Spatial transformer-based Machine learning architecture for bridge damage detection via car-mounted sensors

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Abstract. Bridge infrastructure plays a vital role in facilitating transportation networks and is subject to various types of damage that can compromise its structural integrity. Early detection of bridge damage is crucial for ensuring public safety and minimizing maintenance costs. The present work proposes a spatial transformer-based machine learning architecture for the detection of bridge damage through computational simulation of vibration data. Traditional methods for bridge damage detection predominantly rely on visual inspections or expensive sensor networks deployed on bridges. These methods are time-consuming, expensive, and often suffer from limitations such as human subjectivity and limited coverage. To overcome these challenges, the proposed solution leverages the advancements in machine learning that allow the detection of damages that can be easily overlooked during the inspection process. Spatial Transformers are a type of neural network module that can learn to perform spatial transformations on the input data. These transformations help the network align and focus on relevant regions of the input data, which can be particularly useful in tasks that involve object recognition, image alignment, and other spatially related problems. The advantages of the proposed system include its non-intrusive nature, cost-effectiveness, and scalability.

Keywords: Machine Learning, Bridge Damage, Bridge Monitoring, Artificial Inteligence, Spatial Transformer

1 Introduction

Prompt detection of bridge damage is of utmost importance to ensure public safety, prevent catastrophic failures, and minimize maintenance costs. Traditional approaches for bridge damage detection have primarily relied on visual inspections conducted by experts or the deployment of expensive sensor networks on the bridges. While these methods have been valuable, they often suffer from limitations such as time-consuming processes, subjectivity in inspection, and limited coverage of all bridge areas. To ensure the operational efficiency of the railway system, various mathematical approaches and techniques are investigated for making decisions regarding the structural safety conditions of bridges that go beyond visual inspections. For instance, sensors and monitoring technologies are utilized to gather highly accurate and efficient structural response data. Structural Health Monitoring (SHM) encompasses the integration of sensors, data transmission, and computational resilience to assess a structure's physical condition, with the goal of gaining insights into its structural integrity, as defined by Balageas et al. [1] and Yuequan et al. [2].

Unlike the direct monitoring of railway bridges, an alternative approach involves situating sensors on trains rather than on the bridges themselves. These sensors capture operational and environmental responses of the train-bridge interaction as the train traverses the bridge. Previous investigations demonstrated that the success of machine learning based structural damage detection techniques predominantly depends on the choice of the extracted features as well as the classifier [3]. This investigation aims to establish a methodology utilizing a spatial transformer neural network to identify scour damage in railway bridges through this indirect monitoring approach. The model combines sensor data, computational processing, and neural network architecture to accurately identify structural abnormalities. The spatial transformer module allows the spatial manipulation of the data [4], enabling input data to align with relevant structural features. Transformed representations are then encoded through subsequent neural network layers, capturing intricate patterns and variations that indicate damage.

2 Damaged and baseline data acquisition

Simulation of dynamic effects caused by trains on railway structures relies on numerical models. Advancements in mathematical approaches and equipment calibration using real experimental data have led to more sophisticated and accurate simulations that closely mimic real train conditions. The Vehicle-Track-Bridge model developed by Cantero [5] was employed in order to generate the simulated vibration data for four classes of damage. Baseline data were also generated, simulating a healthy behavior of a railroad bridge. This study focuses on analyzing a specific form of structural damage known as scour. Scour is a phenomenon characterized by the erosion and removal of soil or sediment from around bridge foundations, leading to potential structural instability. The scour-induced damage is particularly crucial for bridge infrastructure integrity, as it can compromise the stability of key elements, as depicted in figure 1. Scour damage is modeled here as the stiffness reduction of the spring of the central support.

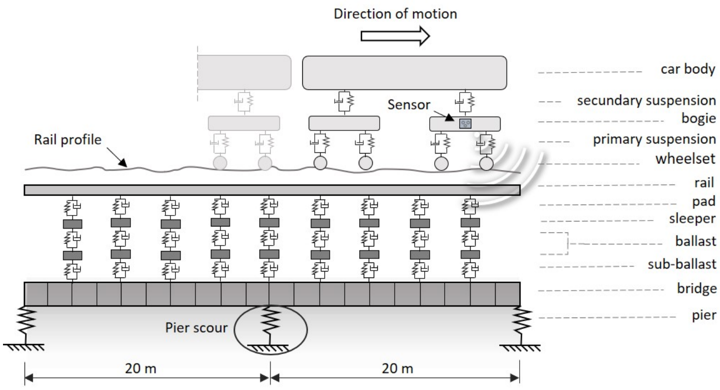

Figure 1. Model of the train-track-bridge interaction, adapted from Fernandes [6]

3 Model proposition and architecture

A spatial transformer neural network was designed for the present investigation, aiming to classify bridge signals based on their healthiness levels. The data set, comprising 5830 acceleration measures categorized into five distinct healthiness classes, underwent stratified random sampling to create separate training, validation, and testing subsets. The model's architecture (see fig. 2) includes a Localization Network that predicts transformation parameters (theta). Reshaped theta tensor undergoes a transformation process involving matrix multiplication, dimensional expansion, and squeezing. Once the input is transformed, data progresses through fully connected layers (fc1 and fc2) dedicated to feature extraction. The process concludes with an output layer utilizing softmax activation for class probability computation, thus enabling efficient classification.

Training occurred over 100 epochs with a batch size of 32. Dynamic learning rate scheduling was employed through an exponential decay strategy tailored to data set traits. The selection of the Adam optimizer was informed by its effective optimization capabilities. The architecture underwent iterative refinement to strike a balance between representation capacity and training speed, achieved by varying dense layer units. Implementation of early stopping helped counter over fitting while expediting convergence.

4 Results and discussion

Machine learning builds mathematical models from data containing multiple attributes [7] and in order to evaluate the trained model's performance, the confusion matrix was analysed for classification accuracy and plotted ROC curves to assess discrimination between healthiness levels. In the evaluated results, the spatial transformer neural network demonstrated promising performance in classifying bridge signals based on their healthiness levels. The model achieved an overall accuracy of approximately 97.2% on the test set, showcasing its ability to accurately categorize signals into the respective healthiness classes.

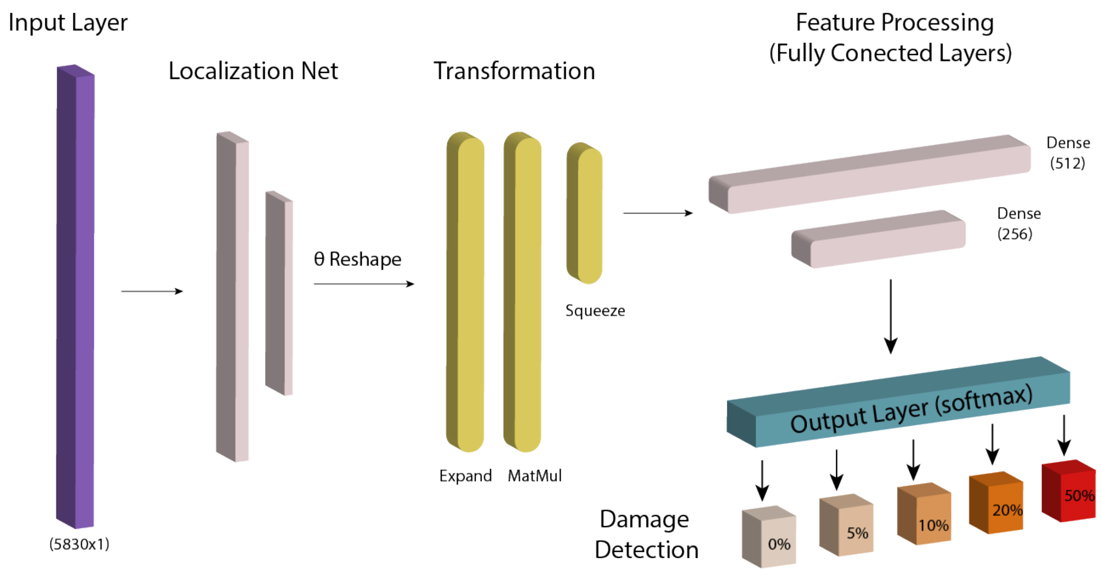

Figure 2. Spatial transformer neural network architecture scheme

4.1 Confusion matrix

A confusion matrix provides a clear visualization of the classification performance by tabulating predicted and actual classes. In this scenario, each row represents the actual damage levels, while each column corresponds to the predicted levels. The confusion matrix (fig. 3) allows the quantification of true positives, true negatives, false positives, and false negatives, enabling a comprehensive assessment of the classification model's accuracy and effectiveness in differentiating between damage states.

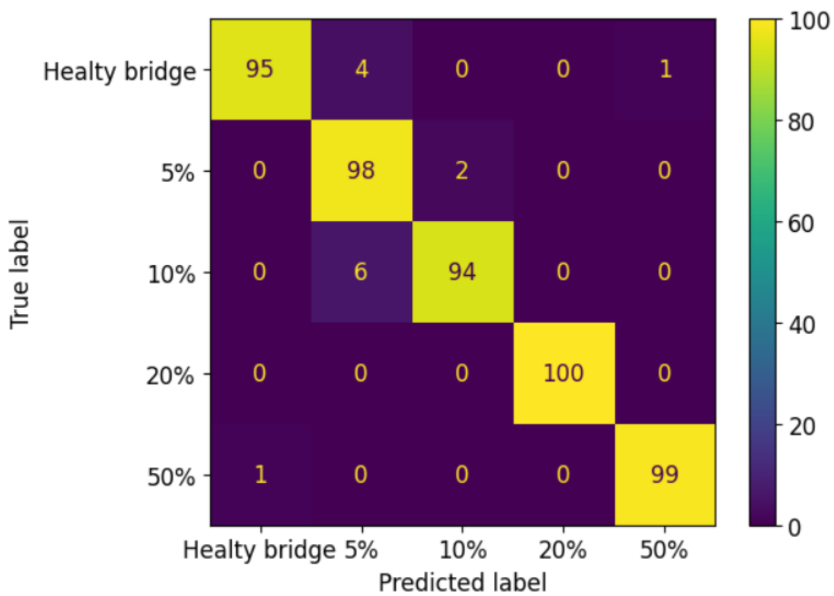

Figure 3. Spatial transformer neural network confusion matrix in test set

4.2 ROC curves

On the other hand, the Receiver Operating Characteristic (ROC) curve (fig. 4) is a graphical representation of the true positive rate against the false positive rate at different classification thresholds. In the bridge monitoring context, the ROC curve showcases the trade-off between correctly identifying damaged signals (sensitivity) and misclassifying undamaged signals as damaged (specificity). The area under the ROC curve (AUC) quantifies the overall performance of the classification model, with a higher AUC indicating a more accurate and robust classifier.

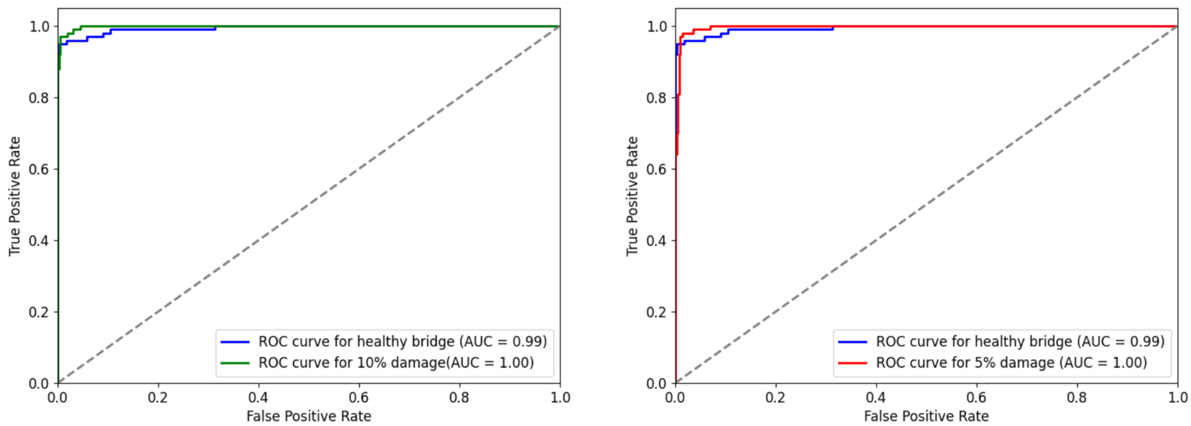

Figure 4. ROC curves comparing learning rate for baseline and five percent damage (left) and baseline and ten percent damage (right)

4.3 Model predictions for different damage scenarios

For five distinct data sets, each containing data associated exclusively with a specific class or level of damage, the model predicts the corresponding class or damage level.

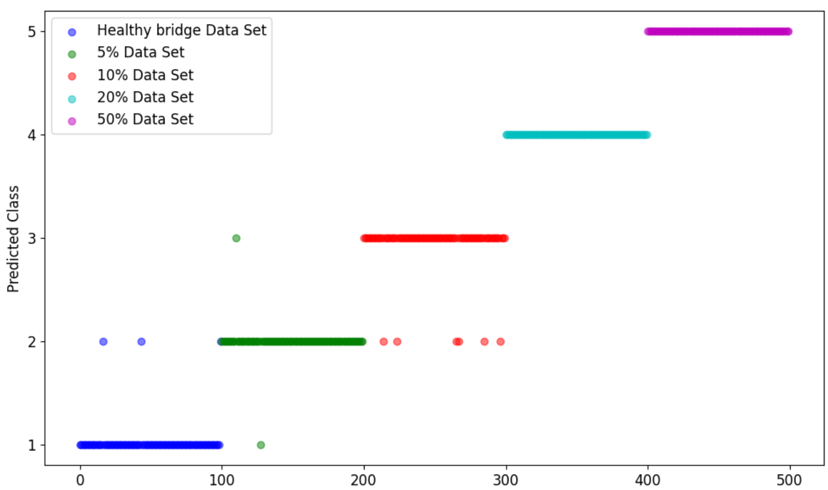

Figure 5. Model predictions for each data set containing data from one class of structural damage

Fig. 5 illustrates the fluctuations in the model's predictions across varying degrees of damage scenarios, showcasing its proficiency in accurately identifying each level of damage severity.

4.4 Discussion

As proposed by James et al. [8], confusion matrices are often a convenient way to display the information about which types of errors are being made. Combining confusion matrices and ROC curves offers a comprehensive framework to evaluate the effectiveness of the signal classification model across multiple damage levels. By analyzing these metrics, one can make informed decisions about the model's ability to accurately classify signals from various damage states, thereby enhancing the understanding of the bridge's structural health and aiding in effective decision-making for maintenance and repairs. Spatial transformer's ability to learn spatial transformations without making any changes to the loss function, as proposed by Jaderberg et al. [4] and related work by Lee et al. [9] enables accurate results, which encourage further exploration and integration of spatial transformer networks into structural health monitoring systems.

5 Conclusion

A spatial transformer neural network has been devised to precisely classify bridge signals according to their healthiness levels, achieving 97.2% accuracy on the test set. Its real-world applicability in structural health monitoring systems holds promise for ensuring public safety and maintaining structural integrity. Exploring the integration of spatial transformation mechanisms with neural networks for structural health monitoring and bridge health assessment was the main goal of this study, through this approach, significant advancements are anticipated in the model's capabilities, making it more relevant and effective in real-world scenarios. The potential impact of spatial transformer model holds promise for ensuring the safety and longevity of critical infrastructure like bridges, ultimately benefiting society as a whole. Continued research and refinements to the model may further enhance its robustness and generalization to various bridge conditions and environments.

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