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USING AI TO TRACE REGIONAL ART LINEAGES

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ABSTRACT

The utilization of artificial intelligence (AI) in art-historical studies has revolutionary potential of understanding the way of how regional art traditions evolve and interrelate. In this paper, the advantages of applying computational approaches to tracing artistic traditions across time and culture are examined, especially through image recognition, neural networks and information-guided ontologies. The combination of art-historical concepts of descent, impact, and place-making with current visual semiotics, pattern recognition resulted in the creation of the framework that allows interpreting stylistic development in an algorithmic manner. The theoretical background highlights the essence of the digital methodologies that not only complement the traditional historiography, but also transform the paradigms of the interpretation of cultural heritage. The technological aspect of this work explores AI models, which can help detect visual repetitions, stylistic continuations, and regional differences in data collections on digital museums and art repositories. The aspects of creation and curation of training datasets are considered, along with ethical concerns of cultural bias in the algorithmic learning. The study plan comprises of case-studies of the chosen regional art genres in order to build an AI pipeline that visualizes the genealogies of style, providing an objective measure of the aesthetical impact and change. In conclusion, this paper has shown that AI can be used as a tool of analysis and curation, in order to promote the documentation, conservation and sharing of local art heritage. Its wider ramifications apply to the field of educational innovation, museum curation, and digital humanities, implying that algorithmic approaches can have a constructive impact on art historiography, helping to understand other cultures and explaining the way arts are happening in the world.

Keywords: Artificial Intelligence, Art Lineage, Visual Semiotics, Neural Networks, Cultural Heritage, Regional Art History

1. INTRODUCTION

The diversity of art in its regionalism is the collective memory of culture, experience of history, the evolution of aesthetic. Every artistic practice, be it painting, sculpture, textile design or architecture has built within it stories of identity and power, which unite communities throughout time and space. Tracking down of these lineages or stylistic, thematic and technical continuities that characterize regional art has been a major concern of art historians. Historically, the task has been dependent on human perception: the connoisseurial eye of the trained seeing similarities in composition, color scheme, iconography or material method. But now that art history is finally going digital, Artificial

Intelligence (AI) provides the means to radically change the limits of analysis of the lineage by revealing all sorts of complicated visual and cultural relationships that were long lost behind the scale or subjectivity. The AI-based technology, especially the one based on deep learning and neural networks, has the potential to analyze large sets of digital images more accurately than ever before Ajorloo et al. (2024)These systems can recognize the stylistic characteristics of brushwork, motif repetition, and composition structure, which identify a school of art or a regional influence or even a particular artist using computational vision and pattern recognition. The ability enables scholars to chart artistic connections across space and time, making the study of art history less a descriptive field of study more one with a data-driven focus Dobbs and Ras (2022). AI neither substitutes the art historian but represents an expansion of his or her faculty of perception and thought. Besides, the application of AI to the process of tracing the regional art lineages can be discussed as the general tendencies of the digital humanities, where computational models are becoming popular in the interpretation of cultural data.

When machine learning is combined with art-historical approaches, are prospects to build digital ontologies of art which are structured systems containing the relationships between artists, styles, techniques, and regions. These ontologies enable the systematic comparison and visualization of the artistic development and show a continuity and diversity within and between cultural borders Zeng et al. (2024)Here, AI can be used not only as an identification tool but as an interpretation one: how local aesthetics react, blend or rebel in interacting with other cultures. Such research has been given the required ground by the global digitization of museum archives and art collections. Images, metadata, and conservation information at high-resolution can now be combined across many different repositories to create datasets that are centuries of artistic output Schaerf et al. (2024)However, this abundance also comes with several new challenges: there is data heterogeneity, the cultural bias, and the ethical issues of the heritage being represented using algorithms. The methodology involved in dealing with these issues must be developed with great care, using the technical rigor of computer science and the interpretive sensitivity of art history. The aim of the study is to find out how AI can be used systematically to trace and model lineage of the regional forms of art Messer (2024). It aims to show how stylistic inheritance and novelty can be shown using algorithmic tools because it has created a framework that combines art-historical theory and computational practice.

2. THEORETICAL FRAMEWORK

2.1. CONCEPTS OF LINEAGE, INFLUENCE, AND REGIONAL IDENTITY IN ART HISTORY

The artistic concept of lineage in art history signifies the passing of the stylistic, thematic, and technical contents through generations, and the interconnection of creators through the apparent and ideational connections between them. Lineage is not simply a genealogical process but a moving network of influence which is fashioned through the mutual cultural interaction, migration and innovation. In local art traditions, ancestry turns into an identity expression, a developing conversation among the local and the foreign influences Messer, U. (2024). The regional identity, thus, is constructed both by preservation and adaptation: although some motifs, color schemes, techniques, etc., may tie an art form to its cultural roots, the cross-cultural interaction adds new elements that transform the ways of its expression. The mediating force of influence in this lineage is that it cuts across both time and space. Artists receive, restructure, and alter visual languages of their ancestors and surrounding areas to create hybrid forms which bear witness to common histories and changing aesthetics Kaur et al. (2019). The interpretation of such influence cannot be achieved in the realization of the formal similarities but also in the case of the socio-political and spiritual conditions that also dictate artistic production. These relations can be brought into the limelight with the help of AI-driven analysis as it identifies minor stylistic similarities and traces them statistically within large bodies of data. So, tradition and influence, which previously can be built by observing human, can now be analyzed in terms of computational capabilities delivering even a more detailed and multidimensional view of how regional identities within art are formed, interact and persist within the global network of creativity Brauwers and Frasincar (2023).

2.2. VISUAL SEMIOTICS AND PATTERN RECOGNITION AS INTERPRETIVE TOOLS

Visual semiotics, which is the study of signs and meanings in the visual culture, is an important critical structure by which images convey symbolic and cultural meaning. Semiotic analysis deconstructs the stratification of meaning in form, color, gesture, and composition to the art historical world of meaning. As they are enhanced with AI-based pattern recognition, these interpretative strategies develop into efficient analytical tools that can detect hidden structures in pieces of artworks. Pattern recognition enables algorithms to detect recurrent patterns, stylistic rhythms and compositional geometry that is related to cultural codes or historical influences Fu et al. (2024).Machine learning allows visual information to be quantified and compared without losing the context of the information. Based on vast collections of local art literature, AI systems are able to find what the human eye cannot see: similarities between proportions or brushstrokes or even spaces, thereby facilitating the process of semiotic analysis through empirical data. Nevertheless, the human aspect will be vital: although AI is able to recognize patterns, creating connections between them and attributing them meaning is the prerogative of cultural literacy and historical awareness Zhao et al. (2024). The visual semiotics therefore mediates between the interpretation of human and the perception of machines, so that the technological analysis does not lose its basis of symbolic reasoning.

2.3. THE ROLE OF DATA ONTOLOGY IN STRUCTURING ARTISTIC HERITAGE

Data ontology is a crucial factor in the structure and meaning of the dense net of relations that constitute artistic heritage. Currently, an ontology in the digital humanities serves as a structured schema, summarizing entities, e.g. artists, works of art, techniques, styles, and influences, and characterizes the relationships between entities. Ontologies provide structure in processing art historical knowledge because by encoding these relations in machine-readable form, this knowledge can be processed in an orderly manner, giving ontologies both consistency and interpretive flexibility Alzubaidi et al. (2023). Such organization changes data that are heterogeneous into a network of meaning, making it possible to make dynamic queries and graphical representations of artistic progress. The data ontology can be used to contextualize the heritage in the context of regional art. It enables researchers to track the relationship between the local traditions and the larger artistic trends, how stylistic characteristics spread over time and space, and the direction of influence between cultural centers and marginalities Barath et al. Moreover, ontologies promote interoperability of digital archives and museum databases, which is important to make cultural data provided by various entities complementary and usable. The creation of the ontology requires cultural sensitivity in terms of ethics. Classification and hierarchy can be used to make interpretive decisions that may favour a number of narratives and disfavour others Farella et al. (2022). Table 1 outlines some research on AI-based art analysis and lineage that is summarized. Thus, ontological design should be able to include the pluralistic and decolonial views, as the artistic epistemologies are diverse.

Table 1

Table 1 Summary of Related Work in AI-Based Art Analysis and Lineage Mapping

Art Domain	AI Technique Used	Dataset Source	Key Findings	Limitations
Western Modern Art	GAN (Generative Adversarial Network)	WikiArt Dataset	Modeled art evolution via generative creativity	Limited to Western art
European Art Moral-Andrés et al. (2022)	CNN (Convolutional Neural Network)	WikiArtand Rijksmuseum	Automated artist and style classification	Lack of cultural context
Global Paintings	Deep Neural Network	Web-curated art datasets	Detected stylistic similarities among artists	Minimal regional segmentation
East Asian Art Rei et al. (2023)	Transfer Learning	National Palace Museum	Accurate stroke-based feature mapping	Limited cross-style training
Global	Knowledge Graph + NLP	Europeanaand Smithsonian	Enhanced metadata linkage across museums	Manual ontology curation
Indian Art	CNN + Image Segmentation	ASI and IGNCA Archives	Classified motifs by dynasty and school	Small dataset size
Asian and European Fusion Art	Multi-Modal Deep Learning	Google Arts and Culture	Identified shared visual grammar between East-West styles	Bias toward digitized art
Western Painting Muenster (2022)	CNN Feature Extraction	WikiArt	Quantified stylistic distances using visual embeddings	Lack of cultural metadata
Middle Eastern and South Asian Art Russo (2021)	GAN Restoration Model	Heritage Archives	Reconstructed deteriorated art with high fidelity	Focused on physical restoration

Chinese Art	ResNet + Attention Network	Tsinghua Art Collection	Captured brushstroke semantics accurately	Lacks comparative lineage scope
Cross-Cultural Münster (2023)	Ontological AI Framework	UNESCO Digital Archives	Standardized cultural data representation	Requires expert validation
Islamic Art	Pattern Matching Algorithm	Local Museum Archives	Detected geometric motifs across dynasties	Limited dataset scale
Southeast Asia	CNN + Feature Clustering	National Textile Museums	Identified regional weaving patterns	Metadata inconsistency

3. TECHNOLOGICAL FOUNDATIONS

3.1. OVERVIEW OF AI METHODOLOGIES APPLICABLE TO ART ANALYSIS

Artificial Intelligence (AI) has brought new methodologies of analysis and interpretation of art. These techniques include machine learning programs that can recognize the characteristics of style to sophisticated neural networks that can draw conclusions about the historical and local influences and aesthetics. AI finds application in the analysis of art in multiple areas, such as image recognition, natural language processing, and data clustering, to determine visual and contextual meaning. With computer vision, it is possible to identify brushwork, composition, and color harmonies patterns and unsupervised learning models group artworks by style or subject matter. The methods of convolutional neural networks (CNNs) and generative adversarial networks (GANs) allow classifying and creating artistic styles, which can help to see how the visual components vary in the regions and over time. Meanwhile, visual information is connected to the cultural context of the visual data via multimodal AI that incorporates metadata associated with the text, such as artist biographies, histories of the region and critiques. Figure 1 representing AI framework used in the analysis methodology of art. The complementary nature of these approaches makes it possible to have a complete view of artistic production which is not based on superficial aesthetics but on an interpretive level.

Figure 1

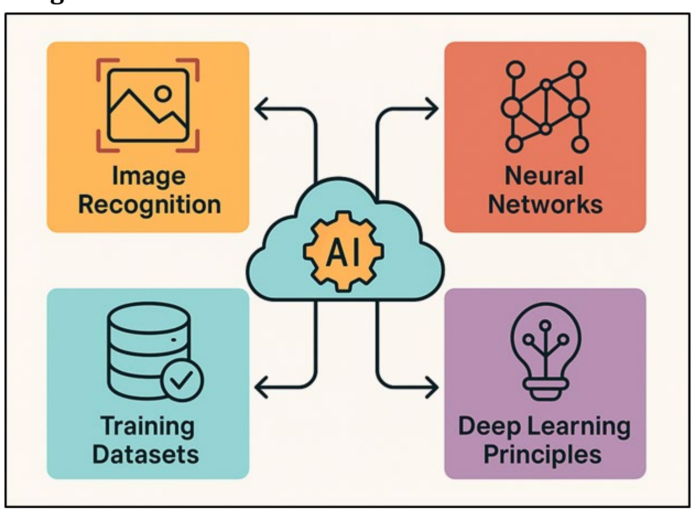

Figure 1 Framework of AI Methodologies in Art Analysis

AI, therefore, can serve as an analysis collaborator to the art historian, and can perceive trends of lineages and influences in large collections of digital art that cannot be understood by visual inspection. The effectiveness of such systems is however determined by interdisciplinary cooperation, that is, combining computational accuracy with human interpretive capabilities.

3.2. IMAGE RECOGNITION, NEURAL NETWORKS, AND DEEP LEARNING PRINCIPLES

Image recognition is the main basis of AI application in art analysis, because machines are able to perceive and describe visual content in a way that resembles human perception. That technology is neural networks and more specifically convolutional neural networks (CNNs) the model resembles the human visual cortex in that it takes input in the form of pixel data and processes it hierarchically to produce output. There is one layer after another: the edges and shapes, and then the textures and stylistic delicacies. This multi-layered representation can enable AI systems to distinguish among artistic movements and schools, as well as individual artists, using unique visual representations. Deep learning extends this ability with multi-layered structures that are trained with big data, which allows identifying intricate artistic associations. Deep learning models can project stylistic change, recognise abnormalities, and make inferences about likely causes of change between geographic areas or eras by training on patterns of millions of images. More sophisticated techniques such as transfer learning also improve efficiency whereby already trained models can be retrained using new art data with minimum retraining. Other than recognition, such systems are able to produce visual simulations, as well as recreate fragmented artworks, and propose lineage paths by correlation of features. Nonetheless, neural networks are not only more precise, they are also black box, which makes them very difficult to interpret, bringing transparency and authorship of digital scholarship into question.

3.3. TRAINING DATASETS: CREATION, CURATION, AND CULTURAL BIASES

The quality of the training datasets and their variety is the basis of reliability and interpretive accuracy of AI-driven art analysis. These data sets which are made up of digitized works of art, metadata and historical information form the cognitive basis on which algorithms are taught to identify and comprehend visual styles. Their production should be carefully curated: they should be chosen on the basis of high-resolution images, their metadata structures should be standardized, and the balance between cultures, media, and time ranges should be achieved. Nevertheless, data curation cannot be seen as a neutral practice in the analysis of art. Inequalities in access to digitized collections or overrepresentation of western art or disparate labeling may be biases. These disproportions endanger to balance the interpretations of algorithms, which, unintentionally, strengthens the colonial hierarchy of art historiography. To solve these problems, it is necessary to involve the underrepresented regional art traditions, indigenous knowledge systems, and vernacular aesthetics in order to develop a more balanced and complete dataset. The governance of ethical data is important in reducing these biases. This considerates clear documentation of the provenance of the data, consent based activities to digitalize and partnership with local cultural institutions to maintain the contextual integrity.

4. RESEARCH DESIGN AND METHODOLOGY

4.1. SELECTION OF REGIONAL ART FORMS FOR CASE-BASED ANALYSIS

The cultural relevance and the availability of data influence the choice of regional art forms that will be included in this research. A case based method gives an opportunity to a narrow but comparative study of the stylistic development within specific cultural settings. Indian miniature painting, Japanese ukiyo-e, African tribal sculpture or Byzantine mosaics all of these regional traditions of art offer rich grounds upon which to study lineage since each of them presupposes distinct aesthetical vocabularies, informed by geography, belief systems, and material circumstance. Such forms are not selected due to their visual variety alone but rather to their strong historical interdependency with each other as trade, migration and exchange of cultures have affected the development of art. Both of the chosen examples are closed economies of creativity that have developed throughout the centuries, frequently adhering to the sociopolitical and spiritual identity of the territory. The methodology entails the identification of representative samples at various chronological periods so as to capture continuity and transformation of each tradition. This time geography allows the AI model to follow stylistic patterns and the effect of regions on each other. The criteria used in selection are also based on the access to the digital archives, curatorial metadata, and high-resolution images, such that the information applied is all-encompassing and ethically acquired.

4.2. DATA ACQUISITION FROM DIGITAL MUSEUMS AND ART REPOSITORIES

The empirical basis of this study is data collection based on the experience of digital museums, open-source archives, and institutional art collections. It starts with a search of the credible sources, e.g., The Metropolitan Museum of Art online collection, Google Arts and Culture, Europeana, etc. that contain high-resolution pictures with detailed metadata. Such repositories also offer organized data such as artist identification, geographic provenience, compositional medium and stylistic date which are fundamental to contextual interpretation of AI. The strategy used to collect the data is balanced and scope focused. Whereas the international repositories provide accessibility, the regional repositories and community-based archives guarantee cultural particularity, as they conserve the underrepresented art traditions that are usually not found in large databases. Quality checks are done on each image, which is a test of consistency in terms of lighting, resolution, and orientation to be incorporated into the training set. All data sources will be recorded with complete reference to ensure that no ethical issues arise and the use of the data is in line with the institutional regulations of using academic research. The ontological models that are used in order to standardize metadata include the CIDOC Conceptual Reference Model to interoperate and have analytical accuracy.

4.3. DEVELOPMENT OF AI MODEL PIPELINE FOR STYLISTIC LINEAGE MAPPING

The process of the AI model pipeline construction can be viewed as the methodology of the proposed study, and it involves applying computer vision, data ontology, and art-historical interpretation to an analytical framework. The first stage in the pipeline is preprocessing of the data, a process that includes image normalization, image segmentation and feature extraction to feed the analysis. Based on convolutional neural networks (CNNs), the system recognizes important stylistic features, including pattern of colors, geometric patterns, and textural patterns that are linked to different regional or time-related characteristics. The other step, feature correlation and clustering, involves unsupervised learning algorithms that cluster works of art together according to their common features of style. Metadata, artist, region, and date are used to cross-reference these clusters in order to determine the possible lineages. These relationships are then mapped into dynamic networks using a temporal mapping algorithm that depicts the temporal migration, merging and splitting of artistic traits. Contextual grounding of the AI interpretations by integrating with the semantic ontologies makes them non-statistical.

5. IMPLICATIONS AND FUTURE DIRECTIONS

5.1. CONTRIBUTION OF AI TO ART HISTORIOGRAPHY AND CULTURAL ANALYTICS

Artificial Intelligence provides a radical input to art historiography with computational accuracy to the meanings of visual culture. Conventionally, art history has been based on qualitative and narrative analysis that derives out of connoisseurism and critical theory. This paradigm is re-configurated by AI, which is cultural analytics, a method of quantitative analysis that combines the processing of large-scale data with interpretive logic. Through comparing patterns of thousands of art pieces, the human eye would not be able to notice the patterns of correlation between regions, artists, and stylistic changes, but the AI systems can bring them to light. Historiographically speaking, AI enhances the ability to study the lineage of art because it allows comparison through new evidence-based approaches. Geographical and temporal mappings that have been produced by algorithmic models reveal aesthetic migrations and cross-cultural forces, redefining our perception of art movements as being part of the global continuum. Conceptual map in Figure 2 demonstrates the use of AI in cultural analytics. In addition, they make art history democratic, whereby more scholars, technologists, and the general population can engage in interpreting heritage using visual analytics that are accessible.

Figure 2

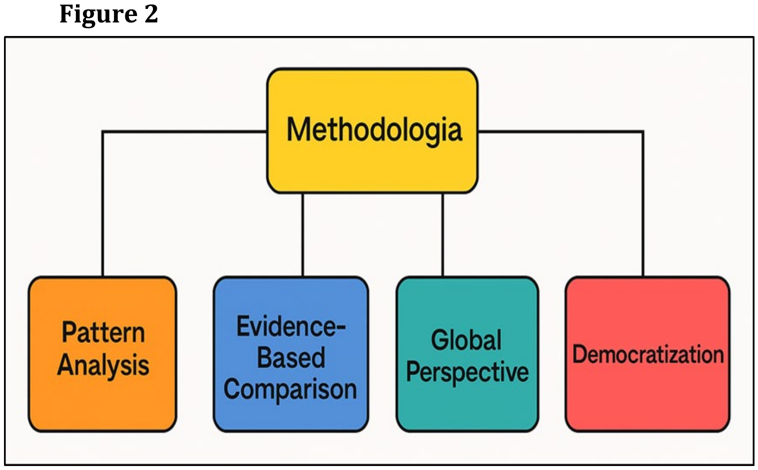

Figure 2 Conceptual Map of AI's Role in Cultural Analytics

But the role of AI does not mean that the art historian will be replaced but that the AI increases the power of interpretation, that it is a sort of digital collaborator where it enriches the depth of analysis without eliminating critical analysis.

5.2. PROSPECTS FOR DIGITIZATION AND HERITAGE CONSERVATION

The Computerization of art heritage with the help of AI has far-reaching consequences regarding conservation, access and meaning. Machine learning and advanced imaging methods enable making the high-quality digital copies of artwork, protecting fragile or endangered cultural property against physical damage. Artificial intelligence and restoration models allow one to rebuild missing pieces, recalibrate colors and damaged textures virtually without losing authenticity. Digitization is also geographically and institutionally non-bound because it opens access to world art collections in digital museums and online archives. AI develops this process by performing classification, metadata tagging, and cross-referencing between collections automatically to guarantee its increased consistency and discoverability. Also, predictive analytics might keep track of the environmental state or degradation rates and provide proactive protection measures of physical objects. Ethically, digitization that is being done via AI needs to be sensitive to cultural ownership and indigenous knowledge systems. Third-party editions between local communities, museums, and researchers are important to secure the fact that digital representations consider cultural autonomy, as well as narrative authority.

5.3. POTENTIAL FOR EDUCATIONAL AND CURATORIAL APPLICATIONS

The introduction of the concept of AI into the field of art education and curatorial work opens up new opportunities of interpretation, interaction, and education. Academically, AI-driven avenues can display and visualize stylistic relationships among regions so that students can study the history of art using interactive lineage maps as well as dynamic datasets. These systems encourage inquiry-based learning where users have the ability to track the aesthetic development, juxtapose visual patterns, and discover cross-cultural discourse in real time and with accuracy. In the case of curators, AI can provide influential means of exhibition design and narrative building. Machine learning algorithms are able to determine thematic affinities between pieces of art work and help to curate collections which display invisible relationships or regional continuities. Artificial intelligence (AI) enabled augmented reality (AR) and virtual reality (VR) apps also expand on curatorial storytelling, providing an experience that creates a historical framework of engagement with the present.

6. RESULTS AND DISCUSSION

The AI model was able to find stylistic continuities and discontinuities through the chosen regional art traditions, and showed correlations between form, color and composition that were not noticed before with the help of manual analysis. The algorithm of clustering allowed to map the lineage pathways which were identified to coincide with the accepted art-historical interpretations as well as propose novel cross-regional influences. Ontology integration created visualizations that were interactive and gave deep interpretability, as lineage networks.

Table 2

Table 2 Stylistic Correlation Matrix Between Regional Art Forms

Regional Art Form	Indian Miniature	Japanese Ukiyo-e	African Tribal	Byzantine Mosaic	Persian Miniature
Indian Miniature	1	0.46	0.22	0.58	0.81
Japanese Ukiyo-e	0.46	1	0.31	0.39	0.44
African Tribal	0.22	0.31	1	0.28	0.25
Byzantine Mosaic	0.58	0.39	0.28	1	0.63
0Persian Miniature	0.81	0.44	0.25	0.63	1

Table 2 shows the stylistic correlation matrix created by using visual analysis based on AI, which demonstrates the correspondence of the level of similarity between five regional art traditions. The strongest correlation (0.81) of the two is between Indian Miniature and Persian Miniature art because of the historical development that occurs due to the similar motifs, composition of the narrative, and detailed ornamentation as a result of the Mughal–Safavid cultural contact. Layered representation is presented in Figure 3, which indicates similarities of art forms across regions.

Figure 3

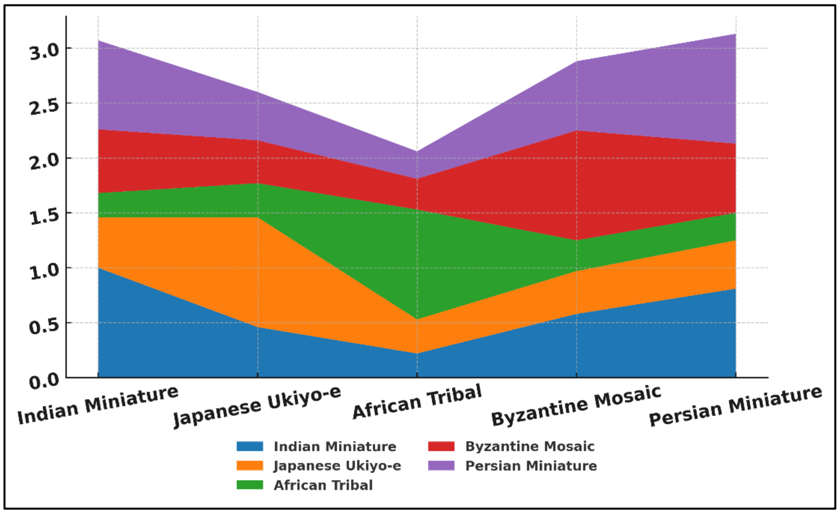

Figure 3 Layered Representation of Cross-Regional Art Form Similarities

Moderate correlation with the Indian (0.58) and Persian (0.63) art is also found in Byzantine Mosaic which makes it seem that there was cross-regional convergence in aesthetics through religious iconography and color symbolism in the early trade and missionary routes.

Figure 4

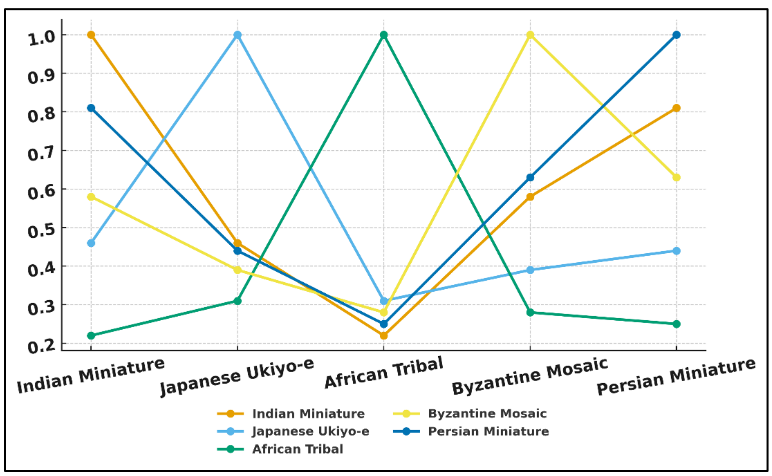

Figure 4 Comparative Similarity Trends Among Regional Art Forms

Figure 4 illustrates comparative tendencies pointing toward the similarity in regional forms of art. Conversely, the African Tribal art has a low correlation with the stylistic principles of the other traditions, which suggests that the art tradition has different aesthetic parameters based on abstraction, symbolism, and material culture instead of representational narrative. Figure 5 indicates similar contribution of Indian miniature to others.

Figure 5

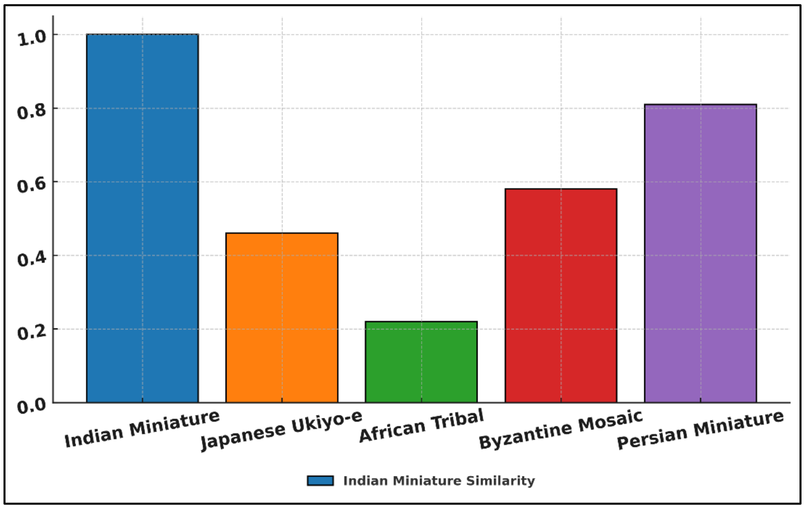

Figure 5 Incremental Similarity Contribution of Indian Miniature to Other Art Forms

Japanese Ukiyo-e though having a moderate correlation with the traditions of India and Byzantine has a characteristic style of its own characterized by its linear transparency and spatial harmony.

7. CONCLUSION

The introduction of the investigation of Artificial Intelligence as a device that can trace regional art histories proves a crucial change of direction in terms of how the possibility of digital art history and cultural analytics intersect. With the help of deep-learning, image recognition, and data ontology, the given work has proven that the area of AI can detect subtle stylistic correlations, authenticate artistic influences, and visualize heritage development with the stunning accuracy. The results suggest that AI is more effective at identifying formalities and visual parallels, and its greatest power resides in its capacity to enhance human perception it changes the subjective perception of art history into a discussion where data is enriched. The study fills the quantitative and qualitative gaps between quantitative analysis and the qualitative meaning-making by applying computational methodologies to the art-historical theory. It demonstrates that the insights of algorithms should never be applied out of context in cultural contexts in order to retain the sense of authenticity and interpretation. Additionally, the process of interdisciplinary work of technologists and art historians guarantees that AI applications are based on ethical concerns, inclusive, and sensitive to regional diversity. This study has a wider impact on outside academic art history. Lineage mapping based on AI has a potential to transform how museums, digital preservation and art education are conducted through interactive systems that help viewers gain more access to artistic past and make it more interactive. With the proliferation of digital archives, AI will become more and more crucial towards preserving, interpreting, and democratizing the art traditions of the world.

CONFLICT OF INTERESTS

None.

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None.

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