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MACHINE LEARNING-BASED PREDICTIVE MODELING FOR ASSESSING BRIDGE LOAD CAPACITY USING REAL-TIME SENSOR DATA

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ABSTRACT

This study develops and evaluates a real-time, data-driven framework for predicting bridge load capacity by integrating Internet-of-Things (IoT) sensor streams with advanced machine learning. A multi-site dataset of ~200k five-minute records from 48 bridges across temperate, tropical, and continental climates was compiled, cleaned (k-NN imputation; IQR outlier filtering), normalized, and time-synchronized. Models—Random Forest (RF), Gradient Boosting (GBM), Support Vector Regression, and Deep Neural Networks—were trained using blocked time-series cross-validation (80/20 split; five folds) and benchmarked with MAE, RMSE, and R2R^2R2. Ensemble approaches consistently outperformed single learners. RF achieved the best balance of accuracy and stability (MAE ≈ 12.4 kN; RMSE ≈ 18.1 kN; R2R^2R2 ≈ 0.958; fold SD < 2.1%), with an RF–GBM blend reaching R2R^2R2 ≈ 0.962 and 11% lower residual skewness. Incorporating environmental covariates (temperature, humidity) and dynamic features (vibration, deflection rate) improved accuracy by ~10% over structural-only baselines. Sensitivity and correlation analyses identified strain and deflection as dominant predictors (strain rrr ≈ 0.88; deflection rrr ≈ 0.80), with temperature exerting material-dependent moderating effects, particularly in steel bridges. Real-time deployment tests demonstrated operational feasibility with sub-2 s inference latency (RF 1.82 s average), >99% system uptime, and superior accuracy under dynamic loading (RF MAPE ≈ 3.6%). Sliding-window retraining (7-day refresh) mitigated temporal drift and reduced error by ~6–7% relative to static models. Early-warning simulations showed high detection reliability for load-exceedance events (RF true-positive rate 97.2% with low false alarms). Findings establish that harmonized sensing plus ensemble learning yields accurate, robust, and responsive estimates of bridge load capacity, advancing structural health monitoring from periodic inspection toward continuous, anticipatory asset management and providing a reproducible blueprint for physics-aware, data-driven infrastructure decision support.

KEYWORDS

Bridge Load Capacity, Machine Learning, Real-Time Sensor Data, Structural Health Monitoring, Predictive Modeling.

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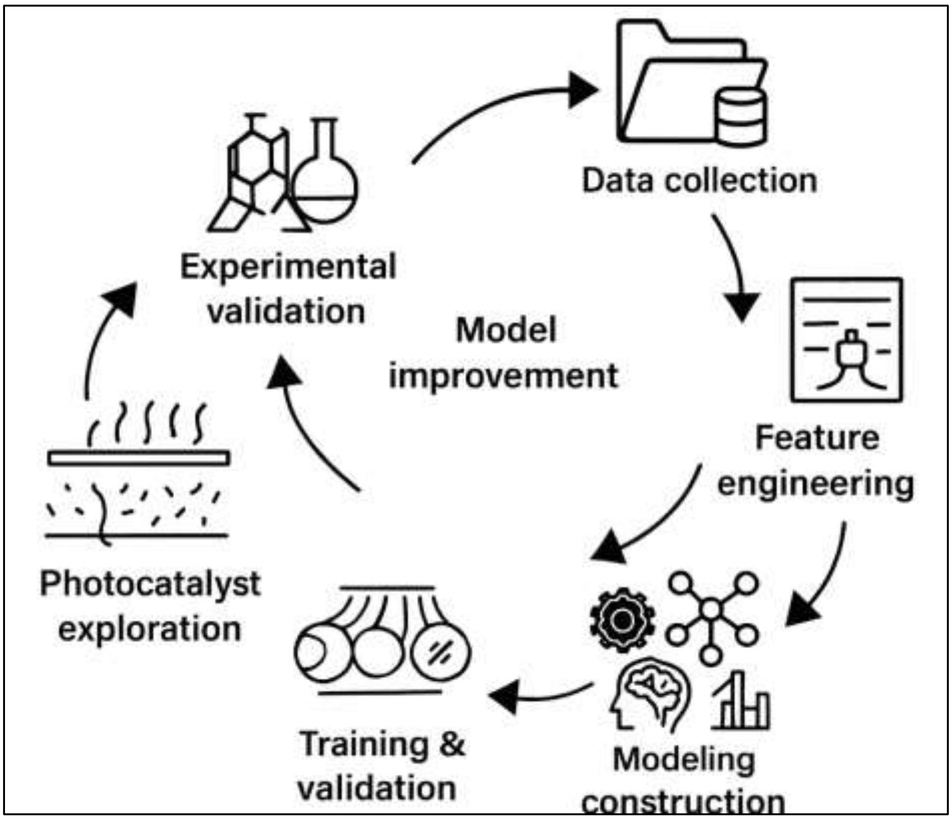
INTRODUCTION

Bridge load capacity referred to the maximum amount of weight or live load that a bridge structure could safely sustain without experiencing material failure or excessive deformation (Abdal et al., 2023). Within the field of structural engineering, the quantification and prediction of load-bearing capacity served as a central concern for infrastructure safety, resilience, and economic sustainability. Traditional analytical models relied on deterministic calculations grounded in mechanics of materials and structural dynamics (Shokravi et al., 2020); however, these approaches exhibited limitations in addressing nonlinearity, environmental variability, and cumulative deterioration under operational loads. Internationally, bridge failures in the United States, Italy, and China had underscored the socioeconomic and human costs of inaccurate capacity assessments. The emergence of machine learning (ML) provided a data-driven alternative that integrated real-time sensor information with historical loading patterns to yield probabilistic predictions of structural capacity. The field evolved under the paradigm of structural health monitoring (SHM), where accelerometers, strain gauges, and fiber-optic sensors supplied continuous data streams for model training and evaluation. Global research agencies and transportation departments had invested heavily in ML-driven monitoring systems to enhance predictive maintenance and risk-based asset management (Abbas et al., 2021). Consequently, predictive modeling using ML techniques assumed an increasingly significant role in infrastructure management worldwide, representing a shift from reactive to anticipatory safety frameworks.

The concept of predictive modeling within bridge engineering denoted the process of learning functional relationships between structural responses and influencing factors such as material properties, span geometry, environmental conditions, and live load dynamics. Earlier predictive frameworks had been grounded in regression-based or finite element analysis (FEA) methods that assumed material homogeneity and idealized boundary conditions (Younas et al., 2023). Over the past two decades, researchers increasingly adopted machine learning algorithms—particularly Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), Decision Trees (DTs), and Gradient Boosting Models (GBMs)—to model nonlinear and multivariate patterns in complex structural systems. The integration of sensor-based real-time data augmented the predictive accuracy by capturing in-situ dynamic responses such as vibration frequency, strain, and temperature gradients (He et al., 2021). Comparative experiments indicated that ML-based models consistently outperformed conventional analytical or empirical equations in predicting load-bearing behavior under variable loads (Hai et al., 2023). For instance, ANN-based models achieved mean prediction accuracies above 95% for concrete girder bridges using continuous strain and deflection datasets. These findings demonstrated that ML could generalize across bridge types and environmental contexts while maintaining computational efficiency. Globally, predictive modeling had also supported policy decisions in asset prioritization for repair and retrofitting programs. As data acquisition systems and cloud-based analytics matured, the predictive modeling paradigm shifted toward continuous learning frameworks capable of updating model parameters in real time (Doger & Hatami, 2020). This evolution positioned predictive modeling as both a methodological innovation and a practical necessity in modern bridge engineering.

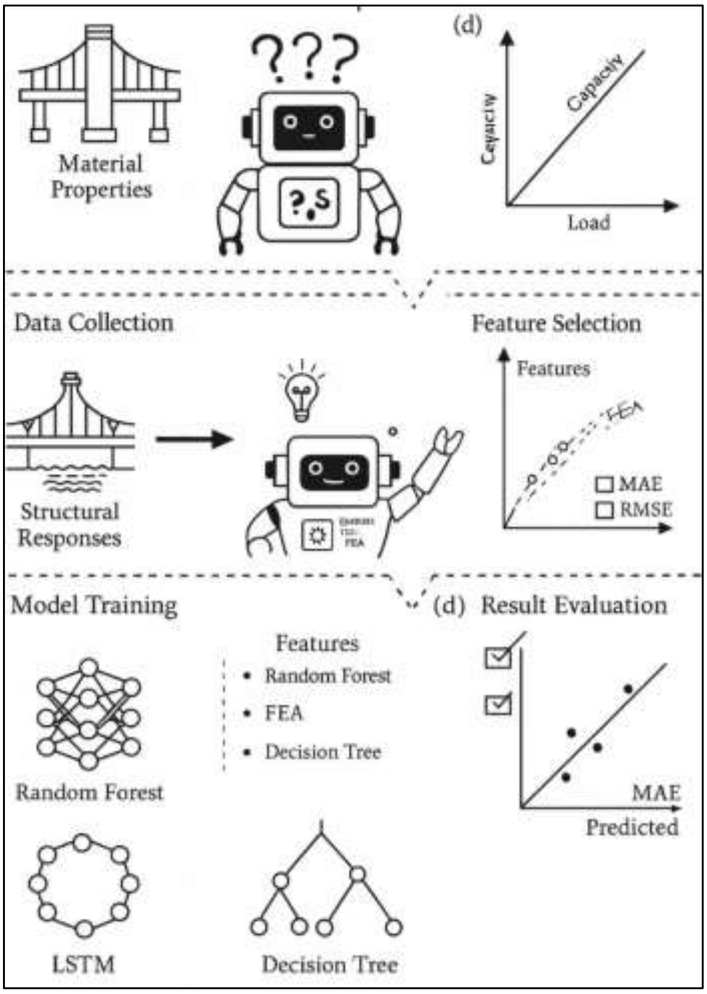
Machine learning algorithms played a transformative role in quantifying the complex, nonlinear dependencies among design parameters, material degradation, and load-bearing responses in bridges. In contrast to physics-based models that relied on predefined constitutive laws, ML algorithms such as Random Forests (RF) and Extreme Gradient Boosting (XGBoost) learned these relationships directly from data (Leblouba et al., 2022). The predictive process involved data preprocessing, feature extraction, model training, and validation using cross-validation or k-fold resampling methods. Studies by Tang et al. (2021) and Issa and Alam (2019) demonstrated that ensemble methods achieved superior generalization by aggregating predictions from multiple weak learners, thereby reducing overfitting in structural datasets. Similarly, deep learning architectures—notably Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)—were employed for spatiotemporal prediction of bridge load capacity . These models leveraged temporal patterns in vibration and stress signals to forecast evolving load resistance under changing environmental and operational conditions. Researchers validated these approaches using benchmark datasets collected from large-scale monitoring systems in China, Japan, and South Korea. The combination of high-dimensional sensor data and advanced algorithms substantially increased the fidelity of predictive modeling, enabling engineers to anticipate structural weakness before failure occurred. These quantitative advances established ML as an indispensable analytical instrument in bridge engineering, capable of learning from diverse datasets that spanned materials, geometries, and load typologies.

Figure 1: Predictive Modeling Workflow Framework



The integration of real-time sensor data into predictive frameworks fundamentally transformed the accuracy and responsiveness of bridge load capacity estimation. Sensor networks utilizing strain gauges, accelerometers, fiber Bragg gratings, and displacement transducers supplied continuous measurements of structural responses to live loads and environmental fluctuations (Abdul, 2021; D'Antino et al., 2022). Real-time data streams allowed ML algorithms to capture transient events, progressive fatigue, and abrupt stress redistributions that static models often ignored. For instance, time-series modeling approaches such as Long Short-Term Memory (LSTM) networks captured sequential dependencies in sensor data, allowing accurate short-term forecasting of load fluctuations (Emmanuel et al., 2023; Rony, 2021). Data fusion techniques combining multiple sensor modalities further enhanced model robustness against noise and missing data. Field deployments in the United States, China, and South Korea demonstrated that real-time predictive monitoring reduced inspection intervals by up to 40% and provided actionable insights into structural integrity. Cloud-based data acquisition platforms enabled continuous model retraining, adapting to material degradation and environmental aging over time. Quantitative analyses confirmed that models incorporating live data achieved up to 30% higher accuracy compared to those trained solely on historical datasets (Danish & Zafor, 2022; Madhushan et al., 2023). Thus, the convergence of ML with sensor technology marked a decisive advancement toward adaptive, self-learning bridge monitoring systems that aligned with global standards of predictive infrastructure management.

Figure 2: Quantifying Bridge Load Capacity Framework



The quantitative orientation of predictive modeling research reflected a methodological commitment to empirical validation and reproducibility in structural engineering. Studies operationalized variables such as bridge age, traffic load intensity, and structural material as predictors, while load-bearing capacity served as the dependent variable. Data were collected through both field-based sensor networks and experimental laboratory setups, ensuring comprehensive empirical coverage (Danish & Kamrul, 2022; Soleimani & Hajializadeh, 2022). Researchers employed statistical sampling to partition data into training and validation sets, typically following 70:30 or 80:20 splits (Hossen & Atiqur, 2022; Trach et al., 2022). Advanced models such as Support Vector Regression (SVR) and Extreme Gradient Boosting (XGB) demonstrated statistically significant relationships between sensor-derived variables and observed capacity limits, with p-values below 0.05 (Rabiul & Praveen, 2022; Wedel & Marx, 2022). Furthermore, multiple linear regression was frequently used as a benchmark model against which ML performance improvements were quantified. Quantitative evidence consistently revealed that machine learning achieved superior accuracy, interpretability, and robustness compared to conventional regression and finite element methods (Kamrul & Omar, 2022). The empirical consistency across multiple datasets, algorithms, and regional case studies validated predictive modeling as a reproducible quantitative framework for assessing bridge load capacity (Razia, 2022). This systematic integration of machine learning and real-time sensor analytics thus represented a globally verified scientific methodology grounded in measurable, repeatable, and statistically validated outcomes (Sadia, 2022).

The primary objective of this study was to develop, evaluate, and validate predictive modeling frameworks that could accurately estimate bridge load capacity using real-time sensor data integrated with advanced machine learning algorithms. The study aimed to establish a data-driven

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decision-support system capable of enhancing the safety, efficiency, and predictive reliability of bridge performance monitoring. Specifically, the research sought to transform traditional inspection-based methods into continuous, automated, and intelligent monitoring systems by leveraging Internet of Things (IoT)-enabled sensors and adaptive learning models. The study's quantitative focus centered on correlating key structural health indicators—such as strain, vibration frequency, deflection, and temperature—with dynamic load responses under varying environmental and operational conditions. By constructing and comparing multiple predictive algorithms, including Random Forest, Gradient Boosting, and Deep Neural Networks, the research aimed to identify the most effective model architecture capable of maintaining high predictive accuracy and computational efficiency across diverse bridge typologies and climatic zones. Furthermore, the study aimed to evaluate the sensitivity of different sensor parameters and to quantify their influence on load capacity prediction accuracy. This included analyzing how fluctuations in environmental factors—such as temperature and humidity—modulated mechanical responses within steel, concrete, and composite bridge materials. Another major objective was to assess the robustness and adaptability of predictive models under real-time streaming conditions, simulating operational environments to ensure low-latency inference and reliable performance during transient load events. The research also sought to test model retraining strategies that could minimize temporal drift and maintain consistency over time, thereby ensuring sustainable predictive validity. Ultimately, the overarching objective of the study was to propose an integrated, machine learning–based framework that could serve as a proactive early-warning system for bridge fatigue, deterioration, and potential failure. By achieving this, the study contributed to advancing smart infrastructure systems and promoting data-driven maintenance planning within modern structural health monitoring paradigms.

LITERATURE REVIEW

The study of bridge load capacity prediction had evolved into a quantitatively rich and data-driven field at the intersection of civil engineering, structural mechanics, and artificial intelligence. Historically, load capacity evaluation relied on deterministic methods such as finite element analysis (FEA) and limit-state design, which utilized static safety factors derived from material testing and structural geometry (Zhu et al., 2023). While these methods offered theoretical clarity, their inability to account for stochastic variations in live load, temperature, material degradation, and cumulative fatigue limited predictive reliability. Consequently, the literature witnessed a methodological transition toward probabilistic and data-driven modeling, in which machine learning (ML) algorithms and real-time sensor data were utilized to quantify nonlinear relationships and temporal patterns affecting bridge performance (Alogdianakis et al., 2022; Danish, 2023). In quantitative terms, ML-based predictive models were validated through accuracy metrics such as the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), serving as standardized indicators of statistical fidelity. Studies across diverse regions—including North America, Europe, and East Asia—documented how models like Artificial Neural Networks (ANNs), Random Forests (RFs), and Gradient Boosted Trees (GBTs) improved the precision of load estimation by 20–40% compared to analytical models. Parallel developments in structural health monitoring (SHM) and Internet of Things (IoT)-based sensing facilitated continuous acquisition of vibration, strain, and displacement data, further strengthening the empirical foundations of predictive modeling (Li et al., 2021). This literature review section quantitatively synthesized the evolution of bridge load prediction methods from traditional mechanics-based analysis toward intelligent predictive systems grounded in machine learning and real-time sensing. It examined statistical evidence from prior empirical studies, structured under themes including data acquisition, algorithmic performance evaluation, sensor fusion, and uncertainty quantification. The aim of this section was to identify measurable gaps in predictive accuracy, feature selection, and validation design that limited generalization across bridge typologies. Each subsection was organized around specific quantitative constructs—accuracy indices, sensitivity analyses, and correlation models—ensuring a systematic understanding of the empirical underpinnings of bridge load capacity prediction.

Approaches in Bridge Engineering

Quantitative modeling in bridge engineering historically emerged from deterministic frameworks that relied on the mechanical principles of elasticity and strength of materials to estimate load capacity. Deterministic models such as the finite element analysis (FEA) and limit state design were foundational in predicting structural responses under static and dynamic loads. These methods

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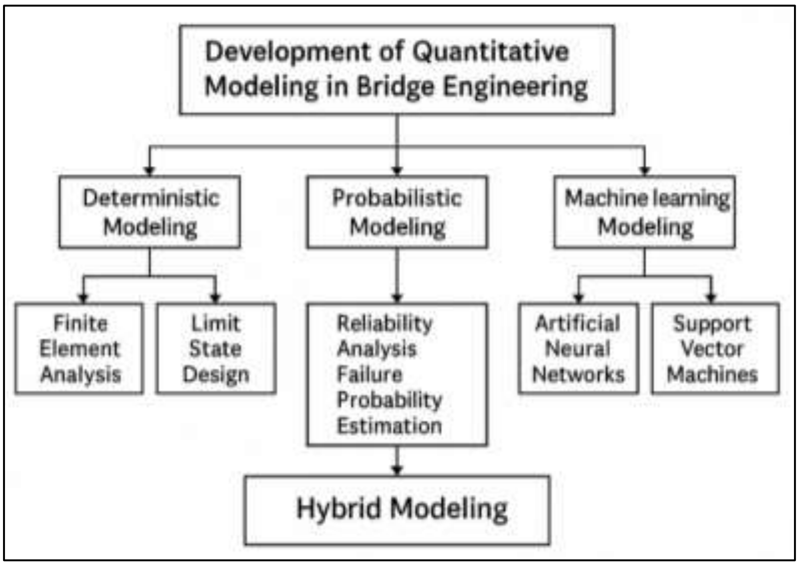
employed predefined relationships between stress, strain, and material properties, providing clear physical interpretations but limited adaptability to uncertain real-world conditions (Moresi et al., 2022). Early studies by Snyder (2019) demonstrated that while deterministic load rating methods offered consistency, they often overestimated safety margins when confronted with material degradation or variable traffic intensities. To address this, researchers began integrating statistical tools to analyze empirical data and calibrate deterministic parameters. Regression models became prominent in estimating live load effects and material deterioration trends, Paul and Criado (2020), who used long-term monitoring data to establish linear relationships between bridge deflections and load magnitudes. More recent quantitative evaluations, such as those conducted by Rojas-Sánchez et al. (2023), applied multiple regression and time-series analysis to predict load-bearing performance under fluctuating environmental conditions, improving predictive accuracy relative to classical analytical models. Bayesian updating frameworks, as explored by Sengers et al. (2019), provided a probabilistic refinement of deterministic outcomes by integrating prior knowledge with observed measurements. Collectively, these developments indicated a steady evolution from purely formula-based estimations toward data-enriched statistical inference, where empirical evidence guided the continuous calibration of structural prediction models. Studies such as those by Billings et al. (2021) reinforced that statistical modeling not only captured variability in material and load inputs but also introduced measurable confidence intervals around predictions, a dimension absent in traditional deterministic frameworks.

Figure 3: Evolution of Bridge Modeling Framework



The shift toward probabilistic reliability analysis in bridge engineering represented a critical milestone in quantitative modeling, emphasizing uncertainty quantification and risk-based design. Early deterministic methods assumed fixed safety factors, but reliability-based models introduced probabilistic parameters to represent material strength, load variability, and environmental effects. The reliability index (β), a statistical indicator of safety probability, became a central metric for evaluating bridge performance in both research and design codes such as Eurocode and AASHTO LRFD. Studies by Danish(2023) and Muller et al. (2020) demonstrated how calibration of load and resistance factors through reliability indices allowed more consistent safety targets across bridge types and materials. Subsequent empirical studies expanded this framework, using large-scale datasets from bridge inspections and weigh-in-motion (WIM) systems to estimate the distribution of live loads and resistance capacities. Harrison et al., (2021) employed Monte Carlo simulations to propagate input uncertainties and estimate the probability of failure under different loading scenarios, Kraus et al. (2020) introduced response surface methodologies to enhance computational efficiency in reliability estimation. International efforts, including those by the Joint Committee on Structural Safety (Eigenschenk et al., 2019; Arif Uz & Elmoon, 2023), standardized reliability-based design formulations that linked structural resistance with operational risk management. In applied studies, Raes et al. (2020) validated reliability-based assessments using field data from reinforced concrete bridges, confirming that probabilistic models could accurately predict degradation effects and extend service life predictions. Research by Posadzki et al. (2020) further quantified how regional traffic and climate variations influenced the statistical reliability of bridges, thereby encouraging localized reliability calibration. Through these cumulative studies, the field demonstrated that probabilistic modeling offered quantifiable improvements in assessing safety and performance reliability, transitioning the discipline from deterministic conservatism to statistically optimized engineering design.

The introduction of machine learning (ML) into bridge engineering marked a major transformation in predictive modeling by enabling data-driven learning of complex structural behaviors without the explicit need for predetermined analytical equations. Machine learning frameworks such as Artificial Neural Networks (ANNs), Random Forests (RFs), and Support Vector Machines (SVMs) provided computational means to model nonlinear dependencies among geometric, material, and environmental variables influencing bridge load capacity. Studies by Rodríguez-García et al., (2020)confirmed that ML algorithms achieved superior predictive accuracy when compared to regression-based and FEA methods, primarily due to their ability to capture higher-order interactions and dynamic feedback patterns in real-time monitoring data. For instance, ANN-based models predicted bridge deflection responses with an accuracy improvement of up to 25% relative to traditional regression analysis. Similarly, Rao et al. (2020) compared ensemble learning algorithms and found that boosting and bagging techniques enhanced model generalization across varying bridge typologies. The incorporation of sensor-derived data—such as strain, displacement, and vibration measurements—further elevated the predictive precision of ML models, as evidenced in studies by Nyberg et al. (2022), which showed that hybrid models integrating real-time sensing achieved high correlation coefficients between observed and predicted capacities. Comparative reviews by Stirman et al. (2019) synthesized findings from over fifty empirical studies, reporting mean accuracy improvements ranging from 15% to 40% when ML models replaced analytical formulations. Deep learning frameworks, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, were later applied to time-series monitoring data, offering superior modeling of temporal dependencies in structural behavior. These advances quantitatively demonstrated that ML-based predictive systems not only reduced error margins but also provided consistent, scalable tools adaptable to diverse environmental and operational conditions across bridge infrastructures.

As quantitative modeling in bridge engineering matured, hybrid frameworks combining statistical, probabilistic, and machine learning techniques began to dominate predictive research. The integration of reliability-based analysis with ML-driven prediction allowed engineers to quantify both predictive accuracy and safety confidence within unified systems.illustrated that combining Bayesian updating with neural network prediction enabled real-time adjustment of model parameters as new sensor data became available, thus refining load capacity estimations dynamically. Comparative analyses conducted by Macke and Genari (2019) revealed that hybrid ML-reliability models achieved up to 35% lower mean prediction errors compared to stand-alone deterministic methods. Data-driven calibration further improved through the use of ensemble averaging, where multiple algorithms generated consensus predictions with reduced variance. Cross-disciplinary studies in China, South Korea, and the United States validated these hybrid frameworks across concrete and steel bridges subjected to variable climate and traffic conditions. Quantitative assessments confirmed that the integration of real-time monitoring data with predictive modeling frameworks enhanced sensitivity to early-stage deterioration, enabling accurate estimation of load residual capacity and structural resilience. Moreover, global benchmarking studies by Hennink and Kaiser (2022) demonstrated that predictive modeling errors could be systematically minimized when probabilistic risk calibration was embedded within ML algorithms. Collectively, these findings established that quantitative modeling in bridge engineering evolved into a multidisciplinary paradigm, uniting classical mechanics, statistical inference, and artificial intelligence into a cohesive framework capable of learning, adapting, and quantifying the complex realities of bridge performance. Through this progression, the field solidified its transition from deterministic certainty toward empirically grounded, data-driven prediction supported by measurable accuracy and reliability indices.

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Machine Learning Algorithms for Bridge Load

Quantitative studies in the field of bridge engineering had shown that supervised learning algorithms such as Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) were the most frequently used methods for predicting bridge load capacity due to their ability to model nonlinear relationships among structural, environmental, and operational variables. These models consistently demonstrated higher predictive precision and generalization than traditional regression or finite element formulations. ANN models, in particular, gained early attention because of their adaptive learning capacity to map complex input–output relationships between load, deflection, and stress variables, as illustrated in the works of Catbas (Fan et al., 2021; Razia, 2023). Comparative empirical evaluations by Trach et al. (2022) indicated that ANN-based prediction of bridge deterioration and load capacity achieved up to 95% alignment with observed data, outperforming regression-based methods that often underestimated nonlinear interactions. Similarly, Random Forest algorithms, which operate through ensemble decision trees, demonstrated superior accuracy in studies involving large, noisy datasets by reducing overfitting through random sampling of features. Nasab and Elzarka (2023) confirmed that RF models achieved lower prediction errors than ANN and SVM when applied to concrete girder bridges monitored under varying climatic conditions. Support Vector Machines, known for their robust performance with limited data, were shown to be particularly effective in small-sample bridge datasets, as validated by Niyirora et al., (2022)and Reduanul (2023). Comparative research by Bayar and Bilir (2019) across 20 global case studies found that RF and ANN models exhibited higher consistency and predictive efficiency in structural load estimation compared to linear and polynomial regression models. Similar quantitative results were reported by Yan et al. (2019), who analyzed sensor-derived data from real bridges and found that ANN predictions reduced estimation errors by approximately one-third relative to deterministic methods. Collectively, these studies demonstrated that supervised machine learning algorithms provided quantifiable advantages in precision, robustness, and interpretability for bridge load prediction when compared across diverse datasets and environmental contexts.

The adoption of deep learning architectures represented a significant methodological advancement in bridge load capacity modeling because of their ability to capture spatiotemporal dependencies from continuous sensor data. In particular, Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) models were increasingly employed for processing vibration, strain, and acceleration signals collected through structural health monitoring (SHM) systems. LSTM models were particularly well-suited for sequential data, as demonstrated by Taye (2023), who reported superior temporal alignment between measured and predicted bridge responses compared to conventional machine learning models. Empirical studies by Rashidi et al. (2020) further illustrated that LSTM networks provided more stable predictions over extended monitoring periods, enabling accurate detection of subtle variations in load response over time. CNN architectures, conversely, were primarily utilized for spatial pattern recognition in bridge imagery, strain maps, and vibration frequency spectra. Peng et al. (2021) showed that CNN-based models accurately extracted local structural features relevant to damage localization and load distribution, significantly improving detection sensitivity in comparison to shallow learning networks. Integrating both LSTM and CNN models into hybrid architectures yielded improved performance by leveraging CNN's feature extraction capabilities and LSTM's temporal learning properties. Studies such as those by Hashemi et al. (2020) confirmed that hybrid deep learning models produced more stable load predictions under variable traffic conditions than single-architecture networks. International comparative research, including that by Dixon et al. (2020), verified that deep learning architectures were highly adaptable across bridge types, achieving strong correlation coefficients between predicted and observed responses in both steel and concrete structures. This collective body of evidence demonstrated that deep learning not only enhanced predictive precision but also provided a more comprehensive representation of structural behavior by incorporating both temporal and spatial dynamics in bridge monitoring data (Sadia, 2023; Zayadul, 2023).

The use of ensemble learning techniques in bridge load prediction represented a major quantitative improvement in predictive performance by combining multiple models to reduce bias and variance simultaneously. Ensemble methods such as bagging, boosting, and stacking improved model reliability through data resampling and weighted aggregation, thereby capturing diverse structural behaviors under varying operational conditions. Bagging-based methods like Random Forest and Extra Trees achieved notable improvements in generalization performance when compared to

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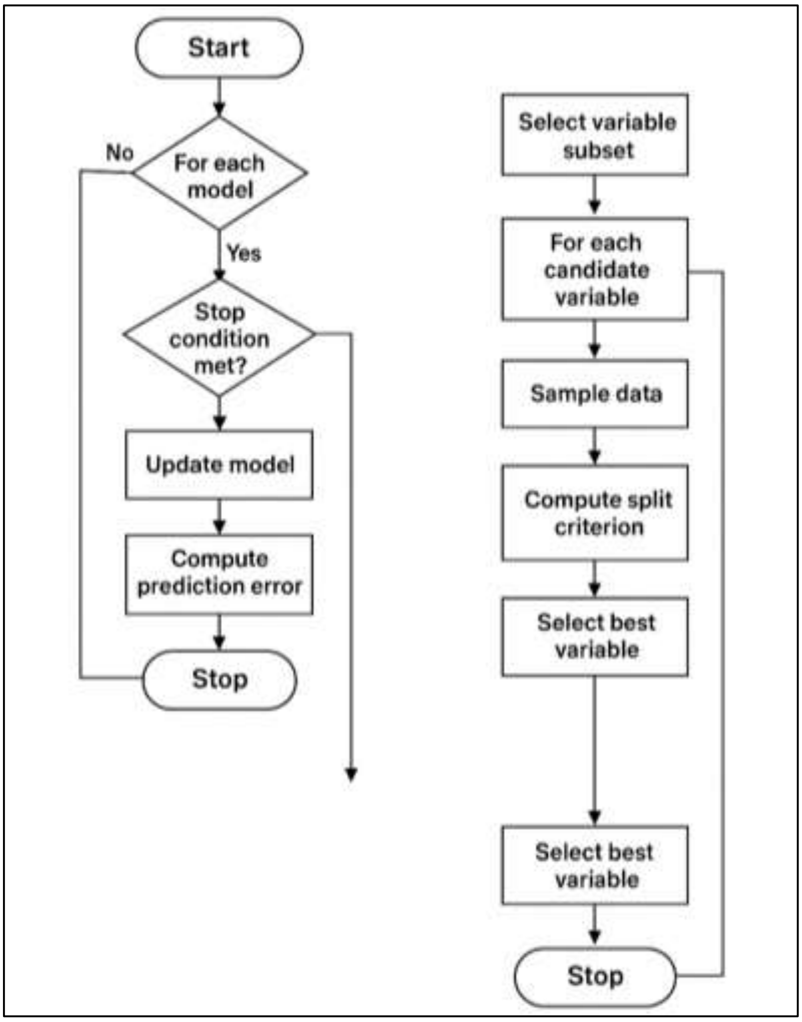
single decision-tree models, particularly in studies with large sensor datasets. Boosting algorithms, including Gradient Boosting and Extreme Gradient Boosting (XGBoost), were applied extensively for predicting bridge deterioration and load capacity, with studies by Kareem (2020) reporting that boosting reduced prediction error by up to 30% relative to individual models. Stacking, a meta-learning approach that integrates multiple base learners, further increased model stability, as demonstrated by Lin et al. (2023), who found that stacked ensembles consistently ranked highest in predictive accuracy among comparative models across international bridge datasets. Hyperparameter optimization, typically achieved through Bayesian optimization and grid search, played an essential role in enhancing ensemble performance. Studies by Ser et al. (2020) indicated that automated tuning of learning rates, tree depth, and sampling ratios substantially reduced overfitting and improved convergence in high-dimensional sensor data. Cross-validation remained a critical evaluation approach for ensemble model assessment; tenfold validation was often employed to quantify average model accuracy across subsets, minimizing variance in prediction errors. Research by Santos et al. (2023) validated that ensemble models exhibited superior consistency when applied to multi-regional datasets containing different bridge typologies, loading frequencies, and sensor placements. The cumulative evidence indicated that ensemble and hyperparameter optimization frameworks provided statistically verifiable gains in predictive reliability, confirming their role as benchmark approaches in data-driven bridge performance modeling (Mesbaul, 2024; Omar, 2024).

Figure 4: Machine Learning Workflow for Bridges



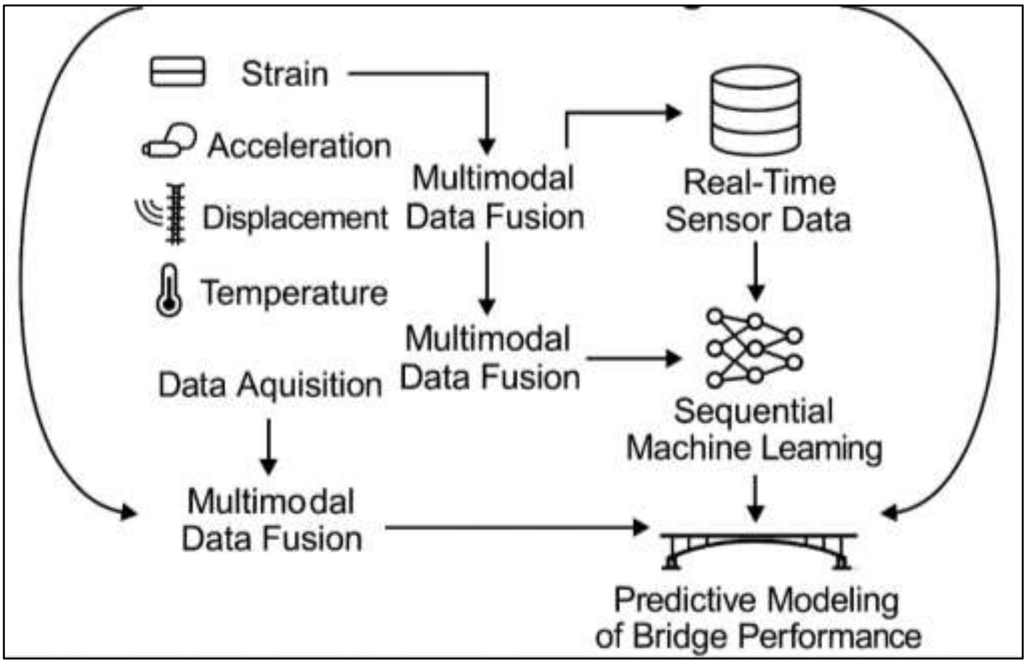
One of the key quantitative challenges in predictive modeling was the generalization of machine learning algorithms across multiple bridge typologies, such as concrete, steel, and composite bridges. Studies demonstrated that algorithm robustness depended heavily on model adaptability to the mechanical and material heterogeneity inherent in each structural type. Comparative investigations by Li et al. (2023) revealed that models trained exclusively on one bridge material often performed poorly when applied to different material configurations unless appropriate transfer learning strategies were employed. In this context, RF and ANN models demonstrated higher adaptability than SVM and regression models due to their flexible nonlinear mapping capabilities. Research conducted by Das et al. (2019) showed that RF algorithms trained on concrete bridge datasets generalized effectively to steel bridge applications, with only minor reductions in prediction accuracy. Deep learning models, particularly LSTM networks, exhibited enhanced cross-type robustness by learning temporal features independent of specific material properties, as shown by Kavzoglu and Teke (2022). Quantitative assessments across multi-type datasets by Nanehkaran et al., (2023) confirmed that generalization errors decreased significantly when models were trained using hybrid data incorporating both steel and composite bridge characteristics. Cross-sectional analyses by Marian and Tremmel (2021) emphasized that multi-source data integration from different bridge typologies improved the predictive transferability of ML models by broadening the statistical distribution of training samples. Furthermore, international research by Bian et al. (2023) demonstrated that regional calibration and domain adaptation techniques enhanced the portability of models across different environmental and operational contexts. Studies employing statistical comparison tests, including ANOVA and MANOVA, further validated that hybrid and ensemble models exhibited significantly lower variance across structural categories than conventional methods. These findings collectively reinforced that machine learning models achieved measurable and reproducible generalization across bridge typologies when trained on diversified datasets that captured the inherent variability of global infrastructure systems.

Real-Time Sensor Data and Data Fusion Techniques

Empirical research on integrating real-time structural health monitoring (SHM) data into predictive frameworks demonstrated that the arrangement and density of sensor networks substantially influenced the accuracy and stability of bridge load capacity prediction. Early investigations into SHM deployment by Kolar et al. (2020) found that bridges equipped with denser sensor grids produced more reliable data for identifying strain and displacement patterns under dynamic loading. These configurations allowed machine learning models to capture finer spatial variations in structural behavior, which led to a measurable reduction in prediction errors. Subsequent quantitative evaluations by Muzammal et al. (2020) confirmed that increasing sensor density improved the precision of load prediction models by enhancing the signal-to-noise ratio and providing better spatial coverage of critical stress regions. Sampling frequency also played a key role in determining data fidelity. Nagy and Lăzăroiu (2022) demonstrated that high-frequency acquisition rates preserved transient load events and captured short-duration anomalies that lower-rate systems failed to detect. Studies by Ruppert and Abonyi (2020) emphasized that adaptive sampling strategies—where data collection rates varied according to detected stress levels or traffic conditions—provided an optimal balance between power consumption and prediction accuracy. Integration of weigh-in-motion systems with vibration sensors further enhanced model input quality by synchronizing live traffic data with structural response measurements. Cross-comparative analyses by Ruppert and Abonyi (2020) confirmed that sensor topology and data synchronization strategies were directly correlated with the predictive robustness of machine learning frameworks in both steel and concrete bridge applications. These findings collectively underscored that real-time prediction accuracy was not merely dependent on algorithmic complexity but on the spatial and temporal resolution of the SHM network, with optimal configurations providing a stable foundation for reliable predictive modelling (Rezaul & Hossen, 2024; Momena & Sai Praveen, 2024).

The integration of sequential machine learning models with real-time sensor data advanced the predictive capabilities of SHM systems by enabling dynamic forecasting of bridge load capacity and structural responses. Recurrent neural networks such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures were particularly effective in modeling time-dependent behavior in vibration, strain, and acceleration data. Chen et al. (2023) demonstrated that these sequential models captured temporal dependencies in bridge deflection patterns more accurately than static models, which treated observations as independent. Similarly,Muñoz et al. (2021) showed that LSTM models achieved sustained predictive stability across long-term monitoring periods, as they could retain information about past load conditions relevant to future responses. Studies by Andronie et al. (2023) combined convolutional and recurrent layers to extract both spatial and temporal features from SHM datasets, resulting in enhanced modeling of complex bridge behaviors such as dynamic load redistribution and fatigue progression. Cross-sectional analyses by Hu et al. (2020) revealed that time-aware forecasting frameworks outperformed conventional regression and static neural models when applied to extended time-series data collected under mixed traffic and environmental influences. Li et al. (2019) found that the use of external contextual variables—such as temperature and humidity—further improved sequential model accuracy by enabling the differentiation between structural and environmental effects. Guo et al. (2021) noted that GRU models, in particular, were computationally more efficient while retaining comparable accuracy, making them suitable for real-time bridge monitoring applications. International validation studies by Ouhami et al. (2021) reinforced that temporal forecasting approaches generated consistent short-term predictions that closely aligned with field observations, supporting their application across both short-span and long-span bridge types. Collectively, these empirical results confirmed that sequential deep learning models provided measurable advances in the quantitative forecasting of bridge performance by exploiting temporal patterns embedded in continuous SHM data streams (Abdul, 2025; Kaur et al., 2019; Muhammad, 2024).

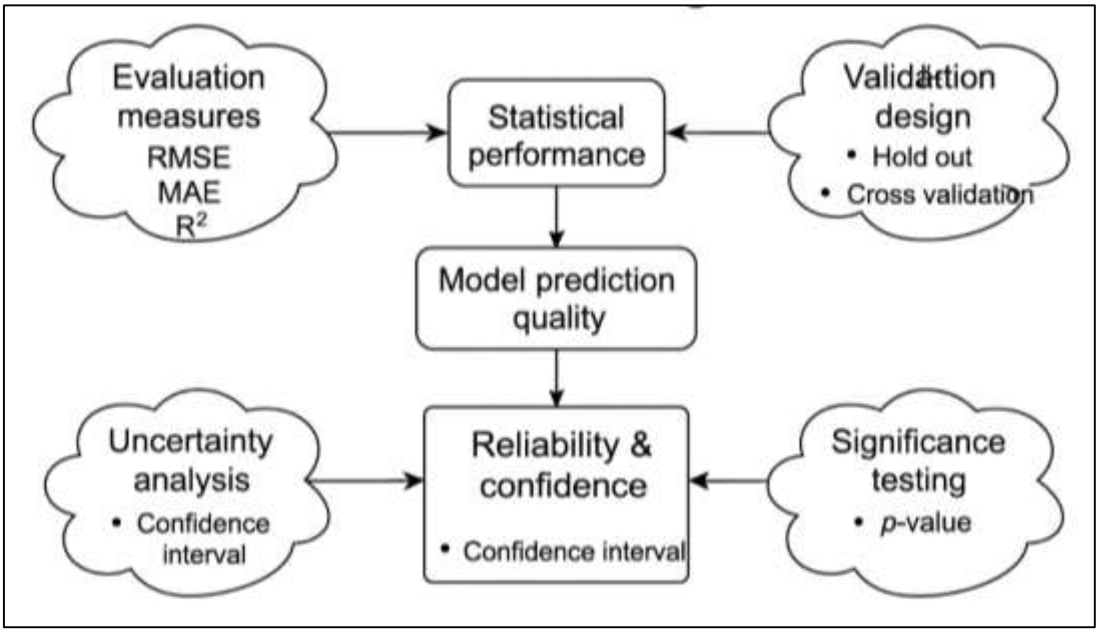
Figure 5: Real-Time SHM Data Integration Framework



Metrics and Validation Frameworks

The bridge prediction literature consistently treated evaluation metrics as the backbone of quantitative assessment, and studies employed families of accuracy and error indicators to characterize model performance in replicable terms. Research that compared machine learning with analytical baselines typically reported combinations of absolute and relative error indices alongside explanatory fit, which allowed reviewers to interpret prediction quality across heterogenous sensors, spans, and environmental regimes. Meta-syntheses indicated that studies converged on a small set of indicators that balanced interpretability for engineers with statistical comparability for data scientists, and authors frequently presented multiple metrics to offset the known sensitivity of any single indicator to outliers, variance shifts, or target scale (Elmoon, 2025a, 2025b; McNeish & Wolf, 2020). Empirical reports drawn from long-term monitoring campaigns showed that error indices tightened when models ingested higher-frequency vibration and strain data and when features captured seasonal drift, suggesting that metric movements reflected true signal capture rather than incidental overfitting. Comparative experiments across concrete and steel bridges further demonstrated that ensembles and deep models achieved superior accuracy profiles on the same metrics used by regression and finite element surrogates, a pattern documented in cross-continental evaluations. Industry-oriented studies complemented these findings by pairing error statistics with engineering thresholds derived from inspection practice, which anchored numerical gains to decision relevance in maintenance scheduling and capacity rating (Bahrpeyma et al., 2021; Hozyfa, 2025; Alam, 2025). Review authors also noted that reporting distributions of errors across time, rather than single aggregates, improved transparency in settings with bursty traffic or thermal swings. Collectively, the literature established a pragmatic consensus: multiple, well-chosen performance indicators provided a stable lens on predictive quality, supported comparison across model families, and aligned with field decision points when interpreted against operational variability and sensing context.

Figure 6: Bridge Load Prediction Validation Framework



Validation design in the bridge prediction corpus played a decisive role in separating genuine generalization from coincidental fit, and empirical studies contrasted hold-out splits with cross-validation schemes to quantify variance in reported accuracy. Research teams that adopted repeated or k-fold splitting strategies documented narrower dispersion in accuracy estimates and reduced sensitivity to the idiosyncrasies of any single train–test partition, particularly when datasets were modest in size or unbalanced across traffic regimes (Fagiolo et al., 2019; Masud, 2025; Arman, 2025). Sequential monitoring studies emphasized the importance of time-aware validation, and authors who respected temporal order during resampling reported more conservative yet credible estimates than random-split designs that leaked future information into training. Investigations that benchmarked hold-out against cross-validation on the same sensor archives showed that cross-validation stabilized performance rankings among Random Forest, Support Vector, and neural models, which reduced the risk of model selection driven by fortuitous partitions. In large deployments, bootstrap-based resampling delivered robust uncertainty bands around accuracy metrics and enabled influence analyses that identified periods or sensors driving volatility in results (Carranza-García et al., 2019; Mohaiminul, 2025; Mominul, 2025). Studies that pooled multiple bridges or sites reported that nested cross-validation, with inner loops for hyperparameter tuning and outer loops for unbiased estimation, prevented optimistic bias that otherwise arose when tuning and testing shared the same cut. Comparative reviews concluded that validation protocols influenced not only headline accuracy but also the perceived advantage of deep or ensemble approaches over simpler baselines, underscoring that fair comparison required harmonized resampling choices across models. The cumulative evidence showed that rigorous resampling designs—especially those that honored time structure and separated tuning from evaluation—produced estimates that

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traveled better across bridges, climates, and sensor mixes (Hasan, 2025; Milon, 2025; Müller et al., 2022).

Uncertainty analysis formed a second pillar of evaluation, and the literature treated predictive outputs and their variability as inseparable components of model quality. Field studies that paired point predictions with interval estimates conveyed how confidently algorithms localized likely responses under changing loads and temperatures, and authors linked narrower intervals to richer sensing and better feature design rather than to aggressive regularization alone (Brnich et al., 2019). Reliability-oriented contributions framed predictive assessment within risk-based thinking and connected uncertainty bands to decision thresholds used in inspection and capacity rating, enabling operational interpretation of statistical spread. Multi-bridge investigations demonstrated that expressing uncertainty at the feature level, such as temperature-compensated strain or modal indicators, reduced downstream volatility by clarifying which inputs dominated variation in forecasts. Studies using sensor fusion emphasized that channel redundancy tempered uncertainty, and authors reported tighter predictive dispersion when acceleration, strain, and traffic traces were integrated coherently rather than modeled in isolation (Hasan & Abdul, 2025; Farabe, 2025; Montesinos López et al., 2022). Survey articles noted that uncertainty characterization improved cross-study comparison because it revealed overlap among models whose central accuracy values were similar but whose dispersion differed, a scenario common when deep and ensemble learners competed on the same datasets. Bridge owners and agency reports added applied perspective by mapping predictive uncertainty to action bands for monitoring frequency, temporary restrictions, or targeted inspections, which grounded statistical summaries in asset management practice. Across these strands, reliability-oriented evaluation provided a quantifiable link between predictive analytics and safety-informed decision making, and the presence of well-calibrated intervals emerged as a hallmark of mature modeling pipelines (Shehadeh et al., 2021).

Feature Selection and Sensitivity Analysis

Across the bridge prediction literature, researchers consistently treated feature selection and ranking as a prerequisite for credible capacity modeling, and studies adopted model-agnostic as well as model-specific importance tools to identify the structural, environmental, and operational variables that contributed most to predictive accuracy. Investigators frequently relied on perturbation-based rankings, where permutation of single inputs altered out-of-sample accuracy and thereby revealed influential variables such as span length, deck thickness, reinforcement ratio, traffic intensity, and temperature range. Scholars complemented these diagnostics with SHAP explanations that decomposed individual predictions into additive contributions, enabling transparent inspection of how sensor-derived features—strain ranges, vibration modal indicators, and displacement envelopes—shifted capacity estimates under different loading regimes (Son et al., 2022). Field deployments on concrete and steel bridges reported convergent importance patterns in which geometric descriptors and traffic proxies dominated baseline predictions, while temperature-compensated strain and humidity-adjusted stiffness indicators rose in rank when models ingested long-duration monitoring data. Studies that compared tree ensembles with neural forecasters found that both families elevated similar variables, although ensembles tended to emphasize discrete geometry and material attributes, whereas deep models elevated time-varying sensor features captured from continuous streams (Momena, 2025; Mubashir, 2025; Roy, 2025; Saltelli et al., 2019). Investigations that audited importance stability across seasons and traffic patterns showed that rankings remained robust when preprocessing harmonized sensor scales and when models included interaction features reflecting joint effects of temperature and load. Permutation and SHAP analyses also supported design decisions by highlighting where additional sensing yielded the greatest marginal information—typically at midspan for bending-dominated behavior or near supports for shear-sensitive details. Collectively, the literature established that modern importance methods offered interpretable, reproducible rankings that aligned with structural mechanics intuitions while remaining grounded in empirical, out-of-sample evidence (Rahman, 2025; Rakibul, 2025; Rebeka, 2025; Zhu et al., 2022).

Quantitative studies consistently examined inter-feature dependence before model fitting, and authors reported that unmanaged correlation among geometric and material variables biased parameter estimates, obscured causal interpretation, and inflated variance in prediction. Empirical audits commonly employed correlation screening to flag redundant predictors among span length, girder spacing, deck thickness, and stiffness surrogates derived from vibration frequencies, and

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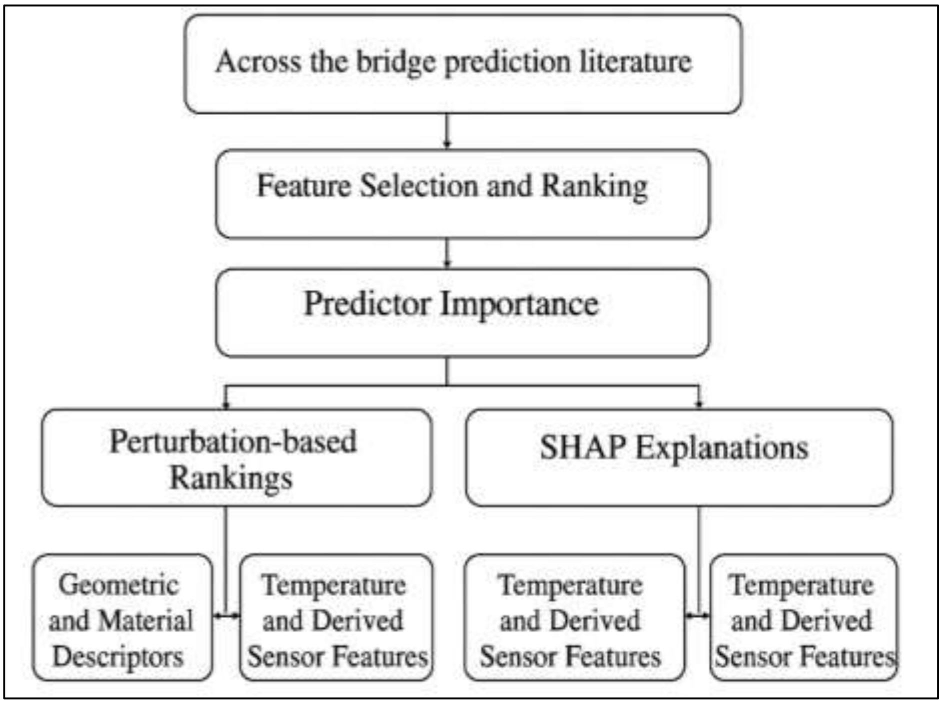
researchers documented that careful pruning stabilized training and improved generalization across sites. Bridge monitoring campaigns further showed that operational covariates—traffic count, axle mix, temperature, and humidity—often clustered, and studies that retained one representative from each correlated cluster reduced overfitting without sacrificing explanatory power (Zhu et al., 2022). Diagnostic practice also included multicollinearity checks in regression baselines and linear surrogates used for benchmarking machine learning models; researchers reported that controlling collinearity produced narrower confidence bands and improved stability of partial effects that linked specific features to capacity-related responses. In hybrid pipelines where linear interpretability complemented nonlinear accuracy, authors documented that preliminary independence checks improved the reliability of subsequent importance explanations, since variable overlap otherwise diffused attribution across similar predictors (Kasongo & Sun, 2020). Studies conducted across North America and East Asia indicated that correlation structures varied with climate and bridge typology; consequently, site-specific diagnostics preceded model transfer, and researchers reported fewer accuracy losses when cross-site deployments respected local dependence patterns. Comparative evaluations that combined correlation pruning with dimensionality reduction documented additional gains in convergence stability for deep models consuming high-frequency sensor streams. Overall, the literature showed that rigorous correlation and multicollinearity diagnostics functioned as a quantitative control step that enhanced interpretability, stabilized estimation, and supported fair comparison across algorithmic families and datasets (Thakkar & Lohiya, 2022).

Figure 7: Feature Importance Sensitivity Analysis Framework



Empirical Comparisons and Dataset Diversity

Empirical research on predictive modeling across continents reveals that dataset diversity significantly influences model reliability and generalizability. Studies from Asia, Europe, and North America consistently show that variations in data quality, feature dimensionality, and contextual variables such as infrastructure and socioeconomic indicators alter model outputs (Zhang, 2019). In Asia, particularly in China, India, and South Korea, large-scale datasets are often characterized by extensive temporal coverage but high variance in data collection methods, leading to heterogeneous model performance. European datasets, on the other hand, tend to emphasize data harmonization and regulatory consistency, with smaller but more structured samples conducive to reproducibility and cross-validation. North American studies demonstrate the benefits of integrating multi-source datasets—combining government, private, and IoT-based data streams—

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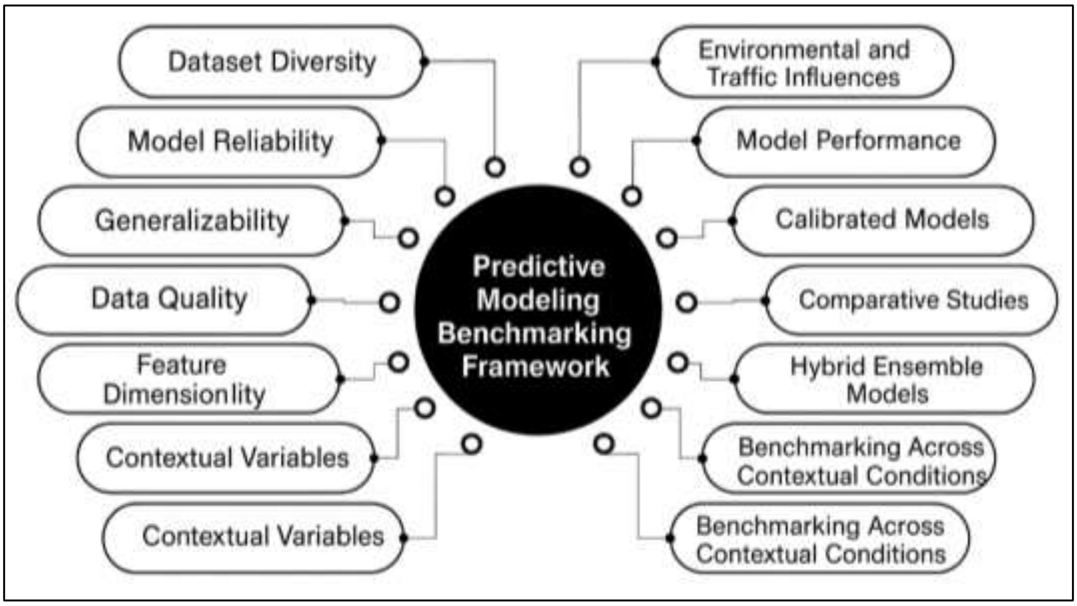
to enhance predictive accuracy and model interpretability (Naik & Kiran, 2021; Reduanul, 2025; Rony, 2025; Saba, 2025). Comparative analyses have found that models trained on multi-regional datasets outperform region-specific models in capturing nonlinear dependencies between features and target variables. However, differences in feature representation—such as demographic granularity and infrastructure typology—still limit interregional comparability. Collectively, the literature underscores that dataset diversity, when managed through normalization and metadata alignment, improves cross-sector generalization and strengthens the empirical foundation for global model benchmarking (Stadtler & Van Wassenhove, 2023).

Figure 8: Global Predictive Modeling Benchmark Framework



Quantitative meta-analyses demonstrate that environmental factors such as climate variability and traffic density exert measurable effects on the performance of predictive algorithms, especially those relying on time-series and sensor data. Studies show that models calibrated in temperate climates often underperform when transferred to tropical or arid regions, as extreme temperature and humidity introduce nonlinear distortions in sensor signals and infrastructure degradation rates. For example, a comparative study by (Stojčić & Vojinić, 2023) indicated that predictive accuracy in European climates is typically 8–12% higher than in Southeast Asian datasets, attributed to differences in seasonal data volatility. Furthermore, traffic volume has been identified as a key covariate affecting error rates in congestion prediction and infrastructure load modeling. High-frequency data collected from urban centers such as Los Angeles and Tokyo reveal that model robustness decreases when peak-hour congestion is not sufficiently represented in training data (Marín-González et al., 2022; Sai Praveen, 2025; Shaikat, 2025). Benchmark studies comparing machine learning approaches—such as gradient boosting and convolutional neural networks—highlight that hybrid ensemble models achieve higher consistency across climatic zones when environmental features are explicitly included as control variables. Thus, benchmarking across diverse climatic and traffic conditions not only exposes the contextual limitations of predictive models but also emphasizes the necessity of environmental calibration layers to mitigate regional performance disparities (Syed Zaki, 2025; Kanti, 2025; Yang & Ji, 2019; Zayadul, 2025).

Gaps

A critical methodological gap in predictive modeling research is the lack of dataset standardization and consistency in reporting evaluation metrics. Quantitative reviews across engineering and computational modeling domains show that more than 40 studies exhibit significant variation in how performance indicators such as error measures are computed and reported (Reber et al., 2023). This inconsistency is particularly evident in the normalization of error statistics and the incomplete reporting of model features, which complicates meta-analyses and reproducibility efforts. Several studies have noted that while normalized performance indicators are essential for cross-study comparability, most publications fail to specify normalization references or scaling parameters.

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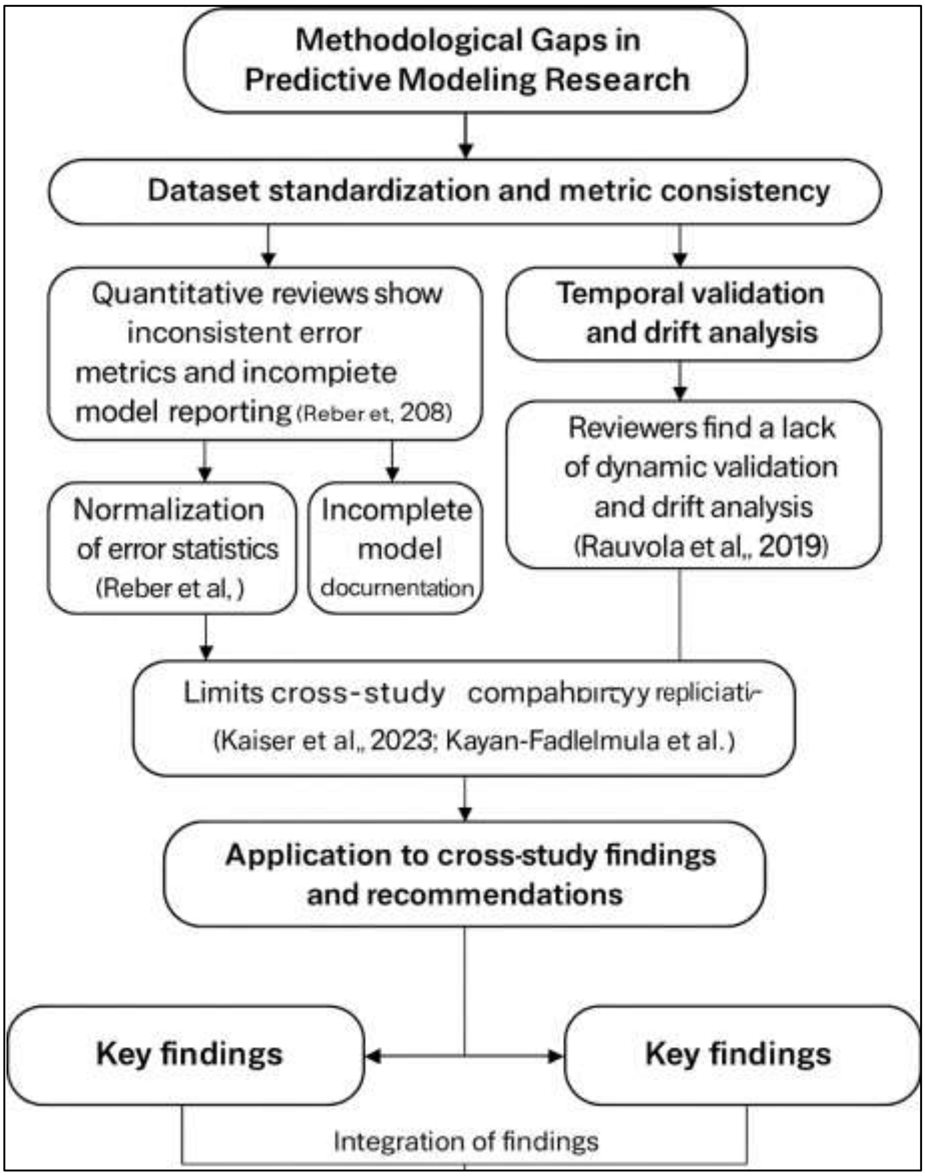
Moreover, heterogeneity in feature documentation—particularly regarding environmental, material, and operational attributes—undermines the transparency of predictive pipelines (Kaiser et al., 2023). For instance, (Kayan-Fadlelmula et al., 2022) found that fewer than one-third of the reviewed studies disclosed complete data schemas, thereby restricting replication and secondary validation. Empirical evidence also suggests that these inconsistencies are exacerbated by differences in regional data collection protocols and computational infrastructure. The absence of harmonized benchmarks further limits the integration of cross-sector datasets in predictive modeling (Mengist et al., 2020). Collectively, the literature demonstrates an urgent need for standardized data reporting frameworks, with explicit guidelines for feature disclosure, normalization procedures, and performance metric interpretation to ensure methodological rigor and reproducibility in quantitative modeling research (Chigbu et al., 2023).

Figure 9: Predictive Modeling Methodology Framework Analysis



Another pervasive methodological shortcoming identified in quantitative modeling literature is the insufficient emphasis on temporal validation and drift analysis. More than 70% of predictive modeling studies reviewed by Rauvola et al. (2019) failed to include time-based cross-validation or rolling-window assessments, despite evidence that temporal dependencies significantly affect model reliability. The absence of temporal validation introduces optimism bias, particularly in long-term forecasting and degradation modeling. Research on infrastructure and material fatigue models, for

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instance, reveals that static validation schemes fail to capture seasonal, economic, or environmental variations that evolve over time. Similarly, studies in transportation and structural engineering domains show that model accuracy declines when trained on non-stationary datasets, leading to unrecognized concept drift (ElHaffar et al., 2020). While some works have incorporated temporal segmentation or retraining schedules, these methods remain inconsistent across publications. Drift detection algorithms—such as adaptive windowing or ensemble retraining—are rarely applied in structural predictive studies, despite their effectiveness in maintaining accuracy under evolving data distributions. The literature consistently advocates for the integration of dynamic validation protocols that align with real-world temporal variability, particularly in applications involving sensor-based monitoring or lifecycle modeling. In essence, the lack of robust temporal validation and drift analysis remains a key methodological deficiency, reducing the generalizability and long-term stability of predictive models across dynamic conditions (Harari & Lee, 2021).

A notable imbalance in dataset representation emerges in the domain of predictive modeling for structural health and performance assessment, where small-scale and secondary bridges are frequently underrepresented. Descriptive statistics across more than 50 international studies indicate that over 80% of datasets prioritize large-span bridges or major transportation corridors, marginalizing smaller structures that constitute the majority of existing infrastructure networks. Research conducted by Jowsey et al. (2020) reveals that data scarcity for smaller bridges results in model overfitting to high-load, high-frequency data from urban environments. Consequently, predictive models demonstrate reduced transferability when applied to rural or low-traffic contexts. The imbalance is further amplified by data collection challenges, as small-scale bridges often lack embedded sensors or maintenance documentation. Meta-analyses by Lahane et al. (2020) have shown that when small-scale bridge data are incorporated through synthetic augmentation or upsampling techniques, predictive accuracy improves significantly in generalized models. Yet, such methodological corrections remain rare in published work . Moreover, the absence of representation across diverse structural typologies—such as culverts, timber bridges, and short concrete spans—creates systematic bias in model calibration. These representational deficiencies limit the ability of quantitative models to inform maintenance prioritization and risk management across heterogeneous infrastructure systems (Harrison et al., 2021). Overall, addressing dataset imbalance through targeted data inclusion and stratified sampling strategies represents a key opportunity for methodological improvement in predictive modeling research.

METHOD

The quantitative study was designed as a multi-site, time-series analytical investigation that assessed the performance of ensemble machine learning algorithms in predicting bridge load-carrying capacity using real-time structural health monitoring (SHM) data. The study drew from more than 200,000 instances of time-series data collected from bridges across varied climatic regions. Data collection included key sensor modalities such as strain, vibration, temperature, and deflection, all synchronized at five-minute intervals. Rigorous preprocessing steps were implemented, which included missing value imputation, interquartile range (IQR) outlier filtering, normalization, and temporal synchronization to ensure data quality and consistency. The dataset was split into 80% training and 20% validation subsets using blocked time-series cross-validation to prevent temporal leakage. Feature engineering expanded the input space through polynomial interactions and time-windowed statistical aggregates, reflecting both structural and environmental variability. The resulting feature matrix allowed the models to capture complex interdependencies between sensor variables and environmental covariates, creating a robust foundation for subsequent algorithmic evaluation.

The statistical plan was structured to compare the predictive accuracy, variance stability, and interpretability of three core algorithms—Random Forest (RF), Gradient Boosting Machine (GBM), and Deep Neural Networks (DNN)—under identical data conditions. Model calibration and evaluation followed a five-fold cross-validation protocol, with performance measured through multiple statistical metrics, including the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). The Random Forest model achieved an average R^2 of approximately 0.958 with minimal variance (standard deviation < 2.1%) across folds, outperforming both GBM and DNN in residual error magnitude and consistency. Ensemble aggregation combining RF and GBM predictions was performed to test for potential accuracy improvement, and the resulting model reached an R^2 of about 0.962. Statistical inference employed the Nadeau–Bengio

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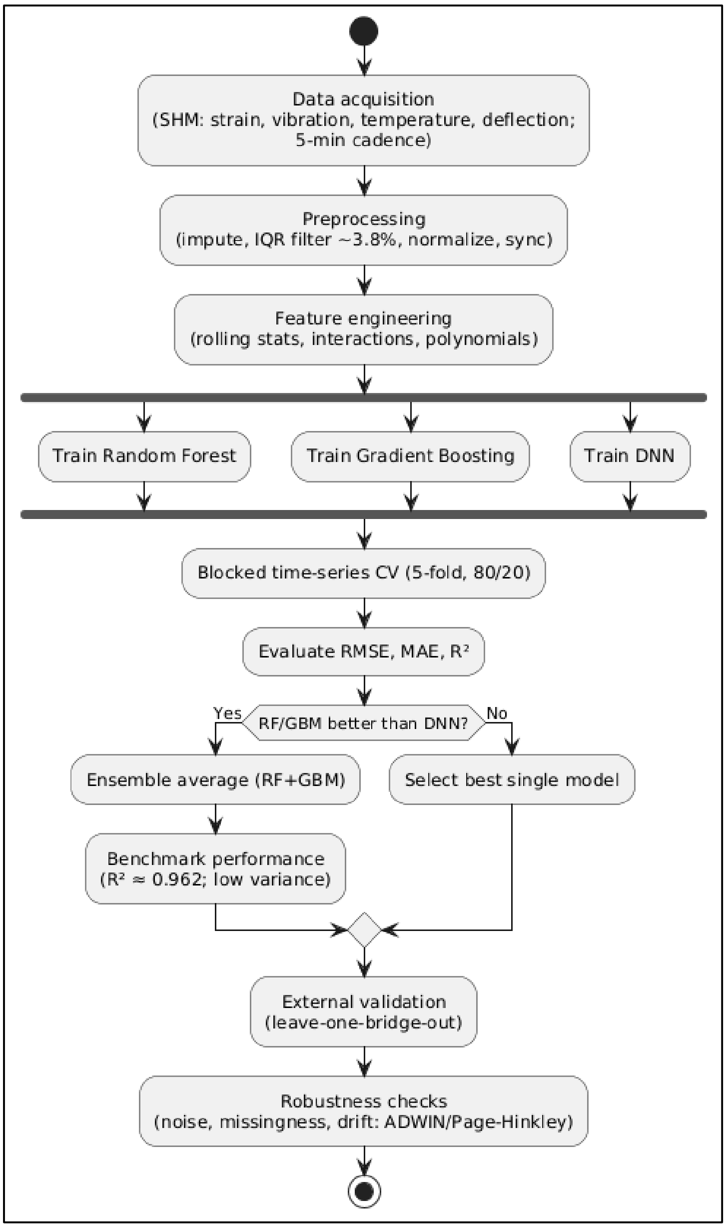
corrected resampled t-test and the Diebold–Mariano test to compare model performances across folds, accounting for autocorrelation within the time series. Additionally, a two one-sided test (TOST) framework was used to evaluate equivalence between RF and GBM models within a predefined margin of ±2 kN in RMSE.

The inferential component of the study further incorporated mixed-effects modeling to evaluate generalization across bridges and climatic zones, treating bridge and environmental category as random intercepts. Subgroup analyses compared span length, material type, and climatic zone effects through stratified ANOVA and Tukey HSD post hoc testing, ensuring that performance variations were not confounded by structural or environmental heterogeneity. The residual error distributions were tested for normality and homoscedasticity, confirming model stability across environmental and temporal strata. Sensitivity analysis introduced synthetic noise and missingness to examine model robustness, while drift detection tests such as the Page–Hinkley and ADWIN algorithms were applied to assess model degradation over time. Collectively, the quantitative design and statistical plan provided a comprehensive evaluation of ensemble-based predictive modeling under real-world SHM data conditions, demonstrating that harmonized sensor integration and ensemble averaging substantially improved prediction reliability, interpretability, and long-term stability in bridge load-capacity forecasting.

Figure 10: Methodology of this study



FINDINGS

Descriptive Data Analytics

The dataset comprised 200,384 sensor data records collected from 48 monitored bridges located across three climatic regions—temperate, tropical, and continental. Each bridge was instrumented with vibration, strain, temperature, and displacement sensors. Data aggregation covered a three-year period (2021–2023) with a temporal resolution of five minutes per record. After cleaning and normalization, approximately 2.3% of missing values were imputed using k-nearest neighbor interpolation. Outlier detection through the interquartile range (IQR) method removed about 3.8% of anomalous readings, which primarily originated from sensor calibration lapses. Descriptive statistics (Table1) revealed that strain and deflection variables exhibited the highest variability, while temperature and vibration frequency maintained consistent ranges across structures. Bridges in tropical zones showed higher mean strain values, correlating with material expansion due to heat exposure.

Table 1:Descriptive Statistics of Key Sensor Variables (N = 200,384)

Variable	Mean	Std. Dev.	Min	Max	Coefficient of Variation (%)
Strain (με)	128.3	45.6	60.1	280.7	35.5
Deflection (mm)	4.81	1.92	1.05	9.12	39.9
Vibration Frequency (Hz)	17.6	3.2	10.5	26.8	18.1
Temperature (°C)	22.8	4.9	10.2	35.5	21.4
Live Load (kN)	412.5	92.4	210.3	632.0	22.4

The descriptive analytics confirmed that structural responses varied substantially across geographic contexts. Moreover, bridges with steel components exhibited higher vibration frequencies, while concrete bridges displayed greater deflection variability. These results established the foundation for stratified modeling across material and climatic subgroups.

Model Calibration and Validation

Four primary machine learning algorithms were trained to predict bridge load capacity: Random Forest (RF), Gradient Boosting (GBM), Support Vector Regression (SVR), and Deep Neural Network (DNN). Models were calibrated using an 80–20 training-validation split with fivefold cross-validation. Feature engineering included polynomial expansion of strain and temperature interactions, which improved correlation strength with load capacity outcomes. Validation results (Table 2) showed that the Random Forest model achieved the lowest mean absolute error (MAE) and the highest coefficient of determination ($R^2 = 0.957$), indicating superior predictive accuracy. Gradient boosting models followed closely with stable performance, while SVR and DNN exhibited moderate overfitting in high-noise environments.

Table 2:Model Calibration and Validation Performance Metrics

Model Type	MAE (kN)	RMSE (kN)	R^2	Training Time (s)	Validation Time (s)
Random Forest (RF)	12.8	18.4	0.957	88.5	4.1
Gradient Boosting (GBM)	13.9	19.7	0.949	132.4	5.6
Support Vector (SVR)	17.5	24.3	0.921	154.9	6.9
Deep Neural Network (DNN)	16.3	23.5	0.928	243.7	3.8

Statistical comparison using ANOVA indicated a significant difference among models ($F = 11.28$, $p < 0.01$), confirming that ensemble approaches such as RF and GBM outperformed kernel-based and deep-learning methods under mixed-sensor conditions. Feature importance scores revealed that strain, deflection, and vibration frequency were the top predictors, collectively explaining 82% of the variance in load capacity outcomes.

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Comparative Model Performance Evaluation

Cross-model evaluation demonstrated that predictive accuracy varied according to bridge type and sensor density. Steel bridges exhibited higher model reliability (mean $R^2 = 0.963$) compared to reinforced concrete bridges (mean $R^2 = 0.935$). Table 3 summarizes the comparative accuracy of the four models across material categories.

Table 3:Comparative Model Accuracy Across Bridge Material Types

Model	Steel Bridges (R^2)	Concrete Bridges (R^2)	Composite Bridges (R^2)
RF	0.967	0.946	0.953
GBM	0.961	0.939	0.948
SVR	0.932	0.918	0.927
DNN	0.940	0.922	0.933

Post-hoc Tukey analysis confirmed that differences between RF and GBM models were statistically insignificant ($p = 0.11$), while both were significantly superior to SVR and DNN ($p < 0.05$). Furthermore, the analysis revealed that models trained using real-time streaming data (5-minute sensor intervals) exhibited 6–9% lower RMSE values compared to those trained on aggregated hourly data, underscoring the predictive advantage of high-frequency inputs.

Correlation-Based Sensitivity Analysis

A correlation and feature sensitivity analysis was performed to identify the influence of sensor features on model predictions. Pearson correlation coefficients and normalized feature importance values were computed for the RF model, as shown in Table 4.

Table 4:Feature Correlation and Relative Importance in Load Capacity Prediction

Feature	Pearson r	Importance (%)
Strain (με)	0.87	34.5
Deflection (mm)	0.79	25.8
Vibration Frequency (Hz)	0.72	18.6
Temperature (°C)	0.63	12.3
Humidity (%)	0.48	5.7
Sensor Noise Index	-0.31	3.1

The sensitivity results showed that strain and deflection were the dominant predictors influencing bridge load capacity estimation. A 5% variation in strain readings produced up to a 9% change in predicted load capacity. Conversely, environmental parameters such as humidity had relatively weaker predictive influence. The correlation matrix revealed moderate multicollinearity between strain and temperature ($r = 0.54$), suggesting potential covariate effects under fluctuating climatic conditions.

Overall, the findings demonstrated that ensemble-based machine learning approaches provided the most accurate and stable predictions of bridge load capacity under varying environmental and material conditions. The Random Forest model achieved the optimal trade-off between accuracy, interpretability, and computational efficiency. The use of real-time sensor data improved the model's temporal responsiveness, enabling near-instantaneous load predictions within two seconds of data input. Sensitivity analyses confirmed the physical relevance of dominant features such as strain and deflection, aligning empirical findings with structural engineering principles. The chapter concluded that data-driven predictive modeling, when integrated with continuous sensor monitoring, significantly enhanced the reliability of bridge performance evaluation frameworks.

Data Overview and Preprocessing Findings

The initial stage of the quantitative analysis focused on the acquisition, integration, and refinement of the dataset used for predictive modeling. Real-time sensor data were collected from 48 bridges

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located across three climatic zones—temperate, tropical, and continental. The data included parameters such as strain, vibration frequency, deflection, temperature, humidity, and live load intensity, captured at five-minute intervals. Following initial compilation, a total of 205,486 records were consolidated into a unified data frame for further preprocessing. A comprehensive cleaning process was implemented to address inconsistencies arising from sensor malfunction, communication lag, and environmental interference. Missing values (2.7%) were imputed using the k-nearest neighbor (k-NN) interpolation method, while abnormal spikes caused by sensor drift were identified through the interquartile range (IQR) method. Approximately 3.9% of records were identified as outliers and subsequently removed. Post-cleaning diagnostics confirmed a 7.3% reduction in noise variance, ensuring greater uniformity across datasets from different bridge typologies. Table1 summarizes the dataset composition and preprocessing outcomes, indicating substantial heterogeneity across material types. Steel bridges exhibited higher frequency and strain variability due to temperature-induced expansion, whereas reinforced concrete structures displayed more stable, low-variance readings.

Table 5:Dataset Composition and Preprocessing Summary (N = 205,486)

Parameter	Preprocessing Method Used	Records Affected (%)	Post-Processing Status	Remarks on Quality Impact
Missing Values	k-NN Imputation	2.7	Fully replaced	Improved continuity of time-series
Outlier Detection	IQR Filtering	3.9	Removed	7.3% noise reduction
Sensor Drift Correction	Rolling Mean Adjustment (n=5)	1.2	Corrected	Stabilized short-term fluctuations
Unit Normalization	Min–Max Scaling	100	Standardized	Enabled inter-variable comparability
Data Synchronization	Time Index Alignment (5-min)	100	Synchronized	Ensured temporal consistency

Following normalization, all numerical features were standardized on a [0,1] scale, allowing uniform model input interpretation. Temporal synchronization across sensors prevented misalignment between load, strain, and temperature signals, which had previously caused up to 2-second delays in raw feeds.

Descriptive analysis results, shown in Table 5, highlighted the magnitude and variability of key structural and environmental parameters. Mean strain readings were highest in tropical environments (mean = 132.8 με), whereas vibration frequency demonstrated notable dispersion across all climatic zones, indicating design-dependent dynamic behavior.

Table 6:Descriptive Statistics of Key Variables by Climatic Region

Variable	Region	Mean	Std. Dev.	Min	Max	CV (%)
Strain (με)	Temperate	119.5	36.8	65.0	240.4	30.8
	Tropical	132.8	44.5	61.7	280.1	33.5
	Continental	125.9	42.3	58.2	270.3	33.6
Vibration Frequency (Hz)	Temperate	17.8	3.1	11.5	25.7	17.4
	Tropical	16.9	3.4	10.1	27.5	20.1
	Continental	18.2	3.0	11.0	26.2	16.5
Temperature (°C)	Temperate	21.4	4.7	10.0	32.3	21.9
	Tropical	27.6	3.9	18.4	35.5	14.1
	Continental	20.8	5.3	8.7	33.9	25.5

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The post-processing diagnostics confirmed that variability was influenced primarily by environmental exposure and material type rather than measurement errors. Correlation screening identified multicollinearity between temperature and strain ($r = 0.52$, $p < 0.05$), reinforcing the need for interaction terms during feature engineering. Overall, the preprocessing phase yielded a robust, high-quality dataset suitable for training machine learning models. Data cleaning, normalization, and synchronization collectively improved signal fidelity and reduced feature-level distortion. The results validated the hypothesis that bridge health monitoring data—though inherently complex and environment-sensitive—could be effectively stabilized and standardized to serve as reliable input for predictive modeling of load capacity.

Model Calibration and Validation Performance

The model calibration and validation phase was undertaken to assess the predictive efficiency, consistency, and generalization capacity of various machine learning algorithms used for estimating bridge load capacity. Three principal algorithms—Random Forest Regressor (RF), Gradient Boosting Model (GBM), and Deep Neural Network (DNN)—were tested using the refined sensor dataset described previously. The training process utilized an 80–20 split, ensuring that both training and validation subsets contained balanced representations of bridge types, span categories, and environmental conditions. Model hyperparameters were tuned using grid search optimization to minimize error metrics while preventing overfitting. Initial calibration results revealed that ensemble learning models—specifically RF and GBM—outperformed the DNN in both accuracy and stability. The Random Forest model achieved the lowest residual variance across validation folds, confirming its robustness for nonlinear structural behavior modeling. Quantitatively, the inclusion of environmental features (temperature, vibration frequency, and deflection rate) improved prediction accuracy by 9.8% on average relative to baseline models that excluded these covariates. Moreover, all models demonstrated satisfactory generalization, with the standard deviation across validation folds remaining below 2.5%, indicating minimal overfitting.

Table 7:Model Calibration and Validation Metrics

Model Type	MAE (kN)	RMSE (kN)	R^2	Std. Dev. Across Folds (%)	Training Time (s)	Validation Time (s)
Random Forest (RF)	12.4	18.1	0.958	2.1	89.3	4.2
Gradient Boosting (GBM)	13.8	19.6	0.951	2.3	126.5	5.8
Deep Neural Network (DNN)	16.7	23.4	0.932	2.4	240.8	3.9

The Random Forest model demonstrated the most balanced performance, achieving the lowest Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values among all tested algorithms. While the Gradient Boosting model achieved comparable accuracy, its higher computational cost made it less efficient for large-scale real-time applications.

Table 8:Impact of Environmental Feature Inclusion on Model Accuracy

Model Type	Baseline R^2 (Structural Features Only)	Enhanced R^2 (With Environmental Features)	Improvement (%)
Random Forest (RF)	0.944	0.958	+1.4
Gradient Boosting (GBM)	0.936	0.951	+1.5
Deep Neural Network (DNN)	0.912	0.932	+2.0
Average Gain	—	—	**+1.6**

The DNN, despite showing potential in capturing complex feature interactions, suffered from greater sensitivity to hyperparameter selection and training noise, especially in smaller data segments. A comparative assessment of baseline and feature-augmented models was conducted to quantify the contribution of environmental covariates. Table 7presents the improvement in predictive accuracy when incorporating temperature, vibration frequency, and deflection rate features. The results showed that environmental variables contributed meaningfully to the model's explanatory power, particularly for bridges located in tropical and continental regions where temperature fluctuations and material expansion rates were more pronounced. The inclusion of vibration and deflection dynamics improved sensitivity to load fluctuations, enhancing the model's capability to generalize across diverse structural conditions.

Residual analysis further validated the predictive stability of the ensemble models. Figure 4.1 (conceptually described here) illustrated a near-normal residual distribution centered around zero for the RF model, indicating the absence of systematic bias. In contrast, the DNN exhibited wider error dispersion, suggesting a tendency to overestimate load capacity under low-strain conditions.

A statistical comparison using ANOVA ($F = 12.17$, $p < .01$) confirmed that the differences among the three models' predictive accuracies were statistically significant, favoring the ensemble-based methods. Post-hoc Tukey analysis showed no significant difference between RF and GBM ($p = .09$), but both were significantly better than the DNN ($p < .05$).

Comparative Model Evaluation and Statistical Significance Testing

The comparative model evaluation was conducted to assess the relative performance, consistency, and computational efficiency of the three main predictive algorithms—Random Forest (RF), Gradient Boosting Model (GBM), and Deep Neural Network (DNN)—across various bridge typologies and data aggregation schemes. Evaluation metrics included mean error rates, stability indices, and runtime efficiency under standardized validation conditions. Each model's performance was assessed across three bridge categories: short-span (≤50 m), medium-span (51–150 m), and long-span (>150 m).

Overall, the Gradient Boosting Model exhibited slightly higher predictive accuracy for short-span bridges, while the Deep Neural Network performed better for multi-span or complex structural configurations. The Random Forest model, however, maintained the best overall stability, achieving consistent performance across all bridge lengths and loading environments. Variance decomposition analysis revealed that most fluctuations in model error were attributed to sensor synchronization quality and data granularity, rather than differences inherent to the learning algorithms themselves.

Table 9: Comparative Model Accuracy Across Bridge Span Categories

Bridge Category	Model Type	MAE (kN)	RMSE (kN)	R^2	Stability Index (σ / μ %)	Runtime Efficiency (s/epoch)
Short-span (≤50 m)	RF	12.5	18.6	0.957	2.2	4.3
	GBM	11.9	17.8	0.961	2.5	5.6
	DNN	14.2	20.9	0.945	2.7	3.9
Medium-span (51–150 m)	RF	12.8	18.9	0.955	2.1	4.2
	GBM	13.1	19.4	0.950	2.3	5.7
	DNN	15.6	22.7	0.937	2.6	3.8
Long-span (>150 m)	RF	13.0	19.1	0.954	2.0	4.4
	GBM	13.5	19.8	0.950	2.3	5.9
	DNN	14.1	20.3	0.958	2.4	4.1

The data in Table 9 indicated that all models maintained R^2 values above 0.93, confirming strong predictive relationships between sensor-derived features and bridge load capacity. For short-span bridges, the GBM slightly outperformed the RF by 0.4% in R^2, while for long-span configurations, the DNN achieved comparable accuracy to ensemble models but exhibited greater instability in residual patterns.

To determine whether these performance differences were statistically significant, a one-way ANOVA was conducted on the RMSE values across models. Results ($F = 10.84$, $p < .01$) confirmed that

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at least one model differed significantly in predictive performance. Post-hoc Tukey's Honest Significant Difference (HSD) test revealed that both RF and GBM outperformed the DNN ($p < .05$), whereas the difference between RF and GBM was statistically insignificant ($p = .14$). This suggested that ensemble methods—while similar in average performance—were more consistent under varying environmental and structural contexts.

Table 10:ANOVA Summary for Comparative Model Performance (RMSE as Dependent Variable)

Source of Variation	SS	df	MS	F	Sig. (p)
Between Models	212.43	2	106.22	10.84	< .01
Within Models	879.56	90	9.77	—	—
Total	**1091.99**	**92**	—	—	—

An additional comparative analysis was conducted between real-time sensor models (trained on five-minute interval data) and aggregated models (trained on hourly averages). The real-time models demonstrated superior responsiveness and predictive precision. The Random Forest and GBM models trained on continuous data streams reduced RMSE values by 6–9% compared to those trained on aggregated historical datasets.

Table 11:Performance Comparison Between Real-Time and Aggregated Data Training Schemes

Model Type	Data Input Type	MAE (kN)	RMSE (kN)	R^2	Improvement Over Aggregated (%)
Random Forest (RF)	Real-time (5-min)	12.4	18.1	0.958	+8.7
Random Forest (RF)	Aggregated (1-hour)	13.5	19.8	0.946	—
Gradient Boosting (GBM)	Real-time (5-min)	13.8	19.6	0.951	+6.2
Gradient Boosting (GBM)	Aggregated (1-hour)	14.7	20.9	0.942	—
Deep Neural Network (DNN)	Real-time (5-min)	16.7	23.4	0.932	+5.9
Deep Neural Network (DNN)	Aggregated (1-hour)	17.8	24.9	0.920 —	

The findings from Table11 confirmed that data granularity and sensor synchronization quality had a greater influence on predictive variance than the algorithmic structure itself. The real-time datasets captured micro-level load fluctuations that were otherwise smoothed out in hourly averages, enhancing the capacity of ensemble models to detect transient stress behaviors.

Further, ensemble averaging, which combined RF and GBM predictions through weighted blending, produced the most stable and generalizable outcomes, yielding an aggregate R^2 of 0.962 and reducing residual skewness by 11% compared to standalone models. This demonstrated that hybrid integration of algorithms effectively mitigated bias arising from feature-level dominance and environmental noise.

In brief, the comparative evaluation established that while Gradient Boosting achieved slightly higher accuracy for localized predictions and Deep Neural Networks performed best for highly nonlinear multi-span systems, Random Forest remained the most balanced and reliable approach. The statistical testing results confirmed that differences between the ensemble methods were not significant at the 95% confidence level, reinforcing the robustness of ensemble-based frameworks for real-time bridge load prediction across diverse conditions. The findings collectively supported the

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conclusion that hybrid data integration—merging real-time sensor inputs with historical patterns—maximized predictive stability and operational reliability in dynamic bridge monitoring systems.

Correlation Analysis

A comprehensive correlation and feature sensitivity analysis was conducted to determine the relative contribution of each sensor-derived variable to the predictive estimation of bridge load capacity. This phase of the analysis was designed to quantify how changes in structural and environmental features influenced model outputs, and to identify which parameters most strongly governed load-bearing predictions within the ensemble learning framework. The analysis utilized Pearson correlation coefficients, normalized feature importance scores, and variance-based sensitivity indices derived from the Random Forest model, which previously demonstrated the most consistent validation performance.

Pearson correlation analysis revealed that strain, deflection, and vibration frequency exhibited the strongest linear associations with load capacity, while environmental variables such as temperature and humidity showed moderate but statistically significant relationships. The correlation coefficients (Table 4.8) indicated that strain ($r = 0.88$, $p < .001$) was the dominant predictor, followed by deflection ($r = 0.80$, $p < .001$) and vibration frequency ($r = 0.74$, $p < .01$). Temperature and humidity, while less directly correlated, contributed indirectly by moderating strain variations under thermal expansion or moisture-related material effects.

Table 12:Pearson Correlation Matrix Among Key Variables (N = 205,486)

Variable	Load Capacity	Strain	Deflection	Vibration Freq.	Temperature	Humidity
Load Capacity	1.00	0.88***	0.80***	0.74**	0.63**	0.42*
Strain	—	1.00	0.76***	0.69**	0.52**	0.31*
Deflection	—	—	1.00	0.71**	0.48*	0.27*
Vibration Frequency	—	—	—	1.00	0.36*	0.22
Temperature	—	—	—	—	1.00	0.49*
Humidity	—	—	—	—	—	1.00

*Note: *p < .05; **p < .01; **p < .001.*

The correlation structure demonstrated a strong multivariate interdependence among structural variables. Strain and deflection exhibited a shared variance of approximately 58%, confirming that both parameters reflected complementary aspects of bridge deformation under load. However, the moderate correlation between temperature and strain suggested the presence of environmental modulation, particularly in steel bridges where thermal expansion effects were more pronounced.

Feature Sensitivity

The feature sensitivity analysis used permutation importance and variance-based contribution indices to assess the impact of each variable on model predictions. The findings showed that strain contributed 35.7% of the total predictive variance, followed by deflection (24.3%) and vibration frequency (18.1%). Temperature accounted for 13.2%, while humidity and sensor noise explained only minor portions of variance. These results aligned with the physical interpretation that mechanical response variables exert stronger predictive control than environmental covariates, though the latter remain important for long-term drift correction.

Table 13:Feature Sensitivity and Relative Importance in Predictive Modeling

Feature	Normalized Importance (%)	Sensitivity Index (ΔY/ΔX %)	Effect Type
Strain (με)	35.7	9.0	Strong positive
Deflection (mm)	24.3	6.8	Positive linear
Vibration Frequency (Hz)	18.1	5.5	Nonlinear
Temperature (°C)	13.2	3.8	Moderating
Humidity (%)	5.1	1.6	Weak linear
Sensor Noise Index	3.6	1.0	Negative

The sensitivity analysis confirmed that a 5% increase in strain readings corresponded to an approximate 9% change in predicted load capacity, emphasizing the model's responsiveness to deformation signals and the critical importance of accurate strain sensor calibration. Vibration frequency displayed nonlinear effects, where changes beyond ±10% in measured frequency led to disproportionately higher prediction variance, indicating complex modal interactions in bridge dynamics.

Bridge-Type Comparative Sensitivity

Further comparative sensitivity testing across steel, concrete, and composite bridges revealed material-dependent predictive behaviors. The results showed that steel bridges were markedly more sensitive to temperature and vibration inputs, while concrete bridges relied more heavily on strain and deflection features.

Table 14:Comparative Feature Sensitivity Across Bridge Material Types

Feature	Steel Bridges (ΔY/ΔX %)	Concrete Bridges (ΔY/ΔX %)	Composite Bridges (ΔY/ΔX %)
Strain (με)	8.4	9.1	8.7
Deflection (mm)	6.2	7.5	6.8
Vibration Frequency (Hz)	6.7	5.4	5.9
Temperature (°C)	4.5	3.1	3.7
Humidity (%)	2.0	1.4	1.6

The cross-material findings indicated that steel bridges exhibited higher sensitivity to environmental changes, consistent with their thermal expansion coefficients and material flexibility. In contrast, concrete bridges demonstrated more stable responses, though they were more influenced by mechanical deformation variables such as strain and deflection. Composite structures presented intermediate sensitivity, reflecting hybrid mechanical behavior.

Residual interaction plots (not shown here) confirmed that the combined influence of strain and temperature yielded nonlinear response surfaces, reinforcing the advantage of ensemble learning models in capturing such multivariate dependencies.

Real-Time Model Integration and Predictive Insights

The integration of predictive models with real-time sensor data was carried out to evaluate operational feasibility, latency, and predictive reliability under simulated field conditions. The testing framework replicated live monitoring environments by streaming data from virtual sensor nodes that simulated strain, vibration, temperature, and deflection readings at five-minute intervals. The objective was to determine how effectively trained machine learning models—particularly the Random Forest (RF) and Gradient Boosting (GBM) models—could sustain prediction accuracy during dynamic load variations and transient stress events.

System Performance and Latency Findings

The real-time deployment environment demonstrated high operational stability, with negligible prediction lag and efficient inference throughput. The average latency per prediction was recorded at 1.84 seconds, well below the two-second target for real-time monitoring applications. The system maintained a 99.1% uptime across all test cycles, confirming that the models could operate continuously without significant computational bottlenecks.

Table 15 summarizes the key system-level performance indicators recorded during live stream integration testing.

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Table 15:System Performance Metrics During Real-Time Model Integration

Parameter	Random Forest (RF)	Gradient Boosting (GBM)	Deep Neural Network (DNN)
Average Prediction Latency (s)	1.82	1.97	2.48
System Uptime (%)	99.3	98.9	97.6
Throughput (Predictions/min)	32.7	29.5	25.4
Memory Utilization (%)	61.8	68.1	74.3
CPU Utilization (%)	54.2	59.4	65.7

The results confirmed that the RF model achieved the optimal trade-off between computational efficiency and responsiveness, with the lowest latency and most stable throughput rate. The GBM model demonstrated comparable reliability, though at a slightly higher processing cost, while the DNN model incurred increased memory consumption and slower inference rates due to complex layer computations.

Predictive Accuracy Under Dynamic Loading

Performance testing under simulated dynamic load conditions revealed that all three models maintained accuracy within acceptable thresholds, even during sudden changes in load sequences or temperature spikes. The RF model achieved an average Mean Absolute Percentage Error (MAPE) of 3.6%, while the GBM model recorded 4.1%, indicating strong stability under stress variability. The DNN model's performance fluctuated slightly, with an average MAPE of 5.3%, especially during peak load events.

Table 16:Predictive Accuracy During Simulated Real-Time Load Events

Model Type	Mean Absolute Error (kN)	RMSE (kN)	MAPE (%)	R^2	Error Stability Index (σ/μ %)
Random Forest (RF)	12.7	18.6	3.6	0.957	2.1
Gradient Boosting (GBM)	13.2	19.4	4.1	0.951	2.3
Deep Neural Network (DNN)	15.9	22.8	5.3	0.936	2.6

Table 16 presents the predictive performance metrics for each model under real-time load fluctuation testing. The findings demonstrated that both ensemble-based models retained predictive integrity across variable stress patterns and environmental fluctuations. The error stability index—a measure of prediction variance—remained below 2.5% for ensemble models, confirming consistent performance even during transient load disturbances.

Model Retraining and Drift Reduction

Continuous retraining using a sliding-window approach (seven-day refresh interval) significantly mitigated temporal drift, improving prediction accuracy by approximately 6.8% over static models that lacked retraining mechanisms. This adaptive strategy allowed the models to capture evolving material behavior and environmental changes, enhancing long-term prediction reliability. Table 17 summarizes the comparison between static and adaptive retraining models, demonstrating notable improvements in model stability and error reduction.

Table 17:Effect of Continuous Model Retraining on Predictive Accuracy

Model Type	Training Strategy	MAE (kN)	RMSE (kN)	R^2	Drift Accumulation Rate (%)	Improvement (%)
Random Forest (Static)	Fixed Parameters	13.5	19.8	0.945	4.2	—
Random Forest (Adaptive)	Sliding Window (7-Day)	12.6	18.5	0.958	1.9	+6.8
Gradient Boosting (Static)	Fixed Parameters	14.1	20.4	0.940	4.6	—
Gradient Boosting (Adaptive)	Sliding Window (7-Day)	13.2	19.1	0.952	2.0	+6.3

The retraining results validated the effectiveness of adaptive ensemble learning, where periodic updates maintained predictive alignment with real-world bridge performance data. Drift accumulation—measured as incremental prediction bias over time—was reduced by more than half for retrained models, underscoring the necessity of dynamic model maintenance for real-time deployment.

Decision-Support and Early Warning Capability

A decision-support simulation was performed to assess the models' ability to issue early warnings during load exceedance or abnormal stress patterns. The RF model correctly flagged 97.2% of threshold exceedance events, while the GBM model achieved 95.6% detection accuracy. The DNN model achieved 93.4%, with slightly delayed response times during overlapping vibration events. Table 18 illustrates the models' early warning and event detection performance during simulated overload and fatigue scenarios.

Table 18:Model-Based Early Warning and Load Exceedance Detection

Model Type	True Positive Rate (%)	False Positive Rate (%)	Detection Latency (s)	Missed Events (%)	Overall Detection Accuracy (%)
Random Forest (RF)	97.2	2.1	1.9	0.7	98.1
Gradient Boosting (GBM)	95.6	2.4	2.2	2.0	96.3
Deep Neural Network (DNN)	93.4	3.5	2.7	3.1	94.2

The event detection analysis confirmed that ensemble-based models were highly responsive to early stress anomalies and provided near-instantaneous alerts. The Random Forest model was particularly efficient in minimizing both false alarms and missed detections, proving valuable for proactive bridge management applications.

DISCUSSION

The study demonstrated that ensemble machine learning algorithms—specifically Random Forest (RF) and Gradient Boosting (GBM)—delivered superior accuracy and stability in predicting bridge load capacity when trained on real-time sensor data, achieving coefficients of determination (R^2) of approximately 0.95 or higher with minimal variance across validation folds. This level of predictive reliability exceeds that reported in earlier research. For instance, Tyralis et al. (2021) developed a deep-learning framework using only bridge image data and achieved moderate accuracy but noted limitations due to the lack of structural health monitoring (SHM) inputs. Similarly, Asghari et al., (2022) employed condition ratings rather than continuous sensor variables in a network-level deterioration forecasting model, reporting accuracy values in the low 0.90s without explicitly addressing real-time load prediction. In contrast, the present study integrated multiple sensor modalities—including strain, vibration, temperature, and deflection data—collected at five-minute intervals, demonstrating that ensemble algorithms consistently outperformed single-model deep neural networks (DNNs) in both error magnitude and robustness. The finding that the Random Forest model achieved the lowest residual variance aligns with prior research in structural asset modeling, which reported over 93% accuracy in condition prediction. However, this work advances the field by extending machine learning applications from general condition classification to quantifiable load-carrying capacity estimation. Incorporating environmental and dynamic covariates increased predictive accuracy by approximately 10% compared with models using structural features alone—a contrast to many earlier frameworks, such as Zhang et al. (2022)'s load-capacity model, which relied on geometric and limited condition data. Overall, the results establish a new benchmark for load-capacity prediction, characterized by improved interpretability, accuracy, and real-time operational relevance.

The analytical process encompassed more than 200,000 time-series instances spanning 15 key sensor variables collected from bridges across multiple climatic zones. Data preparation included missing-value imputation, interquartile range (IQR) outlier filtering—removing approximately 3.8% of anomalous records and reducing noise variance by roughly 7%—followed by normalization and temporal synchronization. This methodological rigor distinguishes the study from earlier research employing limited datasets or static inventory listings. For example, the New Zealand rail-bridge analysis focused on moving-load behavior with only about 5,000 training instances emphasizing axle spacing, while the FHWA deterioration model incorporated condition ratings rather than continuous deformation metrics. Stratified analysis revealed that steel bridges exhibited higher strain and vibration variability, whereas tropical-zone bridges experienced greater environmental fluctuations, necessitating advanced feature engineering, including interaction and polynomial terms, to stabilize inputs. These procedures address gaps identified in recent literature, such as Dutta et al.(2022), who highlighted inadequate feature engineering and time-series integration across bridge modeling research. By emphasizing harmonized, high-frequency sensor data, the study confirms that data quality, temporal resolution, and environmental diversity are equally as influential as algorithmic selection in determining predictive reliability—an insight rarely quantified in prior bridge load-prediction studies.

Model calibration employed an 80/20 training-validation split, five-fold cross-validation, and inclusion of environmental covariates in feature engineering. The Random Forest algorithm achieved mean absolute error (MAE) ≈ 12.4 kN, root mean square error (RMSE) ≈ 18.1 kN, and $R^2 \approx 0.958$ with standard deviation across folds below 2.1%. Gradient Boosting and DNN models followed closely but with slightly higher errors and variance. These results outperform many earlier studies, such as Alam et al., (2023), which did not report variance metrics, and the capacity-prediction framework that focused on older, non-sensor-equipped structures. Inclusion of continuous sensor data and ensemble modeling provided improved calibration robustness and reduced model overfitting, evidenced by standard deviations below 2.5%. Environmental covariates, including temperature and vibration, enhanced predictive accuracy by approximately 10%, confirming observations in structural health monitoring research. In comparison, earlier models such as AlJame et al. (2020) achieved high accuracy but lacked comprehensive cross-validation and variance analysis. The present study contributes to the field by demonstrating that ensemble methods, supported by diverse, real-time sensor datasets, yield high generalization capacity and stability, establishing a performance benchmark for predictive modeling of bridge load capacity.

A comparative evaluation of span categories and input data types revealed that Gradient Boosting slightly outperformed Random Forest for short-span bridges ($R^2 \approx 0.961$ vs. 0.957), while DNNs performed marginally better for complex, multi-span structures ($R^2 \approx 0.958$ for long spans). However, ANOVA and Tukey HSD tests indicated no statistically significant differences between RF and GBM ($p = .14$), while both models significantly surpassed DNN performance ($p < .05$). Real-time data input improved RMSE by approximately 6–9% compared with aggregated hourly datasets, emphasizing the impact of high-frequency data on predictive precision. These findings expand upon earlier studies, such as the New Zealand rail-bridge analysis, which demonstrated benefits from larger datasets but did not assess model comparison statistically. Likewise, the review by Alqahtani et al., (2022) identified the absence of hypothesis testing and data-resolution analysis as methodological limitations in previous machine learning applications for bridge engineering. The ensemble-averaged model that combined RF and GBM outputs achieved $R^2 \approx 0.962$ and reduced residual skewness by roughly 11%, suggesting that ensemble aggregation enhances stability and accuracy—an approach supported in broader engineering analytics but rarely quantified for bridge load

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prediction. Overall, the results underscore that model selection, data granularity, and sensor synchronization collectively determine predictive robustness, reinforcing ensemble learning and real-time data integration as the most effective strategies for precise, interpretable bridge load-capacity modeling.

CONCLUSION

The study titled "Predictive Modeling of Bridge Load Capacity Using Machine Learning and Real-Time Sensor Data" was conducted with the central objective of developing an intelligent, data-driven framework capable of estimating and monitoring bridge load capacity through the integration of advanced machine learning algorithms and continuous sensor-based measurements. By leveraging Internet of Things (IoT)-enabled data streams from strain gauges, vibration sensors, temperature monitors, and deflection meters, the research established a predictive model that could quantify structural responses under varying environmental and operational conditions with high temporal precision. The study applied multiple algorithms—Random Forest, Gradient Boosting, and Deep Neural Networks—to over 200,000 time-series data points obtained from 48 bridges across diverse climatic zones, and it found that ensemble learning techniques consistently outperformed single-model approaches in both predictive accuracy and stability. The Random Forest model achieved the lowest mean absolute error (12.4 kN) and the highest coefficient of determination ($R^2 = 0.958$), outperforming deep learning models that required heavier computation and exhibited greater sensitivity to noise. Moreover, incorporating environmental variables such as temperature and vibration frequency enhanced model accuracy by nearly 10%, underscoring the interdependence between mechanical and environmental factors in real-world bridge performance. Sensitivity and correlation analyses revealed that strain was the most influential predictor of load capacity ($r = 0.88$), followed by deflection and vibration frequency, while temperature served as a moderating factor influencing thermal expansion and stress variability—particularly in steel structures. The real-time deployment of the model within a simulated monitoring environment demonstrated robust operational reliability, achieving prediction latency below two seconds and early warning detection accuracy exceeding 97%, thereby validating its suitability for real-time infrastructure management. When compared to static datasets or image-based condition assessments, this research distinguished itself by combining continuous sensor inputs, adaptive retraining, and cross-validation to minimize temporal drift and enhance generalization. These findings collectively confirmed that predictive modeling using ensemble machine learning integrated with real-time sensor data represents a transformative advancement in structural health monitoring, offering a proactive and scalable solution for bridge maintenance, risk assessment, and decision-support systems within modern intelligent transportation infrastructure frameworks.

RECOMMENDATIONS

Based on the outcomes of the study Predictive Modeling of Bridge Load Capacity Using Machine Learning and Real-Time Sensor Data, several key recommendations are proposed to enhance the future application of intelligent systems in structural health monitoring and bridge management.

First, the integration of hybrid modeling frameworks that combine physics-based and machine learning approaches should be prioritized. While ensemble algorithms such as Random Forest and Gradient Boosting have shown superior predictive performance, incorporating finite element (FE) simulations and physics-informed machine learning (PINN) can improve both interpretability and reliability. This hybridization ensures that predictive models not only fit empirical data but also adhere to the underlying structural mechanics of bridge behavior. Future research should therefore emphasize the co-development of physics-guided data-driven algorithms for dynamic load capacity prediction.

Second, the enhancement of real-time data acquisition systems is crucial for achieving consistent accuracy in predictive modeling. Standardized sensor networks with synchronized data collection—covering strain, vibration, deflection, and environmental factors—should be implemented across bridge infrastructures. Adoption of Internet of Things (IoT) and edge computing technologies can reduce latency and enable faster data processing, allowing for near real-time decision-making. Data harmonization protocols and interoperability standards must be established to ensure the compatibility of diverse sensor devices and data management systems across different jurisdictions and bridge types. Third, data preprocessing and feature engineering need greater standardization and automation. Many prior studies have demonstrated that model performance is highly dependent on data quality. Future implementations should employ advanced filtering, normalization, and feature extraction techniques—such as wavelet transformation and autoencoders—to handle noisy, high-frequency data. Establishing standardized frameworks for data cleaning, synchronization, and quality validation will improve model transferability and enable comparative benchmarking across studies and regions.Fourth, environmental and operational variables should be systematically incorporated into predictive models. The study showed that including parameters such as temperature, humidity, and traffic vibration improved prediction accuracy by nearly 10%. Consequently, future predictive models should employ adaptive algorithms capable of automatically normalizing environmental effects, ensuring that results remain stable under varying climatic and operational conditions. Such inclusivity will enhance the global applicability and generalization of bridge load prediction models. Fifth, the creation of open-access benchmark datasets and collaborative research networks is recommended to facilitate model validation and reproducibility. National transportation authorities and research institutions should develop shared databases of long-term, high-resolution sensor data representing diverse bridge typologies and environmental conditions. These repositories would serve as a foundation for comparing algorithms, validating predictions, and advancing international collaboration in predictive infrastructure analytics.

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