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DATA-DRIVEN OUTPUT-ONLY METHODS FOR DAMAGE DETECTION WITH A FOCUS ON DEEP LEARNING ALGORITHMS

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Summary. *This paper investigates methods for damage identification in bridge structures by using Structural Health Monitoring (SHM) techniques. The study uses Frequency Domain Decomposition (FDD) to estimate modal parameters such as natural frequencies and mode shapes, which can indicate damage through changes in modal parameters. Additionally, the paper explores the application of deep learning, specifically Bidirectional Long Short-Term Memory (BiLSTM) networks, for damage localization and quantification. Synthetic acceleration data from a single-span beam model was generated and used to train these neural networks. The research demonstrates that both FDD and BiLSTM networks can effectively localize damage related to a reduction in stiffness. The BiLSTM also quantifies damage with high accuracy, highlighting the potential of deep learning in SHM. Future work will focus on refining the beam model, incorporating noise in the data, and optimizing neural network architectures for real-world applications.*

1 INTRODUCTION

Bridges are central components of infrastructure systems. Due to their exposure, they are constantly subjected to external influences that affect their structural health. A usual problem of bridges, e.g. in Germany or the USA [1], is a high backlog in refurbishment due to a lack of continuous maintenance over the last few decades in combination with an extensive usage. Especially railway bridges are subjected to high dynamic loads caused by the crossing of trains, which can result in structural damage to the supporting structure. Early detection of damage can help to maintain and extend the lifetime of a bridge. As part of the Structural Health Monitoring (SHM), the determination of the dynamic characteristics is a key element to monitor the system behavior and to derive conclusions on the service life of the structure. The modal-based damage analysis is based on the assumption that damage to the structure is accompanied by changes in stiffness or mass. Due to this physical correlation damage processes change the dynamic response of a structure. In the context of the Operational Modal Analysis (OMA), the structural response of the bridge is measured under operating conditions, i.e. closing of bridges for measurements are not necessary.

In this research the OMA technique Frequency Domain Decomposition (FDD) was used. This method enables the estimation of modal parameters of the structure based on time histories (velocities, accelerations). Damage accompanied by a reduction in stiffness can be detected as a result of a change in the modal parameters like natural frequencies and related mode shapes. Damage identification in SHM involves four steps: detection, localization, quantification, and remaining useful life prediction [2]. Previous own research was carried out to detect and localize damage on single-span concrete beams trough changes in modal parameters and to develop a measurement system. This measurement system has made it possible to detect and localize stiffness reductions as a consequence of bending cracks by using the FDD. [3]

In this paper, an alternative method is researched to localize and even quantify damage based on the structural response by using deep learning algorithms like neural networks. A of proof of concept is presented using synthetic acceleration data of the previous experiments to be analyzed by deep learning algorithms.

2 BACKGROUND

2.1 Frequency Domain Decomposition

The behavior of a multi-degree of freedom structure under external excitation can be described mathematically by a system of second-order differential equations as follows

$$M\ddot{x} + Kx \ = \ F(t). \tag{1}$$

M and $K$are the mass and stiffness matrices respectively, x is the displacement and $\ddot{x}$ the acceleration of the structure. $F(t)$ is external excitation which, in context of OMA, is unknown. The modal characteristics of the structure cannot be determined by solving the matrix eigenvalue problem because in case of real measurements, the mass- and stiffness matrixes are unknown. The Frequency Domain Decomposition enables the estimation of eigenvalues and mode shapes based on measured time histories of the structural dynamic response. This is based on the idea of representing the structural response of an overall system by the sum of the reactions of many single degree of freedom (SDOF) systems. Each SDOF system reflects a mode [4]. The distribution of the response spectrum or the structural response of the overall system to the individual degrees of freedom of the system is achieved by the singular value decomposition (SVD) of the Power Spectral Density (PSD) matrix. The transformation of the signals from the time domain to the frequency domain results in the dependence on the frequencies ω_i and so for each discrete frequency there is a corresponding PSD matrix. The singular value decomposition of the PSD matrix therefore provides the singular values as a function of the discrete frequencies. The PSD matrix of the structural response $G_{yy}(j\omega)$ can be expressed as [5]

$$G_{yy}(j\omega) = \sum_{k \in Sub(\omega)} \frac{d_k \phi_k \phi_k^T}{j\omega - \lambda_k} + \frac{\bar{d}_k \bar{\phi}_k \bar{\phi}_k^T}{j\omega - \bar{\lambda}_k}, \tag{2}$$

where d_k is a scalar constant, ϕ_k is the mode shape vector and λ_k is the pole consisting of resonance frequency and damping value. At a specific frequency ω, only a limited number of modes will contribute significantly. Let $Sub(\omega)$ denote that set of modes. The singular value decomposition is performed for each discrete frequency ω_i

$$\hat{G}_{yy}(j\omega_i) = U_i S_i U_i^H . \tag{3}$$

According to [6], the diagonal matrix $S_i \in \mathbb{R}^{nxn}$ contains for the discrete frequency ω_i the scalar singular values s_{ij} in descending order.

$$S_i = \begin{bmatrix} s_{i1} & & \\ & \ddots & \\ & & s_{im} \end{bmatrix}, \qquad s_{i1} > s_{i2} > \ldots > s_{im}, \qquad j = 1, \ldots, m. \tag{4}$$

As a result of the decomposition of the overall system into SDOF systems and the descending order of the singular values, the first singular value contains the information about the dominant mode at this frequency. The matrix $U_i \in \mathbb{C}^{nxn}$ contains the associated singular vectors for the singular values. For the discrete frequency ω_i, this means that the matrix U_i contains the eigenvectors u_{ij}.

$$U_i = [u_{i1}, u_{i2}, \ldots, u_{im}], \qquad j = 1, \ldots, m. \tag{5}$$

The first singular vector u_{i1} is an estimation of the mode shape [4]

$$\hat{\phi} = u_{i1} . \tag{6}$$

Based on the above formulations, it can be observed that any change in stiffness or mass will lead to changes in the dynamic response and then its natural frequencies and mode shapes. Therefore, damage accompanied by a reduction in stiffness can be detected as a result of a change in the modal parameters. Damage quantification by FDD is the subject of current research. Therefore, a Bidirectional Long Short-Term Memory Network was investigated as an alternative method of damage identification.

2.2 Bidirectional Long Short-Term Memory Network

Machine learning is an effective strategy to extract features from data because it enables a computing device to identify implicit relationships within data for the purpose of classification or prediction [7]. Deep learning is a subset of machine learning. Deep learning methods like neural networks are a common way to handle time series data. One class of neural networks are Recurrent Neural Networks (RNN).

The recurrent connections allow the network's hidden units to see its own previous output, so that the subsequent behavior can be shaped by previous responses. These recurrent connections are what give the network memory. [8] This class of neural networks is suitable for sequential data. RNNs are specifically designed to capture time-dependent characteristics, but they are considered to have shortcomings in handling long-term dependencies of time series. If the processing signal is very long, RNNs tend to may lose some important information from the beginning. Long Short-Term Memory networks (LSTM) [9] are one variant of RNNs with the capability to learn long-term dependencies in time series data. The gate units of LSTM networks regulate the state of the memory cell and enable the LSTM to deal with long sequence signals. A variant called Bidirectional LSTM (BiLSTM) is a more efficient extension of LSTM. BiLSTM contains two unidirectional LSTMs that process the input signal in opposite directions to capture information that may be overlooked by unidirectional LSTM networks [10]. The BiLSTM layer processes the input sequence simultaneously in the forward and reverse directions. The literature [11] verified the advantages of the BiLSTM suggesting the use of the BiLSTM instead of the unidirectional LSTM in time series analysis. In this research, a bidirectional LSTM network was used, because it enables information from the past and the future to be recorded.

3 NUMERICAL BEAM MODEL

3.1 Beam model

The single-span beam has the dimensions 6.5 m x 0.2 x 0.3 m (L x W x H) and was modeled as a simply supported Euler-Bernoulli beam in Matlab software. The beam length was mapped trough 104 elements with an element length of 6.25 cm in order to be able to map both the dynamic behavior of the beam and the sensor positions. At each element node, two degrees of freedom are considered. These are the displacement transverse to the longitudinal axis and the rotation of the node. The displacement in the longitudinal direction is not taken into account. This proof of concept neglects damping characteristics and reinforcement. Stiffness reduction was simulated as Young’s Modulus reduction on each element in turn. The damage has also been modeled on two and three neighboring elements. Eight damage degrees were modeled, ranging from 10 to 60 % reduction of Young’s Modulus. Figure 1 shows the damage scenario on two elements in the middle of the beam depending on all damage degrees.

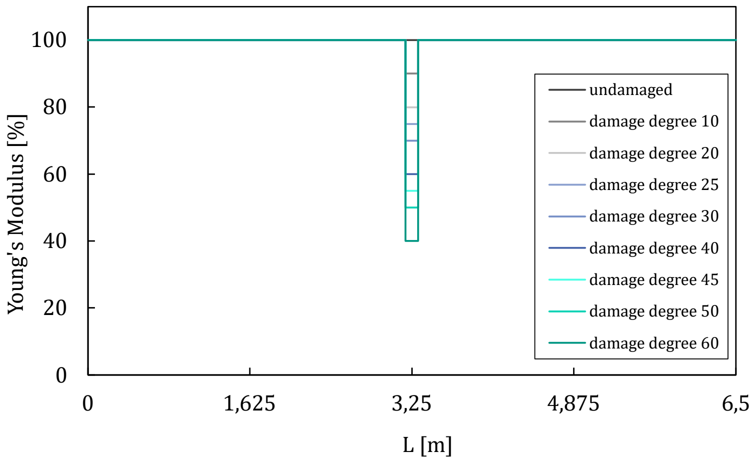

Figure 1: Simulated damage degrees on two elements in the center of the beam

3.2 Acceleration time-histories

For extracting the acceleration $\ddot{x}$ numerically, a time integration is necessary. In this research the Newmark method [12] for second order differential equations was chosen. To ensure unconditional stability of the method, the integration parameters δ and α were selected as follows

$$\delta = \frac{1}{2}, \quad \alpha = \frac{1}{4}. \tag{7}$$

The time step was set to

$$\Delta t = \frac{1}{f_s}, \tag{8}$$

where f_s is the sampling frequency.

The single-span beam was excited by an impulse at beam length x = 0.2 m. The vertical acceleration of 25 element nodes was used as virtual accelerators. The distance between the used element nodes is 0.25 m each. The sampling frequency of the vertical accelerations is 4000 Hz. In this proof of concept, the virtual sensors work in ideal conditions, which means there is no noise included in the obtained acceleration time series. The structural response was simulated for each damage scenario. Therefore, the variation of responses is only a result of the different damage scenarios.

4 DAMAGE LOCALIZATION USING FREQUENCY DOMAIN DECOMPOSITION

The Frequency Domain Decomposition was used to estimate the mode shapes based on the acceleration signals of the 25 virtual sensors. Figure 2 shows the mode shapes of the first three vertical bending modes depending on the various damage degrees for a simulated damage at elements 37 - 39 at approximately 2.4 m. The slight changes in the amplitudes of the mode shapes are an indicator for changes of the properties of the beam.

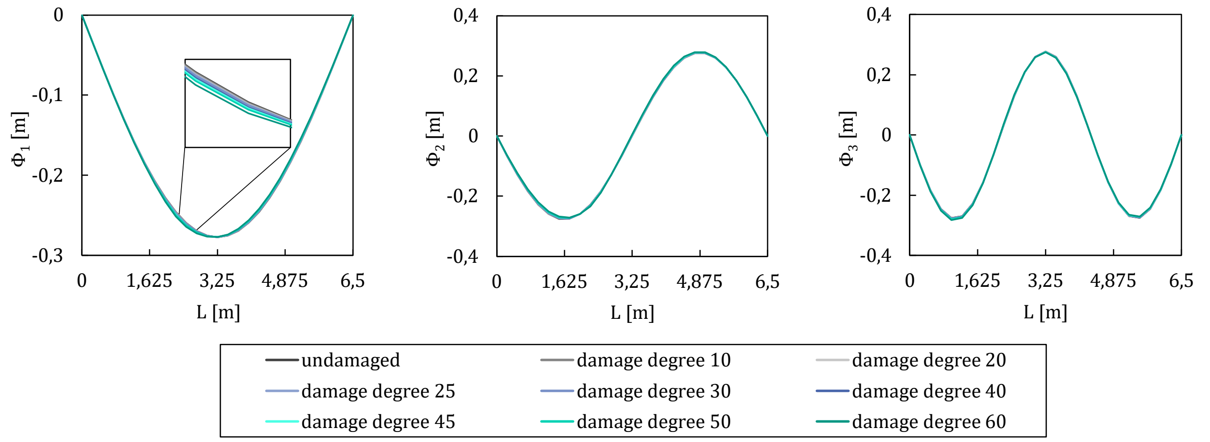

Figure 2: Mode shapes depending on various damage degrees

Figure 3 shows the curvature of the first three vertical bending modes depending on the various damage degrees. The curvature of the mode shapes was determined by the second derivation of the estimated amplitudes of mode shapes by using the central difference approximation method [13] as follows

$$D_4 f(x_0, h) = \frac{f(x_0 + h) - 2f(x_0) + f(x_0 - h)}{h^2}, \tag{9}$$

where h is the distance between the virtual sensors.

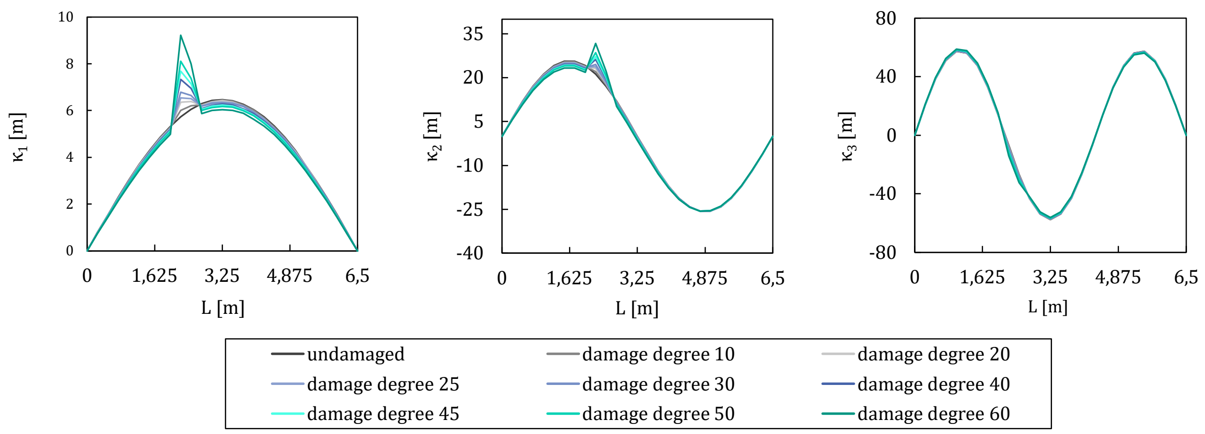

Figure 3: Mode shape curvature depending on various damage degrees

The curvatures increase significantly in the area of the damaged elements, especially in the first and second mode. Thus, the FDD enables the localization of areas with reduced stiffness.

5 DAMAGE IDENTIFICATION USING DEEP LEARNING ALGORITHMS

The neural networks used in this work were implemented in Matlab. The network architecture (Figure 4) contains an input layer, a BiLSTM layer with 200 hidden units, a fully connected layer, a softmax layer and an output layer. The number of neurons of the output layer is the number of labels to predict. Details on BiLSTM will not be discussed further due to the scope of the report. Further information and a general introduction to bidirectional RNN and LSTM networks can be found in [9, 14, 15].

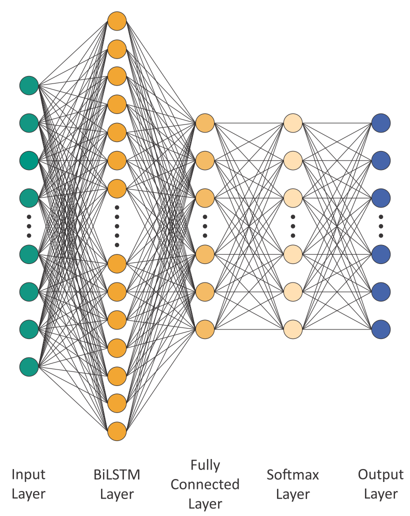

Figure 4: Network architecture

For training, Adam optimizer with a learning rate of 0.002 was used and the loss was minimized by using the cross-entropy loss function [16]

$$\text{loss} = -\frac{1}{N}\sum_{n=1}^{N}\sum_{i=i}^{K} w_i t_{ni} \ln y_{ni} \ , \tag{10}$$

where N is the number of samples, K is the number of classes, w_i is the weight for class i, t_{ni} is the indicator that sample n belongs to class i (1 if true, 0 otherwise), and y_{ni} is the output (probability) for sample n for class i, which comes from the softmax function.

Table 1 shows the used settings used for the training. Shuffling of data was not applied. Other parameters were left at their default settings.

Table 1: Settings used to train

Gradient Decay Factor	0.9
Square Gradient Decay Factor	0.999
Epsilon	1e-8
L2Regularization	0.0001
Gradient Threshold Method	l2norm
Gradient Threshold	1.0
Mini Batch Size	128
Validation Frequency	50

The network architecture and hyperparameters are selected via an extensive trial-and-error approach. It is likely that a different network architecture and/or different parameters will deliver better results. The networks were trained using acceleration response histories directly without requiring an additional step to extract structural characteristics such as modal identification (end-to-end network). Depending on classification task (damage localization, damage quantification and damage localization and quantification simultaneously), different data bases were used. Table 2 contains the information about the data basis, respectively.

Table 2: Overview of the generated data bases

	Data basis A	**Data basis B**	**Data basis C**
Used for Damage	Quantification	Localization	both
Number of Elements	104	100	100
Element Length [cm]	6.25	6.50	6.50
Number of Beam Areas	13	10	10
Number of Virtual Sensors	25	9	9
Sampling Frequency f_s [Hz]	4000	1900	1900
Simulated Damage Degrees	8	4	4
Time Signal [s]	15	10	10
Number of Data Sets	2473	1189	1189
Number of Impulse Forces	2	2	3
Total Number of Data Sets	4946	2378	3567
Number of Labels	9	11	41

To reduce the number of labels for classification, 10 (data basis B and C) or 8 (data basis A) beam elements are grouped together to form a damage area. This led to a subdivision of the beam into 10 (data basis B and C) or 13 (data basis A) damage areas. For data basis B and C, the simulated damage degrees were modeled as 10, 25, 50 and 75 % reduction of Young's Modulus. In addition to the damaged areas, there is also the undamaged state. By exciting the beam with an impulse, the data sets were created depending on the number of elements and simulated damage degrees. This was repeated for several impulse forces in order to create the entire data basis in each case. The data sets containing in data bases were normalized before training. The entire data bases were randomly divided into training, validation and test subset with a ratio of 80:10:10.

First, separate neural networks for damage localization and damage quantification were trained. For the investigations of damage localization based on deep learning algorithms, data basis B was used. The 11 labels to be classified are the 10 damaged beam areas (beam area 01 - 10) and the undamaged state. Figure 5 shows the training accuracy and loss for 1500 epochs. The testing accuracy with unseen data was 94.14 %. Overall results are graphically represented as a confusion matrix where the diagonal cells are the number of correctly detected labels (highlighted in green) and the off-diagonal cells contain the number of incorrect results (highlighted in yellow). The result of the testing is presented in Figure 5. Sometime, the damaged beam area 10 was swapped with the beam area 01 and sporadically the neighboring beam area was predicted.

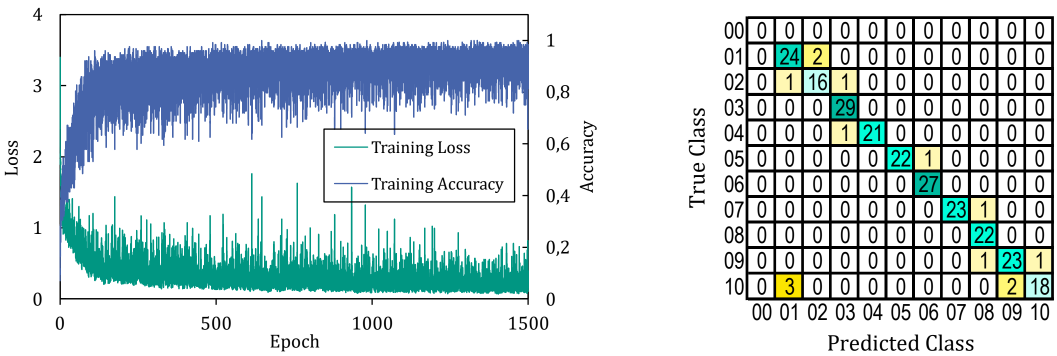

Figure 5: Training progress (left) and confusion matrix (right) for damage localization

Then the damage quantification was investigated. For this case, data basis A was used. In this case, the labels contain the 8 different damage degrees (Figure 1) and the state of the undamaged beam. Compared to data evaluation with FDD, the length of the time signals here is 10 seconds. The first 5 seconds of the vibrations were not used for training. Figure 6 shows the training accuracy and loss for 20 epochs. The testing accuracy with unseen data was 99.19 %. Confusion matrix (Figure 6, right) shows only 4 false damage degree predictions.

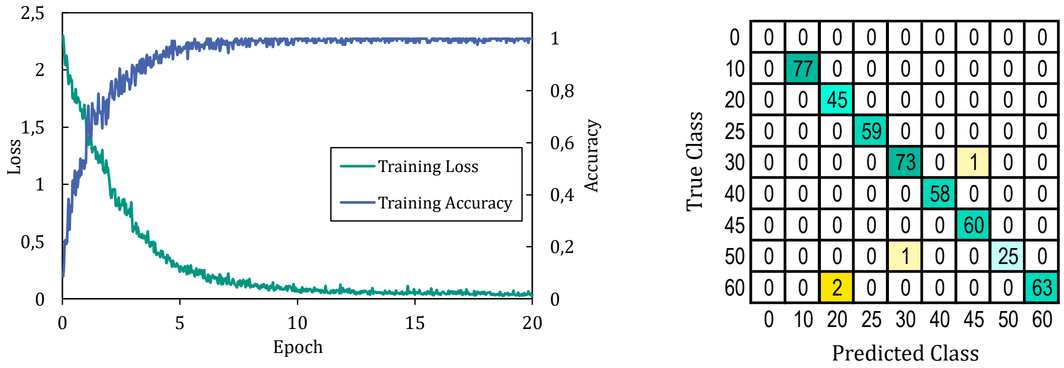

Figure 6: Training progress (left) and confusion matrix (right) for damage quantification

At last, simultaneously prediction of damage localization and damage quantification was investigated. For the sake of simplicity, the data basis C with 4 damage degrees and 10 damaged beam areas was used. This means that the required computing power could be reduced to a reasonable level without reducing the informative value. A network of combined output labels was applied. The label contains both, the damage location and the damage degree. For example, label 0250 classifies a damage in beam area 02 with a damage degree of 50 %. In total, 41 labels are to predict. Figure 7 shows the training accuracy and loss for 1000 epochs. The testing accuracy was 63.69 %. The trained network often predicts the right damaged area, but not the right damage degree. This is shown by the yellow diagonals above and under the green one. In some cases, the network classified the right damage degree but the neighboring beam area.

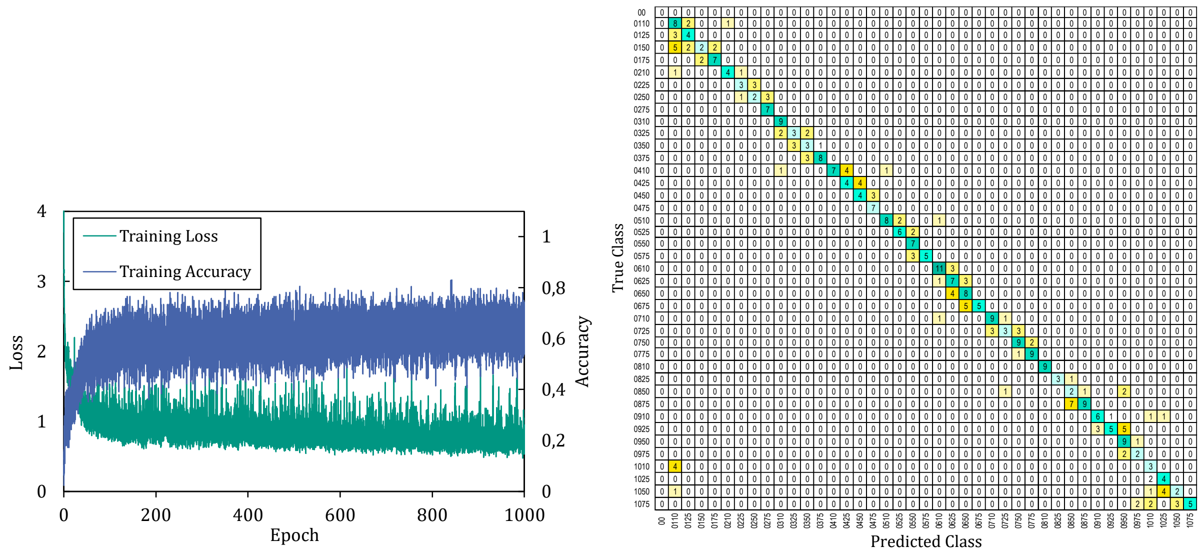

Figure 7: Training progress (left) and confusion matrix (right) for damage localization and quantification

6 CONCLUSIONS

In this paper, modelling of a single-span beam with matlab software and generation of acceleration time histories depending on various damage locations and damage degrees was investigated. The damage localization by using modal curvature estimated by the Frequency Domain Decompisition was presented. Afterwards BiLSTM networks for damage localization and damage quantification were designed and implemented to directly take numerical acceleration data as input. The networks for damage localization and damage quantification provided highly accurate results (> 90 %) thanks to the capacity of capturing implicit dependencies from raw sensor data.

The research has shown that the information about the location and damage degree is inherent in the structural response. This proof of concept also shows that deep learning algorithms are able to detect and correctly classify these damage characteristics. However, great attention must me paid to a sufficient data basis. These should contain a sufficient number of samples and a balanced labeling of the labels for a successful training of the network.

7 OUTLOOK

The synthetic data was generated using the described simplifications. In further research the beam model will be improved, for example adding the reinforcement and non-linearity of reinforced concrete. Damage will be modeled more realistically and multiple damage locations can be added. Adding noise to the time histories is another next step as well as investigation of noisy signals. In addition, further parameters such as batch size, batch normalization layer or a dropout layer are to be varied or added. According to neural networks further research will subject predicting damage location and damage degree simultaneously as separate labels by one network. The goal is to optimize neural network performance in such a manner that vibration data from real experiments can be used as testing set.

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