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Prediction Model of Ancient Village Pottery Building Microspace Design Style by Integrating Machine Learning

Abstract: - Microspace design styles on pottery fragments offer a captivating window into the artistic heritage and cultural practices of past societies. These intricate details and recurring patterns hold valuable clues about rituals, beliefs, and artistic expressions. However, existing approaches struggle to capture the relationships between design elements within a single piece. This limitation hinders the ability to capture the holistic meaning conveyed by the microspace design style. To overcome this limitation, this research proposes a novel approach called MoANN-DSOA for predicting microspace design styles based on ancient village pottery. MoANN-DSOA utilizes a Mosaic Attention Neural Network (MoANN) to analyze both the visual image and the relationships between design elements. This allows for a more detailed understanding of the artistic message encoded within each fragment. Additionally, a Dove Swarm Optimization Algorithm (DSOA) optimizes the MoANN architecture, potentially enhancing the accuracy of capturing intricate details. The proposed MoANN-DSOA method attains 7.78%, 27.89% and 33.335% higher accuracy and 14%, 20.81% and 32.36% higher F-Score compared to the existing methods like Categorization and Retrieval of Painted Pottery with CNNs (CNN), Utilizing CNN-VGG16-VGG19 Approach for Distinguishing Surface Treatments in Wheel-Thrown Pottery (CNN-VGG16-VGG19) and Unsupervised Feature Extraction of Ceramic Profiles using a Deep Variational Convolutional Autoencoder (DVCA) respectively. By this, the proposed MoANN-DSOA methodology paves the way for efficient information extraction from pottery image, unlocking deeper understanding and facilitating the construction of more informed historical narratives.

Keywords: Microspace design styles, ancient village pottery image, Dove Swarm Optimization Algorithm, Mosaic Attention Neural Network, Cultural Heritage.

1. INTRODUCTION

The artistic heritage of ancient villages holds a wealth of information about past cultures. Intricate details and recurring patterns found on pottery objects (pots, vessels, and bowls) hold valuable clues [1]. This concept is known as microspace design styles. Imagine these objects (pots, vessels, and bowls) were not simply functional vessels, but canvases for stories [2]. Decorative elements, filled with symbolic meaning, and crafted with distinct artistic choices, offer a window into the lives of these communities [3]. By meticulously analyzing these microspace design styles, researchers can gain valuable insights into the cultural practices and artistic expressions that shaped these ancient communities [4]. The recurring patterns, symbols, and design choices might offer clues about the villager's rituals, beliefs, and symbolic systems [5-7]. Studying these styles can also reveal artistic techniques employed by the potters, preferred symbols or patterns used in decoration, or the evolution of artistic expression over time within the village [8]. Additionally, the pottery designs might showcase social hierarchies, reflect economic activities, or even hint at trade relations with neighboring communities [9]. In essence, microspace design styles serve as a window into the artistic heritage of past societies [10].

Traditional archaeological methods, such as analyzing pottery typology and decorative elements, offer valuable insights but can be time-consuming and subjective. Machine learning offers a promising alternative for objectively analyzing microspace design styles. Existing machine learning approaches, particularly those focused on image classification, have achieved remarkable success in various tasks [11-13]. However, these methods often struggle to capture the intricate relationships between different design elements within a single pottery piece [14-15]. These relationships are crucial for understanding the holistic meaning conveyed by the microspace design style [16].

This research addresses this limitation by proposing a novel approach that leverages a Mosaic Attention Neural Network (MoANN) optimized with a Dove Swarm Optimization Algorithm (DSOA). Unlike traditional image

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classification models, MoANN can analyze both the visual image and the relationships between different design elements. This allows for a more nuanced understanding of the artistic message encoded within each piece. Furthermore, DSOA optimizes the MoANN architecture, potentially leading to improved accuracy and efficiency in capturing the intricate details of these design styles.

By applying this optimized MoANN to a rich dataset encompassing design details and cultural context, this research aims to achieve more accurate and detailed insights into the cultural practices, artistic expressions, and social structures reflected in ancient village pottery. This has the potential to revolutionize archaeological research by offering a more sophisticated and objective approach. Accurately predicting these design styles can significantly benefit archaeologists by enabling them to efficiently extract a wealth of information from pottery, unlocking deeper understanding of past cultures and facilitating more informed historical narratives. The main contribution of this proposed MoANN-DSOA: Predicting Microspace Pottery Styles methodology is given below,

- It creates a rich dataset of ancient village pottery with high-resolution images and detailed cultural context, which enables the MoANN-DSOA: Predicting Microspace Pottery Styles model to learn diverse styles and their significance.
- It implements a pre-processing process with resizing, normalization, and data augmentation to ensure consistent image format, training stability, and generalizability for the MoANN model.
- It introduces a new deep learning model with FDCT-WRP specifically designed for analyzing microspace design styles. MoANN utilizes the Fast Discrete Curvelet Transform with Wrapping (FDCT-WRP) for effective feature extraction, specifically designed to analyze microspace design styles by handling image data and relationships between design elements within the pottery.
- It recognizes the potential to further enhance MoANN's performance by exploring the integration of a novel DSOA algorithm, which leads to even more accurate insights into cultural practices.
- It offers a significant advancement in analyzing ancient village pottery. This approach has the potential to revolutionize archaeological research by efficiently extracting a wealth of information from pottery and unlocking deeper understanding of past cultures.

The rest of the manuscript is as follows: Section 2 examines related work, highlighting limitations in analyzing microspace design styles. Section 3 details about proposed MoANN-DSOA: Predicting Microspace Pottery Styles methodology. Section 4 evaluates MoANN-DSOA's performance and presents experimental results. Finally, Section 5 concludes by summarizing our findings, acknowledging limitations, and suggesting future directions for this research on predicting microspace design styles in ancient village pottery.

2. Related Works

Numerous recent studies have investigated for predicting the design styles of ancient village pottery. Below are some of the recent studies closely related to this topic,

In 2023, Zhao, X. et.al [11] investigated categorizing and retrieving pottery types using Convolutional Neural Networks (CNNs). Their approach involved training a CNN to extract feature vectors from pottery images. These feature vectors captured essential characteristics of the pottery, allowing for the calculation of similarity coefficients between the images. This enabled the CNN to categorize pottery based on cultural types. While the study achieved high precision, a potentially low F-score suggested a trade-off between correctly identifying pottery types.

In 2022, Wilczek, J. et.al [12] have utilized Transfer learning approach for distinguishing Surface Treatments in Wheel-Thrown Pottery. They classified pottery images using three convolutional neural network (CNN) architectures: VGG16 and VGG19 pre-trained with transfer learning, and a custom CNN. However, the study achieved a low accuracy rate.

In 2022, Cardarelli, L., [13] have suggested Unsupervised Feature Extraction of Ceramic Profiles using a Deep Variational Convolutional Autoencoder. Here, Deep Variational Convolutional Autoencoder was employed to extract features from drawings of archaeological ceramic profiles. Additionally, it utilized multivariate analysis for dimensionality reduction. However, the method achieved a low precision value.

In 2022, Wang, N., [14] presented LeNet image classification algorithm in fostering the innovative design of freshly painted pottery pieces. Here Majiayao colored pottery was utilized for LeNet image classification algorithm. It analyzed the pattern of pottery culture. It attains a low F-Score value with low error rate.

In 2022, Anglisano, A. et.al., [15] investigated the effectiveness of supervised machine learning techniques for predicting the provenance (origin) of archaeological pottery fragments. They compared the performance of various classifiers, including weighted k-nearest neighbors (kkNN), random forest (RF), artificial neural network (ANN), linear discriminant analysis (LDA), and generalized linear models (GLM). However, their approach resulted in both high computation time and a high error rate, suggesting limitations in accurately identifying pottery origins using these methods.

In 2021, Pawlowicz, L.M. and Downum, C.E., [16] explored the application of deep learning for classifying pottery types, using Tusayan White Ware, a specific type of ancient painted pottery from the American Southwest, as a case study. Their approach utilized convolutional neural network (CNN) models for image classification. While the study demonstrated the potential of deep learning in pottery classification, it also reported a high error rate, suggesting room for improvement in accuracy.

3. PROPOSED METHODOLOGY

In this section, the proposed MoANN-DSOA methodology for Predicting Microspace Pottery Styles is discussed. The block diagram of the proposed MoANN-DSOA methodology is given in Figure 1. The detail description about each stage is given below,

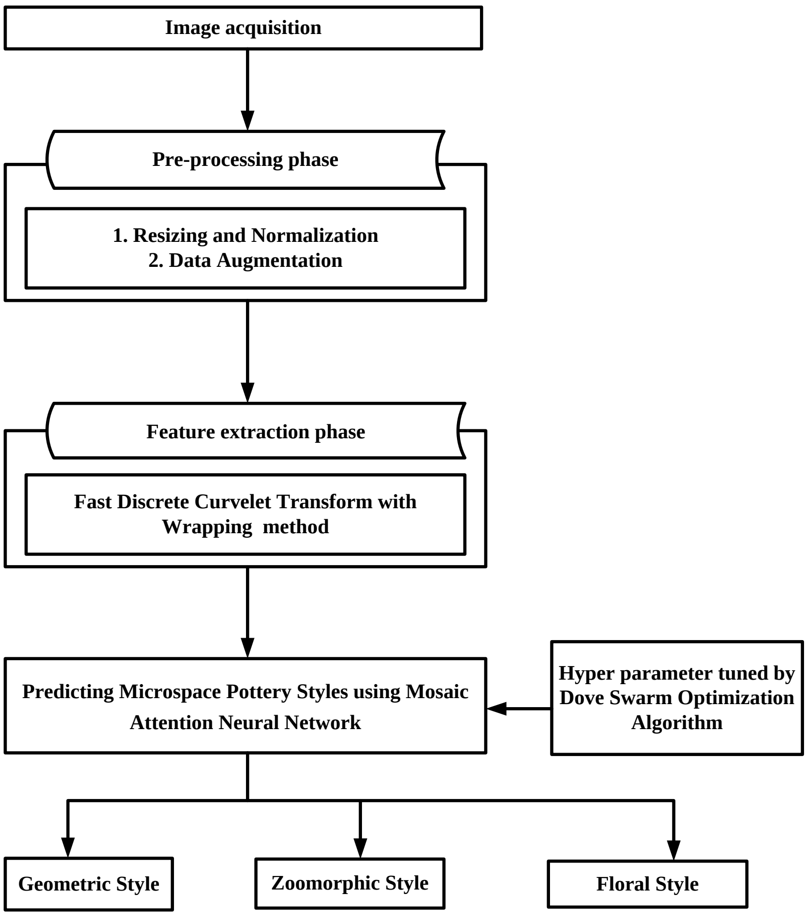

Figure 1: Block diagram of Proposed MoANN-DSOA methodology

3.1 Image acquisition

To explore microspace design styles based on ancient village pottery, this work employed a multifaceted data acquisition strategy. Collaborations with museums in prominent Taozhu cultural regions (Yellow & Yangtze River

Valleys) yielded high-resolution images of diverse ancient village pottery (pots, vessels, bowls). Archaeological institutions with Taozhu pottery collections or excavation experience in relevant sites further enriched the dataset with data on pottery origin (location, culture), types, and archaeological context (settlement type, social context). This multifaceted approach ensured a comprehensive dataset encompassing both pottery images and architectural styles.

3.2 Pre-processing phase

To optimally identify design styles from ancient pottery images, this work employs a crucial pre-processing stage. This stage ensures the deep learning model receives data in a consistent and well-formatted manner. To achieve this, two core techniques for pre-processing were utilized, such as Resizing and Normalization. Along with that, the Data Augmentation process is also employed. The detail description about pre-processing process is given below,

Step 1: Resizing and Normalization

For Resizing process, all pottery and microspace design input images are converted to a standard dimension, based on the input requirements of proposed MoANN. This guarantees a consistent input format for all images. Then for Normalization process, pixel values within the resized images are transformed to a specific range, typically between 0 and 1 or -1 and 1. This step improves the training stability and efficiency of the proposed MoANN.

Step 2: Data Augmentation

During data augmentation process, it enriches the training normalized image by applying random transformations. The random transformations such as rotations (90 degrees left/right) and flips (vertical/horizontal) create variations in the input pottery and microspace design images. Fundamentally, data augmentation expands the dataset for training without requiring additional image collection. By encountering a wider range of variations during training, the model learns features robust to slight changes in orientation or mirroring, common in real-world pottery images. This ultimately leads to a more generalizable model, capable of making accurate design style predictions based on unseen pottery data.

3.3 Feature extraction phase

The feature extraction phase utilizes the Fast Discrete Curvelet Transform with Wrapping (FDCT-WRP) method. This method is particularly effective for capturing the intricate design styles present in ancient village pottery. It exploits the curvelet transform's ability to capture curvilinear features. Mathematically, this feature extraction finds the similarity between the pre-processed ancient village pottery image represented as $\left[\mathrm{I}(\mathrm{x,y})\right]$ and the curvelet basis function $\psi_{p,q,r}$ at a specific scale (p), position (q), and orientation (r). It is given in equation (1)

$$CC\left(p,q,r\right)=\langle \mathrm{I}(\mathrm{x,y}),\psi_{p,q,r}(\mathrm{x,y})\rangle \tag{1}$$

Where $CC\left(p,q,r\right)$ denotes the curvelet coefficient representing the similarity between the image and the curvelet basis function at a particular scale, position, and orientation [17]. However, FDCT-WRP uses the Discrete Curvelet Transform (DCT) for a more efficient implementation and it is given in equation (2)

$$CC^{D^*}\left(p,q,r\right)=\sum_{a_1,b_1}\mathrm{I}(a_1,b_1)*\overline{\psi^{D^*}_{p,q,r}(a_1,b_1)} \tag{2}$$

Here, $CC^{D^*}\left(p,q,r\right)$ represents the discrete curvelet coefficient, $\mathrm{I}(a_1,b_1)$ represents the pixel intensity value at a specific location (a_1,b_1) in the pre-processed image, and $\psi^{D^*}_{p,q,r}(a_1,b_1)$ signifies the discrete curvelet waveform.

To achieve faster computations, FDCT-WRP employs a series of steps. Initially, 2D FFT is used which converts the ancient village pottery image from the spatial domain (pixel intensities) to the frequency domain. Next Windowing focuses the analysis on specific scales and orientations by applying a window function in the frequency domain. Next Wrapping, here the curvelet domain exhibits symmetries that can be exploited for efficiency. This step re-indexes the product from the previous step to take advantage of these symmetries. Then Inverse FFT transforms the data back from the frequency domain to the spatial domain, resulting in the final discrete curvelet coefficients. Finally Feature Vector Creation was used, here FDCT-WRP coefficients for all scales and orientations are combined into a single feature vector for further analysis.

Then the number of scales ($Scale$) is determined by image size $m_r \times m_c$ and it is represented as equation (3)

$$Scale = ceiling\ Function\left[\log_2\left(\min\left(m_r, m_c\right)\right) - 3\right] \tag{3}$$

By following these steps, FDCT-WRP efficiently extracts features that capture the curvilinear characteristics present in ancient village pottery and microspace design images. These features are given as the input for proposed Mosaic Attention Neural Network (MoANN).

3.3 Predicting Microspace Design Style Phase

In this section, the proposed Mosaic Attention Neural Network (MoANN) is discussed to predict the design style for microspace design based on ancient village pottery. It tackles the challenge of understanding the intricate relationships between design elements within a single pottery image. The Network Architecture of MoANN can be visualized as a multi-stage architecture, which consists of Input Layer, Superpixel Segmentation, Mosaic Attention Module, Relationship Modeling Layer, and prediction layer.

In Input layer, it receives a pre-processed pottery image represented as a 3D tensor of dimensions $\left(Ht, Wd, Cl\right)$, where Ht and Wd represent the pre-processed image height and width, and Cl denotes the number of color channels. In the Superpixel Segmentation layer, the proposed MoANN method begins by segmenting the pre-processed image into smaller, more manageable regions called superpixels. This is achieved using simple linear iterative clustering (SLIC) algorithm, which generally works by iteratively grouping neighboring pixels with similar characteristics. These superpixels become the building blocks for further analysis in the Mosaic Attention Module.

The Mosaic Attention Module is responsible for identifying design elements and their relationships within a superpixel. This module is armed with knowledge about common design symbols found in Taozhu pottery culture. It utilizes a set of pre-defined design element priors. These priors, acting as a reference guide, are encoded as reference feature vectors $(P_j \in \mathrm{Real}^{\mathrm{Dim}})$. Where Real signifies the set of real numbers (index of the design element), Dim represents the dimensionality of the feature space. During the superpixel feature analysis stage, MoANN leverages these priors to recognize potential design elements within superpixels. Feature extraction using FDCT-WRP is applied to each superpixel, resulting in feature vectors denoted by ($(Feature_i \in \mathrm{Real}^{\mathrm{Dim}})$, where i denotes the superpixel [18]. To assess the similarity between a superpixel's features and a particular design element prior, MoANN calculates a similarity score using Euclidean distance. This distance function, $\mathrm{distance}\left(Feature_i, P_j\right) = \left\|Feature_i - P_j\right\|^2$, measures the difference between the superpixel's feature vector ($Feature_i$) and the design element prior (P_j). A lower distance indicates a closer match between the superpixel's features and the corresponding design symbol.

Generally, Not all superpixels hold equal weight in determining the overall design style. So, MoANN incorporates an attention mechanism to identify the most informative superpixels likely containing crucial design elements. This mechanism assigns an attention weight (aw_i) to each superpixel based on the relevance of its features to the design style. It is represented in the following equation (4)

$$aw_i = \text{softmax}\left(Feature_i^T * Weight_a * \left(Feature_1, Feature_2, ..., Feature_S\right)\right) \quad (4)$$

Where $Feature_i^T$ represents the transpose of the feature vector $Feature_i$ for superpixel i . $Weight_a$ is a weight matrix learned by the network during training. It has dimensions ($Dim \times Dim_S$), where Dim is the dimensionality of the feature space and Dim_S is the total number of superpixels S in the image. $\left(Feature_1, Feature_2, ..., Feature_S\right)$ represents the concatenation of feature vectors for all superpixels in the image. The SoftMax function ensures that the attention weights sum to 1, indicating the relative importance of each superpixel based on its features and their alignment with the design element priors. Superpixels with features closely matching the priors will receive higher attention weights, signifying their potential role in defining the pottery's style.

This information is then processed in the subsequent Relationship Modeling Layer. It analyzes the connections between design elements found within superpixels, providing a deeper understanding of the overall artistic language. This layer constructs a graph where nodes represent superpixels and edges connect them, capturing the relationships between design elements across the image. Then the strength of the connection (EW_{ij}) between superpixels i and j is determined by their spatial proximity $(Feature_{spatial}(V_i, V_j))$ and design element similarity $(Feature_{design}(aw_i, aw_j))$. Spatial proximity is calculated as a function of the physical distance between superpixels. Design element similarity leverages the attention weights (aw_i) assigned by the Mosaic Attention Module, reflecting the alignment of features in superpixels i and j with design element priors. A hyperparameter (λ) controls the relative importance of these factors in the overall edge weight with equation (5)

$$EW_{ij} = \lambda * Feature_{spatial}(V_i, V_j) + \left(1 - \lambda\right) Feature_{design}(aw_i, aw_j) \quad (5)$$

Information about design elements flows across the graph. Each superpixel i iteratively updates its representation (h_i^*) by considering weighted messages ($message_{ij}^*$) from its neighbors (j). The weight (aw_{ij}) of a message reflects its importance and is calculated using a learnable weight matrix ($Weight_a$) and activation function (σ) is represented in the following equation (6)

$$aw_{ij} = \sigma\left[\text{LeakyReLU}\left(Weight_a^T * CONCAT\left(h_i, h_j\right)\right)\right] \quad (6)$$

Where $CONCAT\left(h_i, h_j\right)$ represents the concatenation of the current superpixel's representation (h_i) and its neighbor's representation (h_j). These scores are then normalized (NWM_{ij}) using SoftMax to ensure they sum to 1, indicating the relative importance of each neighbor's message with equation (7)

$$NWM_{ij} = \text{SoftMax}_j \left\{aw_{ij}\right\} \quad (7)$$

The normalized attention weight (NWM_{ij}) is then applied to the message ($message_{ij}$) before it's used to update the superpixel's representation (h_i^*) with equation (8)

$$message_{ij}^* = NWM_{ij} * message_{ij} \quad (8)$$

Finally, an aggregation function (AF) combines the weighted messages using equation (9)

$$h_i^* = AF(\ \{\ message_{ji}^*\ \mid\ \left(V_j,\ \mathrm{V}_i\right) \in \mathrm{Edge}\ \}\ ) \tag{9}$$

Finally, the output layer predicts pottery design style. It analyzes enriched superpixel data (h_i^*) that captures design elements, relationships, and artistic language. This data can be processed individually using SoftMax function to predict a style (Geometric, Floral, Zoomorphic) for each superpixel, or combined using SoftMax function to generate overall probabilities for the entire image. By considering relationships between design elements through the Relationship Modeling Layer's graph, the proposed MoANN method predicts the dominant microspace design style for the pottery image.

3.3.1 Hyperparameter Optimization for MoANN using DSOA:

The effectiveness of MoANN in capturing intricate design details from ancient village pottery depends on optimal hyperparameter configuration. These hyperparameter settings, such as learning rate, number of hidden layers, and neurons per layer, significantly impact the network's ability to capture intricate design details, affecting both accuracy and efficiency. Traditional manual tuning is a time-consuming process with no guarantee of finding the best configuration.

So, Dove Swarm Optimization Algorithm (DSOA) offers a solution inspired by the foraging behavior of doves. Each dove represents a candidate hyperparameter configuration for MoANN. DSOA initializes a flock of "doves" with random hyperparameter settings within the defined search space.

Then each dove's fitness is evaluated by training MoANN with its corresponding hyperparameter configuration and measuring performance on the validation set is denoted as $\left(Fitness\ \ Function\left(Z\right)\right)$. Here, Z represent a hyperparameter configuration with a specific learning rate, a certain number of hidden layers, and a particular number of neurons per layer.

Generally, Doves keep track of their performance compared to others. Here "satiety degree" (SD_v^t) is calculated for each dove, reflecting its relative performance (higher satiety indicates a configuration closer to the optimal settings). This update considers both their past performance and the current performance landscape of the flock with epoch t. It is represented in equation (10-11)

$$\mathrm{d}_v^t = \arg\ \max\left\{\text{Fitness Function}\left(\mathrm{Z}_v^t\right)\right\};\ \ for\ \ v = 1, 2, \ldots\ldots, P \tag{10}$$

$$SD_v^t = \beta * SD_v^{t-1} + e^{\left(Fitness\ Function\left(Z_v\right) - Fitness\ Function\left(Z_{HF}\right)\right)} \tag{11}$$

Where β is a learning rate parameter that controls the influence of previous satiety on the update. $Fitness\ Function\left(Z_{HF}\right)$ represents the fitness value of the dove with the highest fitness at epoch t.

Then doves update their positions (hyperparameter settings) based on social learning. They are influenced by their own past performance and the location of the dove with the highest satiety $\mathrm{d}_{satisfied}^t$ (best performing configuration) [19]. The influence of the top performer is controlled by a social influence term. It is mathematically represented in equation (12-13)

$$\mathrm{d}_{satisfied}^t = \arg\ \max_{1 \le v \le P}\left\{SD_v^t\right\};\ \ for\ \ v = 1, 2, \ldots\ldots, P \tag{12}$$

$$\mathrm{Z}_v^{t+1} = \mathrm{Z}_v^t + \eta * \alpha_v^t\left(\mathrm{Z}_{d_{Satisfied}}^t - \mathrm{Z}_v^t\right) \tag{13}$$

Where $Z^{t}_{d_{Satisfied}}$ signifies the position (hyperparameter settings) of the dove with the highest satiety ($d^{t}_{satisfied}$) at epoch t . η represents the learning rate controls the overall step size of the update. A higher learning rate leads to larger movements towards successful doves. α^{t}_{v} is a social influence term determining how much dove v is influenced by the best performer ($d^{t}_{satisfied}$). The process iterates until a termination criterion $(t = t+1)$ is met till achieving a desired performance level.

By leveraging the collective intelligence of the flock, DSOA efficiently explores the hyperparameter space, guiding the search towards configurations that improve MoANN's ability to analyze pottery designs. This allows for more accurate and efficient extraction of intricate details from ancient village pottery.

4. Results and Discussion

This section delves into the performance of the proposed MoANN-DSOA methodology for Predicting Microspace Pottery Styles in ancient village pottery. The experiment was conducted on a system equipped with an Intel Core i5, 2.50 GHz CPU, 8GB RAM, and running Windows 7. The initial dataset consisted of 7,358 high-resolution pottery images. Data preprocessing was performed in Python using libraries like OpenCV for image resizing and normalization. Data augmentation techniques were employed in Python to enrich the dataset and improve model generalizability. This process increased the dataset size to 58,864 high-resolution pottery images. The training set is used to train the MoANN-DSOA model; the validation set is used for hyperparameter tuning with DSOA optimizing a subset of MoANN's hyperparameters, while leveraging fixed settings for core functionalities; and the testing set is used for final evaluation.

Following this, evaluation metrics such as Accuracy, F-Score, Precision and Recall are analyzed. The performance of the proposed MoANN-DSOA: Predicting Microspace Pottery Styles methodology is then assessed and compared with existing methods like Categorization and Retrieval of Painted Pottery with CNNs (CNN) [11], Utilizing CNN-VGG16-VGG19 Approach for Distinguishing Surface Treatments in Wheel-Thrown Pottery (CNN-VGG16-VGG19) [12] and Unsupervised Feature Extraction of Ceramic Profiles using a Deep Variational Convolutional Autoencoder (DVCA) [13] respectively.

4.1 Performance measures

The confusion matrix visually represents the number of correct (True Positives) and incorrect predictions (False Positives, False Negatives) for each style category. These counts from the confusion matrix are then used to calculate scaled performance metrics like accuracy, precision, recall, and F1-score.

- True Positive (TP): These represent the pottery pieces where the model correctly predicted (particular) style, and the actual style according to the ground truth was also that (particular) style.
- False Positive (FP): These represent the pottery pieces where the model incorrectly predicted (particular) style, while the actual style according to the ground truth was different style.
- False Negative (FN): These represent the pottery pieces where the model failed to predict (particular) style correctly, while the actual style according to the ground truth was (particular) style. The model might have predicted other style.

True Negative (TN) is not applicable in multi-class classification.

4.1.1 Accuracy: It measures the overall proportion of pottery pieces where the predicted style matches the ground truth. This is computed via following equation (14)

$$\text{Accuracy}=\frac{(\text{Sum of True Positives across all Style})}{\text{Total Samples}} \tag{14}$$

4.1.2 Precision: It reflects the model's ability to identify true positives for a specific style (avoiding false positives). This is computed via following equation (15)

$$\text{Precision (for particular Style)} = \frac{\text{TP for that Style}}{(\text{TP for that Style} + \text{FP for that Style})} \tag{15}$$

4.1.3 Recall: It indicates the model's success in capturing all instances of a particular style (avoiding false negatives). This is scaled via equation (16)

$$\text{Recall (for a specific style)} = \frac{\text{TP for that style}}{(\text{TP for that style} + \text{FN for that style})} \tag{16}$$

4.1.4 F Score: It is a mean harmonic of precision and recall, providing a balanced view of model performance. This is determined by equation (17)

$$\text{FScore} = \frac{2 * (\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \tag{17}$$

4.2 Performance Analysis

The proposed MoANN-DSOA methodology for Predicting Microspace Pottery Styles was evaluated on a testing set containing approximately 17,658 images (from augmented dataset of 58,864 images). The confusion matrix for proposed MoANN-DSOA: Predicting Microspace Pottery Styles methodology is given in Table 1.

Table 1: Confusion matrix

Predicted Style	**Geometric**	**Floral**	**Zoomorphic**	**Total**
Geometric (Actual)	5862	11	24	5897
Floral (Actual)	7	5881	17	5905
Zoomorphic (Actual)	12	9	5835	5856
Total	5881	5901	5876	**17,658**

Figure 2-5 shows the performance of the proposed MoANN-DSOA methodology to the existing method such as CNN [11], CNN-VGG16-VGG19 [12] and DVCA [13] respectively.

Figure 2 shows the accuracy analysis of Pottery Style Prediction. The proposed MoANN-DSOA method shows significantly higher accuracy compared to existing methods for all three pottery styles (Geometric, Floral, and Zoomorphic). The proposed MoANN-DSOA method attains 7.83%, 38.59% and 21.02% higher accuracy for Geometric Style; 6.32%, 26.12% and 44.73% higher accuracy for Floral Style; 9.19%, 18.97% and 34.24% higher accuracy for Zoomorphic Style compared to the existing method such as CNN, CNN-VGG16-VGG19 and DVCA respectively. These results indicate that MoANN-DSOA predicts pottery styles more accurately than the other methods.

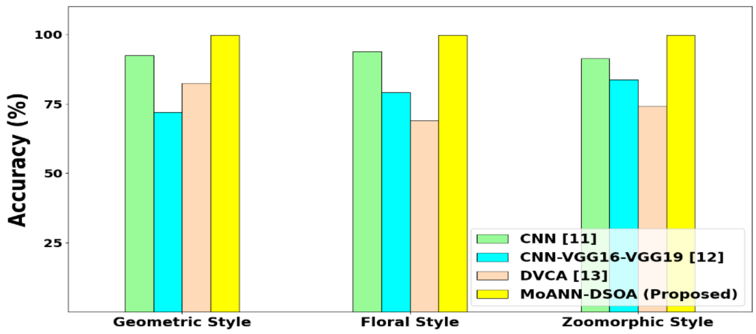

Figure 2: Accuracy Analysis of Pottery Style Prediction

Figure 3 shows the Precision analysis of Pottery Style Prediction. The proposed MoANN-DSOA method again outperforms existing methods in precision for all pottery styles. The proposed MoANN-DSOA method attains 11.29%,47.05% and 18.19% higher precision for Geometric Style; 20.71%,42.41% and 12.87% higher precision for Floral Style; 25.603%, 37.06% and 21.05% higher precision for Zoomorphic Style compared to the existing method such as CNN, CNN-VGG16-VGG19 and DVCA respectively. High precision suggests that the proposed MoANN-DSOA method classifies a pottery piece into a particular style compared to other methods.

Figure 4 shows the Recall analysis of Pottery Style Prediction. The proposed MoANN-DSOA method attains 18.45%, 25.703% and 15.54% higher recall for Geometric Style; 36.32%, 21.81% and 55.71% higher recall for Floral Style; 56.61%,27.81% and 18.1% higher recall for Zoomorphic Style compared to the existing method such as CNN, CNN-VGG16-VGG19 and DVCA respectively. Like accuracy and precision, the proposed MoANN-DSOA method demonstrates considerably higher recall for all pottery styles. High recall means proposed MoANN-DSOA method is more effective in identifying all instances of a particular style, minimizing false negatives.

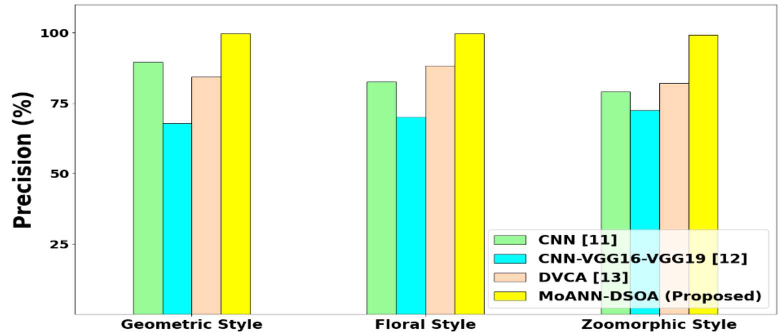

Figure 3: Precision analysis of Pottery Style Prediction

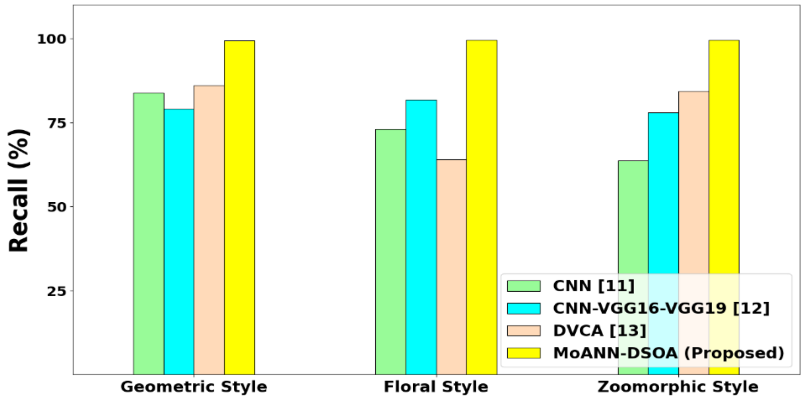

Figure 4: Recall analysis of Pottery Style Prediction

Figure 5 shows the F-Score analysis of Pottery Style Prediction. The proposed MoANN-DSOA method attains 12.67%,22% and 26.74% higher F-Score for Geometric Style; 15.86%,19.906% and 35.94% higher F-Score for Floral Style; 13.46%, 20.52% and 34.41% higher F-Score for Zoomorphic Style compared to the existing method such as CNN, CNN-VGG16-VGG19 and DVCA respectively. The F1-score, combining precision and recall, highlights MoANN-DSOA's overall superior performance in both identifying true positives and avoiding false positives/negatives.

The proposed MoANN-DSOA methodology demonstrates promising results for predicting microspace design styles based on ancient village pottery. A key strength lies in its Mosaic Attention Module, which focuses on identifying design elements and their relationships within the pottery image. This allows MoANN-DSOA to capture the overall design style more comprehensively compared to methods that might only focus on individual features. Additionally, the data augmentation process used in MoANN-DSOA likely contributes to its robustness against slight variations in pottery images.

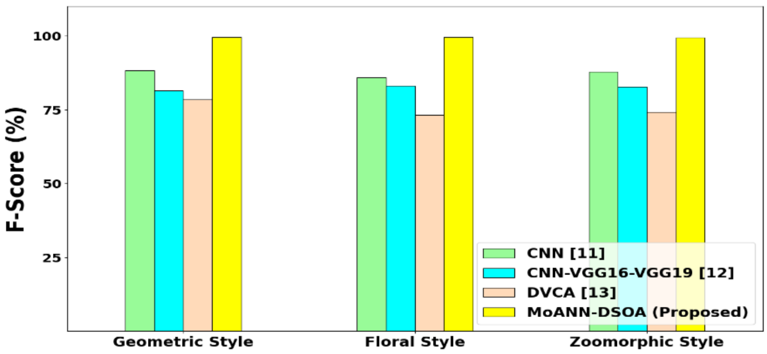

Figure 5: F-Score analysis of Pottery Style Prediction

While current results are promising, future work can further enhance MoANN-DSOA's capabilities. One potential direction involves incorporating 3D scans of pottery to capture the full design elements in three dimensions, potentially leading to even more accurate style prediction. Additionally, investigating the application of MoANN-DSOA to study the evolution of design styles over time could provide valuable insights into cultural and artistic development. By addressing these future directions, MoANN-DSOA has the potential to revolutionize archaeological research, offering a robust and efficient approach to unlocking the wealth of information hidden within ancient village pottery. This can significantly benefit archaeologists by enabling them to extract deeper cultural understanding and inform more comprehensive historical narratives.

5. Conclusion

This research presented MoANN-DSOA, a novel approach leveraging a Mosaic Attention Neural Network (MoANN) optimized by a Dove Swarm Optimization Algorithm (DSOA), for predicting microspace design styles based on ancient village pottery. MoANN tackles the challenge of understanding complex relationships between design elements within a single pottery image, while DSOA optimizes MoANN for better accuracy and efficiency. The proposed methodology offers several advantages. A rich dataset with cultural context empowers MoANN-DSOA to learn diverse styles. Robust pre-processing techniques ensure consistent image format and training stability. FDCT-WRP feature extraction effectively captures intricate design styles. Finally, the Mosaic Attention Module focuses on identifying design elements and their relationships, leading to a more comprehensive understanding of the overall design style. The proposed MoANN-DSOA method attains 19.2%,42.17% and 17.37% higher precision value and 37.13%, 25.1% and 29.78% higher recall value compared to the existing method such as CNN, CNN-VGG16-VGG19 and DVCA respectively. Future research can further enhance MoANN-DSOA's capabilities. Incorporating 3D pottery scans could potentially lead to even more accurate style prediction, paving the way for a deeper understanding of ancient cultures and artistic traditions.

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