Predicting Deflections in Beams using Machine Learning Algorithms[1]

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ABSTRACT

Prediction of deflections in structures is imperative for safety and stability. Classical approach and numerical solutions are currently being employed to predict the deflections of beams. However, the results from these approaches varies when compared to tests. But testing is time consuming and expensive. During the initial design stages, designers would like to quickly perform various design iterations. In order to get a quick and accurate prediction, Machine Learning models are used. In this study, regression algorithms like linear, Lasso and Ridge are used to predict the deflections in three different beams: cantilever, clamped-clamped and overhang. The database for training the algorithm is generated using the principle of superposition of forces. Around 100 datasets were generated for each type of beams in excel. Python Scikit Learn library is used to train and test the regression algorithm. The root mean square error (RMSE) for the three types of beams is nearly zero. Hence, the linear regression model resulted in high accuracy predictions. This study proposed an effective model that is cheap, accurate and efficient, to help designers predict deflections at an early stage of the design.

Keywords: *Deflection; beams; Superposition of forces; Machine learning; regression.*

INTRODUCTION

Safety of a structure depends on many parameters like strength, stiffness etc. In structures like bridges and wing of an aircraft, deflection is an important parameter for safety, stability, integrity and performance [1]. Hence, estimating the deflections of a structure is one of the important criteria in any structural design. Deflection of a structure under any load circumstance is estimated using the classical method for simple determinate structures and numerical solution for complex structures.

Structural engineering problems are solved using both classical analytical approach (Mechanics of solids) and numerical solutions approach. In Mechanics of Solids approach, the principle of superposition of forces method is used when forces are applied at different locations [2]. This approach becomes complicated when forces act on the entire surface. For example, on an aircraft wing, load is applied all over the wing's top and bottom surface. Calculating deflection of such a structure using the superposition method becomes further complicated. Hence, Finite Element Method (FEM) is used to solve such complex structural problems. But the results from analytical and FEM approach varies when compared to test results. This is due to the assumptions and mesh sensitivity while developing the analytical and FE methods. Besides, test specimens also bring in ambiguities like rigidity of boundary conditions, test specimen variance and human error. Industry wide accepted variance between test and FE results was approximately 10-15% [3, 4].

Tests are time consuming and expensive. The developments in technology, especially, machine learning (ML), can help in addressing these issues in early design stages. Designers can perform different design iterations during

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the initial phase using machine learning techniques. The trials would otherwise be practically difficult using conventional design techniques.

ML has been used as an alternative tool in predicting the behaviour of structural elements. Papers [5, 6] present the application of artificial neural network to predict bending moments in continuous beams. Neural networks have been used for prediction of deflection in steel-concrete composite bridges [7]. Linear regression and neural network are used to predict deflection of concrete deep beams [8]. Neural network is used to predict the deflections of reinforced concrete beams using experimental data [9]. Various machine learning tools like support vector machine, decision tree and linear regression are used to predict long term deflections in reinforced concrete flexural structures [10]. These papers used extensive data from experimental tests for their prediction algorithm. Machine learning techniques can help reduce the dependence on tests.

In this context, a study has been carried out using the Machine Learning (ML) algorithm to predict the deflection of the structure. The deflections of a beam for cantilever, clamped-clamped and overhang boundary conditions are calculated using the method of superposition of forces. Concentrated loads, at 30 different locations on the cantilever beam and 27 locations on clamped-clamped and overhang beam, are used to generate the dataset. Around 100 different load combinations are generated and deflections at the tip for cantilever beam, at the centre for clamped-clamped beam, and at the tip of overhang beam was calculated using superposition of forces method.

The deflections were varied by 10% using random error in Python. This was done to artificially introduce the variance obtained during experiments. Deflections are continuous data hence regression algorithms like multiple linear regression, Lasso regression and Ridge regression are used for predictions. The predicted deflections are also within the 10% variance.

MATERIALS AND METHODS

According to Arthur Samuel, Machine Learning (ML) is a field of study that gives computers the ability to learn without being explicitly programmed [11]. ML uses statistics and algorithms to predict the unknown data [12]. Statistical models in ML algorithms utilizes input data to train its model for predictions. ML tasks are categorised into supervised, unsupervised and reinforced learning [13]. Supervised learning is a type of algorithm which learns patterns in the data and builds rules to map input to the output [14]. Supervised algorithms are mainly of two types, regression and classification problems. When the predicting value is a continuous data, Regression method is used.

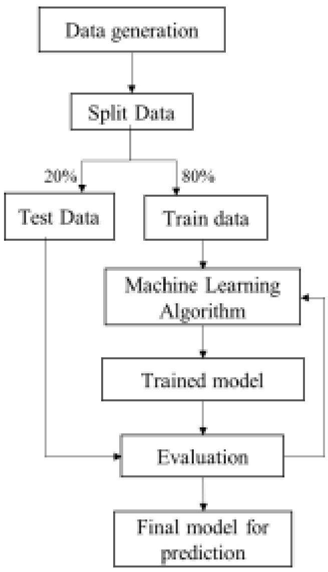

Figure 1. Flowchart for training and evaluation in machine learning

Any supervised learning model has three stages namely, training, testing and prediction. Training is a process in which the input data along with the output data is fed to the algorithm. The algorithm learns the patterns in the input data for each output data and generates a mathematical model. The test dataset (which was not used for training) is used to evaluate the model. This phase is called the testing phase. The last phase is the prediction where the trained model is used to predict output for a dataset which was neither used for training nor testing. Figure 1 presents the process of training and evaluation in machine learning models.

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SUPER POSITION OF FORCES

The first step in developing a ML model is the data generation. In the present study, the classical approach of superposition of forces is used to generate the data. A force acting on a structure changes its shape and size. The structure is said to be elastic in nature when it returns to its original shape on removing the force acting on it. Such elastic structures obey Hooke's law. Hooke's law states that deformation is proportional to the applied force within the elastic limit.

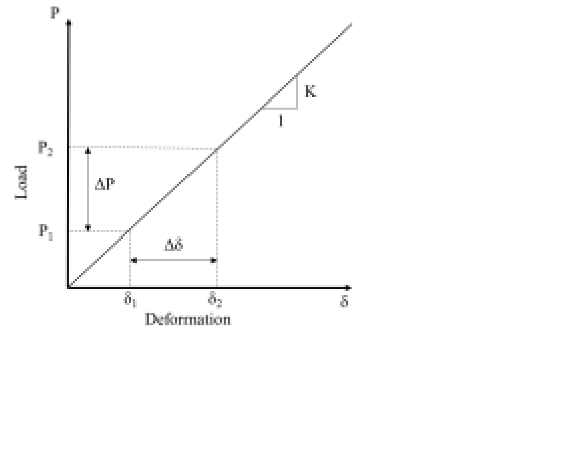	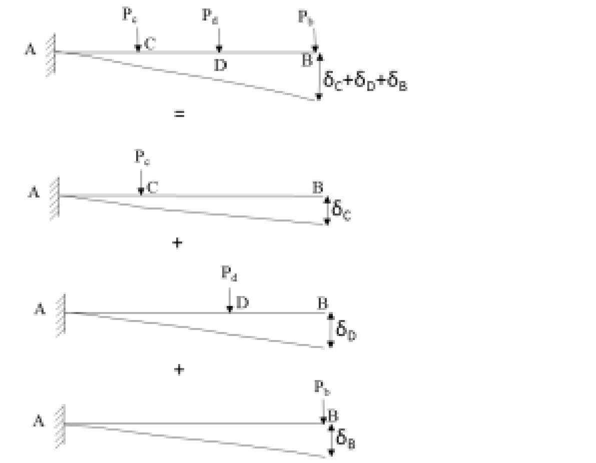
Figure 2. Load Deformation Curve	Figure 3. Superposition of Forces in a Cantilever Beam

Mathematically, Hooke's law is defined as

$$P = K.\delta \tag{1}$$

Where k is proportionality constant called the stiffness of the structure which depends on the material of the structure. The load deformation curve of any elastic structure is as shown in Figure 2.

For an initial load of P_1 on the structure, we have $P_1 = K.\delta_1$. Now if we apply ΔP load on top of P_1 the final load deformation equation is,

$$P_1 + \Delta P = K.\ \delta_1 + K.\ \Delta\delta$$

$$= K\ (\ \delta_1 + \Delta\delta) \tag{2}$$

But from Figure 2, $P_2 = P_1 + \Delta P$ and $\delta_2 = \delta_1 + \Delta\delta$, thus we have: $P_2 = K.\ \delta_2$ (3)

Thus, the deformation caused by a load can be added to the deformation caused by another load to get the net deformation due to both the loads acting simultaneously. This is called the principle of superposition. Thus, for a linearly elastic structure, the load effects caused by two or more loadings are the sum of the load effects caused by each loading independently as illustrated in Figure 3.

DATA ACQUISITION

For the present study, an aluminium beam of length 100mm, width 10mm and 6mm thick is taken. The beam is divided into 20 rectangular grids. A concentrated load is applied at the grid junctions of 30 points in cantilever beam as shown in Figure 4 and 27 points in clamped-clamped and overhang beam.

100 different load combinations are considered for each beam (cantilever, clamped-clamped and overhang). Only downward (positive) loads are used in various combinations to generate the data sets as shown in Figure 5. The deflections are calculated at the points where the deflections are maximum. The deflections are calculated at the tip of the beam for cantilever and overhang beams. For clamped-clamped beams the deflections are calculated at the centre of the beam. The dataset for three boundary condition of beam was generated in excel using the principle of superposition of forces. The deflection formula for the beams is shown in Table 1.

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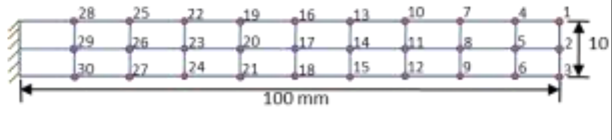


Figure 4. Load Points in the Beam

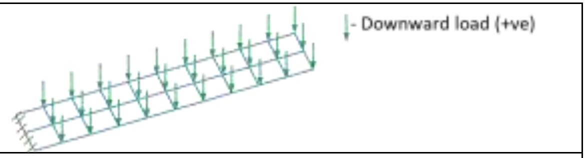
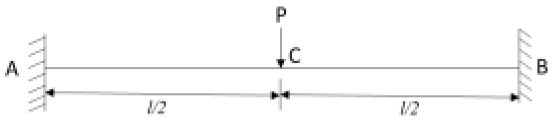


Figure 5. Typical Loading Directions in the Beam

Table 1. Deflections in beams

Boundary conditions in Beams		Deflection
Cantilever (deflection at tip)		$\delta_B = \frac{Pl^3}{3EI}$
Clamped – clamped (deflection at centre)		$\delta_C = \frac{Pl^3}{192EI}$
Overhang (deflection at overhang tip)		$\delta_B = \frac{Pa^2(l+a)}{3EI}$

METHOD OF LEAST SQUARES

As the load and deflections are linearly varying, regression techniques are used to develop the ML model. Regression is a statistical approach dealing with modelling the relationship between variables. Simple linear regression is used to evaluate the relationship between two variables. Mathematically, it is expressed as:

$$y = \beta_0 + \beta_1 x \quad (4)$$

where, y is the dependent variable, x is the independent variable, β_0 is the intercept and β_1 is the slope or the regression coefficient. Simple linear regression finds the line of best fit through the data by searching for the regression coefficient (β_1) that minimizes the total error in the model.

The least-squares method is one of the most effective ways used to draw the line of best fit. It's called "least squares" because the best line of fit is one that minimizes the variance (the sum of the squares of the errors). Figure 6, shows the graphical representation of the line of best fit. The line of best fit should be such that it reduces the error in prediction.

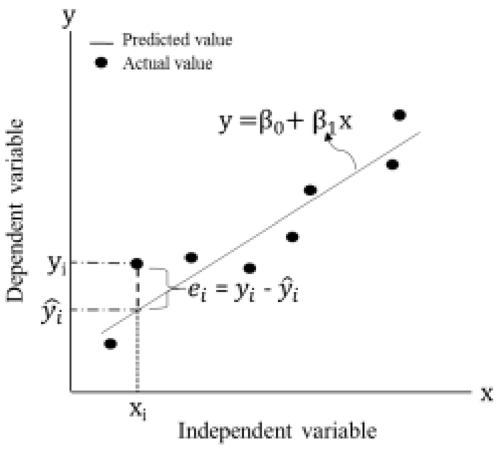


Figure 6. Linear Regression Model

ERROR METRICS

The accuracy of a regression model is reported as an error in the predictions. The error shows how close the predictions are to the expected values. Of the many error metrics available to evaluate the performance of a regression model, Root Mean Squared Error (RMSE) is widely used, as the units of error are the same as the that of predicted and actual values. It is calculated as:

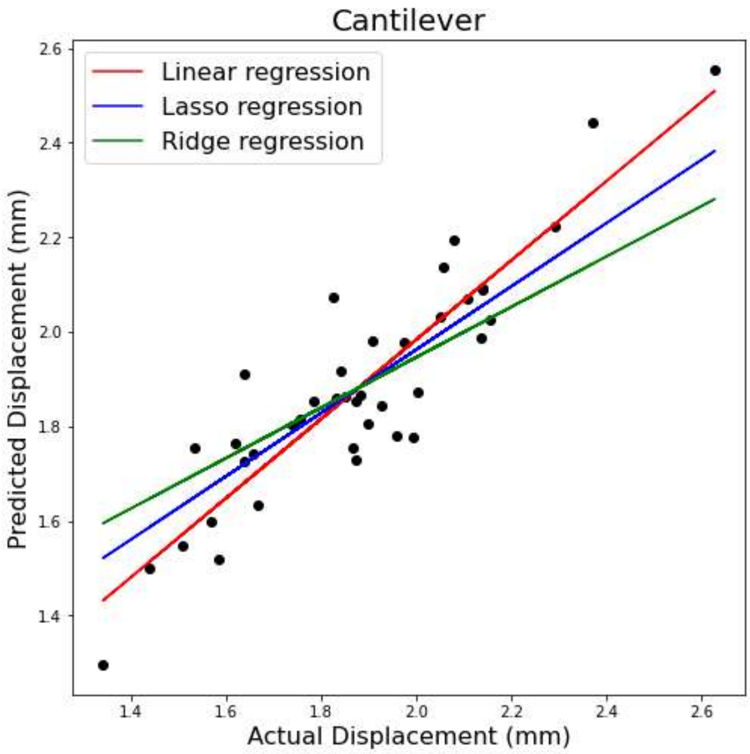
$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \qquad (5)$$

Where, y_i is the actual value and $\hat{y}_i$ is the predicted value. A perfect RMSE value is 0.0, which means that all predictions matched the actual values exactly. But this is never the case. A good RMSE is relative to the specific dataset. For a good model, the RMSE value is expected to be low.

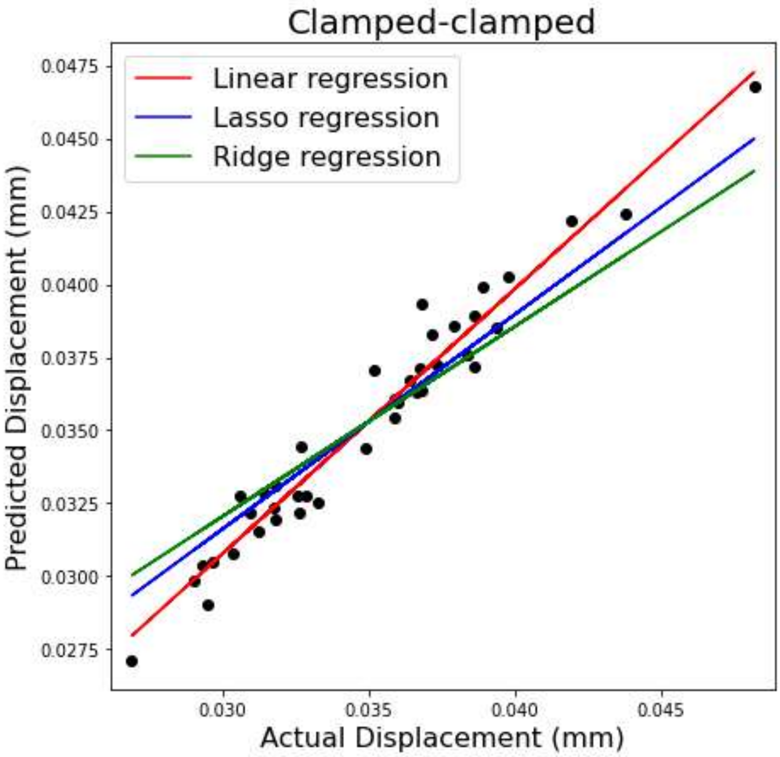
Jupyter Notebook and python was used to generate the model. Python libraries like Pandas, NumPy, Matplotlib were used to implement the model. Python Scikit Learn Library was used to train and test the data. Three different regression techniques like Linear, Lasso and Ridge Regression was used. Testing was done using train test split technique. Generally, 80: 20 split percentage of dataset is used in most models. 80% of the data generated was used to train and the remaining 20% of the data was used to test the model. The performance of ML model verified by the error metrics as shown in below section.

RESULT AND DISCUSSIONS

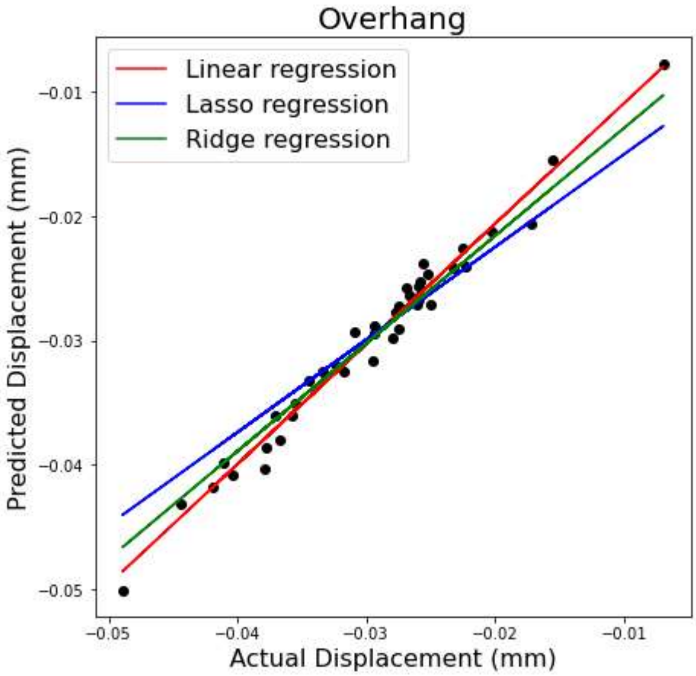
The performance of machine learning models is shown as a parity plot. The parity plot (Figure 7) showed a satisfactory correlation between the actual and predicted values of displacement. The actual displacement points cluster around the diagonal line which indicates the optimal fit of the model, since the deviation between the actual and predicted values was less.



a) Parity plot for Cantilever Beam



b) Parity plot for Clamped – Clamped Beam



c) Parity plot for Overhang Beam

Figure 7. Performance of ML prediction model

Both the clamped-clamped and overhang beam have a rigid boundary condition compared to the cantilever beam, hence the deflections are less. Thus, it can be seen from the parity plots, the data points were closely clustered in the clamped-clamped and overhang beams in spite of the 10% variance in the data. All the three regression methods used had very good correlation to the actual test value. But the RMSE value for linear regression is much lower compared to other regression technique.

The root mean squared error between the actual and predicted values can be calculated using the mean_squared_error() function from the scikit-learn library. The RMSE value for the linear regression model

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is given in Table 2. The RMSE value is always between 0 and 1. The closer the RMSE value is to 0, the stronger the model is and the better it predicts the response.

Table 2. Error metrics of the ML Prediction model

Type of Beam	RMSE value
Cantilever	0.1099
Clamped - Clamped	0.0010
Overhang	0.0012

MODEL VALIDATION

The model is validated now with a completely new set of data. The model was trained and tested with only downward loads of different values. But the model is validated for different set of load cases, which has a combination of downward and upward loads as given in Figure 8. Table 3 gives the validation results for three sets of load cases for each of the three beams. The actual deflection given in Table 3 is calculated value using superposition method and without any error variance. The predicted result is from the linear regression model. The predicted deflections are within the 10% variance used in training the model. Thus, the ML model was able to predict the deflections for each of the three boundary conditions of the beam.

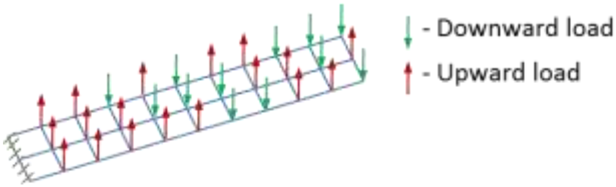
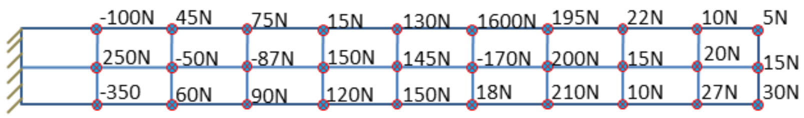
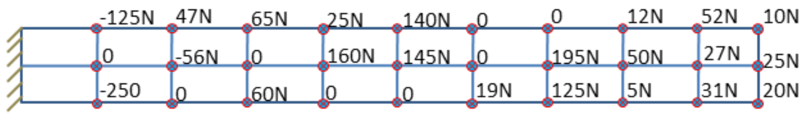
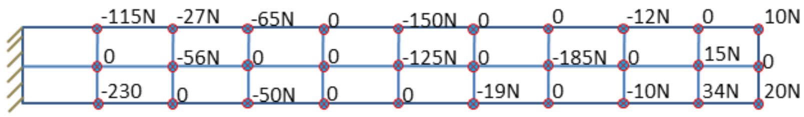
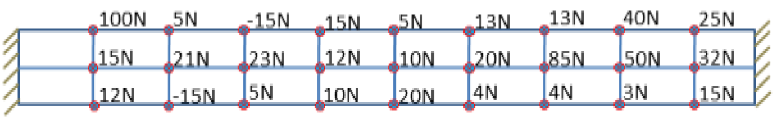
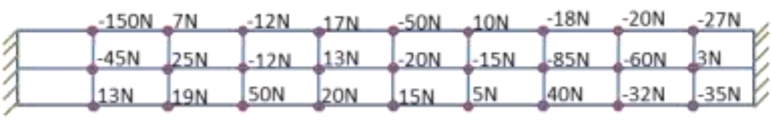
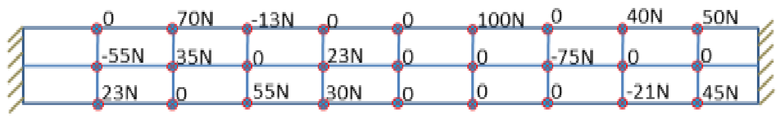


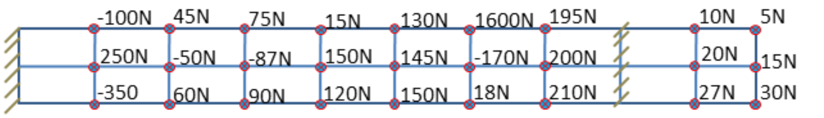
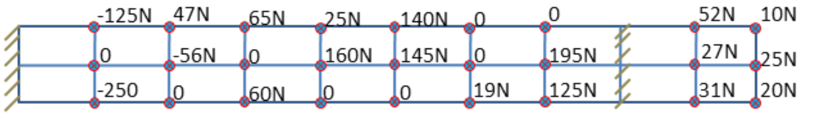
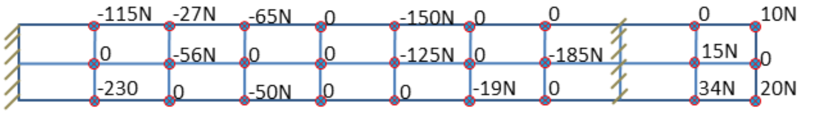
Figure 8. Loading directions for Validating the model.

Table 3. Validation Results for the Beams

Sl. No.	Validation for Cantilever Beam With various load combinations	Actual deflection (mm)	Predicted deflection (mm)
1.		13.873	12.485
2.		-1.270	-1.333
3.		-11.392	-10.822

Sl. No.	Validation for Clamped-Clamped Beam With various load combinations	Actual deflection (mm)	Predicted deflection (mm)
1.		0.097	0.106
2.		-0.033	-0.031

3.		0.069	0.074

Sl. No.	Validation for Overhang Beam With various load combinations	Actual deflection (mm)	Predicted deflection (mm)
1.		-1.411	-1.368
2.		-0.294	-0.317
3.		0.473	0.425

CONCLUSION

A study to utilize machine learning for predicting deflections in structures having three different boundary conditions was conducted. The machine learning model could predict the deflections with good accuracy. RMSE value using linear regression model for cantilever beam is 0.1099, clamped-clamped beam is 0.0010 and overhang beam is 0.0012. This study can be used in preliminary deflection estimation of structures like aircraft, bridges etc. Thus, an effective model to help designers in predicting deflection at an early stage of design was developed. It can be extended in future to beams of varying thickness, material and boundary conditions.

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