Hybrid and Advanced Technologies – S. Prasad Jones Christydass, Nurhayati Nurhayati and S. Kannadhasan. (Eds) © 2025 the Authors, ISBN 978-1-032-90254-8
Open Access: www.taylorfrancis.com, CC BY-NC-ND 4.0 license

Integrating structural health monitoring and intelligent transportation systems for bridge condition assessment: A GA-CNN-BiGRU approach

Vishwayogita Amol Savalkar
Assistant Professor, Bharati Vidyapeeth Deemed to be University, Department of Engineering and Technology, Kharghar, Navi Mumbai, Maharashtra, India

Vandana Salve
Assistant Professor, Department of Computer Engineering, K.J. Somaiya Institute of Technology, Sion, Mumbai, India

T. Karthikeyan
Department of Biomedical Engineering, Sona College of Technology, Salem, Tamilnadu, India

Joel Josephson Pottipadu
Associate Professor, Department of ECE, Malla Reddy Engineering College, Maisammaguda, Medchal, India

Medha V. Deshpande
Assistant Professor, Department of Civil Engineering, Dr.D.Y.Patil Institute of Technology, Pimpri, Pune, India

Gourav Kalra
Assistant Professor, Maharishi Markandeshwar (Deemed to be University), Mullana, Ambala, India

ABSTRACT: There must be zero downtime for our nation's bridges since they are vital to our transportation networks. However, due to function modification, increased and faster-moving traffic loads, and capacity overload, many bridges, including Busway accommodation, are currently operating at overloaded levels. In order to ensure that some bridges remain structurally sound, structural health monitoring (SHM) systems are installed to assess the bridges' present condition and forecast when the structures might collapse.To train the model, feature extraction is an important step. Two steps in feature extraction are data reduction and blind separation. The model was trained using the Feature rich RNN-CTC to ensure it was as accurate as possible. While competing methods such as RNN and CTC achieved accuracy rates of 95.38%, the proposed method achieved a significant improvement.

Keywords: Structural Health Monitoring (SHM), Bridge Health Monitoring (BHM), Principle Component Analysis (PCA), Independent Component Analysis (ICA), Recurrent Neural Networks

1 INTRODUCTION

Contemporary bridges routinely face a broad variety of operational and environmental challenges. These outside forces are detrimental and will certainly speed up the

DOI: 10.1201/9781003559115-84

deterioration of the structure. Furthermore, catastrophic events like earthquakes might happen throughout a bridge's operational life. Consequently, ensuring safety necessitates the prompt identification of structural concerns. Visual inspection played a major role in the past in assessing the condition of buildings and detecting surface defects. However, even with well-trained inspectors, visual inspection is still inefficient, subjective, and time-consuming, making it unable to identify changes in circumstances in real-time. In the last several decades, structural health monitoring (SHM) techniques have gained popularity as a way to address this problem, especially with long-span bridges. Inadequate maintenance, weather-induced rebar corrosion, train and traffic movements, damaged piers, and other causes can cause bridge sections to deteriorate. Due to the work, traffic delays, and bridge closures involved in repairs or replacements, the original construction cost can be doubled.An instance of this may be seen in the shocking finding that the city's railway officials discovered when inspecting a strategically located Sivas overhead traffic bridge not long ago. The bridge failed the basic load tests due to excessive deflection, which was caused by a large amount of corrosion.

2 LITERATURE SURVEY

Visual inspections of bridges were once the norm, but they had their limits when it came to resolution, unpredictability, and the capacity to spot obvious problems. [1]The evolution of signal gathering and data transmission technology has given rise to new methods of monitoring and maintaining bridges, one of which is vibration-based Bridge Health Monitoring (BHM). [2]. A trend in BHM techniques away from contact sensors and toward non-contact ones has emerged in recent years as a result of next-gen, inexpensive sensors such as robots, cameras, and drones [3].Typically, a multitude of instruments and actuators spread out throughout the bridge are required for conventional monitoring in the vast majority of BHM investigations[4]. By combining deflection data from the road with weigh-in-motion data from the vehicle's two wheels, researchers were able to pinpoint damaged sections of the bridge.[5]In order to locate damage, one could look for changes in stiffness brought on by factors such as high vehicle speeds, uneven profiles, and noisy data. Decision analysis based on posterior, prior, and preposterior principles well-established in Bayesian decision theory formed the basis of the aforementioned paradigm[6]. The two methods are based on the same foundation: the linear utility theory originally proposed by von Neumann and Morgenstern and the expected value requirement for decision making[7]. The methods described here are broad strokes when applied to the problem of assessing bridge health with discrete state variables; for example, see [8] for a broad strokes descriptionin the continuous realm for making decisions. For the purpose of clarification, decision trees and influence diagrams are also included. Three or five factors are taken into account by the choice analysis methodologies that were previously mentioned[9]. The choice to reinforce, repair, or replace the structure relies on the bridge's state, which might range from broken to worthless. Previous work has attempted to model and predict the heavy traffic LEs of bridges. To predict future severe LEs, the studies used the normal probability idea to fit the maximum traffic LE extremes to a normal distribution[10]. [11]The most severe traffic LEs have been predicted by scientists utilizing the Rice formula-based level crossing technique. [12]among the many scholars that have attempted to predict LEs caused by extremely heavy traffic using extreme value analysis methods such as peak-over-threshold or block maxima. On the other hand, research has been conducted by [13] outlined all the possibilities for bridge traffic LE projections.

3 PROPOSED SYSTEM

The fundamental objective of this research is to provide a standard method of assessing bridge durability. In order to monitor the development of damage, the system needs to integrate the findings of real-world visual inspections with more accurate degradation models and a number of trustworthy sensors strategically distributed throughout the structure.

3.1 *Feature extraction*

3.1.1 *Data reduction*

In order to minimize the size of the final intrinsic mode functions, principle component analysis (PCA) is employed to decipher[14]. The altered new variables are described by their key components. Here are a few things that set those primary components apart:The main components are all independent and perpendicular to one another; they are also organized in a precise order, with the first component having the most variance and the last component having the least).

3.1.2 *Blind seperation*

The inability to track the source signals—like the building's reaction to changes in wind speed, traffic volume, or temperature and the lack of understanding of the mixed signal are essential features of blind separation. The blind separation problem is solved using independent component analysis (ICA), which is considered the gold standard.Matrix A, which represents the set of observations in Equation 1, can be used to illustrate ICA. In Equation 1, the transposition of matrix A is illustrated, with the sample index $h$equalling $1, 2, \ldots, b_h$.

$$A^h = \begin{bmatrix} A_1(h_1) & \ldots & A_1(h_{b_h}) \\ \vdots & \ddots & \vdots \\ A_{b_a}(h_1) & \ldots & A_{b_a}(h_{b_h}) \end{bmatrix} \tag{1}$$

3.1.2 *Residual network-RNN-CTC model training*

3.1.2.1 *RNN* Among the many types of neural network models, recurrent neural networks are characterized by a directed cycle of connections between neurons. The vanishing gradient problem, however, severely restricts the variety of context that may be practically accessed by conventional RNN[15]. An RNN with an imposed memory structure, often known as an LSTM cell, is one such option. LSTM-RNNs are able to efficiently train to resolve long-term dependency issues, and they also manage to circumvent some of the foundational issues with standard RNNs. In recent times, LSTM has emerged as a prominent RNN.

3.1.2.2 *CTC* Connectionist temporal categorization is one kind of output layer. It is mostly useful for two things. One of them is figuring out the loss, and the other is understanding RNN's output[16]. The inclusion of a new label called blank creates a new set $S' = S \cup \{blank\}$. The input sequence $w = w_1, \ldots w_H$is accepted by CTC, where H is the sequence length. The corresponding label that provides is G above $\mathfrak{R}$.

$$r(G|, w) = \sum_{\pi \in \mathfrak{R}^{-1}(G)} r(\pi|, w) \tag{2}$$

being defined as the conditional probability of π:

$$r(\pi|, w) = \prod_{h=1}^{H} w_{\pi_h}^{h} \tag{3}$$

A label's likelihood of being present at timestep h is denoted as $w_{\pi_h}^{h}$. Directly computing Equation 2 is not feasible. The CTC object function $\mathcal{O}(A)$is defined as the negative logarithm of the ground truth probability for all cases for each training set A.

$$\mathcal{O}(A) = -\sum_{(q,g)\in A} logr(G|, w) \tag{4}$$

4 RESULT AND DISCUSSION

The most common way to assess the condition of bridges is through visual inspections. Every two years, bridges should be checked for damage. This may be useful for noncritical, physically acceptable structures, but it is not reliable for determining a building's actual health.

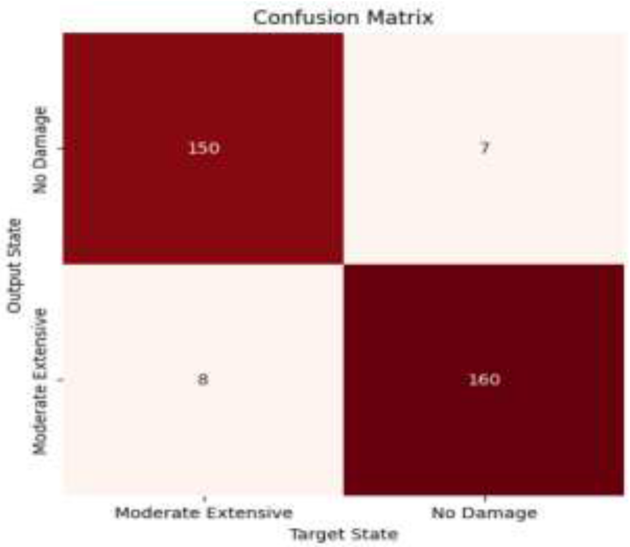

Figure 1. Confusion matrix for residual network-RNN-CTC model.

Figure 1 shows the result of the Residual Network-RNN-CTC confusion matrix, which showed that a condition with substantial damage was incorrectly classified as moderate damage.

Figure 2 displays the merged network's performance. It displays the accuracy for both training and validation.

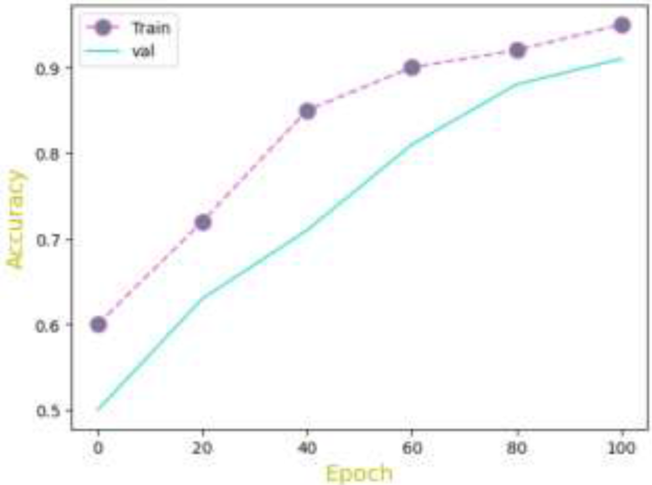

Figure 2. Training and validation accuracy.

Figure 3 illustrates that the loss curves exhibit saturation as the number of iterations grows following 20 epochs of training the Residual Network-RNN-CTC model.

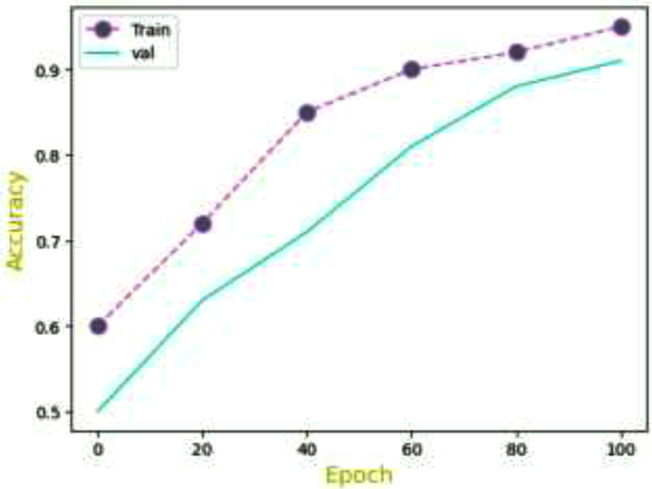

Figure 3. Training loss of residual network-RNN-CTC.

5 CONCLUSION

A growing number of small and medium span bridges are putting a strain on society's resources for upkeep and repair. The foundation of this approach to bridge management is developing a method for assessing safety (conditions) using criteria like remaining life and load bearing capacity. When compared to more traditional methods, bridge health monitoring that makes use of sensors and information technology provides more accurate insights into the performance of bridges.Data reduction and blind separation are the two stages of feature extraction. The model is trained using feature-rich Residual Network-RNN-CTC. With a consistency rate of 95.38%, the suggested technique surpasses both the RNN and CTC models.

REFERENCES

[1] An, Y., Chatzi, E., Sim, S. H., Laflamme, S., Blachowski, B., and Ou, J. (2019). Recent progress and future trends on damage identification methods for bridge structures. *Structural Control and Health Monitoring*, 26(10), e2416.

[2] Dertimanis, V., and Chatzi, E. (2020). Sensor networks in structural health monitoring: From theory to practice. *Journal of Sensor and Actuator Networks*, 9(4), 47.

[3] Kaloop, M. R., Kim, K. H., Elbeltagi, E., Jin, X., and Hu, J. W. (2020). Service-life evaluation of existing bridges subjected to static and moving trucks using structural health monitoring system: case study. *KSCE Journal of Civil Engineering*, 24(5), 1593–1606.

[4] Meng, D., Xiao, F., Zhang, L., Xu, X., Chen, G. S., Zatar, W., and Hulsey, J. L. (2019). Nonlinear vibration analysis of vehicle–bridge interaction for condition monitoring. *Journal of Low Frequency Noise, Vibration and Active Control*, 38(3–4), 1422–1432.

[5] Nie, Z., Lin, J., Li, J., Hao, H., and Ma, H. (2020). Bridge condition monitoring under moving loads using two sensor measurements. *Structural Health Monitoring*, 19(3), 917–937.

[6] Ding, Y., and Li, A. (2011). Assessment of bridge expansion joints using long-term displacement measurement under changing environmental conditions. *Frontiers of Architecture and Civil Engineering in China*, 5, 374–380.

[7] Huang, H. B., Yi, T. H., Li, H. N., and Liu, H. (2018). New representative temperature for performance alarming of bridge expansion joints through temperature-displacement relationship. *Journal of Bridge Engineering*, 23(7), 04018043.

[8] Ni, Y. Q., Wang, Y. W., and Zhang, C. (2020). A Bayesian approach for condition assessment and damage alarm of bridge expansion joints using long-term structural health monitoring data. *Engineering Structures*, 212, 110520.

[9] Honfi, D., Leander, J., and Björnsson, Í. (2017, September). Decision support for bridge condition assessment. *In fourth international conference on Smart Monitoring, Assessment and Rehabilitation of Civil Structures* (SMAR 2017).

[10] Ma, Y., Wang, L., Zhang, J., Xiang, Y., and Liu, Y. (2014). Bridge remaining strength prediction integrated with Bayesian network and in situ load testing. *Journal of Bridge Engineering*, 19(10), 04014037.

[11] Ni, Y. Q., Xia, H. W., Wong, K. Y., and Ko, J. M. (2012). In-service condition assessment of bridge deck using long-term monitoring data of strain response. *Journal of Bridge Engineering*, 17(6), 876–885.

[12] Xia, M., Cai, C. S., Pan, F., and Yu, Y. (2016). Estimation of extreme structural response distributions for mean recurrence intervals based on short-term monitoring. *Engineering Structures*, 126, 121–132.

[13] Xia, Q., Cheng, Y., Zhang, J., and Zhu, F. (2017). In-service condition assessment of a long-span suspension bridge using temperature-induced strain data. *Journal of Bridge Engineering*, 22(3), 04016124.

[14] Zhu, Y., Ni, Y. Q., Jesus, A., Liu, J., and Laory, I. (2018). Thermal strain extraction methodologies for bridge structural condition assessment. *Smart Materials and Structures*, 27(10), 105051.

[15] Zhan, H., Wang, Q., and Lu, Y. (2017). Handwritten digit string recognition by combination of residual network and RNN-CTC. In *Neural Information Processing: 24th International Conference, ICONIP 2017*, Guangzhou, China, November 14–18, 2017, Proceedings, Part VI 24 (pp. 583–591). Springer International Publishing.

[16] Chen, Z., Zhou, X., Wang, X., Dong, L., and Qian, Y. (2017). Deployment of a smart structural health monitoring system for long-span arch bridges: A review and a case study. *Sensors*, 17(9), 2151.