IMPERFECTION DETECTION AND LOCALIZATION IN THE HOHENZOLLERNBRÜCKE STRUCTURE USING DEEP LEARNING TECHNIQUES

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This study explores the application of deep learning (DL) techniques, specifically Long Short-Term Memory (LSTM) and U-Net models, for imperfection detection and localization in the Hohenzollernbrücke structure. Utilizing a comprehensive dataset comprising nodal information under various loading conditions, the LSTM model is employed for binary classification of perfect and imperfect structural states. Results demonstrate the efficacy of LSTM in capturing long-term dependencies, enabling accurate prediction of structural imperfections. Additionally, a U-Net model is utilized for image segmentation, although further refinement is suggested for improved performance. The findings underscore the potential of DL methodologies in enhancing structural health monitoring, facilitating proactive maintenance strategies for ensuring the resilience and safety of critical infrastructure like the Hohenzollernbrücke. Moreover, this research contributes to advancing structural health monitoring practices globally, promising longevity and safety for essential structures.

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INTRODUCTION: The utilization of deep learning techniques in structural health monitoring has witnessed significant advancements in recent years, facilitating the acquisition of dynamic and real-time insights into the integrity of critical infrastructure. The motivation behind such endeavors encompasses the imperative need to ensure the sustained reliability and safety of structures, particularly iconic landmarks like the Hohenzollernbrücke. In our endeavor an equivalent Computer-Aided Design (CAD) model of the iconic structure was used to simulate. Leveraging advanced Deep Learning (DL) techniques, particularly the LSTM model, our aim was to discern between perfect and imperfect bridge structures. Through meticulous examination under various loads and defects, our primary objective was twofold: classify the structure as perfect or imperfect and precisely pinpoint any identified imperfections. Harnessing DL algorithms such as LSTM and U-net models, our focus extended to quantifying the individual impact of load components, deciphering their relative contributions, and uncovering potential vulnerabilities. This endeavor represents a commitment to enhance our understanding of the Hohenzollern Bridge's structural dynamics. By integrating cutting-edge DL methodologies, we strive not only to classify the bridge's condition but also to illuminate the exact locations of imperfections, facilitating proactive maintenance strategies and ensuring the enduring resilience of this architectural gem.

METHODS: The dataset that was given for developing the model containing node's temporal information on x-axis deformation, y-axis deformation, z-axis deformation, total deformation, and shear stress on the XY, YZ, and ZX planes for all the nodes present in the bridge under different loading conditions for both perfect and imperfect cases. To enhance the model's efficiency and accuracy, the Pearson correlation coefficient method with a threshold value of 0.7 was employed to identify redundant features. The correlation analysis showed a high correlation between timesteps. In addition, since the total deformation contains all the

information about the x,y, and z deformation, these features also had a high correlation. This leads to a reduced feature set containing only the total deformation and shear stress on the XY, YZ, and ZX planes for unique time steps 0.1,1.1,2.1, and 3.
Our initial approach uses a standard U-net model, as CNNs have shown to be capable of performing well on time series data[5], to predict the state of each node by transforming sensor data into a 2D grayscale image. Masks (labels) for training the model for the segmentation task can be created by black and white images where missing nodes of the imperfect structures are white pixels.

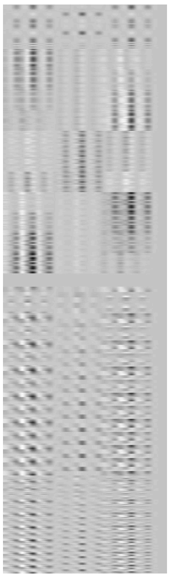

Figure 1 Transformed Sensor Data.

Later, the LSTM network known for its efficiency in handling sequential data, was implemented using Python with the support of the TensorFlow library[1].LSTM network was implemented for both binary and multi-class classification.LSTM Network Architecture which is implemented for binary classification of perfect and imperfect structure contains two layers with 50 neurons in each layer. The model was trained with different learning rates for 10 epochs, the model with a learning rate of 0.005 performed better and yielded the highest accuracy. Early stopping was used on validation loss for early convergence and to avoid overfitting. The allocation of data was 80% for the training set and 20% for the validation set. F1 score and accuracy were used as metrics for the performance of the model.

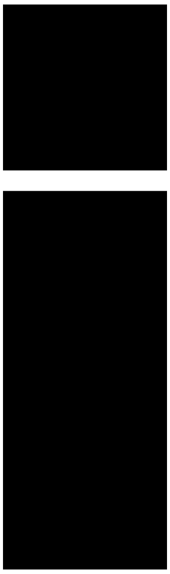

Figure 2 Mask (Label).

RESULTS: The best-performing model of LSTM architecture had F1 score of 0.88644 and an accuracy of 0.8099 on the training dataset converged in 30 epochs. However, performance dipped on the test set, recording an F1 score of 0.764 and an accuracy of 0.619. The difference in performance in the validation set and test set can be seen by the confusion matrix in Figures 3 and 4. This is possibly due to the imbalance of data available for perfect and imperfect cases.

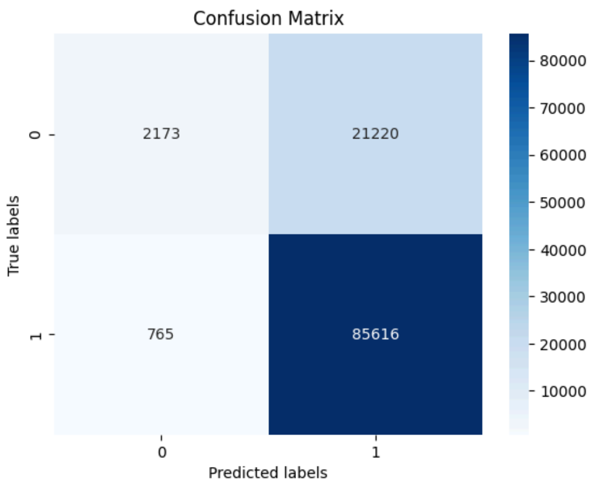

Figure 3 Confusion Matrix for Validation Set.

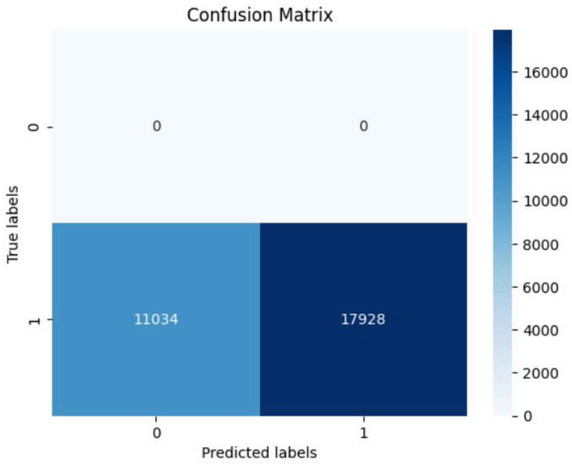

Figure 4 Confusion Matrix for Test Set.

U-Net's predicted image for the state of nodes is in Figure 5, the U-Net model does not perform well for segmentation of the transformed sensor images. More data is required and a custom U-net with a larger convolution matrix and custom architecture. The network cannot probably relate nodes that are far away from each other in the feature matrix, which is due to the limited size of the filter matrix.

Figure 5 Prediction of the Model where the white pixels are depicted as the imperfect nodes.

DISCUSSION: The results of this study reveal that it is possible to use the LSTM method to predict structural imperfections in the Hohenzollern bridge model. Even though the given dataset for this study doesn't have any dependencies that need LSTM, for practical case scenarios where the corresponding node is affected by the previous node this architecture performs well in capturing long-term dependencies, allowing it to remember and utilize information over extended periods. This capability ensures high accuracy in predicting structural issues, essential for making informed maintenance and safety decisions in the

future. Additionally, LSTMs for multi-class classifiers to predict the type of imperfection is also possible has been revealed and implemented in this study. Their adaptability and precision make them a preferred choice for this complex engineering project, offering reliable insights into the temporal dynamics of structural integrity.
Also, U-Net stands out for engineering applications, notably in detecting the structural state of individual nodes, due to its exceptional image segmentation precision. Its architecture is adept at preserving contextual information, crucial for a detailed understanding of structural integrity from visual data. It adapts to varying image scales and supports real-time analysis, essential for rapid assessment and decision-making in structural health monitoring of the Hohenzollern bridge model. Furthermore, its versatility extends to integrating with various data types, making U-Net a preferred choice for accurate and imperfection detection.

CONCLUSION: In conclusion, our project has demonstrated the efficacy of utilizing advanced Deep Learning (DL) techniques, particularly the LSTM model, in discerning between perfect and imperfect structural states of the Hohenzollern Bridge. This comprehensive approach provides invaluable insights into the structural dynamics of the Hohenzollern Bridge, enabling proactive maintenance strategies to ensure its enduring resilience and safety.
Moving forward, our findings pave the way for further advancements in structural health monitoring and maintenance practices, not only for the Hohenzollern Bridge but also for other critical infrastructure worldwide. By continuing to leverage the power of DL methodologies, we can enhance our ability to safeguard against structural deficiencies, ultimately contributing to the longevity and safety of essential structures for generations to come.

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