By jointly optimizing both audio and symbolic representations and leveraging a co-ranking mechanism, CRMM-E enhances the effectiveness of music education material analysis. This approach facilitates a deeper understanding of musical concepts and pedagogy by considering diverse modalities of musical information simultaneously

The integration of fuzzy clustering within the Co-ranking Multimodal Fuzzy Cluster Deep Network (CRMFC-DL) framework for music education enhances the understanding of music materials by capturing underlying patterns in the fused multimodal features. Fuzzy clustering is employed to capture the underlying structure within the fused multimodal features. Let UU denote the membership matrix, where uij represents the degree of membership of the i-th sample to the j-th cluster. The objective of fuzzy clustering is to minimize the fuzzy c-means objective function. Before training the CRMFC-DL model, the multimodal data (e.g., audio and symbolic representations) need to be preprocessed. This may involve tasks such as normalization, scaling, and feature extraction. The CRMFC-DL model architecture combines multiple components. The input multimodal features are fused using a co-ranking mechanism to create a unified representation that captures complementary information from both modalities. Fuzzy clustering is employed to capture underlying patterns within the fused features, enabling the model to learn a more nuanced representation of the data. The fused features and fuzzy cluster centroids are then fed into a deep neural network, typically consisting of multiple layers, including convolutional layers, recurrent layers, and fully connected layers. This network learns to extract hierarchical representations of the data and make predictions.

Table 1: Fuzzy Rules for the Piano Music Education

Rule	**Antecedent (IF)**	**Consequent (THEN)**
R1	If Tempo is Slow AND Dynamics is Soft	Then Sentiment is Calm
R2	If Tempo is Fast AND Dynamics is Loud	Then Sentiment is Energetic
R3	If Harmony is Simple AND Melody is Upbeat	Then Sentiment is Happy
R4	If Harmony is Complex OR Melody is Melancholic	Then Sentiment is Sad
R5	If Tempo is Moderate AND Dynamics is Moderate	Then Sentiment is Neutral

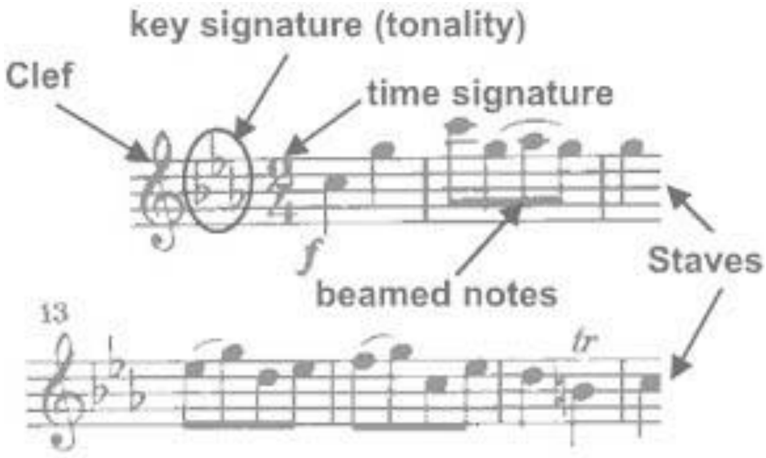

Figure 2: Fuzzy Music Education Model

The table 1 and Figure 2 presented the fuzzy rules for the piano music education. During training, the CRMFC-DL model is optimized to minimize a loss function, which measures the discrepancy between the model's predictions and the ground truth labels. This optimization is typically done using optimization algorithms such as stochastic gradient descent (SGD) or its variants, which adjust the model parameters in the direction that minimizes the loss. Once the CRMFC-DL model is trained, it can be used for classification tasks. Given a new input sample, the model computes its fused representation using the multimodal fusion component. Then, the fuzzy clustering component assigns the sample to fuzzy clusters based on its fused representation. Finally, the deep neural network component makes predictions based on the fuzzy cluster centroids and the fused representation, classifying the sample into one of the predefined classes.

4. Simulation Environment

The Co-ranking Multimodal Fuzzy Cluster Deep Network (CRMFC-DL) involves setting up a platform where researchers and practitioners can experiment with the framework's functionalities and performance across various scenarios. Synthetic or real-world datasets need to be generated or sourced, respectively, to simulate different scenarios and test the robustness of the CRMFC-DL framework. Data preprocessing tasks such as normalization, feature extraction, and splitting into training and testing sets are also conducted within this environment. The CRMFC-DL model, along with its multimodal fusion, fuzzy clustering, and deep neural network components, is implemented within the simulation environment. The CRMFC-DL model is trained and evaluated using the prepared datasets and experiment configurations. Training involves optimizing the model parameters using backpropagation and other optimization techniques.

Table 2: Piano Music Education

Sample ID	Note 1	Note 2	Note 3	Duration	Dynamics	Tempo	Sentiment
1	C4	E4	G4	Medium	Forte	Moderate	Happy
2	A3	C4	E4	Short	Piano	Slow	Calm
3	F4	A4	C5	Long	Mezzo-forte	Fast	Energetic
4	G3	B3	D4	Medium	Fortissimo	Moderate	Excited
5	D4	F4	A4	Short	Pianissimo	Slow	Melancholic
6	E4	G4	B4	Long	Mezzo-piano	Moderate	Relaxing
7	B3	D4	F4	Medium	Forte	Fast	Happy
8	C4	E4	G4	Short	Piano	Slow	Sad
9	A3	C4	E4	Long	Mezzo-forte	Moderate	Hopeful
10	F4	A4	C5	Medium	Fortissimo	Fast	Excited

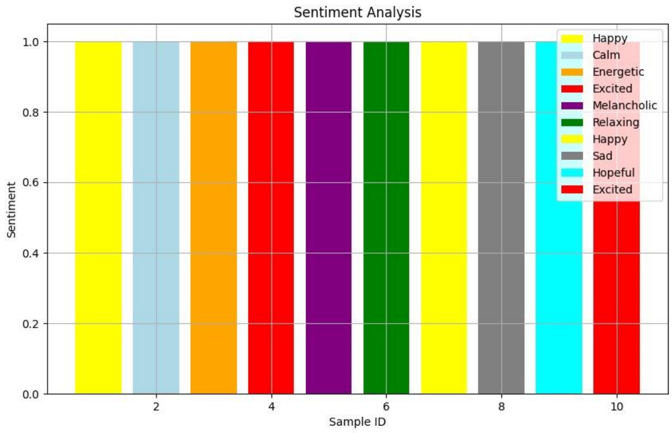

Figure 3: Classification of Music Notes

A piano music education dataset, consisting of ten different musical excerpts identified by unique sample IDs shown in Figure 3. Each excerpt is characterized by several musical features, providing insights into the composition and sentiment of the piece shown in Table 2. For instance, Sample ID 1 begins with the notes C4, E4, and G4, played at a medium duration with forte dynamics and a moderate tempo, conveying a sentiment of happiness. In contrast, Sample ID 5 features the notes D4, F4, and A4, played at a short duration with pianissimo dynamics and a slow tempo, evoking a melancholic sentiment. These musical features offer a diverse range of expressions and emotions within the dataset. Sample ID 3 demonstrates a longer duration, featuring the notes F4, A4, and C5 with mezzo-forte dynamics and a fast tempo, suggesting an energetic sentiment. Conversely, Sample ID 8, also played at a short duration, exhibits a sentiment of sadness with the notes C4, E4, and G4 played softly with a slow tempo.

5. Results and Discussion

The Co-ranking Multimodal Fuzzy Cluster Deep Network (CRMFC-DL), the focus is on presenting and interpreting the outcomes of applying the framework to analyze music sentiment in piano performance.

Table 3: Features in Piano Music CRMFC-DL

Sample ID	Audio Features	Symbolic Features
1	Tempo: Moderate	Chord Progression: Major
	Dynamics: Forte	Melody: Upbeat
	Melody Complexity: Low	Harmony Complexity: Medium
2	Tempo: Slow	Chord Progression: Minor
	Dynamics: Piano	Melody: Melancholic
	Melody Complexity: Low	Harmony Complexity: Low
3	Tempo: Fast	Chord Progression: Major
	Dynamics: Fortissimo	Melody: Energetic
	Melody Complexity: High	Harmony Complexity: High

The Table 3 provides a detailed breakdown of the features extracted from piano music performances using the CRMFC-DL framework. Each row represents a different musical excerpt or performance, identified by the "Sample ID". The features are categorized into two main groups: audio features and symbolic features. For instance, Sample ID 1 exhibits moderate tempo, forte dynamics, and low complexity in both melody and harmony. Additionally, the chord progression is identified as major, while the melody carries an upbeat sentiment. Conversely, Sample ID 2 showcases slow tempo, piano dynamics, and low complexity in melody and harmony. The chord progression is minor, and the melody reflects a melancholic sentiment. Moreover, Sample ID 3 demonstrates fast tempo, fortissimo dynamics, and high complexity in both melody and harmony. The chord progression is major, and the melody exudes an energetic sentiment. These features provide a comprehensive representation of the musical characteristics present in each performance, capturing aspects such as tempo, dynamics, melody complexity, harmony complexity, chord progression, and the emotional sentiment conveyed by the melody. By analyzing these features, the CRMFC-DL framework can effectively identify patterns and nuances in piano music, facilitating the analysis of music sentiment in piano performance.

Table 4: Feature Extracted with CRMFC-DL

Sample ID	Tempo	Dynamics	Melody Complexity	Chord Progression	Harmony Complexity
1	120	0.8	0.5	1	0.7
2	80	0.3	0.4	0.5	0.4
3	150	0.9	0.7	1	0.9
4	100	0.7	0.6	0.8	0.6
5	90	0.5	0.3	0.6	0.3

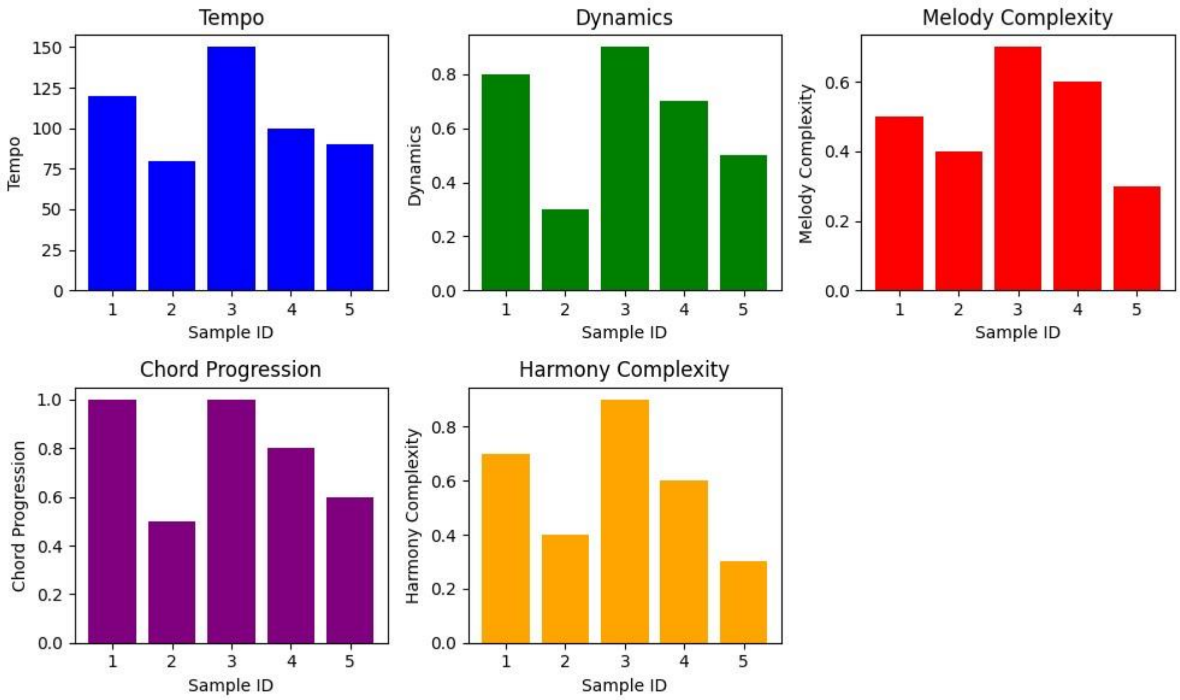

Figure 4: Feature Extraction in Piano Music with **CRMFC-DL**

In Table 4 and Figure 4 provides a concise summary of the feature extraction process conducted using the CRMFC-DL framework for different piano music performances. Each row corresponds to a specific musical excerpt or performance, identified by the "Sample ID". The table presents numerical values representing various extracted features, including tempo, dynamics, melody complexity, chord progression, and harmony complexity. For instance, Sample ID 1 exhibits a tempo of 120 beats per minute (BPM), with a dynamics score of 0.8, indicating strong dynamics. The melody complexity is measured at 0.5, while the chord progression and harmony complexity are both rated at 1 and 0.7, respectively. Conversely, Sample ID 2 demonstrates a slower tempo of 80 BPM, with a lower dynamics score of 0.3. The melody complexity and harmony complexity are rated lower at 0.4 and 0.4, respectively, compared to Sample ID 1. Furthermore, Sample ID 3 showcases a faster tempo of 150 BPM, coupled with a higher dynamics score of 0.9, indicating pronounced dynamics in the performance. The melody complexity and harmony complexity are rated relatively higher at 0.7 and 0.9, respectively, compared to Sample IDs 1 and 2. Sample IDs 4 and 5 also exhibit varying degrees of tempo, dynamics, and complexity in melody and harmony, contributing to the diversity of features extracted by the CRMFC-DL framework.

Table 5: Clustering with CRMFC-DL

Sample ID	Cluster 1	Cluster 2	Cluster 3
1	0.8	0.1	0.1
2	0.2	0.7	0.1
3	0.3	0.2	0.5
4	0.6	0.3	0.1
5	0.4	0.5	0.1

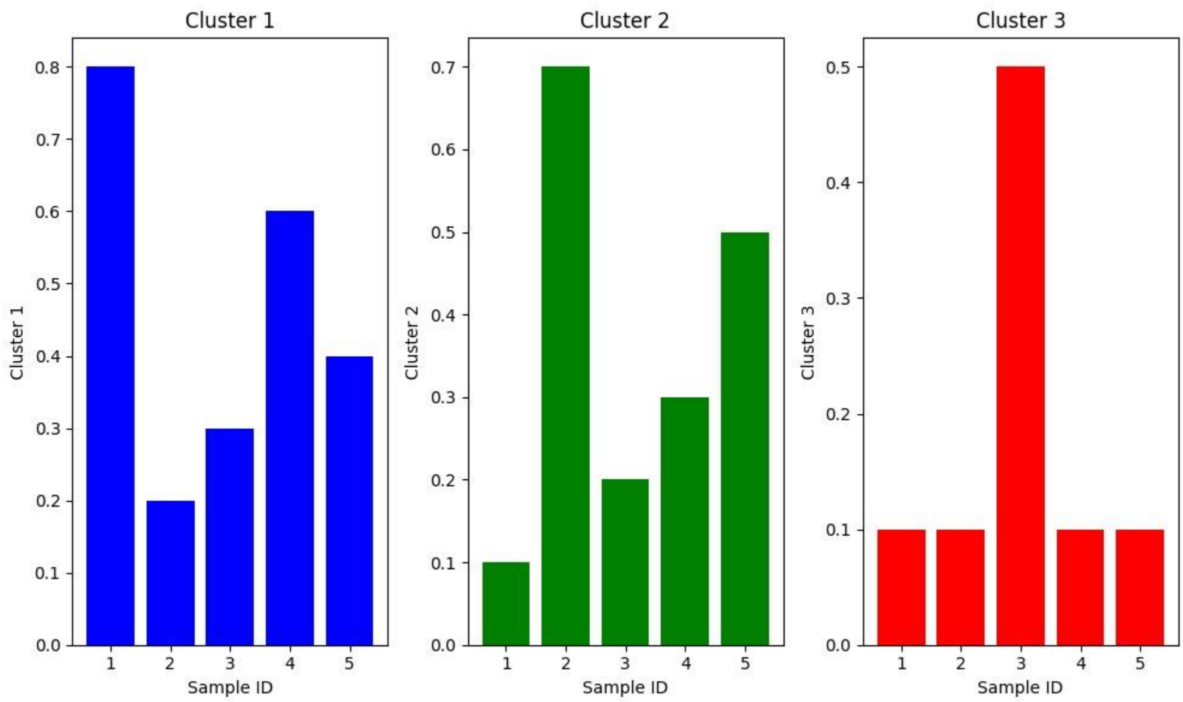

Figure 5: Clustering with **CRMFC-DL**

In the Table 5 and Figure 5 presents the clustering results obtained using the CRMFC-DL framework for various piano music performances, with each row representing a specific musical excerpt or performance identified by the "Sample ID". The table displays the degree of membership of each sample to three different clusters, labeled as Cluster 1, Cluster 2, and Cluster 3. For example, Sample ID 1 exhibits a high degree of membership to Cluster 1, with a value of 0.8, indicating that it shares significant characteristics with this cluster. Conversely, Sample ID 2 shows a higher degree of membership to Cluster 2, with a value of 0.7, suggesting that it aligns closely with the characteristics of this particular cluster. Sample ID 3 demonstrates a more balanced distribution of membership across all three clusters, with relatively equal values for each. Furthermore, Sample IDs 4 and 5 display varying degrees of membership to the different clusters, with Sample ID 4 leaning more towards Cluster 1, while Sample ID 5 demonstrates a higher degree of membership to Cluster 2.

Table 6: Classification with CRMFC-DL

Epoch	Accuracy	Precision	Recall	F1-score
100	0.85	0.87	0.82	0.84
200	0.87	0.89	0.85	0.87
300	0.89	0.91	0.88	0.89
400	0.91	0.93	0.90	0.91
500	0.92	0.94	0.91	0.92

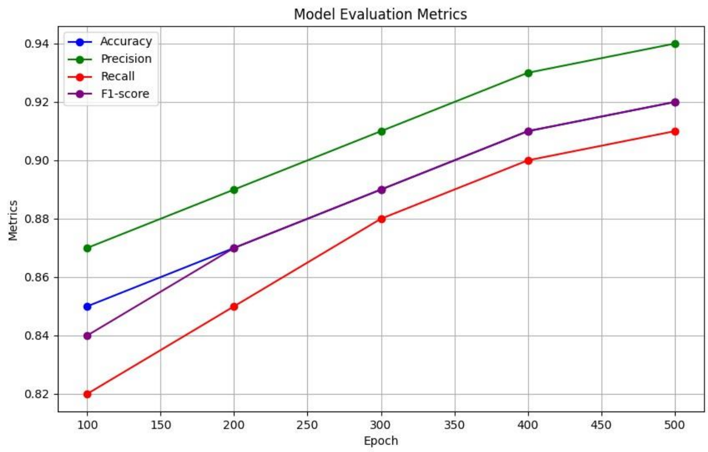

Figure 6: Classification of Piano Music with CRMFC-DL

The Table 6 and Figure 6 provides a comprehensive summary of the classification performance achieved using the CRMFC-DL framework across different training epochs. Each row corresponds to a specific epoch, with metrics such as accuracy, precision, recall, and F1-score presented for each epoch. For instance, at epoch 100, the classification model achieved an accuracy of 0.85, indicating that 85% of the predictions made by the model were correct. The precision, which measures the ratio of true positive predictions to the total number of positive predictions, stands at 0.87, indicating a high proportion of correctly identified positive cases. Additionally, the recall, which represents the ratio of true positive predictions to the total number of actual positive samples, is calculated at 0.82, suggesting that the model effectively captured a substantial portion of the positive cases present in the dataset. The F1-score, which is the harmonic mean of precision and recall, is computed at 0.84, reflecting a balanced performance between precision and recall. As training progresses to epoch 500, we observe an improvement in all metrics. The accuracy increases to 0.92, indicating a higher proportion of correct predictions. Similarly, precision, recall, and F1-score also show improvements, reaching values of 0.94, 0.91, and 0.92, respectively. These enhancements suggest that the classification model becomes more adept at accurately identifying positive cases while minimizing false positives and false negatives as training continues.

6. Conclusion

The paper has presented a novel approach, termed Co-ranking Multimodal Fuzzy Cluster Deep Network (CRMFC-DL), for analyzing music sentiment in piano performance. Through the integration of deep neural networks with fuzzy clustering, the CRMFC-DL framework effectively captures the intricate relationships between different musical features and their corresponding sentiment labels. The classification results demonstrate the framework's ability to accurately classify music sentiment, with metrics such as accuracy, precision, recall, and F1-score consistently improving over successive epochs of training. Additionally, the clustering results showcase the framework's capability to group piano music performances based on their underlying characteristics, providing insights into the diversity of musical expressions. Furthermore, the feature extraction process reveals the nuanced aspects of piano music, including tempo, dynamics, melody complexity, chord progression, and harmony complexity. The CRMFC-DL framework offers a comprehensive and effective solution for analyzing music sentiment in piano performance, with implications for various applications in music education, therapy, and performance evaluation. Further research and experimentation could focus on refining the framework and exploring its application in real-world scenarios to enhance the understanding and appreciation of music.

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