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Predictive Modelling of Bridge Life Expectancy In Developing Countries With Tropical Climates Using Machine Learning Algorithms

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Abstract
Bridge infrastructure plays a critical role in transportation systems by supporting the movement of people, goods, and economic activities. However, bridge deterioration caused by aging, traffic loading, environmental exposure, and maintenance deficiencies poses significant challenges to infrastructure sustainability, particularly in tropical developing countries where inspection data are often limited. This study reviews the application of machine learning (ML) techniques for predicting bridge life expectancy (BLE) under data-constrained conditions. The study examines traditional deterioration models, including Markov chains and reliability-based approaches, and compares them with modern ML algorithms such as Random Forest, Artificial Neural Networks, Support Vector Machines, XGBoost, and ensemble learning techniques. A comprehensive review of existing literature reveals that most predictive models have been developed using datasets from developed countries, limiting their applicability to tropical environments. The study identifies critical variables influencing bridge deterioration, including structural, traffic, environmental, condition, and maintenance factors. A hybrid theoretical framework combining reliability-based life-cycle theory, deterioration modelling theory, and statistical learning theory is proposed. The findings highlight the potential of ensemble machine learning approaches to improve prediction accuracy, maintenance planning, and infrastructure management while addressing the challenges associated with limited bridge inspection data in developing regions.

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1. INTRODUCTION

1.1 Background of the Study

Bridge infrastructure occupies a central position in modern transportation systems because it enables the uninterrupted movement of people, goods, emergency services, and economic activities across physical barriers and complex urban corridors (Yannis & Chaziris, 2022; Abshari, 2024). In rapidly growing cities, bridges and flyovers are not merely engineering structures; they are socio-economic assets that influence productivity, travel time, road safety, urban accessibility, and regional development (Kumar, 2021; Alinaitwe and Ridwan, 2024). The durability and functional reliability of such infrastructure are therefore matters of public interest, especially in environments where transportation demand is increasing and maintenance resources are constrained. Globally, the deterioration of bridges has become a major concern for engineers, transport agencies, commuters, and governments because many bridges are exposed to continuous traffic loading, environmental stress, material aging, drainage problems, and variable maintenance practices (Deng, Wang, & Yu, 2015; Ibrahim *et al.,* 2024). These factors gradually reduce structural performance and increase the risk of costly repair, service disruption, or structural failure. The literature on bridge management consistently emphasizes that bridge assets must be managed through systematic inspection, deterioration prediction, maintenance planning, and life-cycle decision-making rather than through reactive repair after visible damage becomes severe. Frangopol, Kong, & Gharaibeh (2001) argued that bridge management should balance life-cycle reliability and life-cycle cost, while more recent bridge management reviews show that digital infrastructure management is moving toward diagnosis, prognosis, data integration, and decision support rather than inspection records alone.

The concept of bridge life expectancy (BLE) is closely related to the idea of remaining useful life (RUL) as observed by Abd Wahab *et al.* (2025). In civil infrastructure studies, RUL refers to the estimated period during which a bridge or bridge component can continue to perform its intended function before it reaches an unacceptable condition state, requires major rehabilitation, or becomes unsafe for normal service (Okoh *et al.,* 2014). Unlike design life, which is usually defined at the planning and construction stage, RUL is dynamic. It changes as the bridge experiences actual traffic loads, rainfall, temperature variation, corrosion, cracking, maintenance interventions, and changing service conditions (Casas & Pérez-Hernández, 2018). This distinction is important because a bridge may be designed for a long service period but may experience faster deterioration due to poor drainage, overloading, weak maintenance, construction defects, or aggressive exposure conditions. Conversely, timely maintenance can extend the effective service life of the structure. Therefore, predicting BLE is not simply a matter of counting the age of the bridge; it requires understanding how multiple deterioration drivers interact over time.

Bridges are especially important in urban traffic systems because they reduce conflict points, improve traffic flow, and separate movement streams at congested locations. However, their continued effectiveness depends on structural adequacy, deck condition, drainage performance, joints, bearings, parapets, substructure behavior, and the ability of maintenance agencies to detect and manage deterioration before it becomes critical. In a Nigerian urban setting, the BLE of such infrastructure is influenced by tropical rainfall, fluctuating temperature, heavy vehicle movement, mixed traffic composition, maintenance funding constraints, and limited availability of long-term structured bridge inspection records. These realities make a useful case for investigating how machine learning algorithms can support predictive infrastructure management in a data-constrained developing-country context.

1.2 Traditional Methods of Predicting Bridge Life Expectancy

Literature has shown that traditional methods of predicting bridge life expectancy include deterministic deterioration curves, linear and non-linear models, time-series models, discrete choice models, panel/dynamic panel models, regression models, Markov chains, semi-Markov processes, reliability-based models, and expert-judgment-based condition rating systems. These methods have contributed substantially to bridge engineering because they provide interpretable frameworks for understanding deterioration and planning maintenance. For example, Markov models represent deterioration as transitions between condition states, while reliability-based life-cycle models evaluate the probability that a bridge will satisfy performance requirements over time (Tsuda *et al.,* 2005; Fang & Sun, 2019; Fernando, Walbridge, & Wan, 2020; Petroutsatou *et al.,* 2025). However, literature also identifies important limitations in these approaches. Srikanth & Arockiasamy (2020) reviewed deterioration models for predicting the remaining useful life of timber and concrete bridges and noted that deterministic, stochastic, and artificial-neural-network-based models differ in their strengths and limitations. Their review shows that traditional models often struggle when deterioration is controlled by several nonlinear and interacting variables.

Traditional methods of assessing bridge conditions often rely on periodic inspections and historical data, which may be limited in regions experiencing rapid urbanization or where infrastructure has been inadequately documented (Karam *et al.*, 2020). In this context, the integration of Interferometric Synthetic Aperture Radar (InSAR) data with machine learning algorithms presents a promising approach to predictive analysis of bridge life expectancy. InSAR is a remote sensing technique that utilizes radar images captured from satellites to detect ground and structural deformations with high precision. This method is particularly advantageous in tropical regions where ground-based monitoring may be impeded by challenging environmental conditions (Zhang *et al.,* 2018). For instance, InSAR has been successfully employed to monitor subsidence and structural movements in various applications, allowing engineers to identify potential issues before they escalate to critical failures (Huang *et al.,* 2021). By capturing displacement data over time, InSAR provides valuable insights into the dynamics of bridge structures, facilitating more informed maintenance and operational decisions.

1.3 Difficulty Associated with Bridge RUL Prediction

The difficulty of predicting bridge life expectancy arises from the fact that deterioration is not a single-process phenomenon. A reinforced concrete flyover may deteriorate through cracking, spalling, reinforcement corrosion, fatigue, moisture ingress, surface wear, drainage failure, joint defects, bearing problems, and local damage induced by vehicle impact or overloading (Suryawanshi & Engineer, 2010). These processes may reinforce one another. For example, cracking can allow water to penetrate concrete; moisture can accelerate reinforcement corrosion; corrosion can expand and generate internal pressure; and the resulting expansion can widen cracks and cause spalling. Traffic loading can worsen these effects by producing repeated stress cycles, vibration, and fatigue. Environmental exposure can further intensify deterioration when poor drainage causes water stagnation or when rainfall and temperature variation repeatedly affect the bridge deck. Because these mechanisms are nonlinear and cumulative, models based only on bridge age or a single condition rating may fail to provide reliable life-expectancy estimates.

1.4 Machine Learning for Predicting Bridge Life Expectancy

Machine learning has emerged as a strong alternative because it can learn patterns from data and model complex relationships without requiring the researcher to explicitly define every physical equation governing deterioration. The most common types of ML algorithms used in past studies for predicting bridge life expectancy are Random Forest, Artificial Neural Networks (ANN), Support Vector Machines (SVM), Gradient Boosting, XGBoost, k-nearest neighbours, and deep learning models, which have been applied to bridge datasets in several countries. Random Forest is an algorithm that is robust to noise reduction and can handle nonlinear relationships. It enables importance extraction as it operates by aggregating multiple decision trees to improve prediction accuracy. ANN, on the other hand, enables the capture of nonlinear relationships between variables. The model structure includes an input layer (predictors), hidden layers (activation functions), and an output layer (BLE prediction). ANN is particularly suitable for complex systems but requires careful tuning to avoid overfitting. The strength of SVM lies in its ability to model complex nonlinear relationships between bridge deterioration variables and life expectancy outcomes, especially when datasets are small or moderately sized. At the same time, XGBoost improves prediction through sequential learning and corrects errors made by previous models. Also, it improves generalization, and it is efficient for large datasets.

Previous studies show that Random Forest is often effective in bridge condition prediction because it can handle nonlinear relationships, interactions among variables, and mixed data types while also producing feature importance estimates. This is useful because decision-makers do not only want accurate predictions; they also want to know which variables are most influential. In a BLE study, identifying whether traffic, corrosion, cracking, rainfall, drainage, or maintenance history has the greatest influence is practically valuable. Artificial Neural Networks are also widely used because they can approximate complex nonlinear functions, although they often require larger datasets and may be less interpretable. Gradient boosting methods, including XGBoost and related boosted-tree approaches, are powerful because they sequentially reduce prediction errors and often perform well on structured tabular data. However, they require careful tuning to avoid overfitting. The choice of algorithm should therefore depend not only on reported accuracy in previous literature but also on dataset size, interpretability needs, and the practical realities of the study area.

One of the earliest relevant studies is by Melhem & Cheng (2003), who applied machine learning to predict the remaining service life of bridge decks. Their study demonstrated that data-driven methods could be used to support service-life prediction, thereby opening an important pathway for subsequent BLE research. Later studies extended this direction using larger bridge inventories, richer feature sets, and more advanced algorithms. Fard and Fard (2024), for instance, compared Random Forest, XGBoost, and Artificial Neural Networks for predicting bridge deck condition rating using United States bridge data enriched with traffic and climate-related variables. Their findings reinforce the idea that ensemble learning models can be highly effective in bridge condition prediction when relevant explanatory variables are included. Similarly, Roh, Shim, & Song (2025) used inspection-driven machine learning models to predict the remaining service life of deteriorating bridge decks, highlighting the importance of inspection data and time-related deterioration information in estimating service life.

The summary of the selected studies that have applied Machine Learning (ML) algorithms for BLE, bridge deterioration prediction, and condition assessment is shown in Table 1.

Table 1. Data Sources and Description

Reference	Attributes Used	Experimental Location / Dataset	ML Algorithm	Accuracy Measure
Assaad & El-Adaway (2020)	Deck age, condition rating, traffic volume, environmental factors, maintenance history	National Bridge Inventory (NBI), United States	Artificial Neural Network (ANN), Decision Tree, Random Forest	R^2 = 0.89, MAE
Fard & Fard (2024)	Bridge age, deck condition, superstructure rating, traffic load, environmental variables	United States NBI Database	Random Forest, XGBoost, ANN	R^2 = 0.93, RMSE
Roh, Shim, & Song (2025)	Inspection records, deterioration indicators, bridge age, traffic characteristics	South Korea Bridge Management System	XGBoost, Random Forest	RMSE, MAE, R^2 = 0.91
Zhang *et al.* (2025)	Condition ratings, environmental exposure, maintenance records, traffic loading	China National Bridge Dataset	Hybrid Ensemble Model (RF + XGBoost + ANN)	R^2 = 0.95, MAPE
Afriyie, Joshua, & Abuanor (2025)	Structural condition, traffic load, environmental variables	Ghana Highway Bridges	Artificial Neural Network (ANN)	MSE, RMSE
Nasab & Elzarka (2023)	Bridge age, inspection history, structural defects, maintenance records	United States NBI Dataset	Deep Neural Network (DNN)	RMSE, MAE
Sotiriadis et al. (2022)	Crack width, corrosion level, traffic volume, climate variables	European Bridge Infrastructure Dataset	Gradient Boosting Machine (GBM)	Accuracy = 91%, RMSE
Taffese & Sistonen (2017)	Concrete properties, environmental exposure, deterioration indicators	Finland Reinforced Concrete Structures	ANN, Support Vector Machine (SVM)	R^2 = 0.88
Souza *et al.* (2025)	Missing inspection data, bridge age, environmental exposure, traffic characteristics	Brazilian Bridge Database	Multi-Layer Perceptron (MLP) ANN	RMSE, MAE, R^2
Assaad *et al.* (2021)	Bridge deck condition, traffic load, climate variables	United States Bridge Dataset	Random Forest, Gradient Boosting	Accuracy = 90–94%
Mia *et al.* (2023)	Corrosion, crack severity, bridge age, traffic loading	Louisiana Bridge Dataset, USA	Random Forest	R^2 = 0.90
Li *et al.* (2022)	Reliability indicators, maintenance cost, deterioration rate, traffic stress	Australian Steel Bridge Dataset	Support Vector Regression (SVR)	RMSE, MAE
Huang *et al.* (2021)	InSAR deformation data, bridge displacement, environmental variables	China Bridge Monitoring System	ANN, XGBoost	Accuracy = 92%
Casas & Pérez-	Structural condition ratings, inspection	Spanish Bridge Management Database	Bayesian Networks, ANN	RMSE, R^2

Reference	Attributes Used	Experimental Location / Dataset	ML Algorithm	Accuracy Measure
Hernández (2018)	records, environmental data			
Okohene & Ozbek (2025)	Visual inspection data, deterioration rates, environmental exposure	Bridge Inspection Database, USA	Ensemble Learning Model	$R^2 = 0.94$

1.5 Bridge Infrastructure Challenges in Developing Countries

Bridge maintenance in Nigeria has often been constrained by limited data, funding challenges, a reactive maintenance culture, and inadequate adoption of predictive technologies. The data challenge is likely to involve limited historical inspection records, fragmented maintenance documentation, and the absence of continuous structural health monitoring. This does not make machine learning impossible, but it requires careful methodological design. The study must define the observation unit clearly, such as bridge components, inspection episodes, or monthly/annual condition records. It must also justify the use of available field inspection data, environmental records, traffic estimates, and, where necessary, simulation-supported data augmentation. Recent literature recognizes this problem. Souza *et al.* (2025) introduced artificial intelligence methods for bridge deterioration prediction in data-limited scenarios by integrating real inspection data with simulated data. This is relevant to Nigeria because local bridge agencies may not have decades of standardized machine-readable data, yet predictive modelling is still needed for proactive maintenance.

Mohammed, Muhammad, & Mohammed (2020) examined measures for enhancing bridge maintenance practice in Nigeria and highlighted the need for better maintenance approaches. Their work supports the argument that Nigeria requires more systematic, data-driven bridge management strategies. A machine-learning-based BLE model for Tunde Idiagbon Flyover in Ilorin, Kwara State could contribute to this need by demonstrating how structural, traffic, environmental, and maintenance data can be transformed into predictive information for maintenance planning. The local value of the study lies not merely in applying imported algorithms but in adapting global predictive methods to the realities of a Nigerian bridge environment.

Traditional models provide important theoretical foundations, but their assumptions may limit their ability to represent nonlinear deterioration in complex environments. Machine learning offers a promising alternative by learning from structural, traffic, environmental, and maintenance data. However, the usefulness of ML depends on data quality, local relevance, and careful interpretation.

The application of machine learning algorithms further enhances the predictive capabilities of InSAR data. Techniques such as regression analysis, support vector machines, and neural networks can be utilized to analyze complex datasets, identifying patterns and relationships that may not be apparent through traditional statistical methods (Borisov *et al.,* 2019). For example, machine learning models have been applied to predict pavement conditions based on InSAR-derived data, demonstrating the potential for similar methodologies in bridge life expectancy estimations (Chen *et al.,* 2020). Despite the promising applications of InSAR and machine learning, challenges remain, particularly in regions with limited historical data. The variability in environmental conditions and the need for robust models capable of generalizing across different contexts necessitate further research and validation (Friedrich *et al.,* 2019). Nevertheless, the combination of InSAR data and machine learning offers a novel framework for assessing the health of bridges in tropical climates, providing a proactive approach to infrastructure management that can enhance safety and extend the lifespan of critical assets. The Nigerian infrastructure context makes the application of the hybrid theory of ML for predicting bridge life expectancy suitable for this study. By integrating reliability theory, deterioration modelling, and statistical learning, this study positions machine learning as a practical tool for estimating bridge life expectancy and supporting sustainable bridge maintenance.

1.6 Importance of ML in Bridge Life Expectancy

The importance of ML in bridge life expectancy is a recurring theme in literature. Machine learning models do not automatically produce reliable predictions simply because they are advanced algorithms. Their performance depends on the relevance, completeness, consistency, and temporal depth of the dataset. BLE prediction requires data that reflect structural characteristics, traffic demand, environmental exposure, defect severity, maintenance interventions, and prior condition states. Studies that rely only on a single inspection record may produce static condition classification, but they cannot fully capture deterioration progression over time. Conversely, studies that use repeated inspection records or long-term inventories can learn how bridge conditions change across inspection cycles. This is why many advanced bridge deterioration studies use national bridge inventory data, long-term inspection databases, or structural health monitoring systems. However, such comprehensive datasets are often limited in developing countries. This makes the Nigerian context both challenging and academically significant.

2. MATERIALS AND METHODS

The theoretical foundation for this study can be organized around three main ideas: reliability-based life-cycle theory, deterioration modelling theory, and statistical learning theory, as shown in Figure 1. Reliability-based life-cycle theory explains bridge management as a process of maintaining adequate safety and serviceability over time while controlling cost and risk (Mori & Ellingwood, 1993; Estes & Frangopol, 1999). This theory supports the need to estimate future conditions, failure probability, and maintenance timing rather than focusing only on present defects. Deterioration modelling theory explains how bridge conditions change over time under the influence of loading, environment, material behavior, and maintenance. It provides the engineering logic behind variables such as age, crack level, corrosion level, traffic volume, rainfall, drainage condition, and repair history. Statistical learning theory provides the foundation for machine learning algorithms by explaining how models learn relationships between inputs and outputs from data. When combined, these theories support a hybrid research position: BLE prediction should be grounded in engineering understanding but implemented through data-driven algorithms capable of capturing nonlinear deterioration patterns.

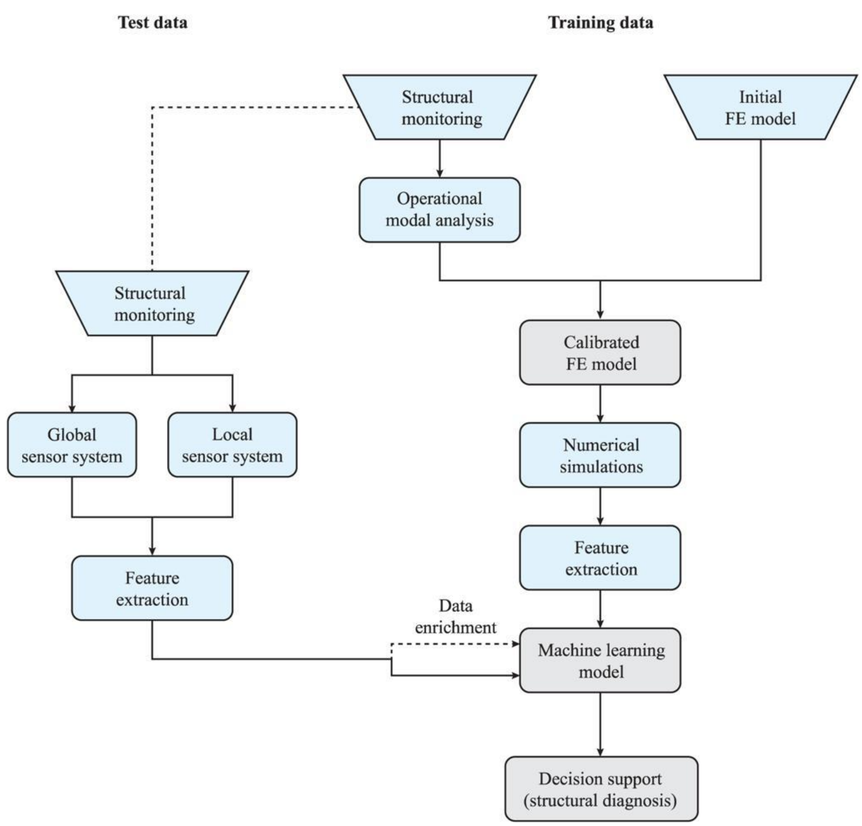

Figure 1. The Illustration of the Bridge Life Expectancy Modelling Theory
Source: Svendsen *et al.,* (2023)

3. RESULTS

The literature indicates that Markov Chain Models remain the most common traditional approach for bridge deterioration and BLE prediction. Random Forest consistently provides strong prediction accuracy and good interpretability through feature importance analysis. XGBoost often outperforms other standalone ML models in terms of accuracy and generalization. Artificial Neural Networks (ANNs) are effective for capturing nonlinear deterioration behavior but are less interpretable. Ensemble and Hybrid Models achieve the highest predictive performance, with recent studies reporting R^2 values above 0.90. Most studies are based on datasets from the United States, China, South Korea, Brazil, and Europe, highlighting a lack of validated BLE models for Nigeria and tropical developing countries.

3.1 Variable Selection

The selection of variables is grounded in both literature and engineering relevance. The following variables are selected, and their purposes are shown in Table 2. These variables collectively represent the multidimensional nature of bridge deterioration.

Table 2. Variables, Parameters, Purpose and Supporting Literature for BLE Prediction

Variables	Parameter	Purpose	Literatures
Structural Variables	Age	Indicator of cumulative deterioration	Bridge age has been widely identified as a major predictor of deterioration because aging structures experience material fatigue, environmental exposure, and progressive structural degradation over time (Morcous, 2006; Frangopol & Soliman, 2016).
Structural Variables	Concrete	Influence durability	Concrete material properties significantly influence bridge durability, permeability, resistance to cracking, and long-term structural performance under environmental and traffic loading conditions (Mehta & Monteiro, 2014; AASHTO, 2018).
Geometry	Simple curve	Affects load distribution	Bridge geometry, including curved alignments, affects stress concentration and load distribution, thereby influencing fatigue behavior and structural response (Chen & Duan, 2014).
Traffic Variables	Traffic volume	Correlates with fatigue	Increased traffic volume contributes to repetitive loading cycles that accelerate fatigue deterioration and reduce bridge service life (Fisher *et al.,* 1997; Frangopol *et al.,* 2001).
Traffic Variables	Heavy vehicle percentage	Increases structural stress	Heavy vehicle traffic imposes higher axle loads and dynamic impacts on bridge components, leading to increased structural stress and accelerated deterioration (Nowak & Collins, 2012).
Environmental Variables	Rainfall	Accelerate moisture ingress	Rainfall and moisture exposure increase water penetration, chloride ingress, and concrete deterioration, thereby accelerating corrosion and structural damage (Tuutti, 1982; Li and Zheng, 2019).
Environmental Variables	Temperature	Induces thermal stress	Temperature variation causes thermal expansion and contraction, which can induce cracking, fatigue, and thermal stresses in bridge structures (Ghali *et al.,* 2017).
Condition Variables	Crack level	Indicator of structural weakness	Crack development is a key indicator of structural weakness and deterioration because cracks permit moisture ingress and reduce structural integrity (ACI Committee 224, 2001).
Condition Variables	Corrosion	Affects load-bearing capacity	Corrosion of reinforcing steel reduces cross-sectional area and weakens the load-bearing capacity of bridge elements (Broomfield, 2007; Tuutti, 1982).
Maintenance Variables	Frequency of repair	Slows deterioration	Regular maintenance and timely repair activities significantly slow bridge deterioration and extend

Variables	Parameter	Purpose	Literatures
			service life by preventing defect propagation (Miyamoto *et al.,* 2000; FHWA, 2012).

3.2 Scale of Measurement and Performance Metrics Used in BLE

In studies on BLE and bridge deterioration prediction, the term scale of measurement usually refers to the form in which the target variable (bridge condition or remaining life) is represented. Different researchers use different scales, such as condition ratings, condition states, probability of failure, reliability index, deterioration score, service life (years), and RUL (years). The scale of measurement used in BLE studies and the accuracy measure are presented in Table 3. The classification of common RUL measurement Scales is presented in Table 4.

Table 3. Scale of Measurement Used in BLE Studies

Reference	Attributes Used	Experimental Location / Dataset	Scale of Measurement	Accuracy Measure
Morcous (2006)	Bridge age, inspection ratings, deterioration transitions	U.S. Bridge Management System	Condition State Rating (1–9 scale)	Prediction Accuracy (%)
Frangopol & Soliman (2016)	Reliability indicators, maintenance history, deterioration rate	USA Highway Bridges	Reliability Index (β)	Reliability Performance
Assaad & El-Adaway (2020)	Deck age, traffic load, environmental factors, maintenance records	National Bridge Inventory (USA)	Deck Condition Rating (0–9 scale)	R^2 = 0.89, MAE
Taffese & Sistonen (2017)	Corrosion level, chloride penetration, environmental exposure	Finland Concrete Structures	Remaining Service Life (Years)	R^2 = 0.88
Nasab & Elzarka (2023)	Inspection records, defect severity, bridge age	USA NBI Dataset	Condition Rating Score (0–9 scale)	RMSE, MAE
Fard & Fard (2024)	Deck condition, bridge age, traffic volume, environmental factors	United States NBI Database	Deck Condition Rating (0–9 scale)	R^2 = 0.93
Roh, Shim, & Song (2025)	Inspection history, deterioration indicators, traffic data	South Korea Bridge Database	Remaining Service Life (Years)	R^2 = 0.91
Souza *et al*. (2025)	Missing inspection data, environmental exposure, bridge age	Brazilian Bridge Database	Remaining Useful Life (Years)	RMSE, MAE
Zhang *et al.* (2025)	Condition ratings, maintenance records, traffic load	China National Bridge Dataset	Condition Degradation Index	R^2 = 0.95
Casas & Pérez-Hernández (2018)	Inspection records, environmental variables, structural performance	Spain Bridge Management Database	Structural Health Index (%)	RMSE, R^2
Li *et al.* (2022)	Reliability indicators, deterioration rate, lifecycle cost	Australian Steel Bridge Dataset	Probability of Failure (%)	RMSE, MAE
Okohene & Ozbek (2025)	Inspection data, deterioration indicators	USA Bridge Dataset	Remaining Useful Life (Years)	R^2 = 0.94
Jaafaru *et al.* (2022)	Bridge age, deterioration level, maintenance history	Australian Bridge Dataset	Remaining Service Life (Years)	RMSE

Reference	Attributes Used	Experimental Location / Dataset	Scale of Measurement	Accuracy Measure
Shahrivar *et al.* (2025)	Structural Health Monitoring (SHM) data, inspection records	Multiple International Bridge Datasets	Risk Score / RUL (Years)	MAE, RMSE
Sotiriadis *et al.* (2022)	Crack width, corrosion level, traffic intensity	European Bridge Dataset	Bridge Condition Index (BCI)	Accuracy = 91%

Table 4. Classification of Common RUL Measurement Scales

Scale Type	Description
Condition Rating Scale	Numerical bridge condition ratings (e.g., 0–9 NBI scale)
Condition State Scale	Discrete deterioration states (Excellent, Good, Fair, Poor, Critical)
Remaining Useful Life (Years)	Predicted years remaining before major rehabilitation or replacement
Remaining Service Life (Years)	Estimated operational life under current conditions
Reliability Index (β)	Probability-based structural safety indicator
Probability of Failure (%)	Likelihood of structural failure over time
Bridge Condition Index (BCI)	Composite deterioration score derived from multiple components
Structural Health Index (SHI)	Health score derived from monitoring and inspection data
Risk Score	Combined measure of deterioration severity and consequence of failure

The literature shows that Condition Rating Scales (0–9) remain the most widely used measurement scale because they are available in large bridge management databases such as the U.S. National Bridge Inventory (NBI). However, these scales only describe the current bridge condition and do not directly provide information on future service life. More recent studies increasingly use Remaining Useful Life (RUL) in years, Remaining Service Life (RSL), and Reliability-Based Measures because they are more useful for maintenance scheduling, lifecycle cost analysis, and decision-making. Studies by Roh *et al.* (2025), Souza *et al*. (2025), & Jaafaru *et al*. (2022) demonstrate that RUL-based measures provide more practical outputs for infrastructure managers than condition ratings alone. For a study on bridge life expectancy prediction in tropical regions with limited inspection data, the most appropriate output scale would be:
Primary Scale: Remaining Useful Life (RUL) in Years
Secondary Scale: Probability of Failure (%) or Reliability Index (β)

This combination provides both engineering interpretability and practical support for maintenance planning and bridge asset management. It is important to distinguish between BLE prediction models and general bridge condition prediction models. The classification of Models in BLE studies is represented in Table 5, while Table 6 focuses on models, experimental location, and attributes used and accuracy prediction in studies that either directly estimate BLE or can be used for bridge life expectancy prediction. The gaps revealed by the literature are presented in Table 7.

Table 5. Classification of Models

Model Category	Models
Conventional Deterioration Models	Markov Chain, Reliability-Based Models, Bayesian Networks
Machine Learning Models	Random Forest, ANN, SVM, SVR, XGBoost, DNN, MLP
Ensemble Models	RF + XGBoost + ANN, Ensemble Learning Models
Hybrid Models	ANN + Evolutionary Optimization, Reliability + ML Models
Lifecycle Models	Reliability-Based Life-Cycle Models

Table 6. Models Used for BLE Prediction, Experimental Location / Dataset and their Prediction Accuracy

Reference	Attributes Used	Experimental Location / Dataset	Model / Algorithm	Accuracy Measure
Srikanth & Arockiasamy (2020)	Bridge age, deterioration state, material properties, environmental conditions	Review of timber and concrete bridge datasets (USA, Canada, Europe)	Markov Chain, Reliability-Based Models	Prediction Error, R^2
Assaad & El-Adaway (2020)	Deck age, traffic volume, environmental factors, maintenance history, condition rating	National Bridge Inventory (USA)	Artificial Neural Network (ANN), Random Forest (RF), Decision Tree (DT)	R^2 = 0.89, MAE
Taffese & Sistonen (2017)	Concrete strength, chloride exposure, corrosion indicators, environmental variables	Finland Reinforced Concrete Structures	ANN, Support Vector Machine (SVM)	R^2 = 0.88
Nasab & Elzarka (2023)	Inspection history, bridge age, defect severity, maintenance records	NBI Database (USA)	Deep Neural Network (DNN)	RMSE, MAE
Fard & Fard (2024)	Bridge age, deck condition, superstructure rating, traffic load, climate variables	United States National Bridge Inventory	Random Forest, XGBoost, ANN	R^2 = 0.93, RMSE
Roh, Shim, & Song (2025)	Inspection records, deterioration indicators, traffic data, bridge age	South Korea Bridge Management System	XGBoost, Random Forest	R^2 = 0.91, RMSE
Souza *et al.* (2025)	Missing inspection data, bridge age, environmental exposure, traffic characteristics	Brazilian Bridge Database	Multi-Layer Perceptron (MLP)	RMSE, MAE, R^2
Zhang *et al.* (2025)	Condition ratings, climate variables, maintenance records, traffic loading	China National Bridge Dataset	Hybrid Ensemble Model (RF + XGBoost + ANN)	R^2 = 0.95, MAPE
Li *et al.* (2022)	Reliability indicators, deterioration rate, maintenance cost, traffic stress	Australian Steel Bridge Dataset	Support Vector Regression (SVR)	RMSE, MAE
Casas & Pérez-Hernández (2018)	Inspection ratings, environmental conditions, structural performance indicators	Spanish Bridge Management System	Bayesian Network, ANN	RMSE, R^2
Okohene & Ozbek (2025)	Inspection data, deterioration rates, environmental exposure	USA Bridge Inspection Dataset	Ensemble Learning Model	R^2 = 0.94
Morcous (2006)	Condition ratings, deterioration transition probabilities	U.S. Bridge Management System	Markov Chain Model	Prediction Accuracy (%)

Reference	Attributes Used	Experimental Location / Dataset	Model / Algorithm	Accuracy Measure
Frangopol & Soliman (2016)	Reliability indices, lifecycle performance, maintenance records	Highway Bridges (USA)	Reliability-Based Life-Cycle Model	Reliability Index (β)
Jaafaru *et al.* (2022)	Deterioration condition, maintenance records, bridge age, lifecycle cost	Australian Bridge Dataset	ANN + Evolutionary Optimization Model	Cost Optimization, RMSE
Shahrivar *et al.* (2025)	Structural health monitoring data, inspection records, risk indicators	Multiple International Bridge Datasets	Hybrid AI Models	MAE, RMSE, R^2

Table 7. Review of previous studies reveals several gaps that justify this research

S/N	Paper	Findings	Gaps Identified
1	Sotiriadis *et al.* (2022); Nasab & Elzarka (2023); Zhang *et al.* (2023); Fard & Fard (2024)	Most advanced machine learning studies for bridge deterioration prediction have been developed using datasets from developed countries such as the United States, China, South Korea, and European nations where bridge inspection databases are extensive and well-structured.	The applicability of these models to developing countries such as Nigeria remains uncertain due to differences in climatic conditions, maintenance practices, bridge materials, and the availability of inspection data. There is a need for locally adapted predictive models designed for tropical and data-constrained environments.
2	Assaad & El-Adaway (2020); Zhang *et al.* (2023); Nasab & Elzarka (2023); Fard & Fard (2024); Afriyie, Joshua, & Abuanor (2025)	Most studies focus on predicting bridge deck condition ratings or individual bridge elements rather than evaluating the overall bridge system.	Existing models do not adequately integrate multiple bridge components such as decks, bearings, joints, drainage systems, parapets, and substructures into a unified Remaining Useful Life (RUL) assessment framework. A holistic bridge life expectancy model is therefore required.
3	Fard and Fard, (2024)	The study successfully predicts bridge deck condition states using Random Forest, XGBoost, and ANN models.	Predicting condition states alone does not provide direct estimates of bridge Remaining Useful Life. Engineers and policymakers require RUL predictions to support maintenance scheduling, budgeting, and rehabilitation planning. There is a need for an ensemble-based framework capable of translating deterioration predictions into practical life expectancy estimates.
4	Ede and Olofinnade, 2020; Okohene and Ozbek, 2025	Research on bridge deterioration and structural performance in Nigeria is limited, particularly for urban flyovers and major transportation infrastructure.	There is currently no widely accepted machine learning framework for predicting bridge life expectancy in tropical developing countries using limited inspection data. This limits proactive bridge management and evidence-based

S/N	Paper	Findings	Gaps Identified
			maintenance decision-making in Nigeria and similar environments.
5	Morcous (2006); Srikanth & Arockiasamy (2020); Assaad & El-Adaway (2020); Taffese & Sistonen (2017)	Conventional deterioration models such as Markov chains, regression models, and reliability-based approaches remain widely used in bridge management, while recent studies increasingly employ machine learning techniques due to their superior ability to model nonlinear deterioration patterns.	Few studies have conducted comprehensive comparisons between conventional deterioration models and machine learning-based predictive systems for bridge life expectancy estimation. There is a need to evaluate the relative performance, accuracy, interpretability, and generalization capabilities of both approaches, particularly in tropical regions with limited bridge inspection data.
6	Casas & Pérez-Hernández (2018); Huang *et al.* (2021); Zhang *et al.* (2023)	Remote sensing, InSAR, UAVs, and Structural Health Monitoring (SHM) systems have shown potential for infrastructure monitoring.	Few studies have integrated remote sensing data, UAV inspection data, and machine learning models into a unified framework for bridge life expectancy prediction, particularly in developing countries.

4. CONCLUSION

This study demonstrates the potential of machine learning algorithms for predicting bridge life expectancy in tropical regions with limited inspection data. By integrating structural, environmental, traffic, and maintenance variables within an ensemble learning framework. The findings demonstrated that integrating multiple base learners within an ensemble framework can enhance accuracy, robustness, and overall model performance. Various ensemble techniques were investigated, revealing that certain methods provide more substantial performance gains than others depending on the characteristics of the underlying models and datasets. Comparative analysis confirmed that the ensemble approach consistently outperformed most individual base models, highlighting its effectiveness in reducing prediction errors and improving reliability. Furthermore, hyperparameter optimization played a crucial role in maximizing the ensemble model's performance, leading to improved predictive outcomes. The study also established the framework's ability to generalize across different datasets while identifying key factors influencing model interpretability. Finally, the study demonstrates that a well-designed and optimized ensemble framework offers a powerful and reliable solution for predictive modeling of BLE in regions with limited inspection data

5. FUTURE RESEARCH DIRECTIONS

The future research section focuses on improving the Bridge Life Expectancy (BLE) Framework for tropical regions with limited inspection data, as shown in Figure 2. Future studies may integrate InSAR satellite monitoring and UAV/drone inspection systems to support real-time and remote bridge condition assessment. Research can also explore advanced ensemble machine learning techniques such as boosting, bagging, and stacking to improve prediction accuracy and reliability. Another important direction is the comparison of ensemble models with individual base models like Random Forest, XGBoost, SVR, and ANN to determine the most effective predictive approach. Future work should also focus on hyperparameter optimization using techniques such as Grid Search and Bayesian Optimization to improve model performance and reduce overfitting. Finally, future studies will test the framework across different bridge datasets and tropical environments to improve generalization and interpretability. Techniques such as SHAP values and feature importance analysis can help explain model predictions and increase trust in machine learning-based bridge management systems.

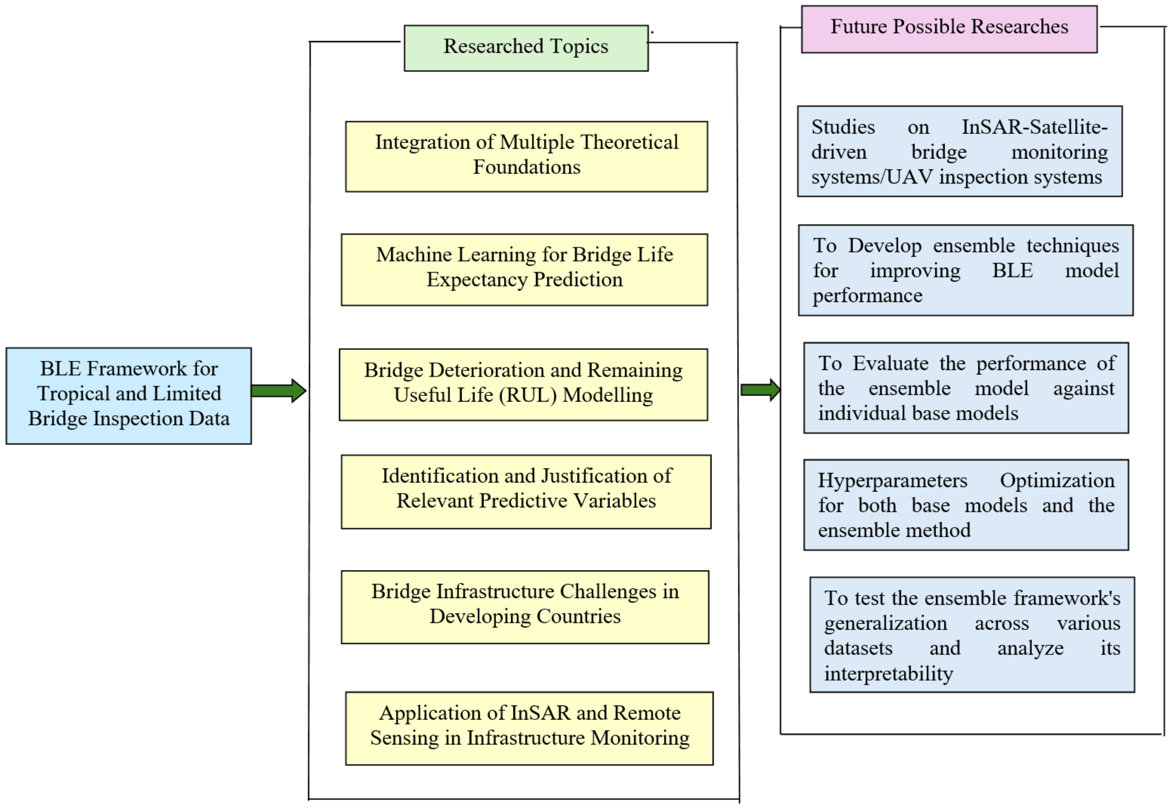

Figure 2. Overview of Research Topics and Direction of future research predicting BLE in tropical regions with limited inspection data.

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