DEEP LEARNING FOR DIAGNOSING STRUCTURAL IMPERFECTIONS

Deven Paul[1] (453329), Jesús García Kawas[1] (453306), Vaibhav Mall[2] (453726), Salah Otthoman[1] (424787)

[1]**General Mechanical Engineering B.Sc.**

Structural health monitoring is crucial for ensuring the safety, durability, and optimal performance of infrastructure. The integration of deep learning techniques offers a revolutionary approach to identifying and diagnosing imperfections within bridges, a key component of global transportation networks. This report showcases the development and application of advanced deep learning models to analyze and interpret time-series data collected from various sensors placed across a bridge. By leveraging these models, we are able to detect, classify, and locate structural anomalies with unprecedented accuracy and efficiency. The findings not only underscore the potential of deep learning in enhancing structural health monitoring practices but also pave the way for predictive maintenance strategies that can prevent catastrophic failures, thereby extending the lifespan of critical infrastructure components. This study represents a significant step forward in the application of artificial intelligence for the maintenance and safety of engineering structures.

KEYWORDS: Structural Health Monitoring, Deep Learning, Random Forest Classifier, LSTM

INTRODUCTION: The Hohenzollernbrücke in Cologne, a prime example of architectural significance and functional necessity, stands as a testament to the value of SHM. Continuously exposed to various loads, bridges like the Hohenzollern require meticulous and frequent monitoring to ensure their longevity and safety. Despite general and principal investigations scheduled at standard intervals, the subjective nature of such inspections and their infrequency necessitate a more robust approach (Chae et al., 2012; Noel et al., 2017).

Advancements in sensing technologies and computational methodologies have unlocked new frontiers in bridge monitoring. These technological strides have made it feasible to gather comprehensive data on bridge performance. The advent of smartphones, equipped with various sensors and significant processing capabilities, offers a novel and cost-effective means for SHM, heralding a paradigm shift in how data is collected and analyzed (Sony et al., 2019; Alavi and Buttlar, 2019).

In this project, we harness deep learning models to analyze the intricate time-series data of the Hohenzollern Bridge. By addressing imperfections and categorizing structural types, these models process data collected from numerous nodes across the bridge, each subjected to different loading conditions. Specifically, the project utilizes a feed-forward neural network and a Random Forest Classifier (RFC) to dissect the vast dataset comprising deformations and shear stresses in multiple directions.

The implementation of deep learning in SHM confronts the challenge of removed nodes within an imperfect structure. Through the preprocessing of the dataset via a user-defined function, the integrity of the labeled dataset for training the models is preserved. This meticulous preparation of data underscores the potential of machine learning in refining SHM practices.

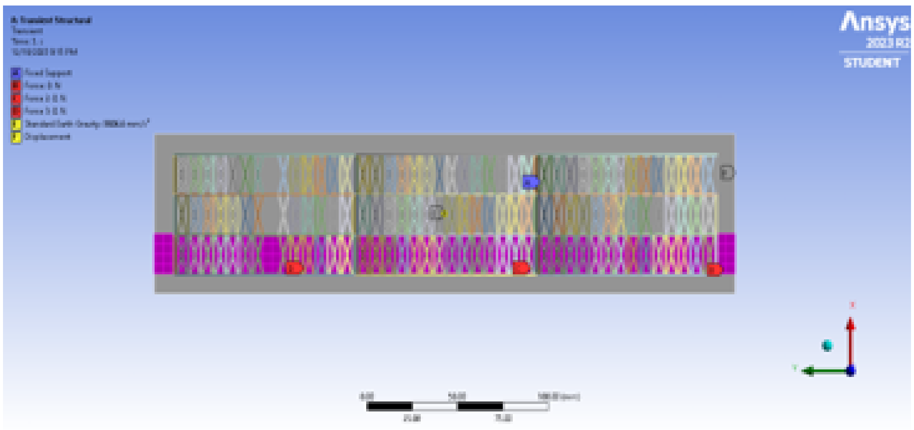
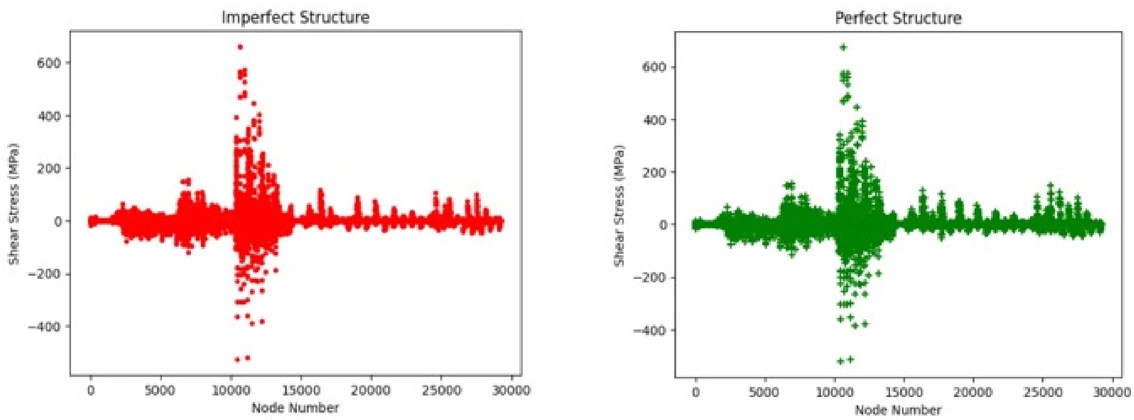


Figure 1: Enter Caption

As we delve deeper, we discuss the versatility and adaptability of deep learning models in identifying and diagnosing structural imperfections. The Hohenzollernbrücke project is a case study in the effective application of these models, demonstrating their proficiency in handling complex, multi-dimensional datasets to provide actionable insights.

METHODS: This study embarked on a comprehensive examination of structural health by analyzing datasets that capture both perfect and imperfect conditions of a bridge structure, subjected to varying loads due to train traffic across its span. The uniqueness of our approach lies in the intricate assessment of time-series data, meticulously recorded for deformations across the x, y, and z axes, alongside shear stresses in the xy, yz, and zx planes, and the cumulative deformation experienced by the structure. Initial observations revealed a distinct characteristic of the imperfect structure dataset—missing nodes, indicative of the structural anomalies. A pivotal moment in our analysis was the identification of shear stresses as a critical feature for our predictive models, particularly the Random Forest Classifier (RFC). This insight was gleaned from an exhaustive manual comparison of features between the perfect and imperfect datasets, highlighting shear stresses' significance in delineating structural integrity.



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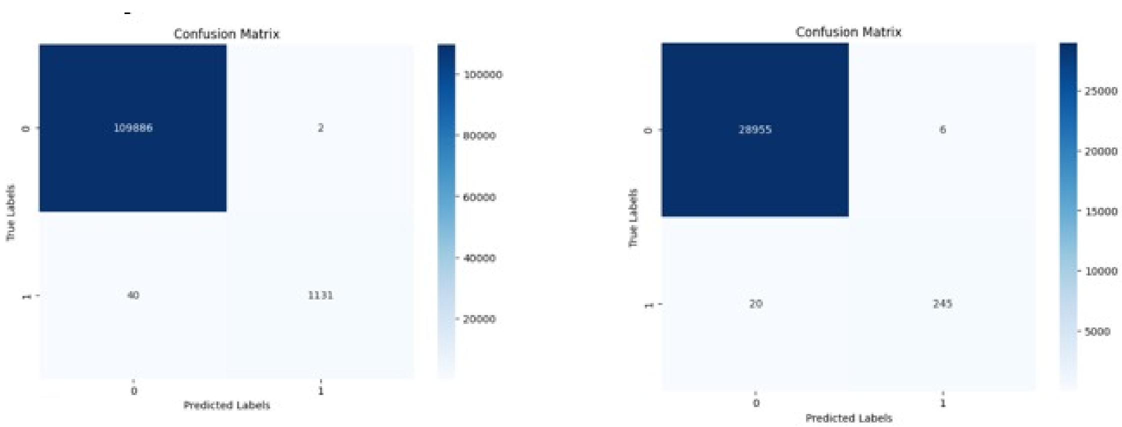
To address the challenge of missing nodes, a novel approach was adopted through the development of a custom function, fill, designed to interpolate these gaps with dummy entries, thereby maintaining the continuity of our dataset. This function ingeniously generated new node entries, ensuring that each was marked to reflect its status pertaining to the structure's imperfection. This preprocessing step was crucial for maintaining a robust dataset conducive to machine learning analysis. Following this, the datasets were transformed into Numpy arrays for computational efficiency. The next phase involved merging the perfect and imperfect datasets, labeling missing nodes accordingly, which was then followed by feature scaling to normalize the data. The prepared dataset was subsequently divided into training and validation sets, ensuring a balanced representation for the model training phase.
For the model training, two distinct approaches were undertaken. The RFC model focused exclusively on shear stresses, leveraging these features' predictive power for structural integrity classification. Conversely, the feed-forward neural network (FFNN) model was trained on a broader spectrum of features, encompassing all 78 identified attributes, to provide a more comprehensive analysis of the structural health.
This structure was chosen to capture the complex relationships within the data, facilitated by multiple dense layers, dropout regularization to prevent overfitting, and L2 regularization for weight constraint. The model was compiled with an Adam optimizer, with a specific learning rate tailored to our dataset's characteristics. To ensure the model's generalizability, an early stopping mechanism was employed, halting training upon stabilization of validation loss, thereby safeguarding against overfitting, while retaining the ability to generalize to new, unseen data.

RESULTS: Especially in the Random Forest Classifier the predictions indicated very good results (accuracy(train) = 0.991, accuracy(test) = 1.0). On the other hand the Feed Forward Neural Network performed equally good (accuracy(train) = 0.999, accuracy(test) = 0.9991) with training and validation loss being 0.0105 and 0.0092 for the training dataset. Comparable losses indicate that the model is not underfitting or overfitting (Fig.), owing to the hyperparameter tuning. The convergence of losses suggests the mean ranges between 0.4 and 0.01.



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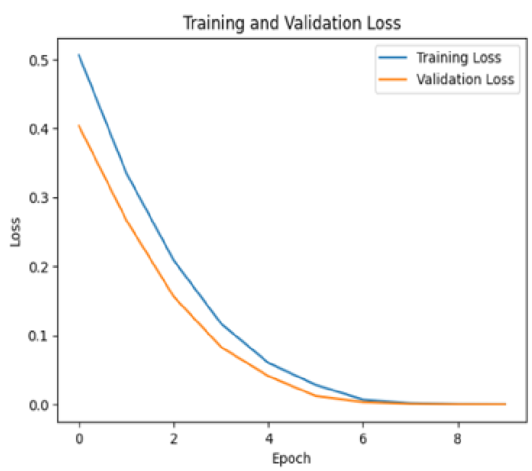
DISCUSSION: The results from the study suggests that it is possible to use a Random Forest Classifier or feed-forward neural network to identify location of deformation in structures like Hohenzollernbrücke. Since the calculation were based on limited time-series dataset an LSTM model was not implemented but such a model might reveal astonishing results. Additionally, none of the studies classified the region of deformation in the structure and was limited to location of nodes of deformation, it is possible to predict early stages of deformation leading to imperfections by classifying the regions of predictive deformation. If it is possible to get time-series data for deformation simulation under varied loading, a more complicated feed-forward neural network with only important features or an LSTM model may increase the possibilities of unrestricted structural health monitoring.The robustness of the neural network against different sensor positions and orientations needs to be further evaluated. It can be assumed that a larger dataset is necessary to further improve the prediction accuracy of the algorithm.



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CONCLUSION: The method proposed here shows its feasibility in estimating joint angles from linear accelerations and angular rates of the different lower body segments. The data used here was simulated from optical data. Since the markers undergo different soft tissue movements than real IMU sensors, the simulated data differs to some degrees from real IMU data. Additionally, these data do not experience any drift, as the gyroscope does. In future, there needs to be a verification of the method using real IMU data. Afterwards, the method can also be applied to in-field motion analysis. It might also be possible to use a recurrent neural network for this prediction task, so that a real-time application becomes possible.

REFERENCES: