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Machine Learning-Assisted Thermo-Mechanical Stress Analysis of Steel IPE Beams Under Asymmetric Thermal Conditions

Himanshu Barhaiya
Department of Master Computer Application
LNCT Bhopal
MP India
himanshub@lnct.ac.in or hemansu008@gmail.com

***Abstract*—Proper prediction of thermally induced stresses in the structural members is still a major task in structural engineering, particularly in the complex real-life scenarios. The research paper introduces a machine-learning-based framework revealing the stress analysis of IPE steel beams based on data. The preprocessing of the Materials and their Mechanical Properties dataset was performed by the inspection of data, the treatment of missing values, the encoding of labels, Minmax normalization and class balancing with SMOTE. A Decision Tree (DT) model was created to predict stress behavior and measured it on the basis of R^2, MSE, RMSE and MAE. The advanced performance of the proposed DT model was 99.4, MSE of 0.0001, RMSE of 0.0114 and a MAE of 0.0073 which means that the model has a strong predictive ability and low deviation to the actual values of the stress. It was found that DT was more effective than Linear Regression and Neural Network models in predicting the two variables in general. The strength and stability of the proposed method was further proven by regression, performance, and residual analysis, which prove the current method to be effective in estimating thermo-mechanical stress in steel structural elements.**

Keywords—Thermo-mechanical stress prediction, Steel IPE beams, Structural engineering, Machine learning, Stress modeling, Structural health assessment.

I. INTRODUCTION

A lot of different businesses use composite parts, which are made up of at least two different materials with different properties. Composite components are often used in construction because they can be designed to maximize the qualities of both materials [1]. The end result is lighter components that require less effort and money to produce. Use of steel-concrete composites in the form of beams or columns is the most common and long-standing method in engineering [2]. Steel beams with either a simply supported or a cantilever design are subject to the same lateral buckling calculations as outlined in the relevant regulations [3]. However, cantilever beams' maximum displacement and buckling angle don't happen in the center of the span, but rather at the free ends, because of the distinct end support circumstances. The buckling modes that emerge from this scenario are distinct from one another [4]. This means that cantilever beams cannot be supported using the same techniques as basic support beams.

They considered the impact of loading positions and the profile section's slenderness in their investigation. Parametric, analytical, and numerical solutions all yielded the same findings. European IPE and IPN beams' lateral torsional buckling loads can be safely calculated using the above equation, allowing for safer design techniques. The shear deformation theory and finite element analysis of beams subjected to a uniformly distributed load [5] both produce bending results that are compatible with one another when applied to the top flange [6]. According to the claim, the validated finite element method allows for the realistic calculation of curvature, taper, and buckling along an I-section's length.

This solidification process happens in a lot of different production and fabrication processes, like foundry shape casting, continuous casting, and welding [7]. Continuous casting, which produces more than 90% of the world's steel, is among the most significant and intricate of these processes. Even though continuous-cast steel is getting better all the time, eliminating flaws and increasing output are perennial goals. Cracking issues are among the most significant faults that affect the continuous casting process. A common cause of cracking is a mismatch between the solidification shrinkage and the taper of the mould. This mismatch creates interfacial gaps and reduces the heat [8] flow between the shell and the mould, which in turn causes thin and hot spots on the shell. One typical issue with heat exchangers is stress corrosion cracking at the tube-to-sheet region of the weld [9]. It is necessary to calculate the thermo-mechanical stress [10] and welding effect [11] at tube-to-sheet junctions in this case in order to analyze failures [12]. Thermal stress [13][14][15][16], mechanical stress [17], and welding residual stress of tube to tube-sheet have all been extensively studied recently.

Steel constructions corroded [18][19] reduce a structure's load-bearing capability [20] due to changes in geometry on the surface of structural members caused by corrosion flaws. Corrosion and fatigue cracks reduce structural performance in civil engineering steel constructions [21]. Machine learning (ML) [22], a popular form of AI [23], can learn any input-output relationship to provide predictions [24]. In numerous engineering contexts, it has been used effectively to create such relationships. Among its many uses in Solid Mechanics are the prediction of material properties, the identification of cracks [25], the classification of damages, and additive manufacturing. The effectiveness of ML in anticipating the mechanical response of AM components has been proven in multiple experiments [26][27]. The capacity of deep learning [28] to automatically acquire numerous ideal properties during learning has made it a popular machine learning technique in recent years. Deep learning relies on multilayered neural networks [29].

A. Motivation and Contributions of the Study

The objective of the study is based on the necessity to enhance the prediction and design of composite steel-concrete members that are exposed to complicated loading, buckling, and deterioration influences. Traditional design procedures tend to be not sufficient in cantilever beam and the elements, which are affected by residual stress and corrosion, and flaws evoked in the manufacturing process. More precise and effective predictive methods are needed in order to come up with the safer, lighter, and more affordable structures. Machine learning and other data-intensive and superior analytical methods are investigated in this study to improve structural behaviour prediction and design integrity. The main contributions of the research are as discussed below:

- Used a huge Kaggle dataset of 1,552 engineering materials and six major mechanical properties to aid effective machine learning-based stress analysis.
- Applied a full preprocessing pipeline that comprised of inspection of the data, the missing values, encoding of labels, Min-Max feature scaling, and class balancing through SMOTE in order to increase the reliability and performance of the model.
- Used the SMOTE technique to mitigate critical imbalance in the Use variable that was very beneficial to the strength and equity of the predictive model process.
- Formulated and developed a Decision Tree model to predict stress in steel IPE beams, which demonstrated excellent results.
- Evaluated model performance based on multiple regression (R^2, MSE, RMSE, MAE) measures and regression, performance and residual plots to ascertain performance prediction and no systematic bias.

B. Justification and Novelty

Safety of structural design of steel components and efficient structural design depend on accurate stress prediction. Traditional methods of analysis and numerical modelling may be computationally expensive in terms of time and resources. Thus, the present study is warranted to choose the machine learning-based method in order to enhance the accuracy of prediction and decrease the amount of the computational efforts. The mentioned framework can be used to increase reliability and offer an effective instrument of estimating thermo-mechanical stress in steel IPE beams. The originality of the current research is combining high-quality data pre-processing, balancing using the SMOTE, and Decision Tree model to achieve accurate predictions of the stress in steel IPE beam. This approach, in contrast to the traditional analytical methods, integrates the data on material properties with machine learning, which leads to the high accuracy and computational efficiency, which proves to be superior to the traditional regression and neural network models.

C. Structure of the Paper

The study is organized as follows: In Section II, the related research on stress analysis of steel and engineering materials is reviewed. Section III outlines the proposed machine learning-based approach and model development of stress prediction of steel IPE beams. Section IV presents the results of the experiment, performance analysis and comparison. In Section V, the conclusion and future research directions are presented.

II. Literature Review

This review summarizes the current development in the stress analysis of steel and other engineering materials. Table I summarizes the methodologies, materials and modeling techniques utilized, important findings, limitations that have been identified as well as propose on future research in structural and material performance evaluation.

In Win, Soe, and Khaing (2025), the research aims to design the arms that can lift a maximum load of 1460 kg to a maximum height of 1800 mm. The thickness of the arm and maximum bending stress are calculated by using bending theory. In design calculation, the allowable stress of the arm is 132.5 N/mm2, the working stress is 115.73 N/mm2, and the maximum von-Mises stress is 115.74 N/mm2. Also, the effective strain is 5.021x10-4. To know the maximum von Mises stress of the arm for a two-post car lift, the static structural analysis is done by using the SolidWorks software 2024. When the theoretical and simulation results of the arm are compared, the deviation results of the arm are 3.6% for von Mises stress, 2.6% for deflection, and 11.96% for effective strain [30].

D. Ma et al. (2025) this paper conducts iron loss tests under multi-physics coupling on two kinds of silicon steel materials, high silicon steel 10JNEX900 (6.5% Si) and conventional silicon steel ST100 (3.0% Si), and analyzed the differential change rule of 10JNEX900 loss. The paper then uses this information to determine the iron loss of a silicon steel sheet and suggests a model for calculating the iron loss of a 10JNEX900 motor that takes into account factors related to multiple physics. At the same time, the permanent magnet synchronous motor's magnetic field, temperature field, and stress field were determined using the finite element approach. Also compared are the motor performance disparities both before and after the multi-physics field effects are taken into account. At last, the motor prototype is built and put through its paces. At no load, there is less than a 10% discrepancy between the projected and actual iron loss in the motor [31].

Z. Ma et al. (2025) investigated the strengthening and toughening mechanisms of 304 austenitic steel at different temperatures. The characteristics of gradient twin structure and gradient phase distribution resulting from pre-torsion under different temperatures were presented. The combination of twin and phase gradients leads to the strengthening and toughening in 304 austenitic steel in the subsequent tension. The number of twin structure gradually increases from core to edge and the number of twin types also increases: in the central region, the main type of twinning is primary twinning, and a large number of secondary twins are observed at the edge with a large shear strain of 0.52 [32].

Zhang, Li and Guo (2024) sugeested on the basis of normalization, a hierarchical clustering algorithm is employed to categorize the data, aggregating data with similar distribution characteristics. Subsequently, the t-SNE algorithm and polynomial regression assess cluster internal consistency, facilitating merging of similar clusters. Finally, mechanical property prediction models are constructed for each cluster to validate the method's effectiveness. The results indicate that after dividing the dataset according to the proposed method, the prediction accuracies of yield strength, tensile strength, and elongation have increased by 2.31%, 1.32%, and 2.28% respectively. This has certain reference value for the industrial application of mechanical property prediction technology [33].

Shen et al. (2023) The thermal elastoplastic finite element approach was suggested for numerically calculating the residual stress during butt welding of AH36 high-strength marine steel. The results showed distributions of residual stress in both the longitudinal and transverse directions of the weld region. The results of the study on the two-path ultrasonic stress release during welding reveal that the ratio of residual stress release during transverse welding is 40-70% and that during longitudinal welding it is 30-60% [34].

Yuerong, (2022) results indicate that high-rise steel frame structures primarily experience an increase in horizontal displacement and a notable rise in horizontal displacement above uneven floors when subjected to the second-order analytical approach. A high-rise steel frame structure's beam column joints experience a 2% increase in horizontal displacement under second-order analysis when compared to first-order. In high-rise steel buildings, the second-order analysis better represents the real-life stress scenario. When designing high-rise steel frame buildings, it is crucial to thoroughly account for the negative impacts of the second-order effect [35].

TABLE I. SUMMARY OF RECENT STUDIES ON STRESS ANALYSIS AND OF STEEL AND ENGINEERING MATERIALS

Authors (Year)	Research Objective	Methodology	Key Results	Contribution
Win, Soe & Khaing (2025)	Design and stress analysis of a two-post car lift arm for lifting 1460 kg at 1800 mm height	Bending theory calculations and static structural analysis using SolidWorks 2024	Close agreement between theoretical and simulation results; small deviations in stress, deflection, and strain	Validated structural design methodology combining analytical and FEA approaches
D. Ma et al. (2025)	Iron loss modeling of silicon steel under multi-physics coupling	Experimental iron loss tests and multi-physics finite element modeling (magnetic, thermal, stress fields)	Predicted iron loss closely matched experimental results (error <10%)	Developed accurate multi-physics iron loss prediction model for motor applications
Z. Ma et al. (2025)	Investigation of strengthening and toughening mechanisms in 304 austenitic steel	Experimental analysis under temperature-dependent pre-torsion with microstructural characterization	Gradient twin and phase distribution enhanced strength and toughness	Demonstrated microstructural gradient engineering for improved mechanical performance
Zhang, Li & Guo (2024)	Improvement of mechanical property prediction accuracy	Data normalization, hierarchical clustering, t-SNE, and polynomial regression	Improved prediction accuracy for yield strength, tensile strength, and elongation	Enhanced machine learning-based mechanical property prediction using clustering strategies
Shen et al. (2023)	Residual stress analysis in welded AH36 marine steel	Thermal elastoplastic finite element analysis and ultrasonic impact assessment	Significant residual stress reduction (30–70%) depending on weld direction	Provided insights into residual stress control in marine steel welding
Yuerong (2022)	Evaluation of second-order effects in high-rise steel frame structures	Structural second-order numerical analysis	Increased horizontal displacement under second-order effects; more realistic stress estimation	Highlighted importance of second-order analysis in high-rise steel structure design

Research Gaps: Past research has used structural analysis, material strengthening, residual stress, and ML-based prediction individually, yet has not combined assessment of mechanical behaviour and advanced ML-based modeling. The interface of structural response, material properties and intelligent prediction methodologies is still not greatly exploited. Hence, it requires one common paradigm that incorporates analytical, simulation, and machine learning algorithms to enhance the accuracy of the predictions and their viability.

III. METHODOLOGY

The specified methodology starts with the Materials and their Mechanical Properties dataset on Kaggle, then, goes on to systematic preprocessing of data consisting of data inspection, handing of missing values, category variables labeling, and feature scaling through MinMax normalization. In order to deal with the imbalance in classes, data balancing using Synthetic Minority Over-sampling Technique (SMOTE) is used. A Decision Tree classification model is then generated using the processed data and the model performance is measured using the classic data modeling measures like R^2, MSE, RMSE and MAE. The analysis of the final results and their interpretation are the end of the workflow. The workflow chart of the study is presented in Fig. 1.

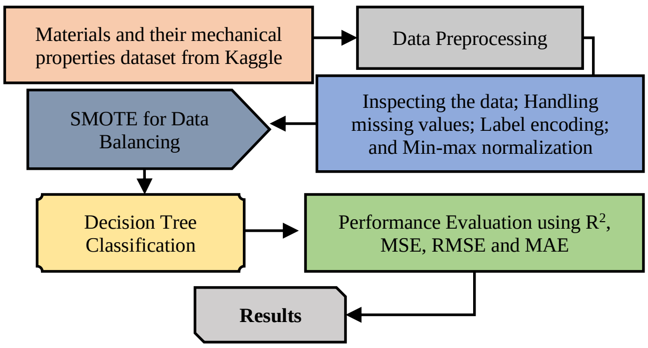

Fig. 1. Proposed Methodology of Stress Analysis of Steel IPE Beams.

The steps of the proposed methodology are explained below.

A. Dataset Collection

This study leveraged the Materials and their Mechanical Properties dataset[1]. There are 1,552 engineering materials

[1] https://www.kaggle.com/datasets/purushottamnawale/materials

with important mechanical properties included in the Kaggle data. These include density, Poison ratio, shear modulus, elastic modulus, yield strength, and tensile strength. The dataset is of the approximate shape (1552, 6), which is adequate to analyze material properties and machine learning in materials engineering. The following are the data visualizations:

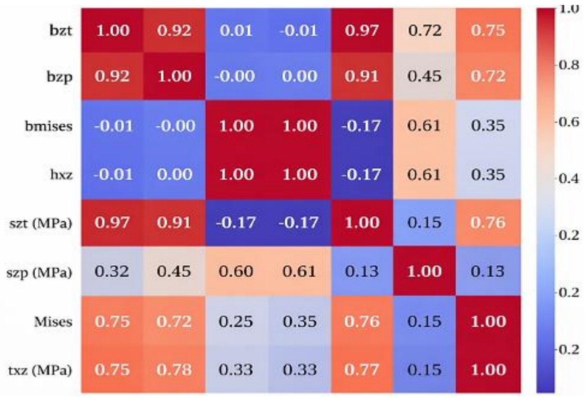

Fig. 2. Correlation Heatmap.

The heatmap of correlation among stress parameters provided in Fig. 2 indicates that stress parameters bzt, bzp, and szt are strongly correlated with each other, and bmises and bxz with Mises and txz. The rest of the variables show moderate to weak correlations, and there are some few negative relationships.

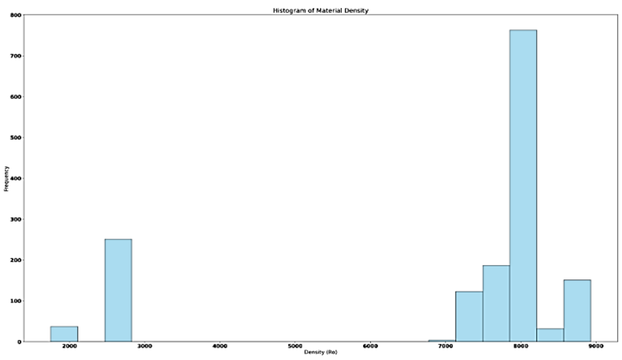

Fig. 3. Material Density.

The distribution of the material density is presented in Fig. 3 where most values fall in the high-density zone (approximately 7000-8000 kg/m3) with a smaller group of those who are less dense, which represents a skewed distribution of density towards the higher density materials.

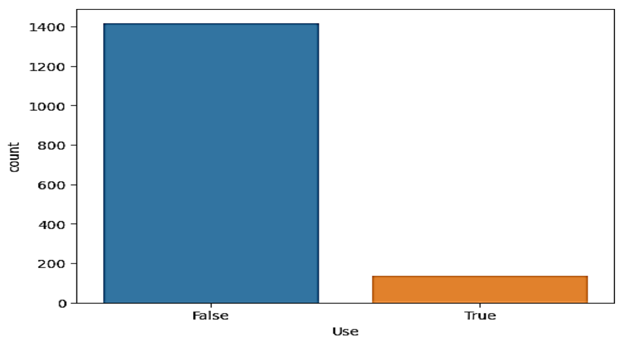

Fig. 4. Imbalanced Class Distribution.

Fig. 4 shows the distribution of the count of the variable Use which has a strong imbalance between the classes. Most of the samples are referred to as False and the percentage of those attributed to True is very low, meaning that the data is highly skewed towards the False category.

B. Data Preprocessing

Pre-processing of data is a normal procedure that is required to ready the dataset to be subjected to analysis and machine learning. In this study, they usually comprise:

- **Inspection of the dataset:** This is done by ensuring that there are no missing, duplicate or inconsistent values in the data and rectifying the data to provide credible input.
- **Handling missing values or inconsistencies:** To avoid errors in training, missing values, e.g. to fill gaps or to drop rows/columns with issues.
- **Label Encoding:** A Machine Learning data preprocessing method is called Label Encoding and is used to transform categorical values into numerical labels. The transformation of the categorical fields into an appropriate numeric format to ensure that machine learning models able to understand them.
- **Feature Scaling:** Scaling of features is done by min-max normalization. This equalizes the numerical scopes of features such that the models are not prejudiced by varied magnitudes. In Equation (1), the scaling of the features is as follows:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where X is the initial value, X_{min} is the lowest value of the feature, X_{max} is the highest value of the feature, and X_{norm} is the normalised value (spanning 0 to 1).

C. SMOTE for Balancing the Dataset

Machine learning systems often fail to classify data that isn't balanced. An imbalance of class can be addressed in several ways. Generating synthetic samples of the minority class is possible using the Synthetic Minority Over-sampling Technique (SMOTE). It is widely used in many applications and usually performs better than simple oversampling. Equation (2) shows how the SMOTE approach creates a synthetic sample by applying a linear combination to two minority class samples (X_i and X_j):

$$X_{new} = X_i + \left(X_j - X_i\right) * \alpha \quad (2)$$

A random sample X_i is chosen for the new minority class artificial instance X_{new}. After then, X_j is picked at random from the five minority class neighbours of X_i that are closest to it, using the distance between them as a measure. The value of the parameter α can be any random integer between 0 and 1. Fig. 4 shows the balanced graph.

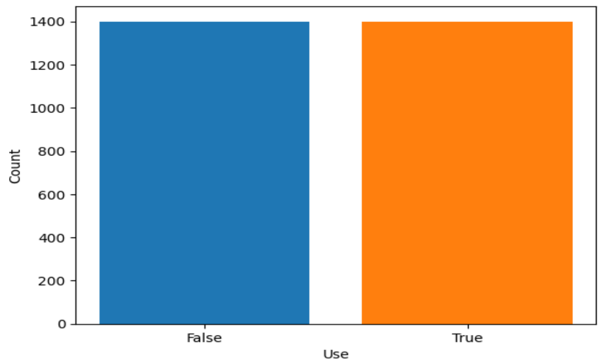

Fig. 5. Balanced Class Distribution.

Fig. 5 shows the balanced balance of the number of classes of the use variable upon implementation of SMOTE. The numbers of False and True classes are almost similar which means that the problem of imbalance in the data set has been resolved successfully. This uniform distribution provides better training to the model and minimizes bias to the majority class and improves classification.

D. *Model Implementation: Decision Tree*

The Decision Tree (DT) method is a supervised machine learning strategy that may be applied to both continuous and non-continuous output value classifications and regressions. The method's name comes from the fact that it resembles a tree, with the class labels acting as the leaves and the features or conditions as the branches [36]. The DT method's strength is in how easy it is to grasp, comprehend, and visualize. The Decision Tree can also be enhanced with the addition of decision-making techniques. Using this strategy, datasets with highly nonlinear relationships between input variables and output can also be modelled. Its inability to categorize numerous output types and susceptibility to overfitting are downsides that should be considered. It is possible to employ a variety of discriminant measures for attribute splitting in practice. The Gini index and entropy are the most fundamental, but other tools like variance reduction and the Chi-squared test are also at disposal. One of the initial metrics utilized in binary trees (CART) was the Gini index, which is also called the Gini impurity. Equation (3) provides its formula:

$$G(v_i) = 1 - \sum_{j=1}^{k} p_j^2 \quad (3)$$

Where:

The potential values of categorical attributes are represented by v_i, the number of data points classified for each v_i value is j, and the fraction of data points holding each v_i value is p_j. Reducing Gini impurity should be the splitting condition.

IV. Performance Evaluation and Results Discussion

The Python framework for simulations was built with the help of many machine learning libraries: SHAP, Seaborn, NumPy, Scikit-learn, Pandas, TensorFlow 2.0, and Matplotlib. The hardware that was used included an Intel i9 11900K processor, 128 GB of RAM, and an Nvidia 1080 11G graphics processing unit.

A. *Performance Evaluation*

In ML, model evaluation is required to obtain a measure of the agreement between predictions and actual results. Four measures, R^2, MAE, RMSE, and MSE, were used to measure regression performance in this research.

A high R^2 value indicates that the regression model provided a good fit to the data. R^2 is a measure of how well the model fits the data; values between 0 and 1 indicate a good fit. When the R^2 score is 1, it signifies that the model accurately predicts the response data, whereas a value of 0 shows **R^2:** that the model does not explain any of the variability around the mean. Equation (4) mentions the formula for R^2:

$$R^2 = 1 - \frac{\sum_1^n (y - y_1)^2}{\sum_1^n (y_{mean} - y_1)^2} \quad (4)$$

MSE: Mean squared error (MSE) quantifies the typical squared discrepancy between actual and anticipated values. In the context of Real Estate Prices prediction, if y_i represents the actual price at the time i and y_i^p represents the predicted price at time, then the MSE is calculated in following Equation (5):

$$MSE = \frac{1}{n} \sum_1^n (y - y_1)^2 \quad (5)$$

RMSE: The root-mean-squared error (RMSE) measures the degree to which the model's predictions differ from the actual scores. Effectiveness of the model is enhanced when the RMSE is reduced. Calculating root-mean-square error is illustrated in Equation (6):

$$RMSE = \sqrt{\frac{1}{n} \sum_1^n (y - y_1)^2} \quad (6)$$

MAE: The mean absolute error (MAE) is a popular statistic for gauging a prediction model's precision. Without taking the direction of the errors into account, it calculates the average magnitude of the predictions. A lower MAE number indicates that the performance is better. Equation (7) provides the formula for calculating MAE:

$$MAE = \frac{1}{n} \sum_1^n |y - y_1| \quad (7)$$

B. *Result Analysis*

As demonstrated in Table II, the Decision Tree model has an extremely high accuracy in predicting the stress in steel IPE beams with an R^2 of 99.41% and very small values of error (MSE = 0.0001, RMSE = 0.0114, MAE = 0.0073). These findings demonstrate good predictive accuracy and little departure of the real stress values.

TABLE II. Model Performance on Stress Analysis of Steel IPE Beams

Parameters	Decision Tree
R^2	99.4
MSE	0.0001
RMSE	0.0114
MAE	0.0073

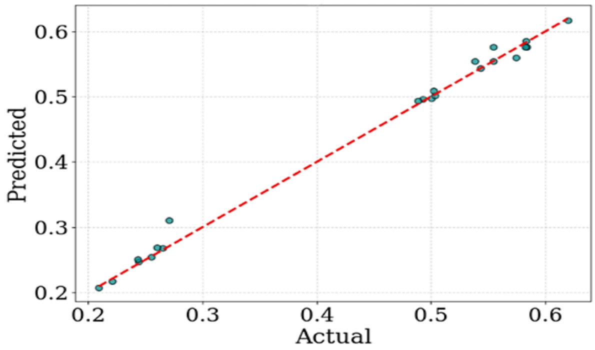

Fig. 6. Regression Plot of DT Model.

Fig. 6 compares the actual and the predicted stress values and indicates that the value of the two are highly linear. The model's predictions are in good agreement with reality, and the results are quite near to the 45-degree line of reference, thus it's safe to say that the prediction is accurate.

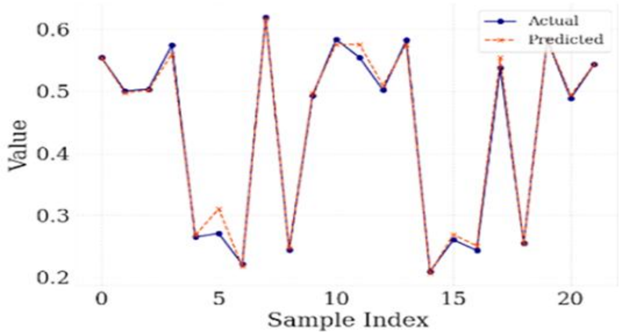

Fig. 7. Performance Plot of DT Model: Actual vs. Predicted Values.

The difference between the expected and measured stress levels at different sample indices is illustrated in Fig. 7. The anticipated curve is very much aligned with the actual data across the dataset and this indicates high level of agreements and also proves that the model is very accurate and stable in its ability to attain stress variation.

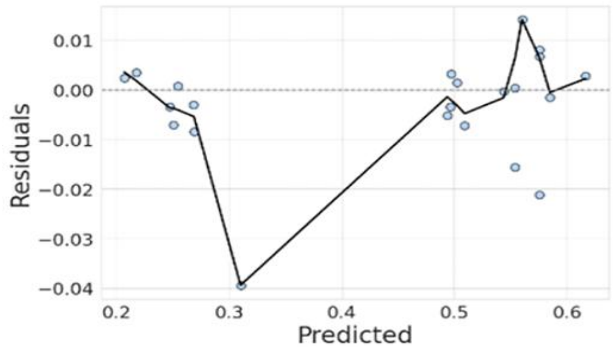

Fig. 8. Residuals vs Predicted values.

Fig. 8 illustrates the distribution of residuals with respect to the predicted values. The residual values are low and are randomly distributed on the 0 reference line, showing little prediction error and significant data are not concentrated in one direction as to cause systematic bias in the stress values.

C. Comparative Evaluation

A comparative assessment of various models used to analyze stress of steel IPE beams is provided in Table III. Decision Tree (DT) model is better than Linear Regression (LR) and Neural Network (NN) because it has the highest R^2 (99.4) and lowest values of the error (MSE = 0.0001, MAE = 0.0073). Although LR correlates well (99.0%), it exhibits very large values of the error, and NN has relatively lower levels of accuracy.

TABLE III. COMPARATIVE EVALUATION ON STRESS ANALYSIS OF STEEL IPE BEAMS

Models	R^2	MSE	MAE
LR [37]	99.0	15.03	32.30
NN [38]	92.8	3.03	98.0
DT	99.4	0.0001	0.0073

D. Discussion

The findings have shown that the Decision Tree model offers stress prediction which is both very accurate and reliable when predicting the stress of steel IPE beams. The regression and performance plots verify a high level of coincidence between the actual and predicted values, and the deviation and the usual tracking of all the samples is low. The residual analysis also shows that there is no systematic bias which portrays the strength of the model. Decision Tree model shows a better predictive outcome than Linear Regression and Neural Network, thus, it is the best model to use in the estimation of thermo-mechanical stress in thermo-mechanical stress estimation in the present study.

V. CONCLUSION AND FUTURE WORK

In Stress Analysis of Steel IPE Beams Using Machine Learning Techniques an analytical framework using machine learning is given to successfully anticipate thermo-mechanical stress behavior in structural steel wastes. The paper used the Materials and their Mechanical Properties dataset and employed the steps of systematic preprocessing, such as data cleaning, label encoding, MinMax normalization, and SMOTE-based class balancing to improve the quality of the dataset. The regression performance measures were used to implement and evaluate a Decision Tree model. The model proposed gave high performance with R^2 value of 99.4, MSE value of 0.0001, RMSE value of 0.0114 and MAE value of 0.0073 depicting a very high accuracy and a very small prediction error. A comparative study proved that Decision Tree was better in predictive performance and stability than Linear Regression and Neural Network models. The residual and regression plots also confirmed that there was no systematic bias in the strong agreement of the actual and predicted values. The suggested method offers a correct, dependable and computationally effective solution to stress estimation of steel IPE beams, which are employed in the state-of-the-art structural assessment and smart engineering design procedures.

The recommendations on how to proceed with work in the future will be to extend the dataset with real-time experimental measurements of stress and introduce other structural parameters to improve the generalization of the model. Further ensemble and deep learning methods can be further developed to achieve better predictive robustness. It is also advisable to be integrated with finite element simulations and structural measurements in the real world.

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