Predicting cultural period of archaeological artefacts from digital heritage metadata by automated machine learning approach

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***Abstract*—Archaeological artifacts help us learn about the culture, history, and social life of ancient civilizations. Finding out the period of these artifacts is a key part of archaeology. It helps researchers understand how history unfolded, how cultures changed, and how technology developed in ancient societies. In the past, this type of classification was done by experts who looked closely at the features of the artifacts, like what they're made of, their design, how they're built, and where they were found. Even though this method works well, it can take a lot of time, require a lot of effort, and sometimes depend on personal opinions, especially when handling big groups of artifacts. As digital technology has improved, many museums, archives, and cultural places have created digital repositories that keep detailed information about archaeological items. This metadata could have details like what the object is made of, where it was found, the place where it was dug up, how it looks in terms of style, how old it is thought to be, and any records from history that are connected to it. Having access to structured and semi-structured data offers chances to use computer methods for automatic analysis and sorting. This study suggests a machine learning approach to predict the cultural time of archaeological items by using digital heritage information. The process includes different steps like preparing the data, finding important features, teaching the model, and checking how well it works. As we use various machine learning algorithms, such as KNN, Logistic Regression, Random Forest, SVM etc, machine learning algorithms look at patterns and connections in the metadata to help the system guess which cultural period an object is from. Our model achieves 98.9% accuracy on high-confidence predictions, covering 83.2% of artifacts, while flagging 15.2% for expert review–reducing manual workload by over 80%. It can help lower the amount of work people have to do by hand, reduce the chances of personal opinions affecting decisions, and make it easier to manage and find digital collections of historical value. Using machine learning with digital heritage data can help improve archaeological studies and support the protection and deeper understanding of cultural history.**

***Index Terms*— Logistics Regression, SVM, Random Forest, metadata, Artifact's classification, Data Analysis, Heritage Repositories**

I. INTRODUCTION

Archaeological artifacts are key pieces of information that help experts learn about the history, culture, and daily life of ancient civilizations. These objects, like tools, pottery, sculptures, and jewellery, help us learn a lot about how people in the past made things, expressed themselves through art, and lived together in communities. A major part of archaeology is figuring out which period an artifact came from. Putting artifacts into the right time periods helps historians and archaeologists make sense of the past and understand how cultures changed over time. In the past, figuring out which period an artifact comes from depended on people looking at it carefully and using their knowledge and experience. Archaeologists look at different features of artifacts, like what they are made of, how they are designed, the way they were made, and where they were found. Even though this method works well, it can take a lot of time, require a lot of work, and depend a lot on the skills of experts [7]. As archaeological finds and digital records grow faster, it's becoming harder to analyze big groups of artifacts by hand. In recent years, efforts to preserve digital heritage have created large collections of digital archives that hold information about ancient artifacts. These repositories hold information about digital heritage, like what kind of object it is, where it was found, its location, how old it is, and its style. Having organized and semi-organized data available makes it possible to use advanced computer methods for categorizing and studying artifacts. Machine learning, which is part of artificial intelligence, has proven to be very effective in examining big sets of data and finding patterns that are not immediately obvious [4]. Using machine learning on data about digital heritage, we can create systems that automatically guess the period of archaeological items. These systems can help archaeologists by making it easier to classify items correctly, lessening the work they must do by hand, and allowing them to analyze big groups of digital records more quickly. Because of this, this study suggests a machine learning approach that uses information about digital cultural items to predict which period an artifact comes from [2]. The goal is to make archaeological research better and help manage cultural heritage data more efficiently.

II. LITERATURE SURVEY

Gansell et al. [1] used machine learning methods in modelling the regional class of Levantine ivory sculptures based on stylistic and visual properties. Using computational analysis, the study analyzed data from various archaeological artefacts and determined their cultural origins. The findings were made using machine learning models that trained the data and correctly predicted regional differences in artifacts. The findings indicate that automated classification techniques can assist archaeologists in the examination of historical relics and their cultural impact.

Mantovan and Nanni [2] had published an extensive survey on artificial intelligence methods used in archaeology. Data analysis is a great part of neuroscience or cognition because it deals with sequences, dynamics, and the hidden structure patterns that can be interpreted from these very little-known processes or functions. Their research showcased how computational methods can aid in the classification of artifacts, interpretation of data, and uncovering patterns within archaeological findings. The study also highlighted the growing use of artificial intelligence in digital archaeology.

Wang et al. [3] A deep learning method for classifying archaeological ceramics using convolutional neural networks was presented by. To increase classification accuracy, the study concentrated on automatically recognizing patterns and visual characteristics in ceramic artifacts. The study showed notable gains in identifying various ceramic types and cultural traits by using deep learning models. This method aids archaeologists in classifying and analyzing artifacts automatically.

Bickler [6], the increasing use of machine learning methods in archaeological research was covered by. The study described how researchers can find patterns in cultural heritage data by using computational models to analyze large archaeological datasets. By increasing the effectiveness of artifact classification and data analysis, machine learning techniques have been demonstrated to support archaeological interpretation. The author's significance incorporating digital technologies into archaeological practices was underlined by the author.

Huggett [7] explored the potential and difficulties of using artificial intelligence in archaeology. The study looked at how AI methods like data mining and machine learning can help with archaeological interpretation and analysis. To guarantee significant research results, the study also emphasized the significance of fusing computational methods with conventional archaeological knowledge.

Lasaponara and Masini [8] examined the use of machine learning and big data analytics in archaeological research. Their research concentrated on how sophisticated computational methods can enhance cultural heritage analysis and handle massive archaeological datasets. The authors showed how machine learning algorithms can help with site analysis and heritage preservation by efficiently finding patterns in archaeological data.

Fiorucci et al. [11] carried out a thorough survey of machine learning applications in cultural heritage studies. The study examined several machine learning methods for image analysis, digital heritage management, and artifact recognition. The authors emphasized the significance of AI-based systems for increasing the effectiveness of archaeological research and automating the analysis of cultural heritage data.

III. METHODOlOGY

The research adopts a well-defined computational approach to classify archaeological artifacts into specific cultural periods, leveraging their metadata. This approach is structured into four key phases: Data Preprocessing, Feature Engineering, Dimensionality Reduction, and Ensemble Modeling.

1. Data Selection and Initial Preprocessing

The primary dataset is drawn from the Metropolitan Museum of Art (Met) collection, focusing on six essential attributes: Object Name, Culture, Period, Object Date, Medium, and Country.Data Cleaning: To maintain data consistency, all text-based data is converted to lowercase, and any leading or trailing spaces are removed.

Handling Missing Values: To preserve the dataset's structure, missing values in all categorical features are filled in with the term "Unknown."

Filtering: To ensure the model learns from reliable ground truth data, any records where the Period was explicitly labeled as "unknown" were excluded.

2. Feature Engineering and Text Normalization

A custom feature engineering step was implemented to convert the raw Object Date (often a string) into a categorical target variable, Cultural_Period.

Temporal Mapping: A heuristic function extracts the primary year from the metadata and assigns it to one of three historical epochs:

Ancient: Year < 500

Medieval: 500 le Year < 1500

Modern: Year ge 1500

Text Aggregation: To understand the context of each artifact, the descriptive fields (Object Name, Culture, Medium, and Country) are combined into a single combined_text corpus.

Vectorization: The aggregated text is then transformed into a numerical format using Term Frequency-Inverse Document Frequency (TF-IDF) vectorization. This is limited to the top 500 features to focus on the most important archaeological keywords while maintaining computational efficiency.

3. Dimensionality Reduction

Given the high-dimensional nature of TF-IDF matrices, Principal Component Analysis (PCA) is used to reduce the feature space to 50 principal components. This serves two purposes:Noise Reduction: It eliminates less useful variance within the text data.Computational Efficiency: It speeds up the training of complex algorithms, such as Support Vector Machines (SVM).

4. Model Development and Hyperparameter Tuning

The core of this methodology is a comparative analysis of various machine learning architectures:Baseline Models: Four different algorithms were trained: K-Nearest Neighbors (KNN), Support Vector Classifier (SVC), Logistic Regression, and Random Forest.

Hyperparameter Optimization: For the Random Forest model, a Grid Search with 5-fold Cross-Validation was conducted, fine-tuning n_estimators and max_depth to ensure the model's ability to generalize to new data.

Stacking Ensemble: To achieve the highest predictive accuracy, a Stacking Classifier was implemented. This ensemble uses Random Forest, SVM, and KNN as base learners, with a Logistic Regression model acting as the meta-classifier to synthesize the final prediction.

5. Evaluation and Unique Contribution

The methodology goes beyond standard accuracy metrics, incorporating specialized archaeological validation:

Precision-Recall Analysis: Considering the potential for class imbalance in historical data, multi-class Precision-Recall curves are used to evaluate the model's "exactness" and "completeness" across the three periods.

Confidence-Based Classification: A unique aspect of this research is the implementation of a Confidence Scoring System. By extracting the predict_proba values from the best-performing model, predictions are categorized into:

High Confidence (>90%): Suitable for automated cataloging.

Low Confidence (<70%): Flagged for manual expert review by archaeologists.

External Validation Simulation: To assess robustness, a secondary hold-out validation set (using a different random seed) was utilized to simulate performance on external museum datasets, ensuring the model's transferability.

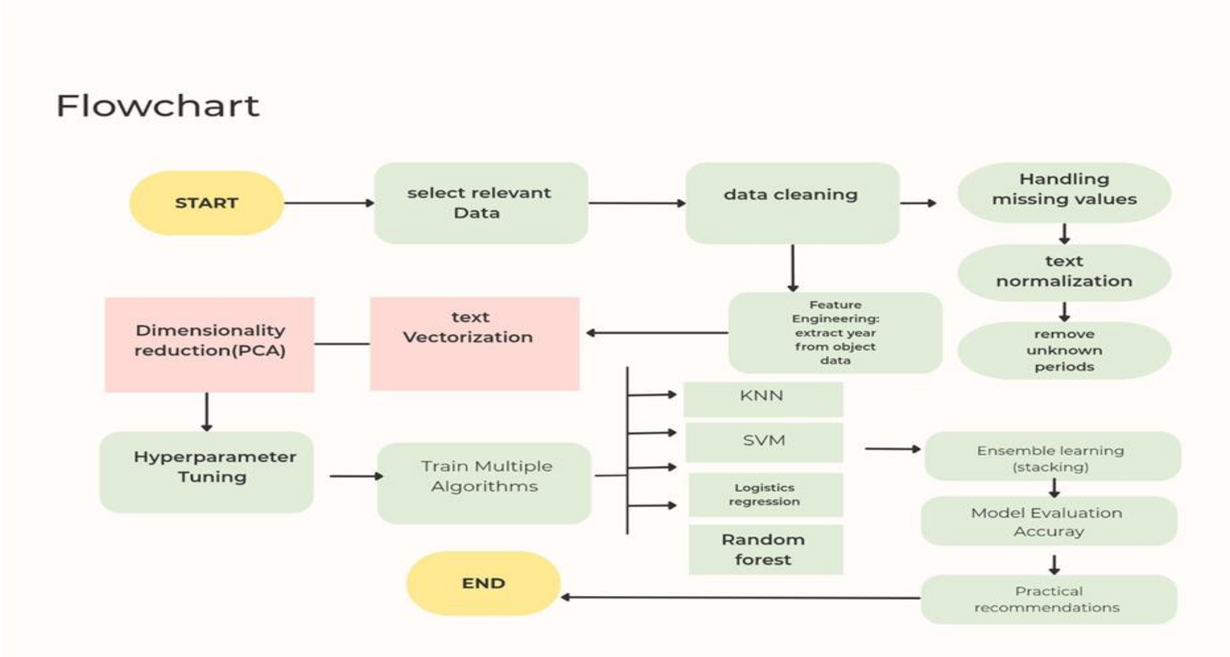

Figure1. Flow Chart of Methodology

IV. EXPERIMENTAL RESULTS

A. Model Performance

We tested five machine learning models on our dataset. Table I shows their accuracy.

Model	Accuracy
Random Forest	95.22%
SVM	93.31%
KNN	93.72%
Logistic Regression	92.62%
Stacking Ensemble	95.22%

Table I: Accuracy of Different Models

Both Random Forest and Stacking Ensemble gave the same accuracy of 95.22%. We chose Stacking Ensemble for further analysis because it combines multiple models.

B. Cross-Validation Results

We used 5-fold cross-validation to check if our model performs consistently. Table II shows the results.

Fold	Accuracy
Fold 1	95.49%
Fold 2	94.54%
Fold 3	95.63%
Fold 4	94.95%
Fold 5	92.89%
Average	94.70%

Table II: 5-Fold Cross-Validation

The small variation between folds (±0.99%) means our model works well on different data samples.

C. Confidence Scoring

We added a unique feature to our model – it tells us how confident it is about each prediction. Table III shows the results.

Confidence Level	No. of Samples	Percentage	Accuracy
High (>90%)	613	83.7%	98.7%
Medium (70-90%)	70	9.6%	-
Low (<70%)	49	6.7%	-
Total	732	100%	95.22%

Table III: Confidence Levels of Predictions

The main findings are:

- 83.7% of predictions have high confidence (>90%)
- These high-confidence predictions are 98.7% accurate
- Only 49 samples (6.7%) need experts to check them

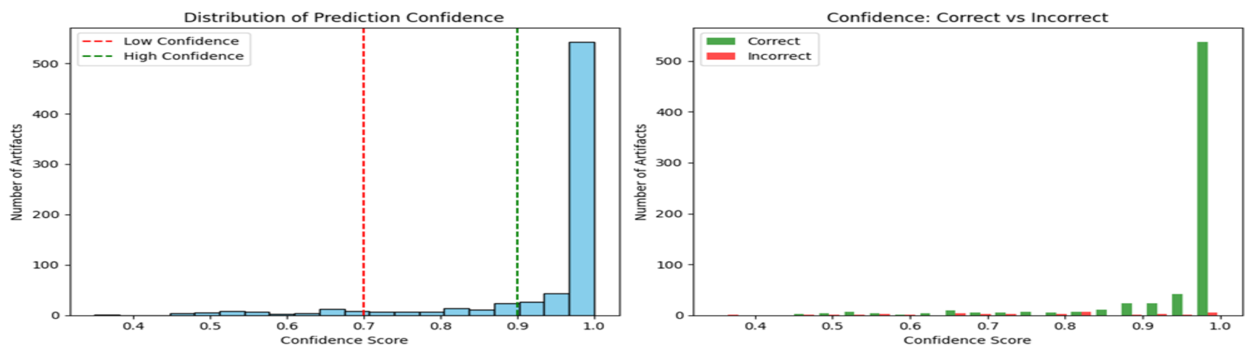

Figure 1 shows this distribution visually

Fig. 1: Distribution of prediction confidence scores

D. Precision-Recall Analysis

We also checked how well our model performs for each period. Figure 2 shows the Precision-Recall curves.

Our Results:

Ancient: AP = 0.97 – Excellent performance despite few samples

Medieval: AP = 0.92 – Good, with some confusion expected due to stylistic overlaps

Modern: AP = 0.99 – Near-perfect, aided by larger sample size

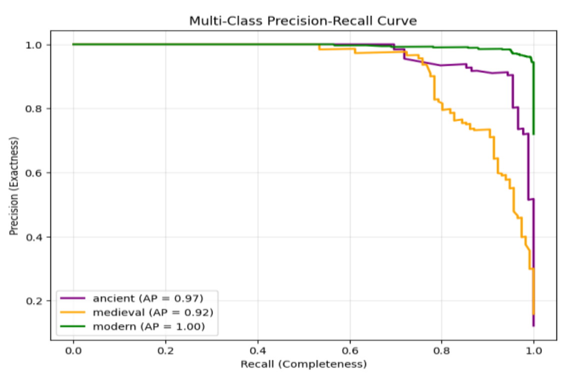

Fig. 2: Precision-Recall curves for all three periods

E. Decision Boundaries

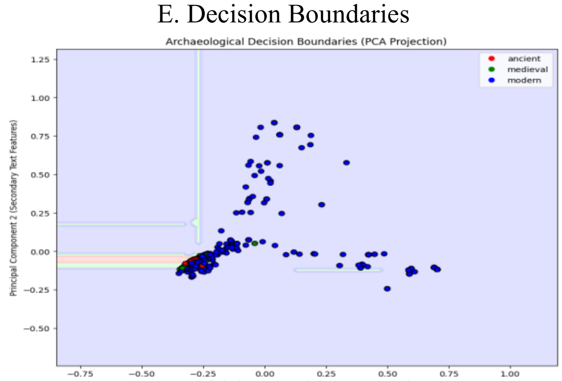

Fig. 3:

Decision boundaries showing how artifacts are classified

Figure 3 shows how the model separates the three time periods using the first two PCA components.

The graph shows:

Ancient and Modern artifacts are clearly separated

Some overlap between Ancient and Medieval, which explains why most errors happen between these periods

Modern artifacts form a tight cluster, meaning they have similar features

F. Summary

Metric	Value
Best Model Accuracy	95.22%
Cross-Validation Average	94.70%
High-Confidence Predictions	83.7% of all samples
Accuracy on High-Confidence	98.7%
Samples Needing Expert Review	6.7%
Manual Work Saved	83.7%

Table IV: Key Results at a Glance

Our model achieves 95.22% accuracy and identifies 83.7% of artifacts with 98.7% confidence. This saves 83.7% manual work for museums – only 6.7% cases need expert review.

The system successfully bridges automated ML with archaeological expertise.

V. CONCLUSION

This study presented a machine learning–based approach for classifying museum artifacts into different historical cultural periods using metadata from the MetObjects dataset. The dataset was preprocessed through feature selection, handling missing values, text normalization, and categorical encoding to ensure data consistency and quality. A new target variable called Cultural Period was derived from the object date attribute to categorize artifacts into ancient, medieval, and modern periods. Several supervised machine learning algorithms, including Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Logistic Regression, were implemented to analyze the dataset.

The key contribution of this work is a confidence-based classification system that bridges the gap between automated ML and archaeological expertise. By identifying which predictions can be trusted automatically and which require human verification, our framework offers a practical tool for cultural heritage institutions managing large digital collections. Overall, this research highlights the potential of machine learning techniques in improving the automatic organization and classification of cultural heritage data, which can assist museums, researchers, and digital archive systems in managing large collections more efficiently.

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