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An Effective and Practical Probabilistic Simplified Neutrosophic Approach for Accurate and Reliable Innovative Design Evaluation for Digital Media Arts

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Abstract: The evaluation and classification of digital artworks remain a challenging task due to the inherent uncertainty, subjectivity, and imprecision in artistic design. Traditional computational techniques are no longer effective and fail to capture the ambiguity and probabilistic behavior associated with artistic evaluation, gradually becoming untrusted for innovative design assessment. To that end, we propose a Probabilistic Simplified Neutrosophic Set (PSNS)-based convolutional art classifier, that integrates neutrosophic logic to foster the representational power of simple Convolutional Network classifier to be able to learn and make a correct decision about uncertain art evaluation scenarios. With the encapsulation of PSNS, we can introduce probabilistic truth, indeterminacy, and falsity values to efficiently model the intrinsic uncertainties in digital media art evaluation. To validate our claims, we carefully choose a public case of digital art classification to conduct experiments to analyze the performance of the proposed approach. The quantitative results prove that our approach not only accentuates the applicability but also can improve decision-making through evaluating and refining the quality of elderly care services.

Keywords: Neutrosophic sets, Probabilistic Simplified Neutrosophic Set (PSNS), Machine Learning, Digital Media Arts, Uncertainty Modeling.

I. Introduction

Digital media arts encompass a wide range of creative disciplines, which include graphic design, animation, visual properties, as well as digital storytelling. The process of evaluation of the quality and effectiveness of digital designs entail a systematic approach that take into account both structured (measurable) and unstructured (subjective) aspects [1]. The swift evolution of digital media arts usually led to cumulative complexity in bright design evaluation. Out-of-date evaluation methods relies deeply on subjective human judgment, which is frequently unpredictable and disposed to bias. With the emergence of artificial intelligence (AI) and machine learning (ML), automated approaches have gained attention for their ability to provides objective and data-driven design assessment [2], [3]. However, prevailing AI-based evaluation approaches are unable to model the uncertainty, imprecision, and contradictory information inherent in artistic design [1].

To provide a solution to that challenges, Neutrosophic Logic (NL) [4], [5] emerged as a innovative mathematical framework to capture truth, indeterminacy, and falsity of data stream at the same time. Though scholars developed different Neutrosophic Set (NS) extensions, most of them suffer from computational complexity or lacks the aptitude to represent probabilistic differences in ambiguous info [6], [7]. This limitations had motivated the development of the Probabilistic Simplified Neutrosophic Set (PSNS), which introduces probability-based weighting to truth, indeterminacy, and falsity membership functions, offering a more flexible and computationally efficient representation of uncertain information [8]. PSNS had been presented to handle uncertainty, imprecision, and indeterminacy in a more organized and probabilistic way. Like NS, PSNS represent an element with three components: truth membership (T), indeterminacy membership (I), and falsity membership (F), nevertheless, it allocates each of these mechanisms with probabilistic values, which tolerates a more elastic representations of information by participating unpredictability as well as indeterminacy alongside [9], [10].

Assuming the dynamic natures of the industry of digital media arts, where design basics are prejudiced by both quantitative attributes (like color balance, contrast, as well as symmetry) and qualitative aesthetics (like artistic creativity, and emotional impact), a PSNS-based solution can offer the ideal framework for innovative design evaluation. In this paper, we propose a PSNS approach for smart design evaluation in digital media arts. The key contributions of this approach are:

- We develop a PSNS-based Convolution classifier to automatically learn inherent evaluation patterns and design features for digital art images.
- With PSNS integration, the representational power of our approach is fostered with probabilistic neutrosophic reasoning capability, handling the ambiguities and

differences in the human insight of design quality.

- Proof-of-concept analysis is made by testing our framework on real-world case study of digital artworks, and the results demonstrated the effectiveness of our framework to provide dependable and robust design evaluations.

The residual part of this research is systematized as follows. Sect. 2 deliberate definitions and critical thoughts. The proposed methodology is defined in Sect. 3. Following, we explain the case study in Sect 4. Sect. 5 debate the results and analysis. Sect. 5 concludes the main findings.

II. PRELIMINARIES

Definition 1. The SVNSs are formulated as:

$$N = \{(\theta, T(\theta), I(\theta), F(\theta)) | \theta \in \Theta\} \tag{1}$$

where $T(\theta), I(\theta), F(\theta)$ is membership, indeterminacy-membership and falsity-membership,$T(\theta), I(\theta), F(\theta) \in [0,1]$, $0 \leq T(\theta) + I(\theta) + F(\theta) \leq 3$.

Definition 2. The PSNSs are formulated as:

$$N = \left\{\left(\theta, T(\theta)(\mathfrak{P}T(\theta)), I(\theta)(\mathfrak{P}I(\theta)), F(\theta)(\mathfrak{P}F(\theta))\right) | \theta \in \Theta\right\} \tag{2}$$

where $T(\theta), I(\theta), F(\theta)$ is truth-membership, indeterminacy-membership and falsity-membership, $T(\theta), I(\theta), F(\theta) \in [0,1]$, $0 \leq T(\theta) + I(\theta) + F(\theta) \leq 3$, $0 \leq \mathfrak{P}T(\theta), \mathfrak{P}I(\theta), \mathfrak{P}F(\theta) \leq 1$, the $\mathfrak{P}T(\theta), \mathfrak{P}I(\theta), \mathfrak{P}F(\theta)$is possibility values of $T(\theta), I(\theta), F(\theta)$. The PSNS is listed as$P = (T(\mathfrak{P}T), I(\mathfrak{P}I), F(\mathfrak{P}F))$.

Definition 3. Let $N_1 = (T_1(\mathfrak{P}T_1), I_1(\mathfrak{P}I_1), \mathrm{F}_1(\mathfrak{P}\mathrm{F}_1))$, $N_2 = (T_2(\mathfrak{P}T_2), I_2(\mathfrak{P}I_2), \mathrm{F}_2(\mathfrak{P}\mathrm{F}_2))$, the basic operations are put forward:

A) add

$$\mathrm{N}_1 \oplus \mathrm{N}_2 = \begin{pmatrix} \mathrm{T}_1 + \mathrm{T}_2 - \mathrm{T}_1 \cdot \mathrm{T}_2 \left(2! \frac{\mathfrak{P}\mathrm{T}_1 \cdot \mathfrak{P}\mathrm{T}_2}{\mathfrak{P}\mathrm{T}_1 + \mathfrak{P}\mathrm{T}_2}\right), \\ \mathrm{I}_1 \cdot \mathrm{I}_2 \left(2! \frac{\mathfrak{P}\mathrm{I}_1 \cdot \mathfrak{P}\mathrm{I}_2}{\mathfrak{P}\mathrm{I}_1 + \mathfrak{P}\mathrm{I}_2}\right), \mathrm{F}_1 \cdot \mathrm{F}_2 \left(2! \frac{\mathfrak{P}\mathrm{F}_1 \cdot \mathfrak{P}\mathrm{F}_2}{\mathfrak{P}\mathrm{F}_1 + \mathfrak{P}\mathrm{F}_2}\right) \end{pmatrix}; \tag{3}$$

B) Multiply

$$N_1 \otimes N_2 = \begin{pmatrix} T_1 \cdot T_2 \left(2!\frac{\mathfrak{P}T_1 \cdot \mathfrak{P}T_2}{\mathfrak{P}T_1 + \mathfrak{P}T_2}\right), \\ I_1 + I_2 - I_1 \cdot I_2 \left(2!\frac{\mathfrak{P}I_1 \cdot \mathfrak{P}I_2}{\mathfrak{P}I_1 + \mathfrak{P}I_2}\right), \\ \mathrm{F}_1 + \mathrm{F}_2 - \mathrm{F}_1 \cdot \mathrm{F}_2 \left(2!\frac{\mathfrak{P}\mathrm{F}_1 \cdot \mathfrak{P}\mathrm{F}_2}{\mathfrak{P}\mathrm{F}_1 + \mathfrak{P}\mathrm{F}_2}\right) \end{pmatrix}; \tag{4}$$

C) Lamda

$$\lambda N = \left(1 - (1 - T)^{\lambda}(\mathfrak{P}T), (I)^{\lambda}(\mathfrak{P}I), (F)^{\lambda}(\mathfrak{P}F)\right), \lambda > 0; \tag{5}$$

D) Power

$$(N)^{\lambda} = \left((T)^{\lambda}(\mathfrak{P}T), 1 - (1 - I)^{\lambda}(\mathfrak{P}I), 1 - (1 - F)^{\lambda}(\mathfrak{P}F)\right), \lambda > 0. \tag{6}$$

Definition 4. Given two PSNSs $\mathrm{N}_1 = \left(\mathrm{T}_1(\mathfrak{P}\mathrm{T}_1), \mathrm{I}_1(\mathfrak{P}\mathrm{I}_1), \mathrm{F}_1(\mathfrak{P}\mathrm{F}_1)\right)$, $N_2 = \left(T_2(\mathfrak{P}T_2), I_2(\mathfrak{P}I_2), \mathrm{F}_2(\mathfrak{P}\mathrm{F}_2)\right)$, then , the following characterstics apply:

A) Subset

$$N_1 \subseteq N_2 \Leftrightarrow \mathrm{T}_1(x) \leq \mathrm{T}_2(x), \mathfrak{P}\mathrm{T}_1(x) \leq \mathfrak{P}\mathrm{T}_2(x); \mathrm{I}_1(x) \geq \mathrm{I}_2(x), \mathfrak{P}\mathrm{I}_1(x) \geq \mathfrak{P}\mathrm{I}_2(x); \mathrm{F}_1(x) \geq \mathrm{F}_2, \mathfrak{P}\mathrm{F}_1(x) \geq \mathfrak{P}\mathrm{F}_2(x)\ for\ x \in X \tag{7}$$

B) Complement

$$A^C = \left\{\left\langle x; F_A(x)\left(P_{F_A(x)}\right), \left(1 - I_A(x)\right)\left(1 - \mathfrak{P}\mathrm{T}_1(x)\right), \mathrm{T}_1(x)\left(\mathfrak{P}\mathrm{T}_1(x)\right)\right\rangle : x \in X\right\} \tag{8}$$

C) Intersection

$$A_1 \cap A_2 = \begin{Bmatrix} \{\langle x; \min\{\mathrm{T}_1(x), \mathrm{T}_2(x)\}(\min\{\mathfrak{P}\mathrm{T}_1(x), \mathfrak{P}\mathrm{T}_2(x)\}), \\ \max\{\mathrm{I}_1(x), \mathrm{I}_2(x)\}(\max\{\mathfrak{P}\mathrm{I}_1(x), \mathfrak{P}\mathrm{I}_2(x)\}), \\ \max\{\mathrm{F}_1(x), \mathrm{F}_2(x)\}(\max\{\mathfrak{P}\mathrm{F}_1(x), \mathfrak{P}\mathrm{F}_2(x)\})\rangle : x \in X \end{Bmatrix}$$

(9)

D) Union

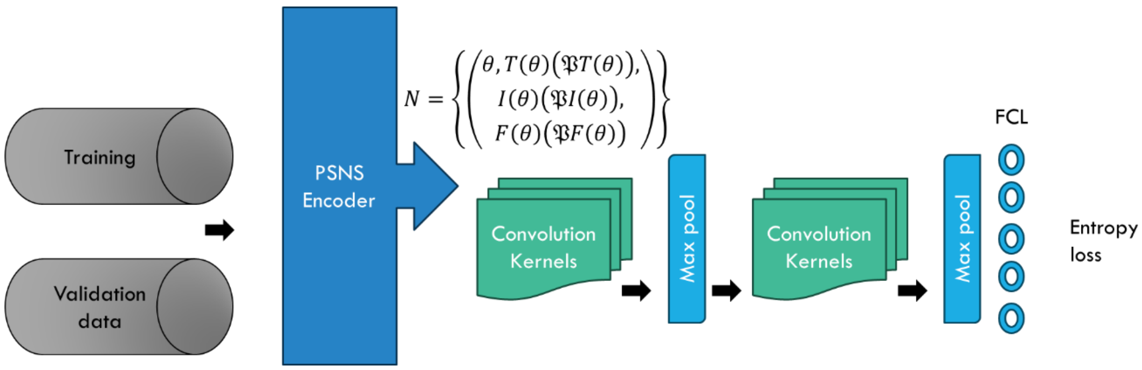
$$A_1 \cup A_2 = \begin{Bmatrix} \langle x; \max\{\mathrm{T}_1(x), \mathrm{T}_2(x)\}(\max\{\mathfrak{P}\mathrm{T}_1(x), \mathfrak{P}\mathrm{T}_2(x)\}), \\ \min\{\mathrm{I}_1(x), \mathrm{I}_1(x)\}(\min\{\mathfrak{P}\mathrm{I}_1(x), \mathfrak{P}\mathrm{I}_2(x)\}), \\ \min\{\mathrm{F}_1(x), \mathrm{F}_2(x)\}(\min\{\mathfrak{P}\mathrm{F}_1(x), \mathfrak{P}\mathrm{F}_2(x)\})\rangle : x \in X \end{Bmatrix} \tag{10}$$

Definition 5. Given $N_1 = \left(T_1(\mathfrak{P}T_1), I_1(\mathfrak{P}I_1), \mathrm{F}_1(\mathfrak{P}\mathrm{F}_1)\right)$, $N_2 = \left(T_2(\mathfrak{P}T_2), I_2(\mathfrak{P}I_2), \mathrm{F}_2(\mathfrak{P}\mathrm{F}_2)\right)$, the Logarithmic distance ($LD_{\mathfrak{P}SNN}$) between N_1 andN_2 is constructed:

$$LD_{\mathfrak{P}SNN}(N_1,N_2)=\frac{1}{3}\left(\begin{array}{l}(T_1\times\mathfrak{P}T_1)\,log\,\dfrac{(T_1\times\mathfrak{P}T_1)}{\frac{(T_1\times\mathfrak{P}T_1)+(T_2\times\mathfrak{P}T_2)}{2}}\\ +(T_2\times\mathfrak{P}T_2)\,log\,\dfrac{(T_2\times\mathfrak{P}T_2)}{\frac{(T_1\times\mathfrak{P}T_1)+(T_2\times\mathfrak{P}T_2)}{2}}\\ +(I_1\times\mathfrak{P}I_1)\,log\,\dfrac{(I_1\times\mathfrak{P}I_1)}{\frac{(I_1\times\mathfrak{P}I_1)+(I_2\times\mathfrak{P}I_2)}{2}}\\ +(I_2\times\mathfrak{P}I_2)\,log\,\dfrac{(I_2\times\mathfrak{P}I_2)}{\frac{(I_1\times\mathfrak{P}I_1)+(I_2\times\mathfrak{P}I_2)}{2}}\\ +(\mathrm{F}_1\times\mathfrak{P}\mathrm{F}_1)\,log\,\dfrac{(\mathrm{F}_1\times\mathfrak{P}\mathrm{F}_1)}{\frac{(\mathrm{F}_1\times\mathfrak{P}\mathrm{F}_1)+(\mathrm{F}_2\times\mathfrak{P}\mathrm{F}_2)}{2}}\\ +(\mathrm{F}_2\times\mathfrak{P}\mathrm{F}_2)\,log\,\dfrac{(\mathrm{F}_2\times\mathfrak{P}\mathrm{F}_2)}{\frac{(\mathrm{F}_1\times\mathfrak{P}\mathrm{F}_1)+(\mathrm{F}_2\times\mathfrak{P}\mathrm{F}_2)}{2}}\end{array}\right) \tag{11}$$

III. RESEARCH METHODOLOGY

This part of our paper presents the systematic approach adopted to achieve the objectives of the study. Our research methodology demonstrates a new approach that integrates PSNS-based reasoning with representational learning of convolutional network to offer uncertainity aware model of visual patterns of digital



arts.

Figure 1. architecture of the proposed PSNS framework for art design evaluation

In step 1, we emphasize encoding art images into PSNS representation. Assume we have an art image $x \in X$ with RGB channels R, G, B, we compute the corresponding PSNS representation as follows:

We calculate the truth membership based on the average of values in RGB channels:

$$T_K(x) = \frac{R+G+B}{3} \tag{12}$$

We calculate indeterminacy membership based on the absolute difference between the green and blue channels.

$$I_K(x) = |G - B| \tag{13}$$

We calculate falsity membership complement of the truth membership

$$F_K(x) = 1 - T_K(x) \tag{14}$$

In step 2, we try to normalize values of T, I, F. But, we begin by adding ϵ as a small value (e.g., 10^{-6}) to avoid division by zero.

$$S = T_K(x) + I_K(x) + F_K(x) + \epsilon \tag{15}$$

Then, the normalized components are given as follows:

$$T_K'(x) = \frac{T_K(x)}{S},\ I_K'(x) = \frac{I_K(x)}{S},\ F_K'(x) = \frac{F_K(x)}{S} \tag{16}$$

Where the sum of new components T', I', F' is 1.

In step 3, we move foreward to calculate the probability of of truth, indeterminacy, and falsity using the softmax function:

$$P_{T_K}(x) = \frac{e^{T_K'(x)}}{e^{T_K'(x)} + e^{I_K'(x)} + e^{F_K'(x)}} \tag{17}$$

$$P_{I_K}(x) = \frac{e^{I_K'(x)}}{e^{T_K'(x)} + e^{I_K'(x)} + e^{F_K'(x)}} \tag{18}$$

$$P_{F_K}(x) = \frac{e^{F_K'(x)}}{e^{T_K'(x)} + e^{I_K'(x)} + e^{F_K'(x)}} \tag{19}$$

Again, this computed probabilities always sum to 1 :

$$P_{T_K}(x) + P_{I_K}(x) + P_{F_K}(x) = 1 \tag{20}$$

By the completion PSNS encoding that converts an image into a 6-channel tensor $(T', I', F', P_T, P_I, P_F)$, we we apply Convolutional Neural Network (CNN) to process these features, as shown in Figure 1.

Indeed, the convolution operation with input feature map X, kernel W, and bias b, is computed as follows:

$$Y = \text{ReLU}\left(\sum_{i=1}^{6} X_i * W_i + b\right) \tag{21}$$

where * symbolize convolution kernel. This is followed by max pooling layer to reduces dimensionality:

$$Y_{\text{pooled}}(i,j) = \max_{(m,n)\in \text{ window}} Y(i+m, j+n) \tag{22}$$

The about of the above layers are flattening, thend passed to linear layers:

$$\begin{aligned} Z_1 &= \text{ReLU}(W_1 Y + b_1) \\ Z_2 &= W_2 Z_1 + b_2 \end{aligned} \tag{23}$$

where Z_2 is the final logit vector for classification.

To convert the final logits into class probabilities:

$$P(y = c \mid x) = \frac{e^{Z_2^c}}{\sum_j e^{Z_2^j}} \tag{24}$$

where c represents class index. Using categorical cross-entropy loss:

$$\mathcal{L} = -\sum_{c=1}^{C} y_c \log P(y = c \mid x) \tag{25}$$

where C symolize number of classes. y_c symolize one-hot encoded ground-truth label. $P(y = c \mid x)$ symolize the predicted probability.

The gradient of the model is updated using the chain rule:

$$\frac{\partial \mathcal{L}}{\partial Z_2^c} = P(y = c \mid x) - y_c \tag{26}$$

where the gradient of linear layer is calculated as follows:

$$\frac{\partial \mathcal{L}}{\partial W_2} = \frac{\partial \mathcal{L}}{\partial Z_2} \cdot Z_1^T, \tag{27}$$

and the gradient of convolutional layer is calculated as follows:

$$\frac{\partial \mathcal{L}}{\partial W_i} = X_i * \frac{\partial \mathcal{L}}{\partial Y} \tag{28}$$

Using Adam optimizer, the model parameters are updated as follows:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\nabla\mathcal{L} \quad (29)$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)(\nabla\mathcal{L})^2 \quad (30)$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t},\ \hat{v}_t = \frac{v_t}{1-\beta_2^t} \quad (31)$$

$$W_t = W_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t}+\epsilon} \quad (32)$$

Where β_1, β_2 symolize decay rates (default: 0.9,0.999). η symolize learning rate.

IV. Implementation Setup & Case study

The procedure of assessing the classification performance is directed founded on common set of assessment metrics drived from particular relation between True positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN).

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP}+\boldsymbol{TN}}{\boldsymbol{TP}+\boldsymbol{TN}+\mathrm{F}\boldsymbol{P}+\mathrm{F}\boldsymbol{N}} \quad (33)$$

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP}+\mathrm{F}\boldsymbol{P}} \quad (34)$$

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP}+\mathrm{F}\boldsymbol{N}} \quad (35)$$

$$\mathrm{F}_{\mathbf{1}} - \boldsymbol{score} = 2\frac{\boldsymbol{precision}\times\boldsymbol{recall}}{\boldsymbol{precision}+\boldsymbol{recall}} \quad (36)$$

Proof-of-concept investigations are steered on a Dell workstation functioned with Windows 10 64 bit. This device was armed by 64 G RAM, and Intel(R) Core(TM) i5-7200U CPU @ 2.50GHz 2.71 GHz. The model implementation is performed using torch library running in python 11 environment. The performance metrics are implemented using Scikil-learn library.

To demonstrate the effectiveness of our approach, a public case study was prudently selected, in which a dataset containing about 9000 images was collected. This case study is highly relevant as it emphasizes evaluation and classifying different styles of art. The data contain 5 main categories that have been taken including drawings and watercolours, works of painting, sculpture, graphic art, and iconography (old Russian art) [11]. The dataset was split into training and validation sets. The class distribution for both sets is displayed in Figure 2.

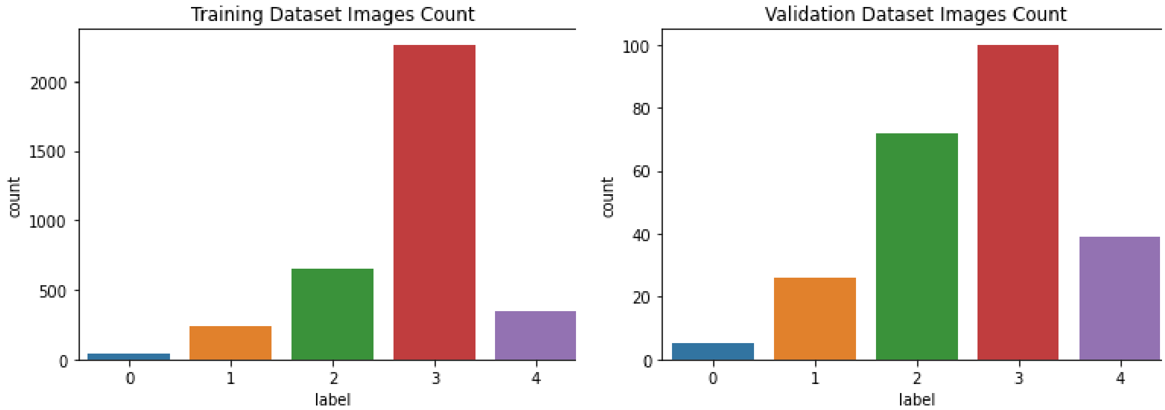


Figure 2. Class distribution for the case study.

Figure 3. Samples of artwork from the dataset case study.

IV. Results and analysis

The classification report, accessible in Table 1, provides a detailed performance analysis of our PSNS-based ML classifier across different evaluation metrics, including precision, recall, and F1-score for each class. These metrics help in assessing the model's ability to correctly classify instances while balancing false positives and false negatives. The macro-average and weighted-average scores offer a comprehensive view of the classifier's overall performance, ensuring robustness across both balanced and imbalanced datasets.

Table 1: Classification report showing performance metrics for each class

Class	Precision	Recall	F1-score
Drawings	0.55	0.57	0.56
Painting	0.66	0.51	0.58
Sculpture	0.89	0.90	0.90
Graphic Art	0.90	0.85	0.88
Iconography	0.77	0.88	0.82

The confusion matrix (CM), illustrated in Figure 4, offer a visual representation of the model's classification performance. This matrix help in understanding where the classifier performs well and where it struggles, providing insights into potential misclassifications. With the analysis the CM, we can identify patterns in errors and refine the model to enhance its predictive accuracy.

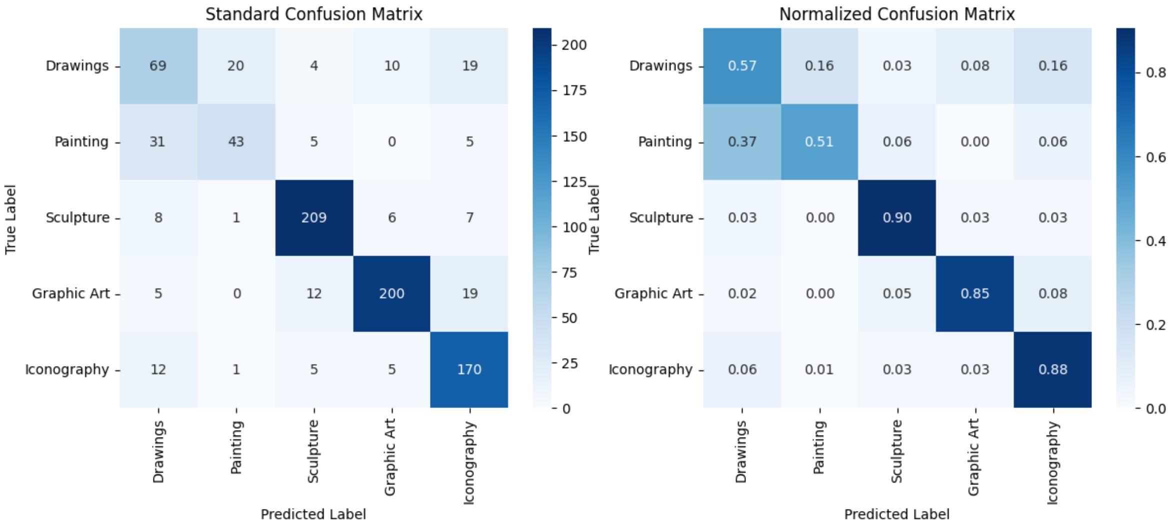


Figure 4: Confusion matrix for the PSNS-based classifier.

To further evaluates the ability of our model to distinguish between different classes, we present the Receiver Operating Characteristic (ROC) curves coupled with the Area Under the Curve (AUC) scores in Figure 5. The ROC curve plots the true positive rate (sensitivity) against the false positive rate, illustrating the trade-off between recall and specificity. The AUC score quantifies the overall model performance, where a higher AUC indicates better classification capability. This analysis is crucial for validating the reliability of our approach, especially in scenarios with varying class distributions.

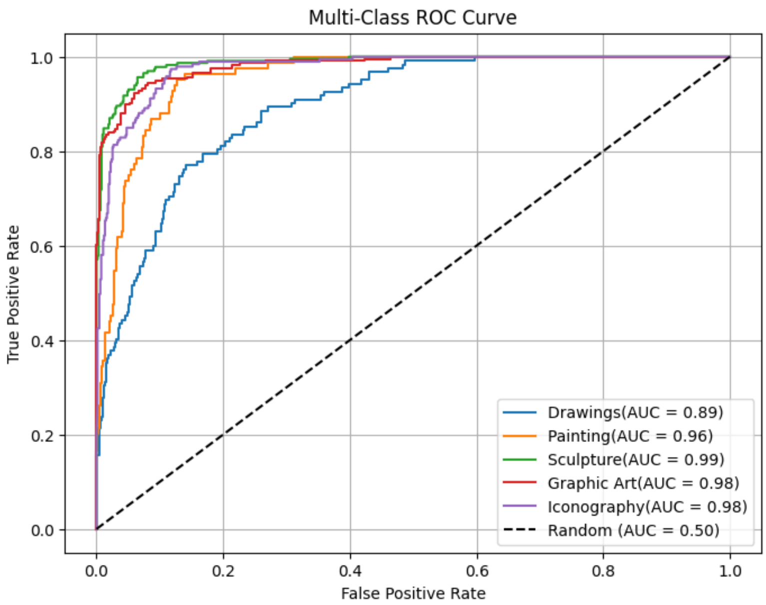


Figure 5: ROC curves and AUC scores to distinguish between different classes.

Furthermore, Precision-Recall (PR) curves and t-SNE (t-distributed Stochastic Neighbor Embedding) are displayed as powerful visualization to asses the performance of our approach with respect to arts data characteristics. As shown in Figure 6, PR curve explain the trade-off between precision and recall at various thresholds, showing that our model well distinguishes between differ classes of arts. On the other hand, Figure 7 show t-SNE for visualizing high-dimensional data in two dimensions by preserving the pairwise similarities between data points.

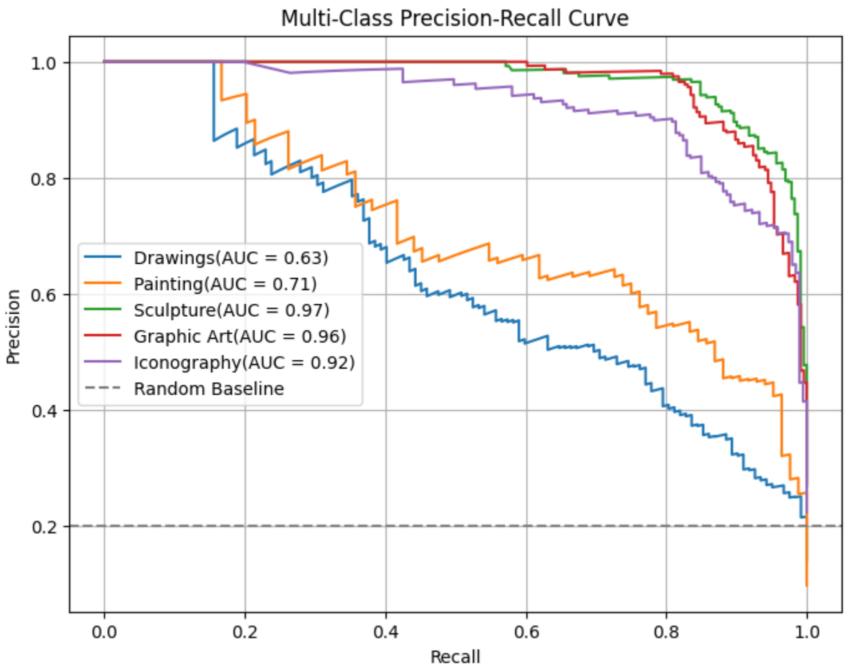


Figure 6: ROC curves and AUC scores to distinguish between different classes.

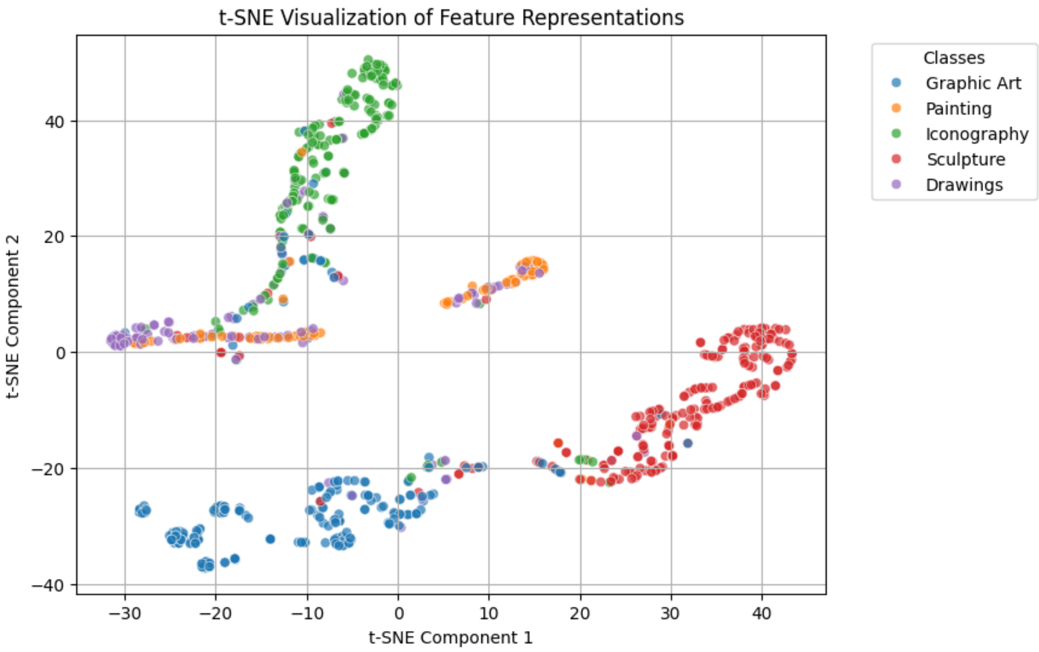


Figure 7: T-SNE plot predictions of different classes.

5. CONCLUSIONS

In this paper, a PSNS-based convolutional art classifier is introduced to take advantage of neutrosophic logic and deep learning to innovatively assess and categorize digital artworks. Our approach enables effective modeling of the uncertainty, indeterminacy, and imprecision intrinsic in artistic evaluation, which provides a vigorous and innovative framework to assess design styles. Through extensive experiments, we demonstrated the efficiency of our approach can classify digital media art with high accuracy and reliability. The quantitative results imply that our PSNS-based classifier can serve as a promising solution for art classification, and computerized design evaluations. Future work will emphasize enhancing the efficiency of the proposed integration by joining attention mechanisms, multimodal data fusion, and generative models to further refine and expand its capabilities.

REFERENCE

[1] R. Earnshaw, “State of the art in digital media and applications,” in SpringerBriefs in Computer Science, 2017.

[2] Y. Gong, "Application of virtual reality teaching method and artificial intelligence technology in digital media art creation," Ecol. Inform., 2021, doi: 10.1016/j.ecoinf.2021.101304.

[3] M. G. Mahdi, A. Sleem, I. M. Elhenawy, and S. Safwat, "Enhancing the Recognition of Handwritten Arabic Characters through Hybrid Convolutional and Bidirectional Recurrent Neural Network Models," Sustain. Mach. Intell. J., vol. 9, pp. 34–56, Oct. 2024, doi: 10.61356/SMIJ.2024.9382.

[4] F. Smarandache, Neutrosophy: neutrosophic probability, set, and logic: analytic synthesis & synthetic analysis. 1998.

[5] F. Smarandache, A Unifying Field in Logics: Neutrosophic Logic, Neutrosophy, Neutrosophic Set, Neutrosophic Probability. 1999.

[6] S. Pramanik, "Single-Valued Neutrosophic Set: An Overview," 2022. doi: 10.1007/978-3-030-94651-7_26.

[7] N. N.Mostafa, A. Krishan Kumar, and Y. Ali, "A Comparative Study on X-Ray image Enhancement Based on Neutrosophic Set," Sustain. Mach. Intell. J., vol. 7, Apr. 2024, doi: 10.61356/SMIJ.2024.77102.

[8] R. Şahin and P. Liu, "Possibility-induced simplified neutrosophic aggregation operators and their application to multi-criteria group decision-making," J. Exp. Theor. Artif. Intell., 2017, doi: 10.1080/0952813X.2016.1259266.

[9] F. Altun, R. Şahin, and C. Güler, "Multi-criteria decision making approach based on PROMETHEE with probabilistic simplified neutrosophic sets," Soft Comput., 2020, doi: 10.1007/s00500-019-04244-4.

[10]H. Wang and G. Chen, "Improving computer network security evaluation with grey relational analysis and probabilistic simplified neutrosophic sets," Int. J. Knowledge-Based Intell. Eng. Syst., 2023, doi: 10.3233/KES-230103.

[11]"https://www.kaggle.com/datasets/thedownhill/art-images-drawings-painting-sculpture-engraving", [Online]. Available: https://www.kaggle.com/datasets/thedownhill/art-images-drawings-painting-sculpture-engraving

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