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Random forest prediction of ACeBS seismic resilience scores for simple residential buildings in Yogyakarta

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Abstract
The Asesmen Cepat Bangunan Sederhana (ACeBS) is a 47-item checklist used in Indonesia to rate the earthquake resilience of simple residential buildings, but its scoring still relies on slow manual field tabulation. This study develops and validates a machine-learning model that predicts the ACeBS resilience score directly from the recorded checklist answers and building age, and identifies which assessment items most influence the score. A dataset of 110 single-storey houses surveyed across the Special Region of Yogyakarta was used; each record contains binary responses to the 47 ACeBS items, the building age, and the percentage resilience score. A Random Forest regressor was trained on 100 buildings using ten-fold cross-validation and tested on 10 unseen buildings, with R-squared, mean absolute percentage error (MAPE) and root-mean-square error (RMSE) as metrics and Gini importance for parameter screening. The model reproduced the score accurately, reaching a cross-validation R-squared of 0.853 (RMSE 8.56 percentage points) and an evaluation R-squared of 0.922 (RMSE 4.21 percentage points). Benchmarking against seven other algorithms showed that linear models reproduce the score almost perfectly because it is a near-linear aggregation of the items, while the Random Forest was retained for its assumption-free, interpretable importance ranking. That ranking found column concrete quality (P21), column stirrup reinforcement (P20) and sloof tie-beam size (P12), together with building age, to be dominant, with 32 of 48 inputs above the threshold. ACeBS scoring can thus be automated and reduced to a smaller set of decisive items, supporting faster and more consistent pre-disaster screening.

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Introduction

Indonesia lies along the Pacific Ring of Fire, where the convergence of the Eurasian, Indo-Australian and Pacific plates produces frequent and damaging earthquakes (Lorito et al., 2015). Residential buildings carry a large share of the resulting losses because much of the housing stock, especially in rural and informal settlements, is built without adequate seismic detailing (Burlotos et al., 2020). The 2006 Yogyakarta earthquake (Mw 6.4) exposed this weakness vividly, with widespread collapse of simple masonry houses that lacked confining elements and adequate connections (Ramdhan et al., 2025; Librian et al., 2024).

To support rapid evaluation of such buildings, the Asesmen Cepat Bangunan Sederhana (ACeBS) framework was developed as a checklist-based method for assessing the

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seismic quality of simple one-storey houses, in the same spirit as the rapid screening and fragility-based approaches applied elsewhere (Weber et al., 2024; Papatheodorou et al., 2023). ACeBS uses 47 evaluation items covering foundations, walls, columns, beams, roof systems and connection details. Each item is answered as present or absent, and the proportion of favourable answers is converted into a percentage resilience score that is then mapped to a vulnerability class. The instrument is deliberately simple so that it can be applied by local authorities and trained surveyors without specialised structural analysis.

Despite its usefulness, ACeBS scoring is still performed manually. Surveyors record answers in the field, tabulate them, and compute the score by hand or in a spreadsheet. This process is time-consuming when many buildings must be assessed, and the reliance on individual judgement introduces variability between surveyors; such manual approaches scale poorly as urban areas expand (Mishra et al., 2024; Suroso & Firman, 2019). Equally important, the relative weight of the 47 items is treated implicitly: it is not obvious which questions actually drive the final score, and therefore which items deserve the most attention during a survey or a retrofitting decision.

Machine learning offers a way to address both issues. Tree-ensemble methods such as Random Forest (Breiman, 2001) and gradient-boosted trees (Chen & Guestrin, 2016) are well suited to tabular survey data: they capture non-linear interactions between items, are robust to correlated inputs, and provide a natural measure of variable importance. In structural health monitoring and earthquake engineering, data-driven models have been used increasingly to assess hazard, predict damage and prioritise inspection effort. However, these techniques have not yet been integrated with the ACeBS instrument, leaving a gap between a widely used field tool and the analytical methods that could make it faster, more consistent and more transparent.

The wider research programme behind this paper aims to enhance ACeBS with artificial intelligence so that it can support proactive, pre-disaster screening. Within that programme, the present paper addresses a single objective: to develop and validate a machine-learning model that predicts the ACeBS resilience score for simple residential buildings, and to identify the checklist items that most influence that score. The corresponding research question is whether a Random Forest model trained on ACeBS survey data can reproduce the resilience score accurately on unseen buildings, and whether the score is governed by a compact subset of the 47 items.

Research Methods

Study area and dataset

The dataset consists of 110 single-storey residential buildings surveyed across the five regencies and the city of the Special Region of Yogyakarta (Daerah Istimewa Yogyakarta): Sleman, Gunung Kidul, Bantul, Kulon Progo and Yogyakarta City. The province is exposed to both crustal-fault and subduction sources, and earthquake-hazard mapping of the area has highlighted its elevated risk (Murjaya et al., 2021; Saputra et al., 2021; Susri Nurhaci et al., 2024). Surveys followed the ACeBS protocol and were compiled with reference to the InaRISK platform of the National Disaster Management Authority (BNPB). For every building the record contains binary responses to the 47 ACeBS items (1 = present, 0 = absent), the building age in years, the total raw score, and the percentage resilience score used in this study. Table 1 summarises the composition of the dataset by regency, including the distribution of vulnerability classes and the mean resilience score.

ACeBS scoring scheme

The 47 ACeBS items are organised into thirteen thematic sections (A–M): plan drawing, land and subsoil, plan regularity, foundation, sloof (foundation tie-beam), column, roof ring beam, reinforcement detailing at ring-beam and column end nodes, connections, wall, roof trusses, gable (ampig) framing, and roof covering. Each item is answered Yes, No or Don't Know, and a higher percentage score indicates a building that incorporates more earthquake-resistant features and is therefore less vulnerable. The percentage score is mapped to three vulnerability classes: Low (high score), Medium, and High (low score). In the present dataset the classes are not balanced, with 38 buildings rated Low, 46 Medium and 26 High vulnerability. Because the percentage score is a continuous quantity that fully determines the class, it was adopted as the regression target; predicting the score therefore also recovers the class boundary.

Table 1. Dataset composition by regency (vulnerability class: Low = least vulnerable).

Regency/City	n	Low	Med	High	Mean (%)
Sleman	36	8	15	13	53.7
Gunung Kidul	21	6	11	4	55.5
Bantul	20	10	7	3	65.8
Kulon Progo	13	5	5	3	60.1
Yogyakarta City	20	9	8	3	59.2
Total	110	38	46	26	58.0

Random forest model and validation

The model uses 48 input variables: the 47 ACeBS items (P1–P47) and the building age. The target is the percentage resilience score. The 110 buildings were divided into a training set of 100 buildings and an evaluation set of 10 buildings held out entirely from training. This 100/10 division was dictated by the size of the available field sample rather than by an arbitrary ratio: collecting ACeBS surveys is labour-intensive, so the priority was to retain as many buildings as possible for learning while still reserving a fully independent subset for an external check. To guard against the optimism and high variance that a single small split can produce, generalisation on the 100 training buildings was estimated with ten-fold cross-validation, in which the data are repeatedly partitioned so that every building is predicted once while held out of the trees that predict it. Cross-validation therefore provides the primary, lower-variance estimate of performance and mitigates overfitting, while the 10 held-out buildings serve only as a confirmatory, never-seen test. A Random Forest regressor (Breiman, 2001) with 100 trees and a fixed random seed was fitted to the training set, using the scikit-learn implementation (Pedregosa et al., 2011). Performance was quantified with the coefficient of determination (R-squared), the mean absolute percentage error (MAPE) and the root-mean-square error (RMSE), the last expressed in percentage points of the 0–100% score. The experimental configuration is given in Table 2.

Table 2. Random forest configuration and validation protocol.

Setting	Value
Algorithm	Random Forest regressor
Number of trees	100
Random seed	42
Inputs	47 ACeBS items + building age (48)
Target	ACeBS resilience score (%)
Training / evaluation	100 / 10 buildings
Validation	10-fold cross-validation
Metrics	R-squared, MAPE, RMSE

Feature-importance screening

After fitting, the relative contribution of each input was measured using the impurity-based (Gini) importance averaged over all trees. A retention threshold of 0.005 was applied to separate items that meaningfully influence the score from those whose contribution is negligible. Items at or above the threshold were retained, and items below it were flagged as candidates for elimination from a reduced instrument.

Hyperparameter tuning and model comparison

Two further checks were carried out to support the modelling choices. First, the

Random Forest hyperparameters were tuned with an exhaustive grid search under the same ten-fold cross-validation, varying the number of trees (100, 200, 300), maximum depth (unlimited, 10, 20), minimum samples per leaf (1, 2, 4) and the number of features sampled per split (square root, base-two logarithm, all). Second, to place the chosen model in context, the Random Forest was compared on identical training and evaluation data against seven alternative regressors: linear regression, ridge regression, k-nearest neighbours, support vector regression, a single decision tree, gradient boosting and XGBoost. Distance-based models (k-nearest neighbours and support vector regression) were standardised before fitting. All models were assessed with the same three metrics, both under cross-validation and on the held-out buildings.

Result and Discussion

Predictive performance

The model reproduced the ACeBS resilience score with high accuracy. On the training data, ten-fold cross-validation gave an R-squared of 0.853, a MAPE of 14.6% and an RMSE of 8.56 percentage points. On the 10 unseen evaluation buildings the model performed even better, with an R-squared of 0.922, a MAPE of 5.31% and an RMSE of 4.21 percentage points. These metrics are summarised in Table 3. The stronger evaluation result reflects the relatively small and well-behaved hold-out set; the cross-validation figures give the more conservative estimate of expected performance.

Table 3. Predictive performance on training (cross-validated) and held-out data.

Metric	Cross-validation (n=100)	Evaluation (n=10)
R-squared	0.853	0.922
MAPE (%)	14.64	5.31
RMSE (% points)	8.56	4.21

The grid search confirmed that the model is robust to its hyperparameters. The best configuration (300 trees, base-two-logarithm feature sampling, unlimited depth, one sample per leaf) raised the cross-validation R-squared only marginally, from 0.853 to 0.880, and did not improve the held-out result (R-squared 0.904, RMSE 4.66 percentage points). Because the gain is small and does not generalise, the default 100-tree configuration was retained for transparency and reproducibility.

Figure 1 plots predicted against actual scores for the evaluation buildings. The points fall close to the 1:1 line across the full range, from highly vulnerable houses near 44% to resilient houses near 89%. A mild tendency to under-predict the highest scores is visible, which is expected from a tree ensemble that averages over leaves and therefore compresses extreme values slightly. The detailed predictions for all 10 buildings are listed in Table 4.

Comparison with alternative algorithms

To place the Random Forest in context, eight regression algorithms were trained and validated on identical data; the results are summarised in Table 5 and Figure 2. The most accurate models are the linear ones: ordinary and ridge regression both reach a cross-validation R-squared of about 0.99 with an RMSE below 1.7 percentage points. This result is expected rather than surprising. The ACeBS resilience score is, by construction, a weighted aggregation of the binary checklist answers, so it is very nearly a linear function of those answers; a linear model can therefore almost recover the underlying scoring rule. Support vector regression also performs strongly (R-squared 0.98), whereas a single decision tree is the weakest model (evaluation R-squared 0.09), illustrating the instability that motivates ensembles. The Random Forest, gradient boosting and XGBoost cluster together at an evaluation R-squared near 0.87–0.92.

The comparison does not imply that the Random Forest should be discarded; rather, it clarifies its role. Where the target is an explicit linear aggregation, a linear model is the natural choice for pure score reproduction. The Random Forest is retained here for two reasons. First, it makes no assumption about the form of the scoring rule and still reproduces the score well, which matters once the relationship becomes non-linear for example when richer, noisier inputs such as image-derived defect features and their interactions with building age are added in the planned extension of this work. Second, its impurity-based importance provides a model-agnostic ranking of which items carry the most information, the principal engineering output of this study. The linear and ensemble results are thus complementary: the former confirms that the score is well-structured and learnable, while the latter supplies the interpretable prioritisation of checklist items.

Influential assessment items

The feature-importance ranking is shown in Figure 3, and the ten leading inputs are listed with their questionnaire items in Table 6. Three checklist items dominate: P21 (column concrete quality, 0.147), P20 (column stirrup reinforcement, 0.121) and P12 (sloof, or foundation tie-beam, minimum size, 0.114). Building age is the fourth most influential input (0.073), confirming that age carries information not already captured by the checklist answers. Together these four inputs account for roughly 45% of the total importance. A second tier of items contributes moderately the roof ring-beam concrete mix (P27), the sloof longitudinal bars (P13), the column-to-foundation anchorage (P9), the gable/accessory wall detailing (P33), and the roof ring-beam size and stirrups (P23, P25) while the remaining items taper off smoothly. Applying the 0.005 threshold, 32 of the 48 inputs were retained and 16 were flagged for elimination.

The concentration of importance in a small number of items has a practical consequence: the ACeBS score is largely governed by a compact subset of the checklist. This suggests that a shortened instrument built around the highest-ranked items, supplemented by building age, could approximate the full 47-item score with little loss of accuracy, which would speed up field surveys. The identity of the dominant items is also engineering-consistent. The three leading questions all concern the vertical confining system and the foundation tie: column concrete quality (P21), column transverse, or stirrup, reinforcement (P20), and the size of the sloof or foundation tie-beam (P12). In confined-masonry houses these are precisely the elements that provide ductility and hold the wall panels together during shaking; weak or porous column concrete, widely spaced stirrups, and an undersized tie-beam are classic precursors of the brittle collapses observed after the 2006 Yogyakarta earthquake. The supporting items reinforce the same picture, emphasising reinforcement continuity (P13, P9), the roof-level ring beam (P23, P25, P27) and gable/accessory walls (P33). That the model recovers this hierarchy from the survey data alone, without being told any structural theory, both validates the ranking and echoes scenario-based fragility studies of Indonesian houses, which attribute large differences in damage to a few key structural deficiencies (Weber et al., 2024). The ranking could therefore be used to weight or shorten the rapid field form around the column, tie-beam and ring-beam items that matter most.

One caveat applies to the ranking. Impurity-based importance can favour continuous or high-cardinality inputs over binary ones, which may partly explain the comparatively high importance of building age relative to individual yes/no items. The ranking should therefore be read as indicative rather than definitive; confirming it with permutation importance and with the coefficients of the near-perfect linear model, and on a larger sample, would strengthen the engineering interpretation.

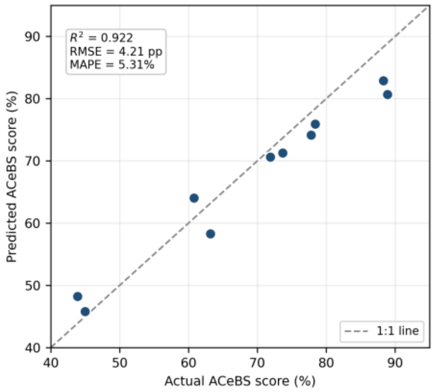

Figure 1. Predicted versus actual ACeBS resilience score for the 10 evaluation buildings.

Table 4. Actual and predicted scores for the evaluation buildings.

Building	Actual (%)	Predicted (%)
1	88.9	80.7
2	63.2	58.3
3	71.9	70.6
4	88.3	82.9
5	77.8	74.2
6	45.0	45.8
7	60.8	64.0
8	43.9	48.3
9	73.7	71.3
10	78.4	75.9

Table 5. Cross-validated and held-out performance of eight algorithms (RMSE in percentage points).

Model	CV R^2	CV RMSE	Eval R^2	Eval RMSE
Ridge regression	0.996	1.45	0.998	0.66
Linear regression	0.995	1.62	0.997	0.83
Support vector regression	0.977	3.38	0.983	1.96
Gradient boosting	0.890	7.39	0.923	4.19
k-nearest neighbours	0.870	8.05	0.974	2.45
Random forest	0.853	8.56	0.922	4.21
XGBoost	0.835	9.07	0.872	5.38
Decision tree	0.577	14.51	0.093	14.35

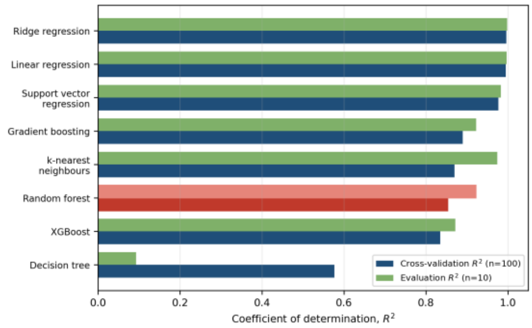

Figure 2. Cross-validation and evaluation R-squared for the eight algorithms (Random Forest highlighted).

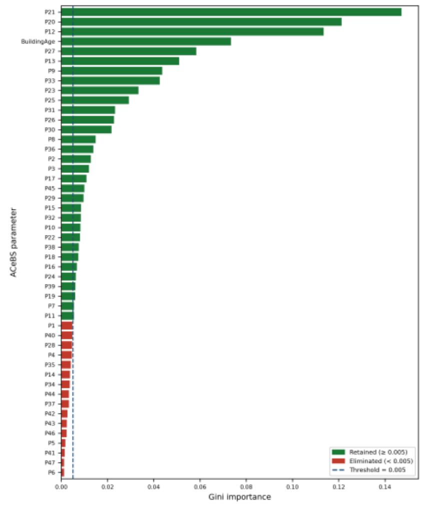

Figure 3. Gini importance of the 48 inputs (green: retained at ≥ 0.005; red: eliminated).

Table 6. Ten most influential inputs with their ACeBS questionnaire items (all retained at ≥ 0.005).

Code	ACeBS item (abbreviated)	Import.
P21	Column concrete quality (not porous)	0.1471
P20	Column stirrup reinforcement (8 mm @ 150 mm)	0.1212
P12	Sloof / tie-beam size (15 × 20 cm)	0.1135
Age	Building age (years)	0.0734
P27	Roof ring-beam concrete mix ratio	0.0584
P13	Sloof longitudinal bars (≥ 4, Ø 10 mm)	0.0510
P9	Column-to-foundation anchorage	0.0437
P33	Accessory / gable wall detailing	0.0426
P23	Roof ring-beam size (12 × 15 cm)	0.0334
P25	Ring-beam stirrup reinforcement	0.0292

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Vulnerability profile and the effect of age

The distribution of vulnerability classes across the 110 buildings is shown in Figure 4. Medium vulnerability is the most common class (46 buildings), followed by Low (38) and High (26). Almost one quarter of the surveyed houses therefore fall in the most vulnerable category, underscoring the value of a fast screening tool that can flag such buildings before an earthquake.

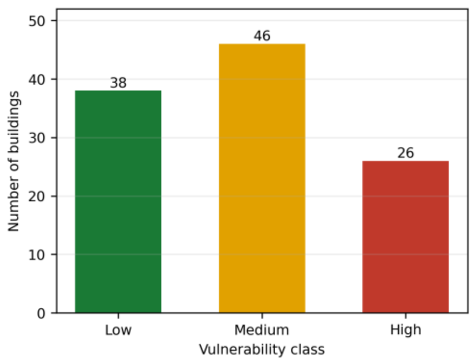

Figure 4. Distribution of vulnerability classes across the 110 surveyed buildings.

Figure 5 relates building age to the resilience score. There is a moderate negative correlation (r = -0.37): older buildings tend to have lower scores and thus higher vulnerability, with the fitted trend losing roughly half a percentage point of score per year of age. This is consistent with the model placing building age among its most important inputs, and with the engineering expectation that older houses were built before current seismic detailing became common and have since experienced material degradation.

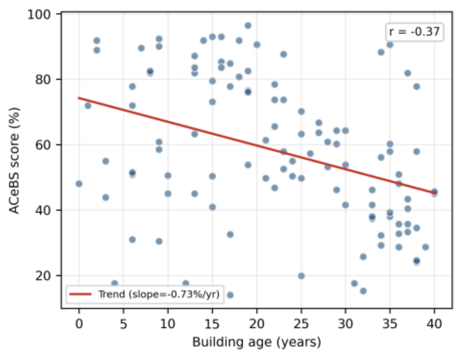

Figure 5. Building age versus ACeBS resilience score for the 110 buildings.

Implications and limitations

From a practical standpoint, an accurate predictive model converts ACeBS from a purely manual tabulation into a tool that can score buildings automatically once the checklist answers are entered, with consistent results that do not depend on which surveyor performs the calculation. Because the model also ranks the items, it can guide surveyors toward the questions that matter most and help authorities prioritise retrofitting, reducing the far larger cost of post-earthquake reconstruction (Hamit et al., 2023). These capabilities align with national efforts toward earthquake-resistant housing under PUPR Regulation No. 5/2016 (Ministry of Public Works and Housing [PUPR], 2016) and with broader goals of urban disaster resilience (Suroso & Firman, 2019), and they complement platforms such as InaRISK that aggregate building-level risk information.

Several limitations should be acknowledged and define the scope of these conclusions. The dataset is modest in size (110 buildings) and confined to a single province, single-storey masonry houses, so the learned relationships and the importance ranking may not transfer directly to other regions, taller buildings or other construction types; external validation on independent surveys is needed. The vulnerability classes are imbalanced, with relatively few High-vulnerability cases, which can limit accuracy at the most critical end of the scale. As noted above, impurity-based importance can be biased toward continuous inputs, so the ranking is indicative and should be cross-checked with permutation importance. No attempt was made here to optimise every competing model individually, so the comparison reflects sensible defaults rather than the best attainable version of each algorithm. Last but not least, this paper addresses only the tabular, checklist-based component of the broader research; the image-based detection of structural defects envisaged in the parent programme is left to future work, and it is in that non-linear, multi-modal setting that the Random Forest is expected to show its main advantage over linear models.

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Conclusion

This paper set out to develop and validate a machine-learning model that predicts ACeBS resilience scores for simple residential buildings and to identify the items that most influence those scores. A Random Forest model trained on 100 buildings and tested on 10 unseen buildings predicted the resilience score accurately, with a cross-validated R-squared of 0.853 and an evaluation R-squared of 0.922, and evaluation errors of 5.31% (MAPE) and 4.21 percentage points (RMSE); a grid search confirmed that this performance is robust to the choice of hyperparameters. A comparison against seven other algorithms showed that linear and ridge regression reproduce the score almost perfectly, because the ACeBS score is by construction a near-linear aggregation of the checklist answers; the Random Forest was nevertheless retained for its assumption-free nature and, above all, for the interpretable importance ranking that is the study's main engineering output. That ranking shows the score is governed by a compact subset of the checklist, dominated by items P21, P20 and P12 (column concrete quality, column stirrup reinforcement and sloof/tie-beam size) together with building age, with 32 of the 48 inputs exceeding the retention threshold. These results show that ACeBS scoring can be reliably automated and potentially condensed into a shorter instrument, providing a faster and more consistent basis for pre-disaster screening of vulnerable houses. Future work will extend the dataset across additional regions and building types, add image-based defect detection — the setting in which non-linear models are expected to outperform linear ones — and develop class-level risk mapping for decision support.

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