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Digispectra: Techno - Archaeo Toolkit

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Abstract: **In recent years, some work has been done to extend machine learning techniques in archeology domain focused mainly on the geospatial data. This paper discusses an attempt to enhance the art fact classification (here, coins) based on broad time periods from entered data and then images directly. The classification of coins is done into Roman and Medieval time periods. The data is gathered from Portable Antiquities Scheme. Initially, predictive models Random Forest and Gradient Boosting are used to get data insights and plot a feature importance graph. The numismatics in order were found to be of utmost importance: mint name, denomination name, material and ruler name. A further attempt is made to retrieve these features used in the predictive model directly from the image by training Convolution Neural Network. Good results are found while identifying images for material and denomination but is a challenge form in tan ruler name. This framework can be used for automating coin identification and on further work can also be used to reconstruct the damaged coins with a possibility of recovering inscriptions. The main challenge faced is the lack of data availability.**

Keywords - **Artifact classification, predictive model, convolutional neural network, coin, numismatics.**

I. INTRODUCTION

In recent years, the intersection of technological aspects and archaeology dataset availability has allowed various applications to be developed in the same field. The digitalization and automation of archeological data is the way to step into a brighter future with much more possibilities to discover the hidden. Machine learning plays a big role in detecting patterns, similarities and uncovering the hidden. The toolkit discussed in the paper aims to integrate traditional archaeological practices with power of machine learning and computer vision techniques with efficiency, accuracy and accessibility in artefact analysis. While some effort shave been made in leveraging geospatial data for clustering applications related to landscapes, the classification of artefacts based on time periods remains Medieval.

limited explored field. This research focuses on providing an approach to artefact classification, particularly focusing on coins from distinct historical periods namely Roman and The data availability remains a challenge throughout, but the work suggests decent results. Further, an attempt is made for automating the feature classifications, artefact enhancement and reconstruction based on computer vision.

A. Objective

Develop an image classification model utilizing machine learning techniques to accurately identify artefacts. Integrate are construction process for better visualizing identified are facts, enabling a deeper understanding of their form and context.

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B. **Novelty and Scope**

Their search offers automating artifact identification which accelerates research, and offers enhanced visualization, changing how ancient artefacts are studied. The techniques used are broken down into data collection and preprocessing, image classification, reconstruction and framework development.

II. PROPOSED METHODOLOGY

A. Data Collection and Preprocessing

Collect and prepare images from Portable Antiquities Scheme Website database. Data related to the images is also downloaded, for coins specifically numismatics. Data preprocessing, image annotation and apply appropriate labeling.

a. Image Classification

Develop a convolutional neural network model for item classification. Training and testing of the model.

The image collection is also carried out along the way where the corresponding images to final data are labelled for further processing.

b. Predictive Modelling

Predictive models applied for broad time period classification and the features are studied for further feature extraction based on which further identification is done.

c. Enhancement and Reconstruction

Computer vision used on labelled images to create 3D models of identified artefacts.

d. Framework Development

Creation of an executable file which users can use for initiating classification and view enhancements and reconstructions.

B. Data Analysis

Object classification based on input image for further processing. Utilizing Tensor Flow and Keras libraries, a deep convolutional neural network architecture was employed for image classification. They automatically extract meaning ful features through layers of convolutional and pooling operations.

C. Predictive Model

Prediction of time period based on learning from data features such as materials, numismatics. The predictive techniques used include random forest and gradient boosting. By leveraging historical data patterns and key features such as mint name, denomination name, material and ruler name, classification of coins into Roman and Medieval time periods. The individual importance of the features use dissuaded further, and an attempt is made to extract these features directly from the image like the material of the coin.

D. Reconstruction

Artefact visual representation and possible reconstruction using computer vision along with enhancements.

E. Deployment Preparation of an executable file in python which can be used as a solution framework.

III. FUNCTIONALITIES

The toolkit provides the following final functionalities for the digitalization of artefact classification. Various techniques of machine learning, computer vision come into action for the same.

Data discovery, collection, preprocessing, cleaning etc. Data is downloaded from Portable Antiquities Scheme Website. Data cleaning carried out on the csv file where extra fields are removed, fields with null values and missing data are also cleaned. After cleaning of the data, the data from different locations and time period is combined to form the final data set of around 13,000entries

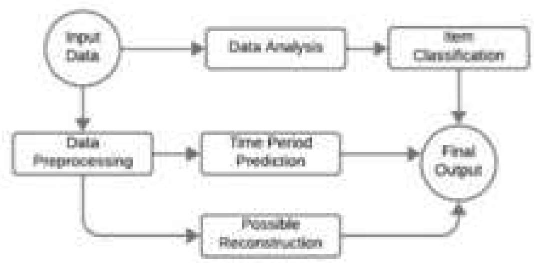

Fig 1: Functionalities

IV. LITERATURE REVIEW

This literature review summarizes insights from two pivotal research papers, each contributing distinct perspectives on the application, challenges, and implications of available technologies in archaeology.

Van der Maaten et al. [1] articulate a prevailing challenge in archaeology – the limited contribution of technology to the field. Traditional classification methods are often labor-intensive and subjective, prompting the exploration of innovative solutions. Mean while, Bickler[3] acknowledges the historical challenges in managing sparse and complex datasets in archaeological work, emphasizing the need for advancements in data sharing and management.

The research by Van der Maaten et al. exemplifies the practical application of computer vision techniques. Their content-based image retrieval system, exemplified in the analysis of historical glass and medieval coins, introduces a novel approach to artifact classification based on shape

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contours [1]. In parallel, Bickler [3] offers a broader perspective, high lighting machine learning's rapid adoption in analyzing geospatial, material cultural, textual, and artistic data, showcasing its versatility in archaeological contexts.Van der Maaten et al. [1] candidly acknowledge challenges faced by their proposed systems, particularly in handling severely damaged artifacts where missing parts affect outer shape. The need for manual adjustments underscores the technology's ongoing refinement. In alignment, Bickler [3] outlines challenges in machine learning, emphasizing hidden complexity, systemic bias, and high validation costs associated with small datasets in archaeology.

The discussion section in both papers extends the discourse on the broader implications of these technologies. Van der Maaten et al. [1] emphasize the influence on excavation decisions and public access to archaeological knowledge through automatic classification systems. Bickler [3] unders cores the evolutionary impact of machine learning, improving analytic tools and offering advantages in research objectives and cultural heritage. Both papers concur on the need for ongoing development and data management to harness the full potential of these technologies.

Both research papers advocate for future developments. Van der Maaten et al. [1] highlight the necessity of incorporating archaeological knowledge into computer vision algorithms, either through collaboration with experts or the development of semi-automatic adaptive systems. Bickler [3] underscores the integration of machine learning outcomes into academic and cultural resource management frame works, emphasizing the challenge of managing richer and more diverse information in archaeology.

V. CONCLUSION

The accuracy increases with the increase in data size which remains limited to some extent. The primary expected outcomes of this project include:

1) Quick identification and categorization of artefacts, potentially saving a significant amount of time during the analysis process.
2) Provides assistance in dating artefacts and understanding the chronological context of a site.
3) Offers visual representations of artefacts and reconstruction for a better detailed study without comprising the item.
4) Availability of an executable solution framework where data can be uploaded to get results.

Future scope of the project includes studies related to site mapping, reconstruction of the detailed landscape environment etc based on remote sensing and other data availability.

VI. CHALLENGES

A. Limited Data Availability

Limited availability of varied and detailed datasets, especially for coins from various historical periods is a big challenge to work well in different situations.

B. Difficulty in Retrieving Specific Features

Training a convolutional neural network for artifact classification faces challenges in accurately extracting mint and ruler names from images. The intricate details necessary for these classifications may be challenging to capture, impacting the model accuracy.

C. Complexity in 3D Reconstruction

While the integration of reconstruction is a key feature, the process may face challenges in accurately reconstructing damaged coins and recovering inscriptions. The complexity increases when dealing with fragmented or incomplete artifacts.

D. Predictive Model Accuracy

While the initial models using predictive model provide insights, ensuring high accuracy in predicting features directly from images using a convolutional neural network remains a challenge, especially for numismatics features like mint and ruler names.

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