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PREDICTION OF VON MISES STRESS OF A 2D I-SECTION USING MACHINE LEARNING

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ABSTRACT

Stress prediction is an important task for the design and analysis of any structure. Finite element analysis and machine learning are widely used to reduce the time, cost, and effort consumed in laboratory experiments. In this paper, multiple machine learning models were built in order to predict the Von Mises stresses at critical locations for any given flange thickness, web thickness, and flange width of an I-Section for a given load condition and compare the accuracies with each other. The machine learning algorithms include linear, polynomial, decision trees, random forest, ADR, gradient boost, bagging, and extra trees, for which the train data was taken from finite element analysis results. Twenty I-section geometries with different dimensions were taken, and analysis was done to create the training set to train the machine learning algorithms. Finally, a comparison between results obtained from finite element analysis and machine learning was made.

Keywords: Stress, Finite Element Analysis, Machine Learning, Von Mises Stress, Flange Thickness, Web Thickness, Decision Tress, Random Forest, ADR, Gradient Boosting, Bagging, Extra Trees.

I. INTRODUCTION

Stress analysis plays a key role in determining the integrity of a structure. Many numerical methods, like finite-element analysis (FEA) and computational fluid dynamics (CFD), are used to perform stress analysis of complex structures and systems in which it may be difficult to get an analytical solution. These analyses can be used to evaluate the design, maintenance, and safety of complex structures in a wide array of applications across many industries, including aerospace, architecture, automobiles, biomedicine, etc. In the finite element method, the main idea lies in simplifying the problem by breaking the structure down into a large number of finite elements and then building up an algebraic equation to compute the coupled mechanical deformations and stresses based on the boundary and load conditions. Although this method gives accurate predictions, it is computationally intensive, especially when multiple runs are required to obtain the statistical variability naturally existent in real-world materials.

Machine learning techniques are becoming popular in the modelling of complex systems because they can serve as lower-order surrogates to approximate higher-fidelity models, which significantly reduces the model's complexity and computation time. Despite recent advances, applying ML models for predicting the internal stress of materials is still limited. Liang et al. [1] created a deep learning approach to estimate the stress distribution of an aorta as a fast and accurate surrogate of finite-element analysis. Nie et al. [2] used an encoder-decoder structure based on a convolutional neural network (CNN) to generate the stress field in cantilevered structures. On the other hand, Atta et al. [3] developed an artificial neural network to predict the failure stages for double-lap joints.

The introduction of machine learning in the field of structural analysis and design is very advantageous, as it is helpful in producing fast and accurate results. The accuracy of any machine learning model depends on the given training data. Since there are many finite element analysis softwares like Abaqus, Ansys, and Star CCM, sufficient training data can be collected in order to train the machine learning models. Since the finite element analysis yields accurate results, the machine learning predictions can be compared with the finite element analysis results for predicting accuracy and are also helpful in optimising the machine learning model.

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II. METHODOLOGY

The aim is to build an ML model that can predict the von Mises stress of an 2D I-section, as shown in figure 1, for any given flange thickness, web thickness, and flange width under a fixed load condition. To train the machine learning model, twenty geometries with different dimensions were modelled, as shown in Table 1. The finite element analysis was done using Abaqus software. Three more geometries were designed, and analysis was done in order to validate the ML predictions with the finite element results. The workflow is depicted in the figure 2.

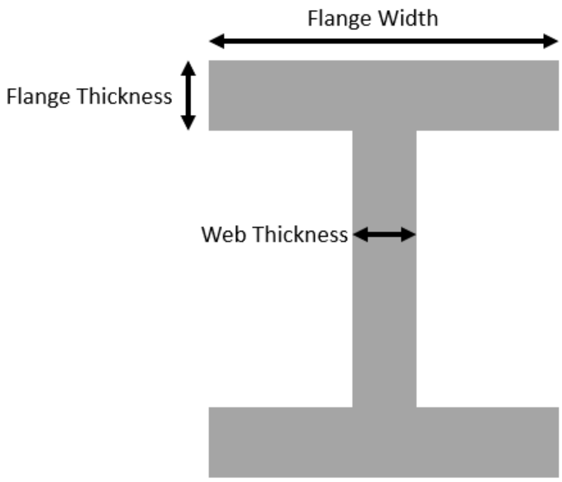

Figure 1: I section

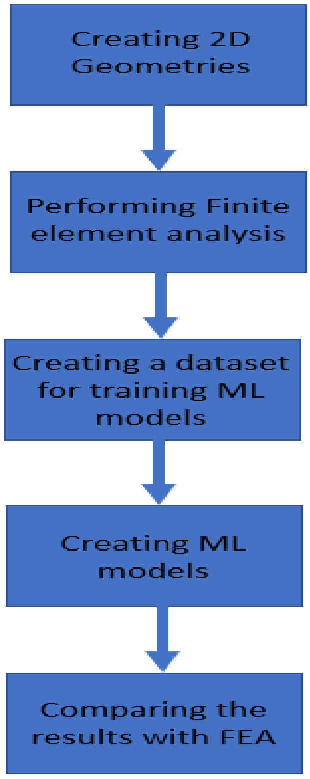

Figure 2: Workflow

III. MODELING AND ANALYSIS

To train the machine learning algorithms, 20 I-section 2D models were created by varying the web thickness, flange thickness and flange width. The material properties are shown in table 1. The static general(linear) analysis was done and a load of 10N was applied on a point which is coupled with the surface of the upper flange so that the load is applied uniformly, and the lower surface of the lower flange is fixed in all degrees of

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freedom as shown in figure 3. Analysis was done for all the twenty models and von mises stress value at one of the four corner points were considered as shown in figure. Since the load applied is uniform and the geometries are symmetrical, the stress values at all the four corner points are the same, so only one point was considered for analysis and prediction. The FEA parameters and results are mentioned in table 2.

Table 1: Material Properties

Material Properties	
Density	7.85E-006 gm/mm3
Young's Modulus	210 Gpa
Poisson's Ration	0.3

Table 2: FEA parameters and results

Model No	Web Thickness	Flange Width	Flange Thickness	Von Mises Stress
1	10	50	10	1.07125
2	10	40	8	1.03635
3	10	60	12	1.09697
4	10	30	6	1.51152
5	8	50	10	1.27493
6	8	40	8	1.24257
7	8	60	12	1.29794
8	12	50	10	0.924199
9	12	40	8	0.88108
10	12	60	12	0.951113
11	12	30	6	0.853063
12	6	50	10	1.57984
13	6	40	8	1.55323
14	6	60	12	1.59831
15	5	50	10	1.82213
16	5	40	8	1.80156
17	5	60	12	1.83656
18	14	50	10	0.812873
19	14	40	8	0.778916
20	14	60	12	0.839835

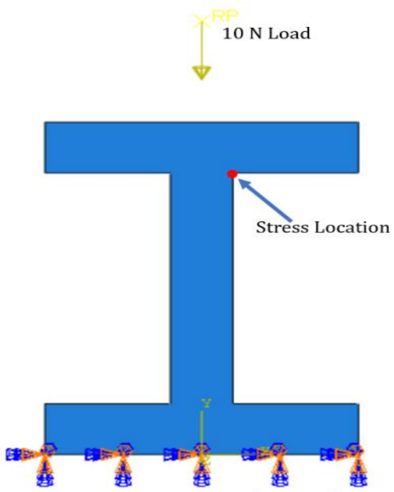

Figure 3: Load and boundary conditions

IV. RESULTS AND DISCUSSION

After building the machine learning models, the models were validated for three other I-section geometries that were not in the training set. The predictions done by the ML models and FEA are mentioned in table 3. In order to measure the accuracy of the ML models, Mean Square Error (MSE) and R2 score were measured for all the machine learning models and tabulated in figure 4 and table 4.

Table 3: Comparison of FEA results with ML predictions

Web Thickness(mm)	Flange Width(mm)	Flange Thickness(mm)	FEA Result (Von Mises stress)	ExtraTrees Regression Prediction(Von Mises stress)
8	54	12	1.29768 MPa	1.2905768 MPa
11	55	11	1.00799 MPa	1.00468301 MPa
10	45	8	1.04122 MPa	1.041236 MPa

All the machine learning models have performed well and are getting closer to the FEA results. Out of all the ML models, extra-tree Regression modal has the highest R2 score and the least mean square error, making it the best model suitable for predicting the stress values for any given 2D I-section. Along with the extra tree regression, gradient boosting regression and decision tree regression, all of which have an R2 score greater than 0.99 and can be considered good models for stress prediction.

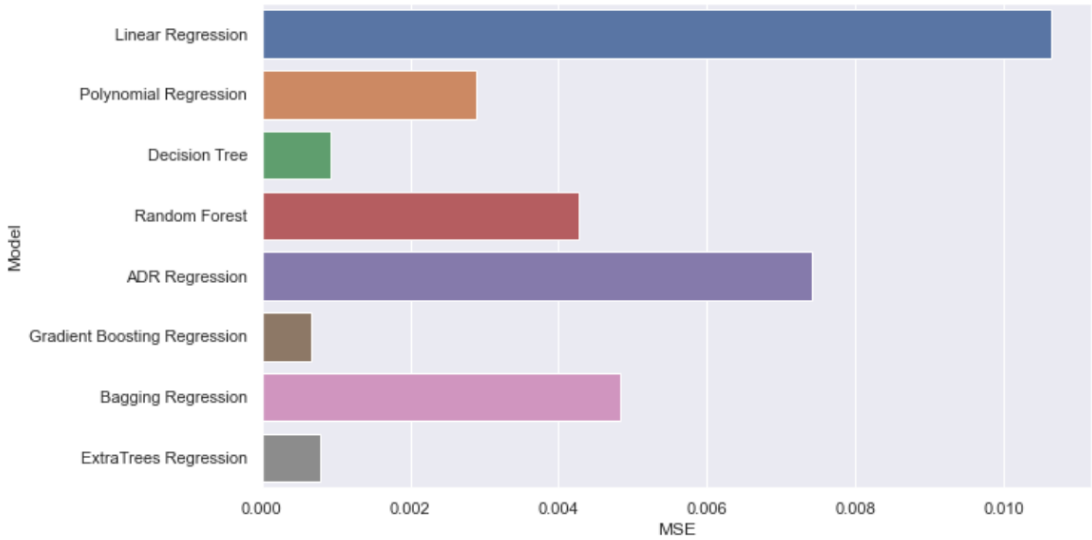

Figure 4: Mean Square Error for all regression moels

Table 4: R2 score for all regression models

Model	R2 Score
Linear Regression	0.9231
Polynomial Regression	0.97915
Decision Tree	0.992674
Random Forest	0.966529
ADR Regression	0.941868
Gradient Boosting Regression	0.994822
Bagging Regression	0.962083
ExtraTrees Regression	0.99387

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V. CONCLUSION

The main purpose of this study is to create a highly accurate machine learning model which can predict the stress outcome for a given geometry instead of performing finite element analysis so that the computation time can be reduced. The predictions that were obtained by the built by using the ML models are pretty accurate and came close to the FEA results. With more data, the accuracy was discovered to lean toward precision. To summarize, if we train our system with a large enough data set, the ML models have the potential to produce significantly more accurate and consistent minimal error predictions.

VI. REFERENCES

[1] Liang, L., Liu, M., Martin, C., and Sun, W., 2018, "A Deep Learning Approach to Estimate Stress Distribution: A Fast and Accurate Surrogate of Finite-Element Analysis," J. R. Soc. Interface, 15(138), pp. 20170844.

[2] Zhenguo Nie, Haoliang Jiang, Levent Burak Kara, "Stress Field Prediction in Cantilevered Structures Using Convolutional Neural Networks", J. Computer. Inf. Sci. Eng. Feb 2020.

[3] M. Atta, A, A, Abd-Elhady, A, Abu-Sinna, H.E.M. Sallam, "Prediction of failure stages for double lap joints using finite element analysis and artificial neural networks", Engineering Failure Analysis 97 (2019) 242-257.

[4] T.G. Ritto, F.A. Rochinha, "Digital twin, physics-based model, and machine learning applied to damage detection in structures", Mechanical Systems and Signal Processing 155 (2021) 107614.

[5] Yu, Y., Hur, T., and Jung, J., 2018, "Deep Learning for Topology Optimization Design," CoRR, abs/1801.05463.

[6] Wu, X., Ghaboussi, J., and GarrettJr, J., 1992, "Use of Neural Networks in Detection of Structural Damage," Comput. Struct., 42(4), pp. 649–659. 10.1016/0045-7949(92)90132-J.