Prediction of stress and strain field based on FEM analysis of cracked and non-cracked beam

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Abstract. Static and dynamic analysis of complex geometry is important to both the scientific community and industry. Based on various types of materials and loads, the stress and strain field on geometry could be different. Prediction of the stress and strain field using the input parameters, which define the geometry and material, can have a great impact on static and dynamic behavior. In this paper structural analysis of cracked and non-cracked beam is investigated. The bending analysis of the cantilever beam is considered by varying different parameters, such as length and height of the beam, force magnitude, number and position of the cracks, different types of materials etc. The results of stress and strain are obtained by FEM analysis and used as output for machine learning (ML) algorithm. Decision Tree (DT) and Random Forest (RF) are used as ML algorithms in which RF is evolved from the decision tree used as an ensemble approach, whereby the main goal is to use collection of trees for higher accuracy. Evaluation of the trained model has been done by mean absolute error and mean squared error. The workflow is divided into five steps: (a) acquisition of the data by FEM analysis, (b) feature engineering and data preprocessing, (c) training of ML algorithms, (d) evaluation and metric of trained model, (e) results and discussion.

Keywords: Structural analysis, cantilever, cracked beam, machine learning.

1 Introduction

Machine Learning algorithms have emerged as powerful tools in various scientific disciplines, revolutionizing the way we analyze and interpret complex data. In recent years, their application has extended to the field of stress and strain prediction, offering new avenues for accurate and efficient modeling in engineering and materials science.

Stress and strain are fundamental concepts in the study of structural mechanics and material behavior. Predicting and understanding the distribution of stress and strain within a given system is crucial for designing reliable and robust structures, optimizing material properties, and ensuring the safety and longevity of engineering applications. Traditional methods for stress and strain prediction have relied on analytical and numerical techniques, which often require simplifying assumptions and extensive computational resources.

In this context, Machine Learning algorithms have emerged as a promising approach to address the limitations of traditional methods. By harnessing the power of data-driven modeling, these algorithms can learn complex patterns and relationships directly from the available data, enabling accurate stress and strain predictions with improved computational efficiency.

The significance of employing Machine Learning algorithms for stress and strain prediction lies in their ability to handle high-dimensional data, capture nonlinear relationships, and adapt to complex systems. These algorithms can learn from historical data, detect hidden patterns, and generalize the learned knowledge to make predictions on unseen data. As a result, they have the potential to enhance our understanding of stress and strain distributions in a wide range of applications, including civil engineering, aerospace engineering, material science, and biomechanics.

By leveraging the strengths of Machine Learning algorithms, researchers and engineers can gain valuable insights into the behavior of structures and materials, optimize designs, and make informed decisions regarding material selection and structural integrity. Moreover, the development and application of accurate stress and strain prediction models can contribute to advancements in areas such as structural health monitoring, fatigue analysis, and predictive maintenance.

In this paper, we present a comprehensive study on stress and strain prediction using Machine Learning algorithms. Our research aims to address the limitations of traditional methods and demonstrates the potential of these algorithms in accurately predicting stress and strain distributions.

Within the scope of our study, we focus on the stress and strain analysis of a simply supported beam element. The behavior of a simply supported beam is of particular interest due to its wide range of applications in various engineering disciplines. Understanding the stress and strain distributions in a simply supported beam is essential for assessing its structural integrity and performance under different loading conditions. By applying Machine Learning algorithms to predict the stress and strain profiles in such beam elements, we aim to enhance the accuracy and efficiency of the analysis compared to traditional approaches.

2 Introduction

2.1 Traditional Methods for Stress and Strain Prediction

The prediction of stress and strain distributions in structural elements has been the subject of extensive research. Traditional methods, such as analytical and numerical techniques, have played a crucial role in this area. For instance, the static analysis of Euler-Bernoulli beams with multiple unilateral cracks under combined axial and transverse loads has been investigated in-depth [1]. Similarly, researchers have proposed a new approach for vibration analysis of cracked beams, exploring their dynamic behavior [2]. Additionally, the finite element method, as demonstrated in studies like the vibration analysis and control of cracked beams using Ansys [3], has provided valuable insights into the behavior of cracked structures.

2.2 Stress and Strain Prediction with Machine Learning Algorithms

Recent advancements in machine learning algorithms have paved the way for innovative approaches to stress and strain prediction. Researchers have begun to explore the potential of machine learning in this field, utilizing its capabilities to improve accuracy and computational efficiency. Notably, studies have demonstrated the application of machine learning algorithms in predicting stress intensity factors of reinforced concrete beams in bending [4]. Furthermore, the modal analysis of cracked cantilever beams using finite element simulation and machine learning techniques has been investigated [5].

2.3 Additional Studies in Stress and Strain Prediction with Machine Learning Algorithms

In addition to the aforementioned studies, several other notable research papers have contributed to the field of stress and strain prediction using machine learning algorithms. Prediction of residual stress induced by welding is studied in Mathew et al. [6]. This paper presents a comparative study of artificial neural networks and fuzzy neural networks, and it is shown that optimized neuro-fuzzy systems gave better results than neural network. Performance of the presented model is analyzed by using root mean square error (RMSE), absolute fraction of variance (R^2) and mean absolute percentage error (MAPE). Algorithms for prediction of deformation, stress and strain field in different complex materials, such as composite materials which contain fibers and lattice metamaterials are established in [7]. The presented model is trained to predict static instability, such as deformation and buckling. Tree-based algorithms are very popular based on their complexity, ensemble learning (Random Forest are ensembles of decision trees), nonlinearity (tree-based algorithms can capture nonlinear relations and interactions between features effectively), feature importance (can provide feature importance measures, indication the relative significance of input features in making predictions), handling missing data (can handle missing values in the dataset without requiring imputation techniques), etc. Based on the mentioned, Feng et al. [8] made ensemble learning algorithm to predict fatigue life of structures with stochastic parameters. The initial application of the extended finite element method (XFEM) involved generating a substantial quantity of datasets linked to structural responses and remaining fatigue life. Deep learning model, based on high-resolution Fast Fourier Transform-based finite element method (FFT-FE) and U-Net convolutional neural network (CNN), is used to capture stress response of additively manufactured metals structures [9]. Dataset consisting of 100,000 random microstructure images based on stress response.

By integrating the strengths of machine learning algorithms with stress and strain prediction, researchers have made significant strides in enhancing the accuracy and efficiency of structural analysis. However, further investigations are warranted to explore the full potential of machine learning in this domain. In the subsequent chapters, we present our methodology, results, and analysis of stress and strain prediction using machine learning algorithms.

3 Methodology

3.1 Dataset Description

In this study, we utilized a dataset obtained through numerical simulation using Finite Element Method (FEM) analysis. The dataset consists of 19,200 different stress and strain results. These results were generated by varying material properties, geometric parameters (such as length, width, and height), the number of cracks, and the depth of notches. Each combination of parameters yielded a unique stress and strain profile, providing a comprehensive dataset for training and evaluation purposes.

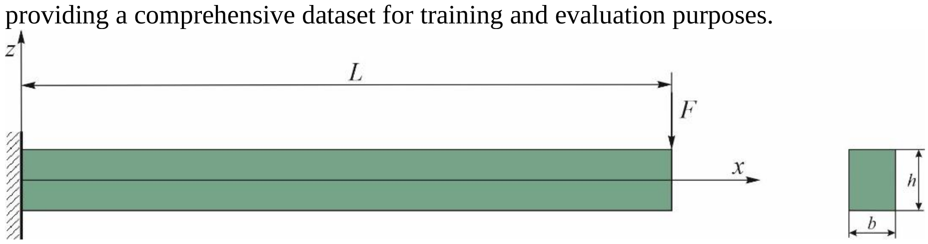

Fig. 1. Geometry of clamped-free beam model.

3.2 Machine Learning Algorithms: Decision Tree and Random Forest

To predict stress and strain distributions, we employed tree-based machine learning algorithms, specifically the decision tree and random forest algorithms. These algorithms are well-suited for regression tasks and are capable of capturing complex relationships between input features and output variables. The decision tree algorithm constructs a tree-like model of decisions and their possible consequences, while the random forest algorithm builds an ensemble of decision trees to improve predictive accuracy and reduce overfitting.

3.3 Preprocessing and Feature Engineering

Prior to training the machine learning models, the dataset underwent preprocessing and feature engineering steps. This included handling missing or erroneous data, normalizing or standardizing input features, and potentially applying dimensionality reduction techniques if necessary. Additionally, relevant features, such as material properties, geometric parameters, and crack characteristics, were selected and transformed to ensure compatibility with the machine learning algorithms.

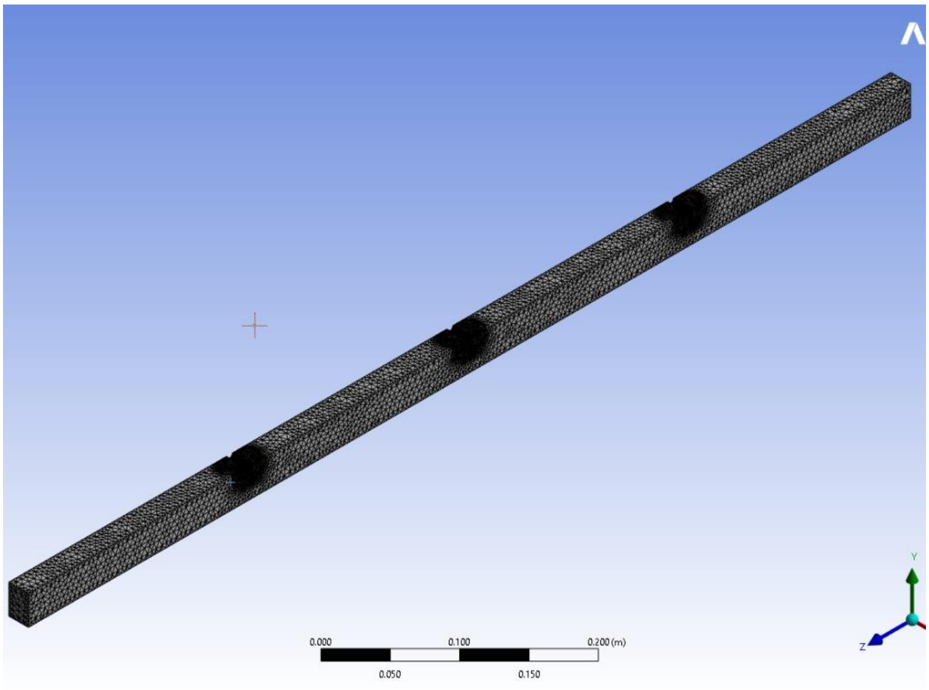

Fig. 2. Meshed model of cracked beam captured through the Ansys (FEM-based software).

3.4 Model Training and Evaluation

For model training, we employed a suitable strategy such as k-fold cross-validation to ensure robustness and minimize bias. The dataset was divided into training and validation subsets, and the decision tree and random forest models were trained using the training subset. During the training process, hyperparameters were tuned to optimize the models' performance.

To evaluate the predictive performance of the models, we utilized several metrics, including mean absolute error, mean squared error, and r2 score. These metrics allowed us to assess the accuracy and generalization ability of the trained models by comparing the predicted stress and strain values with the actual values obtained from the FEM analysis. Additionally, visualization techniques such as scatter plots and regression curves were used to analyze the model's predictions in relation to the ground truth values.

3.5 Experimental Setup and Computational Environment

The experiments were conducted on a high-performance computing cluster, utilizing specialized software libraries and tools for implementing the decision tree and random forest algorithms. The computational environment ensured efficient training and evaluation of the models, taking advantage of parallel computing capabilities to handle the large dataset and optimize the algorithmic performance.

By leveraging the power of decision tree and random forest algorithms, preprocessing techniques, and comprehensive evaluation metrics, we aimed to develop accurate stress and strain prediction models in this study. In the following chapter, we present the results of our experiments and a detailed analysis of the predicted stress and strain distributions.

4 Methodology

4.1 Analysis of Strain Field

In this chapter, we present the results of our analysis on the strain field prediction using the Decision Tree and Random Forest algorithms. The strain field provides crucial insights into the deformation and structural behavior of the analyzed system. By accurately predicting the strain distributions, we can gain a comprehensive understanding of the system's response under various conditions.

4.2 Performance Metrics

To evaluate the performance of the Decision Tree and Random Forest models, we utilized three key metrics: the coefficient of determination (R^2), mean absolute error (MAE), and mean squared error (MSE). These metrics provide quantitative measures of the models' predictive accuracy and reliability.

Table 1. Comparative results of tree-based algorithms

	Decision Tree	Random Forest
MAE	0.002757053	0.000219628
R^2 score	0.98429387	0.986197642
MSE	5.76e-07	5.06e-07

For the Decision Tree model, we obtained an R^2 score of 0.98429, indicating a high degree of correlation between the predicted strain values and the actual values obtained from the FEM analysis. The low MAE value of 0.000275 suggests that, on average, the predicted strain values deviated from the ground truth values by a very small magnitude. Furthermore, the MSE value of 5.76e-7 demonstrates the accuracy of the model by measuring the average squared difference between the predicted and actual strain values.

Similarly, the Random Forest model achieved excellent predictive performance. The obtained R^2 score of 0.986197 indicates a strong correlation between the predicted and actual strain values. The low MAE value of 0.000219 suggests that the predicted strain values closely matched the ground truth values. Additionally, the MSE value of 5.06e-7 further highlights the accuracy of the Random Forest model by measuring the average squared difference between the predicted and actual strain values.

4.3 Comparative Analysis

Based on the performance metrics (Table 1), we observe that both the Decision Tree and Random Forest models achieved remarkable predictive accuracy in capturing the strain field. The slightly higher R^2 score and lower MAE and MSE values obtained by the Random Forest model suggest its superior performance compared to the Decision Tree model.

The high R^2 score indicates that the models captured a significant portion of the variance in the strain field, highlighting their ability to learn and generalize complex patterns from the training data. The low MAE and MSE values demonstrate the models' ability to provide accurate predictions, with minimal deviation from the actual strain values.

4.4 Visualization and Interpretation

To gain further insights into the performance of the models and the predicted strain field, we conducted visual analyses of the results. Scatter plots comparing the predicted and actual strain values provide a visual representation of the model's accuracy.

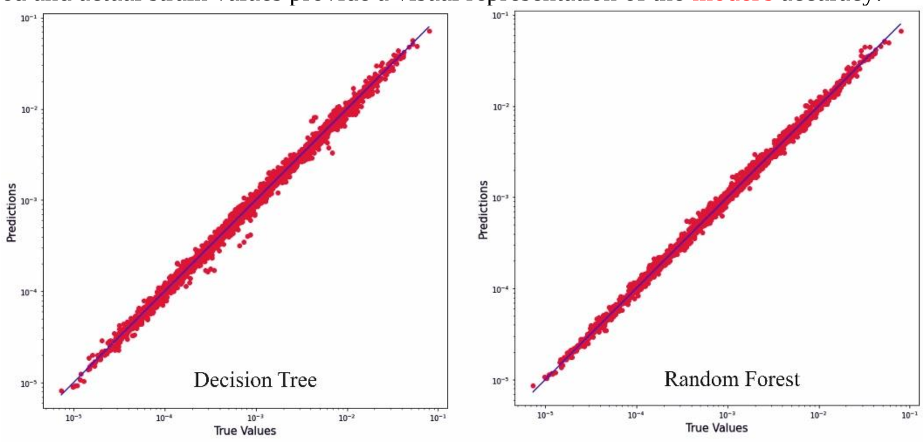

Fig. 3. Performance of trained model.

Through those visualizations, the presented model can predict accurately strain field, and it evident through the tight clustering of data points around diagonal line, indicating a strong positive correlation between the true and predicted values. The R^2 score of 0.98 further reinforces the accuracy of our model, indicating that 98% of the variance in the true values can be captured by the predicted values.

5 Discussion

The results of our study demonstrate the successful application of decision tree and random forest algorithms in predicting the strain field of the analyzed system. Both models exhibited high levels of accuracy, as indicated by the high r2 scores and low MAE and MSE values. The random forest model showcased superior performance compared to the decision tree model, emphasizing the benefits of ensemble learning and aggregation of multiple decision trees.

The accurate prediction of the strain field holds significant implications for engineering and materials science. It provides valuable insights into the structural behavior, deformation, and potential failure points of the analyzed system. By leveraging machine learning algorithms, we have improved the efficiency and accuracy of strain prediction compared to traditional methods, enabling engineers to optimize designs and make informed decisions regarding structural integrity.

The methodology employed in this study, combining FEM analysis, a comprehensive dataset, and tree-based machine learning algorithms, has proven effective in capturing the complex relationships between input features and strain distributions. The preprocessing and feature engineering steps ensured compatibility with the machine learning algorithms, while the evaluation metrics provided quantitative measures of the models' performance.

6 Conclusion

In conclusion, this research has presented a robust methodology for stress and strain prediction using decision tree and random forest algorithms. Through the analysis of the strain field, we have demonstrated the effectiveness of these machine learning techniques in accurately predicting strain distributions. The high-performance metrics achieved, including the r2 scores, MAE, and MSE values, validate the efficacy of the models in capturing strain patterns and providing reliable predictions.

The successful application of machine learning algorithms in stress and strain prediction opens new avenues for advanced structural analysis and design optimization. By harnessing the power of these algorithms, engineers can improve the understanding of system behavior, optimize designs, and ensure structural integrity. Furthermore, the methodology presented in this study can be extended to other engineering domains and materials, contributing to advancements in various fields.

While the results obtained are promising, further research is warranted to explore the full potential of machine learning algorithms in stress and strain prediction. Investigating alternative algorithms, incorporating additional features, and expanding the dataset can further enhance the accuracy and applicability of these models.

Overall, this study demonstrates the value of machine learning algorithms in stress and strain prediction, offering a promising avenue for future research and practical applications in engineering and materials science.

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