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Abstract
The construction sector is the largest consumer of raw materials and accounts for 25% to 40% of the total CO_2 emissions globally. Besides, construction activities produce the highest amount of waste among all other sectors. According to the waste hierarchies, reuse is preferred to recycling; however, most of the recovery of construction and demolition wastes happens in the form of recycling and not reuse. Part of the recent efforts to promote the reuse rates includes estimating the reusability of the load-bearing building components to assist the stakeholders in making sound judgements of the reuse potentials at the end-of-life of a building and alleviate the uncertainties and perceived risks. This study aims to develop a probabilistic model using advanced supervised machine learning techniques (including random forest, K-Nearest Neighbours algorithm, Gaussian process, and support vector machine) to predict the reuse potential of structural elements at the end-of-life of a building. For this purpose, using an online questionnaire, this paper seeks the experts' opinions with actual reuse experience in the building sector to assess the identified barriers by the authors in an earlier study. Furthermore, the results of the survey are used to develop an easy-to-understand learner for assessing the technical reusability of the structural elements at the end-of-life of a building. The results indicate that the most significant factors affecting the reuse of building structural components are design-related including, matching the design of the new building with the strength of the recovered element.

Keywords
Reuse; Building structure; Supervised machine learning; Random forest; K-Nearest Neighbors; Gaussian process

1. Introduction
The construction sector is a leading economic sector that employs around 7% of the global workforce [1] and accounts for 6% to 9% of the Gross Domestic Product (GDP) worldwide [2]. The construction industry is also a leader in the consumption of resources and the emission of greenhouse gases (GHG) [3,4]. According to [4], this sector is the largest consumer of raw materials, and the construction-related activities account for 25% to 40% of the total CO_2 emissions globally. Besides, construction activities produce the highest waste among all other sectors [5–8].

According to [9], most of the embodied energy and CO_2 impacts of buildings are related to the load-bearing systems. Therefore, methods for extending the life of the structure of buildings can potentially improve the environmental footprint of this sector.

According to the waste hierarchies, reuse is preferred to recycling [10,11]; however, most of the recovery of construction and demolition wastes (CDW) happens in the form of recycling and not reuse. For example, nearly 91% of the non-hazardous CDW of the UK is recovered through recycling [5]. While recycling can divert waste from landfills, the processes involved are energy and resource-intensive and impose a noticeable pressure on the environment in terms of GHGs and other sorts of emissions [12,13]. On the other hand, reused load-bearing building elements (beams, columns, truss, etc.) have far lower environmental impacts when compared with recycled materials [14]. The above fact is primarily due to significantly lower treatment and reprocessing required for reusing these components than recycling them [15].

Although efforts have been made to increase the reuse rates of building structural elements in recent years, there are yet no signs of improvements. Contrarily, the reuse rates in the building sector have declined in the last two decades in countries like the UK, and only a fraction of load-bearing building components are reused [12,16]. Part of the recent efforts to promote the reuse rates includes estimating the reusability of the load-bearing building components to assist the stakeholders in making sound judgements of the reuse potentials at the end-of-life of a building and alleviate the uncertainties and perceived risks. However, the continuous decline in reusing the structural elements of buildings shows the need to develop robust interdisciplinary reusability evaluation tools to improve the reuse rates.

In 2020, [17] conducted a systematic literature review to identify factors affecting the reuse of the structural elements of a building at the end of its lifecycle (known as the reusability factors in this article). The authors reviewed 76 journal papers and identified main reuse barriers and drivers. They classified these factors under six categories and twenty-three subcategories. They eventually studied the interdependencies between the reuse barriers. While the authors concluded that a holistic approach is required to promote the reuse of load-bearing building components, they advised prioritising the social, economic, and regulatory barriers.

While the reviewed articles by Rakhshan et al. [17] show that a wide range of studies has extensively tried to identify the barriers ahead of the widespread reuse of building structural elements, they did not provide any indication of the reusability of these components based on the identified barriers. Some authors recognised this gap and attempted to fill it by estimating the physical properties (dimensional or mechanical) of the recovered building structural elements as an indication of their reusability and ignored the impact of other variables.

For instance, focusing on the dimensional aspect, [18] studied the impact of accurate geometric characterisation of the steel structure of a building (at its end-of-life) on the decision process for reusing the structural components. The authors initially developed a decision-making framework to facilitate the stakeholders in identifying the reuse potentials for recovered building structural steel. They then presented an automated object recognition algorithm to identify the member cross-sections. They eventually performed a reliability analysis to evaluate the performance of the proposed geometric identification method. Based on the results of the reliability analysis, the authors proposed a semi-automatic geometric identification method to enable designers to employ the reused structural elements at their maximum capacity.

In another study focused on determining the physical properties of the structural steel, the authors developed a performance evaluation procedure to estimate the mechanical properties of reused structural elements using non-destructive testing (NDT) [19]. Fujita and Kuki [19] estimated the Vickers hardness using portable ultrasonic hardness testers and rebound-type portable hardness meters. They used the estimated values as the basis to calculate the mechanical properties of the reusable elements. The results of the test specimens showed good agreement with the standard values.

Similarly, [20] used wireless sensors to monitor the stresses induced during the construction of a steel-framed building to evaluate the reusability of steel members. According to this study, the authors observed that the maximum measured stresses were almost half of the nominal yield strength, confirming that the current design practices allow the reuse of structural steel (see also [21] for similar studies in different systems and industries).

In a relevant study focused on estimating the mechanical properties of timber, [22] developed linear regression models to predict the Modulus of Elasticity and Modulus of Rupture of in-use and recovered timber sections based on the NDT methods. According to this study, the developed models can assess the reusability of timber structures on site. Notwithstanding, the proposed linear regression-based models are too simple to model the complex system described above, and the predicted values are not accurate. Therefore, the derived results using the linear regression models are not reliable, and considerable care should be taken to use the outcomes of this study. However, this study shows the substantial potential of the machine learning techniques in determining the reusability of the load-bearing building components.

The above studies concentrate on discovering the technical reusability of the building structure by focusing on one aspect, like determining the mechanical properties or dimensional details of potential structural components for reuse. The only exception is a study performed by [23], in which the authors developed an indicator for estimating the technical reusability of steel-framed buildings considering a combination of variables. These variables include the impact of disassembly technique, handling, availability of the earlier design documents, potential new deployment (same purpose or repurposing), and the need for quality and dimensional checks. Nevertheless, this study is limited to steel-framed industrial buildings, the developed predictive method is not based on actual reused components, and the interdependencies of the affecting variables are not considered.

This study aims to develop a model that can efficiently and accurately predict the reuse potential of structural elements at the end-of-life of a building based on the experts' opinions using several advanced supervised machine learning methods. For this purpose, using an online survey, this paper uses the expert opinion of the professional experts in the building sector with actual reuse experience to assess the identified barriers by the authors in an earlier study [17]. This paper is a part of a series of studies that tend to provide a set of interdisciplinary predictive tools to assess the technical, economic, and social reusability of a building's structural components. In this study, the focus is on the technical reusability of these components, which is defined as the extent to which a reused structural element in its new life could perform similarly to its earlier life.

The paper continues with the research method (Section 2), results and discussions (Section 3), and the conclusion (Section 4).

2. Method and data collection

This study seeks the experts' opinions to quantify the factors affecting the reuse of building structural elements and intends to develop a predictive model to determine the technical reusability of the load-bearing components using supervised machine learning techniques.

The experts' opinions were elicited by developing a comprehensive online questionnaire survey research methodology in this field to provide a numeric description of the variables described above and a primary evaluation of the relationship between the variables. Using the Online Surveys [24], an online questionnaire survey was developed based on an earlier systematic literature review performed by the authors [17], and its link was shared with the potential respondents. In this study, the variables (reusability factors) identified in the questionnaire (both independent and dependent) are in the form of closed questions with the Likert-style ratings [25]. While the Likert response sets can include four or more points, this study uses a five-point system, which is more common [26]. A copy of the survey is available in Appendix A. It should be noted that some questions in the provided copy are removed because they target other aspects of the reusability of the structural components of a building, which are not covered in this study.

In this questionnaire, Section A contains demographic questions and seeks the details of the respondents. Section B deals with the structural element that the respondent used in the past and would complete the rest of the questionnaire by referring to it. This section contains 11 questions and is in two parts. Questions 1 to 6 seek the details of the reused element, and 7 to 11 compare the current use of the component (or use after deconstruction) with its previous deployment before it was removed/deconstructed from a building. Section C is concerned with the barriers to reuse, as identified by the authors during a systematic literature review [17]. Section D contains those factors that can act as either a barrier or a driver in different circumstances. And Section E inquires the reusability of the structural element that the respondent used before and, based on that, replied to the questions in Sections B, C & D.

In total, 481 invitations were sent to the experts to complete the online questionnaire. To increase the response rate, the corresponding author sent out several reminders in fixed intervals to the potential respondents. As advised by [27], the first reminder was sent one week after sending the questionnaire link to the recipient. A second reminder was sent after three weeks, and a third follow-up email was sent after another two weeks. After all the above steps, the total number of received questionnaires reached 90, yielding a response rate of 18.7%.

As shown in Table 1, 67.7% of the respondents are managers (44.6%) and top managers (23.1%), 10.8% are architects, 7.7% are engineers, 4.6% are consultants, 4.6% are deconstruction experts, and others are reuse experts and construction waste prevention experts. In this study, all the experts were located using the companies' websites and LinkedIn. It should be noted that for selecting the potential respondents, using the provided information on their LinkedIn page or company website, the education and background of the reuse experts were carefully reviewed to make sure they match the desired profile. According to the provided details, all selected experts had more than six years of experience in the construction sector. Moreover, most of them were either civil/structural engineers by education or were closely working with civil/structural engineers. Please refer to another publication by the same authors focused on the economic reusability of the load-bearing building components for a broader explanation of the sampling technique employed in this research [28].

Table 1 Position of the respondents.

Position of the respondent	Percentage (%)
Architect	10.8
Consultant	4.6
Deconstruction expert	4.6
Designer	1.5
Engineer (Civil/Structural)	7.7
Manager (e.g. project managers, design managers, marketing manager, etc.)	23.1
Reuse expert	1.5
Top manager (e.g. head managers, owner of companies, executive managers, managing director, CEO, etc.)	44.6
Waste prevention specialist	1.5

The reliability of the responses refers to the capacity of the results to be reproduced by other researchers. Therefore, reliability is linked with the respondents being representative of the targeting population. While one of the indicators of reliability is the response rate, it is still possible to have a low response rate with a sample that represents a population [29]. Because this study targets experts with previous experience in reusing the structural elements of a building, the chance that the questionnaire is completed by an inexperienced respondent is low. Moreover, at the beginning of the online questionnaire, and after elaborating the focus of the research, the respondent should answer a question about his/her previous experience with reused building structural elements. All the respondents confirmed that they have this experience. Hence, they are representative of the target population.

Another option to check the reliability of a questionnaire is checking the internal consistency of the responses by calculating Cronbach's alpha value [27]. In this study, before using the collected data to develop the models, the authors checked the reliability of the survey by checking the internal consistency of the responses by calculating the Cronbach's alpha value using SPSS version 25. If Cronbach's alpha value is equal to or greater than 0.7, then the combination of the questions measures the same thing [30]. Nevertheless, while 0.7 depicts acceptable reliability, higher values up to 0.9 are more desirable [31].

Based on the reliability analysis, the value of the Cronbach's alpha for this survey satisfies the minimum requirement of 0.7. In fact, in most cases, this value is above 0.9. The only exception is the reliability of questions B10 and B11. These questions have a Cronbach's alpha of 0.263, which is below the minimum acceptable value of 0.7 [30]. Hence, questions B10 and B11 were not used in constructing the models of interest in this study. Nevertheless, checking the reliability of the responses using Cronbach's alpha value revealed a high consistency of the received questionnaires. The results of the reliability analysis are available in Appendix B.

3. Results and discussion

The unit of analysis of this study is the structural elements of a building. Initially, the authors used a non-parametric test to evaluate if there are statistically significant differences between the types of structural elements (question B1) regarding the independent and dependent variables asked in the questionnaires. The null hypothesis is that there is no difference between the groups of structural elements. The purpose of this test is to make sure that combining the responses for all the components for further analysis will not affect the overall reliability of the dataset. Using SPSS version 25, the Kruskal-Wallis H test is performed at the 5% significance level to determine if the type of the element (question B1) affects the scores provided for the factors affecting the reusability of the structural components [30]. As presented in Appendix B, the Kruskal-Wallis H test results indicate that none of the p-values of the technical factors is less than 0.05 and that there is not enough evidence to reject the null hypothesis. Therefore, it can be concluded that the entire dataset can be used for further analysis regardless of the type of structural element the respondents considered to complete the survey.

Based on the reliability analysis illustrated in Section 2 and the result of the Kruskal-Wallis H test (the above discussion), the type of the element (B1), the amount of load supported by the component (B10), and its life expectancy (B11) are excluded from the list of features used for developing the predictive models.

3.1 Developing the best-practice predictive model

Since this study aims to predict if a structural element at the end-of-life of a building is reusable or not, the outcome of the predictive models should be binary (non-reusable or reusable). Therefore, following the approach adopted by [32], the authors converted the response (question E1 in Appendix A) to a binary scale with 0, for non-reusable, and 1, for reusable. While this conversion simplifies the interpretation of the results by the practitioners, the proposed methodology in this study can be conveniently generalised to multi-classes responses variable. Instead of relying on five points to decide if a component is reusable or not, the stakeholders have a straightforward basis for deciding on the fate of a structural element. Likewise, for a supervised machine learning method to perform effectively with a multi-class response, a large sample size is required. However, since the reuse of the load-bearing components of a building is not a widespread practice, collecting more data was not practical. Moreover, the uncertainties in the assessment of the reusability factors (features or independent variables), which is based on expert opinion, limits the effectiveness of a multi-scale response. Therefore, the authors categorised the dependent variables with Likert scale values of 1 to 3 as non-reusable (represented by 0) and the remaining responses (Likert scale values 4 and 5) as reusable (converted to 1). Consequently, the dependent variable (E1) transforms from a multi-scale response to a binary response.

3.1.1 Oversampling

After converting the multi-scale responses to binary ones, it was observed that there was a considerable imbalance in the classification with 34% (non-reusable) and 66% (reusable) responses. While the questionnaire was distributed to a wide range of professionals in the building sector, it was observed that the respondents with successful reuse experience were more responsive. It can be argued that the initial data collection could be continued to have more balanced responses; however, due to the time constraints, as well as the limited number of experts in this field, this option was not practical. Nevertheless, even if the data collection continues, since the respondents are free to choose any structural component with any level of reusability to complete the questionnaire, it is impossible to guess the outcome of the new survey, which might end up with a similar imbalanced dataset.

In this study, the oversampling technique developed by [33] is employed to pre-process the datasets and minimise the class imbalance impact. This technique is identified as Synthetic Minority Over-sampling Technique (SMOTE) by the developers. Unlike other oversampling techniques that rely on replacement in data space [34], the SMOTE technique creates synthetic examples of the minority class in feature space using the K-Nearest Neighbours (KNN) algorithm (with the default value for k=5) [33].

In this study, following the approach adopted by [35–38], the SMOTE was performed on the imbalanced dataset discussed above, which resulted in a new dataset with 192 observations. This new dataset, which contains the collected data using the online survey, is used to develop the predictive models in this study. A comparison between the oversampled and original dataset reveals that the imbalance has improved from 34% (non-reusable) and 66% (reusable) to 50% (non-reusable) and 50% (reusable). In this study, R package mlr [39] is used to perform SMOTE-NC (SMOTE for Nominal and Continuous) [33].

3.1.2 Feature selection

Feature selection is a vital stage in supervised machine learning [40]. It includes selecting a subset of features (independent variables) in a dataset for efficient and optimum analysis of the problem in hand [40,41]. In supervised machine learning, there is always a chance that some variables are irrelevant to the response or redundant. In such cases, their presence negatively affects the performance of a predictive model. Proper feature selection results in the development of predictive models that perform optimally on both seen and unseen data. Therefore, feature selection focuses on identifying relevant features and discards irrelevant or redundant independent variables [42]. In this study, feature selection is performed using recursive feature elimination (RFE) methods. For this purpose, the authors computed RFE methods in R (version 4.0.2) using some functions embedded in the Caret package [43,44].

RFE is known as a backward variable selection wrapper technique [45]. Initially, a dedicated machine learning method is used to develop a model with all available independent variables and rank the features based on a measure of importance. Next, the least important feature is eliminated, and a new model is developed based on a smaller number of variables. Then, the remaining independent variables are re-ranked [45]. In this method, the model identifies two parameters: the first parameter is the number of subsets to evaluate, and the second parameter is the number of features in each of the subsets. For each subset, the method continues to eliminate the least-important features until it reaches the determined subset size. Next, it compares the performance of each subset and determines the best subset size with the best accuracy [45]. In this study, the performance of the wrappers is assessed using k-fold cross-validation (k=10), which repeats five times.

Figure 1 shows the graphs representing the performance of these RFE models based on the ranks of the variables. In these graphs, the performances of the wrapper models are plotted based on the rank of the variables. For instance, in the Random Forests graph (panel A of Figure 1), the accuracy of the model using only C28 is around 65%. By adding variables based on their rank (Table 2), the accuracy of the model improves. In the case of the Random Forests graph, after adding D24, the accuracy increases to 71%, and so on (panel A of Figure 1).

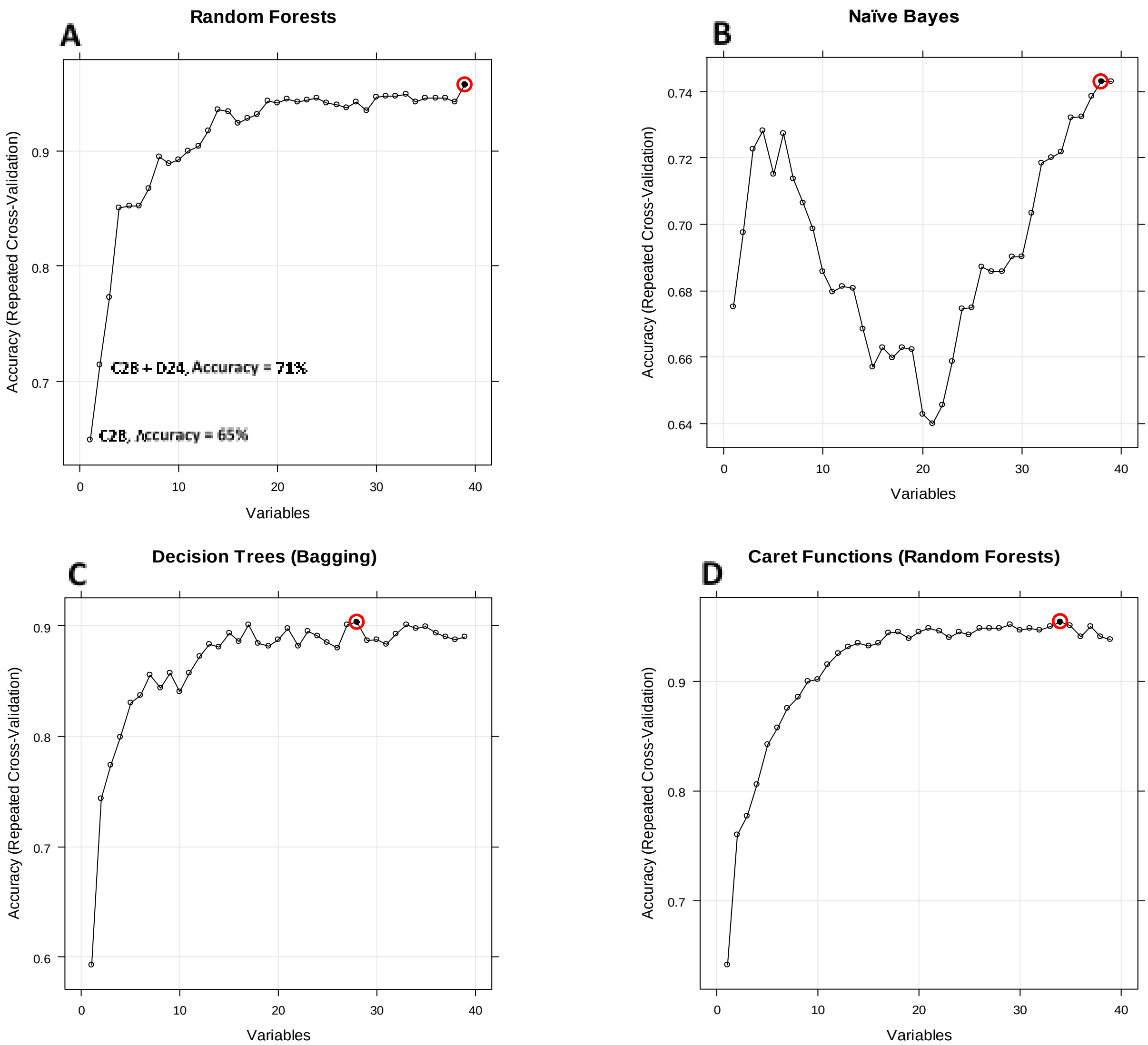

Figure 1 Performance of the RFE based on the ranks of the features. Panel A: Random Forests. Panel B: Naïve Bayes. Panel C: Decision Trees (Bagging). Panel D: Caret Function (Random Forests). The red circle shows the maximum achieved accuracy.

The results of variable selection are presented in Table 2. According to Table 2, the complete list of all selected variables that were used for developing the predictive models are as follows: B3; B5; B6; B7; B8; B9; C1; C2; C3; C5; C6; C9; C10; C12; C15; C16; C17; C18; C19; C20; C25; C27; C28; D22; D23; D24.

Table 2 Status and rank of the variables using the RFE method.

Variable	RFE Random Forests	RFE Naïve Bayes	RFE Decision Trees (Bagging)	RFE Caret Functions (Random Forests)	Final decision
B2	38	Rejected	26	Rejected	
B3	4	8	2	2	Selected
B4	37	38	Rejected	Rejected	
B5	5	33	3	3	Selected
B6	28	27	20	29	Selected
B7	18	13	14	14	Selected
B8	11	7	8	16	Selected
B9	20	29	18	19	Selected
C1	12	37	12	10	Selected
C2	27	17	23	23	Selected
C3	24	22	24	30	Selected
C4	33	34	25	Rejected	
C5	29	26	28	28	Selected
C6	16	14	9	13	Selected
C7	30	11	Rejected	27	
C8	39	32	Rejected	Rejected	
C9	15	25	19	15	Selected
C10	14	15	15	17	Selected
C11	35	24	Rejected	33	
C12	9	36	16	11	Selected
C13	32	28	Rejected	Rejected	
C14	31	16	Rejected	34	
C15	21	20	17	22	Selected
C16	3	3	5	4	Selected
C17	7	5	11	7	Selected
C18	19	18	27	21	Selected
C19	17	10	22	20	Selected
C20	10	9	13	12	Selected
C21	26	21	Rejected	26	
C25	6	2	6	5	Selected
C26	25	12	Rejected	24	
C27	13	6	10	9	Selected
C28	1	1	1	1	Selected
D18	34	35	Rejected	31	
D19	23	23	Rejected	25	
D21	36	31	Rejected	32	
D22	22	30	21	18	Selected
D23	8	19	7	8	Selected
D24	2	4	4	6	Selected

3.1.3 Models development

The process of selecting an appropriate method for developing a predictive model using machine learning techniques is of ample importance because there is not a unique best model available for all problems [46]. This study intends to develop a predictive model to estimate the technical reusability of the structural elements at the end-of-life of a building with the highest possible accuracy. While accuracy is a driving metric in choosing a model, the interpretability of the selected model plays an important role, as well [47]. It is because this study intends to provide an easy-to-understand model that can be used by various stakeholders in the building sector who necessarily might not be able to use complex predictive models [47,48]. The above property is essential for the selected predictive model because it encourages the stakeholders to use the model effectively.

Based on the above discussion, it seems reasonable to choose interpretable methods such as linear discriminant analysis to develop the model [49]. Nevertheless, interpretable models are not always accurate and might have a high bias in their predictions [46]. It is because these models are mostly less flexible, and some of them consider a functional form for the relationship between the predictors and the response (parametric models) [46]. On the other hand, there are very flexible models such as the support vector machine (SVM) or KNN classifier (mostly nonparametric methods) that produce models with very accurate predictions on the training dataset [46,50–52]. However, this flexibility comes at the cost of losing interpretability, high variance, and sometimes overfitting, which results in inaccurate predictions on unseen data [46]. Therefore, in selecting the proper method for developing a predictive model, this trade-off between bias and variance should be considered [51,53,54].

Besides, the limited number of observations in the dataset and unawareness of the nature of the relationship between the predictors (independent variables) and the response brought new dimensions to the challenge of selecting a proper machine learning method. Therefore, it was decided to study a wide range of machine learning methods to develop an optimum predictive model. The above decision is in line with the 'no free-lunch' theorems suggested by [55]. These models are listed in Table 4. Details of these models could be found in Appendix D and [51,53,56].

It should be noted that, as described in Appendix D and mentioned in the footnote of Table 4, K-Nearest Neighbours (KNN), Random Forests (RF), Artificial Neural Networks (ANN), and Support Vector Machines (SVM) use hyperparameters, which require to be set before training\predicting the reusability of the structural elements using these methods. For further details about encoding the hyperparameters, please refer to Section 3.2.2 of [51].

3.1.4 Model selection

The accuracy and interpretability of any machine learning model play an important role in choosing the best predictive model for the study at hand [46]. In this study, a k-fold Cross-Validation (kfCV) method with k=10 is employed to assess the performance of the developed models. In the kfCV method, the original dataset is randomly divided into k folds (k groups of observations) with approximately equal size [46]. Then, the first fold is used as the testing set, and the k-1 remaining folds are used to train a predictive model. Next, the performance of the fit is determined using the held-out set. The process repeats k times with all folds, and each time a different group of observations is considered as the validation set. Simultaneously, the performance results are recorded for all k folds, and eventually, the performance of the predictive model is determined using the mean performances of the k folds. According to James et al. [46], while k can take any number less than n (n is the number of observations in a dataset), values of k equal to 5 or 10 have empirically shown resistance against high bias or variance. The choice of k=10 in this study enables a higher number of training observations at each fold, which improves the performance of the classifiers [46].

In a binary classification problem such as the ones of interest in this study, where the methods classify the test observations to one of the two classes as reusable (1) or non-reusable (0), the outcomes (predictions) fall under one of the following categories. To evaluate whether the selected classifier correctly predicts and classifies the reusable and non-reusable items into correct classes, the true negative (TN) and true positive (TP) criteria, as represented in the confusion matrix (Table 3), were used. The confusion matrix provides additional information about the rates of the predicted responses that were misclassified, which is a reusable item is classified as non-reusable (false negative or FN) or vice-versa (false positive or FP) [46]. It should be noted that the rows and columns of Table 3 represent the actual and predicted values of the responses, respectively.

Table 3 Confusion matrix

		Predicted response values	
		Non-reusable (0)	Reusable (1)
True response values	Non-reusable (0)	True negative (TN)	False positive (FP)
	Reusable (1)	False negative (FN)	True positive (TP)

Based on Table 3, there are two types of misclassification. The first one, which is called Type I error, is when a non-reusable item is by mistake classified as reusable. Eq. 1 represents the Type-I error rate, which is the number of non-reusable items misclassified as reusable by a classifier divided by the total number of non-reusable components in the test dataset.

$$Type - I\ error\ rate = \frac{FP}{TN + FP} \qquad \textit{Eq. 1}$$

The second type of error happens when a reusable element is misclassified as non-reusable by a classifier. The ratio of this type of error, which is known as the Type-II error rate, is calculated as follows.

$$False\ negative\ error\ rate = \frac{FN}{TP + FN} \qquad \textit{Eq. 2}$$

Model classification error rates or Type I and Type II errors are significant indicators of the performance of a predictive model. According to James et al. [46], low error rates on a given dataset guarantees the safe use of a particular supervised learning model. While both error rates should be minimum, Type I error has a pronounced impact on the success of a project with recovered building structural elements. Type I error happens when a predictive model (Table 4) classifies a non-reusable component as reusable. This mistake causes several logistic, financial, and technical costs by providing a false indication about the reusability of an element, which could risk the entire project. However, the consequences of a Type II error are manageable. While reuse aims to improve the circularity of materials in the building sector, a Type II error only troubles the design team to focus on other available recovered structural components. It is because by making a Type II error, a reusable section is discarded, and a designer needs to look for other recovered elements or purchase a new component. While this is not favourable in terms of the circularity of materials, unlike a Type I error, it doesn't jeopardise the entire project. Either way, by integrating proper waste management plans considering sustainability at their core, elements misclassified as non-reusable will still go through recycling or down-cycling processes, which are still far better solutions than landfilling.

According to the above discussion, this study uses the Type-I error rate as one of the metrics to compare the performance of the developed models (Table 4).

The second metric used to evaluate the performance of the developed models in this paper is the overall accuracy. To calculate the overall accuracy of a classifier, the total number of correct classifications is divided by the total number of observations in the test dataset (Eq. 3) [33,36,46].

$$Overall\ accuracy = \frac{TP + TN}{TN + FP + FN + TP} \quad \text{Eq. 3}$$

The third metric used to compare the performance of the developed models is the area under the receiver operating characteristics (ROC) curve (also known as the AUC). The ROC curve is used to observe the performance of a classifier with different threshold values and to decide which threshold value works the best for a classifier (Figure 2). The Y-axis of this graph shows the sensitivity or true positive rate (the number of correctly classified reusable items by a model divided by the total number of reusable components in the test dataset), and the X-axis shows the false positive or Type-I error rate. Then, for different threshold values, these two metrics are calculated, and a graph is drawn by connecting the identified points on the X-Y plane [46]. The area under the ROC curve (also known as the AUC) is a significant and helpful metric because it shows the overall performance of a classifier considering all possible threshold values [46]. Ideally speaking, if an AUC value is close to 1, it is preferred. The baseline value for the AUC is 0.5, and a classifier should always perform higher than this minimum value (for further details, please refer to Section 5.7.2 of [51]).

In a binary setting such as this study, a classifier identifies the probability that a component is non-reusable (0) or reusable (1). In this paper, the authors considered the Bayes classifier threshold value of 0.5. Then, for probabilities greater than 0.5, the classifier predicts the element is reusable (different values are shown on the ROC curve) [46]. However, as a conservative measure, a higher threshold value could be selected to decrease the probability of making a Type-I error [46]. The ROC curve in Figure 2 shows that the selected threshold value of 0.5 works fine because of the low false-positive error rate. Moreover, this figure shows that the AUC is almost equal to 1, which is desirable.

The summary of the Type-I error rate, overall accuracy (or predictive accuracy), and the area under the ROC curve (AUC) used to compare the performance of different models is provided in Table 4.

Table 4 Mean values of the metrics used to assess the performance of the models (10-fold CV method)

Model	Parametric / Non-parametric	Type-I error	Overall accuracy	AUC
K-Nearest Neighbours (KNN)[1]	Non-parametric	0.03	0.92	0.98
Linear Discriminant Analysis (LDA)	Parametric	0.18	0.81	0.90
Quadratic Discriminant Analysis (LDA)	Parametric	0.09	0.91	0.96
Naïve Bayes (NB)	Parametric	0.28	0.72	0.82
Decision Trees (DT)	Non-parametric	0.29	0.71	0.73
Random Forests (RF)[2]	Non-parametric	0.01	0.96	1.00
Adaptive Boosting (AB)	Non-parametric	0.08	0.87	0.95
BART Machine (BM)	Non-parametric	0.11	0.85	0.94

Model	Parametric / Non-parametric	Type-I error	Overall accuracy	AUC
Artificial Neural Networks (single-layer perceptron) (ANN)[3]	Parametric	0.13	0.88	0.93
Gaussian Processes (GP)	Non-parametric	0.12	0.84	0.92
Propositional Rule Learner (PRL)	Non-parametric	0.19	0.80	0.83
Support Vector Machine (SVM)[4]	Non-parametric	0.07	0.93	0.98
Hyperparameters (calculated using 70% of the dataset that was selected randomly): [1] k = 6 [2] ntree = 500, mtry = 5, nodesize = 1 [3] Size = 9, Decay = 0.09 [4] Cost = 1.601470833, Sigma = 0.047078172				

In this study, following [57], a maximum threshold of 10% is considered acceptable for the Type-I error rate. Moreover, the minimum threshold values of 85% and 90% are considered acceptable for the models' overall accuracy and AUC, respectively. Based on Table 4, the random forests model (RF) has the lowest Type-I error rate (0.01), the highest overall accuracy (0.96), and the highest AUC (1.00) among all other models. So, the RF model is selected as the best-practice model to predict the technical reusability of the building structural elements. The details of the selected RF model and other methods used to develop the predictive models (Table 4) are provided in Appendix D of this paper.

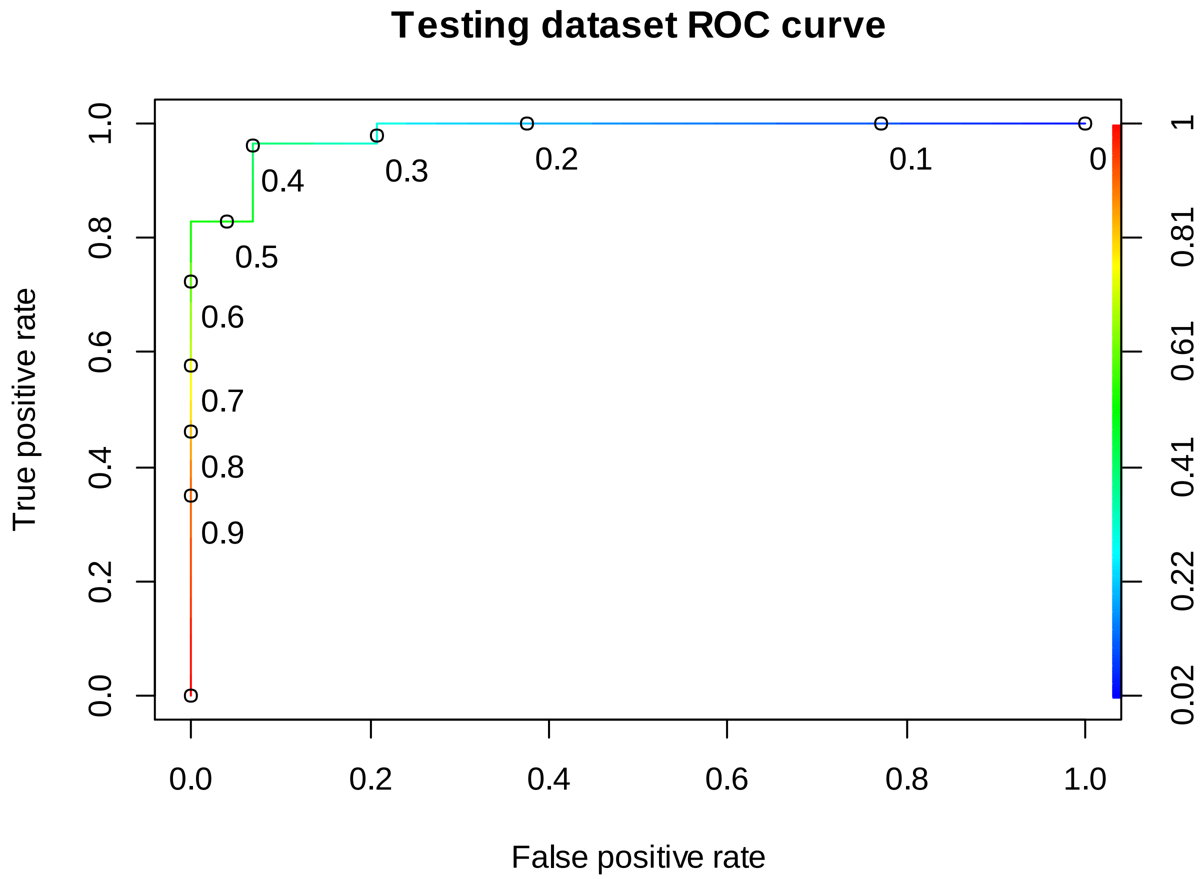

Figure 2 ROC curve of the random forest model for the testing set (trained by 70% of the dataset that was selected randomly).

3.2 Mining the selected RF model

While the selected RF model in Section 3.1 has high overall accuracy, high AUC, and low Type-I error rate, it lacks transparency. It is because RF models are categorised under black-box methods, and they cannot be easily interpreted [58]. As discussed in Section 3.1.3, the interpretability of the results of the selected predictive models is essential to encourage the stakeholders to employ the outcome of such models for assessing the reusability of building structural elements at the end-of-life of a building. Therefore, when such easy-to-understand models are not available, it is necessary to make the results of the selected models transparent.

In this paper, two techniques are used to improve the transparency of the selected RF model. First, the sensitivity analysis and visualisation techniques suggested by [50] are employed to identify the importance of the variables and open the RF model (Section 3.2.1). Next, using the rule extraction method suggested by [59] and based on the results of the previous technique, a set of decision rules was produced to explain the ensemble of trees developed in the selected RF model (Section 3.2.2). While both techniques fulfil the aim of this study, the latter provides a simple and understandable set of rules for the stakeholders to estimate the reusability of building structural elements at the end-of-life of a building.

3.2.1 Improving the transparency of the selected RF model

According to [50], to perform the sensitivity analysis (SA), a sensitivity method needs to be identified first. A sensitivity method (SM) performs by varying a given reusability factor from its minimum to maximum possible values while conditioning the remaining independent variables and observations. For the nominal features (age of the building/component (B3), and the number of existing connections (B5)), the SM alters the values of the variables based on the variable levels (B3 has three levels, and B5 has five levels, see Appendix A). For the categorical features, following Cortez and Embrechts [50], the SM varies the value of the predictors from one to five in seven intervals (x-axis of Figure 4). As recommended by Cortez and Embrechts [50], in this research, data-based SA (DSA) was used as the SM. The DSA method randomly selects several samples from the dataset, alters the values of an independent variable for all data points and records the responses while not changing other features. This process is performed for all reusability factors in the dataset. The sensitivity responses identified using the DSA method can be used to determine the feature importance using a sensitivity measure. This research uses the Average Absolute Deviation (AAD) from the Median as the sensitivity measure, as advised by [50]. According to Cortez and Embrechts [50],

$$AAD = \frac{\sum_{j=1}^{L} \left| \hat{y}_{a_j} - \tilde{y}_a \right|}{L} \qquad \textit{Eq. 4}$$

where L =7 (seven intervals between one to five), $\hat{y}_{a_j}$ is the sensitivity response for $x_{a_j} \in \{1, 1.67, 2.33, 3, 3.67, 4.33, 5\}$ (jth level of input $\boldsymbol{x}_a$: $a \in \{1, \dots, p\}$ for p features), and $\tilde{y}_a$ is the median of the responses. The higher the value of the AAD for an independent variable, the more important is the feature. This measure is then used to develop the relative importance of the input variables. It is noteworthy that following Cortez and Embrechts [50], this research uses the complete dataset to perform the SA.

Figure 3 shows the results of the feature importance for the RF model. In this figure, the x-axis shows the relative importance of the variables, and the y-axis shows the features. Based on Figure 3, only some of the variables are relevant, and others have negligible importance. In this study, features with relative importance greater than 2% are considered for developing the rules in Section 3.2.2, and the remaining are ignored. It results in a total number of fourteen independent variables including, B3, B5, B7, B8, C6, C12, C15, C16, C20, C25, C27, C28, D23, and D24.

Based on Figure 3, the most significant factor affecting the reusability of the building structural elements is the mechanical properties of the component (D23). This observation is in line with the attempts of some researchers to estimate the mechanical properties of the load-bearing components as an indicator of reusability [19,22,60].

The next important variable is the design challenges observed by the stakeholders (D24). In the literature, these challenges are identified as integrating reused and new components into the new building, the need for flexibility in the design [61], and overdesigned structures due to the available supply [62].

The third variable affecting the reusability of building structural elements is the presence of hazardous, banned, or contaminating coatings (C28). This variable has been reported in various articles in the literature as a barrier to the reuse of building structural components [63–65]. If such coatings are present on the structural elements, the chance for recovery and reuse decreases drastically. As a solution, and to overcome this barrier in new buildings, [66] proposed a reusable fireproofing system to promote the reusability of the building structure.

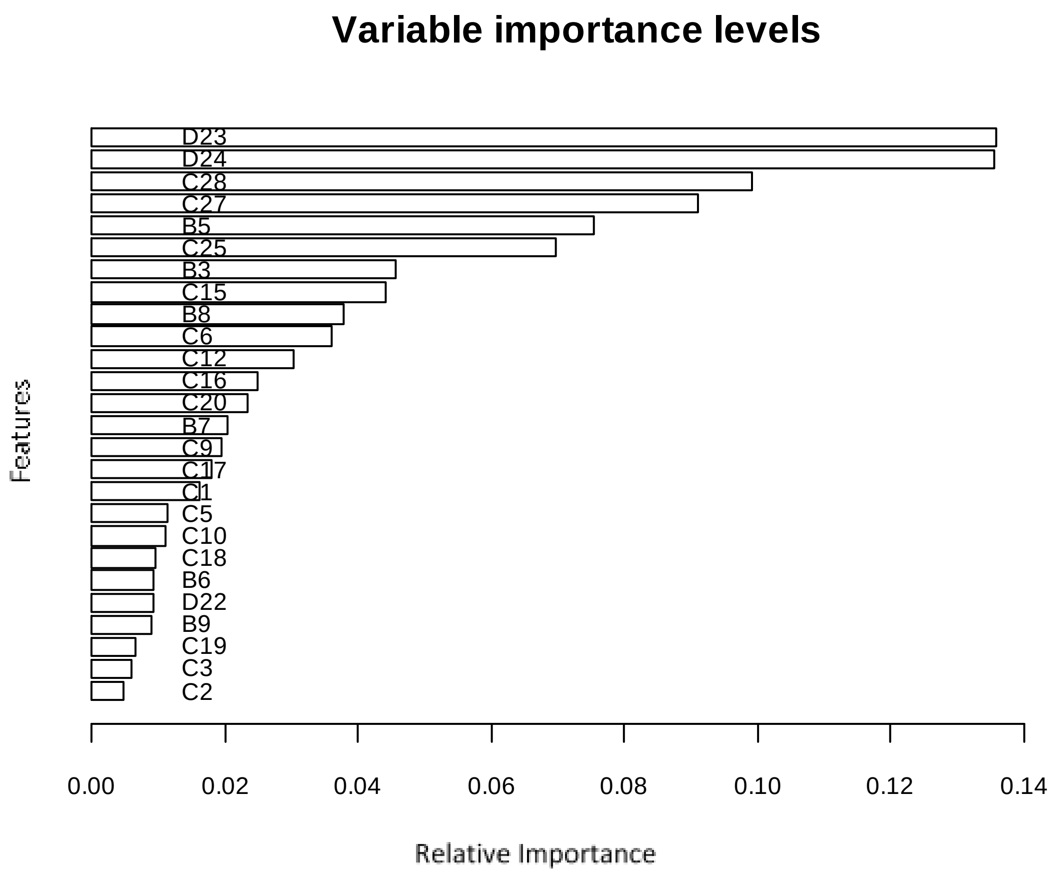

Figure 3 Bar plot with DSA and AAD relative feature importance based on the selected RF model.

According to Figure 3, the fourth most important barrier is a potential problem with collateral warranties. Surprisingly, this barrier was not observed by other researchers. However, according to [12], issues related to the performance of the recovered structural element should be resolved early to avoid a problem with collateral warranties.

In the next stage, and to present how different values of a feature affect the technical reusability of building structural elements on average, a set of Variable Effect Characteristic (VEC) curves are plotted for the top-four variables. A VEC curve plots the average impact of different values of a reusability factor (x-axis) on the probability that a structural element is reusable (y-axis).

Figure 4 shows the sensitivity analysis of the top-four factors (D23, D24, C28, C27) based on Figure 3. According to Figure 4, the reusability probabilities of a building's structural elements improve when the values of these variables increase from one (the highest negative impact) to five (the most positive effect). For D23, Figure 4 reveals that if the design could be modified to match the remaining strength of a recovered structural element, its reusability probability would increase. In the case of D24, Figure 4 shows that if the challenges of designing with recovered load-bearing building components go beyond dimensional and strength requirements, the reusability declines further. Regarding C28, Figure 4 portrays that in the presence of hazardous coatings on the recovered structural elements, there is a lower chance of reuse. Eventually, Figure 4 shows that the problem with collateral warranties (C27) could negatively affect the reuse rates due to increased liabilities. Reusing recovered structural components in the design of new buildings might increase contractual requirements to obtain collateral warranties, which could eventually discourage the reuse of these elements.

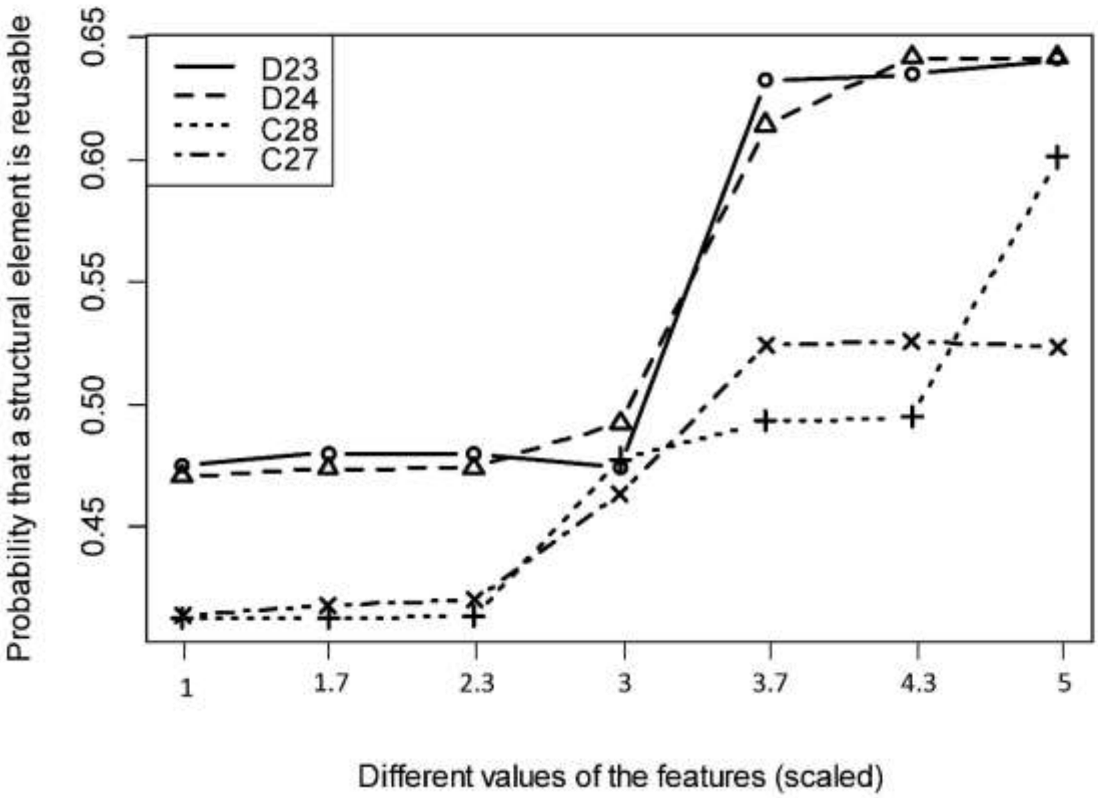

Figure 4 The impact of different values of the features on the reusability probabilities of the elements (sensitivity analysis) for D23, D24, C28, and C27 (the top-four variables in the RF model)

Figures 3 and 4 might imply that these features could be directly used to evaluate the reusability of the load-bearing building components. However, it is essential to avoid such generalisation because of the interdependencies of the features. This effect can be shown by drawing the VEC curves while showing the range of the sensitivity at each point. For this purpose, the most suitable feature (D23, the mechanical properties of the component) and the least significant variable (B7, the future deployment of the element, identified based on a minimum 2% threshold for the relative importance) are plotted in Figure 5. According to this figure, the average VEC curve for B7 is nearly flat (the diamonds on the curve). Moreover, while there is a leap from three to four for D23, the rest of the curve remains almost flat. However, the range of the sensitivity is high for both variables, as shown by the box plots in Figure 5. The above observation acknowledges that the technical reusability of the structural elements of a building depends on the interactions between the predictors, as well [50].

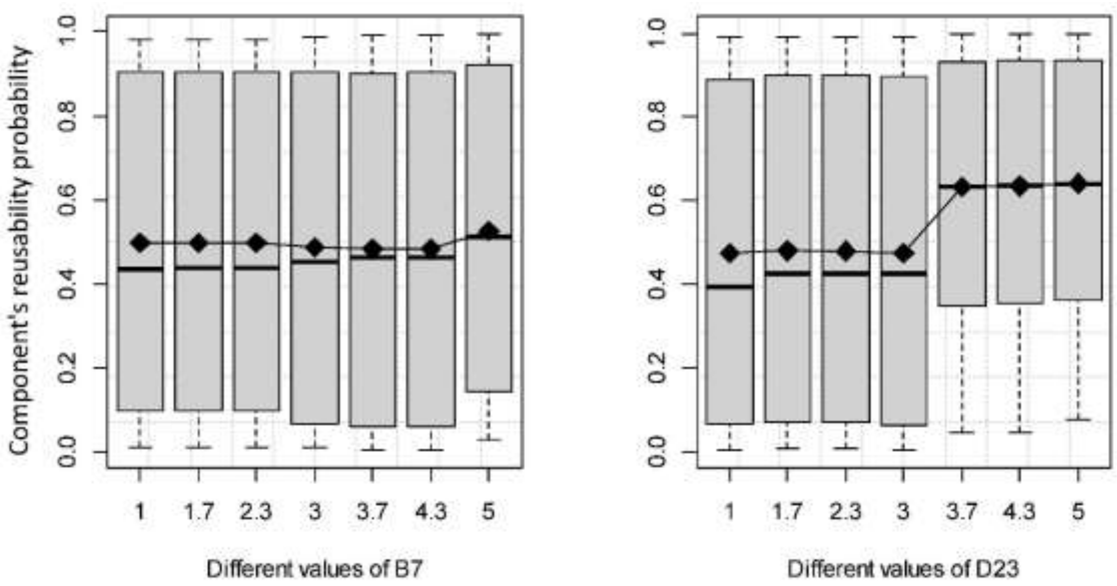

Figure 5 The VEC curves with box plots (to show the range of sensitivity at each point) to compare the impact of different values of B7 (left) and D23 (right) on the reusability probabilities of the elements.

3.2.2 Developing an easy-to-understand learner

While the SA and visualisation techniques presented above help in opening the selected RF model, it still lacks the clarity level required by the stakeholders to make sound judgments about the reusability of the structural elements of a building at its end-of-life phase. Hence, as mentioned earlier, the results of the SA are used to develop a set of easy-to-understand rules that can be effectively used by the practitioners.

In this section, a set of rules (presented in Table 5) are developed based on the method suggested by [59]. The steps followed for developing these rules are available in Figure 6.

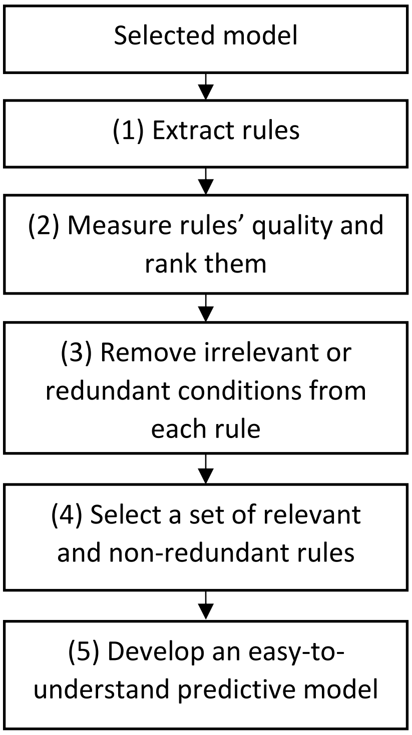

Figure 6 The process of developing the rules set from the selected RF model [59].

The first column of Table 5 contains the sequence of the rules that need to be followed strictly. It means that checking should start with rule number one, and if its conditions are not satisfied, the next rule should be checked. This sequential process continues until a rule's conditions are satisfied. At this point, checking stops and the rule number and prediction result should be recorded against the observation.

The second column shows the length of a condition, which is the count of variable-value pairs in a rule [59]. For example, rule number 7 has three circumstances to be satisfied; hence, the length of its condition is equal to 3.

The third column is the frequency of a rule, which is defined as the proportion of the observations in the training dataset that satisfy the rule condition(s). For instance, the total number of observations in the training set is equal to 134, out of which twenty-one fall under the first rule. Therefore, the frequency of the first rule becomes 0.157 (the sum of frequency values is equal to one).

The fourth column is the error rate of each set of conditions, which is equal to the number of misclassifications made by a rule divided by the number of observations satisfying the rule condition(s) in the training dataset. According to Table 5, out of 15 rules, only one (rule number 9) makes misclassifications on the training set. Rule number 9 covers 16 observations in the training set, out of which only one is wrongly classified as non-reusable, resulting in a misclassification error rate equal to 6.25%.

Column five of Table 5 shows the conditions of the rules. And the last column contains the predicted responses by the rules, which are equal to zero (0) for non-reusable elements and to one (1) for reusable components. As an example, rule number one states that if C12 (damage caused by living organisms), C20 (lack of earlier certificates), and D23 (the process of matching the design of the new building with the strength of the recovered element) are less than or equal to 3, then the component is not reusable.

Table 5 The learner (rules set) developed based on the selected RF model

Rule No.	Length	Frequency	Error	Condition	Prediction
1	3	0.157	0	C12<=3 & C20<=3 & D23<=3	0
2	2	0.134	0	C16>4 & D24>2	1
3	2	0.112	0	B8<=3 & C12>4	0
4	3	0.075	0	C20<=2 & C28>3 & D24>2	1
5	3	0.067	0	B3 = c ('4') & C27>3 & C28>2	1
6	1	0.045	0	D24>3	1
7	3	0.030	0	B3 = c ('1','2','3','5') & B5 = c ('3','4') & C12>4	0
8	4	0.022	0	B5 = c ('1','3','4','5') & C6>3 & C15<=4 & C28<=3	1
9	2	0.119	0.0625	C28<=4 & D23>2	0
10	4	0.119	0	B5 = c ('1','2','5') & C6>3 & C20>3 & C28>2	1
11	5	0.060	0	B3 = c ('1','2') & B5 = c ('1','2','3','5') & C20>1 & C28<=3 & D23<=3	0
12	3	0.015	0	B7>4 & C27>2 & D23>1	1
13	3	0.022	0	B5 = c ('1','5') & C28<=4 & D24<=3	0
14	3	0.015	0	B5 = c ('1','2','3','5') & B8>3 & C28>3	1
15	1	0.007	0	Else	0

Table 5 is developed based on a randomly selected training set comprising 70% of the entire dataset. While the above set of rules provides an easy-to-understand and implement collections of conditions, it is essential to make sure that the resulting predictions on the unseen data satisfy the minimum requirements set in Section 3.1.4. Therefore, the authors used the remaining 30% of the dataset (unseen observations by the learner (classifier) in Table 5) to evaluate the performance of the learner presented in Table 5. For this purpose, we followed the rules sequentially (from 1 to 15), identified the applicable set of conditions to each observation, and recorded the resulting prediction for each element. Next, we compared the prediction results with the correct responses and recorded the errors to evaluate the performance of the learner.

As a result, the classifier misclassified two (2) non-reusable elements as reusable (Type-I errors) and eight (8) reusable components as non-reusable (Type-II errors), resulting in the Type-I error rate equal to 6.9%, and the overall accuracy equal to 85.3%. Therefore, this learner satisfies the minimum performance requirements defined in Section 3.1.4. Moreover, the learner in Table 5 is transparent, easy-to-understand, and can be easily implemented in practice. It should be noted that the Type-II error rate is the number of the reusable items misclassified as non-reusable by a model divided by the total number of reusable components in the test dataset.

According to Table 5, C25 is not available in any of the rules. Hence, a practitioner may not need to collect data on this variable. Appendix C summarises the survey that the practitioners need to perform before being able to use the learner in Table 5. In Appendix C, the variable codes (Code) are kept equal to the original survey (Appendix A) to maintain uniformity.

4. Conclusion

This paper has contributed to promoting the reuse of building structural elements in two ways. First, using advanced supervised machine learning techniques, this paper identifies and ranks the main reusability factors based on the experience of the stakeholders with the recovered building structural elements in the building sector. Second, it develops an easy-to-understand learner that can be used by practitioners to have an initial assessment of the technical reusability of the load-bearing components. The developed learner can be easily used by various stakeholders and has the potential to promote the reuse rate of the structural elements of the existing buildings, which were not designed for deconstruction. This learner can also encourage more deconstruction projects since the developers would have a better judgment about the technical reusability of the structure of an existing building at its end-of-life.

The most significant factors affecting the reuse of building structural components are design-related such as matching the design of the new building with the strength of the recovered element. Moreover, the presence of hazardous, banned, or contaminating coatings play a vital role in the success of projects with reuse. The fourth main barrier is a potential problem with collateral warranties, which has not been observed in other studies. Therefore, research should be conducted to explore this factor and devise solutions to overcome this barrier.

To the knowledge of the authors, no other research has ever used advanced supervised machine learning methods to estimate the reusability of the structural components based on the experience of the stakeholders. So, it contributes to the field of reuse in the building sector by introducing the feasibility of using advanced AI tools to promote the circularity of components and materials. Moreover, unlike the other publications that focus on only a specific material (timber, concrete, or steel), since this is a comparative study, the results of this study can be used to assess the technical reusability of the building structural elements regardless of the material of construction. However, the use of the learner developed in Table 5 should be restricted to timber, concrete, and steel structures since the respondents completed the questionnaires based on these three materials.

In contrast to the mentioned contributions, this study has some limitations. The most important limitation is the low rate of reuse in the building sector that restricts access to more experts with such experience. Moreover, while the authors tried to decrease error by considering a wide range of machine learning methods to develop the predictive models, there still might be some errors due to a missing key factor that has not been integrated into the questionnaire. Likewise, the questionnaire is developed based on a systematic literature review focused on the superstructure of a building. Therefore, the results of this study cannot be generalised to the substructures. While this paper is limited to the building sector, the authors strongly believe that similar studies can be performed in other sub-divisions of the construction industry to develop tools that can assess the reusability of the structures.

This paper was focused on developing a model that can efficiently predict the reuse potential of structural elements at the end-of-life of a building and did not assess the causal relationship among the variables. Hence, as future research, methods such as Agent-Based Modelling (e.g., [67–69]) could be used to analyse the relationship among the reusability factors. The results of such a study could be used to develop a set of instructions to promote the circularity of load-bearing building components.

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Appendix A. Example of the questionnaire survey

Section A: Respondent's details:

Please answer the following questions by choosing the applicable boxes or filling in the blank spaces.

1. Where is the geographic location of your organization (Country name)?

   ……………………………………………………………………

2. What is the type of organization you work in?

☐Client ☐Consultancy (architectural, structural, etc.)
☐Contractor ☐Deconstruction/Demolition ☐Supplier/Stockist
☐University/Academic institution ☐other (please specify):

………

3. How many years of experience do you have in the construction sector?

☐1-5 ☐6-10 ☐11-15 ☐16-20 ☐21-25 ☐26-30
☐31-35 ☐36-40 ☐over 40 ☐other (please specify):

…………………………………………………………………………………………………

4. What is your position/job title (Architect, CEO, etc.)?

   ……………………………………………………………………………………………

5. Do you or your company have any experience with the reuse of the building structural elements? ☐Yes☐No

Section B: Details about the reused structural element

Based on your experience, **please select only one structural element** that you reused in the past and complete the rest of the questionnaire based on that.

1. Which structural element that you reused before are you basing your answers?

☐Beam ☐Brace ☐Column ☐Slab ☐Truss
☐other (please specify):

………

2. What is the material of construction (MoC) of the structural element that you reused?

☐Concrete ☐Steel ☐Timber ☐Cast Iron ☐Wrought Iron
☐Composite ☐other (please specify):

………

3. What is the approximate age of the building from which the element is recovered?

☐0 to 40 ☐41 to 60 ☐61 to 80 ☐81 to 100 ☐100 years and older
☐other (please specify):

………

4. What is the recovery technique used to recover the particular element?

☐Demolition ☐Component-specific recovery ☐ Deconstruction
☐other (please specify):

………

5. What is the number of existing connections fixed to the element when purchased/acquired (plates or angles fixed to a beam, etc.)?

☐1 to 2 ☐3 to 4 ☐5 to 7 ☐8 to 10 ☐11 and above ☐other (please specify):

……

6. What are the types of the end connections (joints) of the element when purchased/acquired?

☐ Reversible (bolts, screws, etc.) ☐ Permanent (welding, cast in-situ concrete, etc.) ☐ Mixed ☐other (please specify):

……

Instructions for questions 7 to 11:

You may ignore any question if not applicable or the details are/were not available.

Questions 7 to 11 compare the current use (or use after deconstruction) of the structural element with its previous use before it was removed/deconstructed from a building.

7. The structural element is serving the same purpose (i.e. as a beam, slab, column, etc.) in its new installation as in its previous installation.

☐ Strongly agree ☐ Agree ☐ Neither agree nor disagree ☐ Disagree ☐ Strongly disagree

8. The cross-section/thickness dimensions of the structural element in its new installation are equal or nearly equal to the cross-section/thickness dimensions of the element in its previous installation.

☐ Strongly agree ☐ Agree ☐ Neither agree nor disagree ☐ Disagree ☐ Strongly disagree

9. The length dimensions of the structural element in its new installation are equal or nearly equal to the length dimensions of the element in its previous installation.

☐ Strongly agree ☐ Agree ☐ Neither agree nor disagree ☐ Disagree ☐ Strongly disagree

10. The amount of load supported by the structural element in its new installation compared to the amount of load supported by the element in its previous installation.

☐ Much lower ☐ Lower ☐ Equal ☐ Higher ☐ Much Higher

11. The life expectancy of the structural element in its new installation compared to the life expectancy of the element in its previous installation.

☐ Much lower ☐ Lower ☐ Equal ☐ Higher ☐ Much Higher

<u>Section C: Factors affecting the reusability of the structural element</u>

You may ignore any question if not applicable or the details are/were not available.

Please rate the followings on the scale of 1 to 5 where:

5 = Very low ***4 = Low*** ***3 = Moderate*** ***2 = High*** ***1 = Very High***

	What was the negative impact of the following factors on the reusability of the structural element?	Scale				
		1	2	3	4	5
C1	Damage during deconstruction/demolition					
C2	Damage due to fatigue					
C3	Damage due to fire					
C4	Damage during transportation					
C5	Damage during storage					
C6	Damage due to the type of joints					
C7	Damage due to corrosion					
C8	Damage due to frost					
C9	Damage due to water penetration/presence					
C10	Damage during refurbishment (nail removal, etc.)					
C11	Damage due to exposure to wind, acidic rain, etc.					
C12	Damage caused by living organisms (termite, bacterial attack, etc.)					
C13	Damage due to earthquake					
C14	Damage due to impact					
C15	Damage due to post-production modifications (e.g. holes, etc.)					
C16	Lack of certificates of quality for the element when acquired					
C17	Lack of standards to certify the element					
C18	Lack of the original drawings					
C19	Lack of the original design calculations					
C20	Lack of earlier certificates (inspection, material, etc.)					
C21	Lack of traceability of the element					
C25	The potential risk associated with the structural integrity					
C26	The potential risk of damage to the machinery (nails in timber, etc.)					
C27	A potential problem with collateral warranties					
C28	Presence of hazardous, banned or contaminating coatings					

Section D: Other factors affecting the reusability of the structural element

You may ignore any question if not applicable or the details are/were not available.

Please rate the followings on the scale of 1 to 5 where:

1 = Very negatively ***2 = Negatively*** ***3 = No real effect*** ***4 = Positively*** ***5 = Very Positively***

	How did the following factors affect the reusability of the structural element?	Scale				
		1	2	3	4	5
D18	Presence of fire protection on the element					
D19	Changes in the design codes (BS codes to Eurocodes, etc.)					
D21	CE marking					
D22	Matching the original design with the dimensions of the reused element					
D23	Matching the original design with the strength of the reused element					
D24	Other design challenges with the reused element					

<u>Section E: The overall reusability of the structural element</u>

Definitions:

<u>Technical reusability:</u>

- The extent to which the reused structural element in its new life could perform similarly to its earlier life.

Please refer to the **definitions** section (above) for further clarity. Please rate the followings on the scale of 1 to 5 where:

1 = Very low ***2 = Low*** ***3 = Moderate*** ***4 = High*** ***5 = Very High***

	Please rate the relative level of reusability of the structural element by providing the actual or approximate answers.	Scale				
		1	2	3	4	5
E1	The technical reusability					

Please feel free to write any additional comments in the space provided below.

………
………
………
……………………………………………………………………………………

If you are willing to know the results of this study, please provide your contact details in the space provided below. Kindly note that this is totally optional.

………
………
……………………………………………………

If you have an experience with another reused structural element, please feel free to fill this survey again based on that other structural element.

Thank you for taking the time to complete this questionnaire.

Appendix B. Preliminary statistical analysis of the survey (the technical aspect)

Table B.1 Preliminary statistical analysis of the survey (the technical aspect)

Section / Question	Variables	Cronbach's alpha if item deleted	Kruskal-Wallis H test p-value
	Section B		
B	**Details about the reused structural element**		
	Overall Cronbach's alpha for Section B, questions B7 to B9 = 0.780		
B7	The structural element is serving the same purpose (i.e. as a beam, slab, column, etc.) in its new installation as in its previous installation.	0.648	0.480
B8	The cross-section/thickness dimensions of the structural element in its new installation are equal or nearly equal to the cross-section/thickness dimensions of the element in its previous installation.	0.641	0.388
B9	The length dimensions of the structural element in its new installation are equal or nearly equal to the length dimensions of the element in its previous installation.	0.814	0.085
	Overall Cronbach's alpha for Section B, questions B10 to B11 = 0.263		
B10	The amount of load supported by the structural element in its new installation compared to the amount of load supported by the element in its previous installation.		0.720
B11	The life expectancy of the structural element in its new installation compared to the life expectancy of the element in its previous installation.		0.386
	Section C		
C	**Factors affecting the reusability of the structural element**		
	Overall Cronbach's alpha for Section C = 0.891		
C1	Damage during deconstruction/demolition	0.887	0.364
C2	Damage due to fatigue	0.888	0.276
C3	Damage due to fire	0.889	0.406
C4	Damage during transportation	0.888	0.635
C5	Damage during storage	0.889	0.116
C6	Damage due to the type of joints	0.885	0.185
C7	Damage due to corrosion	0.884	0.307
C8	Damage due to frost	0.888	0.213
C9	Damage due to water penetration/presence	0.885	0.405
C10	Damage during refurbishment (nail removal, etc.)	0.887	0.342
C11	Damage due to exposure to wind, acidic rain, etc.	0.890	0.499

Section / Question	Variables	Cronbach's alpha if item deleted	Kruskal-Wallis H test p-value
C12	Damage caused by living organisms (termite, bacterial attack, etc.)	0.892	0.919
C13	Damage due to earthquake	0.891	0.559
C14	Damage due to impact	0.888	0.160
C15	Damage due to post-production modifications (e.g. holes, etc.)	0.888	0.322
C16	Lack of certificates of quality for the element when acquired	0.884	0.505
C17	Lack of standards to certify the element	0.886	0.652
C18	Lack of the original drawings	0.881	0.130
C19	Lack of the original design calculations	0.885	0.351
C20	Lack of earlier certificates (inspection, material, etc.)	0.883	0.273
C21	Lack of traceability of the element	0.882	0.324
C25	The potential risk associated with the structural integrity	0.886	0.090
C26	The potential risk of damage to the machinery (nails in timber, etc.)	0.885	0.572
C27	A potential problem with collateral warranties	0.888	0.167
C28	Presence of hazardous, banned or contaminating coatings	0.885	0.875
	Section D		
D	**Other factors affecting the reusability of the structural element**		
	Overall Cronbach's alpha for Section D = 0.847		
D18	Presence of fire protection on the element	0.820	0.325
D19	Changes in the design codes (BS codes to Eurocodes, etc.)	0.843	0.552
D21	CE marking	0.814	0.884
D22	Matching the original design with the dimensions of the reused element	0.822	0.282
D23	Matching the original design with the strength of the reused element	0.795	0.761
D24	Other design challenges with the reused element	0.836	0.341

Appendix C. The required survey for assessing the technical reusability of a structural element using the learner in Table 5

Table C.1 The required survey for assessing the technical reusability of a structural element using the learner in Table 5

<table>
<tr><th>Seq.</th><th>Code</th><th colspan="5">Question / Options</th><th>Selected answer</th></tr>
<tr><td rowspan="3">1</td><td rowspan="3">B3</td><td colspan="5">What is the approximate age of the building from which the element is recovered?</td><td rowspan="3"></td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>0 to 40</td><td>41 to 60</td><td>61 to 80</td><td>81 to 100</td><td>Above 100</td></tr>
<tr><td rowspan="3">2</td><td rowspan="3">B5</td><td colspan="5">What is the number of existing connections fixed to the element when purchased/acquired (plates or angles fixed to a beam, etc.)?</td><td rowspan="3"></td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>1 to 2</td><td>3 to 4</td><td>5 to 7</td><td>8 to 10</td><td>Above 10</td></tr>
<tr><td rowspan="3">3</td><td rowspan="3">B7</td><td colspan="5">The structural element is intended to be used for the same purpose (i.e. as a beam, slab, column, etc.) in its new installation.</td><td rowspan="3"></td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Strongly disagree</td><td>Disagree</td><td>Neither agree nor disagree</td><td>Agree</td><td>Strongly agree</td></tr>
<tr><td rowspan="3">4</td><td rowspan="3">B8</td><td colspan="5">The cross-section/thickness dimensions of the structural element in its new installation are expected to be equal or nearly equal to the cross-section/thickness dimensions of the element in its previous installation.</td><td rowspan="3"></td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Strongly disagree</td><td>Disagree</td><td>Neither agree nor disagree</td><td>Agree</td><td>Strongly agree</td></tr>
<tr><td rowspan="3">5</td><td rowspan="3">C6</td><td colspan="5">Estimated level of damage to the element due to the type of joints.</td><td rowspan="3"></td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Very high</td><td>High</td><td>Moderate</td><td>Low</td><td>Very low</td></tr>
<tr><td rowspan="3">6</td><td rowspan="3">C12</td><td colspan="5">Estimated level of damage to the element caused by living organisms (termite, bacterial attack, etc.)</td><td rowspan="3"></td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Very high</td><td>High</td><td>Moderate</td><td>Low</td><td>Very low</td></tr>
<tr><td rowspan="3">7</td><td rowspan="3">C15</td><td colspan="5">Estimated level of damage to the element due to post-production modifications (e.g. holes for duct work, etc.)</td><td rowspan="3"></td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Very high</td><td>High</td><td>Moderate</td><td>Low</td><td>Very low</td></tr>
<tr><td rowspan="3">8</td><td rowspan="3">C16</td><td colspan="5">Negative impact of the lack of certificates of quality for the structural element.</td><td rowspan="3"></td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Very high</td><td>High</td><td>Moderate</td><td>Low</td><td>Very low</td></tr>
<tr><td rowspan="3">9</td><td rowspan="3">C20</td><td colspan="5">Negative impact of the lack of earlier certificates (inspection, material, etc.)</td><td rowspan="3"></td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Very high</td><td>High</td><td>Moderate</td><td>Low</td><td>Very low</td></tr>
<tr><td rowspan="3">10</td><td rowspan="3">C27</td><td colspan="5">Negative impact of a potential problem with collateral warranties.</td><td rowspan="3"></td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Very high</td><td>High</td><td>Moderate</td><td>Low</td><td>Very low</td></tr>
</table>

<table>
<tr><th>Seq.</th><th>Code</th><th colspan="5">Question / Options</th><th>Selected answer</th></tr>
<tr><td rowspan="3">11</td><td rowspan="3">C28</td><td colspan="5">Negative impact of the presence of hazardous, banned or contaminating coatings.</td><td rowspan="3"></td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Very high</td><td>High</td><td>Moderate</td><td>Low</td><td>Very low</td></tr>
<tr><td rowspan="3">12</td><td rowspan="3">D23</td><td colspan="5">How do you expect that matching the design of the new building with the strength of the recovered element affects its reusability?</td><td rowspan="3"></td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Very negatively</td><td>Negatively</td><td>No real effect</td><td>Positively</td><td>Very positively</td></tr>
<tr><td rowspan="3">13</td><td rowspan="3">D24</td><td colspan="5">How do you expect that challenges in designing with the reused element affects its reusability?</td><td rowspan="3"></td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Very negatively</td><td>Negatively</td><td>No real effect</td><td>Positively</td><td>Very positively</td></tr>
</table>

Appendix D. Details of the supervised machine learning methods used in this research

Due to the binary nature of the responses (either reusable or non-reusable), the process of predicting the reusability of the structural elements of a building is a classification problem. In a classification setting, the classifier would predict if an element is reusable (1) or not (0). An optimum classifier is the one that can classify unseen observations with the minimum incorrect classifications [46]. In this study, thirteen different methods are used to develop the BSE-RPMs (Table 4). These models are fitted to the training sets of the dataset and then used to predict the technical reusability of the elements in the testing sets to evaluate the performance of the fits. In the next subsections, each of these methods are discussed briefly.

It should be noted that this research adopts a probabilistic approach, meaning that a predictive model selects the label with maximal probability given the features. This rule, which is known as the conditional probability, is defined as follows.

$$pr(A|B) = \frac{pr(A \cap B)}{pr(B)} \; if \; pr(B) > 0 \qquad \textit{Eq. (D.1)}$$

In Eq. (D.1), $pr(A|B)$ is "the conditional probability of event A, given that event B is true", $pr(A \cap B)$ is the joint probability of both events, and $pr(B)$ is the probability of event B [51].

It should be noted that this research considers the Bayes classifier threshold value of 0.5 for the probability of an element to be reusable or not. It means that if the conditional probability of an element being reusable given the features is being calculated (i.e., $pr(reusability = 1|\boldsymbol{X} = \boldsymbol{x})$), the probabilities above 0.5 conclude that the item is reusable. Otherwise, it would be classified as non-reusable.

D.1 K-Nearest Neighbours (KNN)

The K-nearest neighbours (KNN) classifier is a method that attempts to estimate the Bayes classifier [46]. The Bayes classifier is a very simple classifier that assigns an observation to the most probable response class based on the values of its feature [46]. This classifier works based on the conditional distribution of the response given the features and results in the highest theoretical accuracy [46]. In this study, the conditional probability of the reusability (response) equal to one (reusable) can be presented as below:

$$pr(reusability = 1 \,\big|\, \boldsymbol{X} = \boldsymbol{x}) \qquad \textit{Eq. (D.2)}$$

In the conditional probability Eq. (D.2), $\boldsymbol{x} = c\,(x_1, x_2, \ldots, x_p)$ represents all applicable features in the dataset for every datapoint. If the value of conditional probability given in Eq. (D.2) is higher than 0.5, then the Bayes classifier classifies the observation as reusable, otherwise, non-reusable ('pr' means probability) [46]. The left-hand panel of Figure D.1 shows a simplified classification problem with two features (x_1 & x_2) using the Bayes theorem [70,71]. The black dashed line is the Bayes decision boundary. The black circles correspond to reusable training structural elements, and the plus signs represent non-reusable training structural components. For each of the values of x_1 and x_2, the probability of an element to be reusable or non-reusable is different. It is imagined that the exact location of the Bayes decision boundary is known because it is assumed that the conditional distribution of the reusability of the elements is known. For an unseen observation, based on the values of x_1 and x_2, if the element falls on the left-hand side of the Bayes decision boundary, the component is reusable; otherwise, it is non-reusable. For those elements falling on the decision boundary, the component is considered non-reusable.

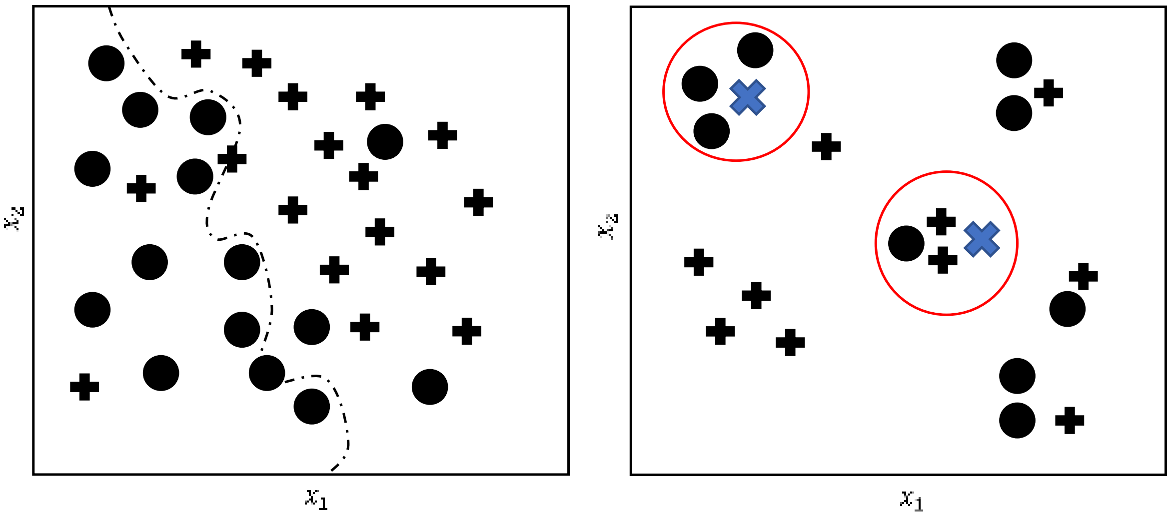

Figure D.1 The Bayes classifier (left) and K-Nearest Neighbours (KNN) classifier (right)

However, the conditional distributions of the technical, social, and economic reusability of the structural elements of a building are unknown. Therefore, for an unseen data point, the KNN classifier looks for the K closest data points to the new observation in the training set (K is an arbitrary positive integer) and classifies the test observation to the class with the highest probability [46,53]. In fact, the KNN method assumes that the reusability of a new recovered structural element is like its nearest neighbours in the training dataset. This process is shown on the right-hand panel of Figure D.1. If K=3, then the KNN classifier classifies the new observation (shown with a cross sign) on the top-left corner as reusable because the three nearest neighbours in the training dataset are reusable, yielding a class probability of 100%. However, the new observation in the centre is adjacent to two non-reusable and one reusable elements in the training dataset. In this case, this new element would be classified as non-reusable since two-third of its nearest neighbours in the training dataset are non-reusable, and only one-third is reusable.

The choice of the number of neighbours has a considerable impact on the prediction results [46,53]. While the number of K depends on the sample size, theoretically, it is possible to assign any positive integer to K [46]. However, if K is too small (for instance, equal to one), the classifier would strictly follow the training observations and becomes highly flexible, it might overfit, and potentially results in a model with high variance and low bias [46]. On the other hand, large values of K can potentially make the classifier less flexible, which results in a low variance model with high bias [46]. In this study, using standard holdout method (equal to two-third of the training observations), the value of the number of neighbours was estimated. Accordingly, the value of K used for modelling is equal to six.

D.2 Logistic Regression (LR)

Logistic regression (LR) directly models the probability that an element is reusable or not [46]. Unlike the KNN method, LR assumes a functional form for the relationship between the response and factors affecting reuse (features) in its attempt to predict the reusability; hence, it is a parametric machine learning approach [46,51]. So, the conditional probability Eq. (D.2) can be written in the following form Eq. (D.3).

$$p(\boldsymbol{X}) = \mathrm{pr}(reusability = 1|\boldsymbol{X} = \boldsymbol{x}) \qquad \text{Eq. (D.3)}$$

LR uses Eq. (D.4), the logistic function, to calculate $p(\boldsymbol{X})$ and employs the Maximum Likelihood estimation method to fit the model based on the training observations [46,51].

$$p(\boldsymbol{X}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p)}} \quad \textit{Eq. (D.4)}$$

It is noteworthy that the logistic function Eq. (D.4) results in values between zero and one. In Eq. (D.4), the β_p (betas) are unknown constants that should be identified [46]. Hence, in LR, the problem of identifying the relationship between $p(\boldsymbol{X})$ and $\boldsymbol{X}$ in the training set is reduced to estimating these coefficients [46]. In this case, the Maximum Likelihood (MLE) seeks estimates of these betas, so Eq. (D.4) yields a probability close to one for reusable elements, and to zero for non-reusable components [46].

After estimating the unknown constants in Eq. (D.4) using the training data, this classifier assigns a new observation given its feature values to one of the two classes based on the quantity of $p(\boldsymbol{X})$ and a threshold value [46,51]. If the Bayes classifier threshold value of 0.5 is assumed, then for $p(\boldsymbol{X}) > 0.5$, the classifier predicts the element reusable [46]. However, a conservative designer might choose a higher threshold value to decrease the probability of making a false positive error [46].

D.3 Linear Discriminant Analysis (LDA)

Like the KNN method, linear discriminant analysis (LDA) attempts to estimate the Bayes classifier [46]. The LDA method considers a functional form (the discriminant function) for the relationship between the response and factors affecting reuse; hence, like the logistic regression, it is a parametric machine learning approach [51]. However, unlike the LR, LDA does not directly estimate the conditional probability Eq. (D.2) [46].

Using the Bayes' theorem [70,71], Eq. (D.2) can be written as follows, where k corresponds to non-reusable (0) or reusable (1) classes.

$$\mathrm{pr}(reusability = k|\boldsymbol{X} = \boldsymbol{x}) = \frac{pr(\boldsymbol{X} = \boldsymbol{x}|reusability = k)pr(reusability = k)}{pr(\boldsymbol{X})} \quad \textit{Eq. (D.5)}$$

In Eq. (D.5), $pr(\boldsymbol{X}|reusability = k)$ is known as the density function of $\boldsymbol{X}$ for a structural element that belongs to class k, $pr(reusability = k)$ is the prior probability which is the probability that a given observation belongs to class k, and $pr(\boldsymbol{X})$ is the overall probability of $\boldsymbol{X}$ in the dataset [46]. In Eq. (D.5), the prior probability is simply the result of the number of elements in each of the training classes divided by the total number of components in the training dataset [46]. The conditional probability in Eq. (D.5) can be re-written as follows [46]:

$$p_k(\boldsymbol{X}) = \frac{f_k(\boldsymbol{x})\pi_k}{\sum_{s=1}^{k} \pi_s f_s(\boldsymbol{x})} \quad \textit{Eq. (D.6)}$$

In Eq. (D.6), $p_k(\boldsymbol{X})$ is the posterior probability that an observation is reusable or not, given the values of its features [46]. Therefore, the LDA classifier needs to estimate the value of $f_k(\boldsymbol{x})$ (the density function) and π_k (the prior probability) and plug them into Eq. (D.6) to evaluate the posterior probability [46,53]. The LDA method assumes a one-dimensional normal distribution for each independent variable in Eq. (D.6) (a multivariate Gaussian distribution) and equal variance for the class responses [46]. The density function in Eq. (D.6) can be then converted to the following (for further details, refer to [46,53]):

$$\delta_k(\boldsymbol{x}) = \boldsymbol{x}^T \Sigma^{-1} \mu_k - \frac{1}{2} \mu_k^T \Sigma^{-1} \mu_k + log\ \pi_k \quad \textit{Eq. (D.7)}$$

The above is known as the discriminant function [46,53]. The LDA method estimates $\sum$ (the covariance matrix that is common to reusable and non-reusable components), and μ_k (mean vector of the features in each class) to evaluate $\delta_k(\boldsymbol{x})$ in the training dataset [46,53]. The Bayes classifier then classifies a new observation as reusable or non-reusable for which the value of the corresponding $\delta_k(\boldsymbol{x})$ is higher [46,53]. The word 'linear' in this method stems from the fact that the discriminant function is a linear function of $\boldsymbol{x}$ [46,53].

D.4 Quadratic Discriminant Analysis (QDA)

Quadratic discriminant analysis (QDA) is a similar approach to the LDA with the exception that, in the QDA method, each class has its covariance matrix [46,53]. Moreover, in QDA, the discriminant function is a quadratic function of predictors $\boldsymbol{x}$ [46,53]. The QDA method is more flexible and can handle the possible non-linear relationship between the features and the response in each dataset [46,53]. For further details, please refer to [46,53].

D.5 Naïve Bayes (NB)

The Naïve Bayes (NB) classifier is a non-parametric method that attempts to estimate the conditional probability of the reusability of a structural element given its features by making the naïve assumption that these features are independent [51,53]. Considering a conditional probability where there is only one independent variable X, Eq. (D.2) can be written as:

$$pr(Y = k \,\middle|\, X = x) \qquad \text{Eq. (D.8)}$$

Eq. (D.8) can be calculated by identifying the portion of the response (a common area) for which the independent variable X is equal to x using the MLE method.

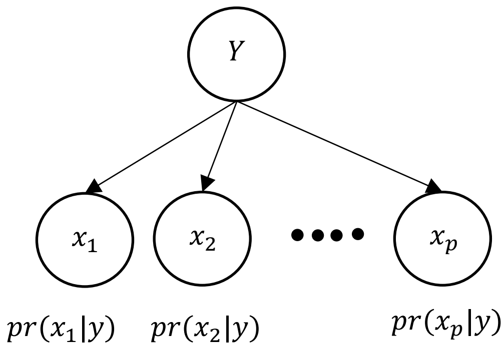

Figure D.2 The independence of features assumed in the Naïve Bayes (NB) classifier

However, considering all the applicable reusability factors in Eq. (D.2), this common area would be very close to zero; hence, the classifier cannot make predictions [72]. The NB method addresses this problem by using Eq. (D.5), the Bayes' theorem [70,71], and making the naïve assumption that all the features are independent, given the response [53,71]. The independence of features assumed in the NB classifier is illustrated in Figure D.2. Therefore, considering the above assumption, the density function $pr(\boldsymbol{X} = \boldsymbol{x}|reusability = k)$ in Eq. (D.5) can be written as follows.

$$pr(\boldsymbol{X} = \boldsymbol{x}|reusability = k) = \prod_{a=1}^{p} pr(\boldsymbol{X} = x_{\mathrm{a}}|reusability = k) \qquad \text{Eq. (D.9)}$$

As discussed in Section D.1, the Bayes classifier then assigns an observation to the most likely response label (here, reusable or non-reusable) using the Bayes' theorem Eq. (D.5) [70,71].

D.6 Decision Trees (DT)

Decision trees are machine learning methods that include stratifying the feature space of the training set into a smaller number of regions (known as terminal nodes or leaves) with similar class labels [46].

The set of possible values of the ‘p’ predictors $(x_1, x_2, \ldots, x_p)$ of the structural elements in the training data is divided into K number of leaves (R_1 to R_k), which are not overlapping [46]. Then, for an unseen observation that satisfies R_k, the DT classifier classifies a new structural element to the most commonly occurring class response of the training set in R_k [46]. This process is shown in Figure D.3. The left-hand panel of Figure D.3 shows the entire dataset with the class labels and splits. In this figure, the training observations are marked with black circles (reusable) and black plus signs (non-reusable). The complete dataset is the combination of regions $R_{1.1}$, $R_{1.2}$, $R_{2.1}$, and $R_{2.2}$. Initially, the dataset was split into two regions or leaves, R_1 and R_2 [46]. Next, to increase the purity of the regions, R_1 was divided into $R_{1.1}$ and $R_{1.2}$, and R_2 was split into $R_{2.1}$ and $R_{2.2}$ [46]. The DT method then classifies a new observation (shown as a cross) as reusable because it is the most frequent class label in region $R_{1.1}$. The right-hand panel of Figure D.3 shows the process of classifying a new observation using the DT method.

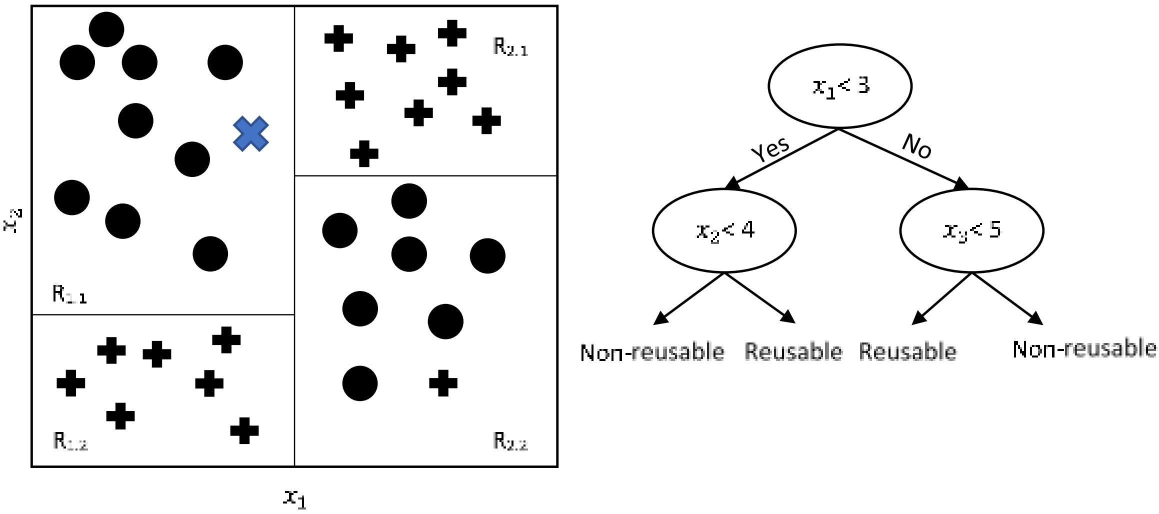

Figure D.3 The Decision Trees (DT) method

The DT method attempt to create a set of leaves for which the resulting splits have the lowest class impurity [46]. For this purpose, the DT method employs recursive binary splitting, which is a top-down greedy approach [46]. At each stage, the recursive binary splitting method selects an independent variable x_j with a cut-point value of s (s is any value belong to x_j) and splits the feature space of an existing node into the new terminal nodes $\{x \mid x_j < s\}$ and $\{x \mid x_j \geq s\}$ with the highest possible purity in response classification [46]. It is noteworthy that the split happens on the training observations available in a region and not the entire training dataset. The DT method uses the Gini index or the entropy impurity function measures to assess the purity of the splits at each stage [46,53]. After each split, if the resulting purity of the new leaves is not satisfactory, the splitting continues to decrease the impurity of the new terminal nodes [46]. This process continues until no further improvement is possible, resulting in a deep tree [46]. Alternatively, the process can be stopped by setting a termination condition, such as reaching a minimum number of observations in a region [46]. For further details on Gini and entropy impurity functions, please refer to [46,51,53].

D.7 Random Forests (RF)

Decision trees (DT) explained in Section D.6 suffer from high variance, which means any change in the training dataset can potentially affect the resulting predictions [46]. One reason is that during the first split, the dataset is roughly divided into two sections [46,50]. Hence, if a predictive model is fit to each of the splits, the resulting predictions are not necessarily the same [46]. One way to address this problem is by decreasing the depth of a DT model [46]. However, this method increases the bias in the model and consequently decreases its accuracy [46]. Another solution is to create an ensemble of decision trees using different datasets drawn from a population and averaging the results to decrease the variance [46]. This notion is the result of the weak law of large numbers [73]. According to this law, averaging various independent observations decreases variance [46]. Ideally speaking, by increasing the number of observations to infinity, the variance should diminish [73]. Nonetheless, this method is also not practical because of the limited access to many training datasets [46].

Random forests (Figure D.4) are machine learning methods that try to address the above issue by creating many trees with maximum depth (yielding in low bias but high variance) and averaging the resulting variance through bagging (bootstrap aggregation) [46,53]. Bagging is an ensemble method that draws many samples with replacement from a dataset $D = (D_1, D_2, \dots, D_m)$ [51,53]. The replacement in this process means that one structural element in the training set can appear more than once in the bootstrap dataset [40]. Then, the RF method fits a decision tree with maximum possible depth to each of the new datasets, creating an ensemble of bagged trees [46]. Before dividing the feature space at every stage, a random number of $m \approx p^{1/2}$ (p is the number of predictors in the dataset) independent variables are selected as eligible predictors from which one is picked by the method to split (without replacement) [46]. The lack of replacement in this process makes sure that the method does not pick a specific predictor repeatedly. This approach is highly advantageous because it makes sure that the bagged trees remain uncorrelated [46,51]. Whereas without this limitation, there is a high chance that all the developed trees become highly correlated, which results in a small improvement in the variance of the final model, compared to a single tree [46]. It is because, in the presence of an influential independent variable, there is a high chance that each tree chooses that strong predictor as its root node, resulting in a similar and highly correlated ensemble of trees [46].

The RF method uses the ensemble of bagged trees to make predictions [46]. While the way every single tree predicts the class of a new observation is like the DT method (Section D.6) [46], the RF method predicts if a new structural element is reusable or non-reusable based on the class label with the highest number of records.

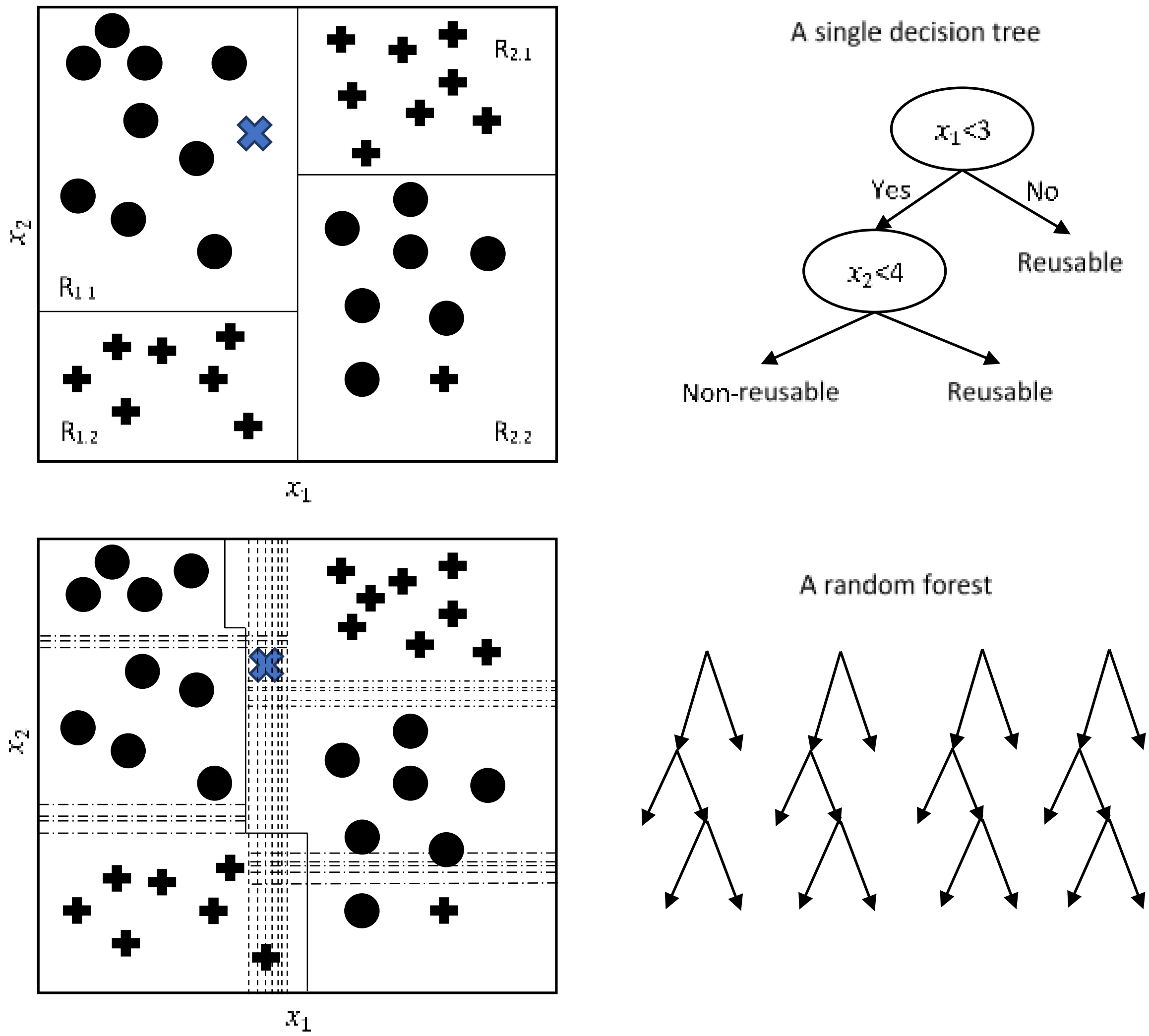

Figure D.4 A simplified Random Forest. Top: A Decision Tree (top right) divides the feature space (top left). Bottom: A Random Forest which is a group of Decision Trees (bottom right) divide the feature space (bottom left). The cross is the new observation.

D.8 Adaptive Boosting (AB)

Boosting methods can be employed to improve the predictions from any machine learning method with high bias and high training error rate (weak learners) [46,51,53]. In this study, the 'AdaBoost' methods introduced by [74] is employed to decrease the bias in decision trees with limited number of nodes (resulting in low variance and high bias) and increase the accuracy of predictions on unseen observations. Like random forests, adaptive boosting is an ensemble technique; however, it works quite differently [46]. Instead of creating an ensemble of decision trees through bootstrapping, adaptive boosting creates $M-1$ new decision trees sequentially, resulting in M number of ensembled decision trees [53]. The first classifier is a conventional decision tree, like the one explained in Section D.6 [53]. However, in creating the $M-1$ decision trees, the AdaBoost method alters the original dataset by weighting observations in the main dataset so that the misclassified observations are weighted higher and the correctly predicted data points are weighted lower [53]. Hence, the next stage decision tree focuses on those observations with wrong classification in the previous stage [53]. Finally, the predictions from the ensemble of the decision trees are weighted by the AdaBoost method, so those highly accurate decision trees on the training data are weighted higher than those with the poor performance [53]. For further details on the AdaBoost method, refer to Section 16.4 of [51].

D.9 BART Machine (BM)

BART (Bayesian additive regression trees) is an ensemble of decision trees with an arbitrary number of trees to be decided by the researcher [75]. Unlike random forests (Section D.7) or adaptive boosting (Section D.8) where a structural element is classified based on the most commonly occurring class response, it relies on Bayesian probability model [51,75]. Therefore, it consists of priors for the structure and the terminal node parameters and a likelihood for data in the leaves [75]. The priors considered guarantee no single decision-tree dominates the total model; hence, regularising the ensemble of trees [75]. It is noteworthy that according to the developers, the optimum number of trees is around 200 [75]. To predict an observation, BART uses the posterior average probability to classify a structural element as reusable or not [75,76]. For further details on the BART method, refer to [75].

D.10 Artificial Neural Networks (ANN)

Neural networks are machine learning methods working based on the way the human brain works [77]. Neural networks attempt to develop new features based on linear combinations of the input variables (reusability factors), and then predict the probabilities of the responses (reusable or non-reusable) using a nonlinear function of the newly extracted predictors [53]. Therefore, neural networks can be categorised as nonlinear parametric models [51,53].

In machine learning, the architecture of any neural network (Figure D.5) consists of a set of inputs (reusability factors), a processing unit (which includes a single or multiple hidden layers), and output(s) (reusable or not-reusable) [53]. There are two main groups of neural networks, feed-forward, and feed-backward neural networks [77]. In feed-forward neural networks, the signal can only move in one direction from the input layer to the hidden layer(s), and finally to the output layer. However, in feed-backward neural networks, before a signal reaches the next level, it can go back to the previous level [77]. Artificial neural networks (ANNs) fall under the former category, while recurrent neural networks (RNNs) fall under the latter [77]. In this study, the reusability of building structural elements is assessed using a special case of ANNs.

An ANN can be a single layer perceptron (with only one hidden layer) or a multiple layer perceptron [53]. The architecture of a double layer perceptron is shown in Figure D.5. According to this figure, the units in the middle layer (hidden units) develop new features. These new features are then used to determine the reusability probability of a structural element at the end-of-life of a building Eq. (D.10) [53].

$$\begin{aligned} D_k &= \sigma\left(\alpha_{0k} + \alpha_k^T X\right) \\ T_l &= \beta_{0l} + \beta_l^T D \\ f_l(X) &= g_l(T) \end{aligned} \qquad \text{Eq. (D.10)}$$

In Eq. (D.10), $X = (X_1, X_2, \dots, X_p)$ denotes the input variables, $k = 1,2,\dots,K$, $l = 1,2,\dots,L$, $D = (D_1, D_2, \dots, D_K)$ represents the derived features, $T = (T_1, T_2, \dots, T_L)$ is the vector of outputs, and α_{0k} and β_{0l} are the intercepts. In Eq. (D.10), the output function $g_l(T)$ is the softmax function, which transforms the vector of outputs T and produces positive estimates that sum to one. Other than the three layers explained earlier (inputs layer, hidden layer(s), and output layer), an ANN consists of weights, biases, and an activation function, as well. In Eq. (D.10), $f_l(X)$ calculates the probability that a structural element is reusable or not, and σ is the activation function, which in the case of the this study (classification problem), is a Sigmoid [53]. The weights are the unknowns in Eq. (D.10) and are summarised in Eq. (D.11) [53]. In Eq. (D.10) and Eq. (D.11), p is the number of independent variables. The goal is to estimate these weights so that the ANN model fits the training dataset well [53]. Therefore, to guarantee an accurate model, a measure of fit is required to evaluate the quality of the model. The measure of fit is calculated using the squared error or cross-entropy [53]. For further details about the measure of fit please refer to [53].

$$\{\alpha_{0k}, \alpha_k; k = 1,2,\ldots,K\}\ K(p+1)\ weights, \\ \{\beta_{0l}, \beta_l; l = 1,2,\ldots,L\}\ L(K+1)\ weights \qquad \text{Eq. (D.11)}$$

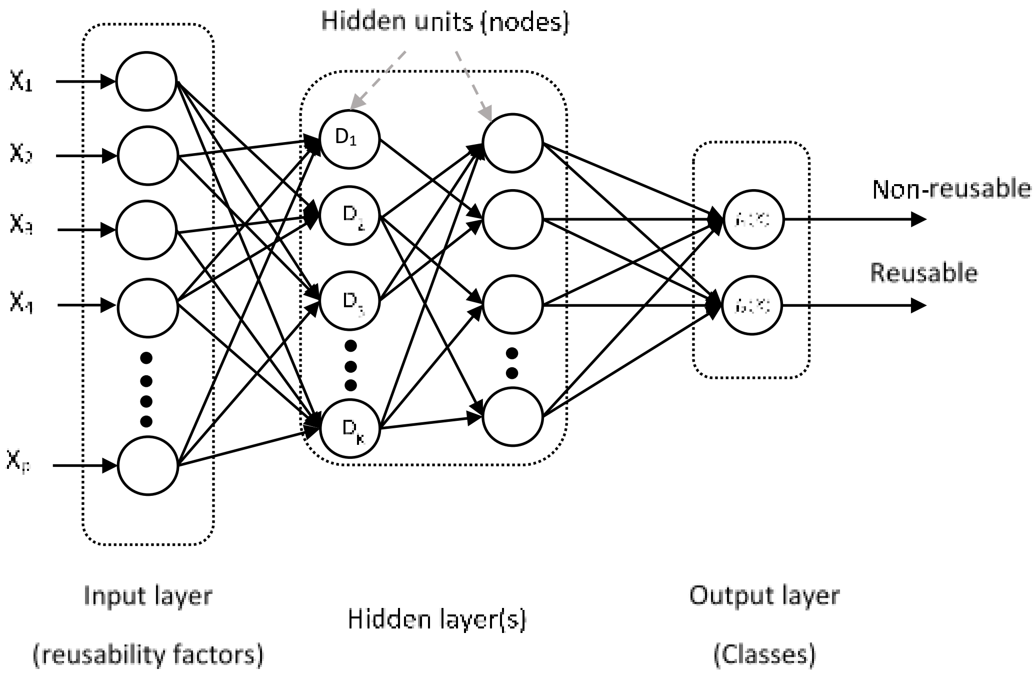

Figure D.5 The Artificial Neural Networks (ANN) architecture (two hidden layers)

The role of an ANN model is then reiterating two major stages until it reaches a minimum training set error rate. Firstly, estimating the reusability of the building structural elements based on weighted inputs, biases, and a specific activation function in the forward propagation stage. Next, determining the error rates and estimating the weights and biases using the backward propagation algorithm [77]. One of the most common problems that one could encounter while training an ANN is overfitting [51]. Because the predicted responses/trends of an overfitted model do not follow the reality present in the data, such a model is inaccurate. There are various techniques to prevent overfitting while training neural networks. One of the widely used solutions is early stopping. Early stopping is a form of regularisation while training a model with an iterative method, such as gradient descent. This method updates the model to make it better fit the training data with each iteration. Up to a point, this improves the model's performance on data on the test set. Past that point, however, improving the model's fit to the training data leads to increased generalisation error. Regularisation is an alternative method that is commonly used to overcome the overfitting problem. This method introduces a weight decay (a penalty term) to the loss function to reduce the model's complexity.

According to Hastie et al. [53] training neural networks requires pre-processing and extra precautions. This can be done by determining an optimum weight decay, scaling of the inputs, and assigning the number of hidden layers and nodes. The neural network method employed in this study is a single layer perceptron that uses Sigmoid function to activate the neurons in the network. Moreover, the input variables are scaled, and two hyperparameters (size of the hidden nodes, and weight decay) are evaluated using ten-fold cross-validation on the training set considering AUC as the determining metric. The estimated hyperparameters (size and decay) for the dataset in this study is as follows: $size = 9, decay = 0.09$

D.11 Gaussian Processes (GP)

Gaussian processes are nonparametric supervised machine learning methods that can be used for both regression and classification problems. In this study, Gaussian processes for classification (GPC) are used to predict the reusability probabilities of the recovered building structural elements. A GPC is a function approximation task where instead of directly estimating the class probabilities considering a predetermined functional form (such as LDA), the functional relationship is determined through a multivariate Gaussian distribution.

We consider a data set D={$(x_i, y_i | i = 1,2, \dots, n\}$, consisting of n samples, wherein x_i denotes the vector of input data taken from the input space, and $y_i = f(x_i)$ denotes the corresponding output (dependent variable) observation. Following [78], the GP prior model is given by Eq. (D.12):

$$f(\boldsymbol{x}) \sim GP\big(m(\boldsymbol{x}), k(\boldsymbol{x}, \boldsymbol{x}')\big) \qquad \textit{Eq. (D.12)}$$

where $m(\boldsymbol{x})$ is the mean function, which is commonly and without loss of generality considered to be zero and the kernel function $k(\boldsymbol{x}, \boldsymbol{x}')$; where $\boldsymbol{x}$ represents the training datapoint in each dataset of the structural elements. We use the radial basis function (or squared exponential) as the kernel function, see [52,78] for the details of this kernel, including the functional form, and how the hyperparameters (smoothness parameters) of this kernel can be estimated in the light of the observed data.

The joint prior distribution of the training outputs, $\boldsymbol{f}$, and the predicted output $\boldsymbol{f}_*$ (corresponding to the test input $\boldsymbol{x}_*$) , according to GP definition given in Eq. Eq. (D.12) and the properties of multivariate normal distribution, is given by Eq. (D.13):

$$\begin{bmatrix} \boldsymbol{f} \\ \boldsymbol{f}_* \end{bmatrix} \sim N(0, \begin{bmatrix} K & K_*^T \\ K_* & K_{**} \end{bmatrix}) \qquad \textit{Eq. (D.13)}$$

Where $K = k(\boldsymbol{X}, \boldsymbol{X})$, $K_* = k(\boldsymbol{X}_*, \boldsymbol{X})$, $K_*^T = k(\boldsymbol{X}, \boldsymbol{X}_*)$, $K_{**} = k(\boldsymbol{X}_*, \boldsymbol{X}_*)$, and $\boldsymbol{X}_{n \times p}$ denotes an $n \times p$ matrix of the training inputs $\{\boldsymbol{x}_i\}_i^n$ (also known as the design matrix), p stands for the dimension of input space $\boldsymbol{X}$, and $\boldsymbol{X}_*$ is the matrix of test inputs. We use the subscript $*$ to differentiate the test/predicted data from the training ones.

The posterior distribution of $\boldsymbol{f}_*$ can be obtained/derived by conditioning the joint prior distribution, given in Eq. Eq. (D.13) on the training datapoint Eq. (D.14):

$$\boldsymbol{f}_* | \boldsymbol{f}, X, X_* \sim N(K_*^T K^{-1} \boldsymbol{f}, K_{**} - K_* K^{-1} K_*^T) \qquad \textit{Eq. (D.14)}$$

The mean and covariance of this posterior distribution can be used as an estimate of the predicted value of $\boldsymbol{f}_*$, and uncertainty/sensitivity [79].

The GP that is briefly explained above, can be used as an efficient classifier by computing predictions in from of class probabilities of $y_* = f(\boldsymbol{x}_*)$ for the new test input $\boldsymbol{x}_*$. This can be done by squashing the output of a regression model through a logistic function (e.g. sigmoid function, $\sigma(.)$) to transform it from a domain of $(-\infty, +\infty)$ to $[0, 1]$ [78]. For a new observation $\boldsymbol{x}_*$, the distribution of the latent variable f_* is calculated using Eq. (D.15):

$$pr(f_*|X, \boldsymbol{y}, \boldsymbol{x}_*) = \int pr(f_*|X, \boldsymbol{y}, \boldsymbol{x}_*) pr(\boldsymbol{f}|X, \boldsymbol{y}) d\boldsymbol{f} \quad \text{Eq. (D.15)}$$

Then, using the above distribution, the probabilistic prediction is performed using Eq. (D.16):

$$pr(y_* = reusable|X, \boldsymbol{y}, \boldsymbol{x}_*) = \int \sigma(f_*) pr(f_*|X, \boldsymbol{y}, \boldsymbol{x}_*) df_* \quad \text{Eq. (D.16)}$$

However, since Eq. (D.15) is non-Gaussian (response is discrete), the above integrals are approximated using the Laplace approximation method [78].

D.12 Propositional Rule Learner (PRL)

Propositional rule learner (PRL) is a classification machine learning method that finds patterns in each dataset and expresses them in terms of a set of if-then rules [56]. These rules are then used to classify new structural elements that satisfy a rule condition. The method develops a predictive model in three stages. A PRL method first converts the features in the training dataset into sets of binary features [56]. Then it constructs the individual rules, each covering a part of the training dataset using a covering method [56]. At this stage, the method learns a rule that covers a part of the training observations. Then it removes those covered datapoints and learns a new rule based on the remaining observations [56]. The method recursively performs these tasks until all training observations are covered by a rule [56]. Finally, it combines all the learned rules and forms the predictive model [56]. For further details about this method please refer to [56].

In this study, the RIPPER (Repeated Incremental Pruning to Produce Error Reduction) method [80] is used to develop the predictive rule learning model [81].

D.13 Support Vector Machines (SVM)

Support vector machines (SVM) are machine learning methods that convert a linear classifier (known as support vector classifier) in a way to produce a non-linear decision boundary between classes (two-class responses) [46].

A support vector classifier is a computationally efficient method for developing linear decision boundaries between two-class responses [46]. The support vector classifier develops a hyperplane to split the observations in the training dataset into two classes (Figure D.6) [46]. This classifier depends only on the training observations close to the hyperplane known as the support vectors [46]. In the left-hand panel of Figure D.6, the left-hand side of the hyperplane represents the circle responses (reusable), and the right-hand side of the decision boundary corresponds to the plus class (non-reusable). The dashed lines in this figure are margins for the hyperplane. In Figure D.6, only the observations on the margin or crossing the margin but on the proper side of the decision boundary are the support vectors [46]. Therefore, training data far from the margins (and the hyperplane) do not play any role in predicting the class-response for a new observation [46].

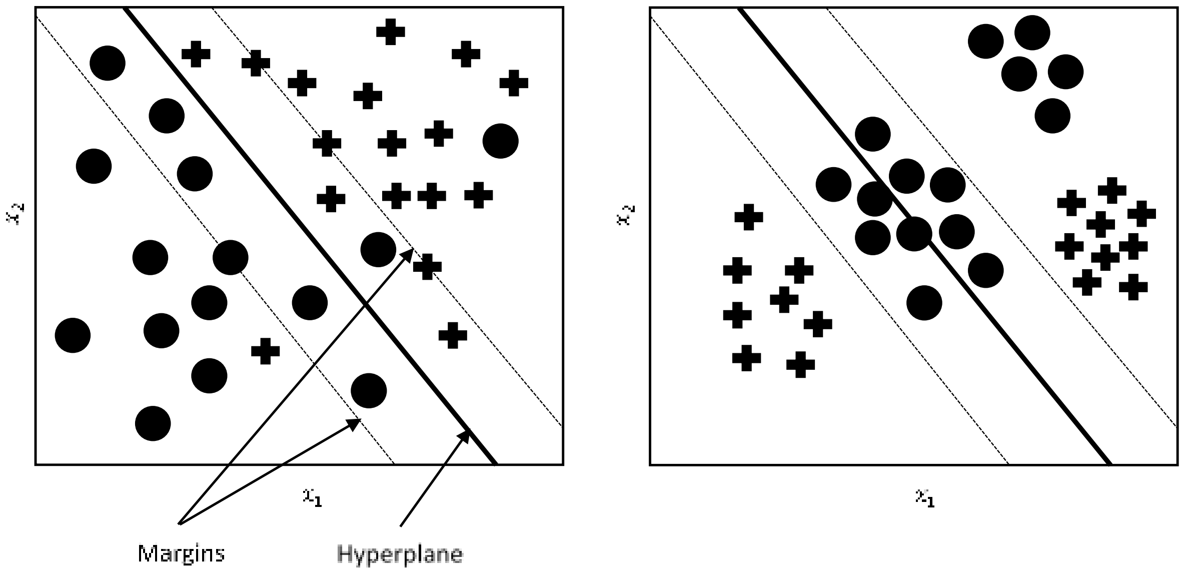

Figure D.6 The Support Vector Classifier

The support vector classifier can be represented as follows [46]:

$$f(x) = b_0 + \sum_{i \in S} a_i < x, x_i >, \quad \text{Eq. (D.17)}$$
$$(S = \ indices\ for\ the\ support\ vectors)$$

In Eq. (D.17), $< x, x_i >$ is the inner product of the new observation x with all support vectors, b_0 is an intercept, and a_i is a parameter required for each of the support vectors [46]. Function Eq. (D.17) is the solution function for an optimisation problem for the support vectors. The details of the optimisation problem are available in Section 9.2.2 of [46]. Moreover, the solution to the optimisation problem can be found in Section 12.2.1 of [53].

The left-hand panel of Figure D.6 represents a classification problem with separable (almost) class responses where the hyperplane does a reasonable job in classifying the non-reusable and reusable classes. However, in many instances, the relationship between the predictors and the responses are not linear [46]. The right-hand panel of this figure shows an example of such a problem. As can be observed, the separating hyperplane is useless in this situation. In this case, no linear classifier can effectively separate the two classes, as the relationship between the predictors and the responses are non-linear.

The support vector machine method attempts to overcome the above limitation by enlarging the feature space using kernel functions; hence, creating non-linear decision boundaries [46]. Kernel functions quantify the similarity of two observations and can have various forms, including radial, polynomial, hyperbolic, Laplacian, etc. [46]. By replacing the inner product in Eq. (D.17) with the kernel, the solution function Eq. (D.17) can be re-written as Eq. (D.18), where $K(x, x_i)$ is the kernel function [46]:

$$f(x) = b_0 + \sum_{i \in S} a_i K(x, x_i), \quad \text{Eq. (D.18)}$$
$$(S = \ indices\ for\ the\ support\ vectors)$$

In this study, a radial kernel is used to expand the feature space, and eventually develop non-linear decision boundaries between the classes. Therefore, Eq. (D.19) formulates the radial kernel.

$$K(x_i, x_{i'}) = \exp\left(-\sigma \sum_{j=1}^{p} \left(x_{ij} - x_{i'j}\right)^2\right), \qquad \textit{Eq. (D.19)}$$
$$where\ \sigma\ is\ a\ positive\ constant$$

In Eq. (D.19), x_i and $x_{i'}$ indicate two different observations in the training set, p is the number of predictors, and σ (sigma) controls the non-linearity of the kernel function [46]. By increasing the value of σ, the fit becomes more non-linear [46]. While this increased non-linearity can decrease the variance on the training dataset, it might increase the chance of overfitting [46]. Hence, care must be taken while choosing the correct value for σ [46]. Another hyperparameter that is required to be selected is known as cost (represented by C) [46]. This quantity determines the width of the margin in Figure D.6, and correspondingly the number of support vectors [46]. This tuning parameter is used to determine a_i in Eq. (D.17) and Eq. (D.18) (see Section 12.2.1 of [53]). In this study, the hyperparameters (C and sigma) are calculated using ten-fold cross-validation on the training set [51]. According to this method, the estimated hyperparameters are as follows: C= 1.601470833, sigma= 0.047078172.

Support vector machines inherit the properties of the support vector classifier, so in predicting the response class of a new observation, only those training observations close to the decision boundary play a role [46].