

Machine Learning Applications in Geotechnical Earthquake Engineering: Progress, Gaps, and Opportunities

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ABSTRACT

The rise of data capture and storage capabilities have led to greater data granularity and sharing of data sets in geotechnical earthquake engineering. This broader shift to big data requires ways to process and extract value from it and is aided by the progress in methodologies from the computer science domain and advancements in computer hardware capabilities. General machine learning (ML) models typically receive a set of input parameters and run them through an algorithm to gain outputs with no constraints on the parameters or algorithm process. Three topic areas of ML applications in geotechnical earthquake engineering are reviewed and summarized in this paper: seismic response, liquefaction triggering analysis, and performance-based assessments (lateral displacements and settlement analysis). The current progress of ML is summarized, while the challenges and potential in adopting such approaches are addressed.

INTRODUCTION

The discipline of geotechnical earthquake engineering encompasses all aspects leading up to and including the seismic-induced failures of geosystems as well as their mitigation. Depending on the system studied, earthquake hazards can be classified as liquefaction triggering, settlements, displacements, accelerations, etc. Various approaches have been developed over the years that quantify earthquake hazards and correlate them to the imposed demands at various scales ranging from empirical and semi-empirical to analytical and numerical methods. Most recently, Machine learning (ML) as a subset of Artificial Intelligence (AI) has been increasingly utilized in geotechnical earthquake engineering towards processing of large amounts of data using specialized algorithms as well as more efficiently extracting value from large bodies of data. This is both due to the development of ML approaches as well as the rapidly increasing availability of data. Advances in sensor technology offer a constant stream of experimental, numerical, and case history data that must be efficiently parsed. Furthermore, data sharing hubs that have been promoting the efficient and permanent curation of datasets (e.g., Natural Hazards Engineering Research Infrastructure (NHERI) DesignSafe Cyberinfrastructure DesignSafe, the Next Generation Liquefaction (NGL) Database, and the New Zealand Geotechnical Database) have been facilitating an unprecedented access to data.

This paper presents a literature review of research efforts that have used ML in the context of geotechnical earthquake engineering. The aim of this work is to critically summarize the methods used as well as identify gaps and challenges towards the future of this rapidly developing subdiscipline. Papers were selected by verifying the combined usage of a ML algorithm and an application in geotechnical earthquake engineering. ML on ground motions and

structural components (e.g., pipelines) were not included in this review as the focus is on geosystem responses, but ground motions as an input parameter have been included. The datasets featured in the papers reviewed were split into four different types: field test, lab test, earthquake, and simulated data. Field test data refers to in-situ field tests such as cone penetration tests (CPT). Lab test data refers to tests performed in a laboratory setting such as triaxial soil tests. Earthquake data refers to earthquake event liquefaction records or ground motion records. Simulated datasets refer to numerical simulations typically performed in a finite element or finite difference platform. Figure 1 illustrates the distribution of these data sources and shows that most geotechnical earthquake engineering ML papers comprise of earthquake event records and field test data.

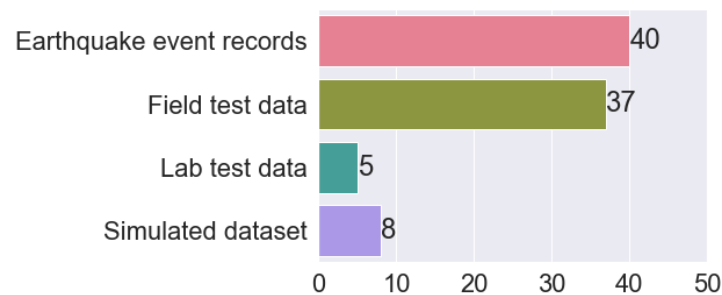


Figure 1: Distribution of ML dataset types for geotechnical earthquake engineering

A brief review of ML algorithms and the separation of the different algorithm types into nine separate subsets are presented. Four areas of geotechnical earthquake engineering that have seen application of ML are then covered: seismic response, liquefaction analysis, lateral displacements, and settlement analysis. Identified challenges and the potential for adopting ML in the context of the previous papers are addressed, and suggestions for future geotechnical earthquake engineering research using ML are provided.

MACHINE LEARNING ALGORITHMS

ML uses algorithms that learn from data to allow computers to find hidden patterns without being explicitly programmed where to look. It can handle large datasets and explore multiple high-dimensional connections not visible otherwise. The product is a response function that maps relationships and identifies patterns between independent and dependent features but does not necessarily explain the algorithm's operations. Nine broad types of ML algorithms were identified in the collected and reviewed papers. These constitute only a subset of overall available and constantly growing ML algorithms: (i) basic regression consists of most types of straightforward regression such as linear or logistic regression in which the product is an easily interpretable formula; (ii) bayesian algorithms consist of versions of other algorithms that have incorporated Bayesian priors and posteriors, or algorithms such as Naïve Bayes that rely on strong independence assumptions between variables; (iii) boosting assembles several weak learners into a strong learner and consists of bagging and boosting algorithms that are explicitly labeled as such (e.g., adaptive boosting AdaBoost or eXtreme gradient boosting XGBoost); (iv) evolutionary algorithms are often modeled off biological behavior such as bee colonies (Artificial Bee Colony) or grey wolves (Grey Wolf Optimizer). Game theory is also a subset of

evolutionary algorithms that has the algorithm compete against itself to find the optimal solution; (v) forest-based algorithms consist of Random Forest algorithms and similar iterations of it; (vi) interpolation consists of algorithms that focus on bridging datapoints with new unknowns such as case-based reasoning (CBR) which requires previous similar knowledge of different cases to extrapolate from to a new case. K-Nearest Neighbors (KNN) and kriging are also included in this subset; (vii) neural networks (NN) imitate neural pathways in a human's brain with layers of neurons that the data passes through towards prediction. The simplest version is an Artificial Neural Network (ANN) that branches into specialized types of NNs such as Convolutional Neural Network (CNN) or Long Short-Term Memory (LSTM) algorithms. By increasing the number of neuron layers beyond one or two, the algorithm can be termed as a deep learning network instead which requires larger datasets for training; (viii) support vectors consist of choosing a subset of data points to act as the “support” for regression instead of the entire dataset. Support vector machines (SVM) and support vector classification (SVC) are examples of algorithms in this subset; (ix) trees consist of the most basic decision tree that can be done by hand and functions off branching at a variable with differing probabilities to gradient boosted regression trees (GBRT).

Figure 2 shows that the distribution of algorithms used in geotechnical earthquake engineering applications varies. Geotechnical earthquake engineering often uses NN algorithms as research questions often deal with input parameters that are not fully known, such as soil parameters, which makes basic regression harder to perform as input parameters and relationships must be pre-specified. NNs can explore parameter relationships without prior assumptions and are thus preferred for geotechnical earthquake engineering applications.

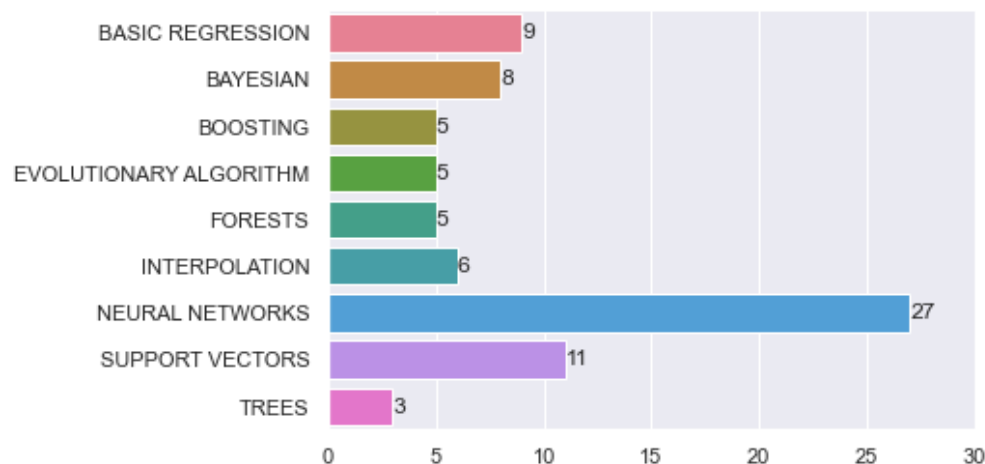


Figure 2: Distribution of ML algorithms used in geotechnical earthquake engineering

Physics-guided machine learning (PGML) is a subset of ML that focuses on incorporating physics-based constraints on the ML algorithms and can be incorporated via adjustment of the algorithm loss functions. A comprehensive literature review (Vadyla et al. 2022) covering some applications of PGML in civil engineering is available to explore approaches outside of geotechnical earthquake engineering alone.

One challenge with using ML algorithms is the issue of interpretability, but several methods have been developed to solve this issue. The most straightforward interpretation method is to

translate algorithm outputs to an equivalent equation. Another method is to translate output ranges to a series of design charts. Naturally, the ability to directly interpret the output as an equation is easier when the algorithm already works on an interpretable set of equations as is the case in basic regression techniques as opposed to NNs. When using tree-based methods, such as decision trees, the results are also easily interpretable as the algorithm mimics hand-drawn decision trees and each branch explains the choices behind it. Assemblages of decision trees such as random forests also have feature importance on hand, which is a step above decision tree interpretability. SHAP (Shapley Additive exPlanations) is another technique to interpret the results of a ML model and utilizes Shapley values to calculate the contribution of each input parameter to an output parameter. It can be utilized for more difficult to interpret models beyond basic regression such as ANN and XGBoost.

GEOTECHNICAL EARTHQUAKE ENGINEERING APPLICATIONS

Categories were identified by the main aim of the research paper reviewed: seismic response, liquefaction triggering analysis, and performance-based assessments (lateral displacements and settlement analysis). Figure 3 shows the distribution of papers within the topic areas.

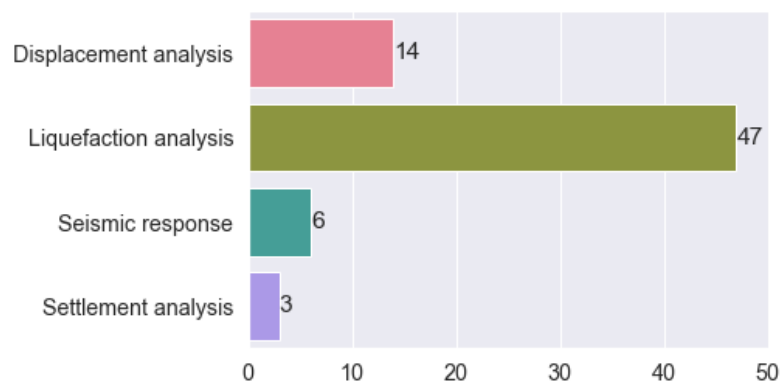


Figure 3: Paper distribution in identified topics

Seismic response

The ability to predict seismic response in terms of specific metrics (e.g., Peak Ground Acceleration PGA) or a time history overall has been explored with several different algorithms and input parameters. Automated ground motion screening using ANNs has been proposed by Bellagamba et al. (2019) to curate the increasing amounts of ground motion data available from sensors. Fayaz and Galasso (2022) utilized a deep neural network (DNN) and the first three seconds of ground motions after P-wave detection to estimate the acceleration response spectrum (Sa(T)) of the expected on-site ground motion waveforms with 85% accuracy. For the prediction of a soil deposit's response, Tsai and Hashash (2008) developed a framework that predicts ground response using ANN-based self-learning simulations (SelfSim) on downhole array data to develop the constitutive response of the soil. Based on recorded ground motions and a range of dimensional variables, Somala et al. (2021) predicted PGA and PGV for the New Zealand (NZ) area with SHAP interpretation using a variety of ML techniques. Tombari and Stefanini

(2019) explored the effect of soil parameter uncertainty on the prediction of surface ground motions and PGA using evolutionary algorithms and fuzzy logic Gaussian processes.

Liquefaction Triggering Analysis

All aspects of earthquake-induced liquefaction have been proven challenging to capture with simple linear regression equations due to the unknown interactive effects of input variables. ML algorithms often remove this constraint and have shown promise in predicting liquefaction as well. Starting with just liquefaction prediction models that cover only one soil type, Ramakrishnan et al. (2008) used ANN to predict the liquefaction susceptibility of unconsolidated sediments. To predict the potential of liquefaction in sandy soils, Pirhadi et al. (2018) used ANN with Monte Carlo simulations to capture the uncertainty in soil parameters from CPT data. Juang and Chen (1999) and Goh (1996) also used ANN to evaluate the liquefaction potential in sandy soils by using CPT data with results equivalent to that of conventional evaluation methods. Rezanian et al. (2010) introduced another approach to evaluating sandy soil liquefaction potential using evolutionary algorithms on CPT data. Roberts and Engin (2019) used Case-Based Reasoning (CBR) to predict the liquefaction potential of natural deposits with CPT data in NZ. Layers prone to liquefaction were identified and the comparison with currently used CPT-based liquefaction triggering procedures showed that the CBR approach was equivalent. Wang et al. (2017) also identified liquefiable soil layers and thicknesses from CPT data with Monte Carlo simulations.

ML algorithms have also been used to encompass more than just one type of soil, often using soil behavior types (SBTs). A BPNN model was also introduced by Eldin Ali and Najjar (1998) who used SBT data to predict soil liquefaction potential and outperformed current approaches at the time. Goh (1994) used a back-propagation neural network (BPNN) to analyze liquefaction with SPT data which was shown to be more reliable than the Seed et al. (1985) simplified procedure. Zhang et al. (2020) constructed a constrained BPNN (C-BPNN) model with SPT data for liquefaction assessment and incorporated known liquefaction triggering knowledge as well as empirical relationships which markedly improved predictions yielding one of the first examples of PGML in liquefaction triggering analyses. Zhao et al. (2021) used a hybrid ML model termed particle swarm optimization-kernel extreme learning machine (PSO-KELM) to also evaluate soil liquefaction potential. The results were shown to be better than other ML methods, showing promise in combining algorithms together for specific applications such as liquefaction. Hu and Liu (2020) also used SPT data to assess liquefaction potential with a variety of ML models ranging from Bayesian Network (BN) to Support Vector Machines (SVM) with BN being the best performing for prediction. Demir and Sahin (2022) used primarily tree-based ML algorithms (Canonical Correlation Forest (CCF), Rotation Forest (RotFor), and Random Forest (RF)) to predict soil liquefaction potential using CPTs with CCF and RotFor performing better than RF. Changing to generalized linear models such as logistic, probit, log-log, and c-log-log, Zhang et al. (2013) used CPT data to explore their applicability for liquefaction potential evaluation with c-log-log and logistic being the most promising models. Goh and Goh (2007) also used CPT data but with SVMs to achieve a 98% accuracy rate. Zhou et al. (2019) used both CPT and SPT data with a stochastic gradient boosting (SGB) classifier for liquefaction potential with SPT giving greater accuracy. Pal (2006) also used both SPT and CPT data but with a SVM classification model for liquefaction potential and the test accuracies were 96% and 97%, respectively. Another approach using a probabilistic neural network (PNN) model for seismic liquefaction by

Goh (2002) was developed for both CPT and shear wave velocity data with a 100% and 98% success rate, respectively. Juang et al. (2003) also used ANN for a binary liquefaction classification approach, then created a boundary with artificially populated points and regressed on it for a usable empirical equation. After that process, Bayesian mapping was utilized to estimate the probability of liquefaction. To add an additional level of data to the analysis, Hoang and Bui (2018) used kernel Fisher discriminant analysis (KFDA) to create another feature for the data structure with respect to the different class labels. Then this extra feature was combined with the original features for a least squares SVM (LSSVM) model for binary liquefaction classification with better results than benchmark tests. Samui and Karthikeyan (2013) also developed a LSSVM liquefaction susceptibility model for the 1999 Chi-Chi Taiwan earthquake that achieved 100% for Chi-Chi earthquake prediction accuracy and 88% for global accuracy. For binary liquefaction occurrence with Turkey and Taiwan earthquake data, Hanna et al. (2007) used a generalized regression neural network (GRNN) model with accuracies greater than 90%.

Focusing on the state parameter, a variety of ML algorithms have been used to develop a probabilistic liquefaction evaluation method with logistic regression being the best performing model. Kamura et al. (2021) directly predicted the degree of excess pore water pressure increase from 3D shake test seismic records with an ANN model. Groholski et al. (2014) also used SelfSim, an ANN based algorithm, to reproduce ground motions and pore pressure from downhole array data in effective stress simulations. Young-Su and Byung-Tak (2006) used a BPNN model to predict the cyclic strength of sands from cyclic undrained triaxial and simple shear testing datasets and showed that the results are sensitive to relative density without prior model specification.

Instead of using numerical soil parameter inputs, an alternative family of methods has been emerging, with some working on merging satellite-based remote sensing data with geologic maps and other satellite-derived information to classify liquefaction potential at a system scale (e.g., Oommen and Baise 2008). The classification was performed with SVM and had 84% test accuracy. Another system-scale approach has been proposed by Greenfield and Grant (2020) utilizing 3D Gaussian processes to model liquefaction triggering at a regional scale. The result is a 3D probability field for ground conditions and liquefaction triggering potentials. Geyin et al. (2022) have trained ML models to predict liquefaction potential index (LPI) values without needing subsurface test data such as CPTs with promising efficient results.

To compare various liquefaction potential evaluation models against one another, Huang et al. (2012) varied input parameters with a Bayesian network to assess the effects of parameter uncertainties in the resultant liquefaction potential prediction of each model. By using Bayesian Markov-Chain Monte Carlo (MCMC), Ueda (2022) estimated the variability of liquefaction resistance values by accounting for differences in individual laboratory tests. Mercado et al. (2019) used a Bayesian approach to estimate uncertain parameters from cyclic triaxial testing for a multi-yield constitutive model. The posterior probability distributions of the constitutive model parameters were used to draw samples from afterwards. Liquefaction probabilities can also be inferred from reliability techniques by using Bayes' theorem as shown by Juang et al. (2000).

Performance-based assessments: Lateral Displacements

The prediction of both liquefaction-induced and more broadly seismic shaking-induced displacements have been explored with various ML algorithms. Starting with the most basic Newmark sliding blocks, displacements were predicted by Wang et al. (2020) using XGBoost

with K-fold cross validation (CV) for hyperparameter tuning. The resultant standard deviations were smaller than the results from traditional empirical models. Cho et al. (2022) used ANNs to predict seismic slope displacements with comparison to analytically derived ones and showed a moderate improvement with the ANN model. For free face and sloping ground conditions, Baziar and Ghorbani (2005) also used an ANN model to predict liquefaction-induced horizontal ground displacement with the model performing better than traditional models via root mean squared error (RMSE) and correlation factors. Similarly, Javadi et al. (2006) used genetic programming (GP) with SPT data for liquefaction-induced lateral spreading predictions for free face and gently sloping ground conditions. The latter model was able to capture relationships between input parameters and proved more accurate than the typically used multi linear regression (MLR) model. Macedo et al. (2021) estimated seismically-induced slope displacements with 19 different ML models and showed that beyond five features there was no appreciable gain in model accuracy. Oommen and Baise (2010) used a support vector regression (SVR) model to predict free face lateral spread displacements and used rigorous validation to identify gaps in the initial data set. MLR, multilayer perceptron (MLPs), and adaptive neuro-fuzzy inference system (ANFIS) models were explored by Kaya (2016) for predicting liquefaction-induced lateral spreading with MLP performing better for free-face and ANFIS better for sloping ground. Woldehellasse and Tesfamariam (2022) used a more complex conditional generative adversarial network (cGAN) for predicting horizontal ground displacements for free-face and sloping ground conditions with 82% and 68% accuracy respectively. A BPNN was also used by Wang and Rahman (1999) with lateral spread case histories to predict horizontal ground displacement. Chiru-Danzer et al. (2001) also used an ANN model to predict liquefaction-induced horizontal displacements and was shown to be more accurate than empirical models at the time. There are inherently differing subjective interpretations when labeling lateral spreading by hand which were all recalibrated amongst each other by using a neurofuzzy system by García et al. (2008) to the same standard to achieve a final model that has lower variability in its results. An evolutionary polynomial regression (EPR) model was explored by Rezaei et al. (2011) for both soil liquefaction and lateral displacement with high levels of accuracy and an ability to identify the complex relationship between the two problems. Durante and Rathje (2021) used NZ lateral spread data with a RF model to predict differing levels of displacement resulting from an earthquake event with a 70% accuracy. The binary liquefaction spread prediction achieved 80% accuracy. Nine ML models were used by Liu and Tesfamariam (2012) to predict lateral spreading for free face and ground slope conditions with RF being the best model that required the least amount of input parameter manipulation for both conditions.

Performance-based assessments: Settlement Analyses

The settlement of geosystems such as embankments during earthquake events has been separately studied as a function of soil property uncertainties. Lopez-Caballero (2018) used a Gaussian process (GP) surrogate model for finite element (FE) modeling with real earthquake ground motions to assess the liquefaction-induced settlement of a levee during an earthquake. The GP surrogate model was more efficient to run than FE modeling and proved to work well in its ability to predict levee damage. Lopez-Caballero (2021) also used a GP surrogate model of FE modeling to assess the damage of an embankment induced by the liquefaction of its foundation. The final accuracy of the surrogate model was comparable to that of the slower FE

analysis. Hwang et al. (2022) used nonlinear regression with LASSO regularization to predict permanent average foundation settlement on liquefiable soils after ground densification improvement with quasi-Monte Carlo sampling of the input parameters. The latter work had limited data to verify and build the model off but showed promise with capturing more aspects of foundation settlement.

CHALLENGES AND POTENTIAL IN ADOPTING ML APPROACHES

While not exhaustive, the collection of ML approaches used in geotechnical earthquake engineering demonstrates both their promise but also the fact that most efforts have been exploratory rather than a formalized new domain. Plenty of potential remains within this field and the expectation is for specialized ML algorithms to appear with higher frequency and better coverage of the research problems to be solved. Challenges to overcome are:

- The size of datasets available in geotechnical earthquake engineering is often very small in the sense that many of the algorithms going over these datasets can be handled by a local computer. This is unsurprising given the rarity of earthquake events and cost of large-scale testing. Many of the algorithms rely on larger datasets to avoid overfitting with K-fold validation or bootstrapping. This issue is evident in the risk of class imbalance interfering with classifying liquefaction manifestation at different scales from none to severe. Severe cases are rare, and if the algorithm is to classify everything as “no liquefaction” the resultant accuracy on the test set would still be above 50% as the dataset is inherently filled with no liquefaction occurrences. Dealing with such extreme datasets still requires solutions that can be drawn from extreme value theory but has not seen much use in geotechnical earthquake engineering yet.
- For PGML, formulating the correct loss functions that will capture the same physical constraints is the greatest challenge as each new physical problem will require new ones.
- Clean and high-quality data that covers all the potential input parameters is required for the satisfactory performance of all these ML algorithms. There have been advances in dealing with lower quality data such as fuzzy algorithms or kriging as can be seen in the models that used neurofuzzy techniques. Dealing with noisy data with transformations such as Principal Component Analysis (PCA) or the more general Singular Value Decomposition (SVD) is also a viable option.
- Identification of pertinent variables and posing the right questions is key to utilizing ML correctly in geotechnical earthquake engineering. Formulating the research question that ML is called upon to answer often requires reframing the task at hand and feature engineering the initial dataset to variables more suited for the chosen algorithm. Variables can be combined, separated, or transformed and categorized to be used to answer a well-posed research question. This is intimately related to domain expertise which is additionally needed for constraining algorithm boundaries.
- ML is a new skillset to be acquired by geotechnical engineers and trust in the ML techniques is key for the widespread adoption of algorithm usage and works in tandem with the necessity for this new skillset to be developed in geotechnical engineering. The more engineers understand the math and logic behind these algorithms, the more rigor and validation specific for these disciplines can be developed.

CONCLUSIONS AND FUTURE STEPS

Machine Learning (ML) in geotechnical earthquake engineering has shown promise with many preliminary explorations using different algorithms for a variety of research problems. A summary of papers for each of the four identified areas in geotechnical earthquake engineering was presented, and challenges were reviewed upon reflection of the current research review.

The intersection of ML and geotechnical earthquake engineering as a cross-discipline is still at its infancy leaving an exciting open space for future research. First and foremost, ML needs to be taught within the civil engineering domain. This can be done either by adding courses within the curriculum that increase proficiency in statistics and coding as well as introducing ML algorithms and concepts into potential solution pathways in capstone design courses.

Datasets are currently still growing and being shared, but there are several gaps in the coverage of soil types and geography. For example, NZ has a robust dataset and benefits from the resultant research conducted with various ML algorithms exploring new possibilities of combining and interpreting the same input parameters. There are not as many datasets with such large coverage for the rest of the world, and to create a less locally restricted ML algorithm, more data from other parts of the world should be incorporated when available. Additionally, more types of data would bolster this new research area, as ML algorithms can find new relationships that may be subtle and glossed over when empirical equations were first made.

An example crossing data scales would be combining image-based data such as geological maps with numerically based CPT data for more layers of verification of soil types or overall expected liquefaction behavior. As adding another parameter would usually not overly affect algorithm initial runtime, there is the possibility of finding new relationships between new input and output parameters. The structure of the datasets is also crucial for quick adoption in usage, as properly formatted and documented input data facilitates better understanding.

Accepted and well-documented benchmark validation sets are needed for testing, comparing, and ranking ML techniques for a specific engineering problem. This can be achieved by repetitions of the same tests for calibration across different laboratories around the world, such as what was performed in the LEAP project (Kutter et al. 2018) with centrifuge tests. Benchmark datasets with pre-established tests to run proposed ML algorithms covering the same research area should be created to identify the differences between new trained algorithms.

New ML techniques appear each day with different specializations tailored to specific theoretical assumptions such as spatial covariance matrices which may prove useful for geospatial applications (Bickel and Levina 2008). By understanding these assumptions and how they could be translated to earthquake engineering, better-tailored ML algorithms specific to the spatial and physics-based problems in earthquake engineering could be created. Hybrid algorithms of the best parts of individual ML algorithms can also be created and made more specialized for earthquake engineering usage by testing on the aforementioned benchmark sets. While PGML is slowly being adopted, it should be incorporated into more base ML algorithms to tailor models to physics-based earthquake engineering all while addressing interpretability.

Papers should have cross-validation, validation, and detailing of the boundaries of the viable input parameter space for predictions. Several of the papers collected and reviewed lack any sort of external validation or cross-validation component, or a train/test split component for internal validation. This should be a requirement across all ML applications, along with a confusion matrix and explanation of the precision and accuracy of the prediction from the testing component if applicable, such as receiver operating curves (ROC) or precision recall curves (PRC) for better visualization of holistic algorithm performance.

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