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A machine learning framework to estimate a simple seismic vulnerability index from a photograph: the VULMA project

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Abstract

The paper presents the *VULMA* project as a machine learning framework for estimating a simplified seismic vulnerability index for existing buildings by exploiting photographs. In detail, *VULMA*, the acronym of VULnerability analysis using MAchine learning, is characterized by four consecutive modules, organized to be part of a specific processing pipeline that allows to train, test, and use the tool. The first module is *Street VULMA*, which allows to systematically download photographs from web services (e.g., Google Street View). The second module is *Data VULMA*, a tool for detecting structural features in the photographs and storing them in a database. The third module is *Bi VULMA*, which allows the training of different machine-learning models on the previously collected data. The fourth module is *In VULMA*, which assigns a vulnerability index to a building based on the detected features. The methodology has been applied to an initial database of photographs regarding reinforced concrete and masonry buildings, showing to be a good and fast way to perform a first screening of existing building portfolios and providing an alternative new method for developing risk mitigation strategies.

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Keywords: Existing Buildings; Vulnerability Analysis; Machine learning

Nomenclature

ΔV_m	Modification coefficient
B1	Building 1

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B2	Building 2
CNN	Convolutional Neural Networks
ML	Machine Learning
RC	Reinforced Concrete
$\widetilde{V}_I$	Vulnerability index
V_I^b	Base value of vulnerability index
VULMA	VULnerability analysis using MAchine-learning

1. Introduction

Over the last few years, public institutions have developed the awareness of the need of requalification strategies of the existing building stock. Consequently, several approaches have been proposed to quantify the vulnerability of existing building stock, providing a wide range of possible tools for vulnerability analysis. The continuous growth of such methodologies has led to two main consequences: on the one hand, the overall quality of achieved results has significantly improved, while on the other, the computational burden related to the use of complex tools has grown. Several methodologies and procedures have been recently developed for large-scale analysis and seismic risk mitigation, such as empirical methods (Casolo et al., 2000, Del Gaudio et al., 2020; Rosti et al., 2021, Leggieri et al., 2022), mechanical methods (Aiello et al., 2017; Leggieri et al., 2021), rapid visual screening methods (Perrone et al., 2015; Ruggieri et al., 2020) and hybrid methods, without neglecting the huge number of studies on building scale (Casolo et al., 2017; Casolo et al., 2019; Casolo, 2021). Nevertheless, the success of the investigation depends on the quality and quantity of available data. Several methodologies can be employed in data collection (see Polese et al., 2019 and references therein), but the increasing visibility that machine learning (ML) techniques have currently acquired opens new perspectives in this field. In particular, the rise in the usage of deep learning-based methods has highlighted the possibility of overcoming the lack of adequate data and using them for risk mitigation strategies. The creation of a proper dataset of buildings for the analysis is fundamental to evaluate different use cases and scenarios: this step represents the basis for identifying and characterizing the distribution of different vulnerability classes over a specific geographic area characterized by the presence of buildings with similar features, according to a specific taxonomy. Another aspect that should be considered when creating a dataset, is the possibility of human errors related to the subjective evaluation of building properties as the input of vulnerability methods/functions.

This paper reports a new tool for automatically identifying the critical structural features of buildings belonging to a specific existing stock by considering a set of images. The proposed tool, named *VULMA* (*VULnerability analysis using Machine-learning*), developed by Ruggieri et al. (2020), consists of four modules, which will be described in Section 3. The main advantage of the proposed approach is to provide an automatic visual-based tool for the evaluation of structural features that can be employed, for example, to calculate a simple vulnerability index (in further developments, it will be used as the input source for mechanical models), reducing the bias introduced by subjective evaluation of domain experts.

2. Related works: data collection and role of machine learning

Seismic vulnerability analysis mainly aims to create a prioritization list to follow when applying mitigation strategies to the existing building stock. In large-scale or class-level investigations, a common approach is to cluster buildings within the area under investigation according to standard morphological and typological features: after preliminary identifying recurrent geometrical and mechanical features of the buildings in the area, a class can be assigned to each building. This procedure presents two main advantages: first, it improves the accuracy of rank prioritization; second, data are collected and managed in order to define specific classes of buildings under standard taxonomies. In these classification schemes, the most critical issue still regards the data retrieval task. As reported in Polese et al. (2019), data collection can be handled using four different data sources, such as census data, interviews-based surveys, GIS and remote sensing techniques and building-by-building surveys. In this broad framework of available methods, it is possible to explore new approaches based on current concepts of ML. Generally speaking, ML approaches can be divided into three main categories: (i) Supervised learning methods, which feed the model with data labeled by a human expert; (ii) Unsupervised learning methods, which establish a structure from data; (iii) Reinforcement learning methods, which have a specific application in tasks where an agent has to learn his behaviour within an environment via a reward function. Several applications have already been developed with a specific focus on structural engineering (e.g., Xie et al., 2020; Sun et al., 2020). It is essential to highlight that for ML problems, the importance of data collection is paramount. Data should be carefully sampled, mainly to avoid undesired effects such as imbalanced data (Visa and Ralescu, 2005), which can lead to overfitting, a common problem, especially in large models (Srivastava et al., 2014). In that sense, several techniques allow to balance and augment the number of available data, such as down-sampling and up-weighting, SMOTE (Chawla et al., 2022), or generative models (Creswell et al., 2018). The use of techniques such as transfer learning and fine-tuning can mitigate the effects of the lack of data. For large-scale analysis, few applications are currently available in the scientific literature. For example, Mangalathu et al. (2020) proposed to use ML techniques to predict damages to buildings caused by earthquakes using a dataset comprising around 2000 buildings and accounting for features such as spectral acceleration, soil category, year of construction, number of storeys, base area and presence of irregularities. In Mangalathu et al. (2019), the same authors proposed an ML method to assess damages caused by earthquakes on bridges. Within the project *VULMA* (Ruggieri et al., 2021), the authors introduced a method to overcome some of the main issues, such as the subjectivity of the surveyor judgments and, above all, the great effort required for direct surveys and interviews. In particular, the paper proposed a pipeline process including four sub-modules that allow to extract structural information from photos of buildings and to assign a simple vulnerability index. The prototype, can be improved by intersecting data from *VULMA* with information, such as the year of construction and localization, derived from other sources.

3. *VULMA*: tool definition and organization of modules

The aim of *VULMA* is to provide a framework for the automatic definition of a vulnerability index starting from raw building data. VULMA is composed of four modules, each one offering specific features. Each module can be used as an individual tool for handling specific use cases, despite they are thought to work consecutively. In the following paragraphs, a detailed description of all modules is provided.

3.1. Street VULMA

Street VULMA is the first module of *VULMA*. It is able to gather image data about buildings starting from online services. *Street VULMA* offers a simplified interface with two main submodules, the *Fetch* submodule, which accepts only a GeoJSON file as input and fetches images of buildings included within the borders of provided data, and the *Clean* submodule, which removes duplicates from fetched data. The fetch module acquires imagery by fixing three different parameters: pitch (i.e., the vertical angle of the camera); field of view (i.e., the horizontal angle of the camera, which can be adjusted to provide a zoom effect); heading of the camera. Data are acquired considering a spatial granularity of 5 meters. After images have been gathered, the clean module compares the SHA-512 hash representation of all pairs of images, discarding duplicate images.

3.2. Data VULMA

The second module of *VULMA*, called *Data VULMA*, allows domain experts to perform labeling. This procedure is of primary interest, mainly because labeled data will be used to build a supervised model for image classification. For the scopes of our application, which aims to define a vulnerability index that usually depends on the subjectivity of surveyors, the proposed data labeling should be performed by a proper domain expert with specific training. Domain experts process images (one at a time) and assign the proposed set of labels only based on figure observation. The labeling phase requires the following operations. Firstly, images should be cropped to highlight the relevant content (e.g., the building itself). Afterward, each image is labeled according to the criteria defined in Ruggieri et al. (2021). If two images depict the same building from different points of view, they are not considered as duplicates. Regarding the labels, the structural typology and the type of roof floor can be defined by observing respectively the structural material (reinforced concrete - RC, masonry, steel) and the kind of roof (dome, pitches, flat). Still, the number of units, storeys, and openings can be defined by counting the feature in the photo. Some properties are described by using a

Boolean notation (True or False). For example, the presence of a basement floor can be inserted if openings are visible at the base of the building, or the presence of a superelevation floor can be inserted if the picture shows both the color and size of the last floor are different from the rest of the building. It may be worth mentioning that not all detected features will be used. Finally, in order to allow the storage of data labeled by domain experts, *Data VULMA* has been structured for providing a specific web service through a specific web architecture. Detailed information on the dataset and the properties of the photos are reported in Cardellicchio et al. (2022).

3.3. Bi VULMA

The third module is *Bi VULMA*, which is used to perform both the training and the classification steps. *Bi VULMA* allows the training of a deep CNN for image classification. CNNs have gained increasing interest after the proposal of AlexNet by Krizhevsky et al. (2012), which achieved outstanding accuracy on the challenging ImageNet dataset (Deng et al., 2009). Afterward, a huge quantity of architectures has been proposed, including mobile-specific architectures such as MobileNet (Sandler et al., 2018), inception-based architectures such as Xception (Chollet, 2017) and InceptionV3 (Szegedy et al., 2016), residual networks such as ResNet and its variants (He et al., 2016).

A way to exploit the internal structure of pre-trained CNNs is the use of transfer learning (Yosinski et al., 2015). Specifically, transfer learning uses CNNs to extract an intermediate representation of the image. This is related to the fact that while low-level layers of a CNN extract generic features, such as edges and basic shapes, high-level layers extract features specific to the domain of the image. As a consequence, training only high-level layers on a specific problem allows the network to achieve optimal results even with a relatively limited amount of data. Optionally, transfer learning can be followed by fine-tuning, which consists of re-training the network using a low learning rate.

Bi VULMA is written in Python 3 using TensorFlow, Keras, and Scikit-Learn. It operates in two main modes: in the *training* mode, the user can train the neural network either from scratch or by using transfer learning and fine-tuning; in the *inference* mode, a previously trained model can classify an input image. In the case under study, both binary and multiclass classifications have been enabled. The number of classes is automatically inferred by the structure of the dataset itself, and both loss functions and accuracy automatically are accordingly adjusted. *Bi VULMA* gives the option to choose from six base models to perform transfer learning: MobileNetV2, Xception, ResNet152v2, InceptionResNetV2, InceptionV3, and NasNet. A prototype of the graphical user interface of *Bi VULMA* is provided in Figure 1.

3.4. In VULMA

The last module of *VULMA* allows to compute a simple vulnerability index for a building for which a photo is available. The tool, named *In VULMA*, currently uses the simple approach proposed by Frassine and Giovinazzi (2004) to compute a vulnerability index. The reason for this choice is mainly due to the necessity to test *In-VULMA* with an already available methodology, which should be simple enough to allow us to assess the efficiency of the proposed procedure. Specifically, this methodology consists of the application of the following formulation:

$$\widetilde{V}_I = V_I^b + \sum \Delta V_m \tag{1}$$

where $\tilde{V}_I$ is the vulnerability index (ranging from 0 to 1, with higher values that imply a more vulnerable building), V_I^b indicates a base value of vulnerability index, defined according to the structural typology that *VULMA* is able to account for (either masonry or RC) and the year of construction (this information must be taken from other sources, e.g., census database), ΔV_m indicate a set of modification coefficients, negative or positive, whose values are established on the base of some parameters influencing the seismic vulnerability quantification. These coefficients shall be added to the base value of the vulnerability index in order to have the final $\widetilde{V}_I$. For the case under study, not all ΔV_m parameters can be considered in the evaluation because VULMA is not able to recognize all the required features. Nevertheless, the original method allows to consider only the known coefficients and to assume the unknown ones as null. The procedure proposed in *In VULMA* considers that masonry buildings are classified according to the year of construction (for masonry) and the level of seismic design (for RC). For the last category, a medium level of seismic design can be attributed to buildings constructed after 1971; absent and low levels of seismic design can be assigned to structures built from 1919 to 1945 and from 1946 to 1970, respectively. Once the value of V_I^b has been established according to the structural typology, the values of ΔV_m can be easily retrieved by *Bi VULMA*, neglecting factors such as the state of preservation, structural system, retrofit intervention and foundation. The modification factors associated with the aggregation of buildings, such as position and elevation, are only considered in the worst-case scenario if the number of units is greater than one. Factors such as the number of openings, the presence of overhangs and higher floors, even if evaluated in *VULMA*, have not been used in this vulnerability index estimate.

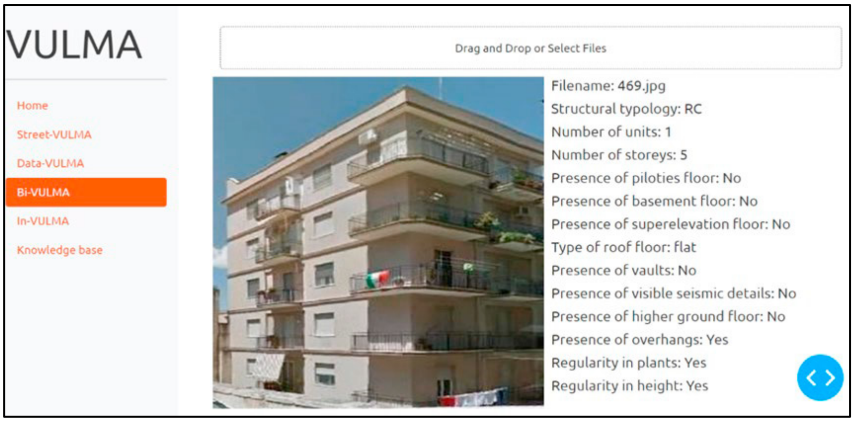

Fig.1. Interface provided by the VULMA toolset.

4. Experimental section

4.1. The case study of Bisceglie, Apulia, Italy

In order to apply the concepts and modules of *VULMA* to a real scenario, a part of the Municipality of Bisceglie, located in the Puglia region, Southern Italy, has been considered. The selected Municipality presents both typologies of RC and masonry buildings, and it is characterized by a homogeneous distribution of these structural typologies within the entire geographic area. For the entire Municipality, there is a wide database from which raw data can be extracted and employed in *Street VULMA*, since the Technic Regional Cartography and Census Data are feely available. Figure 2 shows the geographic area for which raw data have been extracted.

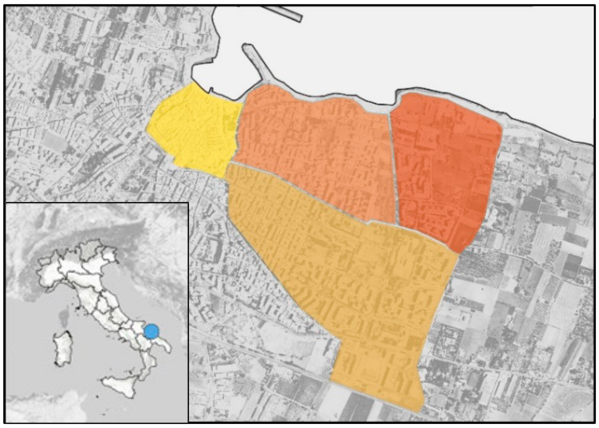

Fig. 2. Selected part of municipality from which input information for *VULMA* are extracted. Different colours indicate different town compartments, defined in accordance with a typological subdivision.

Table 1 reports information about the total number of buildings belonging to the selected area, percentages of buildings according to their construction material, and year of construction. The total number of buildings considered is 817. Raw data, in GeoJSON format, have been then extracted and transferred as an input for *Street VULMA*. About 20.000 photos have been gathered and labeled by domain experts according to the abovementioned features. After this step, all images have been stored within the *Data VULMA* service, and after a pre-processing and cleaning procedure, almost 2.500 labeled photos have been stored, which represent the input of *Bi VULMA*. It is worth observing that the gathered dataset is highly unbalanced, meaning that the number of images containing a certain feature may be greater than the number of images not containing that feature. Hence, a data balancing procedure has been performed before training *Bi VULMA* on the gathered dataset. This has been done by using new images with specific features, downloaded by means of *Get VULMA*, which is the tool to automatically download photos with the feature of interest from web services like Google.

Table 1. Summary of features for the buildings in the selected area.

Parameter	**Number of buildings**	**Percentage of buildings [%]**
Construction typology RC	435	50.00
Construction typology Masonry	351	43.00
Construction typology Other	85	7.00
Year of construction <1919	228	27.91
Year of construction 1919-1945	83	10.15
Year of construction 1945-1970	212	25.95
Year of construction >1970	294	35.99

The current size of the training dataset has also required to use of transfer learning instead of training a network from scratch. Within this study, MobileNetV2 has been chosen as the base network, with base parameters weighted from training on the ImageNet dataset. As for the training algorithm, cross-entropy (either binary or categorical, according to the specific number of classes involved in the sub-problem) has been used as the loss function, while ADAM has been selected as the optimization algorithm with a learning rate of 0.01. A machine equipped with an Intel Core i7 10700H, 32 GBs of RAM, and a GeForce RTX 3070 with 8 GBs of RAM has been used. The training/test split of the dataset is in a standard 70/30 percentage. Each parameter has been identified by a single network, specifically trained to identify the declared features. This results in a set of 15 networks, which can be used as a cascade of models to determine the overall characteristics of each building. The results in terms of validation accuracy for the labels concerning structural typology, number of storeys, irregularity (both in plan and height), and superelevation floor show that, even using a small dataset, optimal values can be easily achieved by means of transfer learning, with an overall accuracy of 97% for each trained model.

4.2. Vulnerability index evaluation

Once machine learning models have been trained, a validation process has been developed, with the aim to asses if *Bi VULMA* is able to recognize the right values of the desired features and to evaluate if the vulnerability index given by *In VULMA* is coherent with the value manually computed. To this end, two buildings located in another part of the selected municipality have been considered. The photos of the buildings have been manually selected by authors from the Google Street View service. Clearly, the selection of these buildings is random and different from the sample of buildings on which the overall network was trained. Figure 3 shows the images of the two buildings, labeled as B1 and B2. It can be seen that B1 is a RC building, while B2 is a masonry one. The building B1 dates back to 80's and presents 5 storeys, flat roof, higher ground floor, and structural regularity. B2 is a masonry one-storey building characterized by a flat roof without visible vaults or seismic details, dating back to a period before 1950. In both buildings, overhangs are always visible.

As a result of the process, the vulnerability index $\tilde{V}_I$ has been calculated: the results provided the values 0.436 and 0.434 for B1; 0.689 and 0.649 for B2 (by-hand calculation and *VULMA* calculation, respectively). Despite the simplicity of the employed methodology and the intrinsic approximations in the estimation of the vulnerability index, results highlight that for B2 there is only 6% difference between the results manually and automatically computed. This difference is mainly due to the limited capability by *VULMA* to predict some coefficients of the method (e.g., wall thickness, wall distance and wall connection). For B1, vulnerability indexes show a difference of about 2%, which is related to a single parameter, as for the previous case. Among the main advantages of *VULMA*, it is worth noting a good capability to predict parameters as number of storeys, regularity parameters, presence of superelevation.

Fig. 3. Case study buildings (B1 – B2) for *VULMA* application.

5. Conclusions and future developments

This study has presented an ML-based tool whose aim is to capture the key features of building in existing stocks starting from pictures of such buildings. The proposed framework, which is composed of four different steps, in each of which a different tool is used, has been tested against data gathered from a Municipality located in Southern Italy to demonstrate the feasibility of the approach and validated in two different case studies buildings belonging to an independent municipality. These results show that, despite the simplicity of the approach, reliable estimates are provided. This application is particularly interesting for the development of several applications and scenarios, considering that *VULMA* provides a method that can reduce the time and effort related to surveys and interviews, usually involved in the fast vulnerability assessment procedures (e.g., Cartis). It provides a base supervised classification of images and, if continuously upgraded, can reduce the usual bias introduced in the phase of subjective evaluation of the building features by the judgmental assignments of domain experts. In the end, *VULMA* can be easily integrated with other data, freely online available, and can be used as input for analytical vulnerability estimates. Currently, there is room for improvement in each module. Among the possible development, *In VULMA* could use a more complex index, and the whole labeling procedure should be revised. Furthermore, photos could be automatically elaborated by proper object detection tools, reducing the burden on domain experts. The training procedure itself could be greatly improved by focusing on three aspects: using a greater amount of data, using different models with fine-tuning and hyperparameter optimization, further refining and extending the index computation by *In VULMA*, embedding contextual information on the building, which cannot be easily extracted via visual inspections.

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