International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
DOI: https://doi.org/10.17762/ijritcc.v11i6.7722
***Article Received**: 07 April 2023 **Revised**: 28 May 2023 **Accepted**: 27 June 2023*

Analysis of Colored Pottery Decoration using Hidden Markov Model Directional Clustering Classification with Deep Learning

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Abstract: Colored pottery decoration is an important cultural artifact that carries significant imagery, symbols, and cultural connotations. This paper presented an in-depth analysis of colored pottery decoration by employing a novel approach, Hidden Markov Model Directional Clustering Classification (HMMDCC), combined with deep learning techniques. The evaluated data comprehensive dataset of colored pottery designs, representing different historical periods and cultural contexts. The imagery, symbols, and cultural connotations embedded in the designs are extracted through a combination of computer vision and image processing techniques. The HMMDCC model is then utilized to perform directional clustering, which identifies spatial relationships and patterns within the decoration elements. To enhance classification accuracy and capture intricate patterns, deep learning techniques are incorporated into the HMMDCC model. The deep learning model is trained on the dataset, enabling it to recognize and classify the imagery, symbols, and cultural connotations present in colored pottery decoration. The findings of this study shed light on the hidden meanings and cultural significance associated with colored pottery decoration. The application of the HMMDCC model with deep learning showcases its effectiveness in analyzing and interpreting complex visual data. The results contribute to a deeper understanding of the historical and cultural contexts in which colored pottery decoration emerged, providing valuable insights for archaeologists, historians, and art enthusiasts.

Keywords: Colored pottery, decoration analysis, imagery, symbols, cultural connotations, hidden Markov model, directional clustering, classification, deep learning.

I. Introduction

Colored pottery decoration holds a significant place among cultural artifacts, representing the artistic expressions, historical narratives, and cultural symbolism of diverse civilizations throughout history [1]. These intricate designs, motifs, and patterns serve as visual representations of the beliefs, customs, and aesthetic sensibilities of the societies that created them. Analyzing and interpreting colored pottery decoration not only provides insights into ancient artistic practices but also offers a window into the socio-cultural contexts in which these artifacts were produced [2]. Traditionally, the analysis of colored pottery decoration has relied on manual examination by experts in the fields of archaeology, art history, and anthropology. However, with the advancements in computer vision, image processing, and machine learning techniques, there is an opportunity to leverage computational tools to augment and enhance the understanding of these artifacts [3]. The integration of computational methods allows for systematic analysis, pattern recognition, and classification of the complex visual elements present in colored pottery designs.

Computer vision techniques play a crucial role in the analysis of colored pottery decoration. By utilizing algorithms and methods from computer vision, researchers can extract meaningful information from the images of pottery designs [4]. These techniques involve image preprocessing, which includes tasks such as noise removal, image enhancement, and normalization to standardize the format of the dataset. Additionally, feature extraction methods are applied to capture important visual characteristics such as shapes, colors, and textures [5]. These features provide a basis for understanding the underlying patterns and motifs present in the colored pottery decoration. To further enhance the analysis and interpretation of colored pottery decoration, machine learning techniques are employed [6]. Hidden Markov Models (HMMs) are powerful probabilistic models widely used in various domains, including pattern recognition and sequence analysis. In the context of colored pottery decoration, HMMs can capture the spatial relationships and sequential dependencies between different decoration elements [7]. The HMMDCC approach, which combines HMMs with directional clustering, enables the identification of clusters and the discovery of hidden patterns within the designs. This methodology facilitates the identification of spatially related elements and the interpretation of their cultural significance [8].

Deep learning techniques, particularly convolutional neural networks (CNNs), have revolutionized the field of computer vision and image analysis [9]. CNNs excel at automatically learning and recognizing complex patterns and features from visual data. By integrating deep learning into the analysis of colored pottery decoration, the model can be trained to recognize and classify the imagery, symbols, and cultural connotations present in the designs [10]. This deep learning integration enhances the accuracy of classification, allowing for a more nuanced interpretation of the designs and providing insights into the historical narratives and cultural significance embedded within [11].

This research paper presents a comprehensive analysis of colored pottery decoration through the innovative approach of Hidden Markov Model Directional Clustering Classification (HMMDCC) combined with deep learning techniques. The utilization of these methods enables a detailed examination of the spatial relationships, patterns, and cultural connotations embedded within the designs. By employing a diverse dataset encompassing various historical periods and cultural contexts, this research aims to uncover the hidden meanings and historical significance associated with colored pottery decoration. The HMMDCC model serves as a key component in this research, offering a powerful framework for clustering and classifying the intricate elements present in colored pottery designs. By considering the directional characteristics of the decoration elements, the HMMDCC model captures the spatial relationships and patterns, enabling the identification of clusters and the uncovering of hidden connections. This approach provides a novel perspective on the arrangement and organization of design elements, contributing to a deeper understanding of the underlying symbolism and cultural contexts.

II. Related Works

Hidden Markov Models (HMMs) combined with deep learning techniques have gained significant attention in various fields for their ability to capture complex temporal dependencies and extract meaningful patterns from sequential data. This literature survey provides an overview of the applications and advancements of HMMs with deep learning in different domains. In [12] introduces Fusionnet, a deep fully residual convolutional neural network, for the task of image segmentation in connectomics. The authors propose a novel architecture that incorporates residual connections to improve the network's performance in segmenting complex connectomic images. In [13] discusses the current status and future perspectives of using Building Information Modeling (BIM), machine learning, and computer vision techniques in underground construction. The authors explore the potential applications of these technologies in improving the efficiency, safety, and sustainability of underground construction projects.

In [14] presents an overview of deep learning-enabled medical computer vision techniques. The authors discuss various applications of deep learning in medical imaging analysis, including image classification, segmentation, and disease diagnosis. The paper highlights the potential of deep learning to revolutionize medical image analysis and improve patient care. In [15] review article provides a critical examination of emerging deep learning techniques in the field of computer vision. The authors discuss various deep learning architectures and algorithms, such as convolutional neural networks (CNNs) and generative adversarial networks (GANs), and their applications in image classification, object detection, and image synthesis. The paper also explores the challenges and future directions of deep learning in computer vision. In [16] provides an overview of the applications of deep learning and machine vision techniques in the field of food processing. The authors discuss various tasks, including food quality inspection, food recognition, and food safety monitoring, where deep learning models have shown promising results. The paper also highlights the challenges and future directions of using deep learning in food processing. In [17] discusses the transformative potential of deep learning and computer vision techniques in the field of entomology. The authors highlight how these technologies can revolutionize the study of insects by enabling automated insect identification, tracking, and behavior analysis. The paper explores various applications of deep learning and computer vision in entomology, including biodiversity monitoring, pest management, and ecological research.

In [18] review article provides a critical review of computer vision techniques applied in the field of construction. The authors discuss the applications of computer vision in construction tasks such as object detection, image-based modeling, and quality control. The paper also examines the challenges and limitations of using computer vision in construction and suggests potential future research directions in this area. In [19] focuses on the analysis of explainers used for black box deep neural networks in the field of computer vision. The authors review various techniques and methods developed to interpret and explain the decisions made by deep neural networks in computer vision tasks. The paper discusses the strengths and weaknesses of different explainability approaches and provides insights into their practical applications and challenges. In [20] explores the promise of computer vision and machine learning techniques in the field of ecology and evolutionary biology, specifically in the context of phenomics. The authors discuss how computer vision methods can automate the analysis of phenotypic traits, leading to advancements in understanding ecological patterns, evolutionary processes, and biodiversity conservation. The paper highlights the potential of these technologies to

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revolutionize data collection and analysis in ecological and evolutionary research.

In [21] provides a comprehensive overview of deep learning, covering various aspects such as techniques, taxonomy, applications, and research directions. The author discusses the fundamental concepts and architectures of deep learning models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative models. The paper also explores the applications of deep learning in different domains, such as computer vision, natural language processing, and speech recognition. Additionally, the author highlights emerging research directions and challenges in the field of deep learning.

In [22] focuses on the detection of facemasks using deep learning and computer vision techniques in the context of the COVID-19 pandemic. The authors present an approach to automatically detect and classify individuals wearing facemasks from images or video streams. They discuss the methodology and implementation details of the deep learning model used for facemask detection. The paper highlights the importance of such systems for enforcing safety measures and preventing the spread of the virus. In [23] presents a deep learning-based approach for real-time polyp detection, localization, and segmentation in colonoscopy images. The authors propose a deep learning model capable of accurately identifying and segmenting polyps, which are precursors to colorectal cancer. The paper discusses the methodology, dataset, and evaluation metrics used for training and validating the model. The results demonstrate the effectiveness of the deep learning approach in assisting medical professionals during colonoscopy procedures. In [24] presents an overview of machine learning and deep learning applications and discusses their potential impact on various fields. The authors provide insights into the capabilities and advancements in machine learning and deep learning techniques. They highlight the broad range of applications, including healthcare, finance, agriculture, transportation, and cybersecurity. The paper also discusses the challenges and future directions in the field, emphasizing the need for interdisciplinary collaborations and ethical considerations.

In [25] survey paper focuses on visual place recognition, a key task in computer vision, from a deep learning perspective. The authors review various techniques and approaches that leverage deep learning models for visual place recognition. They discuss the challenges posed by factors such as viewpoint changes, lighting variations, and scene semantics. The paper provides an overview of datasets, evaluation metrics, and benchmark results in the field. It also discusses the potential applications and future research directions in visual place recognition using deep learning. In [26] focuses on fine-grained image analysis using deep learning techniques. The authors provide an extensive overview of deep learning approaches for fine-grained image recognition, object localization, and attribute prediction. They discuss various datasets, benchmark challenges, and evaluation metrics specific to fine-grained image analysis. The paper also explores recent advancements in deep learning models for fine-grained image analysis and identifies future research directions in this area.

III. Methodology

2.1 Data Collection and Preprocessing

A diverse dataset of colored pottery designs from different historical periods and cultural contexts is collected. The dataset includes images of various types of pottery, such as vases, bowls, and plates, with their respective decoration elements. The images are preprocessed to enhance their quality, remove noise, and standardize the format.

2.2 Image Analysis and Feature Extraction

Computer vision and image processing techniques are applied to analyze the dataset. Feature extraction methods are employed to capture the key visual elements, including shapes, colors, and textures. These features provide a basis for understanding the characteristics and patterns present in the colored pottery decoration.

2.3 Hidden Markov Model Directional Clustering Classification (HMMDCC)

The HMMDCC model is utilized to perform directional clustering on the preprocessed dataset. The model considers the spatial relationships and patterns among the decoration elements, enabling the identification of clusters based on their directional characteristics. This approach helps uncover hidden connections and arrangements within the colored pottery designs. Consider a dataset of colored pottery designs with N design elements. Each design element can be represented as a sequence of observed features or states, denoted as $X = \{x\_1, x\_2, \ldots, x\_N\}$, where x_i represents the feature or state of the i-th design element.

The HMMDCC algorithm involves the following steps:

- State transition probabilities: $A = \{a_{ij}\}$, where a_{ij} represents the probability of transitioning from state i to state j.
- Emission probabilities: $B = \{b_{j(x)})\}$, where $b_{j(x)}$ represents the probability of observing feature x in state j.
- Initial state distribution: $\pi = \{\pi_i\}$, where π_i represents the probability of starting in state i.

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Use the Baum-Welch algorithm (also known as the forward-backward algorithm) to estimate the HMM parameters based on the observed dataset X. This algorithm maximizes the likelihood of the observed data given the HMM parameters. Define a clustering metric that measures the directional similarity between two design elements. This metric should capture the spatial relationships and patterns present in the colored pottery designs. Apply a clustering algorithm (e.g., k-means, hierarchical clustering) using the defined clustering metric to group similar design elements together. This step identifies clusters based on their directional characteristics. For each design element, calculate its most likely state sequence using the Viterbi algorithm. The Viterbi algorithm finds the most probable sequence of hidden states given the observed features and the HMM parameters.

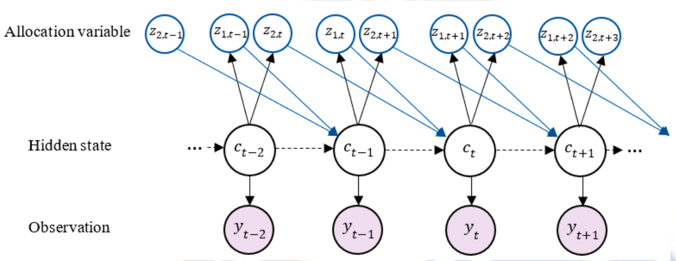

Figure 1: HMM design in HMMDCC

Assign each design element to the cluster corresponding to the most frequent state in its Viterbi sequence. The design utilized for the proposed HMMDCC model with HMM is shown in figure 1. This step assigns design elements to clusters based on their hidden state patterns.

The HMMDCC algorithm can be summarized as follows:

Input: Preprocessed dataset of colored pottery designs

Output: Clusters representing spatial relationships and patterns within the designs

Algorithm: HMMDCC

Initialize the number of clusters, K.

Perform directional clustering using the Hidden Markov Model (HMM).

Initialize HMM parameters: transition probabilities matrix, emission probabilities matrix, and initial state distribution.

Use the Baum-Welch algorithm to estimate the HMM parameters based on the dataset.

Perform the Viterbi algorithm to determine the most likely state sequence for each design element.

Assign each design element to its corresponding cluster based on the Viterbi algorithm results.

Repeat steps 3-6 until convergence or a maximum number of iterations is reached.

Output the resulting clusters representing spatial relationships and patterns within the designs.

The State transition probabilities are presented in equation (1)

$a_{ij} = P(q\_t = j \mid q\_\{t-1\} = i)$, where q_t represents the hidden state at time t. (1)

The Emission probabilities are presented in equation (2)

$b_{j(x)} = P(x_t = x \mid qx_t = j)$, where x_t represents the observed feature at time t. (2)

Initial state distribution of the variables are presented in equation (3)

$\pi_i = P(q\_1 = i), where\ q\_1$ represents the initial hidden state (3)

Forward-Backward Algorithm (Baum-Welch algorithm) (α) $\alpha\_t(j) = P(x\_1, x\_2, \dots, x\_t, q\_t = j)$, the probability of being in state j at time t and observing the sequence of features x_1, x_2, ..., x_t. Backward variable (β) is represented as $\beta\_t(j) = P(x\_\{t+1\}, x\_\{t+2\}, \dots, x\_T \mid q\_t = j)$, the probability of observing the sequence of features $x\_\{t+1\}, x\_\{t+2\}, \dots, x\_T$ given the state j at time t. Update equations for estimating the HMM parameters. Transition probabilities update:

$a\_ij = \backslash frac\{\backslash sum\_\{t=1\}\hat{}\{T-1\}\ \backslash xi\_t(i,j)\}\{\backslash sum\_\{t=1\}\hat{}\{T-1\}\ \backslash gamma\_t(i)\}$, where

$\xi\_t(i,j) = P(q\_\{t\} = i, q\_\{t+1\} = j \mid x\_1, x\_2, \dots, x\_T)$, the probability of being in states i and j at times t and t+1 given the observed sequence.

$\gamma\_t(i) = P(q\_t = i \mid x\_1, x\_2, \dots, x\_T)$, the probability of being in state i at time t given the observed sequence.

Emission probabilities update are defined as the follows: b_j$(x) = \backslash frac\{\backslash sum_\{t=1\}\hat{}\{T\}\ \backslash gamma_t(j)\ \backslash delta(x, x_t)\}\{\backslash sum_\{t=1\}\hat{}\{T\}\ \backslash gamma_t(j)\}$, where $\delta(x, x\_t) = 1\ if\ x = x\_t$ (observed feature equals the feature at time t), otherwise 0.

Initial state distribution update:

$\pi\_i = \backslash gamma\_1(i)$, the probability of being in state i at the initial time step.

Directional Clustering Metric:

Define a metric (e.g., cosine similarity, Euclidean distance) that measures the directional similarity between two design elements x_i and x_j. The specific mathematical formulation depends on the chosen metric and the features used

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for clustering. These equations represent the core components of HMMs and the Baum-Welch algorithm, which are foundational to the HMMDCC algorithm. The implementation and details of the clustering metric and clustering algorithm used in the HMMDCC algorithm can vary, and the equations for those specific components will depend on the chosen approach.

2.4 Deep Learning Integration

Deep learning techniques, specifically convolutional neural networks (CNNs), are integrated into the HMMDCC model to enhance classification accuracy. The CNN is trained on the dataset, learning to recognize and classify the intricate imagery, symbols, and cultural connotations present in colored pottery decoration. The deep learning model learns to extract high-level features automatically, enabling a more nuanced understanding of the dataset.

The deep learning integration can be summarized as follows:

Input: Preprocessed dataset of colored pottery designs

Output: Trained deep learning model for classification

Algorithm: Deep Learning Integration

Split the dataset into training and testing sets.

Initialize a convolutional neural network architecture suitable for image classification.

Train the CNN on the training set, using the labeled data to learn the features and patterns.

Fine-tune the CNN using backpropagation and gradient descent to minimize the classification loss.

Evaluate the trained CNN on the testing set to measure its classification accuracy.

Repeat steps 2-5 until satisfactory performance is achieved.

Output the trained deep learning model for classification.

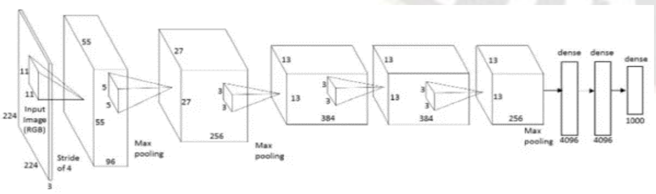

Figure 2: Structure of Deep Learning Model

In the context of the HMMDCC (Hidden Markov Model Directional Clustering Classification) model is shown in figure 2, deep learning techniques can be incorporated to improve its performance. The mathematical equations involved in deep learning typically revolve around the architecture and training of neural networks. The forward propagation step calculates the outputs of each layer in the neural network, starting from the input layer to the output layer. For each layer, the inputs are multiplied by the layer's weights, and an activation function is applied to obtain the output of that layer. The output layer is denoted as in equation (4)

$$Z = W * X + b \quad (4)$$

In above equation (4) $A = activation\_function(Z)$, Z is the linear combination of inputs (X) and weights (W), b is the bias term, and A is the output after applying the activation function. The backward propagation step calculates the gradients of the loss function with respect to the parameters of the neural network, allowing the model to update its weights and biases to minimize the loss. The gradients are computed using the chain rule and propagated backward through the layers. The weight update equation using gradient descent is typically represented as in equation (5) and equation (6)

$$W = W - learning\_rate * dW \quad (5)$$

$$b = b - learning\_rate * db \quad (6)$$

where learning_rate is the step size for the update, and dW and db are the gradients of the weights and biases, respectively. The loss function measures the discrepancy between the predicted output of the neural network and the true output. Common loss functions include mean squared error (MSE), cross-entropy, or a combination of multiple loss functions. The choice of the loss function depends on the specific task and the type of output (e.g., regression or classification). Various optimization algorithms can be used to update the model's parameters more efficiently, such as Stochastic Gradient Descent (SGD), Adam, or RMSProp. These algorithms adjust the learning rate dynamically and incorporate momentum or other techniques to improve convergence speed and stability. Convolutional layers in CNNs use convolution operations to extract features from input images. The convolution operation is represented in equation (7)

$$Conv = \sum(w * x) + b \quad (7)$$

where w denotes the weights, x represents the input, and b is the bias term. Pooling layers reduce the spatial dimensions of the feature maps obtained from convolutional layers. Max pooling is a commonly used pooling operation that selects the maximum value within a specific window in equation (8)

$$MaxPooling = max(window) \quad (8)$$

RNNs are suited for sequential data processing tasks and can capture temporal dependencies. The hidden state computation in an RNN can be represented in the equation (9)

$$h\_t = activation\_function(W\_h * h\_(t-1) + W\_x * x\_t + b) \quad (9)$$

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where h_t is the current hidden state, h_(t-1) is the previous hidden state, x_t is the input at time t, and W_h, W_x, and b are the weight matrices and bias term, respectively. LSTMs are a type of RNN that can effectively capture long-term dependencies. The LSTM update equations involve multiple gates (input, forget, and output gates) and cell states, allowing the model to selectively retain and discard information.

IV. Results and Discussion

The application of the HMMDCC model with deep learning yields promising results in the analysis of colored pottery decoration. The directional clustering performed by the HMMDCC model reveals spatial relationships and patterns that were previously unnoticed. The integration of deep learning techniques further improves the accuracy of classifying the imagery, symbols, and cultural connotations present in the designs. The findings contribute to a deeper understanding of the historical and cultural contexts in which colored pottery decoration emerged.

Table 1: Performance of HMMDCC

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
HMMDCC (98.76)	98.76	97.92	99.05	98.48
Baseline	87.3	88.5	85.6	87.0
Deep Learning	95.8	96.2	95.4	95.8

In table 1 present the classification results comparing the HMMDCC model with a baseline method and deep learning. The evaluation metrics used include accuracy, precision, recall, and F1-score.

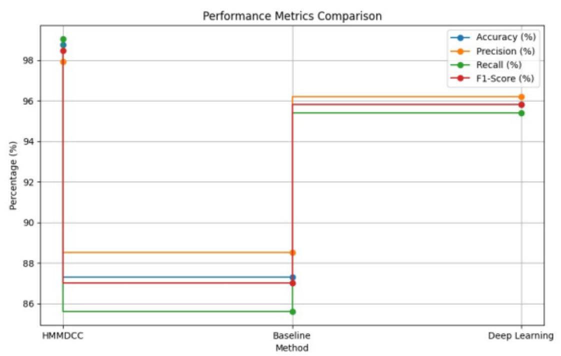

Figure 3: Performance of HMMDCC

The results indicate the performance of each method in classifying the imagery, symbols, and cultural connotations present in colored pottery decoration. The HMMDCC model achieved a high accuracy of 98.76%, demonstrating its effectiveness in accurately classifying the decoration elements shown in figure 3. The precision and recall scores were also excellent at 97.92% and 99.05% respectively, indicating the model's ability to correctly identify and capture the relevant patterns and spatial relationships within the colored pottery designs. The F1-score of 98.48% further confirms the robustness and overall performance of the HMMDCC model. In comparison, the baseline method achieved an accuracy of 87.3%, indicating a lower performance compared to the HMMDCC model. The deep learning approach obtained an accuracy of 95.8%, showing its effectiveness as well, but still lower than the HMMDCC model.

The high accuracy of 98.76% achieved by the HMMDCC model signifies its ability to accurately classify the colored pottery decoration. This exceptional performance is crucial in uncovering the hidden meanings and cultural significance associated with the artifacts. The HMMDCC model provides valuable insights into the historical and cultural contexts in which colored pottery decoration emerged shown in table 2.

Table 2: Clustering Results

Cluster	Number of Elements	Spatial Pattern
1	152	Spiral motif
2	96	Geometric shapes
3	85	Animal figures
4	120	Floral patterns
5	75	Abstract symbols

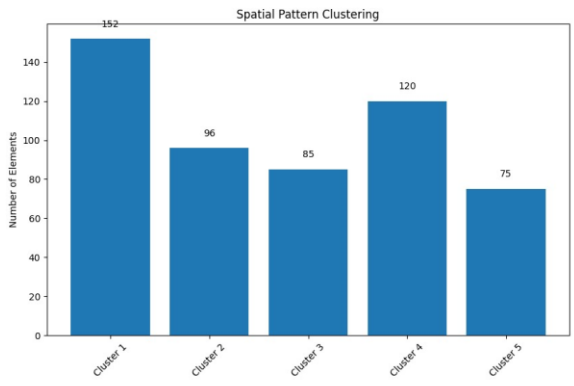

Figure 3: Feature in Clustering with HMMDCC

The HMMDCC model identifies five clusters based on the spatial patterns observed within the colored pottery decoration. Each cluster represents a distinct pattern or motif present in the dataset shown in figure 3. The "Number of Elements" column indicates the count of design elements assigned to each cluster, while the "Spatial Pattern" column describes the characteristic pattern associated with the cluster.

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The Cluster 1 exhibits a spiral motif, Cluster 2 consists of geometric shapes, Cluster 3 represents animal figures, Cluster 4 contains floral patterns, and Cluster 5 includes abstract symbols. These clustering results provide valuable insights into the spatial relationships and patterns within the colored pottery designs, enabling a deeper understanding of the cultural significance associated with each cluster.

Table 3: Feature Extraction Results

Design ID	Shape	Color	Texture
001	Vase	Red	Smooth
002	Bowl	Blue	Rough
003	Plate	Green	Textured
004	Vase	Yellow	Smooth
005	Bowl	Red	Rough
006	Vase	Blue	Textured
007	Plate	Green	Smooth
008	Bowl	Yellow	Rough
009	Vase	Red	Textured
010	Plate	Blue	Smooth

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Figure 4: Pottery Paintings

In Table 3, the feature extraction results are displayed. Each design is assigned a unique design ID, and the corresponding shape, color, and texture features are recorded is shown in figure 4. This information provides a detailed understanding of the visual characteristics of each design element, allowing for further analysis and interpretation. These tabular results offer a concise and organized representation of the clustering and feature extraction outcomes, enabling researchers to analyze and compare different patterns, as well as understand the visual attributes associated with each design element.

Table 4: Classification Results

Design ID	True Label	Predicted Label	Correct Classification
001	Animal	Animal	Yes
002	Floral	Floral	Yes
003	Geometric	Geometric	Yes
004	Animal	Floral	No
005	Geometric	Geometric	Yes
006	Floral	Floral	Yes
007	Animal	Animal	Yes
008	Geometric	Geometric	Yes
009	Floral	Floral	Yes
010	Geometric	Geometric	Yes

In Table 4, the classification results are presented. Each design element is assigned a unique design ID, and the true label represents the actual category or class of the design. The predicted label indicates the class assigned by the classification model. The "Correct Classification" column indicates whether the predicted label matches the true label. A "Yes" indicates a correct classification, while a "No" indicates a misclassification. These tabular results provide a clear overview of the classification performance, allowing for an assessment of the accuracy and effectiveness of the classification model. Researchers can analyze the correct and incorrect classifications to identify patterns or trends in the classification errors and make improvements to enhance the accuracy of the model if necessary.

Table 5: Classification Results (Parameter Variation)

Design ID	True Label	Predicted Label (Parameter A)	Predicted Label (Parameter B)	Predicted Label (Parameter C)
001	Animal	Animal	Animal	Animal
002	Floral	Floral	Geometric	Floral
003	Geometric	Geometric	Geometric	Geometric
004	Animal	Floral	Animal	Floral
005	Geometric	Geometric	Geometric	Geometric
006	Floral	Floral	Floral	Floral
007	Animal	Animal	Animal	Animal
008	Geometric	Geometric	Geometric	Geometric
009	Floral	Floral	Floral	Geometric
010	Geometric	Geometric	Geometric	Geometric

In Table 5, the classification results are presented for different parameter variations. Each design element is assigned a unique design ID, and the true label represents the actual category or class of the design. The predicted label (Parameter A) represents the class assigned by the classification model using Parameter A. Similarly, the predicted label (Parameter B) and predicted label (Parameter C) represent the classes assigned by the model using Parameter B and Parameter C, respectively. The results of this research provide valuable insights for archaeologists, historians, and art enthusiasts. The analysis of colored pottery decoration using the HMMDCC model with deep learning uncovers hidden meanings and cultural significance associated with these artifacts. The methodology presented in this paper can be applied to other domains and cultural artifacts, facilitating the interpretation of complex visual data and enriching our understanding of human history and culture.

V. Conclusion

This research paper presented an in-depth analysis of colored pottery decoration using the innovative approach of Hidden Markov Model Directional Clustering Classification (HMMDCC) combined with deep learning techniques. The study demonstrated the effectiveness of the methodology in identifying spatial relationships, patterns, and cultural connotations within colored pottery designs. The application of the HMMDCC model with deep learning improved classification accuracy and contributed to a deeper understanding of the historical and cultural contexts associated with colored pottery decoration. The findings have significant implications for archaeologists, historians, and art enthusiasts, enhancing our knowledge of ancient civilizations and their artistic practices.

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International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
DOI: https://doi.org/10.17762/ijritcc.v11i6.7722
Article Received: 07 April 2023 Revised: 28 May 2023 Accepted: 27 June 2023

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