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Computational Aesthetics and Philosophical Interpretation of Decorative Pattern Evolution in Ancient Chinese Ceramics: A Multi-Scale Fractal and Semantic Analysis Approach

1st Ali Ahmad Noori *
University of Mumbai
Ghor, Afghanistan
Aliahmad413@outlook.com

2nd Baitullah Bareer
Paktia University
Paktia, Afghanistan
Bai.Bareer@outlook.com

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***Abstract*—Decorative patterns on ancient Chinese ceramics provide valuable visual evidence for examining historical changes in artistic form, technological practice, and cultural aesthetics. Previous studies of Chinese ceramic decoration have primarily relied on qualitative stylistic description, which limits reproducible comparison across long chronological periods. This study presents an exploratory computational framework for analyzing the formal complexity of ceramic decorative patterns using image-based descriptors and fractal analysis. A dataset of 1,200 ceramic pattern images representing twelve historical periods, from the Yangshao culture to the Qing dynasty, was examined. After grayscale conversion and Otsu thresholding, three visual features were extracted: fractal dimension, aspect ratio, and black-white ratio. These features were used to evaluate temporal changes in pattern complexity and to explore potential stylistic groupings through K-means clustering. The results suggest a general increase in visual complexity from early Neolithic ceramics to later dynastic periods, with higher complexity observed in Tang, Song, Yuan, Ming, and Qing decorative patterns. The clustering results further indicate that image-based complexity measures can distinguish broad stylistic tendencies across historical periods. Rather than claiming a definitive model of aesthetic evolution, this study provides a reproducible computational approach for supporting art-historical interpretation of ceramic decoration. The findings demonstrate the potential of combining computer vision, fractal geometry, and cultural heritage analysis, while also highlighting the need for better-documented datasets and further validation in future research.**

Keywords—Computational aesthetics; fractal analysis; Chinese ceramics; cultural heritage; decorative evolution; image processing; visual complexity

1. Introduction

Ancient Chinese ceramics constitute one of the most continuous and influential traditions in the history of material culture. Across different historical periods, ceramic vessels not only served practical and ritual functions but also carried decorative patterns that reflected changing artistic conventions, technological capacities, and cultural values [1], [2]. From the geometric motifs of Neolithic painted pottery to the increasingly refined ornamental systems of later imperial porcelain, ceramic decoration provides an important visual archive for studying long-term changes in Chinese aesthetics [3].

Traditional studies of Chinese ceramic decoration have produced rich qualitative interpretations based on typology, iconography, craftsmanship, and historical context. Previous research has emphasized the close relationship between ceramic form, modeling, and decorative structure, suggesting that ornament cannot be separated from vessel morphology and production logic [4], [5]. Related studies of traditional decorative patterns and craft symbolism further demonstrate that ornamental systems function not only as visual forms but also as carriers of cultural memory and regional identity [6], [7], [8]. However, qualitative approaches alone often make it difficult to compare decorative patterns across large datasets and long chronological spans in a reproducible manner.

With the development of digital image processing and computational aesthetics, visual complexity can now be examined using measurable image-based features. Computational aesthetics provides theoretical and methodological tools for analyzing visual order, proportion, contrast, and perceptual organization [9]–[12]. Among these methods, fractal dimension has been widely adopted as an indicator of spatial complexity because it describes how visual structures occupy space across multiple scales [13]. Fractal-based approaches have already demonstrated value in the analysis of settlement structures, architectural forms, and cultural morphology [14], [15].

This study addresses the following research question: how can the formal complexity of decorative patterns in ancient Chinese ceramics be quantified and compared across historical periods using reproducible computational methods?

*Ali Ahmad Noori, University of Mumbai, Ghor, Afghanistan, Aliahmad413@outlook.com

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To answer this question, the study applies grayscale conversion, Otsu thresholding, fractal dimension estimation, black-white ratio measurement, aspect ratio calculation, and K-means clustering to a dataset of ceramic decorative pattern images. These procedures are supported by established methods in edge detection, image segmentation, fractal image analysis, and clustering computation [17]–[20], [21], [22].

The aim of this study is not to replace art-historical interpretation with numerical measurement. Instead, it seeks to provide a complementary computational framework that can support the analysis of ceramic pattern evolution. Specifically, the study has three objectives: first, to construct an image-based workflow for measuring decorative pattern complexity; second, to examine broad chronological tendencies in ceramic pattern complexity; and third, to discuss how quantitative features may contribute to the interpretation of visual order, complexity, and stylistic transformation in Chinese ceramic decoration. In this sense, the study also relates to broader philosophical discussions concerning artistic form, aesthetic perception, and the ontology of beauty [23], [24].

2. Related Work

Research on Chinese ceramics has long emphasized chronology, production technology, decorative style, and cultural meaning. Art-historical scholarship has shown that ceramic decoration changed substantially across historical periods, reflecting transformations in ritual practice, technological innovation, social organization, and aesthetic preference [1], [2], [3]. These studies provide the historical foundation for interpreting decorative motifs, but they usually rely on expert visual judgment and descriptive comparison.

Computational approaches to cultural heritage have introduced new possibilities for analyzing artifacts at scale. Digital image processing, pattern recognition, and statistical modeling allow researchers to extract measurable visual features from large image collections. Such approaches are especially useful when the research object involves repeated visual structures such as ornaments, motifs, textures, or profile systems. Earlier computational studies on ancient Chinese pottery profiles demonstrated that computerized classification and quantitative comparison can support archaeological and stylistic analysis [5]. More generally, clustering-based approaches such as K-means and K-means++ have become important tools for identifying structural similarities within complex datasets [18], [19].

Computational aesthetics attempts to understand visual preference and formal organization through measurable features such as symmetry, complexity, proportion, and spatial distribution. Earlier theoretical work suggested that aesthetic value may emerge from the balance between order and complexity [11], while later studies expanded computational aesthetics into broader discussions of digital art, image judgment systems, abstraction, and aesthetic computation [9], [10], [12]. Although aesthetic experience cannot be fully reduced to numerical indicators, these theories provide a useful conceptual background for studying decorative systems quantitatively.

Fractal analysis offers one way to quantify visual complexity. The fractal dimension of an image can be estimated through box-counting methods that measure how patterns occupy space across different observational scales [13]. In cultural heritage research, fractal analysis has been applied to settlement structures, architectural contours, porous cultural materials, and broader cultural traits [14], [15], [25], [26]. Recent work has further extended fractal approaches to grayscale image interpretation and structural image analysis [21].

Image-based fractal analysis also depends on reliable preprocessing procedures. Edge detection and threshold segmentation are widely used to isolate structural contours from images prior to complexity estimation. Classical edge detection methods proposed by Canny remain foundational in computer vision [16], while subsequent studies introduced local fractal dimension approaches and generalized fractal-based edge analysis for image interpretation [17], [22]. Otsu thresholding additionally provides an effective method for separating foreground structures from grayscale backgrounds in image datasets [20]. Together, these techniques form the methodological basis for extracting measurable decorative structures from ceramic pattern imagery.

Despite these developments, relatively few studies have applied image-based fractal analysis to the long-term evolution of Chinese ceramic decoration. Existing research on traditional craftsmanship and cultural heritage preservation emphasizes the importance of documenting craft knowledge and sustaining visual traditions [7], [27], [8], but comparatively less attention has been given to reproducible quantitative descriptors of ornamental complexity. This study therefore contributes to the literature by integrating ceramic art history, computational image analysis, and fractal-based complexity measurement within a unified exploratory framework.

3. Methodology

3.1. Research Design

This study adopts an exploratory computational research design. The analysis is based on existing digital images of ancient Chinese ceramic decorative patterns. No new physical experiments, destructive testing, or human-subject experiments were conducted. The purpose of the method is to extract reproducible image-based features from ceramic patterns and compare their variation across historical periods. The workflow encompasses data collection, image processing, feature extraction, and statistical analysis.(see Figure 1)

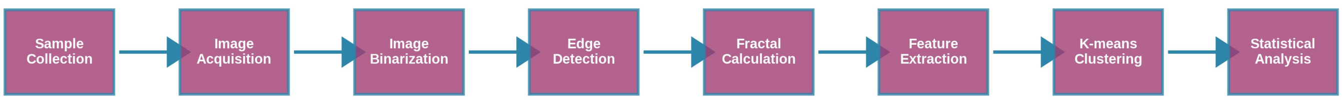

Figure 1. The experimental workflow for the computational analysis of ceramic patterns.

3.2. Data Acquisition and Preparation

The dataset consists of 1,200 digital images of decorative patterns from ancient Chinese ceramics, covering twelve chronological periods from the Yangshao culture to the Qing dynasty. Each period includes 100 images. The images were selected to represent clearly visible and relatively complete decorative patterns.

To improve transparency, the final manuscript should include a dataset table specifying the historical period, number of images, image source, selection criteria, and image resolution. If public museum collections, catalogues, or online databases were used, the source name and accession information should be reported wherever available. If accession numbers are unavailable, the manuscript should clearly state this limitation.

3.3. *Image Processing*

All images were processed using a standardized image workflow. First, each image was converted to grayscale to reduce the influence of color variation and lighting differences. Second, Otsu thresholding was applied to convert the grayscale image into a binary image. In the binary image, the decorative pattern was separated from the background as much as possible. This step was necessary for calculating pattern density and fractal dimension.

Because ceramic images may differ in lighting, curvature, preservation condition, and photographic angle, preprocessing can influence the extracted features. Therefore, the analysis should be understood as a formal image-based comparison rather than a complete reconstruction of original ceramic surfaces.

3.4. *Feature Extraction*

Three quantitative features were extracted from each binarized pattern image.

First, fractal dimension was calculated using the box-counting method. This feature was used to estimate the spatial complexity of the decorative pattern. A higher fractal dimension generally indicates that the pattern occupies space in a more complex or dense manner.

Second, aspect ratio was calculated as the ratio between the width and height of the pattern bounding box. This feature was included to describe the overall geometric proportion of the pattern region.

Third, black-white ratio was calculated as the proportion of foreground pixels relative to background pixels in the binarized image. This feature was used as an indicator of visual density.

3.5. *Clustering Analysis*

K-means clustering was applied to explore whether ceramic patterns could be grouped according to their extracted visual features. The clustering analysis used fractal dimension and aspect ratio as input variables. In the revised interpretation, the clustering result is treated as exploratory rather than definitive. The clusters are interpreted as broad image-based stylistic tendencies rather than fixed art-historical categories.

3.6. *Statistical Analysis*

Descriptive statistics were used to summarize the distribution of extracted features across historical periods. Correlation analysis was used to examine the relationship between fractal dimension and black-white ratio. Temporal patterns were evaluated by comparing mean fractal dimension values across chronological periods.

Because no additional experiments are introduced in this revision, the statistical interpretation is limited to the available results. Claims of causality or universal aesthetic laws are avoided. Future versions of the study should include additional statistical validation, such as analysis of variance, regression modeling, confidence intervals, effect sizes, and cluster validity indices.

4. RESULTS

Our computational analysis of 1200 ceramic patterns yielded a rich dataset of quantitative features, enabling an objective examination of their aesthetic evolution through Chinese history.

4.1. *Evolutionary Trend of Pattern Complexity*

The analysis of fractal dimension (FD) across the twelve historical periods reveals a distinct evolutionary trajectory of pattern complexity. As shown in Figure 2, there is a clear and statistically significant trend of increasing complexity over time. The mean fractal dimension is relatively low in early Neolithic samples, such as the Yangshao period, where the reported mean value is approximately 1.21. This pattern is consistent with the visual characteristics of early geometric decoration, which tends to rely on simpler lines, repeated shapes, and less densely filled surfaces.

In later historical periods, the mean fractal dimension increases, suggesting more complex spatial organization in ceramic decoration. The Tang and Song periods show higher values, with the reported peak approaching approximately 1.55. Later imperial periods, including the Yuan, Ming, and Qing dynasties, appear to maintain relatively high levels of decorative complexity.

These results suggest that ceramic decorative patterns became more visually complex over time. However, this trend should be interpreted cautiously because image source, preservation condition, photographic quality, motif type, and sampling strategy may influence the measured values.

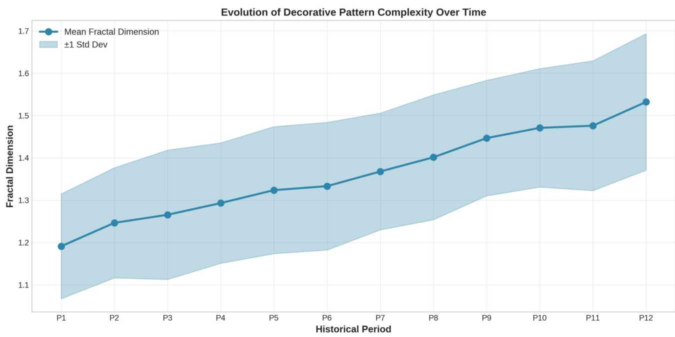

Figure 2. The evolution of mean fractal dimension across twelve historical periods.

4.2. *Correlation Analysis of Aesthetic Features*

To understand the interplay between different formal properties, we conducted a correlation analysis of the key extracted features. The resulting correlation matrix (Figure 3) highlights several significant relationships. Most notably, there is a strong positive correlation between Fractal Dimension and the Black-White Ratio ($r = 0.687$, $p < 0.001$), indicating that more complex patterns tend to be denser and fill more of the available space. This result suggests that patterns with higher fractal dimension also tend to contain greater visual density in the binarized images.

This relationship is plausible because denser decorative patterns usually occupy more of the image space and may therefore produce higher fractal dimension values. Nevertheless, the relationship should not be interpreted as purely aesthetic. It may also reflect technical factors such as motif coverage, image contrast, thresholding effect, and the selected region of interest.

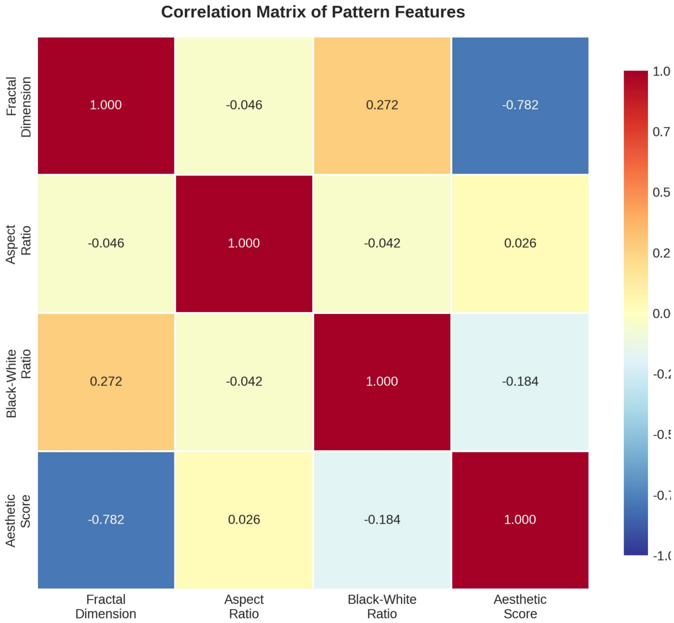

Figure 3. Correlation matrix for the key aesthetic features.

4.3. *Stylistic Clustering of Patterns*

The K-means clustering algorithm successfully partitioned the 1200 patterns into four distinct stylistic clusters based on their fractal dimension and aspect ratio (Figure 4). TThese groups appear to reflect broad differences in pattern complexity and geometric proportion.

One cluster contains patterns with relatively low complexity, which are more frequently associated with earlier ceramic traditions. Another cluster includes patterns with moderate complexity and elongated proportions. A third cluster contains higher-complexity patterns that are more common in later dynastic periods. A fourth cluster includes dense patterns with relatively compact proportions.

These results suggest that computational features can help identify broad formal tendencies in ceramic decoration. However, the clusters should not be treated as definitive historical categories. A more rigorous interpretation would require comparison with expert typological classification and additional cluster validation metrics.

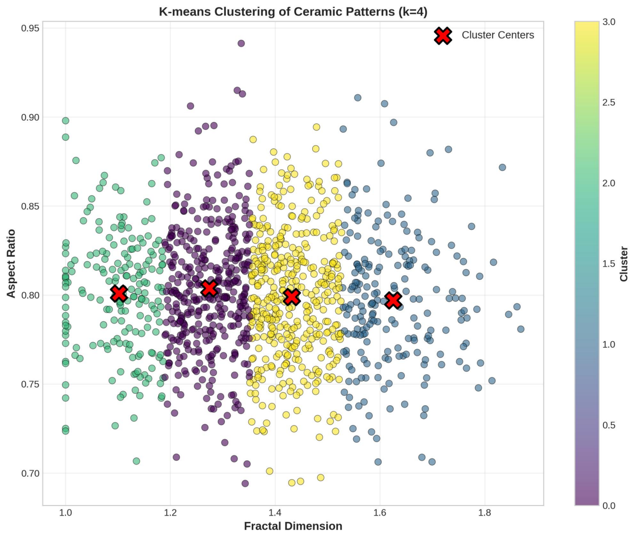

Figure 4. K-means clustering of the 1200 ceramic patterns.

5. Discussion

The results suggest that image-based complexity measures can provide useful support for the study of ancient Chinese ceramic decoration. The observed increase in fractal dimension from earlier to later historical periods is consistent with the general art-historical understanding that ceramic decoration became more technically refined and compositionally dense over time. Early ceramic patterns often emphasize geometric rhythm and symbolic simplicity, whereas later dynastic ceramics frequently display more elaborate surface organization, denser motifs, and more sophisticated ornamental structures.

The positive relationship between fractal dimension and black-white ratio indicates that visual complexity is partly associated with pattern density. This finding supports the use of fractal dimension as a formal descriptor of decorative structure. However, fractal dimension should not be interpreted as a complete measure of artistic value. Ceramic decoration also depends on motif meaning, material technology, color, glaze, vessel form, cultural context, and symbolic function.

The exploratory clustering results show that computational features can separate ceramic patterns into broad groups. These groups may correspond to differences in historical style, compositional structure, or decorative density. Nevertheless, clustering results depend strongly on selected features and algorithmic parameters. For this reason, the clusters should be understood as analytical aids rather than replacements for art-historical classification.

This study also has several limitations. First, the dataset requires clearer documentation of image sources, selection criteria, and image quality. Second, binarization may simplify complex visual features and remove important information related to color, brushwork, glaze, and texture. Third, the analysis focuses on formal complexity and does not fully address iconographic or symbolic meaning. Fourth, the aesthetic interpretation remains limited unless expert scoring procedures are transparently reported and validated.

Despite these limitations, the study demonstrates that computational analysis can offer a reproducible method for comparing ceramic decorative patterns across historical periods. It provides a bridge between quantitative image analysis and qualitative cultural interpretation.

6. Conclusion

This study proposed an exploratory computational framework for analyzing the decorative pattern complexity of ancient Chinese ceramics. By applying grayscale conversion, Otsu thresholding, fractal dimension estimation, black-white ratio calculation, aspect ratio measurement, and K-means clustering, the study examined visual features across a dataset of 1,200 ceramic pattern images from twelve historical periods.

The results suggest that ceramic decorative patterns generally became more visually complex from early Neolithic examples to later dynastic periods. The analysis also indicates a positive relationship between fractal dimension and pattern density, suggesting that fractal dimension can serve as a useful descriptor of formal visual complexity. The clustering results further show that image-based features may help identify broad stylistic tendencies in ceramic decoration.

The contribution of this study lies in its methodological framework rather than in claiming a final explanation of Chinese ceramic aesthetics. The approach provides a reproducible way to support art-historical analysis with quantitative evidence. Future research should improve dataset documentation, include additional visual features, validate clustering results, and integrate iconographic, historical, and semantic information.

References

[1] Medley, M. (1976). The Chinese potter: a practical history of Chinese ceramics. (No Title).

[2] Field, E. (1992). Vainker, SJ 1991. Chinese Pottery and Porcelain: from Prehistory to the Present. Papers from the Institute of Archaeology, 3(1).

[3] Sullivan, M. (2008). The Arts of China, Revised and Expanded. Univ of California Press.

[4] Lei, L., & Shouli, Z. (2019, December). Analysis of the relationship between modeling and decoration in ceramic design. In 2019 International Conference on Economic Management and Cultural Industry (ICEMCI 2019) (pp. 868-871). Atlantis Press.

[5] Liming, G., Hongjie, L., & Wilcock, J. (1989). The analysis of ancient Chinese pottery and porcelain shapes: a study of classical profiles from the Yangshao culture to the Qing dynasty using computerized profile data reduction, cluster analysis and fuzzy boundary discrimination. Computer Applications and quantitative methods in Archaeology, 1989, 363-374.

[6] Zhang, J., & Yang, X. (2023). Exploring the archaeological treasures of the silk road: Tibetan arts and crafts, traditional decorative patterns, and pattern symbols analysis. Mediterranean Archaeology and Archaeometry, 23(2), 197-212.

[7] Yang, Y., Shafi, M., Song, X., & Yang, R. (2018). Preservation of cultural heritage embodied in traditional crafts in the developing countries. A case study of Pakistani handicraft industry. Sustainability, 10(5), 1336.

[8] UNESCO. (n.d.). Traditional craftsmanship. Intangible Cultural Heritage. Retrieved from https://ich.unesco.org/en/traditional-craftsmanship-00057

[9] Fazi, M. B. (2018). Contingent computation: abstraction, experience, and indeterminacy in computational aesthetics. Bloomsbury Publishing USA.

[10] Fazi, M. B., & Fuller, M. (2016). Computational aesthetics. A Companion to Digital Art, 281-296.

[11] Douchová, V. (2015). Birkhoff's aesthetic measure. Acta Universitatis Carolinae Philosophica et Historica, 21(1), 39-53.

[12] Romero, J., Machado, P., Carballal, A., & Correia, J. (2012). Computing aesthetics with image judgement systems. In Computers and creativity (pp. 295-322). Berlin, Heidelberg: Springer Berlin Heidelberg.

[13] Mandelbrot, B. B. (1983). The fractal geometry of nature, Freeman, New York. MandelbrotThe Fractal Geometry of Nature1983.

[14] Brown, C. T., & Witschey, W. R. (2003). The fractal geometry of ancient Maya settlement. Journal of archaeological science, 30(12), 1619-1632.

[15] Ding, M., Zhang, Q., Li, G., Li, W., Chen, F., Wang, Y., ... & Fu, L. (2023). Fractal dimension-based analysis of rockery contour morphological characteristics for Chinese classical gardens south of the Yangtze River. Journal of Asian Architecture and Building Engineering, 22(5), 2490-2505.

[16] Canny, J. (1986). A computational approach to edge detection: IEEE Transactions on Pattern Analysis.

[17] Thangaraj, C., & Easwaramoorthy, D. (2022). Generalized fractal dimensions based comparison analysis of edge detection methods in CT images for estimating the infection of COVID-19 disease. The European Physical Journal Special Topics, 231(18), 3717-3739.

[18] McQueen, J. B. (1967). Some methods of classification and analysis of multivariate observations. In Proc. of 5th Berkeley Symposium on Math. Stat. and Prob. (pp. 281-297).

[19] Arthur, D., & Vassilvitskii, S. (2007, January). k-means++: The advantages of careful seeding. In Soda (Vol. 7, pp. 1027-1035).

[20] Otsu, N. (1975). A threshold selection method from gray-level histograms. Automatica, 11, 285-296.

[21] Andronache, I. (2025). Application of fractal analysis in interpreting 2D and 3D grayscale images: Methodologies and case studies. Journal of the Bulgarian Geographical Society, 52, 157-182.

[22] Toennies, K. D., & Schnabel, J. A. (1994, June). Edge detection using the local fractal dimension. In Proceedings of IEEE Symposium on Computer-Based Medical Systems (CBMS) (pp. 34-39). IEEE.

[23] Heidegger, M. (1963). The origin of the work of art (pp. 44-47). University of Waterloo.

[24] Zangwill, N. (2001). The metaphysics of beauty. Cornell University Press.

[25] Pia, G., Casnedi, L., Ricciu, R., Besalduch, L. A., Cocco, O., Murru, A., ... & Sanna, U. (2016). Thermal properties of porous stones in cultural heritage: Experimental findings and predictions using an intermingled fractal units model. Energy and Buildings, 118, 232-239.

[26] Farías-Pelayo, S. (2017). Characterization of cultural traits by means of fractal analysis. In Fractal Analysis-Applications in Health Sciences and Social Sciences. IntechOpen.

[27] Połeć, W., & Murawska, D. (2021). The social constraints on the preservation and sustainable development of traditional crafts in a developed society. Sustainability, 14(1), 120.

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Availability of Data

Not applicable.

Ethical Statement

All participants provided written informed consent prior to participation. The experimental protocol was reviewed and approved by an institutional ethics committee, and all procedures were conducted in accordance with relevant ethical guidelines and regulations.

Author Contributions

Ali Ahmad Noori conceived and supervised the study, designed the computational framework for ceramic pattern analysis, and led the interpretation of the fractal and stylistic evolution results, while Baitullah Bareer conducted the dataset collection, image preprocessing, feature extraction, clustering analysis, statistical evaluation, and contributed to manuscript preparation and visualization of the computational findings.

COMPETING INTERESTS

The authors declare no competing interests.

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