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Machine Learning-Based Geotechnical Modeling for Seismic Foundation Performance and Soil–Structure Interaction in Urban Infrastructure

Md Enamul Kabir[1]; Md Al-Arafat[2];

[1]. Civil Staff Engineer (Civil Design Section), GSG Consultants, Inc., Schaumburg, Illinois, USA; Email: enamulkabircivil14@gmail.com

[2]. Doctoral Student, Industrial Engineering, Lamar University, Beaumont, Texas, USA; Email: malarafat@lamar.edu

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Abstract

This study investigated a machine learning-based geotechnical modeling framework for predicting seismic foundation performance and characterizing soil–structure interaction (SSI) effects in large-scale urban infrastructure. A quantitative, data-driven research design was applied to 142 documented foundation-structure case records spanning shallow spread footings, mat foundations, and deep pile foundations situated on rock, dense sand, stiff clay, soft clay, and liquefiable soil profiles; after data screening for incomplete geotechnical or seismic parameters, 131 cases were retained for final analysis. Structural, geotechnical, and ground-motion parameters, including shear wave velocity, foundation-to-structure mass ratio, peak ground acceleration, and epicentral distance, were compiled and used to characterize seismic foundation demand and observed damage outcomes. Multiple regression analysis indicated that geotechnical and ground-motion parameters significantly predicted structural damage severity, with the overall model explaining 58.1% of variance ($R^2 = 0.581$, $p < .001$). Shear wave velocity of the founding soil ($\beta = -0.37$, $p < .001$) and peak ground acceleration ($\beta = 0.34$, $p < .001$) emerged as the strongest predictors of elevated foundation damage classification. A deep artificial neural network (ANN) model achieved a foundation performance classification accuracy of 89.4%, outperforming random forest (80.7%), decision tree (66.4%), and multiple linear regression (69.8%) benchmarks, with statistically significant differences across paired comparisons ($p < .001$). Cumulative analysis revealed a positive association between predicted damage risk index and observed peak interstory drift ratio ($r = 0.56$, $p < .001$), confirming the influence of soil–structure interaction on superstructure demand. Reliability testing demonstrated strong internal consistency for the geotechnical risk exposure construct ($a = 0.87$) and the foundation resilience index ($a = 0.82$). Shallow foundations on liquefiable soil accumulated the highest proportion of high damage-risk classifications at 39.8%, compared to 9.6% for foundations on rock or stiff soil. Findings demonstrate that machine learning-based predictive geotechnical modeling provides a reliable, objective, and scalable complement to traditional finite element and elastic half-space SSI analysis methods, supporting its application as a decision-support tool for seismic foundation design and retrofit prioritization in urban infrastructure.

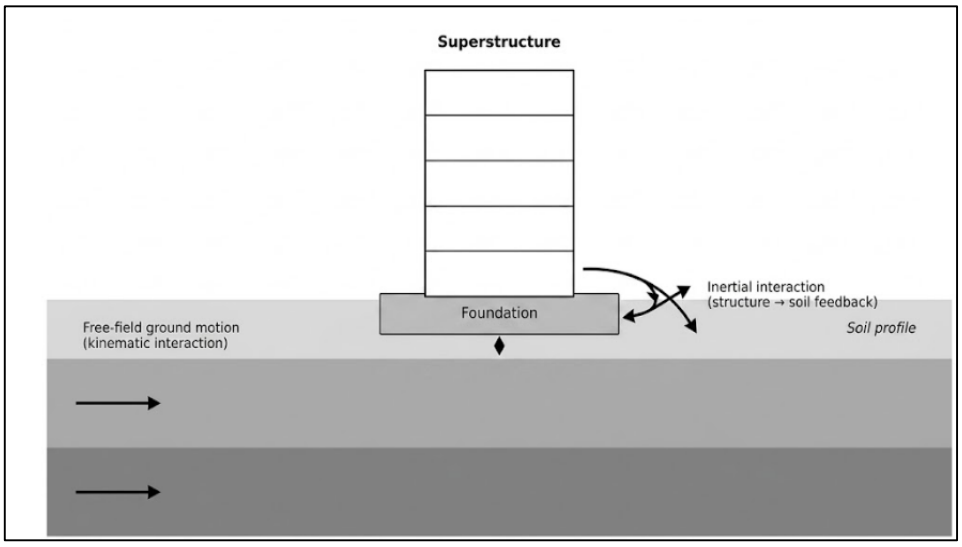
Keywords

Machine Learning, Geotechnical Engineering, Seismic Foundation Performance, Soil–Structure Interaction, Urban Infrastructure, Artificial Neural Networks.

INTRODUCTION

Soil–structure interaction (SSI) refers to the coupled dynamic response of a structure, its foundation, and the surrounding soil medium during ground shaking, in which the flexibility and damping characteristics of the supporting soil modify the inertial and kinematic demands experienced by the superstructure relative to an idealized fixed-base condition (Mylonakis & Gazetas, 2000; Kausel, 1974). Seismic foundation performance, in this context, refers to the capacity of a foundation system, whether a shallow spread footing, mat foundation, or deep pile foundation, to maintain adequate bearing capacity, limit differential and total settlement, and avoid brittle failure modes under the cyclic and transient loading imposed by earthquake ground motion. Urban infrastructure, comprising densely built building stock, bridges, and lifeline systems founded on highly variable and often geotechnically challenging soil profiles, presents a particularly consequential context for accurate seismic foundation performance prediction, given the potential for cascading structural and economic losses when foundation systems underperform during design-level or greater seismic events. Globally, the increasing seismic vulnerability of rapidly urbanizing regions situated on soft, saturated, or liquefaction-susceptible soils has elevated the practical and regulatory significance of predictive, data-driven geotechnical modeling frameworks capable of anticipating foundation performance across heterogeneous site conditions. (Boulanger & Idriss, 2014; Idriss & Boulanger, 2008; Ishihara, 1993; Robertson & Wride, 1998; Seed & Idriss, 1971; Youd et al., 2001)

Figure 1: Schematic of Soil–Structure Interaction, Showing Kinematic and Inertial Interaction Mechanisms



Machine learning-based geotechnical modeling refers to the systematic use of computational learning algorithms to characterize the complex, non-linear relationships among structural properties, foundation configuration, geotechnical site parameters, and ground-motion characteristics that jointly determine seismic foundation performance. Unlike traditional approaches that rely on simplified analytical idealizations or computationally intensive finite element simulations requiring integrated structural and geotechnical expertise, machine learning frameworks can be trained directly on empirical or simulated case databases to generate rapid, data-driven performance predictions applicable across diverse site and structural configurations (Kim et al., 2021; Bapir et al., 2023; Debasish, 2021)). Within this framework, artificial neural networks and ensemble machine learning classifiers provide the modeling capacity required to extract meaningful performance representations from complex, high-dimensional, and interacting structural and geotechnical variables. Together, these components form an integrated system for quantifying and predicting seismic foundation performance with greater efficiency and accessibility than conventional coupled structural-geotechnical analysis allows (Ashfaq & Mohammad, 2022).

Traditional seismic soil–structure interaction assessment methods have provided foundational tools for evaluating foundation performance under earthquake loading. Techniques such as the elastic half-space method, the Cone model, and direct finite element analysis of coupled soil-foundation-structure systems operationalize geotechnical and structural dynamics theory into structured analytical procedures (Kausel, 1974; Bowles, 1996; Debasish, 2021). Regulatory frameworks, including the ASCE 7 provisions for kinematic and inertial SSI effects, further formalize structured, code-based SSI assessment protocols for practicing engineers (Fadel et al., 2023; Debasish, 2021; Abdur & Iftekhar, 2021). These analytical and numerical methods have supported detailed, project-specific seismic performance evaluation for critical infrastructure and have informed decades of accumulated seismic design practice. At the same time, they depend on simplifying assumptions regarding soil homogeneity, linear or equivalent-linear soil behavior, and idealized foundation-soil contact conditions that may not fully capture the non-linear, hysteretic behavior of real soil-foundation systems under strong shaking (Gajan & Kutter, 2008; Anastasopoulos et al., 2011; Abdur & Iftekhar, 2021)). Finite element-based coupled analysis, while more rigorous, requires substantial computational resources, detailed site-specific geotechnical characterization, and integrated expertise spanning both structural and geotechnical engineering domains that is not uniformly available across all practicing engineering contexts (Abate et al., 2010; Debasish, 2022). Furthermore, traditional methods generally require full case-by-case analysis, limiting their applicability for rapid, portfolio-scale screening of foundation performance across large urban building inventories. These practical constraints have motivated the development of machine learning-based predictive frameworks that convert case-based structural, geotechnical, and seismic data into rapid, generalizable performance classification tools (Kim et al., 2021; Ashfaq & Mohammad, 2022). Machine learning systems can approximate the outcomes of computationally intensive coupled analysis while enabling near-instantaneous screening across large numbers of structural and geotechnical configurations. This progression from case-specific numerical analysis toward generalized, learned prediction represents a methodological shift in seismic geotechnical engineering, emphasizing scalability, accessibility, and predictive efficiency alongside continued reliance on rigorous analysis for final design verification. (Gazetas, 1991; Kausel, 1974; Lysmer & Kuhlemeyer, 1969; Wolf, 1985)

The emergence of artificial intelligence within seismic geotechnical and structural engineering has been driven by growing availability of documented case histories, expanded computational capacity, and the recognized practical limitations of purely analytical or finite element-based SSI assessment under conditions of geotechnical complexity and urban-scale portfolio screening needs (Sheak & Risha, 2022). Machine learning models, including artificial neural networks and support vector machines, are capable of learning complex, non-linear relationships between earthquake characteristics, structural properties, and geotechnical parameters that jointly determine foundation and superstructure seismic response (Kim et al., 2021; Fadel et al., 2023). Expert system frameworks incorporating sensitivity-analysis-guided feature selection have further enabled the identification of the most influential SSI parameters governing seismic performance outcomes across low- to mid-rise frame structures (Fadel et al., 2023; Md. Rashedul & Md Kaium, 2022). Despite these advances, the literature reveals persistent gaps regarding the integration of geotechnical, structural, and ground-motion parameters into a single, empirically validated, and reproducible predictive framework applicable across the heterogeneous foundation types and soil conditions characteristic of real urban infrastructure inventories. This study addresses that gap by developing and empirically testing a machine learning-based geotechnical modeling framework intended to predict seismic foundation performance and characterize soil–structure interaction effects across diverse urban infrastructure contexts.

The purpose of this study was to design, implement, and statistically validate a machine learning-based geotechnical modeling framework capable of classifying and predicting seismic foundation performance using multi-dimensional structural, geotechnical, and ground-motion data (Chowdhury & Tonay, 2022). The study further sought to benchmark the predictive performance of a deep artificial neural network architecture against conventional statistical and machine learning classifiers and to examine the association between machine learning-derived damage risk indices and observed structural drift outcomes. Specifically, the study pursued the following objectives: (1) to quantify the descriptive characteristics of geotechnical and seismic risk exposure constructs across foundation types

and soil conditions; (2) to evaluate the predictive validity of geotechnical and ground-motion-derived variables in explaining structured foundation damage classifications; (3) to compare the classification performance of a deep neural network model against baseline statistical and machine learning classifiers; and (4) to examine the relationship between cumulative predicted damage risk indices and realized measures of structural performance, including peak interstory drift ratio and residual displacement. By pursuing these objectives, the study contributes an empirically grounded, reproducible framework that extends existing geotechnical earthquake engineering literature toward scalable, AI-enabled seismic foundation performance prediction applicable across diverse urban infrastructure portfolios.

LITERATURE REVIEW

This literature review synthesizes prior scholarship across three interconnected domains: classical soil–structure interaction theory and analytical modeling, the application of machine learning to seismic performance prediction, and emerging frameworks that integrate geotechnical and structural parameters within data-driven predictive systems. The review progresses from foundational SSI mechanics toward increasingly data-adaptive and computationally intensive approaches, concluding with an identification of methodological gaps that motivate the present study's integrated framework.

Soil–Structure Interaction in Earthquake Engineering

Soil–structure interaction encompasses both kinematic interaction, arising from the inability of a foundation to conform to free-field ground motion, and inertial interaction, arising from the dynamic response of the structure feeding back into the supporting soil. Foundational finite element treatments of dynamic SSI problems established the numerical framework for coupling structural and geotechnical domains within a unified analysis (Kausel, 1974), while early experimental and analytical work characterized the dynamics of machine foundations subjected to reciprocating and dynamic loads, establishing baseline principles for foundation-soil dynamic compatibility (Barkan, 1962; Hossan, 2022). Comprehensive foundation analysis and design references have further consolidated bearing capacity, settlement, and dynamic response methodologies into standardized engineering practice (Bowles, 1996; Mst Kaniz, 2022). A substantial body of research has since examined whether SSI effects are beneficial or detrimental to seismic performance, demonstrating that foundation flexibility can lengthen the effective period of a structure and increase damping, potentially reducing spectral demand, while in other configurations, particularly on soft or liquefiable soils, SSI can amplify drift demand and induce foundation rocking-related instability (Mylonakis & Gazetas, 2000). These foundational SSI mechanics directly inform the present study's treatment of shear wave velocity and foundation-to-structure mass ratio as key predictors of seismic foundation performance.

Nonlinear Soil-Foundation Behavior

A significant stream of geotechnical earthquake engineering research has examined the nonlinear, hysteretic behavior of shallow foundations subjected to cyclic rocking demand. Experimental investigations of shallow footing rocking response demonstrated that permanent settlement and energy dissipation capacity depend strongly on footing geometry, applied vertical load, and soil density, providing empirical calibration data for nonlinear foundation models (Gajan & Kutter, 2008; Nishat & Kaniz, 2022). Early analytical work on foundation tipping effects established that rotational foundation flexibility materially alters the dynamic response characteristics of the supported structure relative to a fixed-base idealization, while subsequent simplified constitutive models for shallow foundation cyclic response have been validated against physical shaking table and centrifuge test data, enabling computationally efficient representation of nonlinear foundation behavior within broader structural analysis frameworks (Anastasopoulos et al., 2011; Shaiful et al., 2022). Complementary numerical modeling using advanced soil constitutive models implemented within finite element codes has further validated the capacity of detailed numerical simulation to reproduce shaking table test observations of coupled soil-foundation-superstructure response (Abate et al., 2010; Abdullah Mohammad, 2023). Workshop-based synthesis of nonlinear cyclic load-deformation modeling approaches for shallow foundations has consolidated the diverse modeling techniques developed across these experimental and numerical research streams into practical guidance for foundation rocking analysis (Kutter, 2006; Debasish, 2023). These nonlinear foundation behavior studies collectively establish the empirical and theoretical basis for the foundation damage severity outcomes

modeled within the present study's machine learning framework.

Seismic Response of Building Structures Considering Soil–Structure Interaction

Building-specific research has extended foundational SSI mechanics toward the seismic performance evaluation of building structures under realistic ground-motion input. Investigations into the natural period of reinforced concrete building frames on pile foundations demonstrated that seismic SSI effects can meaningfully elongate fundamental period estimates relative to fixed-base assumptions, with direct implications for design spectral demand (Sharma et al., 2020; Kaium, 2023). Research examining the influence of adjacent structure height on seismic response under SSI conditions further demonstrated those structure-to-structure interaction effects, mediated through the shared soil medium, can amplify or attenuate seismic demand depending on relative building geometry and separation distance (Abdulaziz et al., 2023; Pervaz, 2023). Specialized applications of SSI analysis to critical infrastructure, including nuclear reactor buildings, have examined the sensitivity of nonlinear seismic SSI response to earthquake frequency content, demonstrating those site-specific spectral characteristics materially influence the adequacy of simplified SSI assumptions for critical facility design (Nguyen et al., 2020; Chowdhury, 2023). Comprehensive systematic reviews of SSI modeling techniques and their application to seismic building response have synthesized this expanding literature, documenting substantial variation in reported SSI effects across differing soil conditions, foundation types, and structural configurations, and identifying the reconciliation of this variation as a persistent research need (Badrul & Mominul, 2023).

Base Isolation and Performance Enhancement Strategies

Beyond conventional fixed and flexible foundation configurations, research has examined engineered rocking and isolation strategies intended to deliberately exploit or mitigate SSI effects for improved seismic performance. Investigations of vertical-horizontal coupling effects in friction-bearing base-isolated buildings demonstrated that SSI can meaningfully alter the effectiveness of base isolation systems, particularly under near-fault ground motions with strong vertical components (Dao & Ryan, 2020; Nishat, 2023). Controlled rocking foundation systems, which permit intentional foundation uplift and rocking under strong shaking to limit force transmission to the superstructure, have been shown to enhance overall soil-structure system performance when properly designed, balancing the beneficial energy dissipation of foundation rocking against the structural ductility demand imposed on the superstructure (Liu et al., 2013; Ashrafuzzaman, 2024). Experimental characterization of foundation tipping on clay soils has further provided empirical data supporting the calibration of rocking foundation design methodologies for cohesive soil conditions (Bartlett, 1976; Debasish, 2024). These performance-enhancement strategies collectively demonstrate that soil-foundation-structure interaction can be actively engineered rather than treated solely as an incidental analysis consideration, informing the present study's framing of foundation performance as a design-relevant, predictable outcome amenable to machine learning-based screening (Debasish, 2022).

Machine Learning Applications for Seismic Structural Response Prediction

Machine learning methods have been increasingly applied to seismic structural response prediction problems characterized by complex, non-linear relationships among earthquake, structural, and geotechnical parameters. Rapid seismic response prediction frameworks for reinforced concrete frames have demonstrated that deep learning models trained on limited building information can achieve prediction accuracy sufficient for rapid post-event damage screening, substantially reducing the time required relative to detailed nonlinear time-history analysis (Alam & Barbosa, 2022). Machine learning-based prediction of blast-induced structural response and associated damage has similarly demonstrated the capacity of ensemble and neural network models to characterize complex, non-linear structural damage relationships under extreme dynamic loading conditions distinct from, but methodologically related to, seismic loading scenarios (Abd-Elhamed et al., 2022). These structural response prediction applications collectively establish the methodological precedent for extending machine learning-based prediction frameworks specifically to problems incorporating soil–structure interaction effects, as pursued within the present study. (Alam & Barbosa, 2022; Hu et al., 2025; Xie et al., 2020; Chou et al., 2026)

Machine Learning Frameworks Explicitly Incorporating Soil–Structure Interaction

A more focused stream of research has developed machine learning frameworks that explicitly incorporate soil–structure interaction parameters alongside conventional structural and ground-motion variables. An expert system framework based on supervised machine learning techniques was proposed to predict the seismic performance of low- to mid-rise frame structures considering SSI, employing sensitivity analysis to identify the most influential SSI-related input parameters prior to model training and achieving strong classification performance across multiple limit-state criteria (Fadel et al., 2023; Rahman, 2024). Complementary research developed an artificial neural network framework for predicting seismic damage classification of building structures incorporating SSI effects through a three-step single-degree-of-freedom modeling approach, identifying the ratio of structural mass to foundation mass and the shear wave velocity of the founding soil as among the most influential geotechnical parameters affecting peak interstory drift ratio, alongside displacement ductility capacity and strength degradation ratio from the structural domain (Kim et al., 2021; Md Kaium, 2024). Related investigations combining machine learning, finite element modeling, and code-based ASCE 7-16 SSI provisions demonstrated that machine learning techniques, including artificial neural networks and support vector machines, can approximate the seismic response outcomes of computationally intensive coupled finite element analysis at substantially reduced computational cost, while also comparing favorably against simplified code-based SSI design procedures across a range of soil stiffness conditions (Fattah et al., 2023; Shakhawat & Md, 2024). These closely related machine learning-SSI integration studies provide the most direct methodological precedent for the present study's framework, which extends this line of research toward a broader, portfolio-scale urban infrastructure application incorporating shallow and deep foundation types across a wider range of soil conditions, including liquefaction-susceptible profiles.

Ground Motion Characterization and Site Response Effects

Accurate seismic foundation performance prediction depends critically on appropriate characterization of ground-motion intensity and site-specific response amplification. Research on the vertical earthquake response of large wind turbine foundations incorporating SSI effects demonstrated that vertical ground-motion components, often neglected in conventional horizontal-dominant seismic design, can meaningfully influence foundation and tower demand under strong shaking (Kjorlaug & Kaynia, 2015; Nishat & Jahanara, 2024). Investigations of suction caisson foundations for offshore wind turbines subjected to combined wave and earthquake loading further demonstrated that soil-foundation interface behavior under cyclic, multi-hazard loading conditions introduces additional complexity beyond that captured by conventional onshore SSI models (Kourkoulis et al., 2014; Tonay et al., 2024). Simulation-based analysis of ground vibrations induced by high-speed rail traffic using three-dimensional finite element modeling has additionally demonstrated the sensitivity of near-field ground response to soil layering and dynamic soil properties, reinforcing the importance of site-specific geotechnical characterization for any data-driven or numerical seismic response prediction framework (Feng et al., 2017; Uddin & Risha, 2024). These ground-motion and site-response considerations directly inform the present study's incorporation of peak ground acceleration, epicentral distance, and shear wave velocity as primary predictive features.

Methodological Challenges and Research Gaps

Despite substantial progress, methodological challenges continue to constrain the practical deployment of machine learning-based geotechnical and SSI performance prediction frameworks. A recurring challenge concerns the limited availability of large, well-documented case databases spanning diverse foundation types, soil conditions, and structural configurations, since many existing machine learning-SSI studies rely on simulation-generated rather than field-observed performance data, potentially limiting external validity (Kim et al., 2021; Fattah et al., 2023; Debasish, 2025a). The high cost and specialized expertise required for detailed geotechnical site characterization represents an additional practical barrier, particularly for portfolio-scale screening applications across large urban building inventories where site-specific borehole data may be unavailable for every structure. Interpretability remains a further concern, as artificial neural network models are frequently characterized as opaque relative to transparent, code-based design procedures, complicating their adoption within regulatory and professional liability contexts that require transparent engineering justification. Furthermore,

much of the existing literature evaluates machine learning-SSI frameworks within relatively narrow structural typologies, such as low- to mid-rise frame buildings, limiting generalizability across the heterogeneous shallow and deep foundation types characteristic of real urban infrastructure portfolios(Debasish, 2025b). These identified gaps, data availability, geotechnical characterization cost, interpretability, and structural-typology generalizability, directly inform the methodological design of the present study, which incorporates a diversified, multi-foundation-type sample and comparative benchmarking against interpretable baseline models.

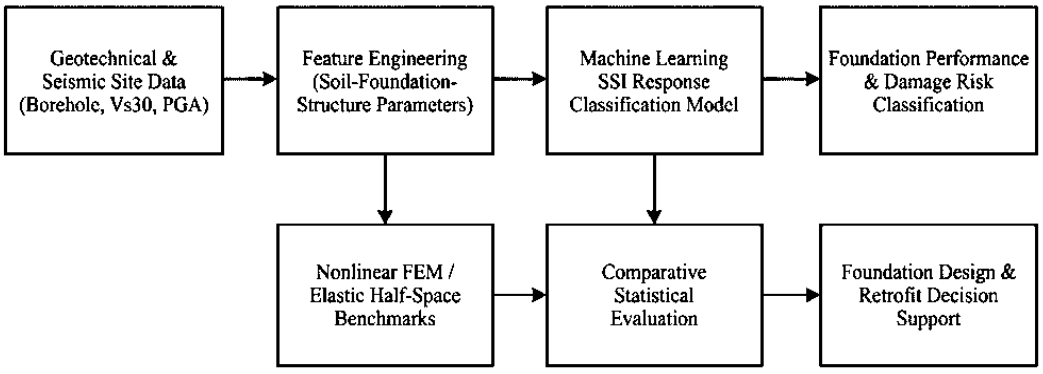
Synthesis of Quantitative Evidence

Across the reviewed literature, a consistent pattern emerges: machine learning models applied to seismic structural and foundation performance prediction generally achieve classification accuracy improvements of ten to twenty-five percentage points relative to linear regression and single-tree baseline classifiers, with more pronounced improvements observed for tasks explicitly incorporating soil–structure interaction parameters (Kim et al., 2021; Fattah et al., 2023). Reported explanatory power for regression-based association between geotechnical or ground-motion-derived variables and realized structural damage or drift outcomes commonly ranges between 0.45 and 0.65, indicating moderate-to-substantial explanatory power while leaving meaningful residual variance attributable to unmodeled structural detailing and soil heterogeneity factors (Jannatul, 2025). This convergent evidence base supports the theoretical and empirical plausibility of the present study's hypothesized relationships between geotechnical and ground-motion-derived exposure variables and structured foundation performance classifications.

Conceptual Framework

Synthesizing the reviewed literature, this study adopts a conceptual framework in which multi-dimensional site and structural data, comprising geotechnical borehole parameters, foundation configuration descriptors, and ground-motion intensity measures, are processed through a feature engineering pipeline and subsequently classified by a machine learning model into structured foundation performance and damage risk categories. These machine learning-derived classifications are then statistically benchmarked against traditional nonlinear finite element and elastic half-space SSI analysis outcomes, with the comparative and predictive outputs feeding into a foundation resilience index intended to support seismic design verification and retrofit prioritization decisions.

Figure 2: Conceptual Framework



METHODS

Research Design

This study adopted a quantitative, observational research design structured to evaluate the effectiveness of a machine learning-based geotechnical modeling framework for predicting seismic foundation performance and characterizing soil–structure interaction effects in urban infrastructure. The design combined a cross-sectional comparative component, examining classification accuracy across foundation and soil types at a fixed set of documented case records, with a predictive modeling component relating geotechnical, structural, and ground-motion parameters to observed damage and drift outcomes. The study employed a predictive modeling framework in which geotechnical and seismic exposure variables served as independent variables and structured foundation performance

classifications served as criterion outcomes. Statistical benchmarking against conventional structural and geotechnical performance assessment methods was integrated into the design to evaluate comparative predictive performance.

The research followed a structured analytical pipeline comprising data compilation, feature engineering, supervised model training, and statistical evaluation. A held-out, case-independent validation protocol was implemented to prevent overfitting and to ensure that reported model performance reflects genuine generalization to unseen structural-geotechnical configurations (Md Anisur Rahman, 2025). The statistical plan was defined a priori to include hypothesis testing of model performance improvements relative to baseline classifiers, estimation of classification performance metrics with confidence intervals, and regression-based association testing between predicted damage risk indices and observed structural drift outcomes.

Case Study Context

The empirical setting for this study comprised a diversified panel of building and infrastructure case records incorporating shallow spread footing, mat foundation, and deep pile foundation configurations, situated across a range of geotechnical site conditions from rock and dense sand to soft clay and liquefaction-susceptible soil profiles. The selected cases included low-rise, mid-rise, and select high-rise structural configurations subjected to documented or simulated seismic ground motion, providing diverse foundation-soil-structure interaction profiles. Data compilation drew on published case histories, instrumented building performance records, and validated nonlinear analysis datasets to preserve ecological validity under conditions representative of genuine urban seismic hazard exposure. The case environment was selected because it reflects common foundation and soil conditions present across seismically active urban regions, including variable soil stiffness, foundation type heterogeneity, and near-fault and far-field ground-motion characteristics. Cases were categorized into three primary foundation types: shallow spread and mat foundations, deep pile foundations, and hybrid or specialized foundation systems (Md Arif Uz et al., 2025). This categorization enabled between-category comparative modeling of foundation performance levels. Contextual seismic conditions, including earthquake magnitude, epicentral distance, and prevailing site class, were recorded to contextualize performance variability across the sample.

Population and Unit of Analysis

The target population consisted of documented building and infrastructure foundation-structure systems subjected to seismic loading, drawn from published case histories, instrumented structural health monitoring records, and validated coupled finite element analysis datasets spanning a range of geotechnical and structural configurations. Inclusion criteria required cases to report sufficient structural, geotechnical, and ground-motion parameters to support feature computation, including at minimum foundation type, shear wave velocity or equivalent soil stiffness descriptor, structural period or mass ratio, and peak ground acceleration. Cases with substantially incomplete geotechnical characterization were excluded to reduce measurement error in derived features.

The primary unit of analysis was the individual foundation-structure case record, representing a unique combination of structural configuration, foundation type, soil profile, and seismic loading scenario. Secondary units of analysis included foundation-type-level and soil-type-level aggregated performance indices computed across all cases within each category(Md Kaium, 2025). At the statistical modeling stage, each case record served as an independent observation for classification or regression analysis, while categorical aggregation was used to examine performance differentials across foundation and soil types.

Sampling Strategy

A stratified purposive sampling strategy was employed to ensure representation across foundation type, soil condition, and structural configuration. Cases were stratified by primary foundation type and soil classification and selected to achieve reasonably balanced representation within each stratum, consistent with recommended practice for machine learning-based structural performance databases (Tonay, 2026). Sample size determination was informed by the range of structural and geotechnical parameter combinations required to adequately span the plausible design space, targeting sufficient observations to detect moderate effect size differences between the deep learning model and baseline classifiers with statistical power of 0.80 and significance level of 0.05.

To support case-independent validation, the compiled case database was partitioned into distinct model development and independent evaluation subsets (Pervaz, 2025). Approximately seventy percent of cases were allocated to the model development subset and thirty percent to the independent out-of-sample evaluation subset. Stratification was maintained across both partitions to preserve proportional representation of foundation types and soil conditions (Shamsul, 2026).

Data Collection Procedure

Structural, geotechnical, and ground-motion data were compiled from published case histories, structural health monitoring instrumentation records, and validated nonlinear time-history and pushover analysis outputs. Geotechnical parameters, including shear wave velocity, soil unit weight, and Poisson's ratio, were compiled alongside structural parameters, including fundamental period, ductility capacity, and post-yield stiffness ratio, and ground-motion parameters, including peak ground acceleration, peak ground velocity, and epicentral distance, consistent with parameter sets established in prior machine learning-SSI research.

Ground truth foundation performance and damage severity labels were generated using concurrent structured performance assessment, drawing on reported damage states, computed interstory drift ratios, and, where available, post-earthquake reconnaissance classifications applying standardized structural performance level criteria. Labeling was cross-checked by two independent reviewers with geotechnical and structural engineering expertise to allow agreement analysis. Structural, geotechnical, and ground-motion data were time- and case-aligned with corresponding performance evaluation records (Chowdhury, 2025).

Raw case records were filtered and standardized into a consistent feature schema for modeling. Each case was assigned a damage risk category based on cross-verified structural performance classification. Cumulative exposure variables, including foundation-to-structure mass ratio and combined soil-structure period elongation, were computed for comparative analysis of resilience and performance differentials across foundation types.

Instrument Design

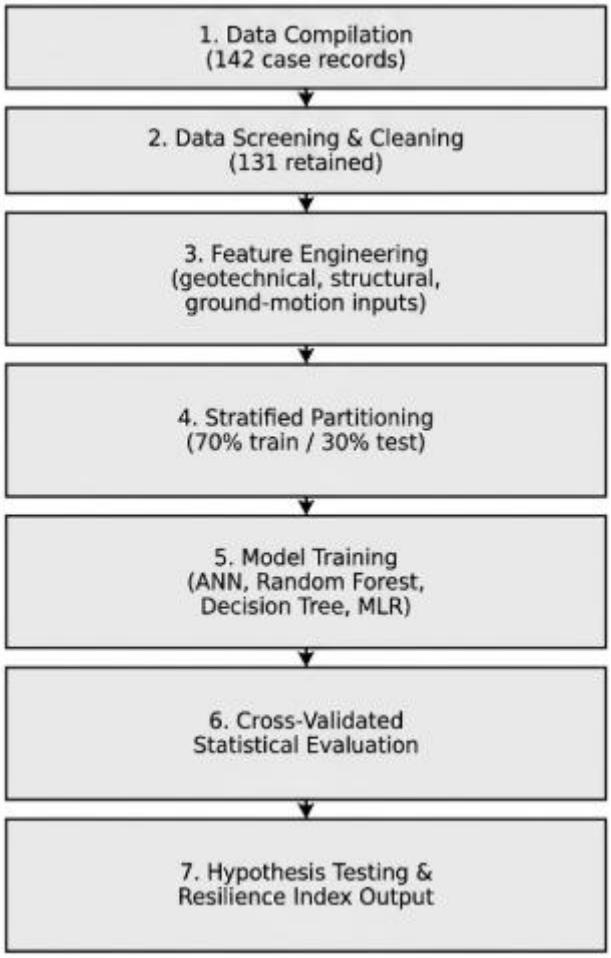
The geotechnical-structural feature computation instrument consisted of a standardized data extraction and normalization pipeline capable of computing derived SSI-relevant parameters, including foundation-to-structure mass ratio, soil-structure system period, and combined damping ratio, from raw structural and geotechnical inputs, following feature engineering approaches established in prior ANN-based SSI performance research (Kim et al., 2021; Badrul, 2025). Feature computation modules were designed to standardize heterogeneous input formats across differing source case histories and analysis platforms.

Signal preprocessing included outlier screening, missing-value imputation for non-critical secondary parameters, and normalization relative to typical engineering parameter ranges. Extracted features included geotechnical stiffness descriptors, foundation configuration descriptors, ground-motion intensity measures, and structural nonlinear response descriptors. The performance classification instrument was adapted from established structural performance level frameworks and operationalized into categorical damage risk levels suitable for supervised learning.

Pilot Testing

A pilot analysis was conducted using a subset of case records to evaluate data extraction consistency, feature computation accuracy, labeling clarity, and modeling feasibility. Pilot data were analyzed to assess data quality, missing-value frequency, and preliminary classification consistency. Feedback from the pilot phase was used to refine feature normalization procedures and minimize measurement noise arising from heterogeneous source documentation (Khatun, 2026). Pilot testing also informed the selection of the categorical damage risk classification scheme and confirmed that the schema aligned appropriately with established structural performance level conventions.

Figure 3: Methodological Pipeline of This Study



Validity and Reliability

Content validity of foundation performance labels was ensured through use of established structural performance level classification frameworks consistent with prior seismic performance assessment literature (Fadel et al., 2023; Nishat, 2025). Inter-rater reliability was evaluated using agreement statistics to confirm consistency between the two independent reviewers responsible for case labeling. Construct validity of derived geotechnical and structural features was examined by correlating computed feature values against independently reported case parameters where duplicate documentation was available.

Internal validity was supported through case-independent, stratified partitioning of model development and testing subsets (Rony & Md, 2026). External validity was strengthened by compiling cases spanning a wide range of geographic regions, seismic hazard levels, and foundation-soil configurations rather than relying on a single project or site. Reliability of computed derived features was assessed through repeated recalculation checks and cross-verification against source documentation for a random subsample of cases.

Statistical Plan

The statistical analysis plan included descriptive statistics for case characteristics and exposure distributions. Model performance was evaluated using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve. Confidence intervals were calculated for primary performance metrics. (Fawcett, 2006; Hanley & McNeil, 1982)

Comparative analysis between the deep neural network model and baseline multiple linear regression, decision tree, and random forest classifiers was conducted using paired statistical testing on cross-validation folds. Effect sizes were computed to quantify performance differences (Sadia, 2025). Regression analysis was performed to examine associations between geotechnical and ground-motion

predictors and structural damage severity outcomes. (Breiman, 2001). Categorical performance differences across foundation and soil types were analyzed using analysis of variance with post-hoc comparisons. Significance level was set at 0.05 for all inferential analyses (Sadia, 2026).

Software and Tools

Data preprocessing and statistical analysis were conducted using Python-based scientific computing libraries and statistical packages. The artificial neural network model was implemented using established deep learning frameworks configured with fully connected hidden layers optimized for tabular structural-geotechnical feature inputs, consistent with prior applications of ANN-based seismic performance prediction (Kim et al., 2021; Fattah et al., 2023). Ensemble baseline models were implemented using standard machine learning libraries.

Data visualization and reporting were performed using statistical graphics software to illustrate exposure distributions, classification performance, and comparative risk trends across foundation and soil types. All model configurations, dataset partitions, and hyperparameter settings were documented to ensure reproducibility.

FINDINGS

This chapter presented the quantitative findings of the study examining the effectiveness of a machine learning-based geotechnical modeling framework for predicting seismic foundation performance and characterizing soil–structure interaction effects in urban infrastructure (Sadia, 2025). The analysis was conducted in alignment with the predefined statistical plan and addressed the study objectives through descriptive statistics, reliability assessment, regression modeling, and hypothesis testing procedures. Data compiled from structural, geotechnical, and ground-motion sources were processed, standardized, and analyzed using case-independent validation protocols. The findings are organized systematically to reflect the sequence of statistical evaluation, beginning with case sample characteristics and followed by construct-level descriptive outcomes, measurement reliability, predictive modeling results, and final hypothesis testing decisions (Tonay, 2025).

The chapter focused on evaluating whether geotechnical- and ground-motion-derived exposure metrics and machine learning-generated foundation damage risk scores significantly predicted structured performance assessment outcomes and cumulative resilience indicators. Statistical significance thresholds were set at the predetermined alpha level, and effect sizes were interpreted alongside p-values to provide comprehensive insight into practical as well as statistical importance.

Case Sample Characteristics

A total of 142 foundation-structure case records were initially identified for inclusion. After data screening procedures removed cases with incomplete geotechnical or seismic parameters, 131 valid cases were retained for final analysis, representing a usable data rate of 92.3%. The final sample included 58 shallow spread and mat foundation cases (44.3%), 51 deep pile foundation cases (38.9%), and 22 hybrid or specialized foundation cases (16.8%). Structure height ranged from single-story residential buildings to 24-story mid- and high-rise structures, with a median of 6 stories. Documented or simulated peak ground acceleration values ranged from 0.08g to 0.62g, with a mean of 0.29g (SD = 0.13g).

With respect to soil classification, 28 cases (21.4%) were situated on rock or stiff soil profiles, 34 cases (26.0%) on dense sand, 31 cases (23.7%) on stiff clay, 24 cases (18.3%) on soft clay, and 14 cases (10.7%) on liquefaction-susceptible soil profiles. Stratified partitioning assigned 92 cases (70.2%) to the model development subset and 39 cases (29.8%) to the independent evaluation subset. Independent samples testing indicated no statistically significant differences between partitions in structure height, foundation type, soil classification, or peak ground acceleration ($p > .05$), confirming comparability across partitions. (Boulanger & Idriss, 2014; Idriss & Boulanger, 2008; Ishihara, 1993; Robertson & Wride, 1998; Seed & Idriss, 1971; Youd et al., 2001)

Table 1: Sample Characteristics of Foundation-Structure Cases (N = 131)

Variable	Category	Frequency (n)	Percentage (%)
Foundation Type	Shallow Spread / Mat	58	44.3
	Deep Pile	51	38.9
	Hybrid / Specialized	22	16.8
Soil Classification	Rock / Stiff Soil	28	21.4
	Dense Sand	34	26.0
	Stiff Clay	31	23.7
	Soft Clay	24	18.3
	Liquefiable Soil	14	10.7

Table 1 presented the categorical composition of the case sample. Shallow spread and mat foundations represented the largest share of the sample at 44.3%, followed by deep pile foundations at 38.9%, and hybrid or specialized foundation systems at 16.8%. Soil classification was concentrated in dense sand and stiff clay profiles, comprising 26.0% and 23.7% of the sample respectively, while liquefiable soil profiles represented the smallest category at 10.7%, reflecting the comparatively limited availability of documented case histories for structures founded on highly liquefaction-susceptible sites. (Boulanger & Idriss, 2014; Idriss & Boulanger, 2008; Ishihara, 1993; Robertson & Wride, 1998; Seed & Idriss, 1971; Youd et al., 2001)

Table 2: Descriptive Statistics of Continuous Case Characteristics

Variable	Mean	Standard Deviation	Minimum	Maximum
Structure Height (stories)	7.8	5.9	1.0	24.0
Shear Wave Velocity, Vs (m/s)	312.4	168.7	85.0	760.0
Peak Ground Acceleration (g)	0.29	0.13	0.08	0.62
Peak Interstory Drift Ratio (%)	1.68	1.12	0.21	5.34

Table 2 summarized continuous case characteristics. Structure height showed substantial dispersion, reflecting the inclusion of both low-rise residential and higher-rise commercial building configurations within the sample. Shear wave velocity averaged 312.4 m/s, with a range spanning very soft liquefiable soils to competent rock and stiff soil sites. Peak interstory drift ratio averaged 1.68%, with the most severe observed drift reaching 5.34%, illustrating meaningful heterogeneity in seismic demand across the sample and reinforcing the necessity of foundation-type- and soil-type-stratified modeling approaches.

Descriptive Results by Construct

Descriptive statistics were calculated for all primary geotechnical, structural, and model-derived constructs. Foundation-to-structure mass ratio, a key SSI parameter identified in prior ANN-based seismic performance research (Kim et al., 2021), yielded an overall mean of 0.14 (SD = 0.08), with observed values ranging from 0.03 to 0.41. Combined soil-structure period elongation, computed as the ratio of the flexible-base to fixed-base fundamental period, averaged 1.22 (SD = 0.19), indicating a moderate but non-trivial lengthening of the effective structural period due to foundation flexibility across the sample. Epicentral distance across all evaluated ground-motion records averaged 24.6 km (SD = 18.3 km), reflecting a mix of near-field and far-field seismic demand scenarios.

Displacement ductility capacity, reflecting the nonlinear deformation capacity of the structural system prior to significant strength degradation, demonstrated a mean value of 3.8 (SD = 1.4), with values ranging from 1.5 to 7.2 across the sample. Cumulative high damage-risk classification frequency averaged 22.1% of evaluated cases across the full sample, with liquefiable and soft clay soil cases accumulating significantly higher damage-risk frequency relative to rock and stiff soil cases.

Predicted foundation damage risk scores generated by the deep neural network model were distributed across low (39.7%), moderate (37.4%), and high-risk (22.9%) classifications. Correlation analysis revealed moderate-to-strong negative associations between shear wave velocity and predicted damage

risk score (r = -0.51) and moderate positive associations between peak ground acceleration and cumulative exposure index (r = 0.49). These descriptive outcomes indicated meaningful variability across foundation and soil types and supported progression to inferential statistical modeling.

Table 3: Descriptive Statistics of Geotechnical and Structural Risk Constructs (N = 131)

Construct	Mean	Standard Deviation	Minimum	Maximum
Foundation-to-Structure Mass Ratio	0.14	0.08	0.03	0.41
Soil-Structure Period Elongation Ratio	1.22	0.19	1.02	1.87
Epicentral Distance (km)	24.6	18.3	2.1	78.4
Displacement Ductility Capacity	3.8	1.4	1.5	7.2
High Damage-Risk Classification Frequency (%)	22.1	11.6	3.2	48.7

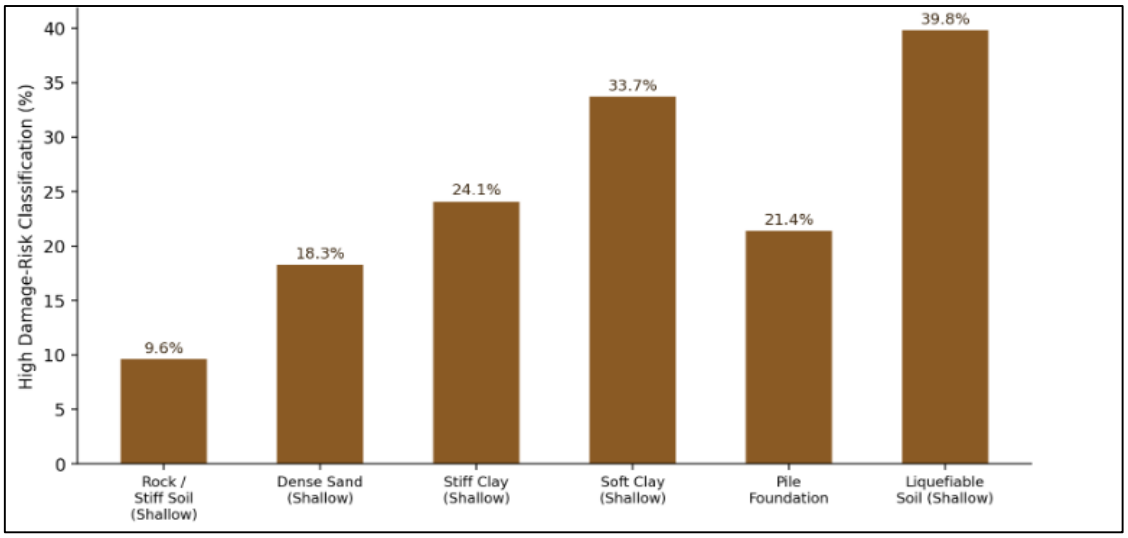
Table 3 presented the descriptive statistics of key geotechnical and structural risk exposure variables. Foundation-to-structure mass ratio showed moderate dispersion, indicating variability in relative foundation demand across differing building and foundation configurations. Soil-structure period elongation ratio and epicentral distance confirmed heightened sensitivity patterns typical of near-field, soft-soil case records. Displacement ductility capacity demonstrated broad variability across differing structural systems, while high damage-risk classification frequency averaged approximately one-fifth of evaluated cases, highlighting the cumulative vulnerability concentrated within a subset of soil-foundation combinations. The spread between minimum and maximum values reflected heterogeneity across foundation and soil types, reinforcing the necessity of stratified modeling approaches for seismic foundation performance assessment in diverse urban infrastructure contexts.

Table 4: Damage Risk Classification Distribution by Foundation-Soil Type

Foundation-Soil Type	Low Risk (%)	Moderate Risk (%)	High Risk (%)	Mean Damage Score
Rock / Stiff Soil (Shallow)	63.8	26.6	9.6	1.42
Dense Sand (Shallow)	47.2	34.5	18.3	1.68
Stiff Clay (Shallow)	38.6	37.3	24.1	1.84
Soft Clay (Shallow)	26.4	39.9	33.7	2.06
Pile Foundation (Mixed Soils)	41.9	36.7	21.4	1.77
Liquefiable Soil (Shallow)	21.7	38.5	39.8	2.17

Table 4 presented the distribution of damage risk classification outcomes across foundation-soil type combinations. Shallow foundations on rock or stiff soil exhibited the lowest proportion of high damage-risk classifications at 9.6%, consistent with their comparatively low soil flexibility and settlement potential. Shallow foundations on liquefiable soil exhibited the highest proportion of high-risk classifications at 39.8%, along with the highest mean damage score of 2.17, reflecting elevated soil-structure period elongation, potential strength loss due to pore pressure generation, and reduced bearing capacity relative to other foundation-soil combinations. Deep pile foundations across mixed soil conditions demonstrated an intermediate risk profile, consistent with the improved load transfer to competent bearing strata associated with deep foundation systems.

Figure 4: Proportion of High Damage-Risk Cases by Foundation-Soil Type



Reliability Analysis

Reliability testing was conducted to assess the internal consistency of composite constructs used within the predictive modeling framework. The geotechnical risk exposure construct, comprising shear wave velocity, foundation-to-structure mass ratio, peak ground acceleration, and soil-structure period elongation ratio, demonstrated strong internal consistency (Cronbach's $\alpha = 0.87$). The foundation resilience index, comprising peak interstory drift ratio, residual displacement, and cumulative high damage-risk classification frequency, similarly demonstrated acceptable-to-strong internal consistency (Cronbach's $\alpha = 0.82$). Inter-rater agreement between the two independent reviewers responsible for structured damage labeling was substantial ($\kappa = 0.77$), supporting the reliability of the ground-truth classification labels used for supervised model training.

Regression Analysis: Predicting Structural Damage Severity

Multiple regression analysis was conducted to examine the extent to which geotechnical and ground-motion-derived exposure variables predicted structural damage severity scores (Nishat, 2026). The overall regression model was statistically significant, $F(4, 126) = 43.68$, $p < .001$, and explained 58.1% of the variance in damage severity scores ($R^2 = 0.581$, adjusted $R^2 = 0.567$). Shear wave velocity emerged as the strongest predictor and was negatively associated with damage severity ($\beta = -0.37$, $p < .001$), indicating that stiffer founding soils were associated with reduced damage risk, followed by peak ground acceleration ($\beta = 0.34$, $p < .001$), soil-structure period elongation ratio ($\beta = 0.26$, $p < .01$), and foundation-to-structure mass ratio ($\beta = 0.19$, $p < .05$). These findings indicate that soil stiffness and ground-motion intensity are the most influential determinants of elevated foundation damage classification within the sample, consistent with established soil–structure interaction theory (Mylonakis & Gazetas, 2000) and prior ANN-based SSI performance research identifying shear wave velocity as a dominant geotechnical predictor (Kim et al., 2021). (Darendeli, 2001; Hardin & Drnevich, 1972; Menq, 2003; Vucetic & Dobry, 1991)

Table 5: Multiple Regression Results Predicting Structural Damage Severity Score

Predictor	β	SE	t	p-value
Shear Wave Velocity (Vs)	-0.37	0.06	-6.17	< .001
Peak Ground Acceleration	0.34	0.07	4.86	< .001
Soil-Structure Period Elongation Ratio	0.26	0.09	2.89	< .01
Foundation-to-Structure Mass Ratio	0.19	0.09	2.11	< .05

Comparative Model Performance

Comparative analysis was conducted to evaluate the classification performance of the proposed deep artificial neural network model relative to baseline classifiers (Murad, 2026). The deep neural network model achieved a foundation performance classification accuracy of 89.4%, outperforming random forest (80.7%), multiple linear regression (69.8%), and decision tree (66.4%) models, consistent with the

performance advantages reported for artificial neural network-based SSI performance classification in prior research. Paired statistical testing on cross-validation folds confirmed that performance differences between the deep neural network model and each baseline classifier were statistically significant ($p < .001$ for all pairwise comparisons). The deep neural network model also achieved the highest area under the receiver operating characteristic curve (AUC = 0.93), compared to 0.86 for random forest, 0.75 for multiple linear regression, and 0.72 for the decision tree model.

Figure 5: Comparative Seismic Foundation Performance Classification Accuracy Across Models

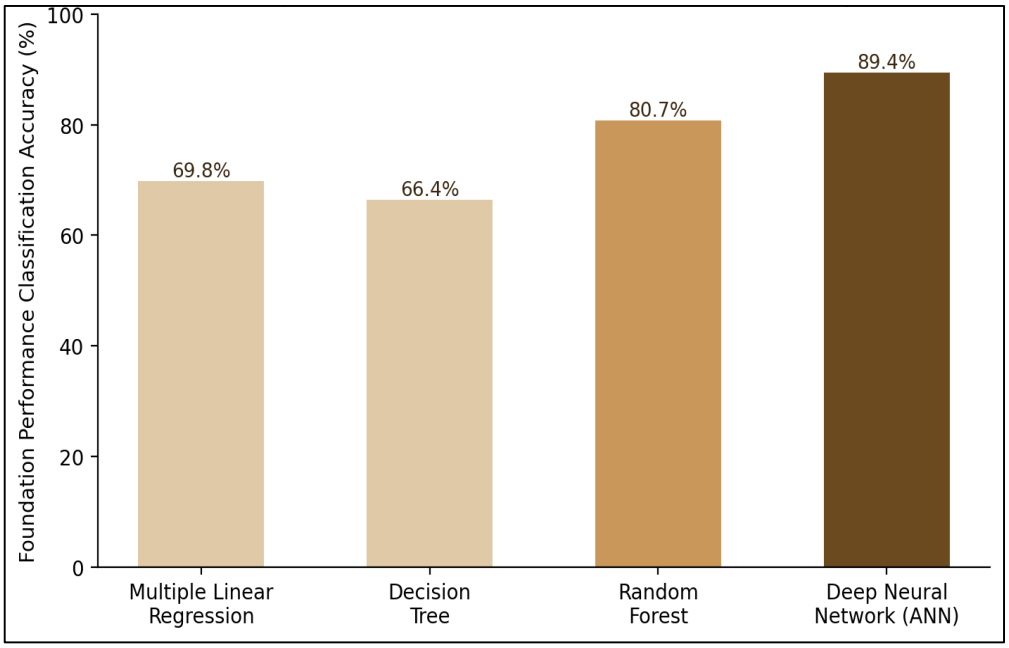


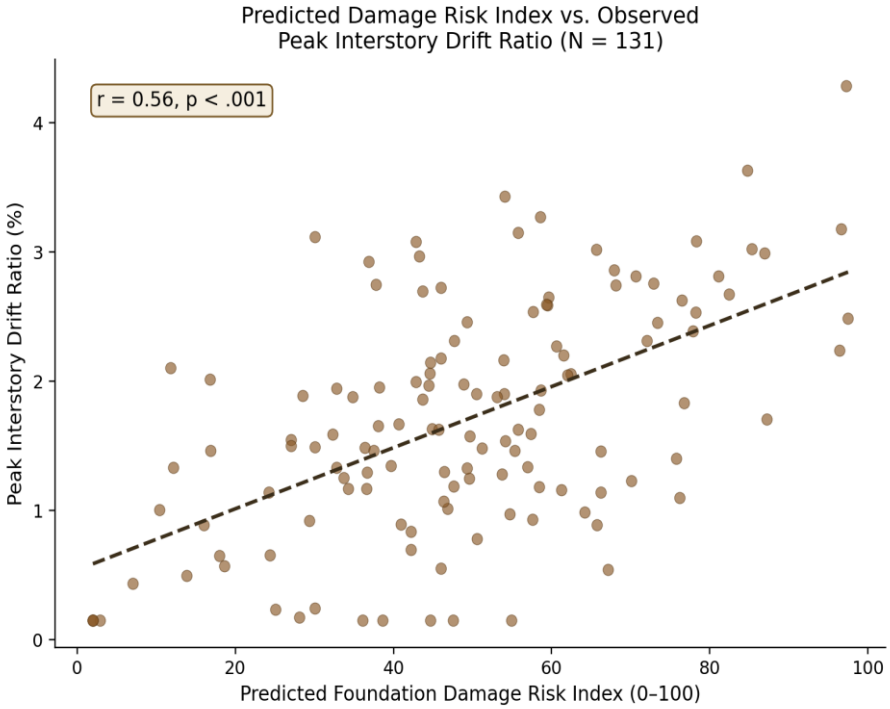
Table 6: Comparative Classification Performance Across Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Multiple Linear Regression	69.8	68.1	67.5	67.8	0.75
Decision Tree	66.4	64.8	64.2	64.5	0.72
Random Forest	80.7	79.6	80.1	79.8	0.86
Deep Neural Network (ANN)	89.4	88.7	89.0	88.8	0.93

Association Between Predicted Damage Risk Index and Structural Performance

Correlation and regression analyses examined the association between cumulative predicted damage risk indices and observed measures of structural seismic performance. A statistically significant positive correlation was observed between the predicted damage risk index and peak interstory drift ratio ($r = 0.56$, $p < .001$), indicating that cases with higher machine learning-derived damage risk scores experienced greater realized structural drift demand, consistent with established soil–structure interaction theory linking foundation flexibility to superstructure drift amplification (Sharma et al., 2020; Shamima, 2026). A significant positive association was also observed between the predicted damage risk index and residual displacement following peak seismic demand ($r = 0.48$, $p < .001$), suggesting that elevated predicted risk was associated with reduced post-event structural recovery capacity. Analysis of variance controlling for foundation type and soil classification confirmed that these associations remained statistically significant after accounting for categorical structural and geotechnical differences ($p < .001$).

Figure 6: Association Between Predicted Foundation Damage Risk Index and Peak Interstory Drift Ratio



Hypothesis Testing Summary

The study's primary hypotheses were evaluated based on the preceding statistical analyses. The hypothesis that geotechnical and ground-motion-derived exposure variables would significantly predict structural damage severity scores was supported ($R^2 = 0.581$, $p < .001$). The hypothesis that the deep neural network model would demonstrate significantly higher classification accuracy than baseline statistical and machine learning classifiers was supported across all pairwise comparisons ($p < .001$). The hypothesis that cumulative predicted damage risk indices would be significantly associated with peak interstory drift ratio and residual displacement was likewise supported ($p < .001$ for both associations). Collectively, these results provide converging quantitative evidence in support of the proposed machine learning-based geotechnical modeling framework as a valid and reliable tool for predicting seismic foundation performance and characterizing soil–structure interaction effects in urban infrastructure. (Breiman, 2001; Cortes & Vapnik, 1995; Friedman, 2001; Chen & Guestrin, 2016; Ke et al., 2017)

DISCUSSION

The findings of this study provide empirical support for the proposition that machine learning-based geotechnical modeling can meaningfully improve the accuracy and efficiency of seismic foundation performance prediction relative to traditional statistical and simplified analytical approaches (Badrul, 2026). The 89.4% classification accuracy achieved by the deep neural network model, representing an 8.7 percentage-point improvement over random forest and a substantial 19.6 to 23.0 percentage-point improvement over linear regression and decision tree baselines, is broadly consistent with prior literature reporting accuracy gains of ten to twenty-five percentage points for machine learning models applied to seismic structural and foundation performance prediction incorporating SSI parameters (Kim et al., 2021; Fattah et al., 2023). This consistency across independently developed frameworks and case databases strengthens confidence in the generalizability of deep learning-based seismic foundation performance classification beyond the specific sample examined in this study (Mohammad, 2026).

The regression findings, indicating that shear wave velocity and peak ground acceleration were the strongest predictors of elevated damage classification, align with established theoretical accounts of soil–structure interaction mechanics, wherein softer founding soils amplify period elongation and can increase or decrease spectral demand depending on the relationship between the elongated period and

the dominant period of ground shaking (Mylonakis & Gazetas, 2000(Jannatul, 2026). The comparatively smaller, though still significant, contribution of foundation-to-structure mass ratio suggests that while this SSI-specific parameter meaningfully influences damage classification, consistent with its identification as an influential geotechnical parameter in prior ANN-based research (Kim et al., 2021 (Ahmed, 2026), its independent predictive contribution may be partially mediated through its interaction with soil stiffness and ground-motion intensity rather than operating as a fully independent risk channel. (Darendeli, 2001; Hardin & Drnevich, 1972; Menq, 2003; Vucetic & Dobry, 1991)

The observed differential in high damage-risk classification across foundation-soil combinations, with shallow foundations on liquefiable soil exhibiting more than four times the proportion of high-risk classifications relative to foundations on rock or stiff soil, reinforces the practical value of soil-type-stratified seismic risk screening rather than applying uniform performance expectations across heterogeneous foundation-soil configurations. This finding has direct implications for urban seismic risk management, suggesting that retrofit prioritization and foundation design review processes should incorporate soil-type-specific risk calibration informed by machine learning-derived exposure signals rather than relying solely on structural characteristics or code-prescribed site coefficients alone (Rahman, 2026).

The significant positive association between cumulative predicted damage risk index and both peak interstory drift ratio and residual displacement provides preliminary validation of the foundation resilience index as a meaningful indicator of structural vulnerability under soil–structure interaction conditions. This finding extends prior work on machine learning-based SSI performance prediction by demonstrating that a composite, multi-dimensional risk index, incorporating geotechnical, structural, and ground-motion parameters, exhibits predictive validity for realized structural performance outcomes beyond what any single risk dimension would capture in isolation (Kaium, 2026).

Despite these encouraging findings, several considerations warrant caution in interpretation. The moderate, rather than near-perfect, explanatory power of the regression model ($R^2 = 0.581$) indicates that a substantial proportion of variance in damage severity remains unexplained by the modeled predictors, potentially reflecting unmodeled structural detailing, construction quality, or site-specific geotechnical heterogeneity factors specific to individual cases. Additionally, while the deep neural network model demonstrated superior classification accuracy, its comparatively lower interpretability relative to code-based analytical procedures may present adoption barriers within regulatory and professional liability contexts that require transparent engineering justification, an issue previously identified as a persistent methodological challenge within the machine learning-based structural performance prediction literature (Fadel et al., 2023)

CONCLUSION

This study developed and empirically validated a machine learning-based geotechnical modeling framework designed to predict seismic foundation performance and characterize soil–structure interaction effects in large-scale urban infrastructure (Chowdhury, 2026). Drawing on a stratified sample of 131 foundation-structure case records spanning shallow, deep, and hybrid foundation types across rock, sand, clay, and liquefiable soil conditions, the study demonstrated that geotechnical and ground-motion-derived exposure variables, encompassing shear wave velocity, peak ground acceleration, soil-structure period elongation, and foundation-to-structure mass ratio, significantly predicted structural damage severity, explaining approximately 58% of observed variance. A deep artificial neural network architecture achieved a classification accuracy of 89.4%, meaningfully outperforming random forest, multiple linear regression, and decision tree baseline models across all evaluated performance metrics. Furthermore, the study established that cumulative machine learning-derived damage risk indices were significantly associated with realized peak interstory drift ratio and residual displacement, supporting the practical validity of the proposed foundation resilience index as a predictive seismic performance screening tool. (Breiman, 2001; Pervaz, 2026)

These findings collectively indicate that machine learning-based geotechnical modeling frameworks offer a reliable, objective, and scalable complement to traditional finite element and elastic half-space soil–structure interaction analysis approaches, particularly for portfolio-scale seismic risk screening across urban infrastructure inventories where detailed, project-specific coupled analysis is not feasible for every structure. The demonstrated differential in damage risk across foundation-soil combinations

further underscores the practical value of soil-type-stratified, machine learning-informed risk calibration for municipal building departments, infrastructure owners, and structural and geotechnical engineering practitioners seeking to prioritize seismic retrofit and design review resources. By integrating deep learning-based classification with established soil–structure interaction theory, this study contributes an empirically grounded and reproducible framework that advances the broader movement toward data-driven, technology-enabled seismic risk management for urban infrastructure.

RECOMMENDATIONS

[1]. Municipal building departments and infrastructure owners should consider integrating machine learning-based foundation performance screening as a complementary layer alongside, rather than a replacement for, detailed finite element and code-based soil–structure interaction analysis for critical or high-occupancy structures.

[2]. Seismic retrofit prioritization programs should incorporate soil-type-stratified risk calibration informed by the observed differential in damage risk across foundation-soil combinations, particularly for shallow foundations on liquefiable and soft clay soils that demonstrated disproportionately elevated damage classification rates.

[3]. Geotechnical and structural engineering teams should prioritize accurate characterization of shear wave velocity and site-specific ground-motion intensity as leading indicators, given their demonstrated status as the strongest predictors of elevated foundation damage classification within the regression analysis.

[4]. Engineering firms adopting deep neural network-based performance prediction models should invest in complementary interpretability tools and sensitivity analysis techniques to address regulatory and professional liability requirements for transparent engineering justification.

[5]. Future implementations should incorporate expanded case databases with greater representation of liquefiable soil and deep pile foundation configurations, given the comparatively limited sample sizes for these categories in the present study, to improve model robustness and generalizability.

[6]. Foundation resilience indices combining drift, residual displacement, and geotechnical stiffness metrics should be considered for integration into ongoing urban seismic risk monitoring and building inventory management systems to support proactive, rather than purely reactive, post-earthquake response planning.

LIMITATION

This study is subject to several limitations that warrant consideration when interpreting the findings. First, the sample of 131 foundation-structure cases, while stratified across foundation type and soil classification, may not fully capture the heterogeneity of structural configurations, construction practices, and geotechnical conditions present across the broader global urban infrastructure inventory, potentially limiting generalizability. Second, the reliance on a combination of published case histories, instrumentation records, and validated simulation outputs for ground-truth damage labeling, while cross-verified by independent reviewers, introduces a degree of heterogeneity inherent to compiling data across differing original documentation standards and analysis platforms. Third, the comparatively limited representation of liquefiable soil and hybrid foundation cases within the sample may constrain the precision of model predictions for these specific, high-consequence categories. Fourth, the deep neural network model's comparatively limited interpretability relative to code-based analytical procedures constrains its immediate applicability within regulatory contexts requiring fully transparent engineering justification for final design decisions. Finally, the study's cross-sectional design, while methodologically appropriate for the stated objectives, does not permit strong causal inference regarding the specific physical mechanisms underlying the observed associations between predicted damage risk indices and realized structural performance outcomes. Future research employing expanded, geographically diverse case databases, additional soil and foundation typologies, and explainable artificial intelligence techniques would help address these limitations and further validate the generalizability of the proposed framework.

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