AI-based prediction model for the „Rockburst“ impact test for reinforced shotcrete slabs

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Introduction

The swiss-based company Geobrugg developed a new high-tensile steel mesh for use in underground construction and mining. To test its fitness, Geobrugg conducted a first test campaign composed of ten tests. The comparison with preliminary Finite-Element-Analysis (FEA) showed sobering results. Hence, this thesis investigated the applicability of Machine Learning (ML) and Deep-Learning (DL) techniques on the existing test database.

All experiments were conducted with the same test frame. The mesh layer is mounted below the 100 mm thick shotcrete plate with 9 anchors. The tests examined different combinations of mesh and anchor types apart from other less important features that were varied between the tests. To test different levels of energy absorption, a concrete block was dropped once from increasing height onto the plate. Six tests used a juvenile plate while in four tests, the plate was already pre-damaged. In those cases, the block got restrained in a first test and was then dropped once again on the damaged plate. As the state of the plate greatly influences its response, this had to be considered with an additional input feature for all models.

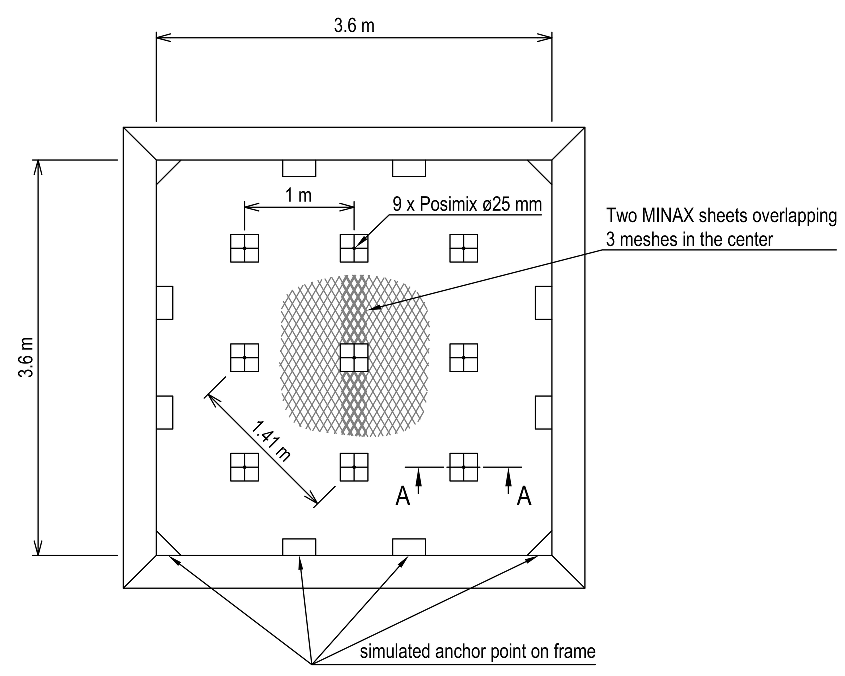

Figure 1: Top view of typical test setup.
[Source: Test documentation Geobrugg]

Figure 2: Freeze frame of experiment on shotcrete plate with failing plate.
[Source: Test documentation Geobrugg]

Classification

Failure / No Failure of system

The objective of the two classification models is to correctly predict failure of the plate-mesh system. Model M1 takes all available features as input. This includes features describing the initial setup and features measured during the tests. The best performing learning algorithm reached an accuracy of 0.78. Model M2 was only given features that were known before the tests were conducted. Consequently, the results were worse and they were only slightly better if one was to always predict the majority class (“No Fail”). The results of the two models are highly influenced by the feature describing the state of the plate before the test. It showed the highest feature importance across different learning algorithms for both M1 and M2. As undamaged plates are of greatest interest, more tests are needed to remove this bias.

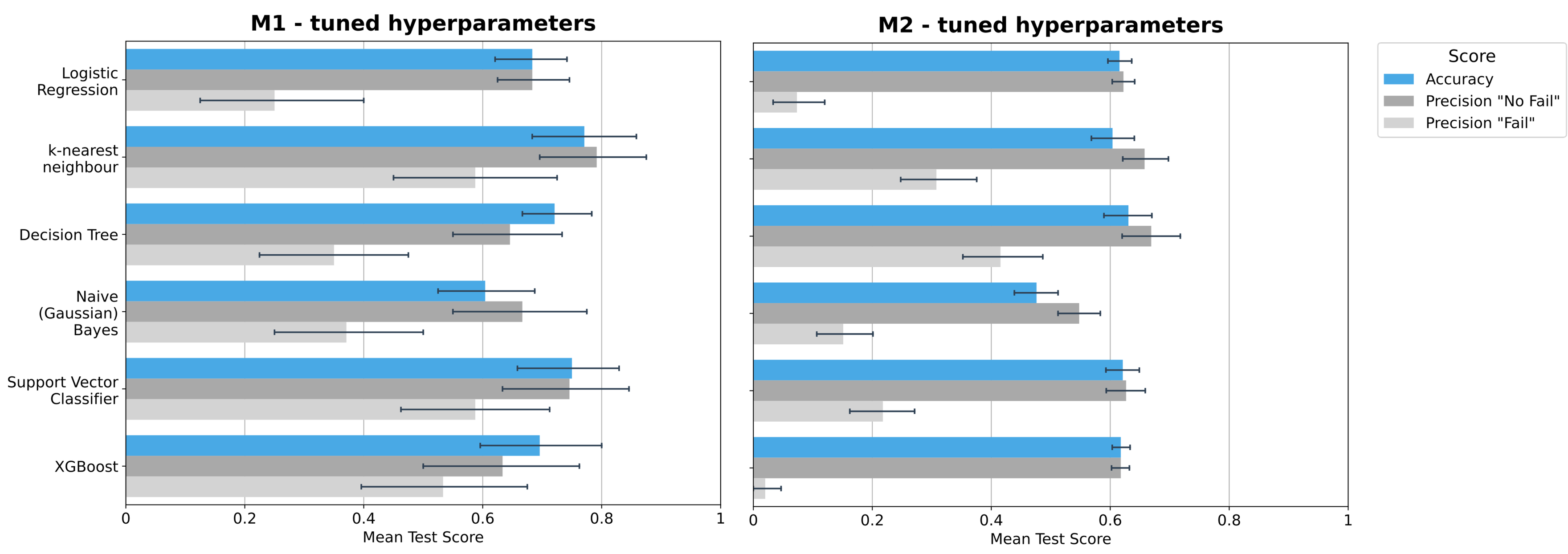

Figure 3: Results of the two classification models. *M1: all available input features; M2: only input features describing the initial setup are used.*

Apart from the mean tests accuracy, another import metric is the precision. It indicates how many times each label was predicted correctly. In both models, the precision of the label “No Fail” is higher than the precision of “Fail”, which indicates more conservative models. As this isn’t safety critical and will mostly lead to over-dimensioning of the system, it is tolerated given the small database.

Graphical User Interface (GUI)

Failure / No Failure of system

For better access, a GUI for model M2 was developed. It allows the user to make predictions for the expected behaviour of the system (“Fail” / “No Fail”) and displays the underlying probability of this prediction. In addition, similar tests are shown to the user, giving an impression of the sampling density of the underlying database.

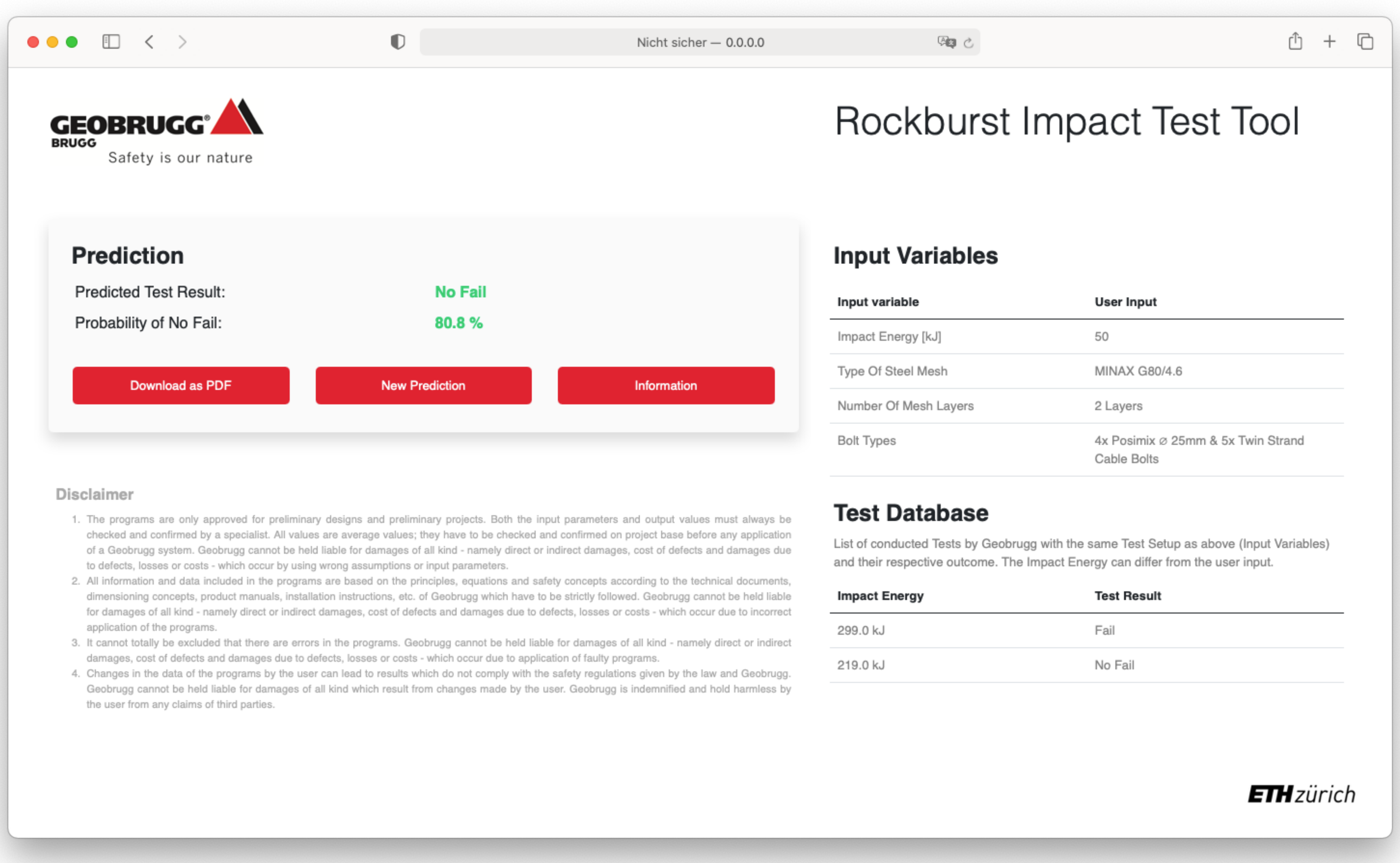

Figure 4: Output page of the Graphical User Interface (GUI) for model M2.

Regression

Maximum anchor forces

The last ML-model predicts the maximum anchor forces of each test. An investigation of the force measurements revealed that the maximum forces vary to a large extent between each test. These variations were especially large when the plate was pre-damaged. In this case, the forces were particularly difficult to model and they displayed the largest deviations from the identity line *(see ’x’ markers in Figure 5).* The observed mean absolute error of 38 kN and root mean squared error of 52 kN show the good prediction quality of the model.

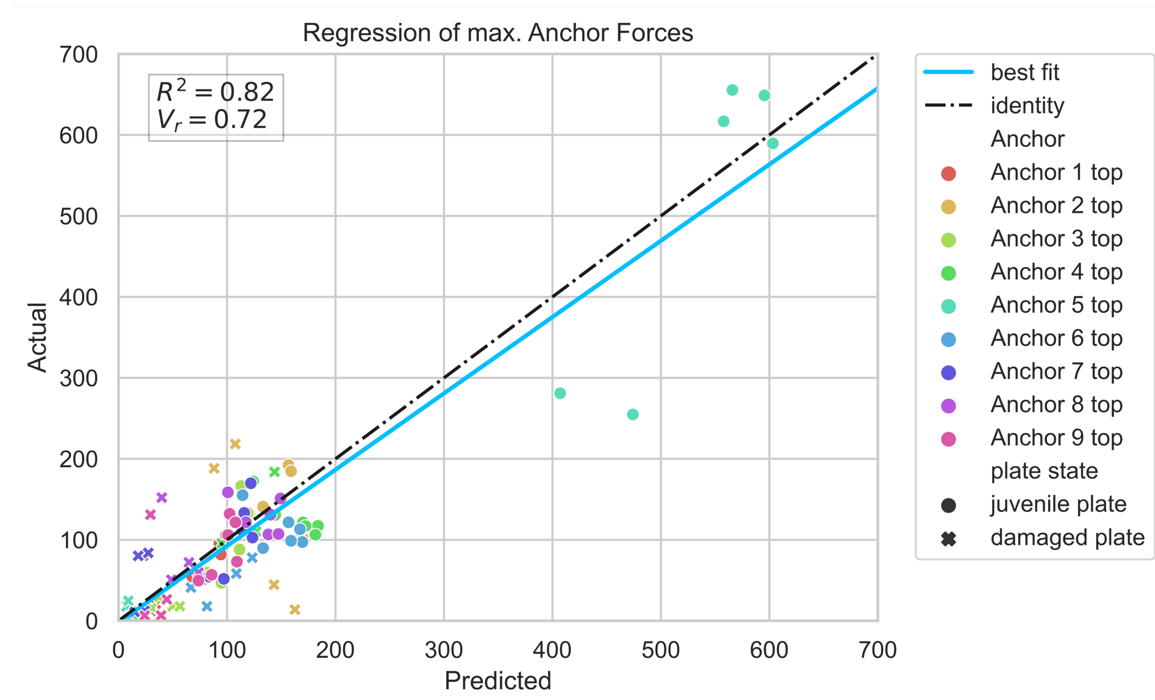

Figure 5: Prediction results of best performing Regression model

Long short-term memory Neural Networks

Prediction of time-dependent anchor forces

In a last step, different Deep-Learning models to predict the time-dependent behaviour of the anchor forces with LSTM Neural Networks were studied. Good results were achieved on the training dataset composed of only one of the ten tests. The prediction results on the validation set were equally promising, considering that those forces showed a different behaviour than the training data. As not all available data was used for training, the performance might still be improved. The findings of this model might be used to combine DL and more traditional FEA into a more refined model in the future.

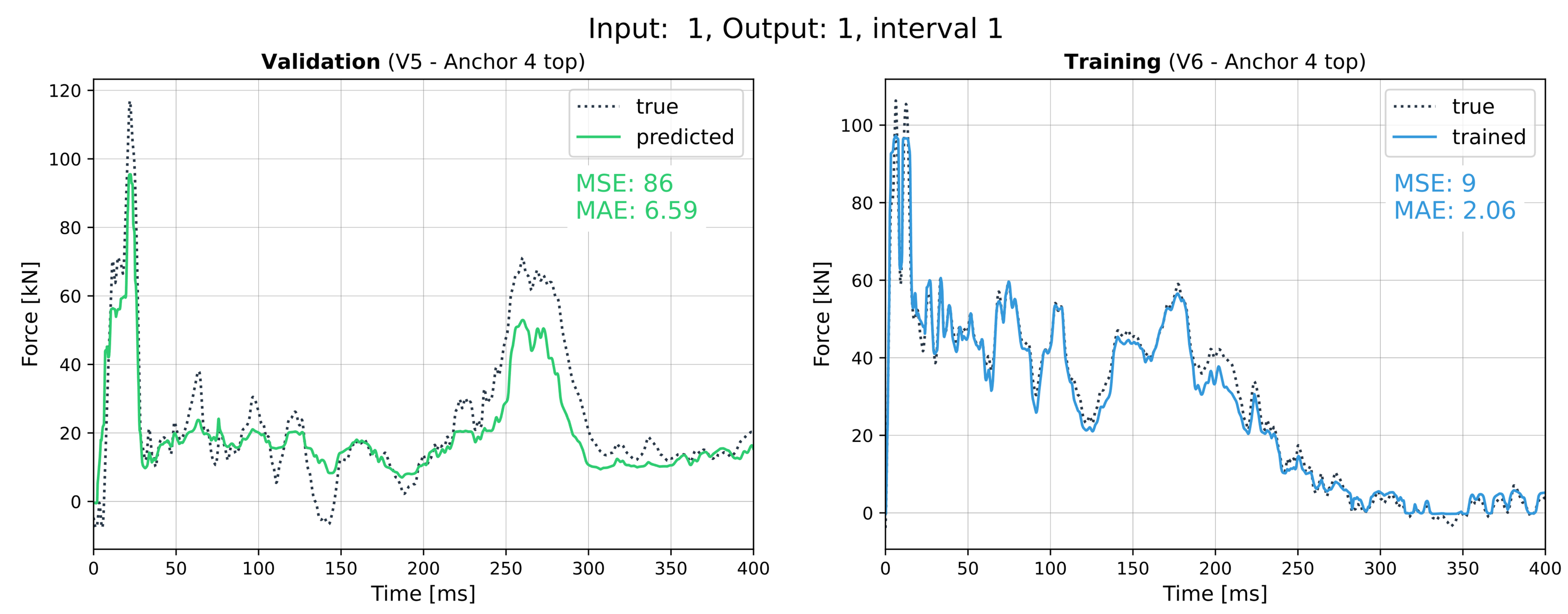

Figure 6: Prediction results of one LSTM model. *Blue: Performance on training dataset; Green: Performance on validation dataset.*

Conclusion

This thesis proved the abilities of ML and DL on the small dataset. To improve the models performances, additional tests may be required. Moreover, ML with a small dataset requires good quality of data and a well-defined problem. In this dataset this is diluted by the already pre-damaged plates. They add a highly non-linear behaviour to the model, which does not add any real value as one is mostly interested in juvenile plates. A future test campaign should avoid pre-damaged plates.