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PERFORMANCE COMPARISON OF VARIOUS TIME-SERIES FORECASTING MODELS FOR BRIDGE SUFFICIENCY RATING PREDICTION

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Abstract. The rapid increase in the number of bridges worldwide has intensified the need for effective maintenance strategies to ensure structural safety and economic efficiency. Accurate predictions of future bridge performance are essential for preventing unexpected failures and optimizing road network maintenance planning. However, existing prediction models frequently overlook the time-series characteristics inherent in bridge inspection data, thereby limiting their accuracy. This study aims to develop improved prediction models by integrating sequential data patterns using advanced deep-learning techniques. Data from the National Bridge Inventory were utilized. As most NBI data lacked explicit sequential structures, preprocessing techniques were applied to generate meaningful time-series patterns. Deep-learning models, including deep neural networks (DNNs), convolutional neural networks, long short-term memory (LSTM), and Transformers, were developed and evaluated using cross-validation to optimize their performance. Results showed that the LSTM model improved prediction accuracy by approximately 46% compared to the baseline DNN model. The Transformer model further improved accuracy by approximately 7% over the LSTM, highlighting its superior ability to capture long-term dependencies. These findings highlight the potential of the Transformer model as a powerful tool for predicting bridge performance, thereby supporting effective maintenance planning and reducing the risk of structural failures.

Keywords: bridge performance, deep learning, maintenance, road networks, time series, transformer.

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Notations

Variables and functions

f_t – forget gate;
i_t – input gate;
o_t – output gate;
c_t – cell state;
h_t – current hidden vector;
σ – activation function;
x_t – input vector;
W_f, W_i, W_o, W_c, U_f, U_i, U_o, and U_c – weight factor terms;
h_{t-1} – previous hidden vector;
c_{t-1} – cell state;
b_f, b_i, b_o, and b_c – corresponding bias terms;
Q – query;
K – key;
V – value;
d_k – dimensionality of the key vector;
x – output vector of self-attention;
W_1 and W_2 – weight matrices;
b_1 and b_2 – bias vectors;
y_i – true value of the i^{th} training data;
$\bar{y}_i$ – predicted value for the i^{th} training data.

Abbreviations

BPM – Backward Prediction Model;
ANN – Artificial Neural Network;
CNN – Convolutional Neural Network;
DNN – Deep Neural Network;
RNN – Recurrent Neural Network;
LSTM – Long Short-Term Memory;
NBI – National Bridge Inventory;

FHWA – Federal Highway Administration;
FNN – Feed-Forward Network;
1D – One-Dimensional;
SR – Sufficiency Rating;
MAE – Mean Absolute Error;
ADT – Average Daily Traffic;
ADTT – Average Daily Truck Traffic;
NLP – Natural Language Processing.

1. Introduction

Bridges play a critical role in modern road networks by regulating traffic flow and ensuring connectivity. The worldwide increase in newly constructed bridges, coupled with the growing number of aging structures, has heightened the importance of effective maintenance strategies. Each country manages bridge conditions and performance through inspection criteria, regulations, and periodic maintenance and reinforcement measures. Inadequate bridge maintenance can lead to higher costs and, in severe cases, structural failures. The collapse of the Seongsu Bridge in South Korea in 1994 caused significant casualties. Similarly, the Morandi Bridge in Italy and Nanfang'ao Bridge in Taiwan failed owing to inadequate maintenance, resulting in numerous fatalities. Extensive research has been conducted to prevent failures caused by inadequate bridge maintenance. Recent studies have enhanced bridge inspection by integrating automated inspection technologies, including drones, robots, and sensors, to improve maintenance systems (Verma et al., 2013; Seo et al., 2018; Choi et al., 2023). Additionally, researchers have combined image processing and deep-learning techniques with these technologies to detect bridge defects, including cracks, leaks, and corrosion (Yeum & Dyke, 2015; Mohan & Poobal, 2018; Kim et al., 2018). Bridge performance data are crucial for assessing safety and making maintenance decisions. However, comprehensive bridge performance inspections are time-consuming and costly. Consequently, bridge performance prediction without physical inspections has been widely explored.

Probabilistic methods are widely used to develop models for predicting bridge performance. For example, Bayesian updating methods have been applied to forecast the future condition of reinforced concrete bridges (Enright & Frangopol, 1999) and to develop deterioration models using Bayesian belief networks (Rafiq et al., 2015). Advanced Bayesian techniques, such as particle filtering, have also been used to estimate performance and maintenance costs for prestressed concrete and I-shape girder bridges (Lee et al., 2019). Other approaches include Markov chain models that predict future states of bridge components, as illustrated by a study that developed a transition probability matrix for deck conditions to estimate service life (Morcous, 2006). Additionally, an integrated method for constructing transition probabilities to predict the long-term performance of bridges was proposed. When data are insufficient, the backward prediction model (BPM) can effectively forecast bridge performance (Bu et al., 2014). Statistical methods, such as regression analysis, have also been used to develop deterioration curves and models. Additionally, research has also developed deterioration curves that account for variability and uncertainty in bridge inspections to predict future conditions (Bolukbasi et al., 2004). A multiple fuzzy linear regression model was introduced to handle fuzzy data and improve bridge condition predictions beyond conventional regression methods (Pan et al., 2009). A study employed the Weibull distribution to develop deterioration curves for bridges in New York State and found them superior to the conventional Markov chain approach (Agrawal et al., 2010). Moreover, a type of generalized linear model, known as the ordinal logistic statistical model, was used to predict the performance of bridge components and compare it with that of conventional regression models (Lu et al., 2019). Bridge deterioration and performance have also been used to analyze and optimize the life cycle of bridges. Studies have developed life cycle models using a reliability-based approach for highway bridge management and quantitatively assessing bridge risks and costs (Frangopol et al., 2001). Additionally, other studies have addressed uncertainties in the life cycle of deteriorated bridges by incorporating reliability analysis to optimize maintenance timing and costs (Kong & Frangopol, 2003). Subsequently, Monte Carlo simulations and genetic algorithms have been applied to optimize bridge maintenance under uncertainty (Liu & Frangopol, 2004). Several studies have evaluated the effectiveness of various probabilistic models and identified key research gaps in bridge performance prediction (Frangopol et al., 2004; Zambon et al., 2017).

In the context of the match between AlphaGo and Lee Sedol, also referred to as the Google DeepMind Challenge Match, there has been increasing interest in machine learning and deep learning, leading to their applications in various fields. With this trend, machine learning and deep learning are also being utilized in the domain of bridge maintenance and performance prediction. Early machine-learning studies applied tree-based algorithms, including classification and regression trees (Bektas et al., 2013), and extreme gradient boosting (XGBoost) methods (Lim & Chi, 2019), to predict bridge conditions. Moreover, several studies have used deep learning, particularly artificial neural networks (ANNs), to predict the deterioration and performance of bridges. One notable study by Lee et al. (2008) proposed the Bridge Performance Model (BPM), an ANN-based predictive model that uses bridge inspection records. Huang (2010) developed an ANN-based deterioration prediction model to overcome the limitations of traditional Markov chain models. Bu et al. (2015) employed Elman neural networks to forecast long-term changes in bridge performance, demonstrating superior accuracy compared to Markov chain-based approaches. Xia et al. (2021) applied an ANN model to highway bridges, contributing to smart maintenance planning. Althaqafi and Chou (2022) further enhanced bridge management systems by developing an ANN model to analyze performance degradation across bridge decks, superstructures, and substructures.

Building on these findings, Martinez et al. (2020) conducted a study in Ontario, Canada, to predict the condition index of bridges using several methods, including k-nearest neighbors, decision trees, linear regression, ANNs, and deep-learning neural networks. Beyond basic ANN-based models, various studies have incorporated advanced deep-learning techniques to account for the time-series characteristics of bridge deterioration, thereby improving predictive accuracy over time. Liu and Zhang (2020) developed a convolutional neural networks (CNNs) model to predict the performance of bridge decks, superstructures, and substructures. Choi et al. (2020) used long short-term memory (LSTM) networks, incorporating layer normalization and label smoothing, to improve the prediction of concrete bridge deck deterioration. Most machine learning and deep neural network (DNN) models for bridge performance prediction focus on forecasting conditions for a one-year timespan. To overcome this limitation, Zhu and Wang (2021) combined a recurrent neural network (RNN) and a CNN to develop a model that predicts bridge performance over a 3–4 years period.

Most existing studies on using machine learning for bridge performance prediction overlook time-series characteristics of accumulated data and rely on basic variables for ANNs and DNNs to predict performance. However, advanced algorithms that incorporate time-series characteristics have been developed. Additionally, a study employed LSTM, a time-series learning technique, to predict bridge performance degradation (Choi et al., 2020). However, the study did not incorporate time-series processing into the bridge-performance data; instead, it relied on basic variables for learning. Choi et al. (2025) developed a gradient-boosting model for the bridge inspection data of South Korea – which had short time-series spans – by treating only the most recent condition as a feature to capture time-series characteristics. Recent electrical load forecasting studies have effectively utilized bidirectional LSTM (BiLSTM) models to capture complex patterns in time-series data. Pavlatos et al. (2023a) developed a prediction framework using a simple RNN to forecast electricity consumption. Subsequently, Pavlatos et al. (2023b) expanded this approach with a BiLSTM-based model that incorporates both past and future information, significantly improving prediction accuracy. The BiLSTM model outperformed RNN, LSTM, and gated recurrent unit models in terms of root mean square error (RMSE) and mean absolute error (MAE). These advanced time-series deep learning models can also be effectively applied to predictive tasks involving cumulative changes over time, such as in bridge performance data.

Recent advances in deep learning architectures, particularly Transformer models, have significantly improved performance prediction tasks owing to their ability to capture complex temporal dependencies and long-term trends. Notable models, such as Guided Approach for Time Series Ensemble Forecasting (GATE) and LFformer, have integrated RNN, LSTM, and convolutional structures to improve predictive performance and reduce overfitting. GATE employs guided network strategies, whereas LFformer applies frequency enhancement layers (Sarkar et al., 2024; Ma et al., 2024). These models, supported by ablation studies, have shown superior accuracy and stability, particularly in long-term forecasting scenarios. Incorporating Transformer-based architectures into bridge performance prediction can enhance the understanding of time-series characteristics and improve predictive accuracy. Moreover, Transformer variants such as Autoformer, Informer, and Reformer have demonstrated significant efficiency in processing long time-series data, making them ideal for bridge performance prediction tasks involving sequential dependencies and complex patterns. Therefore, in this study, we performed preprocessing to capture the time-series characteristics of the data and applied it to newly developed high-performance algorithms, which are capable of handling these characteristics, unlike basic machine learning algorithms. This highlights the importance of identifying data characteristics and incorporating them into the model for learning rather than merely applying algorithms designed for time-series data. Additionally, the findings of this study can be applied to the maintenance of various facilities – another domain where performance data is accumulated.

In this study, two strategies were employed to train the models and predict bridge performance using time-series characteristics of bridge inspection data. First, data were collected from the National Bridge Inventory (NBI), initiated by the Federal Highway Administration (FHWA). As most of the collected data lacked time-series characteristics, preprocessing was performed to incorporate them. Second, deep-learning techniques, renowned for their excellent performance in processing time-series data, such as natural language, were selected. The models were trained to predict bridge performance, and the results were analyzed and compared. Compared to conventional probabilistic models, such as Bayesian updating, Markov chains, and regression-based deterioration curves, the proposed deep-learning-based time-series forecasting models offer a data-driven, end-to-end solution. These models do not require manual feature engineering or predefined transition probabilities. While most existing deep learning approaches treat bridge data as static or use only the most recent condition rating, this study integrates sequential historical data through preprocessing and utilizes the Transformer architecture to capture both short- and long-term temporal dependencies. This represents a significant advancement over previous methods, enabling more precise, interpretable, and generalized predictions for individual bridge performance.

The remainder of this paper is organized as follows. Section 2 provides an overview of the theoretical background for time-series forecasting models. Section 3 explains the concept of sufficient rating (SR), a performance indicator for bridge construction. Section 4 discusses the data preprocessing methods used. Section 5 describes the development of bridge-performance prediction models. Section 6 compares the performance of the developed models. Sections 7 and 8 predict the actual bridge performance and compare the generalization performance of the models. Section 9 interprets and discusses the developed model. Finally, the conclusion summarizes the results of this study.

2. Background for time-series forecasting

Time-series data are defined as collections of data points recorded over fixed intervals, with an inherent chronological order and correlations among consecutive observations. Such data appear in various fields, including meteorology (for example, temperature) and finance (for example, stock prices). Lim and Zohren (2021) introduced various deep-learning techniques to enhance the management of time-series data. In civil engineering, deep-learning models utilizing time-series data have been developed, with several studies focusing on bridge anomaly detection. These studies rely on data collected from sensors, such as accelerometers, velocimeters, and displacement sensors, attached to bridges. Recent research on health monitoring using time-series data includes the application of CNN techniques to analyze acceleration and displacement data. These techniques facilitate the detection of longitudinal rebar damage in bridges (I. M. Mantawy & M. O. Mantawy, 2022). Additionally, autoencoder-based damage detection methods have been used to identify potential structural damage using real-time time-series data (Giglioni et al., 2023).

Bridges are inspected at regular intervals to verify their performance and plan for maintenance. Over several years, the collected data become sequential, exhibiting time-series characteristics in which past conditions influence future performance. This study developed a model to predict the future performance of bridges using these data. In this section, an explanation of the theories behind the four algorithms used in the time-series forecasting models is presented; their basic structures are shown in Figure 1.

2.1. DNN model

The DNN model, a type of ANN, is a multilayered neural network with simple yet powerful performance, making it one of the most widely used deep-learning techniques. The DNN model consists of an input layer, hidden layers, and output layer, with each layer containing neurons. This model processes input data through multiple layers by performing nonlinear transformations and learning, ultimately predicting the desired output. In a fully connected layer of a DNN, each neuron is connected to all neurons in the previous layer, with each connection having weight. The output of a neuron is calculated as the activation of the weighted sum of the outputs from the previous layer, where the weights determine the connection strength. The DNN model can learn complex patterns by stacking multiple layers, with higher-level learning occurring as the number of layers increases. Although the DNN model is not specifically designed for time-series data, its simplicity and strong performance make it a suitable baseline for comparison with other models in this study.

2.2. CNN model

CNN, initially designed for processing spatial data like images and videos, detects and learns local patterns in the input data. Consequently, CNN can effectively perform tasks like image classification, object detection, and segmentation. By leveraging this principle, a CNN can analyze time-series data to detect and learn temporal patterns. A CNN model for processing time-series data typically includes one-dimensional (1D) convolutional and pooling layers. The 1D convolutional layers detect patterns, while the pooling layers reduce dimensions by extracting essential information. Through this process, the CNN model learns local patterns in time-series data and utilizes them for making predictions.

2.3. LSTM model

LSTM is a type of RNN that specializes in processing sequential or time-series data by utilizing a recurrent structure where the output from the previous step becomes the input for the current step. However, when RNNs are used

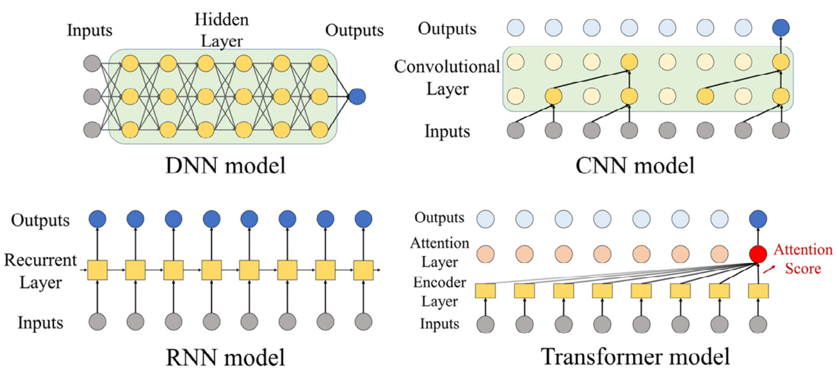

Figure 1. Sequence modeling architectures for time-series forecasting used in this study

for time-series forecasting, the vanishing gradient problem occurs during training. Furthermore, long-term dependency issues arise when the time gap between steps increases, thereby reducing the influence of past information on the current step. LSTM was developed to overcome the limitations of conventional RNNs (Hochreiter & Schmidhuber, 1997). LSTM incorporates gate mechanisms that allow the model to remember or forget information, enabling it to learn correlations over longer time intervals. This helps address the issue of long-term dependencies in time-series data. The mathematical equations for LSTM are given in Eqns (1)–(5) (Graves, 2012), and its architecture is illustrated in Figure 2.

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right); \quad (1)$$

$$i_t = \sigma\left(W_i x_t + U_i h_{t-1} + b_i\right); \quad (2)$$

$$o_t = \sigma\left(W_o x_t + U_o h_{t-1} + b_o\right); \quad (3)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \left(W_c x_t + U_c h_{t-1} + b_c\right); \quad (4)$$

$$h_t = o_t\left(c_t\right), \quad (5)$$

where f_t represents the forget gate; i_t represents the input gate; o_t represents the output gate; c_t represents the cell state; h_t represents the current hidden vector; σ represents the activation function and x_t represents the input vector. W_f, W_i, W_o, W_c, U_f, U_i, U_o, and U_c represent the weight factor terms while h_{t-1} and c_{t-1} represent the previous hidden vector and cell state, respectively, and b_f, b_i, b_o, and b_c represent the corresponding bias terms.

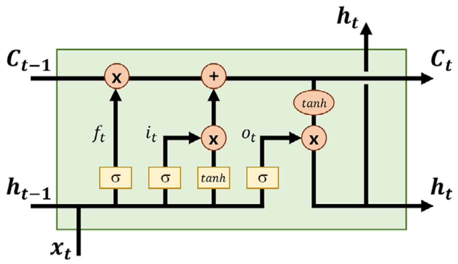

Figure 2. Architecture of LSTM

2.4. Transformer model

The transformer, introduced by Vaswani et al. (2017), relies on an attention mechanism that has proven highly effective in natural language processing – an application that also involves time-series data. The transformer model comprises two main components: a self-attention mechanism and feed-forward network (FFN). The self-attention mechanism evaluates the relevance and importance of each element in the input sequence in relation to other elements. To achieve this, three vectors were generated for the input: query (Q), key (K), and value (V). Subsequently, the attention scores for the three vectors were normalized using the softmax function, resulting in attention weights that represent the interrelationships among the input vectors. The mathematical expression for self-attention is given in Eqn (6):

$$\text{Attention}\left(Q,\ K,\ V\right) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V, \quad (6)$$

where d_k represents the dimensionality of the key vectors.

The FFN is a neural network that follows the self-attention layer. The output from the self-attention layer serves as the input to the network and passes through an activation function. The FFN is represented by Eqns (7)–(9) as follows:

$$FFN_1\left(x\right) = W_1 x + b_1; \quad (7)$$

$$FFN_2\left(x\right) = \max\left(0,\ FFN_1\left(x\right)\right); \quad (8)$$

$$FFN\left(x\right) = W_2 {}^* FFN_2\left(x\right) + b_2, \quad (9)$$

where x represents the output vector of self-attention; W_1 and W_2 represent weight matrices and b_1 and b_2 represent bias vectors. In FFN_1, the first linear transformation was applied to the input, and in FFN_2, a nonlinear activation function–typically the rectified linear unit–was applied to the output of FFN_1. Finally, FFN applied a second linear transformation to the output of FFN_2. Essentially, the FNN takes the input vector, projects it into a lower-dimensional space to extract features through the nonlinear activation function, and then maps it back to a higher-dimensional space. This action enhances the complexity of the model and its feature extraction and representation capabilities. The constructed transformer is capable of parallel processing, enabling it to simultaneously consider information from all positions in the sequence, regardless of its length, which allows a fast training speed and greater representational power. The structure of the transformer used for processing the time-series data in this study is shown in Figure 3.

3. SR-based bridge-performance indicators

The FHWA of the United States issued a coding guide (Federal Highway Administration [FHWA], 1995) that forms the basis of the NBI database. The NBI serves as a comprehensive repository for bridge information across the United States, detailing aspects such as bridge location, type, size, construction year, and inspection dates, making it an essential resource for infrastructure design, management, and operation. A key metric for evaluating bridge performance and conditions based on the NBI database is the SR. This rating ranges from 0 to 100 and reflects the overall condition, importance, and extent to which maintenance, repair, or replacement is required for a bridge. According to surveys conducted by the FHWA, SR and similar ratings are widely used in recent practical applications for assessing bridge performance (Yang & Frangopol, 2018). The SR is determined by considering structural adequacy and safety, serviceability and functional obsolescence, and essentiality for the public, along with any special reductions. SR plays a crucial role in bridge management and maintenance planning. Bridges with lower SRs are more likely to require repairs or improvements, making SR a vital tool for bridge management authorities when making decisions.

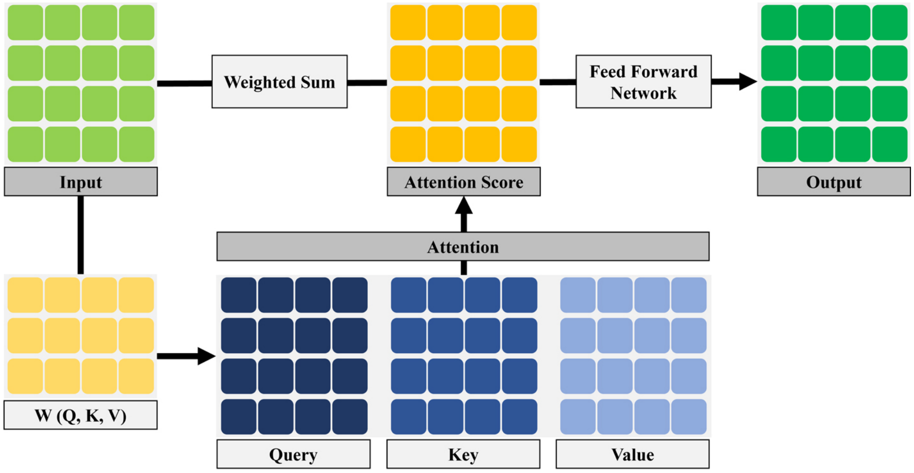

Figure 3. Transformer architectures for time-series forecasting used in this study

Additionally, SRs help prioritize future investments, with bridges with lower SRs requiring repairs or replacements receiving higher priority. SR is also instrumental in providing a comprehensive understanding of the condition and performance of a bridge, incorporating both structural and functional evaluations, thereby facilitating a comprehensive assessment of the state of the bridge. Recent studies have also employed SR as a key performance metric to rank bridges within a road network (Yang & Frangopol, 2018). Furthermore, ANNs have been used to predict SRs (Bianchi & Biondini, 2022). In this study, SR is utilized as a key performance indicator for developing a bridge-performance prediction model. Among the data used to calculate the SR, the condition rating for each component is of importance, with detailed classifications presented in Table 1.

The SR was calculated using Eqn (10), which incorporated the condition ratings of critical components along with the geometric and traffic characteristics of the bridge.

$$\text{SUFFICIENCY RATING (SR)} = S_1 + S_2 + S_3 - S_4, \quad (10)$$

where S_1 represents the structural adequacy and safety, S_2 represents the serviceability and functional obsolescence, S_3 represents the essentiality for public use, and S_4 represents the special reduction.

4. Data preprocessing

In this study, a time-series forecasting model was developed to predict the performance of bridges using the data provided by the NBI initiated by the FHWA. The preprocessing phase involved two main steps. First, relevant features were extracted to construct the dataset, and records with missing or erroneous values were removed. Second, to facilitate time-series learning, sequences and windows were generated on bridge inspection data.

Bridge inspection data from the NBI covering the period from 1992 to 2022 were collected and merged to

Table 1. Description of condition ratings (FHWA, 1995)

Condition Rating	Condition	Description
N	N/A	N/A
9	Excellent	
8	Very good	No problems noted.
7	Good	Some minor problems.
6	Satisfactory	Structural elements show some minor deterioration.
5	Fair	All primary structural elements are sound but may have minor section loss, cracking, spalling, or scour.
4	Poor	Advanced section loss, deterioration, spalling, or scour.
3	Serious	Loss of section and deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present.
2	Critical	Advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present, or scour may have removed substructure support. Unless closely monitored it may be necessary to close the bridge until corrective action is taken.
1	Imminent failure	Major deterioration or section loss present in critical structural components or obvious vertical or horizontal movement affecting structure stability. Bridge is closed to traffic but corrective action may put it back in light service.
0	Failed	Out of service; beyond corrective action.

form a comprehensive dataset. Subsequently, features with time-series characteristics and those used to calculate the SR were selected to build the dataset. Missing or erroneous values in each feature were removed, and scaling was applied to the feature values. Additionally, to account for time-series trends, cumulative features for traffic volume and maintenance costs were computed and incorporated into the dataset. The final dataset consisted of various attributes, including bridge codes, years of service, deck condition ratings, superstructure condition ratings, substructure condition ratings, structural evaluations, deck geometry evaluations, cumulative traffic volumes, and cumulative maintenance costs.

Preprocessing for time-series learning is crucial for applying the dataset to different time-series forecasting models. The key steps involve sequence generation, which organizes continuous values into ordered time-series sequences and creates windows for analyzing these data. In time-series forecasting, windows are typically used to input historical data and predict future values. The distribution of inspection frequencies for each bridge was analyzed to determine the appropriate sequences and window sizes, as illustrated in Figure 4.

In this study, data from bridges with at least 12 inspection records were selected to create sequences of sufficient length. For data with 29 or more inspection records,

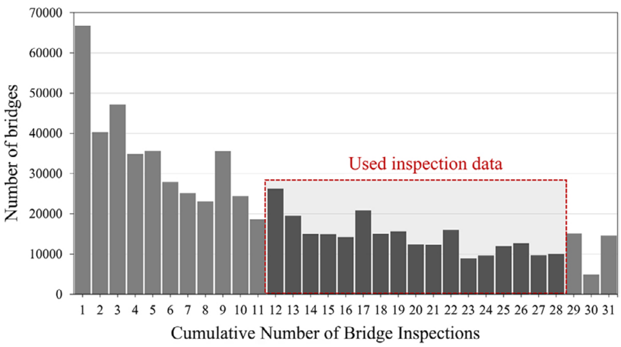

Figure 4. Distribution of cumulative bridge inspection data

duplicate entries that artificially inflated the inspection history were identified and excluded from the analysis.

The method of sequence and window generation for bridge inspection data differs significantly from those used in previous studies. Conventional models arrange data from all bridges chronologically and employ a sliding window technique to train forecasting models. While this approach provides insights into overall performance trends, it exhibits limited accuracy in predicting individual bridge conditions. The process used in a previous study (Choi et al., 2020) to predict the overall trend in bridge performance is shown in Figure 5.

The time-series forecasting process applied in this study is illustrated in Figure 6. This approach is similar to natural language processing (NLP) models, where each sentence is learned individually. In this study, sequences and windows were structured to train the model on the inspection history of individual bridges throughout their lifecycle. The final preprocessed data set used for model training is presented in Section 7 as an example.

5. Development of the deep learning-based time-series forecasting model

In this study, deep-learning models capable of predicting bridge performance were developed using data obtained through basic and time-series-based preprocessing. The models accept multivariable inputs with time-series characteristics to predict the SR, which serves as the bridge-performance metric in this research. The time-series dataset comprised a sequence of 12-time steps, where the first eight-time steps served as input data, and the remaining four-time steps were used as prediction targets for model training. Various models were developed, and performance comparisons and validation procedures were performed to determine the optimal parameters. The model development process is illustrated in Figure 7.

The model development process began by splitting the dataset into training and testing sets in an 80:20 ratio.

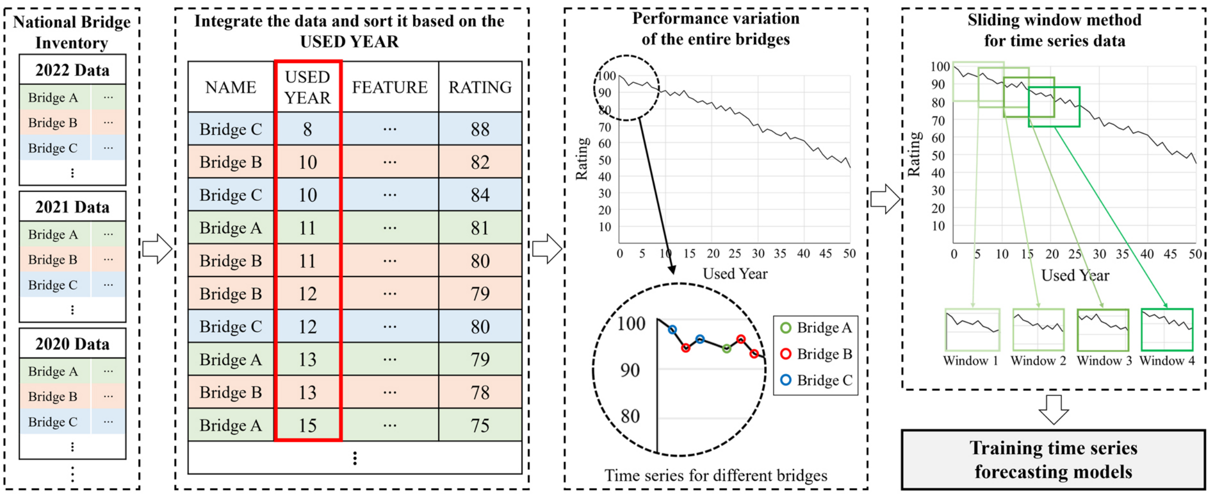

Figure 5. Time-series forecasting process for overall bridge performance

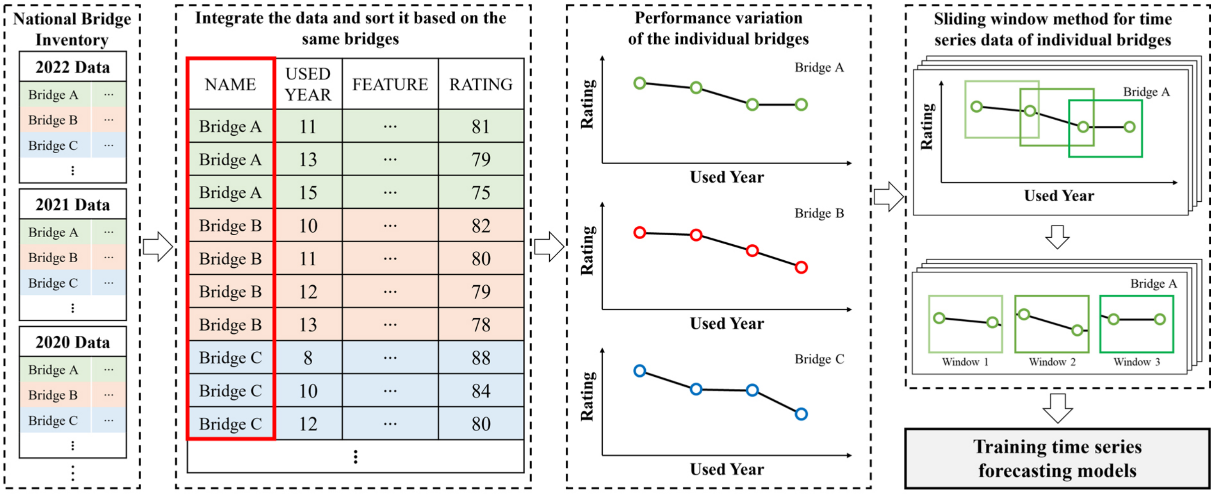

Figure 6. Time-series forecasting training process specialized in individual bridge performance

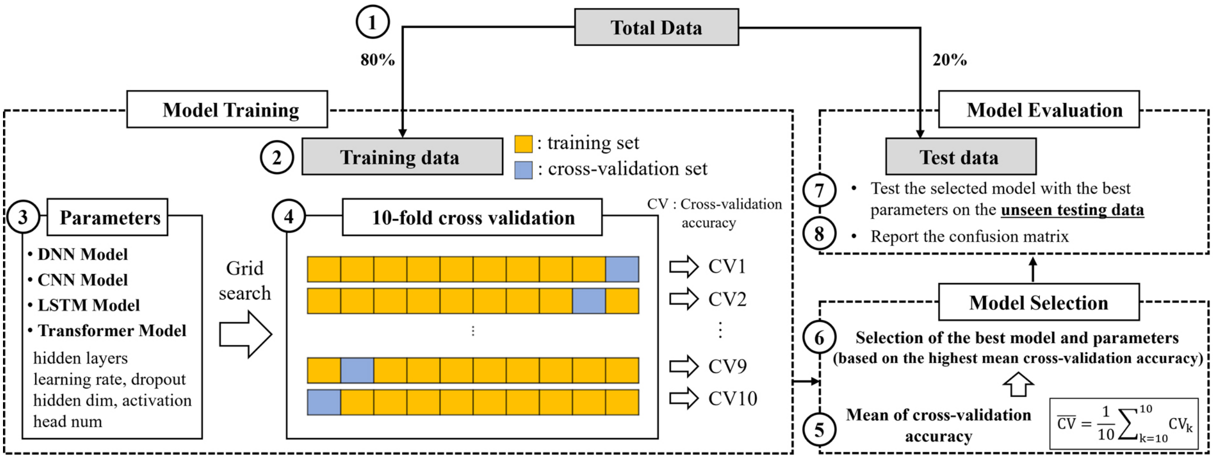

Figure 7. Development process of the deep learning-based time-series forecasting model

Next, various parameters for each methodology were organized to determine the optimal configuration for the models. A grid search was then conducted to combine these parameters and conduct the training. During this process, the training data were further divided into ten subsets, with nine subsets used for training and one subset used for validation in cross-validation. The cross-validation results were averaged, and the model performance for each parameter combination was calculated using the loss value. The MAE was used as the loss function, as expressed in Eqn (11).

$$\mathrm{MAE} = \sum_{i} \left| y_i - \bar{y}_i \right|, \quad (11)$$

where y_i represents the actual value of the i^{th} training data and $\bar{y}_i$ represents the predicted value for the i^{th} training data. Through a comparison of the model performance, the parameter combination that yielded the highest performance was selected for the final model in each methodology. The final models for each methodology were developed using the selected parameter combinations. In the final step of the model development process, the initially separated test dataset was used to evaluate and compare the performance of the prediction models across each methodology.

6. Comparison of model performances according to various time-series forecasting methods

During the model development process, the performances of different time-series forecasting methods were compared by evaluating their results on the training, validation, and test sets. Table 2 presents a comparison of the loss values for each method during the training and validation stages. This comparison helped identify the most accurate forecasting approach for predicting bridge performance.

The loss functions of various time-series forecasting models were compared during training and validation. The DNN, which did not directly handle time-series data, exhibited the lowest average performance, while the CNN showed similar results to the DNN. However, specialized models designed for time-series data, such as LSTM and Transformers, demonstrated higher performance than the DNN and CNN. The Transformer model exhibited the lowest loss value, thus yielding the highest performance. The learning curve for this model is shown in Figure 8.

The performance of the developed time-series forecasting models, optimized through cross-validation, was

Table 2. Training and validation loss values of various time-series forecasting models

	DNN		CNN		LSTM		Transformer	
	Training loss	Validation loss	Training loss	Validation loss	Training loss	Validation loss	Training loss	Validation loss
CV01	5.9201	4.2331	4.9552	4.9564	3.7684	3.6199	3.3575	3.3176
CV02	7.1377	5.8868	4.9334	4.9427	3.7119	3.5874	3.3203	3.3102
CV03	7.0708	5.9867	4.9466	4.9325	3.8612	3.4895	3.4253	3.3432
CV04	6.2728	4.7193	4.9088	4.9146	3.8060	3.6498	3.3878	3.3407
CV05	6.8254	5.7320	4.9121	4.8884	3.7818	3.4957	3.3696	3.3158
CV06	6.2607	4.1454	4.9791	4.9473	3.8562	3.4891	3.3769	3.2913
CV07	6.3871	4.5129	4.9510	4.9896	3.6945	3.5762	3.3919	3.3749
CV08	5.7563	4.7512	4.9555	4.9231	3.6379	3.5229	3.3668	3.3230
CV09	6.7224	6.5431	4.9353	4.9661	3.8054	3.6102	3.3681	3.3060
CV10	6.0942	5.3341	4.9350	4.8867	3.6392	3.5147	3.3437	3.2967
Mean	6.4448	5.1845	4.9412	4.9347	3.7563	3.5555	3.3708	3.3219
Standard deviation	0.4509	0.7839	0.0200	0.0311	0.0776	0.0570	0.0269	0.0237

evaluated using test data that were not included in the training phase. The final performance comparison for each method is shown in Figure 9. Beyond prediction accuracy, the training times of each model were compared using the Texas concrete bridges dataset, the largest in volume. All models were trained on an NVIDIA RTX 3080 GPU. The computation times were as follows: DNN – 6 min 48.4 s, CNN – 7 min 49.5 s, LSTM – 8 min 15.6 s, and Transformer – 13 min 58.0 s. While the Transformer model demonstrated the highest accuracy, it also required the longest training time, highlighting a trade-off between predictive performance and computational efficiency.

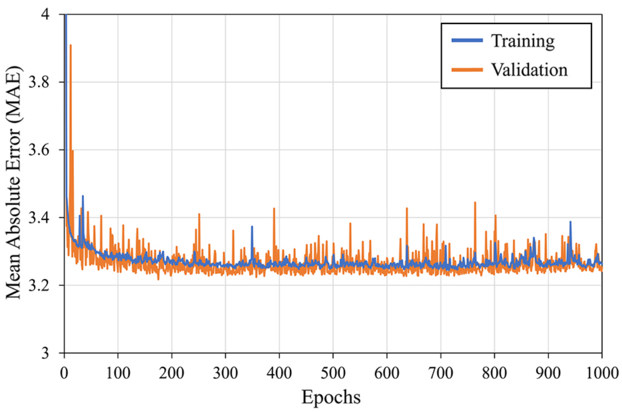

Figure 8. Distribution of bridge inspection data frequencies

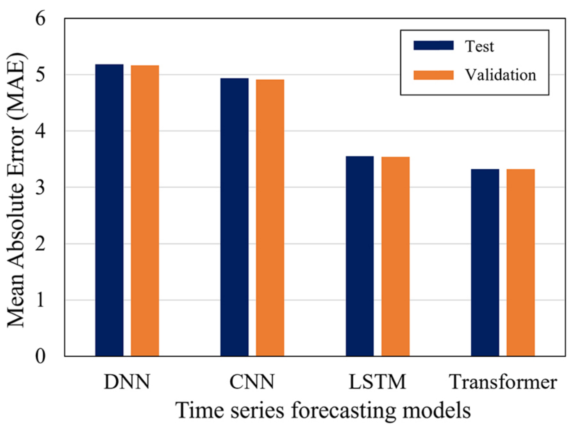

Figure 9. Performance comparison of time-series forecasting models

The final performance closely matched the training and validation results, with the Transformer-based time-series forecasting model exhibiting minimal loss in predicting the SR of the bridge.

In conclusion, the LSTM model, recognized for its effectiveness in time-series forecasting, outperformed the baseline DNN model by approximately 46%. The Transformer model further improved performance by approximately 7% compared to the LSTM. This confirms that the NBI data on bridge inspection history possess time-series characteristics and that applying appropriate time-series forecasting methods allows for making more accurate performance predictions with reduced incidence of errors.

7. Comparison of performance predictions for actual bridges

This study predicted and compared actual bridge performances using forecasting models developed with different methods. To evaluate predictive accuracy, two bridge examples from the test dataset were selected: one in Delaware (2001C001 in the NBI dataset) and another in Alabama (013521 in the NBI dataset). Bridge 2001C001, a prestressed concrete structure constructed in 1995, spans 107.9 m and carries an average daily traffic (ADT) of 22,296 vehicles and average daily truck traffic (ADTT) of 3,344. Bridge 013521, a prestressed concrete structure built in 1985, spans 410.1 m and carries an ADT of 13,236 vehicles and ADTT of 662 trucks. The input data formats for the two selected bridges are presented in Tables 3 and 4, respectively. This format was identical to the preprocessed data. For features such as daily traffic volume, ADT volume, and maintenance cost, scaling was applied because of significant variations in the data. The results of predicting the following four time steps of performance changes, based on eight-time steps of bridge-performance inspection histories for the two selected bridges using the example data, are shown in Figures 10 and 11.

The performance prediction results for the two bridges showed that the DNN model failed to capture trends in bridge performance changes. The CNN model provided improved predictions over the DNN model by closely following previous performance trends. However, its predictive performance remained inferior to models specifically designed for time-series data and forecasting. Both the LSTM and Transformer models performed well, with predictions closely matching the actual performance trends.

Table 3. Input data of bridge 2001C001 in Delaware

Time step	Condition ratings			Structural evaluation	Deck geometry	ADT	ADTT	Improvement cost	SR
	Deck	Superstructure	Substructure						
T1	7	8	7	7	9	0.015	0.010	8.534e–07	97.78
T2	7	8	7	7	9	0.016	0.011	9.957e–07	97.78
T3	7	8	7	7	9	0.019	0.012	1.138e–06	97.74
T4	6	6	7	6	9	0.019	0.014	1.280e–06	95.88
T5	6	6	7	6	9	0.021	0.015	1.422e–06	95.88
T6	6	6	7	6	9	0.024	0.017	1.565e–06	95.65
T7	6	6	7	6	9	0.026	0.018	1.701e–06	95.65
T8	6	7	7	7	9	0.027	0.019	1.849e–06	95.62

Table 4. Input data of bridge 013521 in Alabama

Time step	Condition ratings			Structural evaluation	Deck geometry	ADT	ADTT	Improvement cost	SR
	Deck	Superstructure	Substructure						
T1	7	7	7	7	7	0.011	0.006	2.845e–07	91.83
T2	7	7	7	7	7	0.013	0.006	2.845e–07	91.93
T3	7	7	7	7	7	0.016	0.008	0.001	91.80
T4	7	6	7	6	7	0.017	0.008	0.001	91.80
T5	7	6	7	6	7	0.017	0.008	0.002	91.80
T6	7	6	7	6	7	0.020	0.009	0.002	91.80
T7	7	6	7	6	7	0.021	0.010	0.003	91.80
T8	7	6	7	6	7	0.022	0.011	0.004	91.78

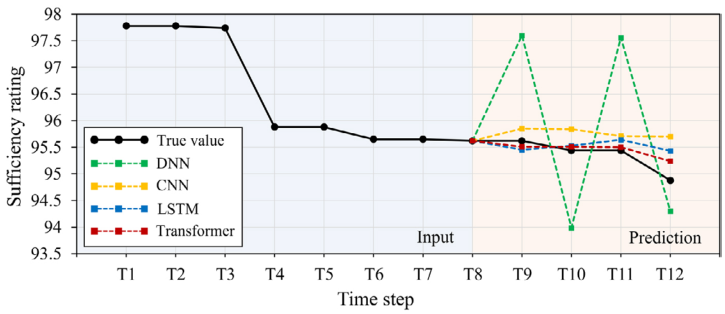

Figure 10. Performance predictions of bridge 2001C001 in Delaware

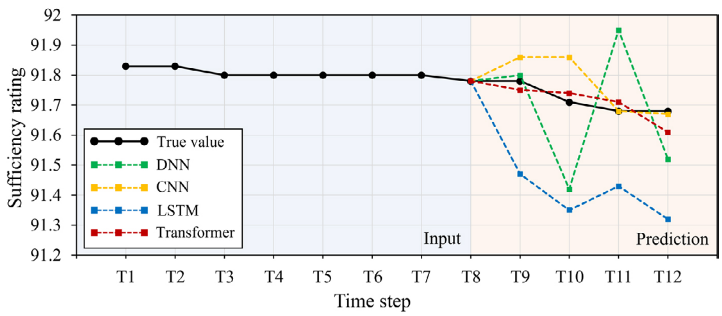

Figure 11. Performance predictions of bridge 013521 in Alabama

The LSTM model exhibited excessive degradation in its predictive performance compared to the actual performance changes for the second bridge, whereas it accurately predicted performance changes for the first bridge. Conversely, the Transformer model generated predictions that closely matched the actual performance changes for both bridges. Consistent with previous loss-based comparisons, the Transformer-based time-series forecasting model demonstrated superior accuracy in predicting bridge performance changes. The difficulty LSTM faced in predicting future performance for the second bridge stemmed from its inherent sequential information processing and memory retention mechanism. Although LSTM mitigated the long-term dependency issues found in basic RNNs, it struggled with longer sequence lengths. Consequently, capturing long-term global patterns in bridge-performance time-series data remains challenging. Conversely, the Transformer architecture, based on the attention mechanism, processes the entire sequence simultaneously. This attention mechanism enables each data to assess its relationship to the entire sequence. This characteristic makes the Transformer model highly effective at capturing global patterns. In the case of the data of the second bridge, the LSTM model shown in Figure 11 may fail to capture the specific sequence patterns of that bridge and instead generalize the average performance trend learned from the entire dataset. Consequently, when predicting the performance of a bridge with an extended sequence and minimal fluctuations, the LSTM tends to produce predictions that exhibit a greater decline in performance than the actual values. This finding suggests that LSTM models struggle to accurately predict performance for bridges with longer sequences and minimal variations in performance. Conversely, the Transformer model effectively addresses these limitations, demonstrating superior predictive capability. As more performance data accumulates over time, the advantage of the Transformer becomes increasingly evident, particularly when handling longer sequences. This underscores its potential for accurate future performance forecasting as bridge-performance datasets grow over time.

A comparison of the performances of time-series forecasting models for the actual bridge is presented in Tables 5 and 6. The performance was evaluated based on the error rate between the true and predicted values for each model. Similar to the performance comparison during the training process, the transformer model exhibited lower error rates overall. For the bridge 2001C001 in Delaware, the transformer model demonstrated an average error rate of 0.16, which is approximately 68% better than that of the second-best LSTM model, with an average error rate of 0.264 For bridge 013521 in Alabama, the transformer model showed an average error rate of 0.044, which was approximately 55% better than that of the second-best CNN model, with an average error rate of 0.068.

8. Comparison of generalization performance of prediction models

In this study, models capable of predicting future bridge performance were developed and evaluated using real-world bridge data. This section presents the generalized performance of these models across multiple bridges to enhance understanding of their ability to predict bridge deterioration and facilitate deeper analysis and interpretation of the results.

To achieve this, second-order deterioration curves derived through regression analysis were established as the standard for generalized performance. These curves were obtained from various concrete bridges in Texas. The developed models were then assessed by comparing their respective deterioration curves. For each model, eight time-step data points were used as input to predict the next four-time steps. In total, 12 data points per bridge were utilized to construct the deterioration curves. The average deterioration curves across all bridges were employed as the generalized performance metric for model comparison.

Table 5. Performance comparison of forecasting models for bridge 2001C001 in Delaware

Time step	True value	DNN model	Error rate	CNN model	Error rate	LSTM model	Error rate	Transformer model	Error rate
T9	95.62	97.60	2.03	95.85	0.24	95.45	0.18	95.51	0.12
T10	95.44	93.99	1.54	95.84	0.42	95.53	0.09	95.51	0.07
T11	95.44	97.56	2.17	95.71	0.28	95.64	0.21	95.50	0.06
T12	94.88	94.3	0.62	95.70	0.86	95.43	0.58	95.24	0.38

Table 6. Performance comparison of forecasting models for bridge 013521 in Alabama

Time step	True value	DNN model	Error rate	CNN model	Error rate	LSTM model	Error rate	Transformer model	Error rate
T9	91.78	91.80	0.02	91.86	0.09	91.47	0.34	91.75	0.03
T10	91.71	91.42	0.32	91.86	0.16	91.35	0.39	91.74	0.03
T11	91.68	91.95	0.29	91.69	0.01	91.43	0.27	91.71	0.03
T12	91.68	91.92	0.17	91.67	0.01	91.32	0.39	91.61	0.08

The generalized performance of the predicted deterioration curves was evaluated based on their similarity to the true-value-based deterioration curve, as shown in Figure 12. The deterioration curves generated using the predicted values for each methodology are shown in Figures 13–16. Additionally, Table 7 compares the similarity between the predicted deterioration and true-value-based curves using two evaluation metrics.

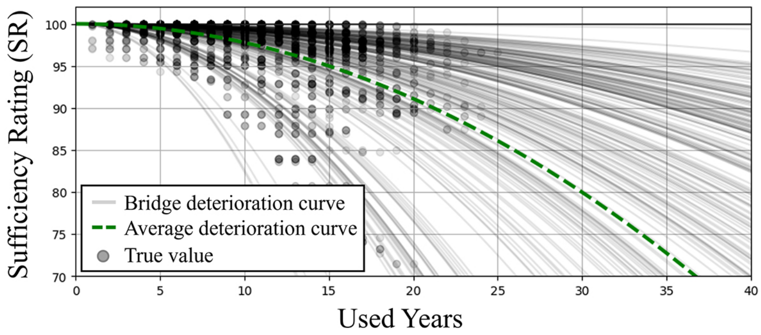

Figure 12. True-value-based bridge deterioration curve

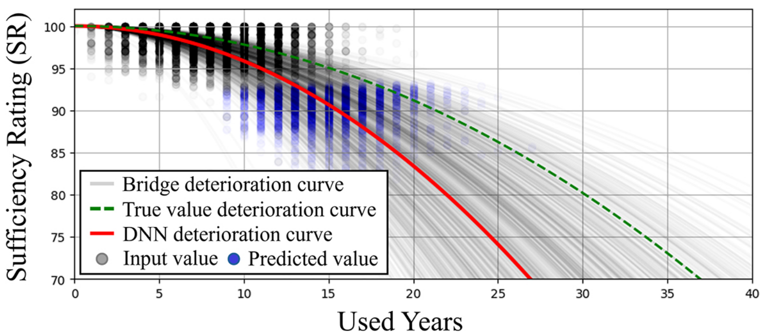

Figure 13. DNN-based bridge deterioration curve

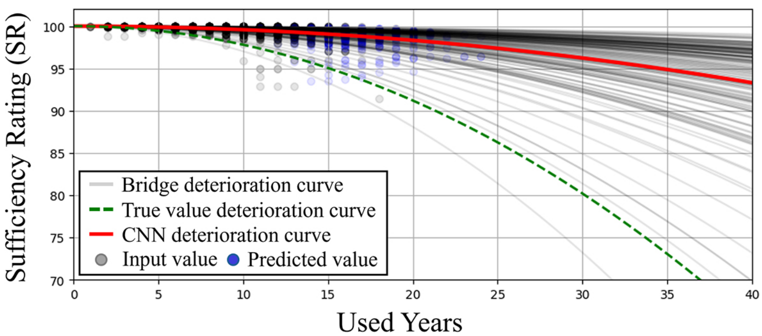

Figure 14. CNN-based bridge deterioration curve

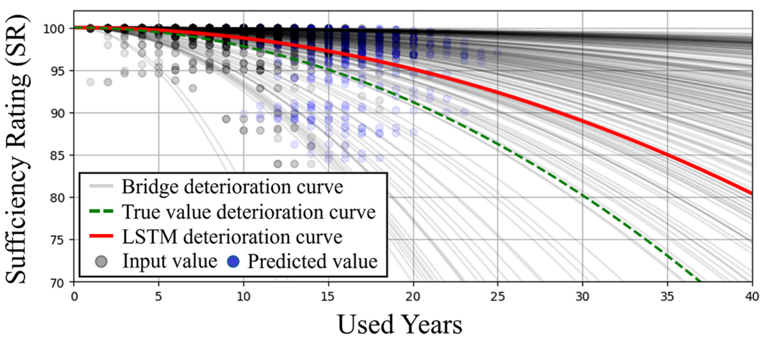

Figure 15. LSTM-based bridge deterioration curve

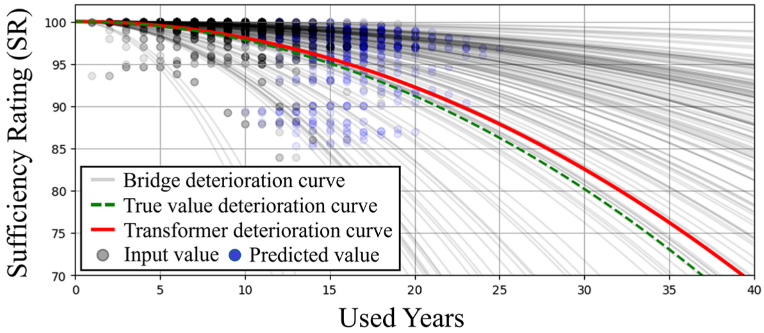

Figure 16. Transformer-based bridge deterioration curve

Table 7. Comparison of the similarity between the true-value- and predicted-value-based deterioration curves by methodology

Model	R-squared	RMSE
DNN	–0.6678	85.6126
CNN	–0.4969	81.1067
LSTM	0.5380	45.0593
Transformer	0.9584	13.5178

By comparing the generalized performance of each methodology based on its similarity to the true-value-based average deterioration curve, the Transformer model exhibited the highest similarity. Additionally, while the performance difference between the LSTM and Transformer models was minimal during training and in predicting individual bridges, a more significant performance gap was observed in the generalized performance evaluation.

9. Interpretation and discussion of the Transformer model

To further investigate the model, we conducted additional visualizations of the attention scores, performed feature importance analysis, and examined the behavior of the model to ensure the reliability of the results. In this study, a Transformer-based time series prediction model was developed to forecast four future time steps based on eight past input time steps. The model architecture consists of two Encoder Blocks, each containing two Heads. The results of visualizing the four total attention scores of the Transformer model are shown in Figure 17.

The attention scores can be interpreted as follows. Figure 17a represents Encoder Block 1-Head 1, where a specific Query position strongly focuses on a particular Key position. This indicates short-term dependency, where abrupt data changes at a specific time point significantly impact the immediate next time step. In the context of bridge data, this behavior reflects responses to short-term load variations, performance drops, or abnormal events such as earthquakes. Figure 17b represents Encoder Block 1-Head 2, where all Queries tend to focus on the first Key position. This suggests that information from a particular time step plays a crucial role in predicting future states. For bridge data, this pattern highlights the dependence on the initial condition or performance level. Figure 17c represents Encoder Block 2-Head 1, where specific Query positions distribute their focus evenly across all Key positions. This represents long-term dependency, indicating that the model has learned broader patterns of structural variation. In bridge data, this pattern suggests that the model captures long-term deterioration trends over time.

Figure 17d represents Encoder Block 2-Head 2, where an overall uniform attention distribution is observed across all Key positions. This suggests that the model recognizes relatively stable patterns, such as periodic trends. In bridge performance data, this may correspond to gradual changes resulting in consistent loads, such as daily traffic and heavy truck volumes. From the interpretation of the attention scores, it is evident that the Transformer model in this study effectively learns both short-term fluctuations and long-term trends. Additionally, it enhances its ability to detect abnormal events and key time points by emphasizing critical moments. Moreover, the model demonstrates long-term prediction stability by capturing periodic deterioration patterns associated with the accumulated traffic loads over time.

Figure 18 shows the feature importance analysis results for the Transformer-based time series prediction model. This analysis identifies the variables at each time step that have the most significant influence on future performance predictions. The top ten influential features are listed in Table 8.

Through this analysis, we compared the importance of features across different time steps and their impact on future performance predictions. Among all features, the historical time series of SR had the greatest influence, with time step 7 – typically the most recent – showing the highest importance. Besides the SR, Feature 7 (ADTT) also had a significant impact on future performance predictions. Additionally, time steps 2, 3, and 4 were found to be influential, while features such as substructure condition, deck geometry evaluation, and bridge improvement cost also played a considerable role.

Table 8. Influential features information from feature importance analysis

Feature 3	Feature 5	Feature 7	Feature 8
Substructure condition	Deck geometry evaluation	ADTT	Bridge improvement cost

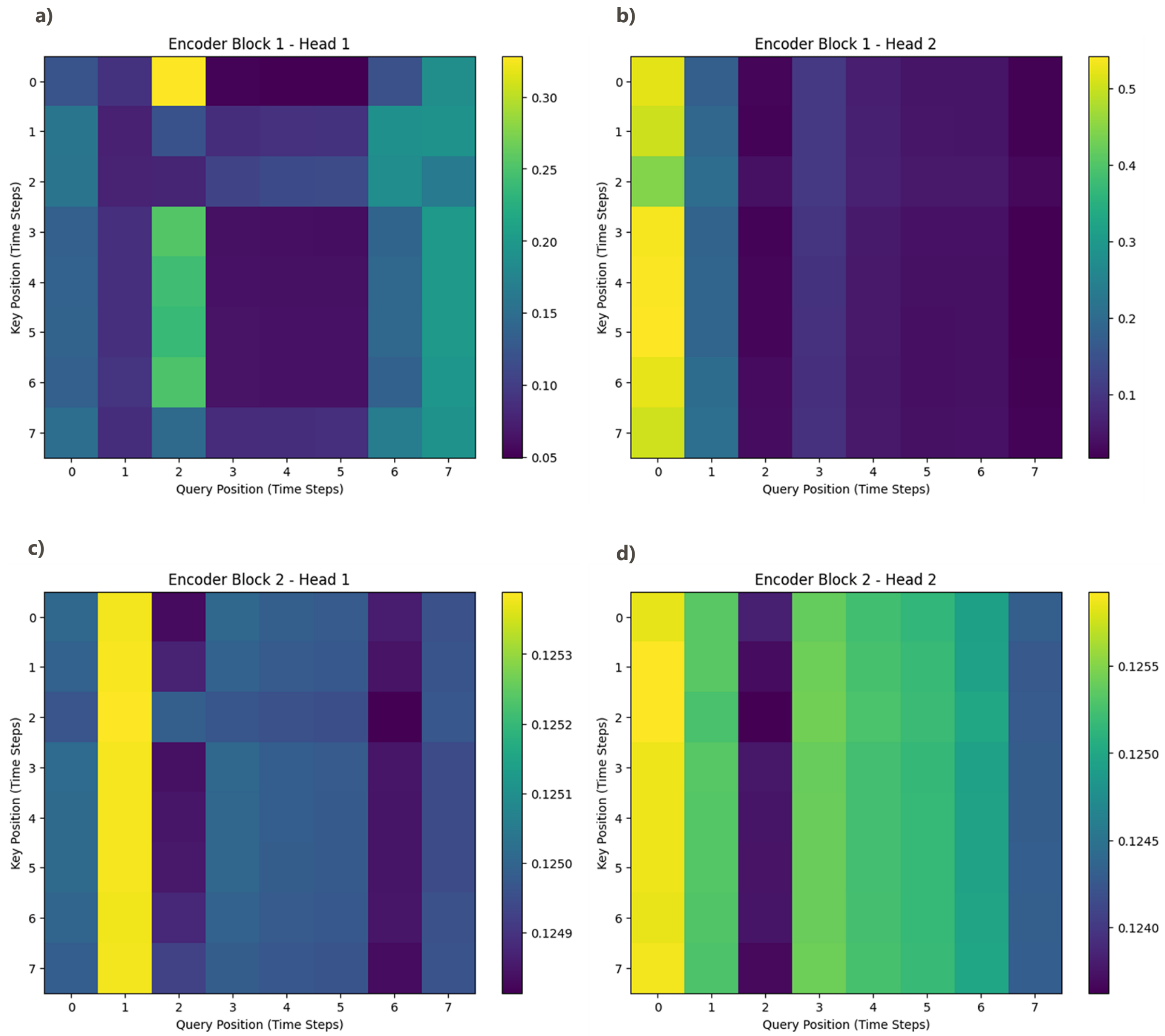

Figure 17. Visualization of attention scores in the Transformer model

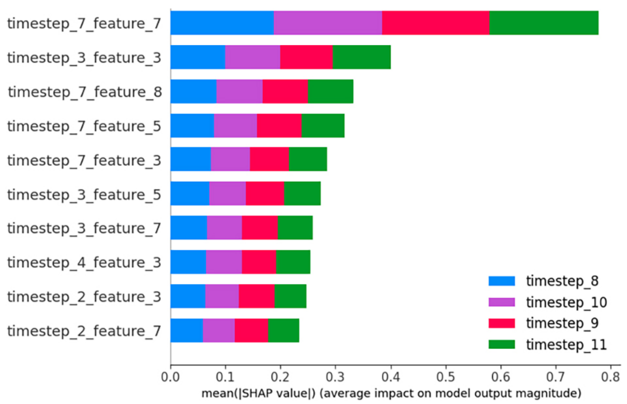

Figure 18. Feature importance analysis results

10. Conclusions

This study evaluated the performance of various deep-learning models for predicting bridge deterioration and examined their mechanisms for forecasting future changes in bridge performance. Given the global proliferation of bridges, efficient maintenance and reinforcement strategies are essential to prevent failures resulting from inadequate interventions. Effective decision-making in bridge maintenance requires a deep understanding of performance evolution over time. While numerous studies have explored bridge performance prediction using various methodologies, this study focused on leveraging deep-learning techniques specially designed for time-series data to improve forecasting accuracy. The novelty of our approach lies in explicitly incorporating the temporal dependencies inherent in bridge-performance data – an aspect often overlooked in previous research. By utilizing the Transformer model, we developed a predictive framework that captures complex temporal patterns, resulting in more precise and reliable long-term forecasts. Unlike conventional deterioration models that rely on manually constructed transition matrices or assume linear or exponential degradation trends, our approach fully captures nonlinear temporal dependencies using advanced sequence modeling. Compared to earlier machine-learning applications that relied on static features or single-year predictions, our model excels in multi-step forecasting, leveraging historical inspection data. The key novelty lies in integrating data preprocessing techniques tailored to individual bridges and applying the Transformer model, initially developed for NLP, to structural time-series forecasting. This significantly enhances prediction accuracy, particularly for long-sequence, low-variance datasets, where models like LSTM tend to struggle. These findings highlight a new direction in infrastructure forecasting, emphasizing the joint optimization of model architecture and data for improved predictive performance.

Preprocessing was conducted to account for the time-series characteristics of the accumulated NBI data, and various deep-learning models, including DNN, CNN, LSTM, and Transformer, were applied to develop predictive frameworks. As changes in bridge performance constitute a type of time-series data, models specifically designed for time-series data demonstrated superior predictive capabilities. Among these, LSTM, a widely used algorithm for time-series learning, achieved approximately 46% higher predictive accuracy than the baseline DNN model. Notably, the Transformer model, which has gained considerable attention in time-series applications such as NLP, outperformed LSTM by approximately 7%, further confirming the strong temporal dependencies within bridge-performance data. These findings demonstrate that the Transformer model is effective in NLP and also highly applicable in diverse time-series forecasting tasks, including infrastructure management. The development of high-performance, time-series-specific bridge deterioration prediction models offers considerable benefits, particularly in enhancing maintenance decision-making and optimizing budget allocation.

However, despite its advantages, the Transformer model presents several challenges, including extensive training time. While it effectively addresses long-term dependencies, its primary development and application have been focused on NLP time-series tasks, leading to potential limitations when applied to industrial datasets. As the use of Transformer-based models expands across various time-series domains, ongoing research focuses on refining its architecture to mitigate computational inefficiencies. The trend is shifting toward modifying the core Transformer framework to reduce training times and enhance adaptability for general industrial time-series applications rather than solely text-based NLP tasks. Such advancements could lead to more stable and accurate bridge-performance forecasting and broader adoption in infrastructure monitoring. Future research will focus on integrating domain-specific attention mechanisms capable of real-time data interaction, enabling the model to track dynamic changes in environmental factors such as temperature variations and structural accelerations. This enhancement aims to improve the interpretation of structural anomalies, thereby improving prediction accuracy and practical applicability within bridge management systems. Additionally, the current models do not incorporate real-time updating capabilities. However, future research will focus on developing predictive models that can continuously integrate real-time sensor data, including accelerometer readings, strain measurements, and temperature fluctuations. To support this, we are currently installing sensors on selected bridges in South Korea to collect continuous monitoring data and construct a corresponding time-series database. This initiative is expected to enable near real-time performance forecasting, facilitating proactive maintenance strategies and improving long-term bridge management systems.

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Author contributions

Conceived and designed the analysis, Yangrok Choi and Jung Sik Kong; Collected the data, Yangrok Choi, Youngjin Choi, Kyungrok Kwon and Jin Hyuk Lee; Contributed data or analysis tools, Yangrok Choi, Youngjin Choi and Jin Hyuk Lee; Validation, Yangrok Choi, Youngjin Choi and Kyungrok Kwon; Writing – original draft preparation, Yangrok Choi; Writing – review and editing, Jung Sik Kong and Youngjin Choi; Supervision, Jung Sik Kong; All authors have read and agreed to the published version of the manuscript.

Disclosure statement

The authors declare no conflict to interest.

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