# Supervised Classification Approach for the Estimation of Degradation

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*Abstract*

The study presents an innovative approach to classify geomaterials using supervised classification methods from orthophotos derived from UAV (Unmanned Aerial Vehicle) and photogrammetric processing. The case study examined is the *Ponte Rotto*, dating back to 20 BC, which in antiquity allowed the Appian Way to cross the Calore River – between the provinces of Avellino and Benevento – to continue towards the port of Brindisi. In previous studies, experts on geomaterial diagnosis estimated – from aerophotogrammetric orthophotos generated for both bridge elevations – the geomaterials and quantities used for the construction of the monument and an overview of the state of conservation of the monument studied. Orthophotos of facades were imported into CAD software and used as the basis for – according to a manual process – the mapping of the materials. The work presents the results according to automatic Machine Learning clustering from the same orthophotos to identify geomaterials.

*Keywords*
UAV, photogrammetry, semantic image segmentation, geomaterial distribution.


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## Introduction

The generation of digital models and outputs for cultural heritage, in the form of point clouds or 2D products, is a powerful tool for scholars, architects, archaeologists and curators to support analysis and planning operations. Therefore, the correct management of these resources is crucial for better understanding the investigated asset and developing appropriate conservation strategies [Álvarez 2021]. Many of these procedures in professional practice are still linked to conventional techniques, such as manual drawing using CAD software. For example, the survey for restoration is characterised by a considerable attention to the reading of the state of conservation, to the stratification of the masonry and to the crack drawing. These representations are made by manual work guided by specialised operators who often rely on in situ analysis and their personal skills.

In parallel to the traditional approach, the analysis and automatic extrapolation of information from digital models is undergoing rapid diffusion, with significant advances in the procedures for segmentation and classification of 3D models or 2D drawings. As known segmentation is the process of grouping data into homogeneous clusters with similar properties, while classification is the operation that labels these clusters [Grilli 2017]. In the literature, we can encounter many studies on the topic, mainly driven by specific needs provided by the field of application (building modelling, heritage documentation and conservation, etc.). Most segmentation algorithms are tailored to work with a 2.5D surface model hypothesis coming, for instance, from a LiDAR-based survey. Many algorithms require fine-tuning of different parameters depending on the nature of the data and applications. Most of these are supervised methods, where a training phase is mandatory and crucial to guide the subsequent machine learning classification solution [Guo 2015; Niemeyer 2014; Xu 2014; Weinmann 2015; Hackel 2016; Qi 2016]. Considering the availability and reliability of segmentation methods applied to imagery and the effectiveness of machine learning strategies, we present our work and methodology developed to assist heritage workers in analyzing artefacts, the core of which consists of 2D segmentation of orthophotos derived from photogrammetric survey for geo-material classification.

The benchmark for the proposed methodology is represented by the *Ponte Rotto* (Broken Bridge). The structures still preserved today can be traced back to a viaduct built with quadrangular pillars in opus quadratum, arches, and gable end walls in concrete covered with bricks. Unfortunately, only the western ramp on the left side of the river Calore, made of bricks and limestone blocks, and three pillars on the opposite bank and an arch are preserved today. These structures have already been the subject of a study that, starting from orthophotos derived from photogrammetric survey, has returned, among other outputs, a lithological map showing the percentages of the different materials making up the artefact [Germinario 2020]. The whole procedure was developed with a traditional approach, reworking the orthophotos in a CAD environment and drawing the boundaries of the different regions. Our research aims to propose a machine learning technique for the localization of the different geo-materials that allows an efficient classification with a reduction of manual input. The segmentation results are then compared with those obtained from the traditional approach, to highlight possible deviations in the percentages. Such operations can facilitate the study of heritage monuments and integrate heterogeneous information and attributes, useful to characterise and describe the surveyed object. The research presented was motivated by the concrete need of archaeologists to identify and map the building functions and materials of heritage structures. To address this need, we developed a method to (i) distinguish different construction techniques, (ii) recognise the presence of specific materials, and (iii) assess their percentages and distribution over the investigated surfaces. Detecting these types of information in historical buildings using traditional methods, such as manual mapping or simple visual examination by an expert, are time-consuming and laborious procedures [Corso 2017]. Therefore this proposal aims to pave the way for less time-consuming solutions and the involvement of specialised personnel while still guaranteeing an accuracy compatible with the objectives of the research.

## Case Study

*Ponte Rotto* is part of the Via Appia, a fundamental road that connected Rome to Brindisi and the East, defined by classical historians for the importance of the route as the regina viarum. The bridge crossed the river Calore near the ancient city of Benevento, on the way to the ancient *Aeclanum* [Aurigemma 1911, pp. 355-359]. It straddles the municipalities of Apice (BN), Bonito (AV) and Venticano (AV). The structures can be traced back to a viaduct bridge from Roman times and cover a chronological span from the 1st BC to the 7th AD, within which at least four different building techniques can be identified, referable to as many historical phases.

Nowadays, only three piers and one archway are preserved, however, historical sources have described six arches (from 10 to 22 m wide) with a total length of 190 m and a variable height of up to 13 m [Galliazzo 1995; Johannowsky 1991]. It was one of the most important bridges in Campania because of its size, unfortunately it has been in a state of neglect in recent years. The bridge was restored in Longobard Era, with the addition of concrete pillars aimed at supporting wooden arches that replaced the collapsed arcades. This intervention, due to the state of degradation of the structure likely aggravated by floods and overflows of the Calore river, was no longer sufficient in Medieval times, when the crossing was moved on a smaller bridge built with recycled materials of the same Hadrian bridge [Santoriello 2014; Santoriello 2018]. However, the bridge has been abandoned for centuries, experiencing carelessness and weathering that have resulted in a bad state of conservation. Actually, the monument in 1980s was interested by restoration and consolidation works with the addition of concrete pillar reinforcements [Quilici 1996]. Since 2011, several institutions, namely DISPAC (Department of Cultural Heritage Sciences) and DICIV (Department of Civil Engineering) of the University of Salerno, started a multidisciplinary project (Ancient Appia Landscapes) for the study and valorisation of the Appian Way. One of the first studies in 2017 was an aerophotogrammetric survey by UAV whose results were used for lithological and damage estimations. This paper describes the results of the photogrammetric survey that allowed the construction of a three-dimensional model of the *Ponte Rotto*, used to estimate – in automatic mode – the geomaterials quantity of the different architectural portions of the monument.

## Photogrammetric Data Acquisition and Elaboration

In May 2017, the bridge was surveyed, and the photogrammetric results were used for the lithological assessment. Details of the analytical approach adopted for the study are given below. The tests carried out on *Ponte Rotto* were aimed at validating the photogrammetric acquisitions from UAV, namely a DJI Phantom 4, a drone weighing about 1400 g, capable of shooting 4K video at up to 30 frames per second and streaming HD video to smartphones, tablets and external devices through a special App (DJI Go).

The camera is equipped with a 12 MPixel Sony Exmor sensor (sensor size 6.3 x 4.7 mm, pixel size 1.56 µm), which has a wide-angle lens with a focal length of 4 mm and FOV (Field of View) of 94°. The camera integrated in the gimbal maximises image stability during filming. To geo-reference and control metric error, six ground control points (GCPs) were placed on the ground and measured by a global navigation satellite system (GNSS). The GCPs were materialised on the ground using photogrammetric targets (30 × 30 cm) and topographic nails. The GNSS survey refers to the Italian geodetic and cartographic system UTM/ETRF00 [Barbarella 2014]. The accuracy of the planimetry is less than 1 cm and 2.5 cm for the altimetry. The photogrammetric shots were acquired in manual mode due to the presence of obstacles on the west side of the bridge (Fig. 1). Three flights were planned, and a total of 273 images, according to 3 consecutive strips, were acquired in time-lapse mode (5 s interval). In the first flight, 74 photographs were acquired in nadir mode (NW-SE direction, average height 19 m, ground coverage approximately 29.9 x 22.3 m).

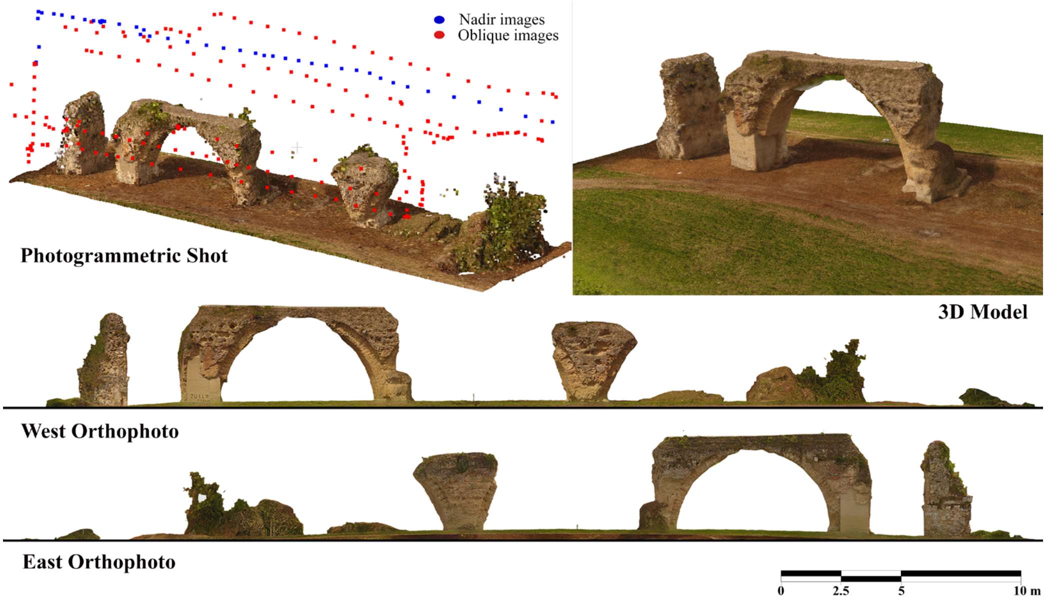


Fig. 1. Image acquisitions. Orthophoto West and East.

Then, two other flights, with the camera tilted at 45° in the horizontal plane, were carried out, acquiring a further 96 and 106 photos (17 m and 9 m on both sides; ground covers of approximately 26.8 x 20 m and 14.2 x 10.6 m, respectively). The aerial photogrammetric images were processed in Agisoft Metashape, version 1.7.3 build 12473.
The orientation parameters were estimated in Metashape, using a self-calibrating bundle adjustment (BA) by including the GCPs. These estimated parameters were then used to orient the images. Additionally, the estimated parameters were kept constant during the entire RGB data processing. The following parameters were set to calculate the point clouds: in the Align Photos phase, accuracy = High (original photos), Key-Point limit = 60,000 and Tie-Point limit = 40,000. To optimize the camera alignment process, f (focal length); cx and cy (principal point offset); and k1, k2, k3, and k4 (radial distortion coefficients) were fitted. In the building of the Dense Cloud, the parameters used were as follows: Quality = High (1/4 of original photos), and Depth Filtering = Disable; once the complete elaboration of the photogrammetric shots were done, it created the texturized 3D model of the bridge, used to extract the orthophotos of elevations, required for the next calculates needed of the geomaterials that compose it (Fig. 1).

## Pixel-Based Segmentation

The applicability of supervised machine learning (ML) algorithms for accurately segmenting pictures was studied in this work. Supervised machine learning creates models in which machines are trained with labelled data (i.e., input data already tagged with the appropriate output) and then predict the outcome based on that data. In supervised learning, the training data presented to the machines acts as a supervisor, instructing the machines on how to anticipate the output accurately.
WeKa (Waikato Environment for Knowledge Analysis), developed at Waikato University in New Zealand, is one of the most well-known workbenches for data mining, employing machine learning to accomplish pixel-based segmentation. Contains a variety of data analysis and predictive modeling visualization tools and algorithms, as well as graphical user interfaces enabling quick access to these operations [Bouckaert 2010; Witten 2002]. Data preprocessing, regression, classification, visualization, clustering, and feature selection are just a few of the usual data mining operations that WeKa offers.
The Trainable Weka Segmentation plugin (TWS) was used to train a classifier, then used to

segment the remaining validation data automatically. The ImageJ plugin is a collection of picture segmentation and machine learning techniques included in the open-source image processing program Fiji and can be installed on the free-access software ImageJ. [Arganda-Carreras 2017].
Pixel-based segmentation is performed using the Fast Random Forest method, a parallel version of the Random Forest classification approach [Breiman 2001; Ho 1995]. Random Forest is a versatile machine learning technique that can be used to a wide range of problems, including regression and classification. It comprises a number of decision trees, each of which represents a unique categorization of data fed into the random forest. The random forest method evaluates each occurrence separately, selecting the one with the most votes as the chosen prediction.
Each classification tree uses samples from the initial dataset as input. The features are then chosen at random and utilized to build the tree at each node. No tree in the forest should be trimmed until the exercise is completed and the prediction is made definitively. Random forests can also handle large datasets with a high dimensionality and a wide range of features. Using a training set of manually annotated images, the Fast Random Forest algorithm is first trained by examples in a supervised manner. Each pixel in these images has been individually labeled with its matching label. Then, the original image is presented to the model in each of these cases, which computes the actual answer. Following that, the model's weights are changed to minimize the difference between this answer and the annotation that reflects the model's predicted answer. Finally, the model's performance is evaluated by comparing it to a different collection of photos than those used during the training phase. When the segmentation is successful, the result is overlaid with the matching class colors just over the original picture. The random forest method was chosen for image segmentation tasks in various disciplines for its accuracy, speed, and multi-class segmentation capabilities. [Belgiu 2016; Mahapatra 2014; Smith 2010].

## Result

The bridge was built with different techniques and geomaterials, as observed in other coeval monuments in Benevento [Grifa 2007], which basically depend on the structural function they had. Lithological mapping highlighted the presence of tuff material, bricks and limestones welded by mortars (Fig. 2; Table 1). Concrete, due to recent restoration works, also occur (Fig. 2).
From the analyses carried out by experts in petrology and petrography, it is possible to identify 4 macro-groups of materials for the construction of the bridge: yellow tuff, bricks, limestone and cement. The yellow tuff material is the predominant building stone in both eastern and western façades (23 % on average, Table 1), covering the lower part of the bigger lateral pillar and the central circular arch.
Yellow tuff can be attributed to pyroclastic trachytic rocks (likely Campanian Ignimbrite in Yellow facies), one of the first building materials since Roman times, largely used for other coeval historical monuments of Campania region [Morra 2010], also outcropping along the Calore river [Vitale 2018], as also observed in nearby contexts [Cilenti 2019].
The framework of tuff blocks is made up in opus incertum, intercalated with bricks. Bricks (8 % on average, Table 1) were used as covering material in the upper part of all the elements of the bridge (arch and pillars). They are generally horizontally oriented (except for the archway where they signed the arch shape).
Limestones, occurring in different percentage on both sides (17 % on average, Table 1), have been recognized as large squared limestone blocks on the base of the pillars of the archway, and fluvial pebbles superimposed on the archway.
It should be remarked that a significant surface of the bridge (eastern façade 11.0%, western surface 6.5%, Table 1) was not investigated due to the presence of plants mainly growing on the top and the bottom of the façades.

| Façade | Tuff | Brick | Limestone | Cement | Mortar | Not observable |
|---|---|---|---|---|---|---|
| Western | | | | | | |
| Manual Analysis | 23.2% | 8.5% | 17.2% | 4.6% | 40.0% | 6.5% |
| ML Analysis | 30.8% | 17.8% | 38.2% | 4.9% | / | 8.5% |
| Eastern | | | | | | |
| Manual Analysis | 23.2% | 10.1% | 15.7% | 4.6% | 39.1% | 11.0% |
| ML Analysis | 27.2% | 12.9% | 34.7% | 4.7% | / | 19.6% |

Table 1. Distribution by manual and ML supervised approach.

Mortar-based materials containing volcanic aggregate and covering around the 40% of the examined surfaces (Table 1) were used to bind the different building materials [Izzo 2016]. These mortar-based binders are highly dispersed within the orthoimages and difficult to bind to pixel-based macro-clusters.
Therefore, the classes analysed by supervised ML algorithms only considered the four macro classes listed at the beginning of this paragraph. From the analyses carried out using ML algorithms, it can be seen that there is an overestimation of the percentage for each class of material compared to the more exact manual techniques.
The principal reason for this is the presence of mortar; in fact, the greatest overestimates occur where mortar is greatest in point form, i.e. in the top part of the bridge, where the geomaterials there are a strong predominance of Limestone. Therefore – as a percentage – the ML analysis for Limestone has a very high error percentage (average error ratio of 2.2 times the percentage estimated by manual techniques).
The best estimates of quantity are for the brick (average error ratio of 1.68) and for the not observable part (average error ratio of 1.54), which are affected by high overestimates due to the participation of point mortar in the areas where these classes have been identified.
The best estimates of the quantity of materials occur where these are continuous and without the presence – at least not excessively punctual – of mortar, i.e. for yellow tuff (mean error ratio of 1.24) and cement (mean error ratio of 1.04), where the percentages estimated by ML algorithms can be considered acceptable.

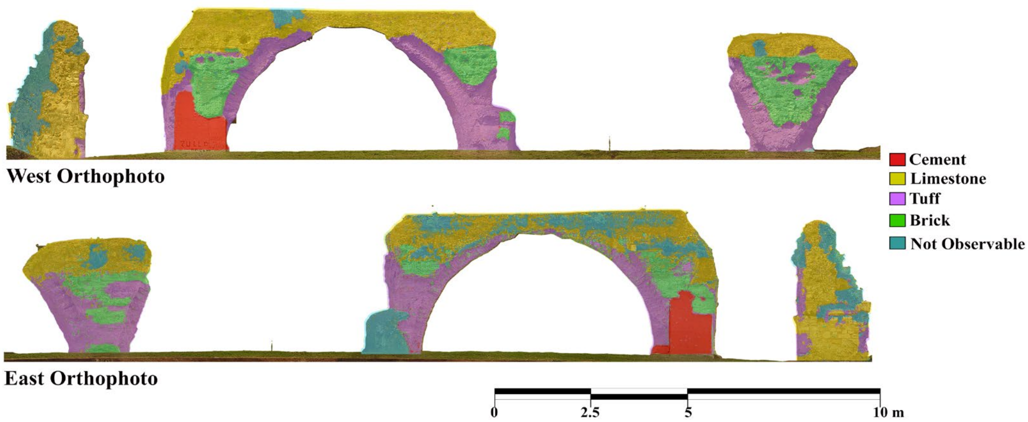


Fig. 2. Geomaterial distribution by ML supervised approach.

## Conclusion

This work aimed to evaluate the detection of different geomaterials within high-resolution orthophotos generated from 3D photogrammetric models, in this case, specifically from UAVs in the *Ponte Rotto*. The applicability of supervised machine learning (ML) algorithms to accurately execute multi-class segmentation on images at a pixel level – in particular, the WeKa algorithm used in this study implementing the Fast Random Forest method – highlighted some limitations in the presence of point and irregular lithotypes within the ortho-

image that are present in this work with the specific case of the mortar geomaterial. From the experimentation carried out in this investigation, even the use of the same orthophoto but at higher resolutions (the one used for the calculations has a resolution of 1 cm, tests were carried out for 0.8 and 0.5 cm) did not lead to gross improvements or acceptable percentages of recognition of that type of geomaterial that carries to a minor difference with the manual analysis.
On the other hand, in the case of compact geomaterials – as was the case of the yellow tuff and cement – continuous along the image surface, the estimations made by the ML algorithm are very close to those analysed by comparison with calculations made in previous works with experienced personnel. Therefore, better results can be obtained for ortho-image studies in which the materials do not have punctual variations, but are arranged continuously along a surface, as is generally the case for building facades.
In fact, specifically in facades characterised by continuous and linear material layers – as already known from other studies cited in the text – in the realisation of clusters, the proposed machine learning algorithm manages to define better the portions of materials characterised by different textures, obtaining better results in the differentiation of geomaterials, and accomplishing percentages of each type that are in agreement with those obtained manually by an expert, reaching a less time-consuming and laborious solution. As future works, subsequent studies will be carried out – always in archaeological contexts – on case studies where the texture is homogeneous in layers, verifying the accuracy in clustering the orthoimage. Subsequently, the orthoimage will be reprojected on the starting point cloud, in order to obtain for each 3d point a "scalar field" relative to the material to which it belongs.

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