
AI for post-earthquake rapid damage assessment

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ABSTRACT

The rapid assessment of damage post-earthquake plays a pivotal role in emergency response, loss modelling, and decision making for building repairs and recovery. Over the past several years, significant progress has been made in utilising AI algorithms in earthquake engineering, with a focus on building seismic performance and risk assessment. This research aims to explore how AI techniques such as machine learning (ML) and deep learning (DL) and the related technologies can be used in real-world practice of rapid building damage assessment after earthquakes in New Zealand. Drawing on large sets of data of building damage from the 1994 Northridge earthquake in the USA and the 2010/11 Canterbury Earthquake Sequence (CES) in New Zealand, this research presented the ML models of building damage patterns of these two events. Then, using qualitative interviews, data was collected from a range of stakeholders in New Zealand about their insights and perspectives on incorporating these AI techniques/models into the Rapid Building Assessment (RBA) process. Findings from this research are hoped to spark conversations and actions for operationalisation of responsible AI that enables efficient building safety evaluations with reliability and rigour.

1 INTRODUCTION

Rapid damage assessment is an integral part of post-earthquake emergency response. In New Zealand, damages to the built environment owing to the 2010-2011 Canterbury Earthquake Sequence (CES) resulted in NZD 40 billion of reconstruction cost (Wood et al., 2016). More recently, Cyclone Gabrielle tore through

the east coast Hawkes Bay, causing more than NZD 2 billion in damage (Science Media Centre, 2024). Both events highlighted the impact such events can have on regional and national levels and the importance of effective disaster response procedures. As the country faces a major threat from a mega earthquake (i.e. Alpine Fault earthquake), it is important that before it occurs, this peace time “window of opportunity” can be used to examine how the building assessment protocol can be improved and effectively deployed for future events.

Similar to New Zealand, many countries follow a rapid visual screening (RVS) framework ATC-20 for rapid building safety inspection developed by the Applied Technology Council (ATC) in the United States (US) during the 1980s. This framework suggests categorisation of the damage state of buildings into three colours, green (useable), yellow (restricted access) or red (unsafe), based on visual assessment of a building’s structural components. Variations to ATC-20 were also introduced across the regions of high seismic risk, considering local contextual factors such as respective building stock, geography and seismicity (Harirchian et al., 2021).

The Ministry of Business, Innovation and Employment (MBIE) has established a set of guidelines for engineers and building inspectors for carrying out RBA assessment. These guidelines were first formulated with inputs from the NZSEE field guide (MBIE, 2014) and then updated in 2018, with the process included in the Building Act. The field guide was completely revised in 2025 and compiled into one document for all event types (MBIE, 2025).

The RBA procedure has room for improvement, which was highlighted following the 2010-2011 Canterbury Earthquake Sequence (CES), where three major issues with the process were identified: 1) on-site inspections put assessors at risk, 2) the degree of damage determined and therefore assigned placard is subject to variability across different ground teams and is highly subjective, and 3) the process is exceedingly time-consuming and resource intensive (Galloway et al., 2014; del Rey Castillo et al., 2021; Li et al., 2025a). This final point regarding the extensive time required to conduct assessment was made primarily due to the fact that 130,000 buildings post-Canterbury earthquakes were registered for rapid assessment, with each requiring a level one assessment at minimum (Khakurel et al., 2023). The sheer number of buildings assessed, combined with the fact that even the preliminary level one RBA assessment requires approximately twenty minutes for each building, underscores the scale of response required in a destructive disaster and the need for more efficient RBA practice (MBIE, 2014).

Recent advances in technologies and computing power have seen extensive research moving into the development of artificially intelligent (AI) models and systems to perform post-disaster building identification and damage classification (Koukouraki et al., 2022). Researchers attempted to identify the most reliable AI models to be used for classifying damage. For instance, the machine learning (ML) algorithm Random Forest (RF) was found to be more effective, compared with other ML models, when predicting damage classification based on tabular data derived from Christchurch RBA reports (Li et al., 2025a). When images of building damage available, the deep learning (DL) algorithm Convolutional neural network (CNN) finds favour for image-based seismic damage assessment and structural characterisation (Xie, 2025). Such AI models have gained popularity due to their capacity to improve time efficiency in standard visual assessment practice, with extensive data processing capabilities. Despite these advances demonstrated by research, there are doubts and concerns among engineering and building practitioners around the reliability and practicality of such AI techniques to improve building safety evaluation.

This research investigates the opportunities and challenges with integrating AI/ML/DL techniques into RBA protocol. It focuses on how AI models such as those for classification of building damage (Li et al., 2025a) and loss of functionality (Li et al., 2025b) can be translated into sound technical solutions to enhance inspectors’ decision making and professional judgement without compromising ethics and professional standards. The paper first presents a review of RBA protocols in selected seismic regions/countries and a

review of existing studies of AI applications in damage assessment of buildings. This is then followed by an introduction of ML models of damage patterns developed from the 1994 Northridge earthquake in the USA and the 2010/11 CES in New Zealand. Presentation and discussion of practitioners' views about where the opportunities lie and what challenges to address to integrate responsible AI in real-world building safety evaluations are provided in the end.

2 DAMAGE ASSESSMENT PROTOCOLS AND PRACTICE

Countries and regions with high seismic risk have developed formal frameworks and guidelines to evaluate damage to earthquake-affected buildings and to support decisions on access and recovery actions. This section reviews post-earthquake building damage assessment and placarding frameworks adopted in the United States, New Zealand, Japan, and Taiwan (See Table 1).

Table 1: Comparison of building damage assessment frameworks and placarding practice

	Framework	Procedure	Placarding
USA	ATC-20 Procedures for postearthquake safety evaluation of buildings	(1) Rapid evaluation (2) Detailed evaluation (3) Engineering evaluation	Green placard: (Inspected) No apparent hazard. No restriction on use or occupancy. Yellow placard: (Restricted use) Dangerous conditions exist. Entry is limited. Red placard :(Unsafe) Extreme hazard. Unsafe for occupancy or entry.
NZ	Rapid building assessment	(1) Overall damage survey (2) Rapid building assessment - Level 1 rapid assessment - Level 2 rapid assessment (3) Detailed damage evaluation	White placard: (Can be used) – Light or no damage. Yellow placard: (Restricted access) - Y1 (Restricted use to part(s)) No entry to part until risk reduced by repair or demolition. - Y2 (Use restricted to short term entry) Entry with or without supervision. Red placard: (Entry prohibited) - R1: (Entry prohibited) Significant damage - R2: (Entry prohibited) At risk from external factors such as adjacent buildings or ground failure
Japan	Guideline for post- earthquake damage evaluation and rehabilitation	(1) Quick inspection (2) Damage evaluation	Green placard (Inspected) – No or few apparent structural damage is found. Temporary use or occupancy is allowed. Yellow placard (Limited entry) - Dangerous conditions exist. Entry is limited. Red placard (Unsafe) - Remarkable danger to aftershocks exists. Entry and temporary use are not allowed.
Taiwan	Rapid-assessment Regulations for Disaster-damaged Buildings	(1) Emergency assessment (2) Preliminary assessment (3) Detailed assessment	Yellow warning placard – Dangerous conditions exist. Entry is limited. Red warning placard – Use and entry are prohibited.

2.1 USA

In 1989, the Applied Technology Council (ATC) introduced the ATC-20 framework to standardise procedures for post-earthquake building safety evaluation (ATC, 1989). Since its initial release, the framework has evolved into a family of guidance documents, most notably the ATC-20-1 “Field Manual: Post-earthquake Safety Evaluation of Buildings, Second Edition” (ATC, 2005), which is widely recognised as the de facto standard for post-earthquake building safety evaluation in the United States and internationally (Peña-Mora et al., 2008; Rossetto et al., 2010). The ATC-20 framework is intended for qualified professionals to support on-the-spot assessments and decision-making concerning the continued use and occupancy of damaged buildings.

The ATC-20 framework defines three levels of post-earthquake safety evaluation, namely, rapid evaluation, detailed evaluation, and engineering evaluation (FEMA, 2019). Also provided in the framework are standardised procedures and assessment forms for rapid and detailed evaluations. Rapid evaluation serves as an initial general assessment to quickly identify apparently safe and obviously unsafe buildings, as well as those requiring detailed evaluations or necessary use restrictions. This evaluation focuses on readily observable hazards, including (1) collapse, partial collapse, or building off foundation; (2) building or story leaning; (3) racking damage to walls, other structural damage; (4) chimney, parapet, or other falling hazard; (5) ground slope movement or cracking; and (6) other hazards (i.e., toxic spill, broken glass, fallen power).

Detailed evaluation involves a more thorough visual assessment of damaged buildings and their structural systems to resolve uncertainties identified during rapid evaluations, to determine appropriate restrictions on building use, or to establish the need for an engineering evaluation. Building inspectors are guided to systematically examine structural, non-structural, and geotechnical hazards. Outcomes of both rapid and detailed evaluations are communicated through a three-colour placarding system, whereby buildings are posted as Inspected (green placard), Restricted use (yellow placard), or Unsafe (red placard). Engineering evaluation is a follow-on professional investigation commissioned by building owners or insurers and involves detailed engineering analysis using construction drawings, damage data, and new structural calculations.

2.2 New Zealand

In New Zealand, post-earthquake building damage assessment was guided by the New Zealand Society for Earthquake Engineering (NZSEE) during the late 1990s and 2000s through a series of nationally adopted guidelines. Inspired by the ATC-20 framework, NZSEE published the “Post-Earthquake Building Safety Evaluation Procedures” in 1998 (NZSEE, 1998), followed by the “Building Safety Evaluation During a State of Emergency” in 2009 (NZSEE, 2009). Based on lessons learned from major seismic events, including the 2007 Gisborne earthquake, the 2009 Padang earthquake, and the 2010-2011 CES, these guidelines were revised in 2014 (MBIE, 2014).

The New Zealand system defines a multi-stage post-earthquake assessment process, comprising rapid impact assessment, rapid building assessment, interim use evaluation, and detailed damage evaluation. Among these, the guidance (MBIE, 2014) primarily focuses on the rapid building assessment, while interim use and detailed damage evaluations are typically undertaken by building owners and their consultants during the recovery phase. The RBA process has included flood and landslide since 2014, and there have been numerous weather event responses since 2016 Kaikoura earthquake. It has taken a while to get an appropriate focus on flooding. The field guide was completely revised in 2025 and now compiled into one document for all event types (MBIE, 2025).

Rapid building assessments involve brief visual inspections of buildings and their immediate surroundings to determine damage severity and appropriate occupancy restrictions. According to the MBIE’s latest Rapid

Building Assessment Field Guide for all event types, the rapid building assessments are categorised as Level 1 rapid assessment and Level 2 rapid assessment. Level 1 rapid building assessment involves a brief visual inspection of damage to individual buildings, and it is an external inspection of building only. Level 2 rapid assessment involves a more detailed inspection that involves both external and internal inspection of building, if the building is safe to enter. Outcomes of rapid building assessments are communicated through a colour-coded placarding system comprising white, yellow, and red placards, with five usability categories (white, yellow 1, yellow 2, red 1, and red 2) reflecting increasing damage severity and occupancy restrictions.

2.3 Japan

In Japan, post-earthquake building damage assessment is guided by the Japan Building Disaster Prevention Association (JBDPA) through the “Guideline for post-earthquake damage evaluation and rehabilitation”, originally issued in 1991 (JBDPA, 1991) and revised in 2001 and 2015 to reflect experience from major earthquakes, including the 2011 Tōhoku earthquake (JBDPA, 2015). The guideline is intended to provide engineers with a technical and quantitative basis for identifying building damage, determining appropriate post-earthquake actions, and developing rehabilitation strategies (Maeda et al., 2017; Kusunoki, 2021).

The Japanese framework adopts a two-stage assessment process, comprising quick inspection and damage evaluation. Quick inspections are conducted immediately after an earthquake to rapidly identify safe buildings and to assess potential risks. This stage relies primarily on external visual inspection of structural and foundation systems and results in the application of a three-colour placarding system, namely, Unsafe (red), Limited entry (yellow), and Inspected (green), which is broadly comparable to systems used in the United States and New Zealand. Unlike those systems, however, building placards in Japan are advisory rather than strictly enforced (Sarrafzadeh et al., 2017).

Following quick inspections, buildings may need detailed damage evaluation, as rapid screening does not provide sufficient information required for long-term occupancy decisions. Damage evaluation separately assesses the foundation and superstructure systems and integrates their results to determine an overall damage rating of each building. For reinforced concrete buildings, damage severity is quantified using the residual seismic capacity ratio (R), ranging from $R \geq 95\%$ (slight damage) to $R < 60\%$ (severe damage) or $R \approx 0$ (collapse). Buildings with $R < 95\%$ are targeted for repair and/or seismic strengthening, forming the basis for subsequent rehabilitation decisions.

2.4 Taiwan

In Taiwan, guidelines for conducting post-earthquake emergency assessments of damaged buildings were first issued by the Construction and Planning Agency, Ministry of the Interior (CPAMI), in 2009 largely in response to the devastating 1999 Chi-Chi Earthquake and subsequently revised in 2014 (CPAMI, 2014; Cheng et al., 2023). These guidelines establish a standardised procedure for rapidly evaluating building safety following earthquakes, with the primary objective of identifying hazardous structures and preventing life-safety risks (Chiu et al., 2022).

Under the guidelines, inspectors first evaluate the damage levels of key structural components based on the structural site inspection. Meanwhile, the potential impacts of non-structural elements and geotechnical conditions are also considered in the safety assessment. Accordingly, the overall damage condition of the building can be determined. Buildings assessed as having severe structural damage are issued red warning placards, indicating prohibited use; while buildings presenting other safety concerns, such as falling or collapsing hazards, are issued yellow warning placards, indicating restricted use. The results of emergency assessments are formally reported to local governments, which notify building owners in writing and require corrective actions within a specified timeframe. Removal of warning placards is permitted only after building

owners provide evidence of improvement or reinforcement, which requires a preliminary or detailed seismic assessment.

3 AI APPLICATIONS IN BUILDING DAMAGE ASSESSMENT

Advances in imagery technologies and data science have seen a multitude of visual techniques showing promise for applications in building identification and damage state classification (Koukouraki et al., 2022). Remote sensing, comprising technologies such as satellite imagery, aerial surveys, radar and advanced sensors, capture information about the earth's surface from distance and has been instrumental to manual building damage assessment conducted by ground teams (Gu et al., 2024). In some cases, data capture technologies using drones or 3D scanners can reduce the requirement for in-situ assessment and allow for engineering analysis of a structure without human presence at the scene. One example is that high-resolution optical images were used for damage assessment in some hard-to-reach areas following the 2008 Wenchuan earthquake (Gu et al., 2024). The damage images from previous events can also be used to validate damage assessment results performed by ground inspectors. For instance, Ogawa & Yamazaki (2000) used stereoscopic aerial photographs, annotated building damage from the 1995 Kobe earthquake and achieved accuracy of 70% compared to on-site evaluations. It needs to be noted that building data captured through remote sensing often require significant human effort to process and professional input to interpret. The rise of AI and the superior computer power have now provided computing capabilities for remote sensing to overcome this shortfall.

AI is a range of technologies aimed at simulating human intelligence. Machine Learning (ML) is a subset of AI in which algorithms allow systems to learn from data over time without being explicitly programmed (Bhadauria, 2024). In earthquake engineering, ML can tackle complex, multi-faceted problems efficiently, handle uncertainty and aid decision making, giving rise to its application across a multitude of domains including in damage assessment (Xie et al., 2020). Much literature presented in reviews on ML for building damage assessment focuses on techniques such as supervised learning, unsupervised learning and deep learning. Compared to supervised learning algorithms which train on labelled datasets, projecting input data to a label, the unsupervised algorithms can infer or recognise patterns within a given dataset without prior indication to label (Bhadauria, 2024). ML algorithms, such as Support Vector Machine (SVM), Decision Trees (DT), Random Forest (RF), K-Nearest Neighbour (KNN) and Extreme Gradient Boost (XGB), are effective in training data collected from past disasters to generate predictive models (Tapeh and Naser, 2023). In training building damage data from 2010/11 Canterbury earthquakes, Li et al. (2025a) compared six ML algorithms and concluded that the RF model performed best at classifying building damage placards.

Deep Learning (DL) is another sub-set of ML and consists of multi-layer artificial neural networks (ANN), termed “deep” due to the number of hidden layers between input and output. It is highly effective for completing classification, identification and segmentation tasks, owing to the additional layers allowing DL algorithms to handle increasingly complex data (Sony et al., 2021; Jia and Ye, 2023). DL methods can learn and extract low-to-high level features from unlabelled input such as image data, which reduces the need for user intervention or manual feature extraction (Matin and Pradhan, 2022). Convolutional Neural Networks (CNN), a class of DL methods has gained popularity due to their capability to perform segmentation, detection and classification for building damage assessment (Xie, 2025). Other notable deep learning architectures that would add value to building seismic performance research include Recurrent Neural Networks (RNN), Generative Adversarial Networks (GAN), Multi-Layer Perceptron (MLP), and Transfer Learning (TL), as they can enhance model capability when there is a lack of high-quality data (Xie, 2025).

Several comprehensive reviews of AI applications in building damage assessment have been published in recent years. For instance, Al Shafian and Hu (2024) undertook a decadal bibliometric review of ML methodologies for post-disaster building damage assessment and reconnaissance and summarised the

landscape of emerging technologies and areas for future study. Bhadauria (2024) examined AI and ML tools for earthquake damage assessment and retrofitting, with a focus on pre-event analysis and improving structural resilience. Xie et al. (2020) explored the promise of ML in the broader field of earthquake engineering, in building functionality and safety assessment. Jia and Ye (2023) focused specifically on DL within earthquake disaster assessment. Similarly, a recent review by Xie (2025) discussed methodological advances of different DL techniques in earthquake engineering.

Tapeh and Naser (2023) conducted a scientometric review of AI techniques and their applications in each structural engineering sub-discipline, including material optimisation, structural health monitoring (SHM) and wind, fire and earthquake resistance, and briefly touched on applications in building damage assessment. Within the DL application domain, Sony et al. (2021) performed a systematic review of CNNs for structural condition assessment and primarily discussed applicability to SHM. Gu et al. (2024) reported the advances in rapid damage detection methods using remote sensing, including a discussion of the evolution of damage recognition methods and a case study comparing seven AI models for classifying remote sensing images from the 2024 Noto Peninsula and 2023 Türkiye earthquake. Chinmayi et al. (2025) reviewed remote sensing techniques for earthquake reconnaissance and highlighted the promise of a method of using DL and remote sensing to carry out building damage assessment.

The limitations and areas for improvement with AI techniques discussed in the literature included data quality and availability, model transferability and generalisability, and ethical considerations around interpretability and transparency of model outputs (Xie et al., 2020; Xie, 2025; Al Shafian and Hu, 2024). Some studies pointed multi-modal data fusion as a direction for future research, which involves integrating heterogeneous data from numerous sources such as satellite, aerial or UAV/drone imagery, radar, and LiDAR pre- and post-disaster into a common model, based on sources of high-quality and availability (e.g. Adriano, 2021; Li et al, 2025a).

Literature highlighted the need for quantifying uncertainties to advance AI applications in performance-based earthquake engineering (Xie, 2025). Chang-Richards et al. (2025) also emphasised the importance of having a global benchmark dataset and a standardised data collection and reporting framework/infrastructure so that capability of AI techniques can be leveraged across different regions, disaster types and structural compositions while retaining high levels of accuracy. Finally, most existing literature is focused on single AI techniques, and there is little discussion on how to practically implement and operationalise AI within building safety evaluation frameworks by emergency responders or building inspectors, and the opportunities and challenges of integration.

4 MACHINE LEARNING (ML) MODELS FOR DAMAGE PATTERNS FROM PAST EARTHQUAKES

4.1 1994 Northridge earthquake

Based on robust performance of the Random Forest (RF) examined under the context of New Zealand (Li et al., 2025a; Li et al., 2025b), it was employed to predict posted damage placards (R, Y, R, CERT, PERMIT Posted) using empirical data from 1994 Northridge earthquake.

The dataset comprises 134,613 buildings with posted damage placards, as indicated in Figure 1, of which the majority are classified as GREEN (106,946; 79.45%), followed by PERMIT (22,220; 16.51%). Higher-severity categories are comparatively scarce, with 4,041 buildings labelled CERT (3.00%), 1,338 labelled YELLOW (0.99%), and only 68 labelled RED (0.05%), indicating a strongly imbalanced distribution of observed damage outcomes. In terms of occupancy, the building stock is mainly residential (R: 127,293; 94.56%), with a smaller commercial subset (C: 6,991; 5.19%) and a marginal mixed-use class (M: 335;

0.25%). A single record is coded as “X”, which is likely attributable coding inconsistency and is removed from the data analysis.

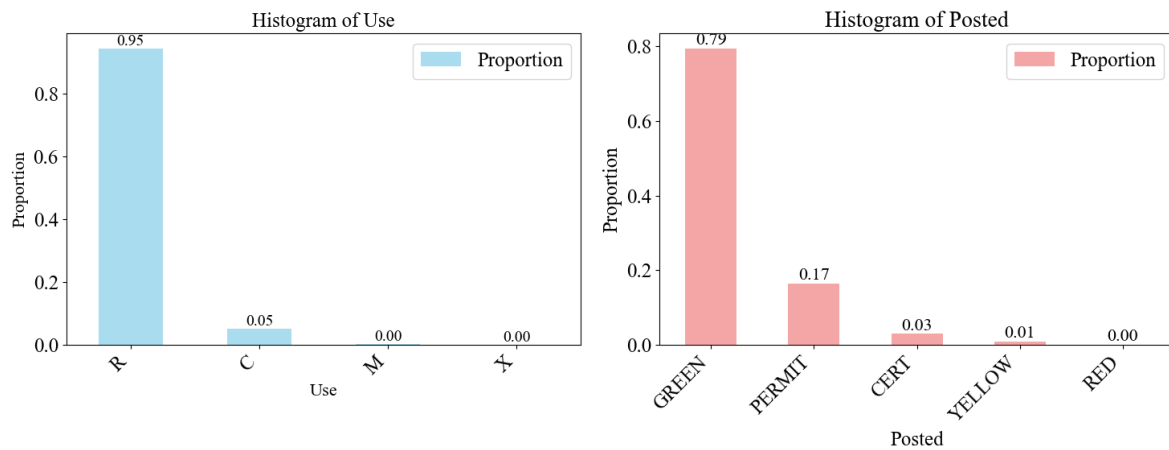


Figure 1: Histogram for building use and posted placards

The modelling dataset is constructed by selecting a structured set of address and context descriptors, building attributes, and impact-related indicators as input features. Specifically, the inputs include (i) record and address identifiers (Rec#, Street#, Street Name, Unit#) and street-location descriptors (Range, Fraction, Direction, street Type); (ii) administrative context (Council District); (iii) building function and occupancy information (Use and Occ); (iv) building stock and physical characteristics (estimated dwelling units, number of storeys, construction type, and an approximate building size; and (v) impact/response-related variables that may encode post-event operational decisions (Vacate Building and Permit Required). Collectively, these features provide a mixed-type predictor set spanning categorical, numeric, and free-text-derived variables, with explicit acknowledgement that several fields exhibit substantial missingness or heterogeneous coding and therefore require standardisation prior to modelling. The output feature is defined as the posted damage placard status, treated as a five-class categorical label: GREEN, YELLOW, RED, CERT, and PERMIT. This outcome variable operationalises the post-event assessment state assigned to each building and serves as the target for supervised classification.

A grid search for hyperparameter tuning, in conjunction with stratified 5-fold cross-validation, is performed to identify the optimal configuration for the RF model. The hyperparameter estimated is the number of estimators (n-estimators), ranging from 50 to 100. The dataset was partitioned into 80% for training and 20% for testing, maximising the data available for model fitting while retaining a sufficiently large hold-out set for independent performance assessment. The performance of the RF model under different hyperparameter configurations is detailed in Table 2 below.

Table 2: Performance of the RF model under different configurations

n_estimators	Accuracy	Precision	Recall	F1-Score
50	0.9447	0.9441	0.9447	0.9432
60	0.9364	0.9362	0.9364	0.9351
70	0.9342	0.9340	0.9342	0.9329
80	0.9345	0.9343	0.9345	0.9332
90	0.9373	0.9370	0.9373	0.9360
100	0.9354	0.9352	0.9354	0.9341

Based on the results presented in Table 2, the optimal hyperparameter configuration is selected using the average performance across accuracy, precision, recall, and F1-score. On this basis, the optimal number of estimators (n_estimators) is 50. The resulting confusion matrix is shown in Figure 2.

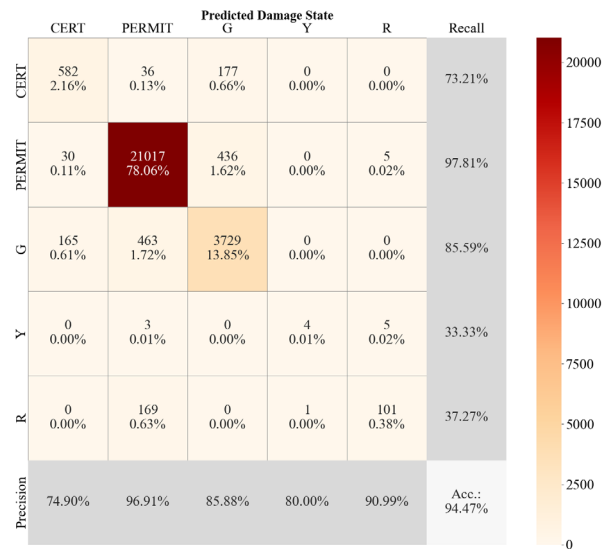


Figure 2: The confusion matrix of the RF model on the testing set

The results of feature importance analysis are shown in Figure 3, indicating that placard classification is governed primarily by post-event disruption and regulatory response, and spatially structured exposure context. Variables that encode disruption and official decision-making, including Est Units Vacated, Vacate Building, and Permit Required, are consistently influential, which accords with the engineering role of placarding as an operational determination of habitability and permissible access. Location-linked attributes, notably Street Name, Street#, and Council District, also exhibit strong influence, plausibly reflecting spatial heterogeneity in seismic demand and local site response, including neighbourhood-scale variation in shaking intensity and liquefaction susceptibility, together with correlated differences in building stock and assessment practice. By contrast, structural proxies such as Stories, Construction Type, and Approximate size provide incremental discrimination by representing first-order differences in building configuration, structural system, and scale that can shape damage development and subsequent safety judgement.

The apparent prominence of identifier-like fields, such as Rec# and address identifiers, is best interpreted as evidence that location exerts strong control on placard outcomes in this dataset. Although these variables are not mechanistic predictors, they index where buildings sit within the urban fabric and can therefore proxy spatial variability in seismic demand and site response, including neighbourhood-scale differences in shaking intensity, soil amplification, and liquefaction susceptibility, as well as correlated patterns in building stock and inspection practice. This interpretation is engineering-plausible, but it also motivates leakage-aware assessment: spatially blocked validation and ablation tests that remove identifier-like fields can help distinguish genuine location-driven hazard signals from database or survey artefacts.

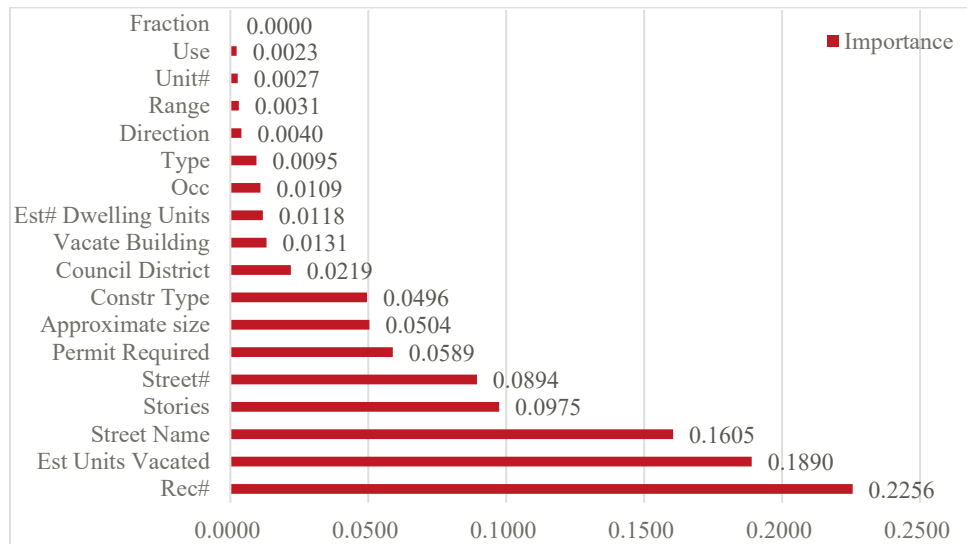


Figure 3: Results of feature importance analysis

4.2 2010/11 Canterbury earthquake sequence

The detailed procedures for applying the RF model to predict rapid building assessment (RBA) placards in the New Zealand context are reported in Li et al. (2025a). The distributions of building damage and occupancy are presented in Figure 4. The RBA dataset comprises 6,078 buildings. Given the rapid and simplified nature of RA1 and RA2 assessments, the RBA records exhibit substantial incompleteness across several candidate predictors. To support model robustness, an 80% data-completeness threshold was applied during feature selection, resulting in 13 input features being retained for the RBA-based analyses.

The selected inputs span three conceptual domains. Building and configuration descriptors include storeys above ground, storeys below ground, ground floor split, floor footprint area (approx.), strengthening present, and building use. Lateral system information is represented by lateral system along and lateral system across. Seismic-demand and site-hazard indicators comprise MMI, PGA, Sa(0.3), Sa(1), and liquefaction susceptibility. The output follows the RBA damage-categorisation protocol, with model targets defined as the posted placard outcomes: Green, Yellow, and Red.

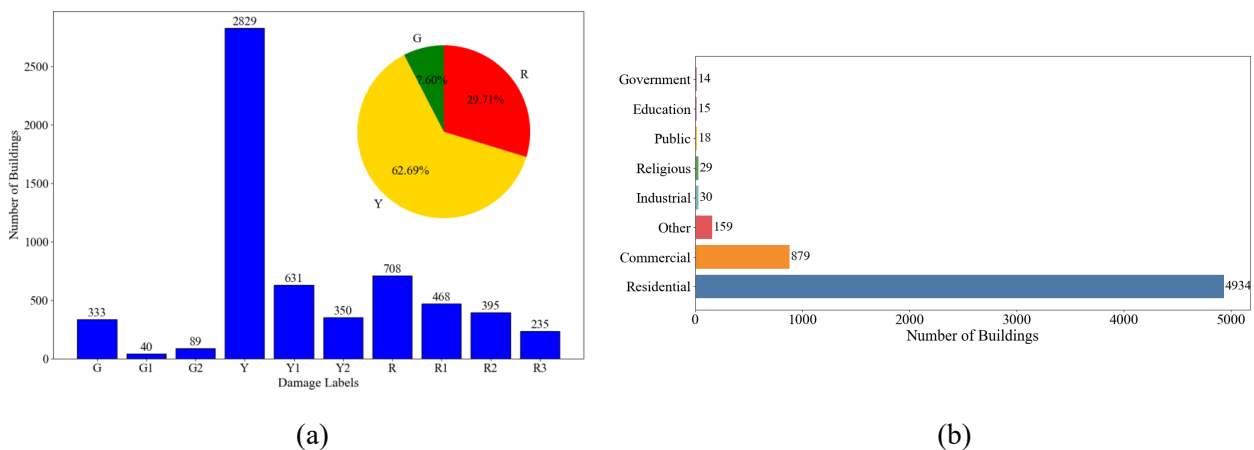


Figure 4: Distribution of (a) damage placards in the RBA database and (b) building occupancy

Following a grid search with stratified five-fold cross-validation, the optimal RF configuration is identified as $n_estimators = 60$. Feature importance is then examined under this configuration to elucidate the dominant predictors of placard classification (see Figure 5). Seismic intensity measures, notably Sa(0.3), PGA, and

Sa(1), attain the highest importance scores, with floor footprint area and MMI forming a secondary tier. In contrast, building configuration variables (e.g., storeys above ground), geotechnical hazard indicators (e.g., liquefaction susceptibility), and structural or functional descriptors (e.g., lateral systems and building use) contribute more modestly to the model's predictions.

The ranking is physically consistent with earthquake engineering principles. PGA and spectral accelerations at short and intermediate periods (Sa(0.3) and Sa(1)) characterise both the amplitude and the period-dependent content of ground motion, thereby governing inertial demand and the associated dynamic response that drives damage. The influence of floor footprint area is similarly interpretable as a proxy for structural scale and mass distribution; larger buildings tend to experience higher aggregate seismic demand and more spatially heterogeneous response, which can increase the likelihood of extensive damage under strong shaking.

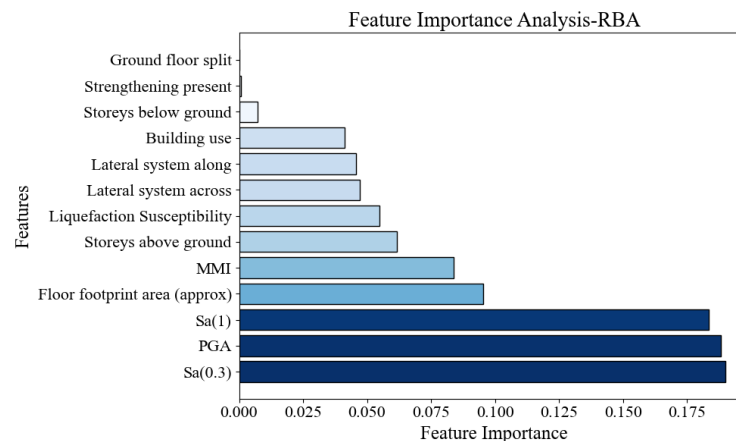


Figure 5: Results of feature importance analysis for the RBA database

5 THE OPPORTUNITIES AND CHALLENGES OF AI-AIDED RBA FRAMEWORK DEVELOPMENT

Semi-structured interviews were conducted between September and October 2025 with seven New Zealand prominent professionals and RBA experts to gain insights into the feasibility of AI-aided RBA practice in New Zealand. Three of the seven interviewed are from the government agencies with a profile of building emergency management. Four are practising engineers who had significant experience in RBA for the Canterbury or Kaikoura earthquakes. The interviews were designed to capture information about 1) issues observed and improvement areas within the current RBA framework; 2) challenges regarding the creation and implementation of an AI-aided damage assessment framework; and 3) opportunities for AI in RBA practice. This section presents the discussion of interview results and the implications.

5.1 Operationalising AI-aided RBA in New Zealand: Challenges and opportunities

5.1.1 Areas for improvement

When asked to identify issues within the RBA framework, and where improvements can be made, one participant from a Territorial Authority (TA) suggested that for RBA to be effective, flexibility must be maintained. Moreover, two participants who are practising engineers highlighted that ground inspection is restricted by time, and despite having guidelines in place, often struggles with consistency due to time constraints.

5.1.2 Challenges

Through interviews, various challenges around the integration of AI in rapid damage assessment post-disaster were identified. First, a significant issue was the availability of remote sensing images as input data to AI

models. In a major event, such as the 2011 Christchurch earthquakes, essential services like Wi-Fi and cell phone reception may not be available. This would mean that remote sensing technologies such as satellite imagery and LiDAR may not be available during this downtime. Similarly, another participant (P4) highlighted that the AI models' reliance on mobile data networks would pose issues for RBA in rural areas where access to mobile data is limited.

Another significant challenge identified was the cost and time required to implement AI modules and methodologies. Participants identified that building inspection teams need to be retrained to be AI competent. This would take a large amount of time and result in significant costs. The purchase/creation of AI models, and creation of new frameworks also require significant time, energy and money. Moreover, one participant warned against the use of AI to standardise frameworks, stating that if the framework is turned into a “checkbox activity”, it limits judgement, in a case-by-case basis, leading to inaccurate results and classifications. Another participant emphasised that one of the biggest factors that contributes to the success of an RBA process is the flexibility of the process, thus suggesting that AI models cannot replace the RBA framework, but should be used as supplementary tools.

One concern reported is the use of AI-based predictive models to adjust insurance premiums. An interviewee suggested that if insurance companies were to obtain these predictive models, they might use them as an ‘excuse’ to increase premiums, creating a significant ethical dilemma. Additionally, participants raised concerns about the accuracy and training of the models. They suggested that if a model were only trained using a specific disaster, such as the 2010/11 Canterbury earthquakes, it may not necessarily be applicable to other disasters and regions outside Christchurch.

5.1.3 Opportunities

A common theme discussed in the interviews was the opportunity to pair AI models with the current ground inspection teams. Five participants identified the opportunity to use remote sensing technologies for triage purposes. This approach would utilise AI-based remote sensing or imagery to identify areas where greater damage has occurred, this would enable a more effective allocation of resources. It would particularly benefit Māori, Pasifika, and individuals from low socio-economic areas. From their experience, the interviewees found that these groups did not particularly trust the public agencies (councils and governments), hence were less likely to report damage to their properties. One example reported by two participants having a role in government was that in the wake of the Auckland Anniversary floods, there were comparatively few calls reporting damages, coming from South Auckland, which is a generally low socio-economic area, when compared to the amount of damage identified upon further inspection. By using remote sensing for triage purposes post-disaster, this issue can be avoided, and these areas can receive the required remediation within a more appropriate timeframe.

Another key opportunity identified was the use of AI for dictation and reporting purposes. Three participants identified that a key problem with RBA efficiency was the time it takes to fill out each form. They suggested that AI could be used alongside dictation to automatically fill these reports by inputting the relevant data into the correct field in correspondence with the inspector’s speaking. Likewise, all interviewees suggested that AI models could be used to assist with administrative tasks during rapid damage assessment. These participants identified that a contributing factor to the inefficiency of RBA process was due to having to enter basic information of each building which inspectors are viewing, such as building address, number of stories, lateral loading structure and footprint area. They suggested the possibility of developing AI models to automatically fill in background information about the building being inspected, which will significantly reduce the inspection time.

One participant suggested the potential use of AI tools as a sense-checking technology. Inspectors could use assessment results from AI tools to retroactively ensure that they have correctly identified the damage level of a building. Or inspectors could use AI analysis outputs to identify potential issues they may have missed. This would also be beneficial for the moderators of rapid damage assessment. Additionally, this participant identified that AI could be used as a pre-analysis tool to identify potential areas for concern through images inputted by the inspector.

Two participants suggested that AI could be used as a training tool for new ground team to use. This requires the development of AI-based virtual reality (VR) assessor training to immerse assessors in realistic scenarios

they may encounter in the field. Scenario generation could be AI-driven, simulating post-disaster situations, where the trainees would then decide upon an appropriate placard and justify their decision. The AI system could then provide feedback to assessors, while adaptively learning from human judgement as indicators of damage.

5.2 Implications and next steps

The results of literature review and semi-structured interviews collectively provide a comprehensive understanding of the current state of AI applications in the RBA space, both internationally and within New Zealand. When combined, they reveal consistent themes regarding both the potential benefits of implementing AI for building damage/safety evaluation, as well as the barriers that hinder its operational use. Issues such as limited data availability, high development and training costs and concerns about ethics and model reliability highlight that although there is a promise regarding the use of AI in improving the speed and consistency of damage assessments. Until these systemic and governance barriers are addressed, AI is likely to remain a supporting tool rather than a fully integrated component of New Zealand's RBA framework.

The perceived role of AI in RBA is clear, that it should serve as a supporting tool, rather than replacing the professional judgement and on-site expertise of inspectors. ML-supported tools can be valuable for rapid triage within a human-in-the-loop framework. Rather than predicting such granular placard categories, it may be more appropriate to adopt a two-stage model that classifies buildings as severe versus non-severe. Buildings predicted as severe would be flagged for prompt engineering review. A non-severe prediction would not imply that a building is safe; rather, it would support prioritisation, deployment decisions, and resource planning.

The interviews align with previous studies that remote sensing technologies, such as satellite and UAV imagery, are highlighted as key uses of AI in RBA protocols for detecting and classifying damage for buildings at a large scale (Gu et al., 2024; Chinmayi et al., 2025). One promising area is the implementation of remote sensing-based AI models for rapid impact assessment (RIA) and initial triaging efforts, able to evaluate area-wide damage and enhance the information available to decision makers. Such a tool can also be integrated with emergency response callout and social media data to provide improved situational clarity.

Compared to full automation of damage classification in literature, where the New Zealand practitioners see the most value AI could add are automating data entry, preliminary screening and identification of damaged areas to reduce inspection time and administrative burden, without disrupting the human-led decision process. These improvements would align with the findings of the literature review, which suggested that time consuming of ground building inspections was one of the biggest disadvantages of the current RBA system (Galloway et al., 2014; Brunsdon, 2012).

Another key factor that needs to be considered when potentially applying AI into RBA frameworks is the importance of flexibility. Research findings highlighted that the flexibility of RBA protocols has been a contributing factor to their success, thus in future if AI is to be implemented into the guidelines, it needs to be in a way where changes can be made quickly and effectively to ensure that the guideline remains flexible. To maintain this flexibility, it is paramount that at this stage that AI tools shall be implemented independently of the current RBA framework to allow the RBA process to evolve with technological improvements.

Despite the potential of AI tools developed by Li et al. (2025a) to decrease subjectivity and improve accuracy of assessment in many situations, ethical and legal integration of such tools would require significant investigation and development. The benefits gained from having assessors on-site during the process for situational awareness and community engagement outweigh the benefits of full AI-automated remote assessment. Galloway et al. (2014) and Brunsdon (2012) stressed the importance of ground inspectors in the response process and emphasised that they are not only important for damage assessment purposes, but also for wellbeing, and interpersonal connection post disaster.

Despite these alignments, the interview results reveal several practical limitations that are largely absent from the literature. The interviews revealed that post disaster data availability and network reliability present major operational issues and barriers for AI implementation. In large events such as the 2011 Christchurch earthquakes, widespread power outages and mobile data blackouts likely hinder access to real-time imagery or assessment in rural remote areas. These conditions were rarely discussed in literature.

The implications of this research are found in guidance for future policy and framework development in New Zealand, and the exploration of AI for RBA purposes globally. To implement some of the findings and suggestions of this research, developing a national building database and an AI-aided dictation tool can be an immediate next step. The plausibility of VR assessor training, and revision of training procedures to incorporate various disaster scenarios can also be pilot projects for trial. In the RBA practice space, while there is much focus on flood events, thinking about how a major multi-centre earthquake operation would be handled deserves top priority.

6 CONCLUSIONS

Having identified the need for more efficient rapid building evaluation practice in New Zealand post-disaster, this research qualitatively assessed the feasibility of operationalising an AI-aided RBA framework in New Zealand and the possibility of an AI damage classification decision-support tool. Although AI-based RBA models demonstrate considerable technical potential, their implementation in New Zealand's frameworks are limited by several considerations. While acknowledging AI's potential, practitioners consistently viewed that current AI technology available is best used for triage, resource allocation and validation of inspector's assessment rather than replacing existing human-led building inspections. Future feasible integration depends on the development of New Zealand specific building datasets and maintaining the flexibility of professional judgement that guide the current RBA process. The insights developed from this research help to provide a conceptual foundation for future research and policy development for the implementation of AI within the RBA process.

This research adds to the existing body of knowledge by investigating the practicality of the acceptance and application of AI/ML/DL tools in RBA as damage classification and placarding tools. Beyond developing ethical and legal policies to support an AI-based decision support tool, establishing data collection and reporting infrastructure is essential for enhancing capabilities of AI models and for improving communication of model output. The development of a global standardised building information model or digital twins with accompanying database could help close the gap to practical application of such a tool. This could be achieved through future research to develop an image-based algorithm to quickly identify information about a structure, or, with its continued development, integration of AI with a nationwide building database, where information about each building could be easily accessed and annotated with a QR code.

Future research should prioritise the development and testing of simple, decision-support oriented AI tools that can be used to enhance New Zealand's rapid damage assessment protocol without major framework changes. Studies should focus on the application of generative AI systems for rapid data analysis, as well as the development of automated data entry models. Additionally, further work should investigate and validate the transferability of existing AI models across hazards and geographical locations.

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