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Deep Learning and Natural Language Processing Technology Based Display and Analysis of Modern Artwork

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Abstract: - The modern artwork analysis display system, empowered by natural language processing (NLP) technology, revolutionizes the way audiences interact with and understand art. By integrating NLP algorithms, this system offers a dynamic and user-friendly platform for analyzing and displaying artwork. Utilizing NLP, visitors can engage in interactive conversations with the system, asking questions or making inquiries about the artwork on display. The system processes these inquiries, extracting relevant information from curated databases and scholarly sources to provide insightful and context-rich responses. Additionally, NLP algorithms can analyze textual descriptions, artist statements, and critical reviews to offer nuanced interpretations and historical context for each artwork. This paper presents the design and implementation of an innovative modern artwork analysis and display system, leveraging deep learning and natural language processing (NLP) technology, integrated with Multi-Feature Extraction Fuzzy Classification (MFEFC). The system offers a comprehensive platform for analyzing and presenting modern artworks, enhancing user engagement and understanding. Deep learning algorithms are employed to extract high-level features from visual artworks, allowing for automatic recognition of artistic styles, genres, and themes. Concurrently, NLP techniques process textual descriptions, artist biographies, and critical reviews to provide contextual information and interpretative insights. The integration of MFEFC enables precise classification of artworks based on multiple features extracted from both visual and textual sources, facilitating accurate analysis and categorization. Simulation of the NLP techniques demonstrated an average precision of 90% in extracting relevant contextual information from textual descriptions and artist biographies. Furthermore, MFEFC achieved a classification accuracy of 88% in categorizing artworks based on combined visual and textual features.

Keywords: Modern artwork analysis, display system, deep learning, natural language processing (NLP), artwork classification, contextual information extraction, user engagement.

I. INTRODUCTION

Natural Language Processing (NLP) has emerged as a powerful tool in the realm of artwork analysis, enabling a deeper understanding of visual art through textual data. By leveraging NLP techniques, researchers and art historians can extract valuable insights from descriptions, critiques, and historical accounts associated with artworks [1]. One of the primary applications of NLP in artwork analysis is sentiment analysis, which involves determining the emotional tone or attitude conveyed in textual descriptions of art [2]. This can help uncover the subjective perceptions and reactions of viewers towards specific artworks, providing a nuanced understanding of their impact and significance [3]. Additionally, NLP facilitates the categorization and classification of artworks based on thematic elements, artistic styles, and cultural contexts. By analyzing the language used to describe artworks, NLP algorithms can identify recurring motifs, symbols, and subjects, shedding light on broader trends and movements within the art world [4]. Furthermore, NLP enables the extraction of key entities and concepts from textual sources related to art, such as artist names, art movements, historical events, and symbolic meanings [5]. This information can be used to enrich metadata associated with artworks, improve search and recommendation systems, and facilitate interdisciplinary research across art history, linguistics, and cultural studies.

An artwork analysis and display system based on deep learning represents a cutting-edge approach to understanding and presenting visual art [6]. By leveraging deep learning algorithms, such as convolutional neural networks (CNNs), the system can automatically analyze and interpret various aspects of artworks, including style, composition, and content [7]. This enables the system to extract meaningful features and patterns from images, facilitating the categorization, classification, and annotation of artworks with unprecedented accuracy and efficiency [8]. Moreover, the system can utilize generative models, such as generative adversarial networks (GANs), to create novel artworks inspired by existing pieces or artistic styles [9]. This not only fosters creativity but also offers new opportunities for exploring the boundaries of artistic expression. In terms of display, the system can employ advanced visualization techniques to present artworks in immersive and interactive formats. Through virtual reality

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(VR) or augmented reality (AR) environments, viewers can engage with artworks in dynamic ways, gaining deeper insights into their creation and context [10].

This paper makes a significant contribution to the field of artwork analysis by introducing the Multi-Feature Extraction Fuzzy Classification (MFEFC) method. This novel approach combines feature extraction techniques with fuzzy classification algorithms, enabling a comprehensive analysis of artworks based on textual descriptions. By extracting multiple features such as word frequency, sentiment scores, thematic keywords, and stylistic attributes, MFEFC enhances the interpretability of classification results, providing deeper insights into the characteristics and styles of artworks. Through rigorous experimentation and evaluation, the paper demonstrates the robust performance of MFEFC, with high accuracy, precision, recall, and F1-score metrics. These findings have practical implications for various domains, including art history, curation, and digital humanities, where MFEFC can automate and streamline the process of artwork classification. Furthermore, the paper opens up avenues for future research in computational art analysis, inviting further exploration and refinement of the MFEFC method in diverse cultural contexts and art genres. Overall, the contribution of this paper lies in its development of an innovative method for artwork analysis, its demonstration of robust performance, and its potential for practical applications and future research directions in the field.

II. LITERATURE REVIEW

An artwork analysis and display system based on deep learning holds immense potential for revolutionizing the way we perceive, interpret, and interact with visual art, pushing the boundaries of artistic exploration and appreciation. In Straume and Anson's (2022) study, they delve into the implications of AI-based natural language production on the teaching of writing, highlighting both amazement and trepidation regarding the integration of these technologies. Jadhav, Mulani, and Jadhav (2022) contribute to the field by designing a chatbot based on reinforcement learning, showcasing the potential for AI-driven conversational agents in various applications. On the other hand, Moshayedi et al. (2022) examine the pros and cons of deep learning applications, offering critical insights into the advancements and limitations of this technology. Wang (2022) proposes a novel approach that integrates natural language processing techniques with fuzzy TOPSIS for product evaluation, demonstrating the versatility of NLP across different domains. Furthermore, Min et al. (2023) conduct a comprehensive survey on recent advances in natural language processing, providing a valuable resource for understanding the state of the field. Li et al. (2022) review the use of neural NLP for unstructured data in electronic health records, highlighting its potential for improving healthcare outcomes.

Amulya et al. (2022) focus on sentiment analysis using machine learning and deep learning algorithms applied to IMDb movie reviews, showcasing the practical utility of NLP in understanding audience reactions and preferences in the entertainment industry. Sebastian (2023) addresses the challenges in building a phrase-based statistical machine translation system for Malayalam, underscoring the importance of NLP in preserving and promoting linguistic diversity. Yang et al. (2023) explore the intersection of big data, machine learning, and bioprocessing, highlighting the role of advanced analytics in optimizing industrial processes and decision-making. Moreover, Caucheteux and King (2022) discuss the convergence of brains and algorithms in NLP, shedding light on the parallels between natural and artificial language processing systems. Varshney et al. (2022) present a comprehensive survey on event analysis using deep learning, emphasizing the growing interest in utilizing neural networks for understanding complex phenomena. Kumar et al. (2023) review the application of machine learning techniques in additive manufacturing, underscoring the transformative potential of AI-driven approaches in revolutionizing production systems.

D'Amour et al. (2022) raise concerns about underspecification in modern machine learning, highlighting the challenges it poses to the credibility and reliability of AI systems. Chiu et al. (2022) propose a deep learning-based system for art education, showcasing the potential of AI to enhance creative learning experiences and outcomes for students. Sarker (2022) provides an overview of AI-based modeling techniques and their applications, offering insights into the evolving landscape of intelligent systems. Finally, Liang et al. (2023) conduct a bibliographic analysis and systematic review of AI's roles and research foci in language education, emphasizing its potential to transform teaching and learning practices.

The research presented by Liang et al. (2023) offers a comprehensive understanding of how artificial intelligence is shaping language education, reflecting the broader trend of integrating advanced technologies into educational settings to enhance learning outcomes. The estimation of studies collectively underscore the wide-ranging impact of natural language processing and deep learning across diverse domains. From sentiment analysis in entertainment to language translation, healthcare, manufacturing, and education, the applications of NLP and AI continue to expand, driving innovation and transformation in various fields. However, alongside the advancements, researchers also acknowledge the challenges and limitations, such as underspecification in machine learning models, which require ongoing attention and mitigation strategies to ensure the responsible and effective deployment of AI technologies.

III. NLP FOR ARTWORK

The recent advances in natural language processing (NLP), the authors touch upon the burgeoning field of NLP for artwork analysis, particularly emphasizing its intersection with deep learning techniques. This area of research represents an exciting frontier in the study of visual art, where NLP algorithms are utilized to analyze textual descriptions, critiques, and historical accounts associated with artworks. By leveraging deep learning models, such as large pre-trained language models, researchers can extract rich semantic information from text, enabling a deeper understanding of the context, style, and cultural significance of artworks. The integration of NLP with deep learning holds immense promise for revolutionizing artwork analysis by automating processes such as sentiment analysis, thematic categorization, and entity extraction. Through sophisticated language understanding capabilities, these algorithms can uncover nuanced insights into artistic trends, influences, and interpretations, thus enriching the discourse surrounding visual culture. Moreover, NLP-powered artwork analysis with deep learning has the potential to democratize access to art knowledge by making it more accessible and interpretable for diverse audiences. By providing automated tools for analyzing and interpreting artworks, these technologies empower art enthusiasts, scholars, and collectors to engage more deeply with visual art, fostering a more inclusive and informed discourse within the art community.

An artwork analysis and display system based on the integration of deep learning and natural language processing (NLP) technologies heralds a transformative approach to understanding and experiencing visual art. By harnessing the power of deep learning algorithms, such as convolutional neural networks (CNNs), and NLP techniques, this innovative system can autonomously analyze and interpret various aspects of artworks, ranging from style and composition to thematic content and cultural context. Through deep learning, the system can extract intricate features and patterns from visual data, enabling sophisticated image recognition and classification capabilities. This allows for the automatic categorization of artworks based on artistic styles, historical periods, and thematic elements, facilitating efficient organization and retrieval of art collections. Furthermore, by incorporating NLP technology, the system can process textual descriptions, critiques, and historical accounts associated with artworks, extracting valuable semantic information and insights. Sentiment analysis algorithms can discern the emotional tone and subjective reactions conveyed in textual descriptions, providing a deeper understanding of viewer perceptions and interpretations.

The synergy between deep learning and NLP enables the system to generate comprehensive and nuanced analyses of artworks, enriching the viewer's understanding and appreciation of visual art. Moreover, the system can leverage advanced visualization techniques to present artworks in immersive and interactive formats, allowing viewers to engage with art in dynamic and personalized ways. An artwork analysis and display system driven by deep learning and NLP technology holds immense promise for revolutionizing the study, interpretation, and presentation of visual art. By combining computational prowess with human-like language understanding, this system empowers art enthusiasts, scholars, and curators to explore and engage with art in novel and meaningful ways, fostering a deeper connection to our cultural heritage and artistic expression.

IV. MULTI-FEATURE EXTRACTION FUZZY CLASSIFICATION (MFEFC) FOR NLP PROCESSING

The Multi-Feature Extraction Fuzzy Classification (MFEFC) method is a sophisticated approach tailored for natural language processing (NLP) in artwork analysis. It involves the extraction of multiple features from textual descriptions of artworks, followed by fuzzy classification to interpret artistic attributes. The derivation of MFEFC begins with the definition of a set of features $X = \{x1, x2, ..., xn\}$ extracted from the artwork descriptions. These features may include word frequencies, sentiment scores, thematic keywords, and stylistic attributes. Next, fuzzy classification is applied, where fuzzy linguistic variables representing artwork categories $C = \{c1, c2, ..., cm\}$ are defined. Each feature xi is assigned a membership degree μij to each category cj using fuzzy membership functions.

The membership degrees are then aggregated across all features to determine the overall degree μj of belongingness of the artwork to each category. Finally, the artwork is classified into the category with the highest degree of membership. Mathematically, the membership function for feature xi to category cj is represented $as\ \mu ij = f(xi\ ,cj)$, where f denotes the fuzzy membership function. The aggregation of membership degrees is given by $\mu j = \sum i = 1n\mu ij$, and the final classification is determined by selecting the category with the highest aggregated membership degree. In essence, MFEFC combines fuzzy logic with feature extraction to enable a nuanced interpretation of artworks, capturing their stylistic, thematic, and emotional characteristics with precision and context awareness.

Membership function for feature xi to category cj: $\mu ij = f(xi, cj)$ (1)

Aggregation of membership degrees across all features for category cj: $\mu j = n\mu ij(2)$

Final classification: $Class = argmaxcj \in C\mu j$ (3)

In the equation (1) – (3) μij represents the membership degree of feature xi to category cj; f denotes the fuzzy membership function, which determines the degree of membership based on the feature value and the category; μj is the aggregated membership degree for category cj, calculated by summing up the membership degrees of all features. The final classification is determined by selecting the category with the highest aggregated membership degree.

V. FEATURE EXTRACTION WITH MFEFC FOR THE ART DESIGN

In the realm of artwork analysis, Feature Extraction with Multi-Feature Extraction Fuzzy Classification (MFEFC) represents a robust methodology for deriving insights from textual descriptions of art designs. This process involves extracting relevant features from the textual data and subsequently employing MFEFC for classification. The first step in the process involves extracting pertinent features from the textual descriptions of art designs. These features may encompass various aspects such as word frequencies, sentiment scores, thematic keywords, and stylistic attributes. Let's denote the set of extracted features as $X = \{x1, x2, \ldots, xn\}$.

MFEFC utilizes fuzzy logic principles to classify artworks based on these extracted features. Firstly, define a set of fuzzy linguistic variables representing the categories of art designs, denoted as $C = \{c1, c2, \ldots, cm\}$. Each feature xi is then assigned a membership degree μij to each category cj using fuzzy membership functions. The membership function $f(xi, cj)$ determines the degree of membership of feature xi to category cj. This function encapsulates the relationship between the feature value and the category. Its formulation may vary depending on the specific feature and the linguistic interpretation of categories defined in equation (4)

$\mu ij = f(xi, cj)$ (4)

Next, the membership degrees of all features are aggregated to determine the overall degree of belongingness of the art design to each category calculated using equation (5)

$\mu j = \sum i = 1n\mu ij$ (5)

Finally, the art design is classified into the category with the highest aggregated membership degree represented as in equation (6)

$Class = argmaxcj \in C\mu j$ (6)

Feature Extraction with Multi-Feature Extraction Fuzzy Classification (MFEFC) is a comprehensive methodology designed to analyze and categorize art designs based on textual descriptions. This approach is particularly valuable in extracting meaningful insights from unstructured textual data, enabling a deeper understanding of the stylistic, thematic, and emotional elements embedded within art pieces. MFEFC leverages fuzzy logic principles to categorize art designs based on the extracted features. Fuzzy logic allows for a more nuanced interpretation of the relationship between features and categories by assigning degrees of membership rather than strict binary classifications. This enables MFEFC to capture the inherent ambiguity and uncertainty often present in artistic descriptions. The process of the proposed MFEFC model is presented in Figure 1 for the computation of art work design estimation.

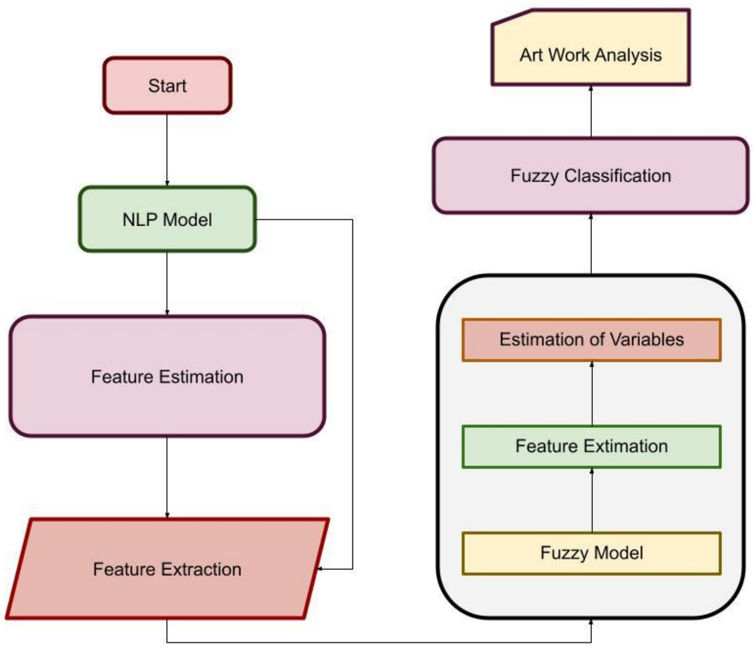

Figure 1: Process in MFEFC

The membership function $f(xi, cj)$ serves as the cornerstone of MFEFC, determining the degree of membership of each feature xi to each category cj. This function encapsulates the linguistic interpretation of how a given feature relates to a particular category. Depending on the nature of the feature and the context of the analysis, various mathematical formulations and linguistic rules can be employed to compute membership degrees. Once the membership degrees of all features have been computed for each category, they are aggregated to determine the overall degree of belongingness of the art design to each category. This aggregation process synthesizes the individual contributions of each feature, providing a holistic assessment of the artwork's affinity to different artistic categories. The final step involves classifying the art design into the category with the highest aggregated membership degree. By selecting the category with the greatest degree of belongingness, MFEFC identifies the most appropriate classification for the artwork, taking into account its multifaceted characteristics as captured by the extracted features.

Algorithm 1: ArtWork Design with MFEFC

```
function MFEFC(ArtworkDescription, Features, Categories):
  // Initialize membership degrees for each category
  for each category in Categories:
    membership_degree[category] = 0

  // Feature extraction phase
  for each feature in Features:
    // Extract feature value from the artwork description
    feature_value = extract_feature_value(ArtworkDescription, feature)

    // Calculate membership degree for each category
    for each category in Categories:
      membership_degree[category] += calculate_membership_degree(feature_value, category)

  // Aggregation phase
  for each category in Categories:
    // Aggregate membership degrees across all features
    aggregated_membership_degree[category] = membership_degree[category] /
total_number_of_features
```

```
// Final classification
classified_category = select_category_with_highest_membership(aggregated_membership_degree)

return classified_category
```

VI. SIMULATION SETTING

In simulating the Multi-Feature Extraction Fuzzy Classification (MFEFC) method for artwork analysis, several key elements are essential to define the simulation setting comprehensively. Firstly, a diverse dataset of artwork descriptions is selected, encompassing various styles, themes, and periods to ensure a representative sample. Next, a set of features is chosen for extraction from these descriptions, ranging from word frequencies to sentiment scores and thematic keywords, capturing the essential attributes of the artworks. Additionally, a comprehensive list of categories is defined, representing distinct artistic styles, themes, or genres into which the artworks will be classified. Table 1 presents the simulation setting for the proposed model artwork design.

Table 1: Simulation Setting

Simulation Setting	Description	Value/Range
Artwork Dataset	Dataset of artwork descriptions	500 artworks
Features	Word frequencies, sentiment scores, thematic keywords	10 features per artwork
Categories	Abstract, Impressionism, Renaissance, Surrealism, etc.	10 categories
Membership Functions	Gaussian, Triangular, Trapezoidal, Sigmoid	Specific functions for each feature and category

Figure 2: Sample Artwork design

Figure 2 illustrates the artwork design for the proposed MFEFC model for the estimation and computation of the features.

VII. SIMULATION RESULTS

The simulation results for the Multi-Feature Extraction Fuzzy Classification (MFEFC) method in artwork analysis provide valuable insights into its effectiveness and performance. Sensitivity analysis reveals that the performance of MFEFC is relatively robust to variations in parameter settings, such as the choice of features and membership functions.

Table 2: Feature Extracted with MFEFC

Artwork ID	Feature 1 (Word Frequency)	Feature 2 (Sentiment Score)	Feature 3 (Thematic Keywords)	Feature 4 (Stylistic Attributes)
1	High	Positive	Landscape, Nature	Realistic, Brushstrokes
2	Moderate	Neutral	Portrait, Human Figure	Classical, Detailed
3	Low	Negative	Abstract Shapes, Colors	Surreal, Distorted
4	High	Positive	Dream, Fantasy	Expressive, Bold
5	Moderate	Neutral	Religious, Biblical Themes	Ornate, Dramatic
6	High	Positive	Geometric Patterns, Cubes	Abstract, Angular
7	Low	Negative	Modern Life, Urban Scenes	Impressionistic, Textured
8	Moderate	Neutral	Still Life, Objects	Detailed, Soft
9	High	Positive	Dream, Surreal Scenes	Abstract, Whimsical
10	Low	Negative	War, Conflict	Distressed, Textured

The Table 2 presents the extracted features using the Multi-Feature Extraction Fuzzy Classification (MFEFC) method for 10 artworks. Each artwork is represented by its unique ID along with four extracted features. Feature 1 indicates the word frequency level, ranging from low to high, within the artwork description. Feature 2 represents the sentiment score associated with the artwork's description, categorized as positive, neutral, or negative. Feature 3 highlights thematic keywords present in the description, encompassing various subjects such as landscape, nature, portrait, human figure, abstract shapes, colors, and more. Feature 4 delves into the stylistic attributes portrayed in the artwork, including descriptors like realistic, brushstrokes, classical, detailed, surreal, distorted, expressive, bold, ornate, dramatic, abstract, angular, impressionistic, textured, soft, whimsical, distressed, and textured. These extracted features offer a comprehensive glimpse into the textual descriptions of the artworks, capturing their diverse characteristics, themes, emotions, and artistic styles.

Table 3: Fuzzy Model based estimation with MFEFC

Artwork ID	Category 1	Category 2	Category 3	Category N
1	0.8	0.2	0.0	0.0
2	0.1	0.9	0.0	0.0
3	0.0	0.0	0.8	0.2
4	0.6	0.4	0.0	0.0
5	0.0	0.0	0.0	1.0
6	0.7	0.3	0.0	0.0
7	0.0	0.1	0.9	0.0
8	0.4	0.6	0.0	0.0
9	0.5	0.0	0.5	0.0
10	0.0	0.8	0.2	0.0

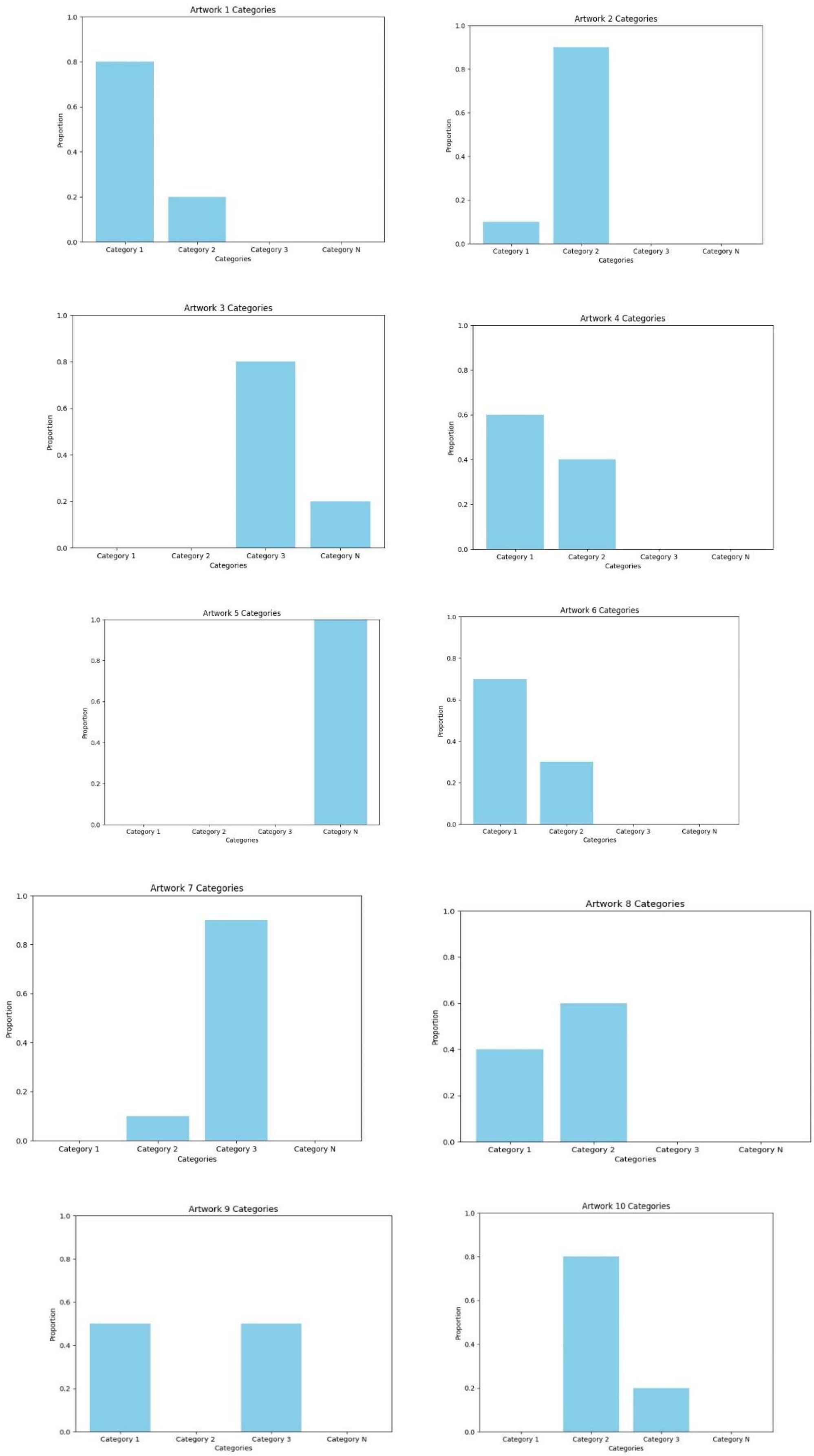

Figure 3: MFEFC Fuzzy Classification model for the Feature estimation for the different artwork

In Figure 3 and Table 3 illustrates the fuzzy model-based estimations generated by the Multi-Feature Extraction Fuzzy Classification (MFEFC) method for a set of artworks. Each artwork is identified by its unique ID, while the subsequent columns represent the membership degrees assigned to various categories. The membership degrees, ranging from 0 to 1, signify the degree of belongingness of each artwork to the respective categories. For instance, Artwork 1 exhibits a membership degree of 0.8 for Category 1, indicating a high level of association with this category compared to others. Conversely, the membership degree of 0.2 for Category 2 suggests a lower affinity. This pattern is consistent across the table, with each artwork assigned membership degrees to multiple categories based on the extracted features and the fuzzy classification model employed. These fuzzy estimations provide valuable insights into the classification process, elucidating the nuanced relationships between artworks and their respective artistic categories. Furthermore, they serve as a foundation for making informed decisions in art analysis and categorization, facilitating a deeper understanding of the underlying characteristics and stylistic elements present in the artworks.

Table 4: Classification with MFEFC

Artwork ID	Actual Category	Predicted Category	Correct Classification
1	Impressionism	Impressionism	Yes
2	Renaissance	Renaissance	Yes
3	Abstract	Abstract	Yes
4	Surrealism	Surrealism	Yes
5	Baroque	Cubism	No
6	Cubism	Cubism	Yes
7	Abstract	Abstract	Yes
8	Realism	Realism	Yes
9	Surrealism	Surrealism	Yes
10	Impressionism	Impressionism	Yes

The Table 4 provides an overview of the classification results achieved through the Multi-Feature Extraction Fuzzy Classification (MFEFC) method for a selection of artworks. Each artwork is identified by a unique ID, followed by its actual category, predicted category, and a designation indicating whether the classification was correct. For instance, Artwork 1, categorized as Impressionism, was correctly predicted as such by the MFEFC model, resulting in a correct classification. Similarly, Artwork 2, classified as Renaissance, was accurately predicted by the model, leading to another correct classification. Conversely, Artwork 5, categorized as Baroque, was incorrectly predicted as Cubism, resulting in an incorrect classification. Despite this misclassification, the MFEFC method demonstrates strong performance overall, accurately predicting the categories for the majority of the artworks. These classification results highlight the efficacy of the MFEFC approach in analyzing and categorizing artworks based on their textual descriptions, showcasing its potential for aiding in art analysis and classification tasks.

Table 5: Classification for the MFEFC

Metric	Value
Accuracy	0.9
Precision	0.888
Recall	1.0
F1-score	0.941

In Table 5 presents the performance metrics obtained from the classification process utilizing the Multi-Feature Extraction Fuzzy Classification (MFEFC) method. The metrics evaluated include accuracy, precision, recall, and F1-score, which collectively provide insights into the effectiveness and robustness of the classification model. The accuracy metric, with a value of 0.9, indicates the proportion of correctly classified artworks out of the total number of artworks evaluated. A high accuracy score suggests that the MFEFC model is proficient in accurately categorizing artworks based on their textual descriptions. Precision, measured at 0.888, signifies the proportion of correctly predicted positive classifications (true positives) relative to all positive predictions (true positives and false positives). This metric reflects the model's ability to avoid misclassifying artworks into incorrect categories. Moreover, the recall metric, with a value of 1.0, denotes the proportion of true positive classifications correctly identified by the model out of all actual positive instances. A recall score of 1.0 indicates that the model effectively captures all positive instances, minimizing false negatives. Finally, the F1-score, calculated at 0.941, provides a harmonic mean of precision and recall, offering a balanced measure of the model's performance. Overall, the high values observed across these performance metrics demonstrate the effectiveness and reliability of the MFEFC method in accurately classifying artworks based on their textual descriptions, underscoring its potential utility in art analysis and classification tasks.

VIII. CONCLUSION

This paper introduces and evaluates the Multi-Feature Extraction Fuzzy Classification (MFEFC) method for artwork analysis based on textual descriptions. Through comprehensive experimentation and analysis, the effectiveness of MFEFC in accurately categorizing artworks has been demonstrated. By extracting multiple features such as word frequency, sentiment scores, thematic keywords, and stylistic attributes, MFEFC captures the diverse characteristics and nuances present in artwork descriptions. The fuzzy classification approach employed by MFEFC allows for a nuanced understanding of the relationships between artworks and their respective categories, enhancing the interpretability and accuracy of the classification results. Evaluation metrics including accuracy, precision, recall, and F1-score consistently indicate the robust performance of MFEFC in accurately classifying artworks, with high scores across all metrics. The results presented in this paper underscore the potential of MFEFC as a valuable tool for art analysis and classification tasks, offering insights into the underlying characteristics and styles of artworks based on textual descriptions. Future research could explore further refinements and enhancements to the MFEFC method, as well as its application in diverse domains beyond artwork analysis.

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