GIS Approach for Mosaic Tesserae Recognition by Supervised Image Classification

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This article describes the methodology used to automatically classify the constituent elements of a monochromatic mosaic from the Roman era. The classification involved the recognition of the tesserae (fragments of black and white materials for the floor ornamentation) of the mosaic using tools and algorithms implemented in Geographic Information System software (GIS). The analyses were performed using sample images expressly created by varying the colors on regular tiles in order to test the validity of the supervised classification in the ArcGIS environment. Subsequently, the same methodology was applied on mosaics from an ancient Roman archaeological site at Saltara; the results obtained from the classification process were compared to those obtained through visual reconstruction and manual vectorization. To assess the final quality and to validate the models obtained, a series of quality indicators were considered. The experimental results demonstrated that this approach offers effective classification in a short amount of time, making it a valuable tool for supporting work in the field of cultural heritage and, in particular, for the restoration and conservation activities of these artifacts.

Keywords:
GIS; Mosaic Tesserae; Supervised Classification; Restoration; Cultural Heritage

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1. INTRODUCTION

A major challenge in the field of cultural heritage, from surveying to cataloging, is the automatic recognition of objects. This is an important challenge to face because the automatic recognition of

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numerous elements in an image makes workflows easier and faster [Brownlee, 2019]. One important application concerns the automatic recognition of mosaic tiles. A mosaic is a decorative art applied to walls or floors that consists of joining pieces of stone, stained glass, or other materials following a precise pattern in order to obtain a fully realized image. Therefore, the mosaic is a collection of numerous objects that, through the eyes of conservation and preservation, must be recognized and surveyed individually [Felicetti et al., 2020]. This means digitizing the outlines of each individual tile and then assigning an attribute (tile color, state of preservation, etc.). For a long time, manual digitization in a CAD environment was the most widely used method for vectorizing and cataloging mosaics [Arinat 2014]; subsequently, manual digitization and attribute assignment in a GIS environment allowed for efficient computer management [Bazan et al. 2009; Baratin et al. 2014; Gasparetto et al. 2022].

Regarding the GIS-based cataloging of data, [Brumana et al. 2005] developed a 3D GIS data management project for the floor mosaic of St. Mark's Basilica in Venice in order to support the conservation and restoration activities. This began with the creation of a 3D digital orthophoto map. However, while attribute assignment in a GIS environment is a rather established method, the automatic digitization of tessellations is an evolving field of research.

In this context, Deep Learning (DL) represents a solution that can improve the quality of the final result. Through a combination of data inputs, objects within the dataset can be recognized, classified, and accurately described. DL algorithms are also very useful in the context of cultural heritage to, for instance, conduct a series of evaluations. In combination with Mobile Crowd Sensing (MCS) techniques, DL algorithms have been used to conduct a series of surveys of the Great Wall of China in order to automatically analyze damage directly on a computer medium [Wang et al., 2019].

Furthermore, in combination with artificial neural networks (ANN), DL algorithms have been used to recognize the effect of weathering on stone in order to improve and support restoration activities and prevent the disappearance of architectural evidence in the heritage domain [Hatir et al., 2020]. In the reconstruction of mosaics, [Fenu et al. 2020] proposed a deep learning approach that includes a pre-processing phase. This phase enables the training of a convolutional neural network (CNN) called U-net, even with limited labeled data. This approach addresses the unique challenge of the task, where manual annotation is generally costly. Similarly, [Gosh et al. 2021] proposed and tested a framework based on that autonomously quantifies the feature map and classifies it; a Roman mosaic, digitally reconstructed by close-up photogrammetry on the basis of standard photos, was considered for the validation of the method. However, the deep learning approach requires high performance computing and software capable of performing this task which is currently still being defined.

Furthermore, in recent years, thanks to the advancement of artificial intelligence (AI), new tools have been developed that can generate high-resolution digital images and complete the missing parts. In the context of cultural heritage, this technology has been applied in order to obtain a virtual reconstruction of some ancient mosaics, demonstrating the efficiency of interpreting the main features and how the further development of AI will enable even more accurate results [Moral-Andrés et al., 2024].

Therefore, we propose using supervised algorithms for image classification, which can be easily integrated into GIS environments. This approach offers the benefits of automatic digitization and efficient cataloging of additional information, such as high-definition TIN models, which are valuable for mosaic analysis. In this study, the mosaics from the archaeological site of Saltara (Marche, Italy) will be analyzed. These mosaics feature black figures on a white background, depicting animals and stylized vegetation enclosed within frames.

2. CASE STUDY

The dataset under investigation consists of a high-resolution image of a series of mosaics belonging to an ancient Roman *domus*. The mosaics, found in the archaeological site of Saltara (Fig. 1a), consist of three black-figure fragments on a white background, with animals and stylized vegetation enclosed by frames. These are three mosaic fragments (2nd-3rd century CE), each about 3.00 x 1.00m in size, found c. 1928 not far from the *mutatio ad Octavo*. The three fragments formed the floor of a *domus* and depict hunting scenes characterized by the representation of several animals, among which a jaguar (Fig. 1b), deer (Fig. 1c) and rabbit (Fig. 1d) can be recognized.

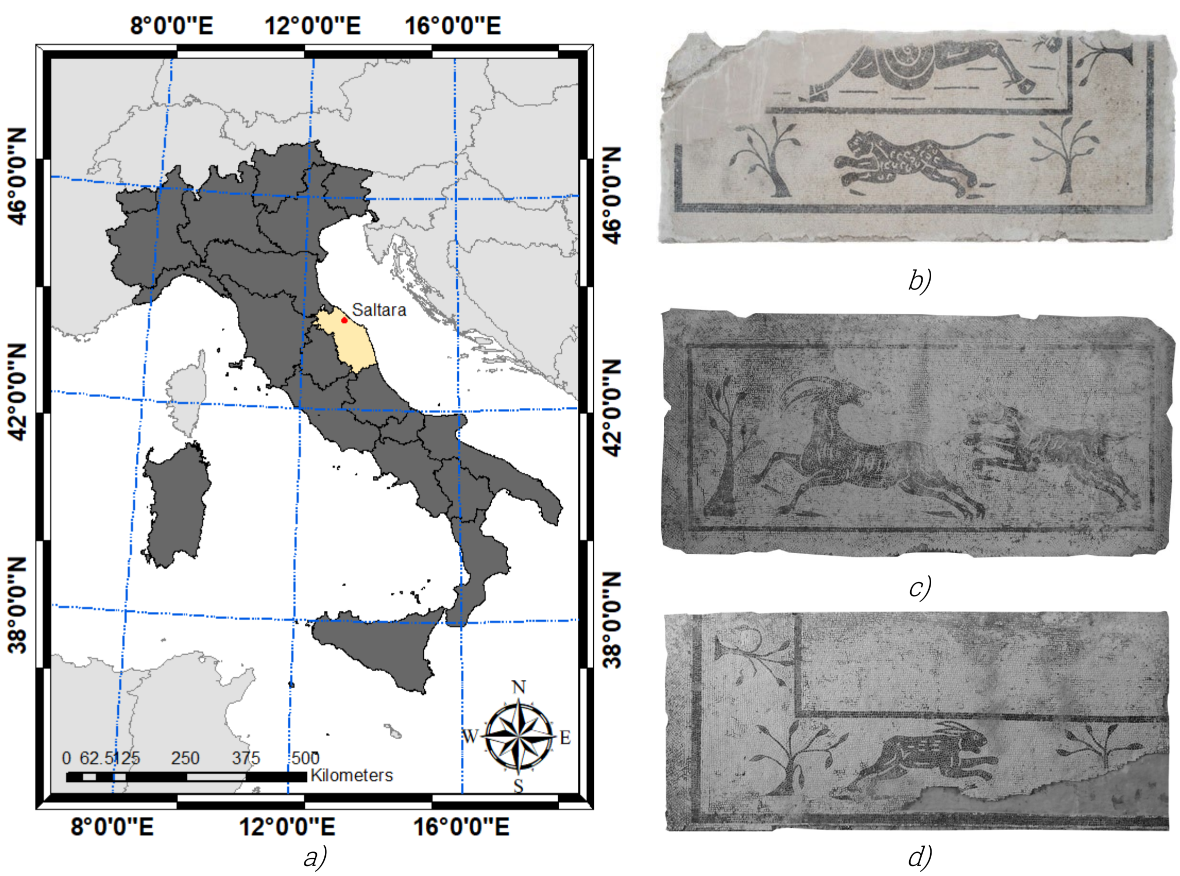


Figure 1. Keymap of archaeological site: a) jaguar; b) deer; c) rabbit; and d) mosaics.

Based on the hypothetical reconstructions of the floor's original layout, only two sections of the mosaic, the ones depicting the rabbit and the deer, appear to belong to the same group. In contrast, the section depicting the jaguar seems incompatible with the other two due to differences in the arrangement of the tesserae and its size. In the present study, we focused on the jaguar mosaic because, compared to the other two, it had more elements that could influence the classifications and analyses conducted using the supervised classification algorithm.

3. MATERIALS AND METHODS

3.1 Methodological Approach

The methodology to be developed can be divided into several steps. The first step involves the acquisition of spatial data using geomatic techniques to reconstruct precise and detailed digital models (see Section 3.2). The next step involves the automatic classification of the acquired data using spatial analysis techniques and Machine Learning (ML) algorithms; each element of the study area is assigned to a specific class and then the accuracy and reliability of the results is evaluated using appropriate statistical parameters (see Section 3.3). Furthermore, in this step, a supervised algorithm is trained using a set of sample images, where the classes are already known in order to recognize the distinctive features of each class (see Section 3.4).

Finally, the supervised algorithm, once trained and validated, is applied to the entire mosaic under study, automatically classifying each pixel according to the defined classes and producing a detailed and accurate map of the distribution of the different classes in the area. The results are statistically analyzed using performance indicators in order to determine the quality level of the proposed method (see Section 3.5).

3.2 Geomatics Survey

The geomatic survey realized by integrating traditional survey techniques with increasingly innovative tools from a technological point of view, are nowadays increasingly fundamental in the processes of knowledge, maintenance, and restoration of existing historical-cultural and architectural heritage.

In fact, thanks to the integration of different survey techniques, it is possible to digitize the object to be represented and process a 3D model with high metric and dimensional accuracy. Subsequently, this can be enriched with a series of material and semantic information at different levels of detail in order to conduct various analyses.

Over the years, numerous experiments have been conducted on creating parametric 3D models in Scan-to-HBIM processes, starting from point clouds generated by integrating various survey techniques [Croce et al. 2019; Coli et al. 2019; Pepe et al. 2020]; in other cases, the geometry survey was used in Scan-to-FEM processes in order to analyze complex structures from a structural point of view [Funari et al. 2021; Alfio et al. 2022]. Furthermore, the integration of different survey techniques allows one to obtain high geometric resolution orthophotos and generate virtual tours linked to relational databases useful for cataloging restoration activities [Balletti et al. 2019].

An element of particular support related to restoration activities is represented by algorithms and tools implemented in GIS software capable of performing analyses both on images (Multispectral Analysis, Change Detection Analysis, Deep Learning, etc.) and on 3D models (TIN, DEM, etc.). Additionally, GIS software enables the management, visualization, and analysis of objects, helping to reveal differences in materials, damage, painting techniques, and conservation interventions, including those from different time periods [Pires et al. 2007; Rahrig et al. 2023]. This analytical approach represents an important control and support tool especially related to the restoration and maintenance activities of existing cultural heritage, useful not only for the representation but also for the archiving, cataloging, management, and referencing of all the varying temporal data acquired [Pepe et al., 2021].

For this case study, a survey using a photogrammetric approach was carried out. In particular, using the Structure from Motion (SfM) and Multi View Stereo (MVS) algorithms, a 3D model of the mosaic was processed in order to obtain a high-resolution metric orthophoto suitable for automatic processing in a GIS environment. In addition, the 3D model obtained with this approach allowed a series of evaluations to be carried out regarding the morphology of the surface and to define any altimetric anomalies present that may be important in the development of the restoration project.

In general, the photogrammetric processing of the acquired dataset allowed us to obtain an orthophoto with a resolution of 0.5 mm/pix. This high resolution makes it possible to perform in-depth analyses and to improve the manual and automatic tile recognition process. After a preliminary phase was conducted using sample images, the manual tile reconstruction process was begun starting from this orthophoto.

3.3 Classification and Evaluation of the Accuracy

Currently, the most commonly used image classification methods are: (i) unsupervised classification; (ii) supervised classification; and (iii) object-based image analysis [Schowengerdt 2012; Hang 2023]. In this paper, supervised classification is used for tesserae recognition due to the flexibility and adaptability of this technique. In supervised classification, training samples are selected, and the image is classified according to the chosen samples. The training samples are crucial because they determine the class to which each pixel belongs in the overall image. The main steps in supervised classification are: (i) select training areas, (ii) generate signature file, and (iii) classify. In step one, it is possible to find the training samples for each class. Therefore, once the training samples have been constructed for each class, the software generates signatures containing all the training sample data collected up to this point, completing step two. The last step can be performed using several methods, such as Maximum likelihood, Iso Cluster, Class probability, Principal components, and Support vector machine (SVM). The software used for the classification of the tesserae is ESRI ArcMap, version 10.8. This software uses the Maximum Likelihood Classification tool. Therefore, the various steps involved in the image classification process are summarized in Fig. 2.

Figure 2: Main steps of Supervised classification in ArcMap software

In computational terms, the training phase is the most time-consuming as it requires the ability to identify the most suitable training samples to achieve the final objective, as well as a complete knowledge of the image to be processed.

Moreover, the choice of training samples must be accurate because the final subdivisions of the various classes will be extracted through the information they contain. In general, it is necessary to select these in homogeneous areas, remove any outliers that leave the class cluster in feature space, avoid transition areas between classes with mixed pixels, and select them in different areas of the same image so as to consider the variability inherent to the class and in an adequate number—in the case of classification techniques that use of statistical parameters, at least k+1 elements in a k-dimensional feature space are required for the k-dimensional feature space for the covariance matrix not to be singular.

As for the final classification phase, the software employed in this experiment uses the Maximum Likelihood algorithm. This algorithm is based on the hypothesis that each class is characterized by a Gaussian probability distribution function [Bolstad and Lillesand 1991]. If this hypothesis is valid, the algorithm can be used and the classification can be carried out according to the Bayesian decision rule for which the pixels are assigned to the class with the highest a posteriori probability [Asad and Bais 2020]. This also results in a class division that minimizes the average probability of error in the data.

In order to evaluate the quality analysis of the classification, it is necessary to build the confusion matrix (or error matrix) which is usually used as the quantitative method of characterizing image classification accuracy.

On the base of this latter matrix, it is possible obtain four performance indicators, i.e. Precision, Recall, Overall Accuracy and F1Measure [Wald 2000; Pepe and Parente 2018; Yekeen et al. 2020].

The Precision indicates the ratio of the correctly segmented classes that are positive for each class which can be measured with TP and FP as shown in the following equation:

$$Precision=\frac{TP}{TP+FP} \tag{1}$$

The Recall is the ratio of the correctly classified positive classes:

$$Recall=\frac{TP}{TP+FN} \tag{2}$$

F1 Measure is the harmonic mean of the precision and recall:

$$F_1 Measure = 2\frac{Precision \cdot Recall}{Precision + Recall} \tag{3}$$

The Overall Accuracy is the ratio of the correct prediction over total observation:

$$Overall\ Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \tag{4}$$

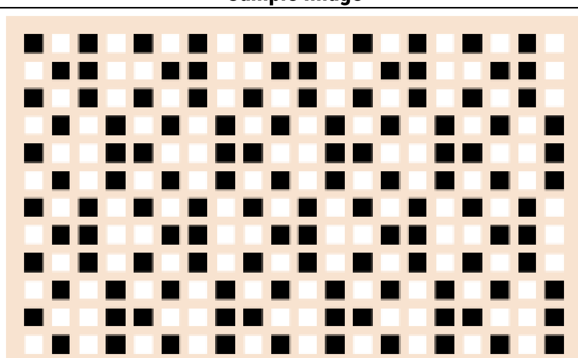
where:
- True Positive (TP) represents a test result that correctly indicates the presence of a condition or characteristic.
- True Negative (TN) represents the result of a test which correctly indicates the absence of a condition or characteristic.
- False Positive (FP) represents the result of a test that incorrectly indicates the presence of a particular condition or characteristic.
- False Negative (FN) represents the result of a test that incorrectly indicates the absence of a particular condition or attribute.

To analyze the quality and the performance achievable using supervised algorithm, two scenarios are taken into consideration: (i) test of sample images and (ii) mosaic datasets. In particular, the test aims to make a preliminary assessment of the probability of success of the supervised algorithm when varying both the colorimetric appearance of the tiles and the addition of disturbing elements to the system such as missing, damaged, or differently colored tiles.

3.4 Application of the Supervised Algorithm on Sample Images

In order to assess the quality in the automatic recognition of black and white mosaic tiles, a test was carried out on a specially produced sample image. The sample image consists of a grid of black and white tiles arranged on a surface that roughly matches the color of the background plaster of the analyzed mosaic. Specifically, the original sample image consists of 120 white and 120 black tiles. Table 1 shows the sample image with the main characteristics in terms of resolution.

Table 1: Sample image and its geometric characteristics

Sample Image	Characteristics	Value
	Resolution [pix]	2841x1536
	Number of bands	3
	Cell Size [m]	0.005x0.005
	Format	TIFF
	Pixel depth [bit]	8

In addition, for experimentation purposes, four more sample images were created, keeping the number of white tiles constant while replacing the black tiles with shades ranging from dark to light grey. The purpose of the test is to show how the algorithm recognizes tiles that are not perfectly black in color; for this reason, suitable datasets were created for varying shades of grey. Table 2 summarizes the sample images realized, the number of tiles, and their RGB tern values. For the plaster-colored background, the same color intensity was used, namely, the RGB tern (240, 227, 208). For each sample image (Test n. 1-5) the following values were obtained (Tab. 3).

Table 2: Sample images realized and its colorimetric characteristics

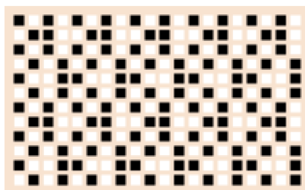
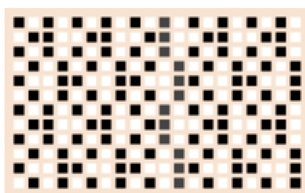
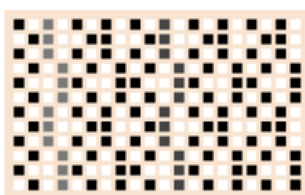
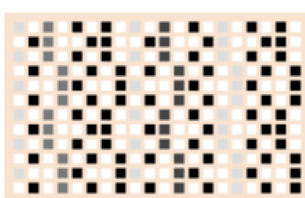
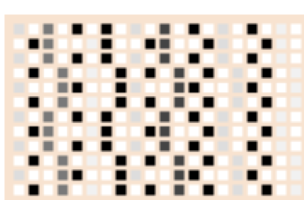
Test n.	Sample Image	RGB value	Number
1		(0,0,0)	120
		(255,255,255)	120
2		(0,0,0)	108
		(70,70,70)	12
		(255,255,255)	120
3		(0,0,0)	96
		(70,70,70)	12
		(120,120,120)	12
		(255,255,255)	120
4		(0,0,0)	84
		(70,70,70)	12
		(120,120,120)	12
		(220,220,220)	12
		(255,255,255)	120
5		(0,0,0)	54
		(70,70,70)	12
		(120,120,120)	12
		(220,220,220)	24
		(240,240,240)	18
		(255,255,255)	120

Table 3: Results of the four performance indicators based on the values derived from the confusion matrix

Value	Test 1	Test 2	Test 3	Test 4	Test 5
Precision	100%	100%	100%	100%	91%
Recall	100%	100%	100%	90%	84%
F1 Measure	100%	100%	100%	95%	87%
Overall Accuracy	100%	100%	100%	90%	78%

3.5 Application of the Supervised Algorithm on the Mosaic

A real test on a mosaic consisting of black and white tiles was conducted. In particular, the research will focus on the jaguar. The first step to evaluate the automatic recognition of the mosaic tiles was the manual photointerpretation of the individual tiles. In the ArcMap environment, all the tiles that made up the entire mosaic were manually reconstructed using a high geometric resolution RGB orthophoto as a basis. In particular, a Polygon type shapefile of the tiles was created for a total of 22,393 tiles; at the same time as the geometric reconstruction of the tiles, an attribute table classifying each element according to the color (white or black), perimeter, and surface area of each tile was implemented. In this way, it was possible to distinguish the various reconstructed mosaic tiles and classify them according to color. Figure 3, shows the result of this manual reconstruction operation. A total of 6,639 black tiles and 15,754 white tiles were reconstructed.

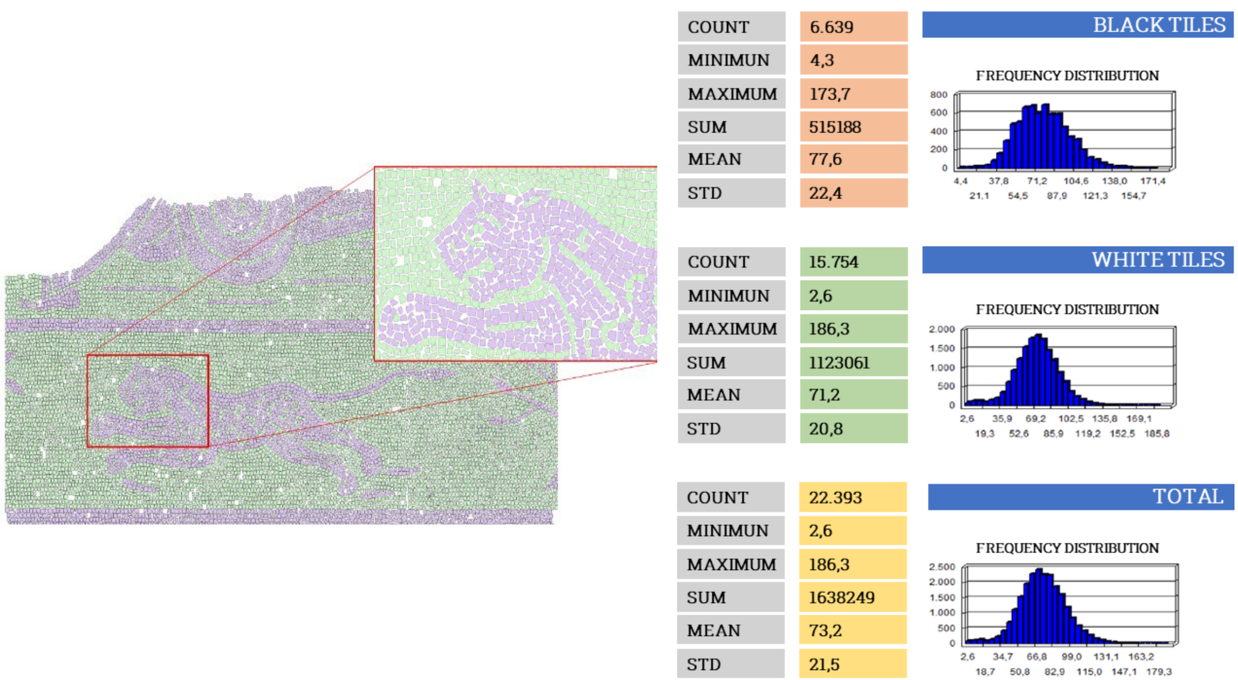


Figure 3: Detail of manual reconstruction and statistics of digitized tesserae with manual approach.

After manual recognition of the mosaic tiles the mosaic was automatically classified based on the results obtained from the automatic classification of the sample images.

Subsequently, after importing the orthophotos into the software, the first step was to select the pixels related to the black tiles and then those related to the white tiles through the “Training Sample Manager” tool. At this stage, a significant challenge was the material composition of the black tiles. Some black tiles contained whitish material, which distorted the final classification results. To address this issue, efforts were made to exclude any tesserae with this material inconsistency during the sample training collection phase.

The next step involved a check of the selected trainings to exclude any kind of pixel classification error. Once the tesserae representing the sample had been uniquely and consistently identified over the entire mosaic in the next classification phase, they were edited, merged, and then exported as a shapefile to be able to manage and, if necessary, modified later on. At the end of this operation, the relevant signature file was created which contains a statistical description of the classes derived from the samples identified on the raster data or input sample features. In general, the signature file consists of two sections: (i) a section containing general information for all classes, such as the number of layers, names of input raster, and number of classes, and (ii) a section containing the signature statistics for each class, consisting of the number of samples and the mean and covariance matrices. In the application of automatic mosaic tile classification, this file represents the relative input for maximum likelihood classification in which both the vectors of class averages and covariance matrices are described.

Using automatic classification and considering the number of black and white tiles obtained, the relevant quality indices were calculated. In particular, figure 4 shows the indicator values obtained and the statistics for the black and white mosaic tiles recognized through the methodological approach illustrated in this paper.

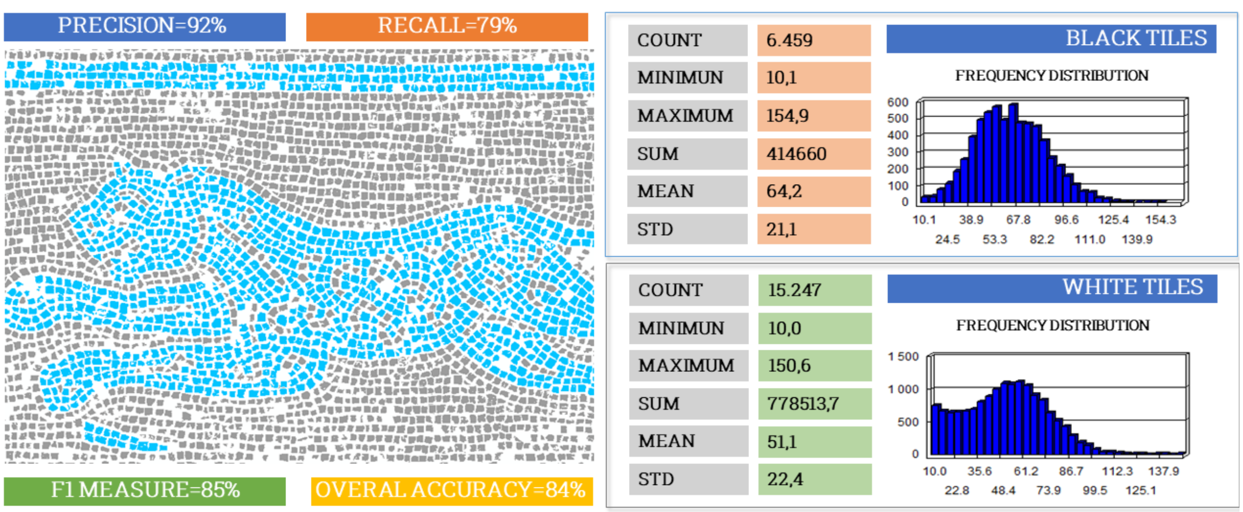


Figure 4: Detail of automatic reconstruction in ArcGIS environment and calculation of performance and statistical indicators obtained.

4. RESULTS AND DISCUSSIONS

The results of the performance indices showed that the application of the likelihood algorithm in the context of automatic digitization of mosaic tiles performs very well and significantly decreases computational time. Moreover, it improves operator-related subjective uncertainties in automatic vectorization processes. In fact, the obtained value of the "Precision" index, which measures the accuracy of the model in classifying a sample as positive, was 92%.

An aspect of particular importance was the performance of the algorithm used where the tiles to be recognized were characterized by material inconsistencies. Some black-colored tiles actually contained intrusions of different materials with colors leaning toward white. In this specific case, the algorithm, although it produced good results, is not highly preformed. Analyzing the "Recall" index, calculated as the ratio of the number of positive samples correctly classified as "positive" to the total number of positive samples, a value of 79% was obtained.

By comparing both indicators, it can be inferred that the model is accurate; in fact, when a model has a high value of the "Precision" index but a low value of the "Recall" index, then the model is accurate. In this case, although the sample was classified as positive with good accuracy, a small number of samples were incorrectly assigned a positive value.

On the other hand, by analyzing the result obtained from calculating the F1 score index, i.e., the F score defined as the harmonic mean of the "Precision" and "Recall" metrics, it is possible to define the accuracy of the test conducted. Generally, this index takes values from 0 to 1.00 (when expressed as a percentage) where the lower limit represents poor accuracy, while the upper limit expresses better result. In the present case, an F1 score value of 85% (i.e., 0.85) was obtained, showing generally good accuracy of the automatic reconstruction. The fourth statistical index calculated, OA, showed a value of 84%, further validating the comparison with the results from the sample image analysis.

In addition to the validation of the results obtained using statistical models, a geometric comparison was performed between the product obtained from manual digitization and that from the automatic approach using the maximum likelihood algorithm. The statistical results from the initial test on sample images were confirmed in the mosaic. In other words, the initial knowledge of the quality of black and white tiles can provide *a priori* information on the ability of the tested algorithm to automatically classify tiles.

5. CONCLUSION

The methodology proposed in the following manuscript highlighted the application of an automatic procedure in a GIS environment for the automatic recognition of mosaic tiles. This procedure was first tested on a series of sample images and then applied to the case study of a mosaic found in the archaeological site of Saltara.

By comparing the performance index values obtained, it was possible to observe that this automatic methodological approach was particularly advantageous in the process of digitizing the tesserae. In fact, the values obtained from the calculation of the indicators show a good accuracy of the tesserae reconstruction process. Another advantage of this approach is the significantly reduced computation time compared to manual digitization, which also minimizes the uncertainty in tile reconstruction caused by operator subjectivity. This subjectivity also affects the process of manual tile reconstruction, which can be improved through the application of the maximum likelihood algorithm.

The analysis of the statistical indices and the comparison with the manual dataset showed that, in the field of cultural heritage, the algorithms and tools available in GIS software not only represent a fundamental tool for the digitization of architectural heritage, but also serve as valuable support in restoration and maintenance processes.

Finally, the functionalities provided by GIS software represent a central tool in the integrated management of all data concerning a cultural heritage, thanks to its ability to organize large masses of data, catalog this data, and its spatial and statistical processing power. The possibility of vectorizing all the tesserae automatically and associating them with a complete relational database, makes it possible to obtain, in a short time, a series of vital spatial data in the in-depth analysis of the mosaic's characteristics. Further, associating vector data with semantic information enables a range of statistical evaluations and enhances the data's granularity.

This approach makes it possible to speed up the decision-making processes related to the maintenance and restoration of cultural heritage assets, especially concerning mosaics. Finally, the proposed methodology, thanks to the functionalities of GIS tools that associate multiple semantic attributes to the geometric data, is also useful for the construction of statistical parameters. This includes the sum of the areas related to the tesserae, the quantity of tesserae, the dimensions, as well as for the storage and dissemination of all the historical-archaeological aspects of the represented object.

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