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Implementing Artificial Intelligence in H-BIM Using the J48 Algorithm to Manage Historic Buildings

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ABSTRACT
The preservation of the architectural heritage is characterized by the intervention of different technicians, who may disagree on decision-making criteria. In recent years, the H-BIM methodology has emerged to manage these buildings, although the multidisciplinary technical personnel make the decision-taking something of a challenge. In this regard, artificial intelligence may be an opportunity to establish automatic responses, thus optimizing the process. This article proposes a methodology to implement models of classification using the J48 algorithm in a H-BIM model. The case study was focused on a tiles panel from a building which belongs to the Real Alcazar of Seville. First, a model of classification was developed to estimate the degree of intervention with an adequate degree of adjustment. Then, the model was implemented in the H-BIM software by programming using GDL. This methodology automates the decision-making and reduces times of assessments, visualizing and managing the information in the H-BIM model.

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atificial intelligence; decision trees; geometric description language; J48 algorithm; H-BIM project; Pavilion of Charles V

1. Introduction

The tangible cultural heritage, also known as architectural heritage (Vecco 2010), is made up of those buildings, monuments, or archaeological areas with a historic, cultural, or landscape value. These architectural goods are non-renewable resources (Krebs and Schmidt-Hebbel 1999), so preserving this heritage for future generations is one of the main society´s duty. Therefore, the management and preservation of the tangible cultural heritage is nowadays among the main activities of the building sector, establishing the restoration and maintenance actions required (Vicente, Ferreira, and Da Silva 2015). This activity is characterized by the interaction of several specialist disciplines which diagnose, assess, and monitor the architectural goods. In this line, there may be coordination difficulties in the processes because different professionals (architects, historians, or archaeologists) are grouped.

Due to this, the use of computer tools could allow the management process to be optimized. In recent years, the Building Information Modelling (BIM) has become the most efficient methodology for the complete management of buildings by combining the volumetric and physical characteristics of a building with all the elements that define that building (Bruno, De Fino, and Fatiguso 2018). Moreover, its work methodology allows a multidisciplinary workflow, optimizing the management process of buildings (Zalama and Lerones 2018) and improving the consumption of natural resources, costs, and time (Volk, Stengel, and Schultmann 2014).

The practical application of BIM in the tangible cultural heritage was called Historic Building Information Modelling (H-BIM) by Murphy, McGovern, and Pavia (2009). It is a new approach for the management and preservation of historic buildings (Zalama and Lerones 2018). The main advantage of this new application of BIM is the modeling of the architectural elements of each building, together with the historic, construction, and artistic data collection (Dore and Murphy 2012; Murphy, McGovern, and Pavia 2011). H-BIM can incorporate several aspects of a heritage building (materials and geometrical shapes, among others) in a BIM model. Likewise, the management using H-BIM allows the data of construction systems from different historic periods to be identified and registered, thus easing the information and the effectiveness of the agents who take part in the preservation. Moreover, H-BIM supports retroactive information in the development of the restoration phase and

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the subsequent management in the next years. Thus, H-BIM establishes the preventive maintenance as an everyday need because it exchanges information and spreads the knowledge of the tangible cultural heritage (Oreni 2013), constituting a solution to the compilation and conservation of the existing document of the architectural heritage (Bruno, De Fino, and Fatiguso 2018).

However, the use of a multidisciplinary platform of work does not guarantee the optimization of the process. This is because each discipline responsible for the maintenance of the cultural heritage has its own characteristics and perspectives of the element to be preserved. The workflow among the disciplines requires a proposal of shared hypotheses, the analysis of results and the exchange of information (Nieto et al. 2016), although there may be problems in the assessment criteria. In this context, the artificial intelligence (AI) plays an important role by homogenizing the decision-making criteria (Chávez-Hernández et al. 2012). In this sense, it is essential to establish a priority in conservation actions due to the budget limitations that usually exist to conduct restoration works. For this reason, having a tool to establish a priority order for the performances as well as to manage intelligently the architectural elements could be studied. Furthermore, one of the main gap of knowledge is the use of the AI applied to H-BIM as an automation process of the decision making (Bruno, De Fino, and Fatiguso 2018).

In the scientific literature, there are some applications in BIM where optimization techniques by means of the artificial intelligence are used (Bloch and Sacks 2018; Juszczyk 2018; Mangal and Cheng 2018), but none of them is applied to the preventive management of historic buildings. There are research studies on the heritage management analysing the application of the AI in different case studies. Some of the most important are as follows: (i) Silva et al. (2012, 2013) used the multiple linear regression to predict the useful life as well as to establish performance decisions on the outside cladding of the façades of buildings; (ii) studies conducted by Macías-Bernal et al. (2014) and Prieto et al. (2017), where the theory of fuzzy sets was applied to estimate the functional useful life of heritage buildings; (iii) Grishkin et al. (2015) developed a model by means of support vector machines for examining biological contaminants on surfaces of the heritage elements; (iv) Bassier et al. (2017) used a model of classification by means of support vector machines to identify the typology of heritage elements in digitized objects; (v) Steinbauer et al. (2013) developed regression trees to detect factors stimulating the appearance of vegetable species in façades of medieval castles; and (vi) Obeso et al. (2016) and Llamas et al. (2017) used convolutional neural networks to classify efficiently the images of architectural heritage. However, none of these research works studies or analyses the application of the model of artificial intelligence proposed to H-BIM.

Therefore, this study proposes a model of cultural heritage management by means of artificial intelligence. Due to the large number of factors which influence each type of element (structural elements, finishing elements, etc.), this research was focused on one of these elements. Therefore, this case study is about the conservation management of the tile panels from the Pavilion of the Emperor Charles V located in the Real Alcazar of Seville (Spain), which was declared an UNESCO World Heritage Site. To generate the model of classification, the J48 algorithm was used on the training dataset. Then, this model was implemented in Geometric Description Language (GDL) for one of the BIM platforms existing in the market (ArchiCAD), and its behaviour was tested in new case studies. This working process can be established as a methodology of developing intelligent H-BIM models, classifying automatically the elements that configure the building and the type of response required by the managers of the model.

2. Material and method

2.1. Decision tree: J48 algorithm

Decision trees are a supervised learning technique that develop models of classification with a structure with the form of a tree, composed by interior nodes corresponding to attributes, arcs corresponding to the values of the source node, and leaves corresponding to the value of classification (see Figure 1). Thus, decision trees determine the system response following the rules fulfilled from the root of the tree to one of its leaves. The algorithm works by dividing the training dataset into smaller subsets until the most adequate configuration is determined. Therefore, the model is directly created, from top to bottom, without using backtracking and with resistance to the noise, provided that the training sample is big.

Traditionally, this classification technique of supervised inductive learning is the most used in the decision-making process. In addition, it is used in several areas, such as quality control, meteorological predictions, or medical diagnosis (Martínez, Roberto, and Carlos Alberto 2009). Thus, its use is in accordance with the recommendations by Bruno, De Fino, and Fatiguso (2018) of taking those algorithms developed in medicine for evaluating diseases as a starting point for implementing algorithms in H-BIM. Consequently, its use in the decision-making on the management of

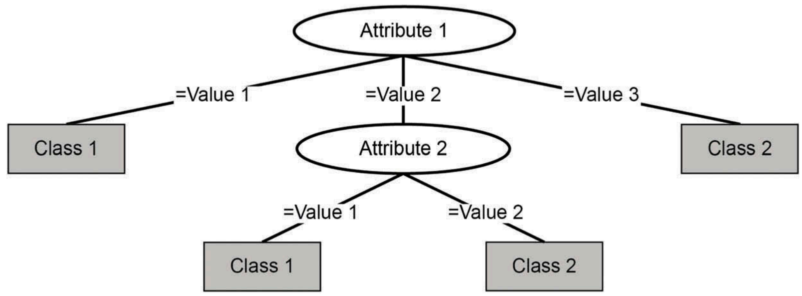

Figure 1. Theoretical scheme of a decision tree.

the architectural heritage is an aspect to be studied. Moreover, the main advantage of these models is that the connection among nodes can be expressed as if-then rules at a computational level, which eases its programming in different languages.

This technique of classification belongs to the Top Down Induction of Decision Trees (TDIDT) family, and two algorithms developing the decision trees are mainly highlighted: ID3 and C4.5 algorithms. First, the ID3 algorithm was developed by Quinlan (1986), allowing decision trees by means of a training sample to be developed. Then, the C4.5 algorithm is a development of ID3 algorithm published by Quinlan (1993). This new algorithm introduces some changes, such as the pruning of the models by developing less complex systems, and therefore easier to understand. An implementation of the C4.5 algorithm is found in Waikato Environment for Knowledge Analysis (WEKA) software by means of the J48 algorithm. This algorithm improves the functional natures of the C4.5 algorithm, including the method of reduced error pruning. In this study, the J48 algorithm was used.

The algorithms of decision trees determine the best attribute in each step through the concept of information gain by using C. Shannon´s information theory (Shannon 1948). To do this, it is essential to assess firstly the entropy, which determines the uncertainty degree of the sample. The entropy is calculated from the probabilities for each value of the classification attribute:

$$E(S) = -\sum_{i=1}^{c} p_i log_2(p_i), \tag{1}$$

where S is the set of samples, c is the number of classes of the classification attribute, and P_i is the probability that S belongs to i class from the classification attribute. If the sample is homogeneous (i.e., all values belong to the same class), then the entropy is null, but if the sample is proportional, the entropy is maximum.

The information gain (Equation (2)) is based on the decrease of the entropy caused by using a training dataset S with respect to an attribute A. Thus, the algorithm builds the model looking for those attributes which give back the biggest possible information gain:

$$IG(S,A) = E(S) - \sum_{v \in V(A)}^{c} \frac{S_v}{S} E(S_v), \tag{2}$$

where S_v is the subset of S with those instances that have the value v in the attribute A, and $V(A)$ is the set of values of the attribute A.

For this study, the determination of the model that presented the best behavior in new instances was needed to implement it later in H-BIM. For this purpose, two models of different decision trees were generated: with pruning (DT1) and without pruning (DT2). The use of the pruning could avoid the overfitting of data, although studying the behaviour of both models was required to determine which model had the most efficient behavior. The confidence factor used for the models with pruning was of 0.25. The training and validation of the models were carried out using WEKA by means of cross-validation of 10 iterations. Likewise, true positive rate (TP) (Equation (3)), false positive rate (FP) (Equation (4)), the kappa statistic (Equation (5)), and the area under the Receiver Operating Characteristic (ROC) curve (AUC) were used as quality statistical parameters. Such parameters were used to determine the most adequate model, considering adequate models when these parameters had values close to 1:

$$TP = \frac{Instances\ correctly\ classified}{Total\ number\ of\ instances} \tag{3}$$

$$FP = \frac{Instances\ incorrectly\ classified}{Total\ number\ of\ instances} \tag{4}$$

$$K = \frac{p_o - p_e}{1 - p_e} \tag{5}$$

$$AUC = \int_0^1 \left(1 - G\left(F^{-1}(1-t)\right)\right)dt, \quad (6)$$

where P_o is the relative observed agreement among the observers, P_e is the hypothetical probability of agreement by chance, G is the distribution of positive samples, F is the distribution of negative samples, and t is a cut point.

2.2. Case study

The case study of this article is the Pavilion of Charles V that belongs to the external areas of the Real Alcazar of Seville. It is a building dating from the Moslem period (12th century) and was transformed in the 16th century (Fidalgo 1990). The building is mixed by Renaissance (such as the capitals) and Mudejar elements (such as the structural organization, very similar to the old *qubba*). One of the elements to be highlighted from this building is the wall cladding with tiling panels, dating from the 16th century. These tiles are the ornamental elements of the building that most require a special treatment due to their singular character and state of conservation based on different factors, such as the deterioration state, the absence of mortar among the walls and the pieces, or their incorrect location in the panel. Therefore, one of the panels from the Pavilion of Charles V was analyzed (see Figure 2) to use the data compiled as a training dataset of the prediction model developed. The tiles panel was selected due to the variety of conservation degrees presented by its pieces.

The sample was constituted by 221 tiles. Each of such tiles corresponded to an instance of the training dataset. The analysis process of this sample was carried out with the help of personnel responsible for preserving the Real Alcazar of Seville. First, all the tiles were numbered and labeled, and then analysed and assessed. Data were grouped in several attributes, and a series of values was assigned to each of these attributes. The attributes (state of conservation, adherence to the support, gripping mortar, dimensions of pieces, position in the panel, volumetric reintegration, and chromatic reintegration) and their values are listed and described in Table 1, and the class of dataset is also described (degree of intervention).

The training of each model was carried out through 10-fold cross validation. This procedure allows the error of the model to be reduced (Kohavi 1995). The training dataset was randomly divided into 10 subsets and an independent training was carried out for each fold (using 9 subsets for the training and the remaining subset for the testing). The performance of the model is obtained by the average value of the 10 folds.

2.3. H-BIM model

As mentioned above, the use of H-BIM models is a new and current approach in the processes of heritage management. By using H-BIM, it is possible that different specialists collaborate in the assessment of the architectural elements and such assessment is registered in a graphic and alphanumeric model, with the resulting advantages of cataloging for public and private

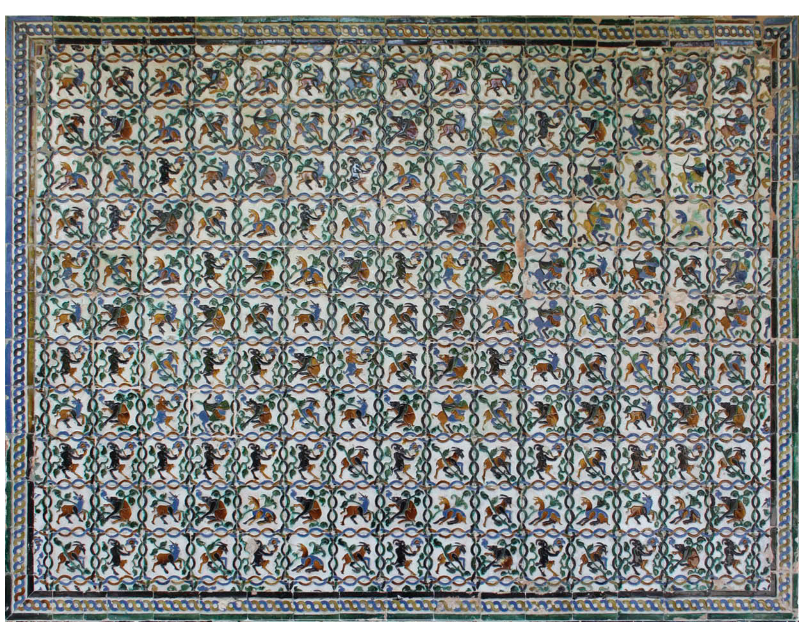

Figure 2. The tiles panel studied.

Table 1. Attributes in the tiles panel analyzed.

Attributes	Description	Values
State of conservation	Determining the circumstances when appearing damages and symptoms which make the study of the specific cases quite challenging. In this attribute, aspects such as the presence of moisture or the erosion by mechanical actions are reflected. The conservation state of the tile determines the assessment degree of the attribute.	Good Regular Bad Very bad
Adherence to the support	Determining the changes experimented by the gripping material from the moment of its placing. The state of the gripping material determines the assessment degree of the attribute.	Good Regular Bad Very bad
Gripping mortar	Determining the type of mortar that nowadays sticks the piece to the wall. If it is a lime mortar, it is ideal. However, if it is a cement mortar, it is not ideal because of its lack of flexibility. If it is a lime mortar, the "original" value is assigned, but if it is cement mortar, the "no original" value is assigned.	Original No original
Dimensions of the piece	Determining the dimensions of the piece in relation to the original ones. The values associated with the attributes are if the dimensions of the pieces are of manufacture or cut.	Of manufacture Cut
Position in the panel	Determining the original or modified position of the piece in the panel set. Values associated with the attribute are for the correct or incorrect position of the tile.	Correct Incorrect
Volumetric reintegration	Determining the reintegration of some part of the piece mass, considering the volume required to be reintegrated. The material volume to be reintegrated into the tile determines the assessment degree of the attribute.	Very high High Medium Low
Chromatic reintegration	Determining the reintegration of some part of glazing considering the surface required to be reintegrated. The material surface to be reintegrated into the tile determines the assessment degree of the attribute.	Very high High Medium Low
Degree of intervention	Determining the priority degree in the intervention in the tile in question. The intervention works to be carried out correspond to aspects such as the manual cleaning, consolidation of pieces, and the reintegration of material and pigment losses, among others. The degree of intervention is determined by the combined decision among several specialists responsible for the conservation depending on the attributes previously indicated.	Urgent High Medium Low

institutions. The use of a H-BIM model for incorporating a methodology of models of classification allows the information to be organized, as well as the update, the sequencing registered in a graphical model with lists of detailed inventories that could be exported, and the understanding of the anatomy and morphology of the building.

For this reason, a H-BIM model from the Pavilion of Charles V was developed for this study (see Figure 3). The H-BIM model was carried out using ArchiCAD. To do this, a construction, technical and geometric data collection of the building was compiled before developing such model (Biagini et al. 2016). Thus, the planimetry of the building was obtained from a photogrammetric study conducted by the School of Arabic Studies in 2000 (Almagro 2000), which provided three views with the updated dimensions of the Pavilion of Charles V, which was the base to make the H-BIM model.

Although software in BIM allows nowadays the development of a huge variety of parametric objects (e.g., walls, slabs, beams or pillars, among others), the modeling of capitals is not possible to carry out through this procedure. In these cases, the 3D scanning allows a precise H-BIM model to be obtained (Logothetis, Delinasiou, and Stylianidis 2015). Therefore, the 3D scanning of the capitals of the building was done by means of the optic scanning technique using a portable Artec MHT manual scanner. After the 3D scanning, the cleaning and optimization of the cloud points was carried out using the Artec Studio software. Then, the point cloud is meshed, generating a .3ds object, which was later introduced as a parametric object (.gsm) in the H-BIM model. A total of 20 different capitals were modelled by using this procedure.

The graphical documentation of the surface elements, such as the tiles, was carried out using orthoimages taken by a single lens reflex (SLR) digital camera Canon EOS 500D. To incorporate the tiles in the H-BIM model, an ortho-restitution was manually processed. GDL objects of type Picture without frame constituting each of the pieces were used. Each GDL object was adapted to the dimensions of the piece represented, and the real texture of the tile (obtained from the orthoimages taken) was incorporated to its being fast identified. This process of implementation allowed the original geometry of each piece to be preserved in the BIM model. Likewise, each piece was identified for its being cataloguing. In addition, relevant information about the pieces was incorporated. The total number of tiles constituted the 57.85% of the modelled elements from Pavilion of Charles V in BIM.

3. Results and discussion

First, the model of classification developed with the J48 algorithm is discussed in this section, and then its

Figure 3. Perspective of the H-BIM model from the Pavilion of Charles V in the real Alcazar of Seville.

implementation in the H-BIM model as well as the proposed methodology are analyzed.

3.1. Decision tree model

As previously mentioned, the training dataset was used for the training and validation of two different models: one model using a tree simplification method by means of pruning (DT1 model), and another without using pruning (DT2 model). In Figure 4, the schemes of both models are represented. As can be appreciated, the model presented a simpler structure for DT1 model with respect to DT2. For both DT1 and DT2, the generated tree scheme considered the attributes of volumetric reintegration, chromatic reintegration, degree of conservation, and adherence to the support as those which best classified the degree of intervention in the tiles.

Thus, it was fundamental to determine which model presented the best behavior. First, the confusion matrix generated by each model was analyzed, since it determined the accuracy of classification obtained with respect to the training dataset used. Tables 2 and 3 include the confusion matrixes obtained for DT1 and DT2 models. The values of the confusion matrix diagonal correspond to the TP rate (percentage of classification carried out correctly for each class), whereas the other values of the matrix correspond to the FP rate (percentage of classification incorrectly carried out). The TP rate represents the percentage of classification carried out correctly for each class. In general terms, the classification results obtained by both models were quite similar, obtaining a TP rate higher than 70% for urgent, high and medium classes. A TP rate lower than 50% was obtained for low class. Moreover, the DT1 model obtained a better prediction for two classes, increasing the TP rate by 18.74% for the urgent class, and 2.63% for the medium class.

Thus, due to the similarity of the confusion matrixes obtained, the most adequate model was determined by the kappa statistic and the area under the ROC curve. First, the kappa statistic determined the coincidence of the class estimated with the real class. Both DT1 and DT2 obtained kappa statistics close to 1: 0.7592 for DT1 and 0.7264 for DT2, although DT1 obtained a value closer to 1.

The area under the ROC curve determined the probability that the model classifies correctly the class analyzed. As can be seen in Figure 5, the AUC was higher than 85% for the different classes in both models, but the values of AUC for DT1 were closer to 1. In this sense, the DT model presented an increase of AUC with respect to DT2 of 12.20% for urgent, 3.82% for high, 0.66% for medium, and 1.88% for low. Therefore, DT1 model had a more efficient behavior than DT2 model, as well as a simpler structure.

3.2. Implementing in H-BIM

After determining the model of classification with the most adequate behaviour, such model was implemented in the H-BIM platform to automate the decision-making process. To do this, the GDL was used. This programming language uses a syntax like Visual Basic. In this research, a GDL object predefined in the library of the BIM tool (in this case, an object of type picture) was used to carry out later its modification by means of the configuration options that the software provides. The object could be opened to be edited, so the variables required were introduced for implementing the model developed by means of the J48 algorithm in the parameters tab to be later programmed (see Figure 6). Both variables classifying the degree of intervention

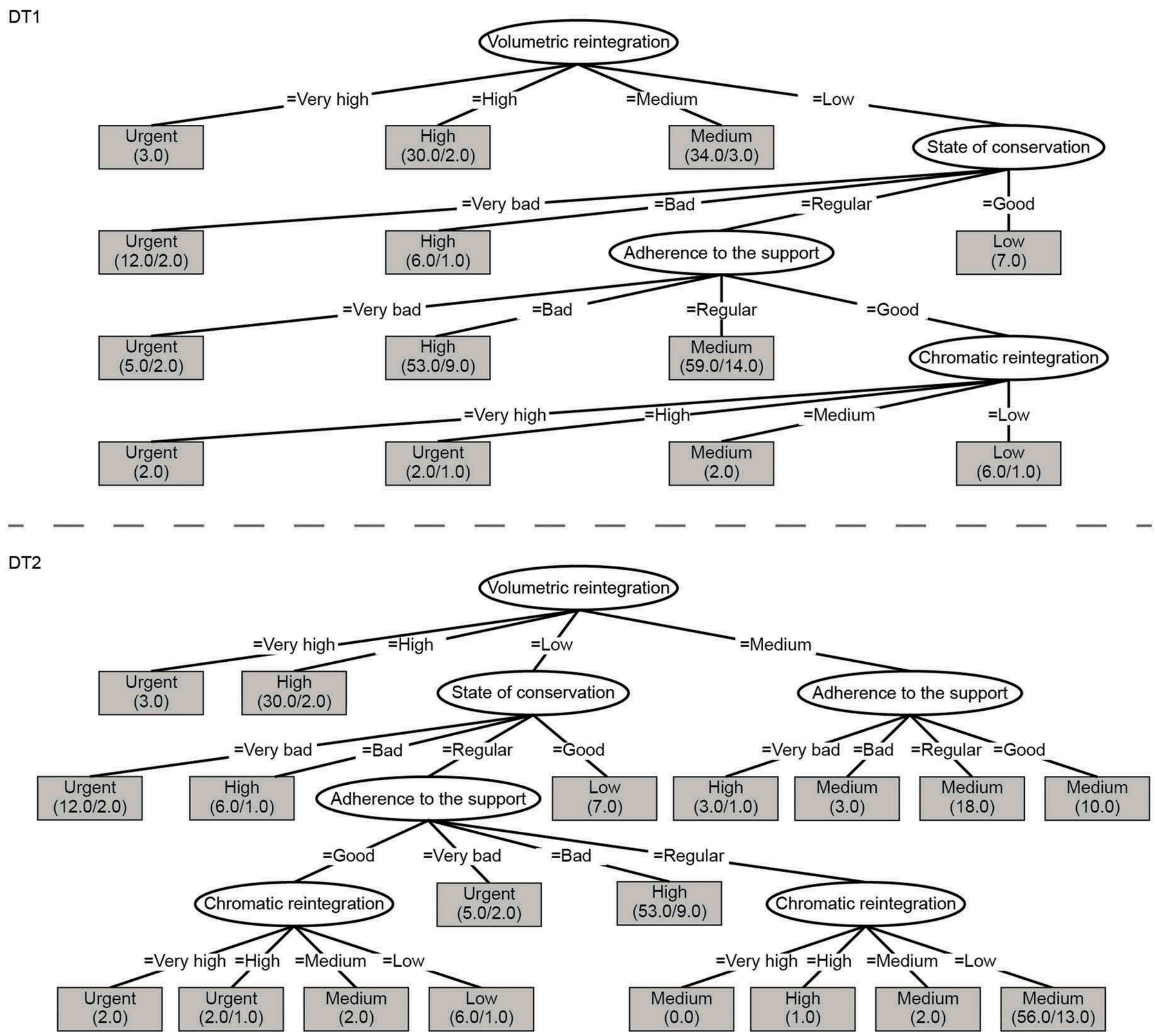

Figure 4. Schemes of both decision tree models developed using the J48 algorithm.

Table 2. Confusion matrix for DT1.

		Predicted label			
		Urgent (%)	High (%)	Medium (%)	Low (%)
Real label	Urgent (%)	86.36	9.09	4.55	0.00
	High (%)	3.61	92.77	3.61	0.00
	Medium (%)	0.00	11.24	87.64	1.12
	Low (%)	7.41	0.00	48.15	44.44

Table 3. Confusion matrix for DT2.

		Predicted label			
		Urgent (%)	High (%)	Medium (%)	Low (%)
Real label	Urgent (%)	72.73	18.18	0.00	9.09
	High (%)	6.02	92.77	1.20	0.00
	Medium (%)	0.00	11.24	85.39	3.37
	Low (%)	7.41	0.00	48.15	44.44

(state of conservation, adherence to the support, chromatic reintegration, and volumetric reintegration) and variables not using the model (the personnel can assign the values of these variables for a documentary compilation) were included. Therefore, a GDL object specific for the tiles of the Pavilion of Charles V was developed.

To implement the model of classification, the parameter script was used and the if-then rules from the decision tree were introduced in the standard programming of the GDL object. The programming of the GDL object was conducted for two different options. In one option, the values assigned to each input attribute of the model (Option A) were used, whereas these values were transformed into numeric digits, from 1–4, in the other option (Option B). The values were transformed because one of the options to introduce the values of the different attributes consisted of importing the datasets carried out in other spreadsheets software (.xls or .xlsx files), so this importation can be done by other professionals who do not have a BIM platform. Given the high possibility of misspelling one of the values if the complete names of the labels or values are used

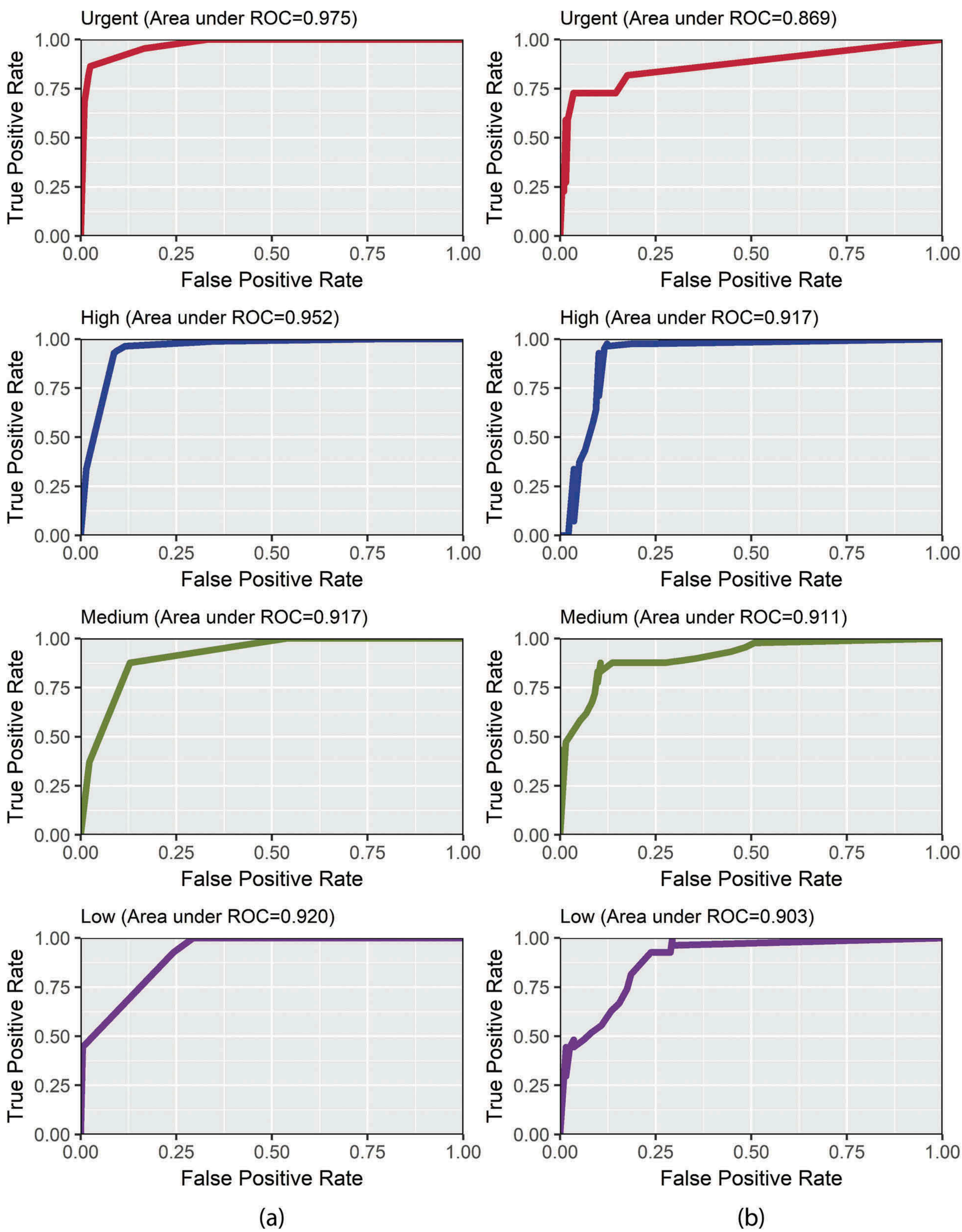

Figure 5. ROC curves for the different classes of both models: (a) DT1 and (b) DT2.

with respect to a numeric digit, another simpler programming was suggested for the model to avoid possible errors in the option of importing the dataset. For each option, the values for each attribute were programmed to be appeared in a drop-down list in the software BIM. Moreover, the program represented the priority of performance in the tiles with a chromatic codification to ease its interpretation at a visual and

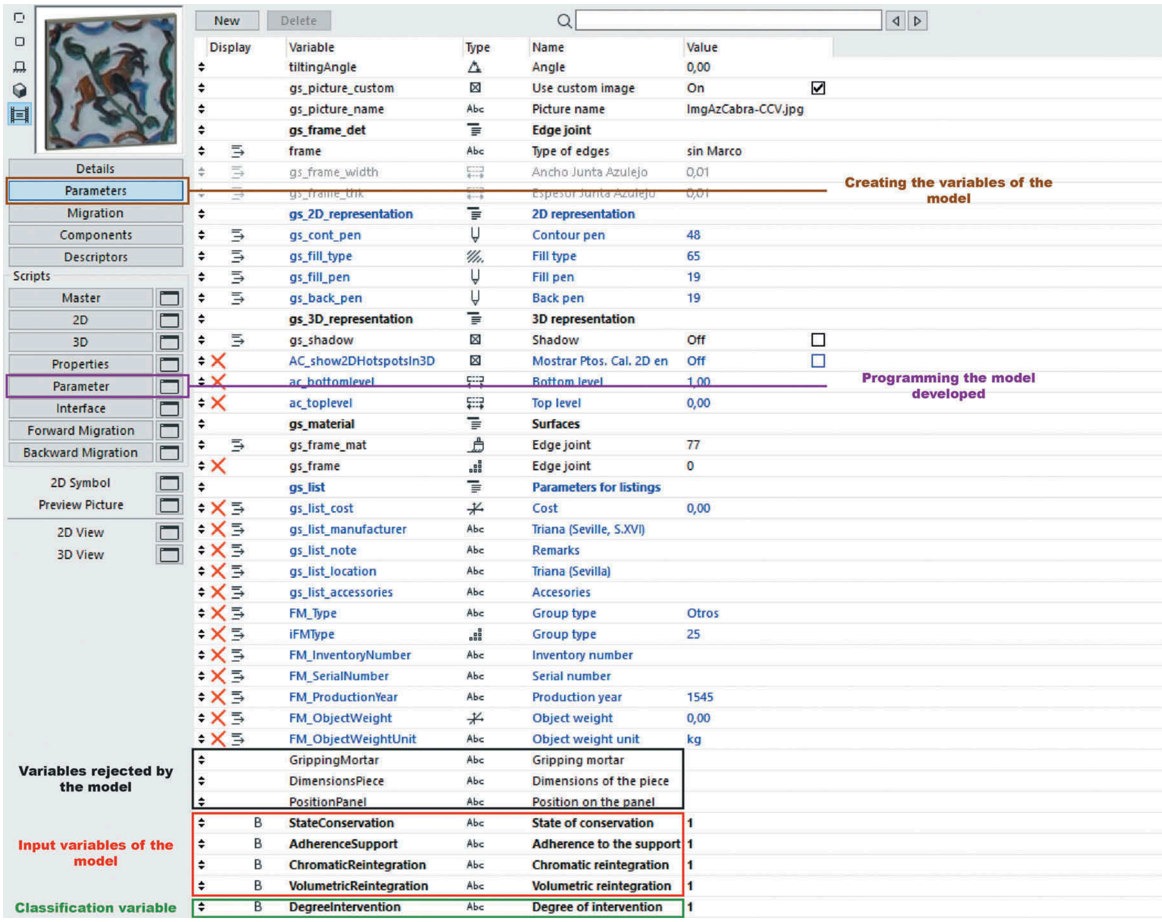

Figure 6. Interface of the parameters of the GDL object for implementing the model of classification. In the inferior part, the input variables of the model, as well as the classification variable are shown.

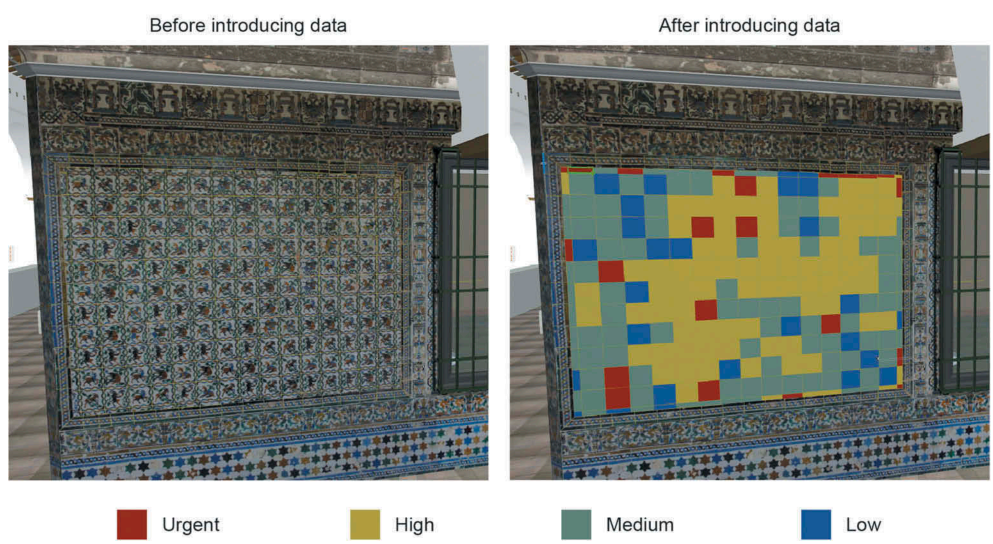

Figure 7. Graphic view of the tiles panel analysed by using the automatic classification carried out by the model of the J48 algorithm.

interaction level in a 3D model, so a texture for each value of the degree of intervention was introduced in the programming. In addition, the priorities of intervening in the tiles panel can be graphically seen in the different views of the program (see Figure 7), as well as the inventory list of tiles (see Figure 8). The interactive relationship between the pieces and the inventory list makes a flexible, reciprocal information flux easier.

LRE-02(R) INVENTORY SHEET OF TILES TO RESTORE															
	ID	Model	Orientation	Position	Ud	Dimensions of the piece	Sector	Position on the panel	Date	State of conservation	Adherence to the support	Gripping mortar	Chromatic reintegration	Volumetric reintegration	Degree of Intervention
Tiles															
	NE.D-001	Az	N	Exterior	1	1	D	2	S. XVI	1	4	1	3	4	1
	NE.D-002	Az	N	Exterior	1	1	D	2	S. XVI	3	4	2	1	4	1
	NE.D-003	Az	N	Exterior	1	1	D	2	S. XVI	3	4	2	4	4	3
	NE.D-004	Az	N	Exterior	1	1	D	2	S. XVI	3	4	2	1	4	1
	NE.D-005	-Az	N	Exterior	1	1	D	2	S. XVI	3	4	2	4	3	3
	NE.D-006	-Az	N	Exterior	1	1	D	2	S. XVI	3	4	2	4	3	3
	NE.D-007	Az	N	Exterior	1	1	D	2	S. XVI	3	4	2	4	3	3
	NE.D-008	Az	N	Exterior	1	1	D	2	S. XVI	3	1	2	4	4	1
	NE.D-009	-Az	N	Exterior	1	1	D	2	S. XVI	3	3	2	4	3	3
	NE.D-010	Az	N	Exterior	1	1	D	2	S. XVI	3	3	2	4	4	3
	NE.D-011	-Az	N	Exterior	1	1	D	2	S. XVI	4	3	2	4	4	4
	NE.D-012	Az	N	Exterior	1	1	D	2	S. XVI	3	4	2	4	4	4
	NE.D-013	Az	N	Exterior	1	1	D	2	S. XVI	3	4	2	4	1	1
	NE.D-014	Az	N	Exterior	1	1	D	1	S. XVI	1	4	2	4	1	1
	NE.D-015	Az	N	Exterior	1	1	D	1	S. XVI	1	4	2	2	1	1
	NE.D-016	Az	N	Exterior	1	1	D	1	S. XVI	1	4	1	1	2	1
	NE.D-017	Az	N	Exterior	1	1	D	1	S. XVI	2	4	1	2	2	2
	NE.D-018	Az	N	Exterior	1	1	D	1	S. XVI	1	4	1	3	2	2
	NE.D-019	Unicorn	N	Exterior	1	2	D	2	S. XVI	3	3	2	4	4	3
	NE.D-020	Goat	N	Exterior	1	2	D	2	S. XVI	3	3	2	4	4	4
	NE.D-021	Minotaur	N	Exterior	1	2	D	2	S. XVI	3	3	2	4	4	3
	NE.D-022	Chameleon	N	Exterior	1	2	D	2	S. XVI	4	3	2	4	4	4
	NE.D-023	Minotaur	N	Exterior	1	2	D	2	S. XVI	3	3	2	4	4	3
	NE.D-024	Unicorn	N	Exterior	1	2	D	2	S. XVI	3	3	2	3	4	3
	NE.D-025	Centaur	N	Exterior	1	2	D	2	S. XVI	3	2	2	4	4	2

Figure 8. Inventory sheet of the tiles analysed using option B from the programming.

In future restoration works, the GDL object developed with the programming of a model of classification using the J48 algorithm will determine the priorities of performance in the other tile panels of the Pavilion of Charles V from the Real Alcazar of Seville. The proposed methodology (see Figure 9), which consists of

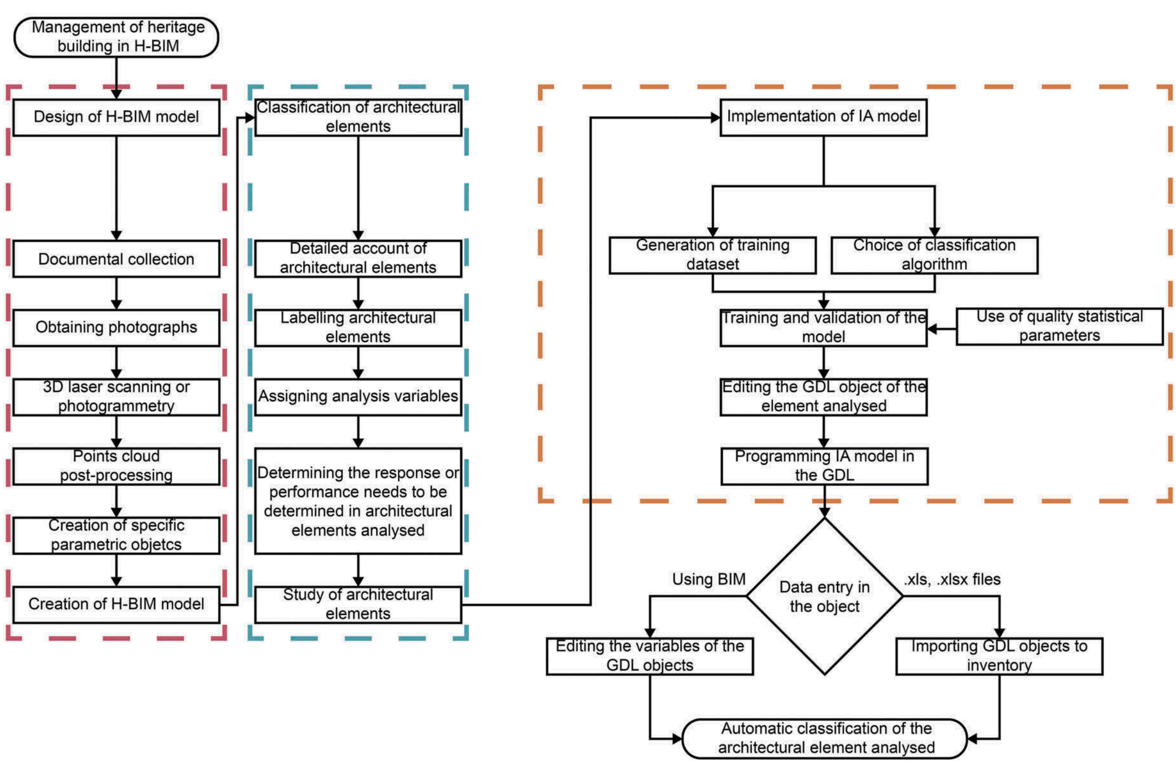

Figure 9. Workflow of using the artificial intelligence by means of models of classification in H-BIM.

obtaining a training and validation dataset to develop a model of prediction and its posterior implementation in a GDL object, can be used to manage other ornamental elements (i.e., this methodology could be used in other architectural elements, such as floorings, capitals or roof tiles, among others) from both the Pavilion of Charles V and other heritage buildings. Given that the essence of BIM is to get a database of graphical and alphanumeric information (Nieto et al. 2016), the automation in the decision-making of such database is achieved with this methodology.

This methodology was limited because the values assigned to the GDL objects should be of qualitative type, so the use of classification algorithms of quantitative variables is restricted. The quality statistical parameters considered in this research can be useful to determine the model with the best behaviour with discrete values. Likewise, the models developed can introduce new variables of classification different from the one used in this research, provided that a strong training and validation dataset is available, hence allowing a larger number of possibilities of implementing automatic response given by H-BIM. In this sense, different aspects of classification could be developed in H-BIM projects, such as the damage level caused by structural deformations, and surface or interstitial condensations, allowing a great variety of intervention scenarios to be evaluated. Thus, automating the process of heritage management, joining decision-making criteria and reducing the times of assessment in a graphical interface are achieved by implementing this methodology. The use of the graphical results (see Figure 7) and the detailed inventory classifying the heritage elements (see Figure 8) are the deliverables that should be used by workers and technicians for preserving the pieces.

4. Conclusions

The management of the existing architectural heritage constitutes one of the main activities of the building sector. This activity is characterised by the intervention of different technicians, such as archaeologists, engineers, and architects, who may disagree on criteria when making decisions. Therefore, having models of classification by means of artificial intelligence in H-BIM models which lead to automate the decision-making can optimize the process, decrease the times, and guarantee an intelligent management of the architectural heritage.

In this article, a solid and practical basis to implement the artificial intelligence by means of models of classification is developed for the preventive management of the heritage in H-BIM. For this purpose, the Pavilion of Charles V in the Real Alcazar of Seville has been used as case study, focusing the research on its tile panels.

The J48 algorithm is used as algorithm of classification because it is an algorithm widely used in the decision-making process, and its implementation at a programming level is simple and intuitive by means of if-then rules. The model of classification was implemented in H-BIM by means of its programming in the GDL. To do this, a specific GLD object was generated for the typology of the element assigned in this study by introducing the attributes required for the model as well as by developing the programming of the model in the parameters script. Consequently, the object classified the response automatically and assigned a chromatic shade to distinguish it visually. In addition, inventory lists of the classification of GDL objects could be done.

To conclude, the main advantage achieved by automating the process is the reduction of time when deciding on a specific aspect of the element analyzed (in this case study, it was the priority of performance on the tile), together with the homogeneity of the decision-making criteria among the technicians assigned for the management of the building. Likewise, the methodology can be used for different problems of classification in various architectural elements (e.g., floorings or woodwork) of heritage buildings. Therefore, the use of the artificial intelligence by means of this methodology is helpful to achieve the objectives of preserving the architectural heritage.

The proposed methodology was limited because the variables of the GDL object were of qualitative type, thus preventing the use of classification algorithms of quantitative variables. For this reason, future steps on this research will be oriented to implement regression algorithms, such as multilayer perceptrons or support vector regression.

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