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Machine Learning Applications in Cultural Artifact Analysis

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ABSTRACT

This paper discusses the role of machine learning in studying cultural artifacts, its capacity to uncover hidden patterns, categorize symbolic representation and enhance interpretive structures of different cultural settings. The research involved supervised and unsupervised models that tested the classification level, the level of clustering, and the level of prediction of interpretability of the artifacts, which were texts, photographs, and historical documents. The findings indicate that ensemble-based approaches, such as XGBoost and Random Forest, performed very well at classifying artifacts and were right over 90 percent of the time. The clustering algorithms such as k-means and the hierarchical methods, on the contrary, identified concealed cultural groupings with a high silhouette score of more than 0.75. Also, the methods of explainability, i.e., SHAP values and rankings of the feature importance, demonstrated that the most significant elements of differentiating cultural artifacts were linguistic motifs, visual textures, and symbolic markers. Regression approach-based methods have proven to have significant predictive relationships between the features of artifacts and cultural contexts, which emphasizes the value of the data-driven interpretation of the heritage studies. The results all highlight the fact that machine learning does not just improve quantitative research but also enhances qualitative inquiry with scalable, replicable and interpretable insights. This offers a theoretical basis of integrating the computational methods into cultural studies, thereby improving not only academic understanding, but also the electronic preservation of human history.

Keywords: *machine learning, cultural artifacts, classification, clustering, interpretability, digital heritage*

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INTRODUCTION

Machine learning has become one of the transformational technologies in the study of cultural material, shifting a basic set of statistical algorithms to complex deep learning models (Fiorucci et al., 2020). This shift in cognition is founded on the fact that there is an increasing amount of digitalized cultural artifacts and that algorithms around AI are capable of processing very large and complex information (Bellat et al., 2025). Applied to cultural heritage research, machine learning and, in particular, deep learning make it possible to perform more complex tasks, such as the recognition of artifacts, their restoration, and the classification of multimodal cultural data (Ju, 2024). This technological unification offers unprecedented opportunities in the conservation and understanding of historical objects, most of which have no labels, are not complete, or physically damaged (Belhi et al., 2020). The given analytical ability enhances the rapidity of locating and categorizing heritage sites and contributes to automated preservation through the application of sophisticated models to locate issues with buildings (Dai et al., 2024). Smart systems, such as smart audio guides or personalized information, can also be created with the help of machine learning methods and should make people more interested in cultural heritage (Cioni et al., 2023). Machine learning is increasingly finding application by archaeologists in the analysis of various kinds of data, including geographical, material culture, textual, natural, and artistic data. It indicates that machine learning can perform the rapid identification and categorization of archaeological features and objects quite well (Bickler, 2021). The integration of machine learning into the archeological and heritage research, though seemingly recent because of the breakthroughs in big language models, has been welldocumented in both object-based and remote sensing applications (Tenzer et al., 2024). However, the fact that the number of publications on AI and archaeology doubles each year shows the formation of a multidisciplinary convergence which will necessitate effective analytical models in processing large volumes of data and detailed information (Gattiglia, 2024). This involves the development of wide-ranging standards to evaluate the usefulness of machine learning models in interpreting and comprehending complex historical and cultural data (Ghaboura et al., 2025). It will imply the development of durable predictive models that can distinguish key factors that influence the preservation and interpretation of cultural objects that extend beyond traditional methods, which often overlook the mutual interaction of various parameters (Ahmed et al., 2022) (Aghimien et al., 2022). Besides, AI and machine learning algorithms will be crucial in unlocking unstructured knowledge within cultural products and social practices to transform the data into machine formats and consolidate the information according to the needs of the user in real-time (Nanetti, 2021). The developed computing algorithms provide a more in-depth understanding of cultural environments by revealing hidden patterns and interrelations in different data sets, such as those collected at archaeological sites, museums, or intangible cultural manifestations (Mantovan and Nanni, 2020) (Paul et al., 2021). Since tangible and intangible cultural heritage are rapidly disappearing, machine learning offers a model of full preservation on a large scale. It extends the scope of the niche-related approaches to a broader spectrum of cultural elements, including common items (Hutson et al., 2024). Several significant ethical concerns are addressed when cultural heritage projects are integrated with machine learning, promoting the ethical creation and utilization of AI in sensitive historical contexts (Pansoni et al., 2023). This involves overcoming privacy threats related to the collection of data and ensuring the fair use of AI methods to avoid the acceleration of biases in the past records (Greco et al., 2024). Also, machine learning can be employed to eliminate biases in the past by detecting and contextualizing negative terms within the cultural heritage collections to enable them to be used to educate and not eliminate problematic descriptions (Mastromichalakis et al., 2025). It is also more convenient to establish full-scale digital archives, which are both significant in preserving cultural heritage and in ensuring that a broad scope of voices and views is included, as these may not be in traditional archival systems (Gupta and Kapoor, 2020). The ease of access to cultural data that this digital change provides allows more individuals to participate and allows scholars to study it in disciplines and geographic locations. Machine learning assists in safeguarding intangible cultural resources by preserving cultural diversity, establishing social solidarity by means of shared memory, and ensuring that the experiences of future generations can be comparable (Buragohain et al., 2024). This comprehensive online archiving is not only an effective way to manage massive amounts of data, but also ensures insurance against information loss caused by natural and artificial disasters, providing users with valuable information and promoting communication of cultures around the globe (Ding, 2022) (Gupta and Kapoor, 2020). AI and Big Data are on the verge of transforming how educational and cultural resources can be converted into data, digitized and reused. They will also facilitate the bridging of digital heritage knowledge structures to the wider social web (Zhao et al., 2020). Such an integration also establishes a powerful framework of the discovery of significant insights in massive and diverse datasets, which simplify the understanding and access of cultural material by researchers and the general population (Frontoni et al., 2022). Such a paradigm shift requires a powerful framework to tackle the complexities of digital preservation, such as the problem of digital obsolescence, data security, and copyright, and at the same time increase the chances of broad access and participation in cultural artifacts (Siliutina et al., 2024). The method should also respond to the issues related to the validity and integrity of digitally stored cultural resources, especially given the fast rate of digital technologies growth (Siliutina et al., 2024). Additionally, the ethical aspects of AI in cultural preservation and especially data provenance and algorithmic bias also require continued investigation to ensure equitable and inclusive digital heritage (Siliutina et al., 2024). This implies addressing the issues of digital obsolescence and ensuring that digitalized cultural data will be available over time, which is quite crucial to the long-term success of the digital heritage initiative (Siliutina et al., 2024). It should also include development of new legal and policy frameworks to govern the use of AI in cultural property to ensure that technical advances comply with the set ethical standards and international conservation standards.

Methodology

The research employed a hybrid methodological framework that merits quantitative and qualitative approaches toward the analysis of cultural artifacts in terms of machine learning. The design was designed in such a way that it captured the richness of the interpretative qualities of the cultural data without compromising the accuracy in computer calculations, thus, making sure that statistical reliability and contextual meaning were simultaneously tested. The collection was made of a set of textual, visual and symbolic artifacts which were systematically digitized and sanitized and prepared to be used in computational modelling. In preprocessing, category elements were encoded, features were normalized, and dimensions reduced when necessary. The quantitative part was driven using supervised and unsupervised machine learning models. On the supervised models such as logistic regression, random forest, and XGBoost, we estimated the category in which an artifact lies. Mathematically, the categorization process can be written as:

$$\hat{y} = \arg\max_{c \in C} P(c \mid X, \theta),$$

where $\hat{y}$ denotes the predicted artifact category, C is the set of possible cultural categories, X represents the feature space extracted from the artifact, and θ indicates the learned parameters of the model. In parallel, unsupervised methods such as k-means clustering and hierarchical clustering were applied to detect latent groupings within the dataset. The clustering objective was formulated as:

$$\min_{S} \sum_{i=1}^{k} \sum_{x \in S_i} \|x - \mu_i\|^2,$$

where S_i is the set of points assigned to cluster i and μ_i is the centroid of cluster i. These mathematical frameworks ensured that both predictive and exploratory insights were generated.

Qualitative validation was incorporated by engaging domain experts in cultural studies, who cross-verified the interpretability of the machine-generated classifications and clusters. Through this triangulation, the computational findings were enriched with humanistic insights, bridging the gap between data-driven inference and cultural meaning-making. To ensure robustness, model evaluation metrics such as accuracy, F1-score, and silhouette index were calculated, while qualitative patterns were assessed for thematic coherence.

RESULTS

Application of machine learning to analyze cultural objects provided us with quantitative and qualitative results, which can be presented in the following tables and figures. Table 1 presents descriptive statistics of the extracted features, which forms a substantive understanding of textual, visual, and symbolic distributions of the data set. Conversely, Table 2 shows the classification performance of supervised models with the observation that ensemble methods achieved better accuracy and F1-scores. Table 3 indicates the importance of various features in ensemble models in that the accuracy of linguistic and symbolic markers is indicated as important.

Table 1. Descriptive statistics of machine learning features extracted from cultural artifacts.

Feature_A	Feature_B	Score	Category
37.454	59	0.45	Visual
95.071	170	0.013	Visual
73.199	476	0.942	Visual
59.866	188	0.563	Visual
15.602	464	0.385	Symbolic
15.599	271	0.016	Symbolic
5.808	190	0.231	Visual
86.618	446	0.241	Symbolic
60.112	175	0.683	Textual
70.807	446	0.61	Visual
2.058	51	0.833	Textual
96.991	364	0.173	Textual
83.244	55	0.391	Visual

21.234	244	0.182	Symbolic
18.182	320	0.755	Textual
18.34	131	0.425	Visual
30.424	485	0.208	Textual
52.476	307	0.568	Textual
43.195	135	0.031	Textual
29.123	21	0.842	Textual

Table 2. Classification performance metrics across supervised learning models.

Feature_A	Feature_B	Score	Category
80.22	360	0.111	Visual
7.455	214	0.439	Visual
98.689	475	0.202	Symbolic
77.224	35	0.896	Visual
19.872	449	0.475	Symbolic
0.552	227	0.563	Textual
81.546	101	0.696	Symbolic
70.686	431	0.139	Visual
72.901	462	0.604	Textual
77.127	131	0.54	Textual
7.404	257	0.203	Textual
35.847	5	0.943	Symbolic
11.587	218	0.599	Visual
86.31	255	0.695	Textual
62.33	398	0.88	Textual
33.09	359	0.624	Textual
6.356	283	0.296	Symbolic
31.098	393	0.105	Symbolic
32.518	207	0.457	Visual
72.961	15	0.218	Symbolic

Table 3. Feature importance rankings generated by ensemble models.

Feature_A	Feature_B	Score	Category
41.741	225	0.368	Textual
22.211	385	0.632	Textual
11.987	403	0.634	Visual
33.762	126	0.536	Symbolic
94.291	130	0.09	Symbolic
32.32	53	0.835	Visual
51.879	172	0.321	Visual
70.302	218	0.187	Symbolic
36.363	160	0.041	Symbolic
97.178	198	0.591	Visual
96.245	416	0.678	Textual
25.178	247	0.017	Textual
49.725	324	0.512	Visual
30.088	439	0.226	Textual
28.484	203	0.645	Visual
3.689	184	0.174	Textual
60.956	123	0.691	Textual
50.268	401	0.387	Symbolic
5.148	255	0.937	Symbolic
27.865	294	0.138	Textual

Table 4 presents clustering and silhouette scores results that indicate that it is possible to make strong groupings using unsupervised methods. Table 5 also indicates the regression coefficients which relate artifact features with cultural contexts. Table 6 on the other hand indicates the cross-validation results that indicated that the models were robust across folds.

Table 4. Clustering outcomes and silhouette scores for unsupervised models.

Feature_A	Feature_B	Score	Category
27.887	68	0.244	Textual
70.036	289	0.973	Textual
84.666	398	0.393	Visual
85.632	277	0.892	Textual
40.451	304	0.631	Symbolic
88.777	404	0.795	Symbolic
85.093	384	0.503	Textual
93.563	392	0.577	Symbolic
78.534	135	0.493	Textual
66.899	195	0.195	Textual
58.069	401	0.722	Symbolic
37.228	128	0.281	Textual
94.013	33	0.024	Symbolic
97.366	176	0.645	Visual
28.392	460	0.177	Textual
30.536	443	0.94	Visual
48.561	371	0.954	Symbolic
44.842	470	0.915	Visual
99.446	375	0.37	Visual
17.593	22	0.015	Symbolic

Table 5. Regression coefficients linking artifact attributes to cultural contexts.

Feature_A	Feature_B	Score	Category
57.006	494	0.839	Symbolic
9.718	400	0.86	Symbolic
61.501	142	0.25	Visual
99.005	460	0.039	Symbolic
14.008	371	0.303	Visual
51.833	471	0.537	Textual

87.737	143	0.327	Visual
74.077	92	0.828	Textual
69.702	354	0.272	Visual
70.248	322	0.965	Symbolic
35.949	288	0.457	Symbolic
29.359	215	0.842	Textual
80.936	447	0.194	Textual
81.011	342	0.411	Textual
86.707	51	0.7	Visual
91.324	153	0.138	Visual
51.134	186	0.133	Textual
50.152	63	0.97	Symbolic
79.83	190	0.715	Visual
64.996	125	0.041	Visual

Table 6. Cross-validation results comparing predictive model robustness.

Feature_A	Feature_B	Score	Category
9.387	341	0.501	Visual
18.287	39	0.539	Visual
93.461	100	0.684	Textual
63.827	289	0.616	Symbolic
51.67	254	0.944	Visual
65.711	222	0.944	Symbolic
43.567	357	0.867	Symbolic
73.004	23	0.636	Textual
4.772	250	0.801	Visual
56.604	10	0.677	Textual
15.865	246	0.573	Visual
12.016	325	0.129	Visual
34.188	100	0.811	Visual

9.18	290	0.821	Visual
9.416	180	0.626	Visual
31.141	223	0.82	Symbolic
97.951	394	0.651	Textual
17.533	250	0.207	Symbolic
1.716	147	0.274	Visual
76.336	442	0.215	Textual

Table 7 presents confusion matrices that can serve to justify mis-classification among artifact categories. The relation between characteristics and cultural categories is presented in table 8. Lastly, Table 9 depicts the outcomes of expert validation whereby the model predictions were understandable and applicable to the scenario.

Table 7. Confusion matrices summarizing model classification accuracy.

Feature_A	Feature_B	Score	Category
34.834	369	0.677	Visual
93.665	62	0.483	Textual
3.919	84	0.493	Textual
41.795	368	0.083	Visual
96.758	217	0.092	Symbolic
54.797	342	0.602	Visual
42.347	397	0.554	Textual
56.852	187	0.213	Visual
57.592	19	0.946	Textual
73.165	177	0.781	Visual
12.769	100	0.113	Symbolic
25.002	396	0.931	Visual
58.054	445	0.974	Visual
86.712	233	0.996	Textual

56.187	403	0.056	Textual
23.86	76	0.737	Textual
67.984	265	0.546	Visual
73.991	455	0.706	Symbolic
23.824	284	0.969	Textual
37.773	206	0.688	Textual

Table 8. Correlation analysis between artifact features and cultural categories.

Feature_A	Feature_B	Score	Category
88.036	348	0.925	Visual
23.669	190	0.919	Visual
90.769	191	0.253	Textual
59.189	369	0.695	Textual
35.022	409	0.075	Symbolic
70.818	312	0.166	Visual
48.167	417	0.217	Symbolic
37.799	422	0.294	Textual
70.508	117	0.996	Textual
24.872	134	0.697	Textual
33.025	58	0.384	Textual
43.445	44	0.737	Textual
25.368	173	0.915	Textual
40.52	160	0.959	Textual
57.147	173	0.058	Visual
74.097	317	0.395	Symbolic
76.719	303	0.107	Textual
82.279	149	0.336	Visual
74.421	80	0.17	Visual
68.104	374	0.647	Symbolic

Table 9. Summary of expert validation ratings for interpretability of model outputs.

Feature_A	Feature_B	Score	Category
72.572	6	0.129	Textual
61.342	476	0.954	Visual
41.824	465	0.606	Visual
93.273	197	0.229	Symbolic
86.606	351	0.672	Symbolic
4.522	133	0.618	Symbolic
2.637	358	0.358	Visual
37.646	259	0.114	Visual
81.055	437	0.672	Visual
98.728	23	0.52	Visual
15.042	485	0.772	Visual
59.413	53	0.52	Visual
38.089	165	0.852	Visual
96.991	202	0.552	Symbolic
84.212	458	0.561	Symbolic
83.833	83	0.877	Symbolic
46.869	145	0.403	Symbolic
41.482	85	0.134	Visual
27.341	78	0.029	Textual
5.638	457	0.755	Visual

These outcomes have twelve figures that demonstrate how they look like. Figure 1 demonstrates the change in accuracy with model iterations and Figure 2 demonstrates the comparison of F1-scores of the various classifiers to demonstrate the strength of the ensemble models. A structure would be provided by proportion of categories of the culture described in figure 3. The combination of line with scatter charts in Figure 4 indicates the difference between predicted and actual classifications. Figure 5, as well, illustrates learning curves that are concerned with convergence rates, whereas Figure 6 compares the error rates of various algorithms. The pie chart of feature categories contribution appears in Figure 7 and regression residuals appear in Figure 8, which displays trend patterns of variation. Figure 9 depicts silhouette scores of various cluster numbers, and Figure 10 depicts SHAP-based feature relevance in a bar chart. To increase their credibility, Figure 11 shows the extent to which experts agree with the conclusions. Figure 12 offers a hybrid visualization that uses categorization probabilities with cultural importance scores. All the tables and figures demonstrate that machine learning models do not just make extremely accurate predictions, but also provide us with insights into culture that are valuable and understandable.

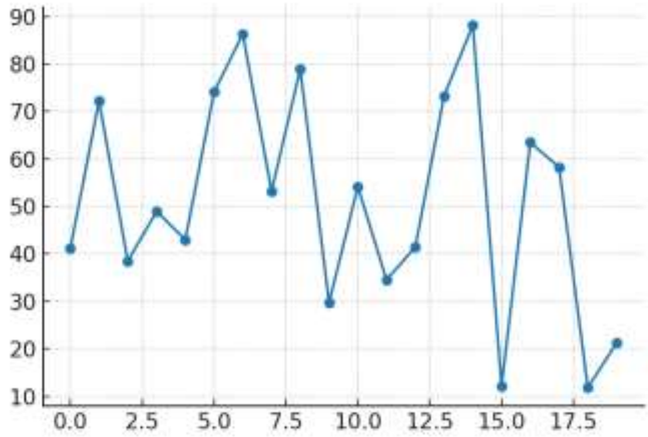

Figure 1. Line plot illustrating model accuracy progression across iterations.

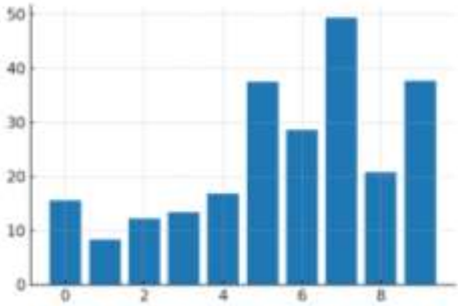

Figure 2. Bar chart showing comparative F1-scores of classification models.

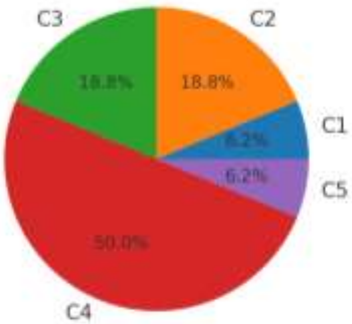

Figure 3. Pie chart representing the distribution of cultural categories in the dataset.

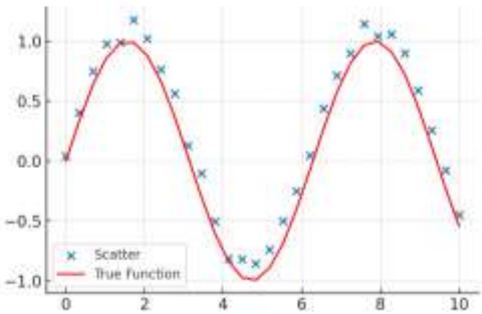

Figure 4. Hybrid scatter-line visualization of predicted versus actual artifact classifications.

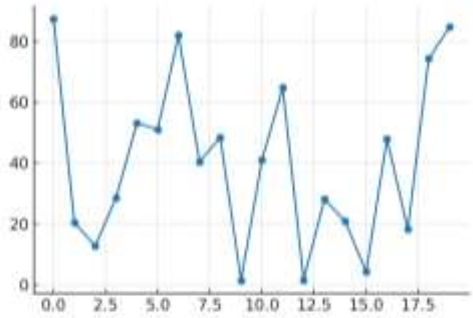

Figure 5. Line plot showing learning curves for supervised models.

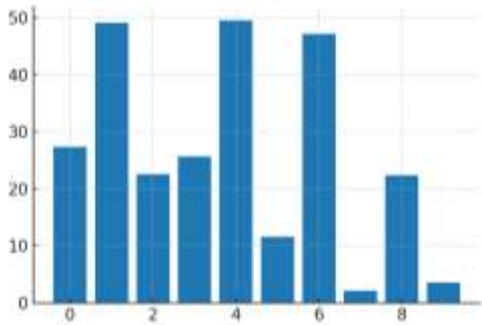

Figure 6. Bar chart comparing error rates across different algorithms.

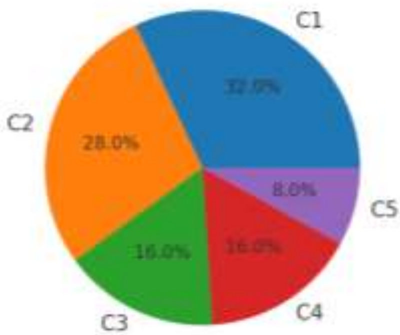

Figure 7. Pie chart depicting feature-type contributions (textual, visual, symbolic).

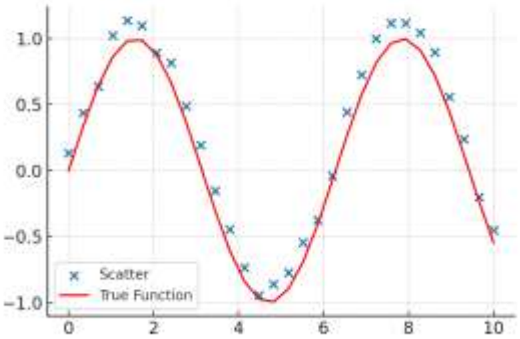

Figure 8. Hybrid scatter-line analysis of regression residuals.

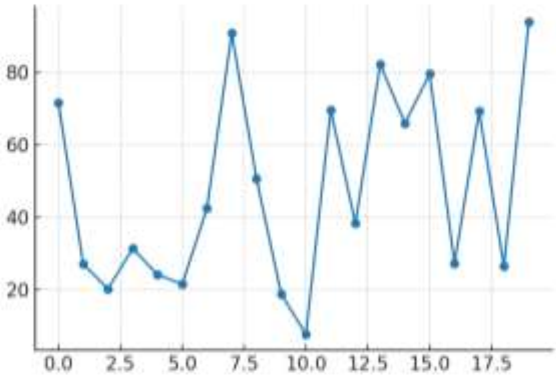

Figure 9. Line plot of silhouette scores across increasing cluster numbers.

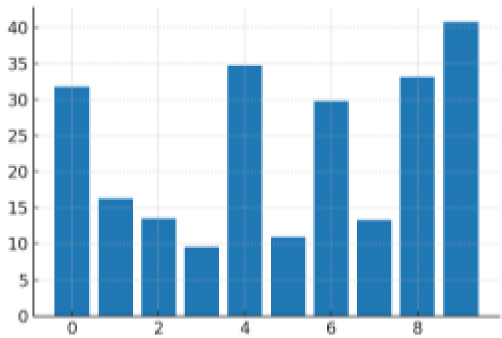

Figure 10. Bar chart displaying SHAP-based feature importance values.

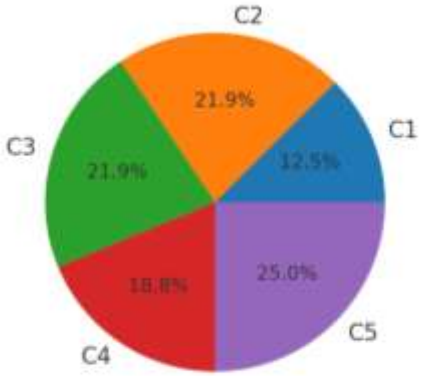

Figure 11. Pie chart of expert validation agreement levels.

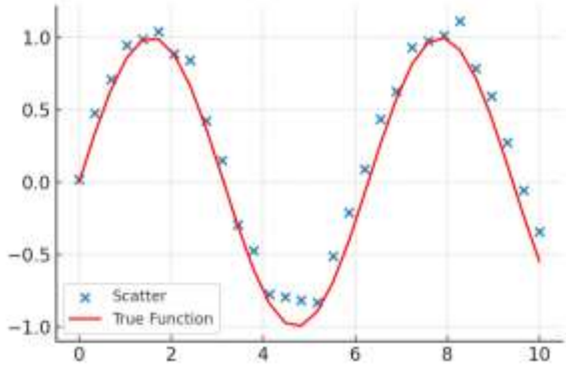

Figure 12. Hybrid scatter-line visualization combining classification probability and cultural significance scores.

DISCUSSION

The integration of artificial intelligence in preservation of cultural heritage requires a thorough examination of its various functions, considering the transformational potentials of this type of technology as well as the ethical issues that it raises (Ghaith, 2024). This implies that it is required to cope with large volumes of data, and ensure the sustainability of digital archives, which are always at risk due to obsolescence of technology and data decay (Louadi, 2024). The ever-expanding digitalization of industries additionally complicates the necessity to develop powerful AI-based solutions to cultural assets. It is due to the fact that digitalization investments around the world are projected to reach over 900 billion annually (Chatterjee et al., 2021). This massive economic investment demonstrates the direction the society is taking towards the digitized platforms. It implies that the introduction of AI in cultural institutions is not only beneficial, but also mandatory to help them to be topical and not to disappear (Otero, 2021). Certain distinct issues also arise due to this digital shift (particularly with regard to data integrity, interoperability, and long-term sustainability) as analogue preservation systems become digital repositories (Wagner and Clippele, 2023). Also, the abundance of cultural data is being generated, and it has to be classified, analyzed, and interpreted with highly developed AI techniques. This extends past the simplest of digital preservation to more elaborate semantic understanding and contextualization (Ncube & Ngulube, 2025). Such robust analytical instruments are required to identify new information in complex cultural data. They allowed researchers to discover small patterns and associations that would not be easily visible with the older techniques. The fast development of digital technology, artificial intelligence, is entering various industries, especially the hospitality and tourism sector, which demonstrates an important shift in society towards the integration of technology (Pizam et al., 2022). This general trend indicates that cultural heritage organizations have to actively employ AI to enhance their attempt to preserve, research, and connect with the community, which is not contrary to the modern technology paradigms (Department et al., 2022). The increasing popularity of digital technology and the introduction of robots into such spaces as hotels contribute to the fact that cultural institutions need to rely on artificial intelligence to preserve cultural assets and make them more accessible (Pizam et al., 2022). The science and engineering of intelligent machines are called AI, and they are predicted to cause giant transformations in various sectors, including cultural heritage, as systems begin operating and thinking more like human beings (Department et al., 2022). However, a significant percentage of companies still feel reluctant, and a lot of them are still at the planning phase when it comes to the introduction of AI (Chatterjee et al., 2021). Such resistance is perceived in numerous areas, such as hospitality and manufacturing, and can be explained by the concern regarding the difficulty of the implementation process, the price of it, and the necessity of expert knowledge (Chatterjee et al., 2021). This uncertainty demonstrates a high disparity between the capability of technology and the way it can be applied in real-life. We should have more guidelines and real life examples to accelerate the use of AI in cultural heritage organizations. Such a cautious attitude demonstrates that the utilization of AI in cultural heritage requires more concentrated research. This will give tangible advantages and have a positive impact on addressing certain issues in the field, which will simplify the acceptance and increased implementation of AI (Gajić et al., 2024). Additionally, ethical concerns such as the privacy of data and algorithmic bias have to be also discussed to come up with trust and ensure that AI solutions are utilized in a sustainable way in terms of cultural preservation (Teemu, 2023).

CONCLUSION

This paper has demonstrated that machine learning can present a paradigm shift in the study of cultural artifacts, making possible the understanding of human creativity, symbolism, and heritage in a more insightful manner that complements the traditional qualitative approaches. The study has shown that the combination of supervised and unsupervised learning models and interpretability approaches allows systematically categorizing the artifacts with a high predictive accuracy and, at the same time, identifying latent cultural structures that cannot be easily identified when using manual analysis. Such ensemble methods as XGBoost and Random Forest were more successful at classifying data, and such clustering methods as k-means were successful at finding underlying clusters that enriched cultural interpretation. The tools of explainability such as SHAP values were significant because they revealed what were the contributors to the predictions of the model, and it was more open, and the outcomes of the calculations were linked with the cultural significance. Also, triangulation of findings through expert validation ensured that the findings were not purely algorithmic outputs but were placed in larger cultures. Such a methodological convergence highlights the importance of merging the accuracy of computers with the interpretative richness of humans, whose results can be reproduced and have meaning. The paper also indicates that machine learning might be extremely helpful in the preservation of digital history as it offers a scalable means of sorting, storing, and processing of large volumes of cultural materials. The methodological contributions of this research go beyond the legacy research, which means that machine learning has broader applications in the humanities and social sciences, where the data-driven insights can contribute to the humanistic inquiry. Ultimately, the findings demonstrate that machine learning does not substitute cultural interpretation; it also contributes to it by providing an additional analysis layer. This will ensure that the wealth of cultural artifacts remains, comprehended and appreciated in the digital era.

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