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Automated Mapping of the roof damage in historic buildings in seismic areas with UAV photogrammetry

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Abstract

The paper presents a fast methodology to quantify the damage to the roof in historic buildings, suggested soon after a light seismic event occurs, in order to evaluate the necessity of provisional interventions to prevent further damages. The survey is based on UAV photogrammetry, a well-known technique that allows inspection and digital documentation even in hardly accessible or dangerous areas. The research aims to analyze the feasibility of the automated mapping of roof damage using an image classification procedure based on supervised machine learning. The procedure is summed up in an efficient workflow, where UAV photogrammetry is combined with other 3D survey techniques, such as terrestrial photogrammetry and laser scanning, to provide comprehensive documentation and quantitative data on a historical building. The methodology was validated on a large historical building, now suffering from a serious state of neglect, which roof was never surveyed before and with different damage types. The output orthoimage of the tiled roof allowed us to understand the past interventions and the current serious damage state with promising outcomes regarding the speed of the survey method.

Keywords: UAVs, Machine Learning, Image Segmentation, Built Heritage, Damage Survey

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1. Introduction

In the domain of built heritage, Unmanned Aerial Vehicles (UAVs) can have a multitude of applications (Barba et al. 2020). The flexibility and ease of use of modern consumer devices allow the visual inspection and digital documentation of even difficult-to-access or dangerous areas, thanks to remote image acquisition and close-range aerial photogrammetry (Ronchi et al 2020). Indeed, a complete and systematic design of the photogrammetric survey ensures accurate metric restitutions to support conservation and maintenance activities. UAVs are also helpful in an integrated survey approach, supplementing other 3D measurements that typically miss the roofing data. The paper proposes an efficient workflow, in which UAV photogrammetry complements other 3D survey techniques (such as terrestrial photogrammetry, terrestrial laser scanning and total station) for the comprehensive documentation of a historical building. The specific focus of this paper is to test and evaluate in a selected case study a semi-automatically mapping of roof damages through automatic image classification based on supervised machine learning (Teruggi et al. 2020, Russo et al. 2021). This methodology could easily be applied to the structural assessment of built heritage, mainly when critical building conditions prevent access to roof structures from the inside, as well as during inspections to be carried out for maintenance work.

2. The case study: a public heritage building of 1930 in Caronno Pertusella (Italy)

The Palazzo Littorio in Caronno Pertusella (VA), a representative building that housed the local branch of the Italian National Fascist Party in Italy, was chosen as a pilot case study.

The building, which later became a House of the People after World War II and then as a police station until it was closed and abandoned in the mid-80s, now shows severe signs of damage and partial collapses, particularly to the roof. The style of the building partly follows the dictates of Italian rationalism and partly the Art Nouveau style, especially the internal theatre space. It presents two lateral additions to the original volume that do not alter the impressiveness of the 3-storey central body, built-in 1930. The additions date only a few years after construction (Balin et al. 2021).

The state of abandonment and degradation of the building for over 30 years necessitates now intervention by the local administration for its preservation, reuse and valorization due to its location in the town center. The main problem of the building is the state of damage to the roof structures, especially in the area of the stairs, which makes at the moment an inspection from below too dangerous. Even without a definitive idea for the reuse of the building, there is an urgent need to protect the existing roof structures, repair the roof, and provisionally cover and protect the entire building from damages caused by water infiltration. Unfortunately, this situation is recurring in earthquake zones, where many historic buildings only partially damaged by the earthquake remain uninhabitable and closed for a long time.

The correct and detailed assessment of their state of preservation needs to be carried out in safety, and the use of the UAV is an ideal method to conduct an investigation that should not only be qualitative. The UAV also proves optimal for complementing surveys carried out with more traditional techniques from ground level, which inevitably leave undetectable areas.

3. The integrated digital survey

A digital survey based on integrating active and passive sensors systems was designed for the heritage adequate 3D documentation.

3.1. TLS acquisition

The complete exterior and interior geometrical survey was accomplished using a TLS (Terrestrial Laser Scanner - Leica RTC360). For architectural scale survey, the instrument has excellent performance and specifications: 0.5-130m acquisition range, 360° (horizontal rotating base) x 300° (vertical rotating mirror), 360° Field of View, 4 mm at 10 m estimated noise range, and 2 million points per second max acquisition speed. For creating 360° spherical panoramas, 3 HDR (High Dynamic Range) cameras allow for 5 bracketing exposures. Each camera station captures 36 images, each with a 4000 × 3000 pixels resolution. The VIS (Visual Inertial System) uses the other 5-cameras to track the laser scanner path. The VIS and IMU platform integration enables real-time raw alignment between pairs of scans during on-site capturing. This raw registration ensures real-time control over the minimal needed overlap among scans and the completeness of surveyed areas. Therefore, the number and position of scans were planned according to a target-less acquisition mode. The survey consists of 84 (34 outdoors) scans with a greater than 50% overlap to ensure proper cloud-to-cloud alignment to optimize the raw registration.

The TLS workflow is performed according to the standard following steps: i) cleaning raw single scans, removing objects that can affect the ICP algorithm efficiency (moving automobiles, vegetation, people, etc.); ii) scans alignment optimization; iii) in-deep individual scans filtering (removing noise, distant points and points measured with a sub-optimal incidence angle with the surface). The acquisitions were generally set with a spatial sampling of 6mm@10m, ensuring the 1:50 graphic representation scale (1cm plotting error). The result is a measurable point cloud that represents the complete geometric model of the building.

3.2. UAV photogrammetric survey

On the other hand, the aerial photogrammetric survey was essential for the roof measurement, which is the focus of this research. The drone acquisitions were designed with 3 main goals: i) obtain an orthoimage of the tiled roof covering (1:50 scale); ii) quantify the extension and localization of the damaged tiles; iii) integrate the terrestrial photogrammetry survey of the vertical facades with inclined shots. In addition, detailed photographic documentation was acquired to gather qualitative information on some critical areas. The flight mission was designed (Fig. 1) to meet the survey criterion (i): the flight height was set at 25m to ensure a 3mm GSD on the roof, and the distance among the photos was set at 5m to achieve more than 80% coverage on the ground level (overlap and sidelap). The instrumentation used is a Phantom 4 pro V.2 with an integrated camera of 8.8mm focal length (2.6µm pixel size, camera sensor size of 12.65 X 9.49 mm and resolution 4864 X 3648 pixels).

The drone acquisition was supported and integrated by terrestrial photogrammetry, terrestrial laser scanning and total station measurements. A terrestrial photogrammetric acquisition was also carried out to produce orthoimages of the building facades, useful for materials and decay mapping (5mm GSD) for cultural heritage restoration projects. The workflow follows the standard steps of the photogrammetric processing: i) images orientation by structure from motion; ii) tie points filtering and camera calibration optimization; iii) absolute orientation (scale and referencing in a local coordinate system); iv) dense image matching (dense cloud elaboration); v) mesh model creation; (vi) orthoimages generation.

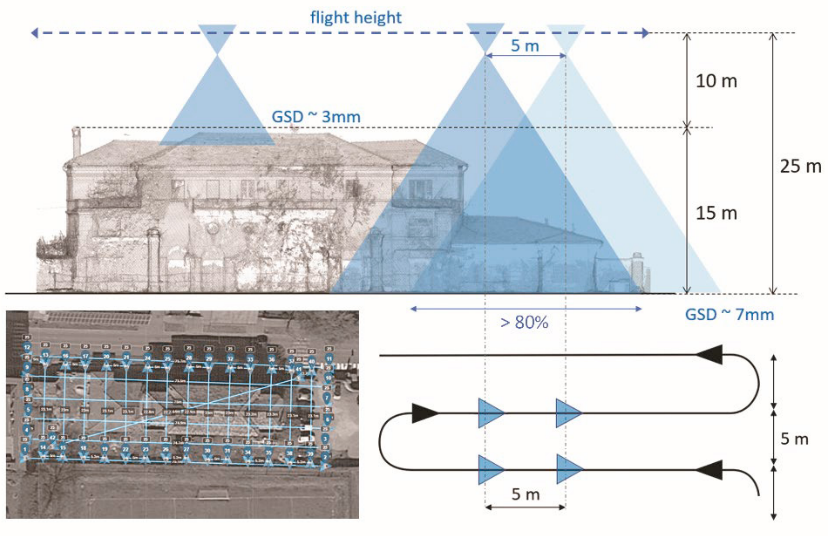

Fig. 1. Aerial photogrammetric survey: shot positions, GSD and overlap determination.

Fig. 2. Palazzo Littorio of Caronno P.: a) a schematic axonometric view of the three volumes; b) Roof photo of the north side towards the west corner before (left) and after (right) the urgent repair works in 2020. 3-types of tiles are easily recognizable: the oldest dark ones, the newest brilliant red ones and the other most diffused dull red ones.

4. The roof orthoimage classification

Drone photos allowed a preliminary visual and qualitative assessment to evaluate the degree of damage and potential risks associated with the roof elements. Together with the aerial photos, the roof orthoimage provided an overall view of the roof covering, combining these initial qualitative considerations with quantitative data such as the position and size of the most damaged areas and the most damaged roof tiles. It is noted that there are more tiles with holes to repair on the North pitch of the roof than on the South pitch. This identified critical area should always be kept under control during routine maintenance. The recent heavy hailstorms and, at the same time, the low quality of the local clay tiles might be responsible for this phenomenon. This justification would also explain why several tile replacement works have been made over the years, as noted by the survey (Fig. 2).

The tiles found are all interlocking tile typologies (Marseillaise tiles) with a dimension of approximately 24x42 cm. Moreover, thanks to the UAV acquisitions, it was possible to identify 3 main categories of roof tiles. The 30s original clay tiles are very dark/black. The faded red roof tiles belong to the early 60s when the significant change of use from the House of the People to the police station took place and to the later years for maintenance, now covered by a very variable grey patina dirt and biological growth. Lastly, the newer ones used during the last urgent repair works in 2020 have an intense red color, partly because they are cleaner (Fig. 2b).

Thanks to an automatic supervised technique of an image segmentation system based on a trainable classifier, these three types of roof tiles and the holes were spotted and categorized on the orthoimage (Grilli et al. 2018; Grilli and Remondino 2019). These experiments were performed using Fiji, open-source image analysis and processing software (Schindelin et al. 2019). WeKa (Frank et al. 2016, 2016) is the engine of the machine learning algorithm inside this software package tested. The method is trained in a supervised manner using an initial dataset of manually annotated image/images where the classes are identified.

In this case, for the classifier training, a mosaic composed of meaningful samples of the original orthoimage is used, where the following 4-classes are visible (Fig. 3): 1) light red clay tiles - the intermediate reference period between 1930 and 2020; 2) dark clay tiles - older original ones from 1930; 3) bright red clay tiles- newer of the latest 2020 repairs, and 4) holes. Each pixel in the image mosaic of the samples has been manually labelled with its corresponding class.

This solution was adopted to facilitate the computational capacity of the image-processing package. For the same reason, the orthoimage was then divided into 75 tiles of around 310x310 pixels to be automatically classified as single images (Fig. 4). Two python scripts were used; the first to automatically divide the orthoimage into identical tiles and the second to reassemble them after classification.

In training the classifier, different sets of image feature parameters were computed and tested to identify the most effective ones in our case. Moreover, the automatic classifier (Fast Random Forest) results were compared against a ground truth reference. Indeed, to assess the automatic procedure performance, the classification was also performed manually on the same orthoimage, relying on the support of photos taken before and after the 2020 roof repairs and limited information from the municipality about maintenance works

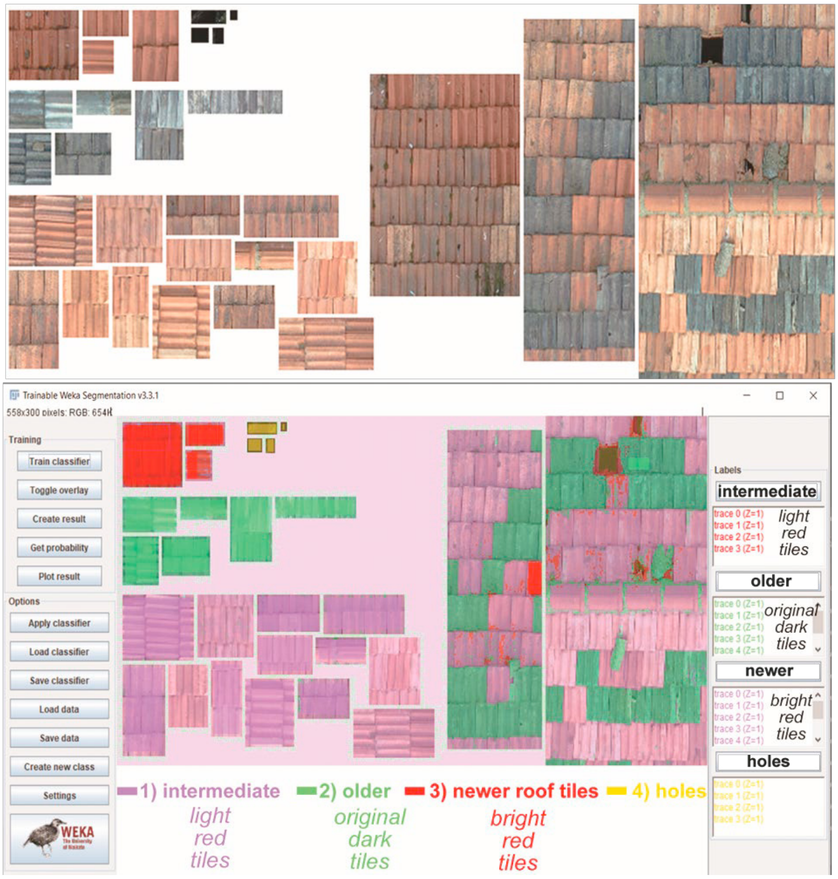

Fig. 3. The mosaic formed by the meaningful fragments of the original orthoimage

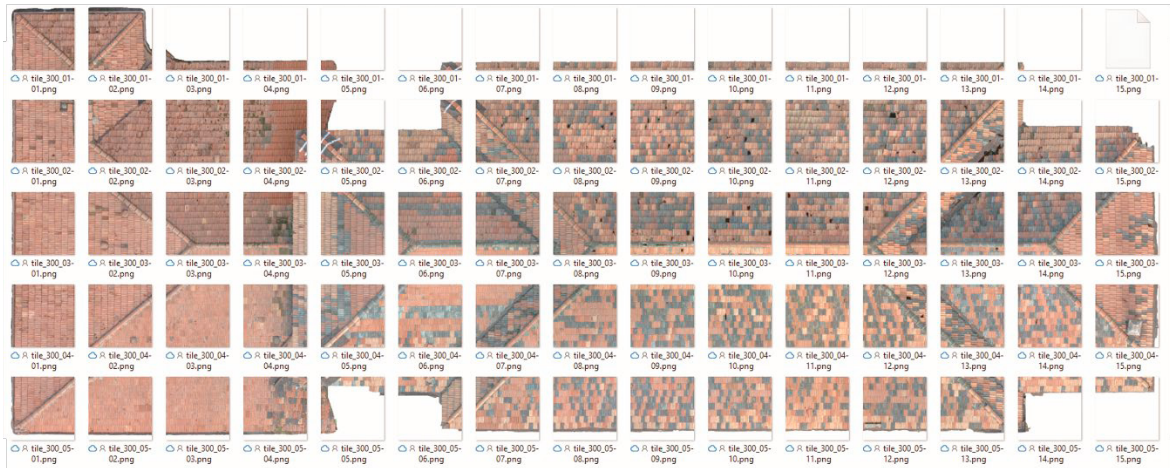

Fig. 4. The roof of Palazzo Littorio: orthoimage decomposition in 75 tiles (5 rows and 5 columns) of about 310x310 pixels resolution

Comparing for each point the label provided by the classifier with the same manually annotated, for each class, true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) are determined at the pixel level and reported in a confusion matrix (Markoulidakis at al. 2021).

The TPs, i.e. the number of pixels that truly belong to a class, are reported on the diagonal; the FPs are in the columns, while the FNs are in the line. For example, 3.3% of the pixels classified as newer tiles are actually of the intermediate category. Simultaneously, 2.9% of pixels classed as intermediate should actually be in the older tile class.

In particular, the precision, recall and F1-score (Mohanchandra et al. 2015) calculated for each class were taken into consideration. The report with these data allows the following considerations. Precision and recall of the intermediate and older roof tile class are very high; which means that the classifier is reliable for these classes. On the other hand, for example, the precision of the newer tiles class is very low (~28%), which means that there are many FP, the majority of which are of the intermediate class; however, the recall is very high; meaning that there are few FN so that most of all new tiles have been identified correctly by the classifier, but many tiles of another class have ended up in this one. Finally, the precision of the holes class is acceptable (~77%); the majority of the holes have been correctly identified (few FP). Nevertheless, the recall is low (~48%), so many holes have not been identified and ended up in other classes (older class) (Fig. 5).

Therefore, this statistical data is helpful for both evaluating machine learning classifier performance and extracting practical information (Fig. 6). Indeed, the sum along the lines of the confusion matrix gives us the number of pixels that belongs to that class according to the ground truth, while the sum on the columns is the number of pixels predicted by the classifier. From this information, it is possible to calculate the corresponding area and, therefore, the number of corresponding tiles for both true and predicted classes. For example, the original tiles (1354876 real pixels and 369445 predicted) occupy an area of about 380m^2, and 370m^2 have been predicted. These values correspond to 6332 real tiles and 6157 predicted ones, with an error of about 10 tiles. The holes class is unquestionably one of the most significant, yet it also has the lowest recall. The classifier has predicted 1.5 m^2 of holes, but there were 2.4 m^2 in total; therefore, 23 instead of 37 tiles to be replaced have been predicted. Future research aims to improve the metrics used to classify these areas.

In summary, the workflow used consists of the following steps: 1) Orthoimage generation; 2) Identification of the classes; 3) Manual categories classification to create the ground truth; 4) Ad-hoc mosaic image creation with all classes visible, composed by orthoimage samples, used for the algorithm training; 5) Orthoimage splitting in identical tiles; 6) Automatic classification of all image-tiles; 7) Re-composition of the classified roof orthoimage; 8) Classifier validation; 8) Metric proper information extraction (Fig. 7). Naturally, once the algorithm and the entire procedure have been validated, the same workflow can be applied to other case studies, omitting steps 3 and 8. Indeed, manual classification is time-consuming, and the research goal is to have the same results automatically.

5. Conclusions

The extent of the roof damage accumulated over time was assessed using a trainable automated image classifier on the orthoimage produced from the drone survey.

Here the method has been calibrated to recognize, in addition to the holes, the types of tiles that can be associated with the repairs over the years. However, it is clearly easier to distinguish just the dark areas that can be attributed to the collapses than the areas still covered with tiles of all types and colors. In addition to giving an accurate geometric survey, the methodology adopted proved an estimate of the urgency and expense of the roofing work, resulting in efficient support for the municipal administration. It is therefore useful not only for digital documentation in general but also and above all for the conservation activities of the built heritage, providing metric data such as those relating to the damaged areas to be repaired.

The proposed approach yields consistent and repeatable results. Generally, a supervised image classification algorithm makes it possible to recognize, locate and measure the size of the regions occupied by each labelled category. Therefore, it is possible to repeat the same procedure for other case studies and/or different classes, such as materials and decay on facades.

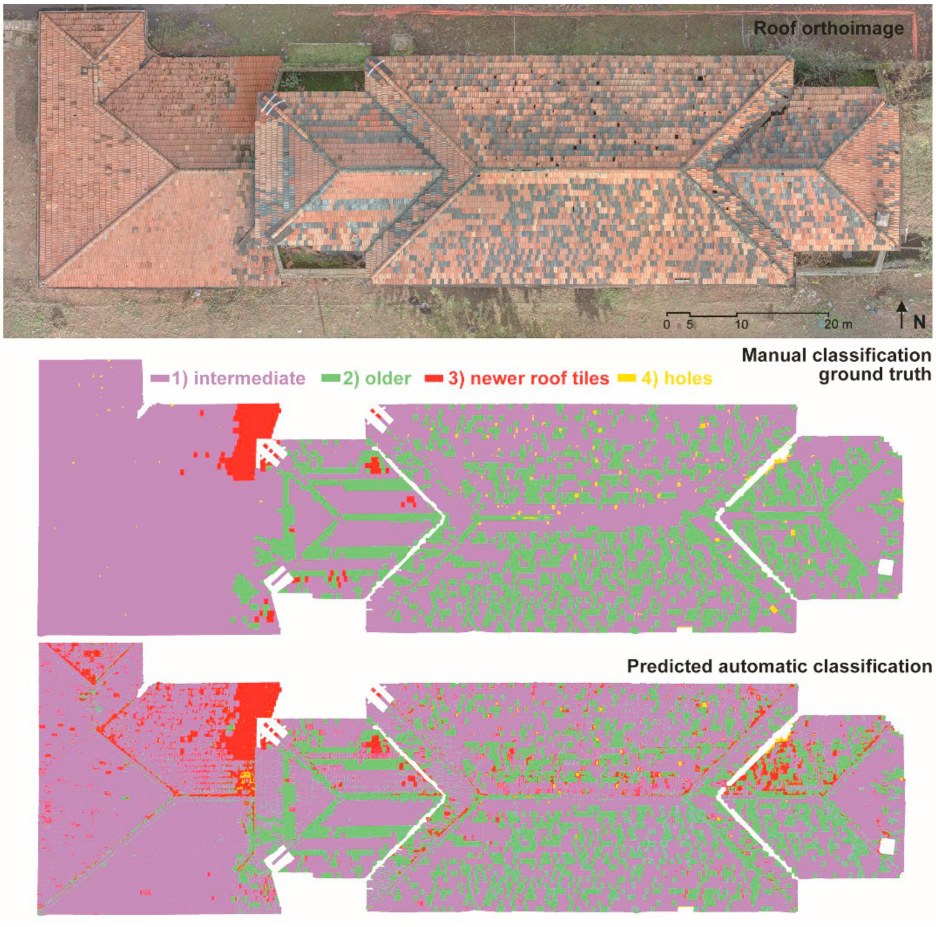

Fig. 5. Original roof orthoimage of Palazzo Littorio and its segmentations (manual and automatic) in the defined classes

confusion matrix (pixel numbers)		PREDICTIONS				TRUTH		
		intermediate	older	newer	holes	pixels	area [m^2]	tile numebers
TRUTH	intermediate (light red tiles)	3524826 66,8%	97432 1,8%	173661 3,3%	3138 0,1%	3799057	379,9	5836
TRUTH	older (original dark tiles)	155669 2,9%	1147038 21,7%	51888 1,0%	281 0,0%	1354876	135,5	2081
TRUTH	newer (bright red tiles)	9975 0,2%	97 0,0%	90839 1,7%	70 0,0%	100981	10,1	155
TRUTH	holes	3980 0,1%	2820 0,1%	5860 0,1%	11682 0,2%	24342	2,4	37
PREDICTIONS	pixels	3694450	1247387	322248	15171			
PREDICTIONS	area [m^2]	369,4	124,7	32,2	1,5			
PREDICTIONS	tile numebers	5675	1916	495	23			

	precision	recall	f1-score
intermediate (light red tiles)	95,4%	92,8%	94,1%
older (original dark tiles)	92,0%	84,7%	88,2%
newer (bright red tiles)	28,2%	90,0%	42,9%
holes	77,0%	48,0%	59,1%

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

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

$$F1 - score = 2\,\frac{Recal * Precision}{Recall + Precision}$$

Fig. 6. Top table reports the confusion matrix and related calculation of area and tile numbers for each class; the lower table reports the parameters for evaluating classifier reality

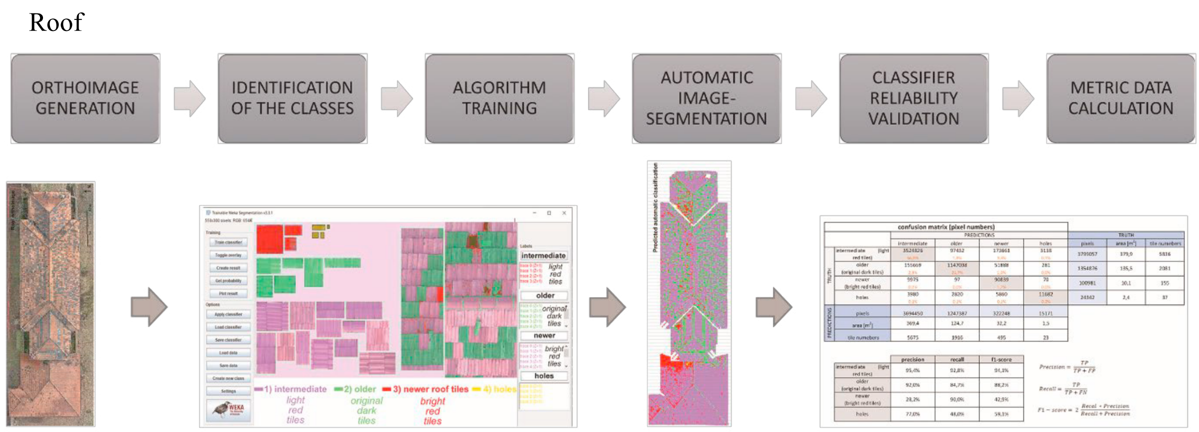

Fig. 7. Workflow of the proposed methodology for damage mapping of roof covering based on supervised image segmentation

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