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Big Data based Machine Learning approach for exploring rock arts

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ABSTRACT

The rock art information as integrated through Service oriented architecture with cloud would be available in abundance; they could be processed in cloud using machine learning approaches. The proposed research explore the visual analysis of rock art, sustaining the finding of insights from complex rock art data that encompasses multiple dimensions, sources, data forms, time variants, and visual depictions. It is taken into consideration that the application of human judgment to make the best possible use of incomplete, inconsistent, and potentially deceptive information from rock arts. Big Data based image processing method is adopted, since the rock art images collected are possessing the characteristics of Big Data. The proposed sense making process involves the analytic workflow to help the requested client make sound decisions from the rock art information.

Keywords – **Big data, Rockarts, Cloud, machine learning Service oriented architecture.**

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I. INTRODUCTION

The major aspire of this paper is to transform the rock art depictions in to information (human understanding). In this research, a Machine Learning approach, an algorithmic technique for learning from pragmatic data, such as, rock art images and then using those lessons to predict future outcomes of the proposed data such as an alphabet, a word or a sentence. A rock art could be examined, based on its style, its genre, the people who made it and the period to which it belongs could also be determined. The rock art images could be classified according to the visual concepts that they contain. The rock art works could be compared according to a number of high-level concepts such as the people's use of space, texture, form, shape, and color. It could also be considered the way the people uses movement in the picture, harmony, variety, balance, contrast, proportion and pattern. Other important elements could include the subject matter, strokes, meaning, and historical context. Comparing rock art images is then a process of comparing the words that describe them, for which there are a number of entrenched techniques available. This process generates a list of describing words that can be thought of as a kind of vector. Similar vectors have to be identified using natural language techniques and a machine learning algorithm. Machine learning helps to extract conclusions/inferences from parts of such huge information from rock art cloud. Contextual comparisons have been executed and changing proportions are identified.

II. RELATED WORKS

A paper [3] described the recent application of Reflectance Transformation Imaging and 3D laser scanning of prehistoric Rock Art. Several aspects of the animals' depiction in rock art can be explained by certain perceptual correlates relating to the visual brain [4] and evolutionary factors. Recent evidence from neuroscience and the visual brain not only confirms this claim , but provides important new findings that can help delineate which graphic features relate to biological/genetic criteria.

The stunning panoramic images captured and the stories they reveal served as the inspiration for the Stories in the Rock project [5]. There are some successful and high profile examples of applying machine learning to the world of art. Babak Saleh and his collaborators at Rutgers University recently used computer algorithms to classify features of digitized paintings to try to automatically discover artistic influence [6].

The authors in [7] described about the dots in cave arts, and they studied about the perception and psychology of dots in those paintings. Ingrid Daubechies, has used image analysis and machine learning [8] and try to judge whether the paintings are forgeries. If a system could be trained to do these kind of tasks reliably and quickly, huge amounts of data could be processed that would have been too time consuming or expensive to accomplish with expert human judgments.When a Machine Learning algorithm is used to analyze the Fine Art Paintings [9], several things are observed that the Art Historians had never noticed. Artificial intelligence discloses the unrecognized persuasion among great artists. The history of art is enthralling a close understanding of how the machine learning techniques could be used in these studies. Imaginative drawings imprinted on rock surfaces are forms of mindful expressions [1] that accentuate deep insight into such depictions.

According to a Neuroscientist Adam Zeman, artists are veteran professional on sight and their exertion has lead to the study of how the brain and the visions working [10]. Another neuroscientist Samir Zeki's idea is that the Artists are fascinating the study of human brain, which is working unique [11].

A cloud based processing of big sensor data is proposed in [12]. Similar to that, this research work proposes the analysis of Rock art data in cloud. A central goal of the rock art project [13] is to facilitate two-way communication between scientists and the public. As a starting point, it was needed to learn more about the subject matter, its interpretation, and the curator's communication and public engagement goals.

Since the rock art data are available in the cloud, the proposed Machine learning process is also to be executed in the Cloud. Applying popular machine learning algorithms to large amounts of data raised new challenges for the ML practitioners. Traditional ML libraries do not support well processing of huge datasets such as heterogeneous rock arts, so that new approaches were needed. Parallelization using modern parallel computing frameworks, such as MapReduce, CUDA, or Dryad gained in popularity and acceptance, resulting in new ML libraries developed on top of these frameworks.

In this proposed work, it is considered to use MapReduce as a framework in which, ML could be used as Software-as-a-Service. Machine learning is the process of using sets of rules and algorithms to train a computer system to automatically accomplish a task. One such task is judging the level of similarity between the content of digital objects of rock art images and to determine what category they fall into. If the system proposed, could be trained to do these similarity tasks reliably and quickly, then it is possible to process huge amounts of data. In this work, data (rock art) analysis platform are provided using machine-learning method on the cloud.

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III. PROPOSED SYSTEM

The process flow is depicted as a layered architecture in figure 1. The module repository contains the English alphabets. The rules engine includes the proposed Rock Art classifier (perceptron), and Euclid LSH to find the nearest neighbor. The architecture control module coordinates all the components. The rules engine and the architectural control constituted as the intelligence unit. The classified rock arts, according to the visual concepts are stored in homogeneous and heterogeneous rock art databases and these two are connected through the data connectivity layer. The top most layers are the sense making space from where the machine learning algorithms are executed and the rock art client gains the access. It goes further down to data visualization and analysis layer for feedback action.

The history of rock art studies has been characterized by a continuous search for reliable and accurate recording techniques. Recently the effectiveness of photography for recording and analysis has been greatly enhanced by the development of ''computer-aided'' or ''digital'' image processing (DIP) techniques. These involve reducing an image to an extremely fine grid of square picture elements or ''pixels'', each of which is given a colour value that can be analysed digitally by computer, thus processing images very much faster than the traditional chemical methods and allowing a huge range of sophisticated effects to be obtained. With the advent of low-cost high-powered computers, access to digital image processing has become more common.

The objective is to investigate and enhance poorly defined areas within the image and extract all information pertaining to the motifs in a form which can best present the interpretation of the rock art. Two major stages can be defined in the application of digital image processing: the preprocessing and the processing. In an ideal world preprocessing the image should not be necessary. In the real world, however, images have a series of problems that have to be dealt with in order to facilitate the processing of the image. These problems relate essentially to the base (i.e. rock) on which the pictographs are painted, the light and the condition of the painting itself. The natural variations in the colour and the texture of the rock can interfere and cause problems in the definition of the image. This gives rise to the appearance of a noise that impedes an easy digital treatment to the painted motifs. The light is an obvious problem in the manipulation of carved images, because of the effect of the shadows. With reference to the painting, the variation in pigment density across the motif may interfere with the digital treatment of the image. In addition, some areas of the painting have been washed down by the effect of water, and this obviously presents problems, first in defining the edges of the motif (i.e. in deciding what is the background and what is the art) and, second, in the decisions on how to represent it.

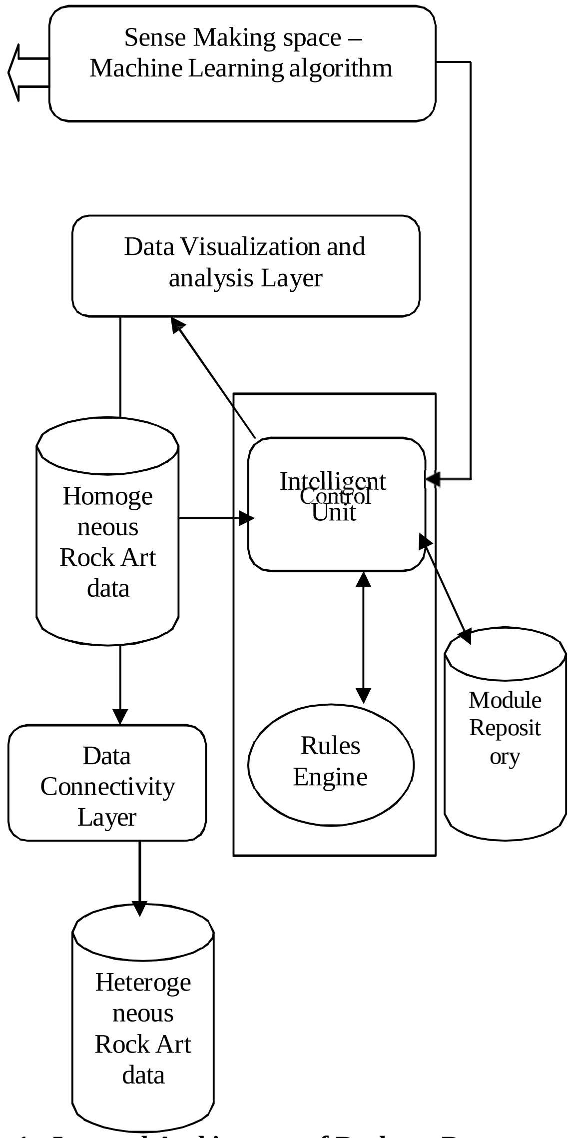

Fig 1. Layered Architecture of Rock art Data processing using Machine Learning approach

A number of standard techniques can then be applied in sequence. These techniques are available in most software

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packages, the main ones being contrast enhancement, edge enhancement, and image sharpening. Contrast enhancement, which may operate within the image by the use of either look-up tables or histogram modifications, can establish greater separation of the paint from the background. Secondly, edge enhancement is able to accentuate edge details and so provide greater definition within the image; for example, the boundary between the paint and the rock.Thirdly, high-pass filters are designed to sharpen details or enhance areas which are blurred.

Another method of extracting information from the whole image is using the technique of edge detection. Edges within a digital image are defined as the boundary between pixels with highly contrasting values. Filters can be applied which enhance these boundaries, thus providing outlines of features within the image.

Initially the collected rock art images are classified according to the visual concepts that they contain. They are scanned using a 3D scanner and converted into images using Multi view stereo algorithm as shown in figure 4. The size of the images obtained from rock art images are 281 x 228. A total of 120 images were gathered. For training and testing process nearly 80 and 32 images were considered respectively. Any mathematical operations can be performed only on square images. Hence the frames were resized to 200 x 200. Preprocessing is done to remove noise. The frame size acquired was 320 x 240. It is sufficient to consider 30x30 portion of the image for further analysis.

IV. BIG DATA PROCESSING OF ROCK ART IMAGES

Big Data analytics is useful for identifying underlying patterns and data intrinsic inter-relationships embedded in large volumes of complex datasets. Primarily, the two facets of data that impact Big Data analytics are data quantity and data quality. While high data quantity helps uncover recurring data patterns, the reliability of the data patterns is dependent on the data sources or the data quality. In the context of Big Data analytics, data quality can be defined as the “fitness” of the data for its intended use or application. This “fitness” quotient, which is dependent on the data source and the data users, determines the extent of beneficial information that can be extracted from data for modeling and predictive purposes.

Cloud-computing platforms provide enhanced storage and sharing capabilities for rock art image data, allowing rock art data to be accessed from multiple devices and different facilities. The cloud-computing frameworks enable distributed processing of the large volumes of acquired rock art images to implement existing, computationally intensive image processing algorithms and to develop and evaluate new image processing techniques. With access to large sets of rock art images, the cloud-computing platforms can be used to benchmark these methods for comparative analysis and standardization. This work is aimed at developing work-flows on cloud-computing platforms that can be useful for guidance of optimal rock art image acquisition and processing protocols.

For benchmarking image processing techniques and optimization of image acquisition parameters, there is a need for quantitative rock art image quality (RAIQ) metrics. There are a multitude of definitions for image quality depending on the rock art task and observer. There are currently no accepted strategies to estimate image noise from rock art images. RAIQ was measured by estimating the variance in pixel intensities within manually-selected spatial regions-of interest (ROI) of a fixed circular size. If an ROI is located in a region of spatially uniform signal intensity, then the measured variance in the ROI is an estimate of the noise added to the signal, which is inversely proportional to RAIQ. This method is dependent on the selection criterion for the fixed ROI that is guided primarily by domain knowledge.

However, this fixed ROI-based RAIQ metric was not found to scale with inter-observer variabilities and large data sets. Additionally, this method suffers from incorrect ROI estimations in patients with minimal fat, or in poorly registered rock art images. In another work [12], the method for detecting the uniform spatial ROIs was automated. Here, a novel Fourier-domain based algorithm was proposed that measures the degree of spatial variation in the regions surrounding each pixel. This Windowed Fourier-domain based Distance Metric (WFDM) can be used to select ROIs with low spatial variation (ROI-LV) to quantify RAIQ, regardless of the spatial orientation or location of these regions. This method is more generalizable that the prior fixed ROI approach for quantification of RAIQ. Also, the WFDM method demonstrated agree-ability with domain knowledge are optimal for ROI selection in rock art images. In this work, we comparatively analyze these existing methods with cloud-based Big Data analytics tools using large numbers of rock art images to realize the most generalizable CTIQ quantification metrics.

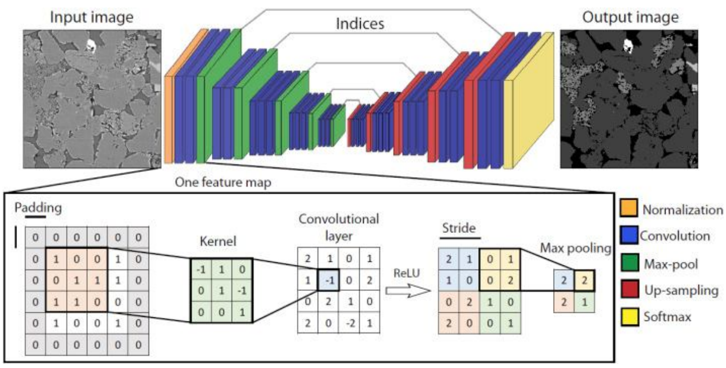

Fig 2. General Architecture of Segnet

Convolutional Neural Networks (CNN) have been identified as a “valuable” Big Data analytics tool when raw image-based data is largely uncategorized. In this work, we developed CNN models using the cloud-based platform of Microsoft Azure machine learning studio (MAMLS) to classify rock art images based on subjective RAIQ scores, thus bypassing the need for ROI selection and image segmentation. The CNN model learns the most significant hybrid features embedded in rock art images from groups of pixels that are identified as feature maps by the convolutional and sub-sampling layers. The final neural network layer provides a probability score for the RAIQ based on the feature map regions. This cloud-based CNN work-flow overcomes rock art image storage and processing

The wide variety of rock art image variabilities posed by the data analyzed in this work are representative of “Big” data analytics. Such rigorous analyses across rock art image granularity, structural and textural variabilities from phantom to rock art images has not been done before. This thesis makes three key contributions. First, three data models with variable computational complexities are comparatively analyzed for predictive modeling of RAIQ. While structural ROI segmentation and pixel variance estimation methods are found to be generalizable models, CNN models are found to be useful for classification of image texture in the absence of structural variabilities. Second, a variety of classification parameters are analyzed for scalability in classification performance from phantom to rock art images. Estimation of variance of pixels within a spatially uniform ROI is a robust classification parameter for segmentation data models. Third, the performance of data models is ranked based on average classification performance and consistency. We observe higher overall classification performances for cross-sectional RAIQ analysis when compared to longitudinal RAIQ classification. While ROI segmentation data models are found to be more consistent for RAIQ estimation and classification, the CNN model shows consistent RAIQ classification performance in the phantom image data set.

V. RESULTS DISCUSSIONS

Jubatus offers a hash-based method for approximate nearest neighbor search (ANN) under UPDATE-MIX- ANALYZE. Original high-dimensional feature vectors of rock art images are represented as a set of bit-arrays. Given a rock art data sample on a server, the UPDATE operation calculates the hash values similar to the algorithm. The ANALYZE operation is similar in computing the approximated distance and obtaining the nearest neighbors that are expected to have the smallest distance values in the original space. In this case, the model of rock art nearest neighbor is represented as a table where columns represent bit-arrays, and rows are rock art samples. The purpose of the MIX operation is to facilitate servers to find nearest neighbors from all of the previous data samples. The newly added samples by UPDATE operations after the last MIX is sent to the parent server, for effectiveness. The parent server combines them into one difference table which is to be shared.

Table I shows the classification efficiency of rock art images in Jubatus environment. This is obtained from the training process of the images.

TABLE I. CLASSIFICATION EFFICIENCY OF ROCK ART IMAGES

Class	**No. of images for training**	**No. of images for testing**	**No. of images for validat ion**	**Classification efficiency (%)**			
				Quassi Newton	***Resilent BPA***	***Conjug ate gradient***	***Marquardt Levenberg***
1	20	8	2	72.98	98.3	76.34	99.72
2	20	8	2	63.21	99.1	73.28	98.56
3	20	8	2	63.21	98.6	73.28	98.22
4	20	8	2	63.21	98.2	62.8	99.83

Table II lists the query-per-second for rock art classifier, (Perceptron model) and rock art nearest neighbor (Euclid Locality Sensitive Hashing) on the distributed environment. The number of rock art servers is assumed from 1 to 8. The rock art data set consists of 258-dimensional random samples. The Perceptron classifier tries to predict random binary labels, and Euclid LSH is based on a 64-bit array. This table indicates that the throughput for both tasks increases nearly linearly with the number of rock art servers. Because of this performance enhancement, the proposed comparison of alphabets with rock art symbols could also be interpreted with quick response time. Because of this performance enhancement, the proposed comparison of alphabets with rock art symbols could also be interpreted with quick response time.

TABLE II. THROUGHPUT ANALYSIS (QUERIES PER SECOND) FOR ROCK ART DATA SET.

Method	**No. of rock Art servers**			
	1	**2**	**4**	**8**
Perceptron classifier	1234	1361	3738	6152
Euclid LSH Nearest neighbor	164	283	405	658

Our results showed that the SegNet with a deeper architecture can be trained more effectively by a large dataset and produce more reliable results. The point is that the overall categorical accuracy (or loss) of the network cannot be used to verify the performance of the network in a multiphase segmentation application. Nevertheless, phase-by-phase categorical accuracy should be considered to accurately evaluate the network's performance. Although the overall accuracies of the basic and extended SegNet in our study were close to each other, the phase-by-phase study showed that the extended SegNet is trained more effectively (with a categorical accuracy of 99%). This network also produced valid results for unseen images with a categorical accuracy of about 96%. A comparison with the results produced by multiphase thresholding also revealed that a substantial improvement is achieved when our reconstruction method is used along with the extended SegNet.

According to the results of this study, automatic CNN-based segmentation produces reliable outputs with higher categorical accuracy. This study shows that even with the very small number of images one can train a CNN if an efficient data augmentation method is used. The implemented reconstruction method presented a successful performance in this study by generating a vast number of images quickly (e.g. here about 28,000). It should be noted that the CPU time for producing each realization is less than 15 ms with a Core-i7 CPU and 8 GB RAM. This type of augmentation may seem unnecessary for the common applications of CNN in other fields, but it is inevitable in DRP and maybe other geosciences related applications. This is mainly due to limited access to a large dataset of images in the engineering processes such as DRP and subsurface problems.

VI. CONCLUSION

This chapter explored the foundations of visual analysis, supporting the discovery of insights from complex data such as rock art images that encompasses multiple dimensions, sources, data forms, and time variants. We take into consideration the application of machine language in the cloud to make the best possible use of incomplete, inconsistent, and potentially deceptive information from rock arts. The simplified symbols of rock art which depicts the complex knowledge are processed using machine learning in the cloud, through training classification. The similarity between rock art images from a diverse rock art cloud server and an alphabet is found using Euclid LSH and the results are evaluated. Machine learning helped to extract conclusions/inferences from huge rock art information. Although the overall accuracies of the basic and extended SegNet in our study were close to each other, the phase-by-phase study showed that the extended SegNet is trained more effectively (with a categorical accuracy of 99%). This network also produced valid results for unseen images with a categorical accuracy of about 96%. A comparison with the results produced by multiphase thresholding also revealed that a substantial improvement is achieved when our reconstruction method is used along with the extended SegNet. The results of this study are not limited to sandstone samples, but the proposed framework can be for any sample.

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Biographies and Photographs

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