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MACHINE LEARNING-BASED IDENTIFICATION OF VULNERABILITY FACTORS FOR MASONRY BUILDINGS IN AGGREGATE: THE HISTORICAL CENTRE OF CASENTINO HIT BY THE 2009 L'AQUILA EARTHQUAKE

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Abstract. *Seismic events in Italy and worldwide have highlighted the high vulnerability of unreinforced masonry (URM) structures in small historical centres. A key feature of these settlements is to be mostly composed of buildings in aggregate, i.e., interconnected by a more or less structurally effective connection. The seismic assessment of such buildings is quite debated in the literature and no shared tools procedures are currently available. The difficulty of standardization derives from the fact that structural units can be characterized by multiple features and configurations that determine a vast number of vulnerability factors, whose interdependency is not straightforward to be identified. The paper addresses this issue by combining evidence-based damage data with the potential offered by Machine Learning (ML) technique. Real data are used in combination with state-of-the-art ML algorithms carefully tuned via an advanced statistical procedure for two main purposes. The first one will be able to predict possible URM damages based on the vulnerability factor in both interpolation and extrapolation scenarios. The second purpose of the ML-based techniques will be to predict the most important vulnerability factors in making these predictions, namely to make the ML-based model explainable and informative about the underlying phenomena and not just predictive. The small historic centre of Casentino, hit by the 2009 L'Aquila earthquake, is adopted in the paper as the first test case study. A large amount of data was collected after the earthquake through in-situ surveys made by the Universities of Genova, Catania and Rome. Data include both geometric and structural factors, i.e., the input data supplied to the ML algorithm, as well as the actual seismic damage mechanisms, i.e., the output data expected to be predicted by the ML algorithm. As first application, ML techniques are applied only to data acquired on out-of-plane mechanisms.*

Keywords: masonry, buildings in aggregate, seismic vulnerability, machine learning

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1 INTRODUCTION

In Italy, most historic centres consist of aggregate masonry buildings, i.e. interacting buildings resulting from the progressive transformation of individual structural units (SU). Damage and losses caused by several seismic events revealed the significant seismic risk of existing unreinforced masonry (URM) structures in aggregate, especially when belonging to historical centers of small municipalities [1, 2, 3, 4, 5]. Small historical centers are frequently the consequence of a centuries-long process of building expansion that results in interacting units with varying materials, construction techniques, heights, states of preservation, and, in some cases, spontaneous repairs. All these complicated factors contribute to the fact that seismic assessment of URM buildings in aggregate still constitutes a challenging topic and an open issue both at research level and in engineering practice. In fact, despite their great diffusion on the Italian territory, characterized by a high seismic hazard, there are no standardized procedures to assess their seismic vulnerability. This lack of regulations already reflects the complexity of the topic of aggregate masonry buildings. The factors characterizing aggregates are so many and so interconnected that it is difficult to unravel it with the classical tools adopted so far to interpret isolated masonry constructions. In recent years, numerous efforts and advances have been made in the literature in this regard, and several methodologies have been proposed for assessing the seismic vulnerability of buildings in aggregate: holistic approach [6]; heuristic approach [7, 8, 9]; mechanical- analytical approach [10, 11]; mechanical-numerical approach [12, 13, 14, 15, 16, 17, 18, 19, 20]; large-scale approaches based on empirical evaluation obtained from post-earthquake data [4]. Also the experimental campaigns specifically addressed to face this topic are very recent and limited in number [21, 22]. Despite the efforts and advances already made in literature, these methodologies still have various limitations, both in their formulation and in their use. Moreover, there isn't a unanimous scientific consensus in establishing the role and weight of vulnerability factors specific of the buildings in aggregate. For this reason, given the complexity of the problem, in this paper it was decided to investigate the topic exploiting the potential of machine learning (ML) techniques. Up to now, the application of ML techniques to existing buildings is still limited, even they are slowly beginning to take hold [23, 24, 25]. As first anticipated, a structural aggregate may be defined as a non-homogeneous set of buildings, interconnected by a more or less structurally effective connection determined by their evolutionary history, which may interact under seismic or dynamic actions. Indeed, the identification of well-defined structural units (SU) constitutes the first challenge in analysing a URM aggregate. Since the assemblage nature characterizes masonry construction at whatever scale one observes it, the lack of an ensemble behaviour is found not only between the buildings forming part of an aggregation but also between the masonry cells of which the buildings are composed and, even, between the individual walls that make up the cells. It follows that, descending from the scale of the city to that of the building, the concept of aggregation continues to be valid: the masonry building is a set of cells whose degree of internal relationship is not such as to annul their individuality, and, in the same way and for the same reason, the individual cells are nothing other than incompletely structured sets of walls Figure 1. It may be said in a completely equivalent manner that, in order to study the mechanical behaviour of a wall that is part of a closed cell (e.g. the wall's response to out-of-plane actions), the presence of the cell is not essential except for the limitations to movement that it imposes on the wall under examination and for the forces that it transmits to it, i.e. the kinematic and static actions that derive from the cell's presence [26].

For this reason, when using the ML, it was chosen to refer not only to the characteristics of

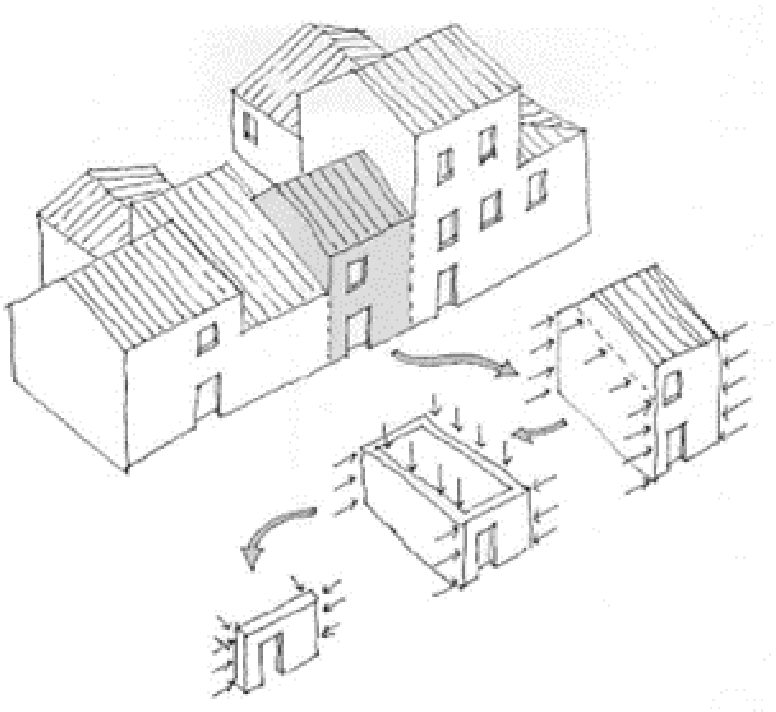


Figure 1: Aggregation - building - cell – wall [26]

the SU but to the individual walls that compose it (i.e. the fronts). The case study adopted in this paper to test the use of ML tecniques is the small historic centre of Casentino (AQ), hit by the L'Aquila 2009 earthquake (Mw=6.3). A huge amount of data available was available for this case study since, after the L'Aquila 2009 earthquake, a working group coordinated by Prof. C. Carocci (University of Catania), Prof. S. Lagomarsino and Prof. S. Cattari(University of Genoa) and Prof. C. Tocci (University of Rome) carried out a detaialed in-situ survey in Casentino [27]. Information on both the structural features of SUs and the post-earthquake damage were collected. This large database offers the unique opportunity to investigate more robust correlations between the different geometric, structural and mechanical properties that characterize such buildings in aggregate and their seismic response. More specifically, as first application, the paper focuses the attention on the use of the ML tecniques only to interpret the activation of out-of-plane (OOP) mechanisms. In Section 2 a description of Casentino's features is illustrated while in Section 3 the methodology adopted is outlined. Then, in Section 4 the preliminary results achieved are presented.

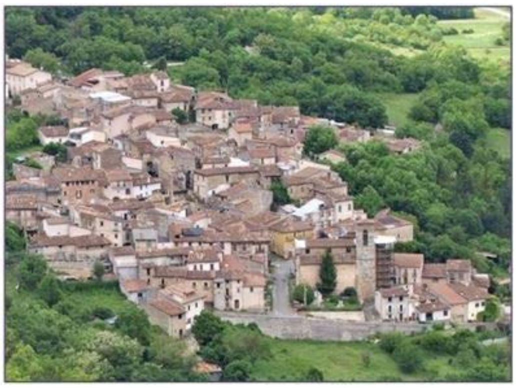
2 CASE STUDY: THE HISTORIC CENTRE OF CASENTINO

The study activity carried out on the Casentino area Figure 2b was addressed to the formulation of a 'Code of Practice' for the repair, seismic improvement and reconstruction interventions necessary to recover functionality and safety of the historical centre and at the same time to preserve the residential building [27]. The in-situ surveys made by the working group allowed the systematic collection of the data on structural details, the damage observed and the state of conservation of all SUs which composed the URM aggregates; moreover, an in-depth analysis of local building techniques and of the historical-evolutionary phases of the building fabrics was made, too.

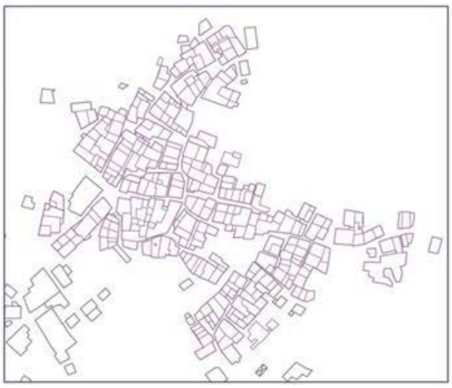
The building stock of Casentino is characterised by the presence of aggregates limited in size,

ALTIMETRIC CONFIGURATION	Number of levels possibly subjected to OOP mechanismss Offset of diaphragms levels between adjacent USs
SITE MORPHOLOGY AND US/FRONT POSITION	US position - flat area Front position in edge area Front position in subsidence area Levels number differentiated on adjacent fronts US position - slope area
VERTICAL STRUCTURAL ELEMENTS	Grounding of the front in flat or slope area
POSITION OF FRONT WITHIN THE AGGREGATE	Position of the front in the aggregate (header-extreme, corner,internal) Summit front Front advancement Position of the front in the aggregate (aligned, encompassed, false, soaring)
STATE OF MAINTENANCE OF VERTICAL STRUCTURES	State of maintenance of vertical structures
STATE OF MAINTENANCE OF ROOF	Maintenance status of the roof
ADDED VOLUMES	Presence of added volumes to the front
RAISING-UP	Presence of raised-up portions
FLOOR ORIENTATION	Floor warping parallel or perpendicular to the front Presence of vaults
ROOFING	Type of covering (flat/shallow) Roof warping parallel or perpendicular to the front Pushing or non-pushing roofing Roofing material (tiber or reinforced concrete) Presence of top ring-beam
CORNER	Interlocking quality on corners
OPENINGS	Regular layout of openings Maximum number of openings between two internal walls Percentage of openings in the front Presence of structural lintel
PRESENCE OF ASEISMIC STRUCTURAL DETAILS	Connection with roofing elements Presence of wall thickening Presence of butresses Presence of arches connecting two Sus Presence of ring-beams Presence of tie-rods
ALTERATIONS / DISCONTINUITIES	Presence of adjacent but not interlocked walls Presence of infilled openings Presence of chimneys Presence of masonry portions inserted after previous collapses

Table 1: Input parameters characterising the fronts belonging to the Casentino building aggregates



(a) Aerial view.



(b) Planimetric schematisation .

Figure 2: Historic centre of Casentino (AQ).

which develop following the morphology of the land on which they are built. The following types of aggregates may be classified: parallel block, block orthogonal to the slope and the range of their intermediate variants. Starting from some basic cartographic documentations (i.e. the regional map 1:5000), the survey of the buildings in aggregate was carried out via the following methods:

- reconstruction of the planimetric configuration of the aggregate by identifying the individual SU and fronts;
- reconstruction of the consistency in elevation of the block;
- in-situ survey of all the street fronts of the aggregate by sketching all cracks, collapsed portions and essential geometrical and architectural feartures;
- systematic collection of information on vulnerability factors, presence of anti-seismic devices, masonry quality, transformations and activated damage modes. To this aim, a specific form was conceived to standardize data gathering by participants in the working group.

In particular, the survey form consists of three basic sections:

- the first one deals with information on the general consistency of the SU, such as: the position of the SU in the topographical context; the aggregate in which it is inserted; the general state of maintenance; the total number of floors);
- the second one is devoted to the structural details and the vulnerability factors. It is subdivided into: a part dedicated to the general transformations undergone by the SU (i.e. presence of added volumes, raising-up); a part addressed acquiring the data on diaphragms and vertical URM walls. Some data are referred to the SU as a whole, while other ones are collected by referring to single perimeter walls (i.e. fronts);
- the third is addressed to collect the data on seismic damage. An abaqus of damage modes has been defined by classifying them into mechanisms associated with the in-plane and out-of-plane response of walls, mechanisms due to interaction effects between adjacent units, and local damage. Moreover, data are collected by distinguishing the structural elements affected by the damage (i.e. walls, diaphragms, vaults, roofs, secondary elements) and associating a damage level graduated from 0 to 5 (according to the EMS98 scale proposed in [28]).

The first and second section constitutes the input data for training the ML algorithm, while the third section constitutes the output data. In particular, data analyzed in the paper refer only to the interpretation of out-of-plane response. Table 2 summarizes all the considered mechanisms. The data collected on 80% of the building stock of the historical centre has been adopted for this research. The data comprise 256 SUs and 475 fronts. A complete summary of the input parameters considered can be found in Table 1.

3 METHODOLOGY BASED ON MACHINE LEARNING ALGORITHMS

The problem described in Section 2 of predicting when an OOP mechanism is activated based on the parameters reported in Table 1 leveraging the data described in the very same section, can be mapped to a typical binary classification problem of Machine Learning [29].

The no-free-lunch theorem [30] ensures that to find the best algorithm for a particular application, it is necessary to test multiple algorithms. In our case, we have tested four state-of-the-art algorithms[1] [31, 32]: Random Forests (RF) [33], XGBoost [34], Kernel Ridge Regression

[1]Results in Kaggle `www.kaggle.com`, the most popular Machine Learning competition website, shows that these algorithms are the top winners.

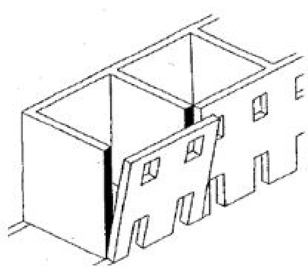
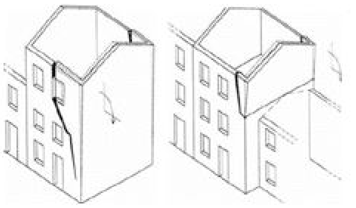
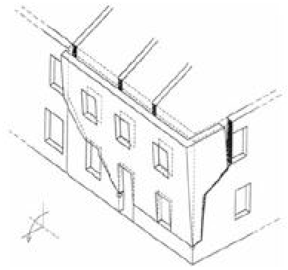
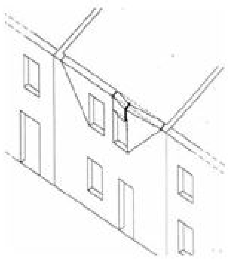
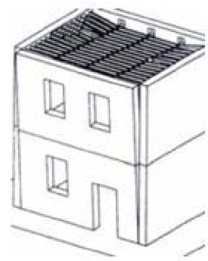
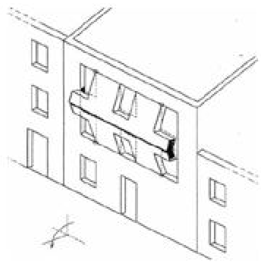
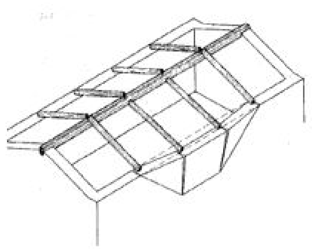
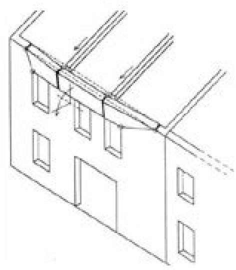
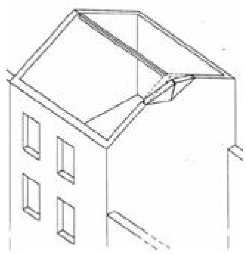
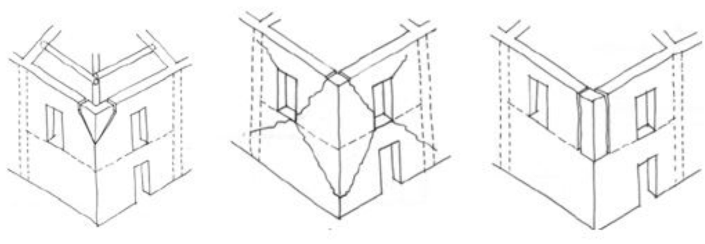
OOP MECHANISMS		
WALL OVERTURNING		
Clamping breakage	Inclined lesion in orthogonal walls	More
		
BENDING WALL OVERTURNING		
Breaking over openings	Clamping breakage	Horizontal injuries to intermediate floors
		
OVERTURNING OF SUMMIT PORTIONS		
Cracks in the cornice	Collapse down to lintel level	More
		
TILTING THE ANGLE		
		

Table 2: OOP mechanisms

(KRR) [35], and the Extreme Learning Machine (ELM) [36] namely a Single Layered Neural Network [37] where the weights of the first layers have been randomly set reducing the computational burden of the training phase with minimal, if not absent, effect on accuracy. For space constraints, we will report just the results of the best performing algorithm: RF. In RF, a set of decision trees is built, and then, in order to classify a new sample, a simple majority vote among the answers of each tree in the set is taken for prediction. Each tree is built using a different bootstrap sample of the original data and using a random subset of features to detect the best cut at each node instead of using all the data and features as in standard decision trees.

In RF, we need to tune the number of features to randomly sample from the whole features during each node of each tree creation n_f. We searched for the optimal value of $n_f \in \{d^{1/16}, d^{1/8}, d^{1/4}, d^{1/2}\}$ where d is the total number of features. As RF performance improves by increasing the number of trees n_t: in this application, we set it to 1000 as a reasonably large number yet computationally tractable. Another aspect to consider in RF is that the available data are unbalanced, i.e., the number of samples labeled with -1 is very different from the ones labeled with $+1$, and RF does not work well with imbalanced datasets poorly performing on the minority class. For these reasons, several techniques have been developed in order to address this issue [38]. In this work, we propose to leverage the proposal of [33]: during the creation of each tree in the RF, the subset of samples bootstrapped from the training set are sampled balanced.

Note that, the selection of the best hyperparameters will depend on the specific scenario under consideration and on the metric exploited.

In our work, we will study three different, increasingly challenging, extrapolating scenarios derived from the characteristics of the problem at hand. This will allow us to understand the extrapolation ability and the robustness of the Machine Learning model:

- Leave one Front Out (LOFO): where we remove just one Front from the training set, keeping it in the test set. The scope of this scenario is to test the extrapolation ability of the model in terms of Fronts, namely to estimate the ability of the model to predict the URM damage of a Front never seen before;
- Leave one Structural Unit Out (LOUO): where we remove all the fronts of a SU from the training set, keeping them in the test set. The scope of this scenario is to test the extrapolation ability of the model in terms of SU, namely to estimate the ability of the model to predict the URM damage of all the fronts of an SU never seen before;
- Leave one Aggregate Out (LOAO): where we remove all the fronts of all the SUS of an Aggregate from the training set keeping them in the test set. The scope of this scenario is to test the extrapolation ability of the model in terms of aggregate, namely to estimate the ability of the model to predict the URM damage of all the fronts of an SU never seen before;

At this point, we can address how to tune the hyperparameters of the RF algorithm to generate the surrogate and how to assess its final performance [39].

For what concerns the last point, the answer is straightforward. Based on the different scenarios (LOFO, LOUO, and LOAO), we have to split the data in Training $\mathcal{D}_n$ and Test $\mathcal{T}_t$ sets using the principle of the different extrapolating scenarios. For example, in the LOUO scenario, we put all the fronts of a SU in $\mathcal{T}_t$ while the remaining ones are kept in the $\mathcal{D}_n$. Then we can use $\mathcal{D}_n$ to train the model and select the associated best hyperparameters and use $\mathcal{T}_t$ to assess the performance of the final model. Repeating multiple times, this procedure will give us the average performance in the different scenarios.

Instead, for tuning the hyperparameters of the different Machine Learning algorithms, we

Scenario	ACC	FP	FN
LOFO	71 ± 2	70 ± 2	73 ± 2
LOUO	70 ± 2	69 ± 2	72 ± 2
LOAO	69 ± 2	68 ± 2	70 ± 2

Table 3: ACC, FP, and FN for LOFO, LOUO, and LOAO.

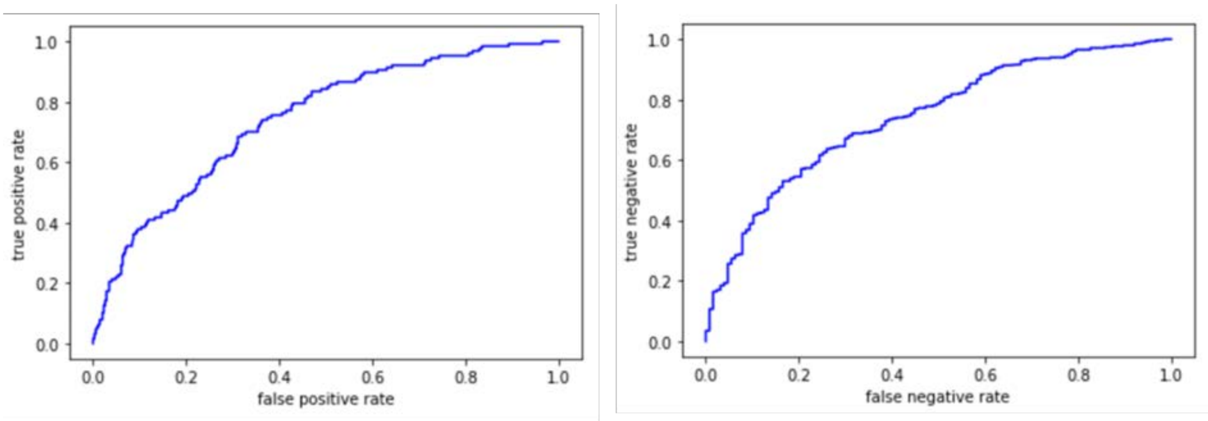


Figure 3: ROC for LOAO the most challenging scenario.

proceeded as follows. First, we took $\mathcal{D}_n$ and split it into Learning $\mathcal{L}_l$ and Validation $\mathcal{V}_v$ sets considering the very same extrapolating scenario that we use for assessing the final performance. Then we train each model with $\mathcal{L}_l$ with many different hyperparameters configurations and measure its performance on $\mathcal{V}_v$ according to the metric of interest. Subsequently, we repeated the experiment multiple times and selected the hyperparameters' configuration, which gives the best average Mean Average error (MAE) on the validation sets. Finally, we retrained the model with the selected best configuration of the hyperparameters on the whole $\mathcal{D}_n$, which is the model that will be used for testing purposes (see the previous paragraph).

As metrics, in this work, we will use the Percentage of Accuracy (ACC) for both optimizing the hyperparameters and evaluating the performance of RF and the Percentage of False Positive (FP), the Percentage of False Negative (FN), and the Receiver Operating Characteristic curve (ROC) as an additional metric to characterize the performance of RF [40].

As a final step, RF effectively and efficiently allows one to understand if the learning from data process also has a physical meaning, namely if it can capture the underline phenomena and not just capture spurious correlation [41]. In particular, we decided to exploit a permutation test coupled with the Mean Decrease in Accuracy metric [42] in RF to identify the importance of each of the parameters reported in Table 1to provide some explanation on the learning process.

4 RESULTS

The results presented in 3 show that the results worsen slightly by moving from the LOFO scenario to the ALAO scenario but still remain substantially stable. The values obtained indicate a satisfactory predictive capacity of the model.

The graph in Figure 4 shows in ordinate, from top to bottom, the most important features in terms of the average accuracy of the expected result. In particular, the parameters which turned out to most affect the OOP response are: i) the state of maintenance of the roof, ii) the state of maintenance of the vertical structures, iii) the quality of the cantilever reinforcement,

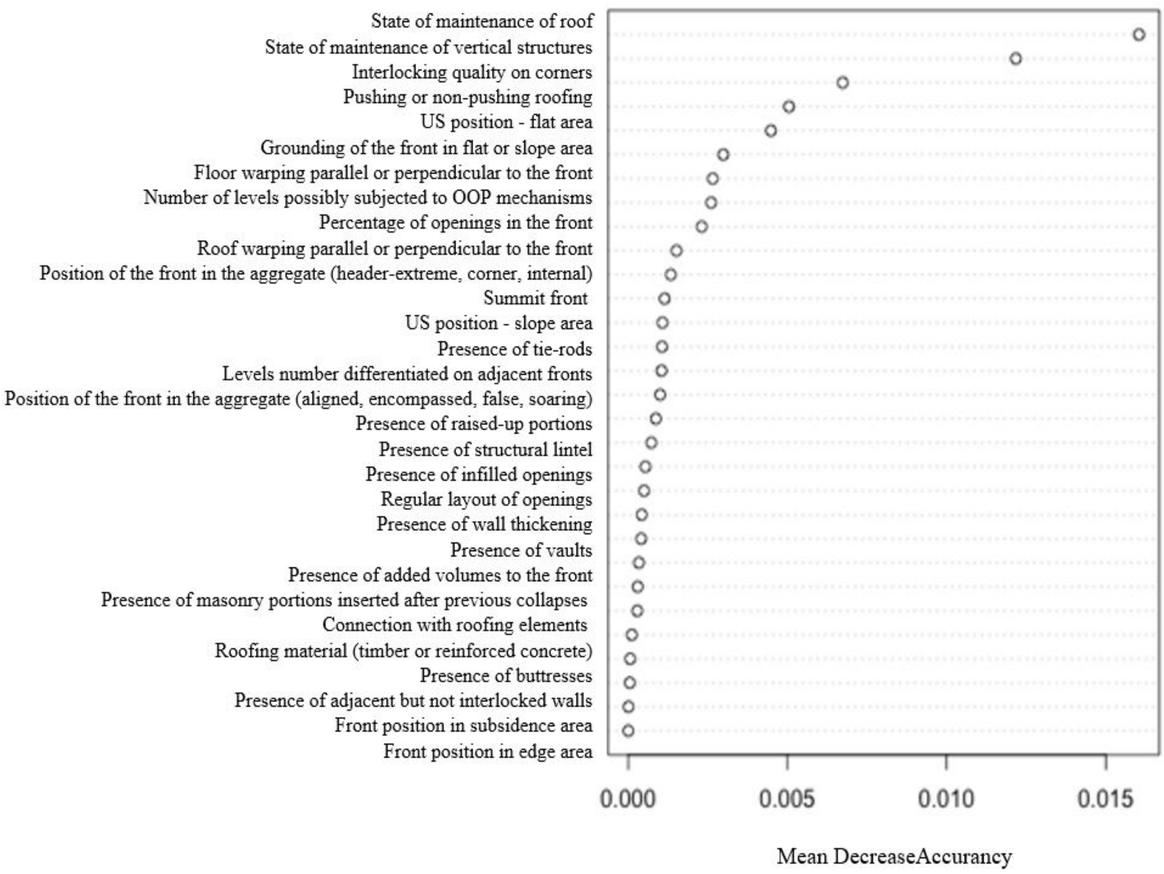


Figure 4: RF parameters importance ranking LOAO, the most challenging scenario.

iv) whether the roof is pushing or not pushing. All these factors are totally in agreement with what was already highlighted in the literature by the expert judgment on basis of past actual evidence.

5 CONCLUSIONS

In the paper, the machine learning technique is proposed to identify the most important vulnerability factors affecting the seismic response of masonry buildings in aggregate. The use of this innovative and powerful approach aims to establish the most relevant correlations on the basis of real data rather than only on basis of expert judgment, as more commonly done in the literature. The results obtained are promising, as the reliability values of the predictive capacity of ML model appear to be good, also by considering the complexity of the phenomenon. In fact,the factors that the ML technique recognizes as being among the most important are entirely reasonable. The added value of the method is that it graduates their importance on the basis of analytical criteria, which can therefore also support in the future the calibration of weights of these indicators in heuristic-based models, which to date have only been defined on the basis of expert judgement. While in the paper the ML technique has been applied only to data on out-of-plane mechanisms, the ongoing research developments concern the application of ML techniques to the sample of the historic centre of Casentino also for the interpretation of the response of in-plane damage modes. Moreover, additional research will be addressed to extend the application to other case study data samples, possibly representative of different intensities of the seismic event and different aggregate configurations (e.g. row aggregates). In fact, that will allow corroborating or refining the parameters that most affect the seismic response of such structural typology.

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