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Reinforced Concrete Beam with Fiber Reinforced Polymer Deflection Prediction Using Machine Learning

Dito Anak Danis[1], Nickholas Anting Anak Guntor[1,2]*.

[1] Faculty of Civil Engineering and Built Environment,
University Tun Hussein Onn Malaysia, Parit Raja, 86400, MALAYSIA

[2] Big Data and Advance Analytics Research Focus Group, Faculty of Civil Engineering and Built Environment,
University Tun Hussein Onn Malaysia, 86400,Parit Raja, Johor, MALAYSIA

*Corresponding Author Designation

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Abstract: RC beam is composite materials that is commonly used in construction. The conventional method to predict the RC beam deflection is always consuming a greater amount of time and the deflection value obtained may be affected by human error. Fiber reinforced polymer (FRP) is a material that use to strengthening beam which aim is to reduce the beam deflection by control the cracks present in the beam. Three methods of FRP reinforcement observed in this study are externally unbonded FRP strip, externally bonded FRP laminate and near-surface mounted FRP bars. The aim of this study is to develop a predictive machine learning model based on the reinforced concrete beam with FRP reinforcement deflection historical data. The data set is obtained from three published articles FRP beam deflection and analyze using PYTHON. The data then feed to the multiple linear regression algorithm to train and evaluate the model. For the machine learning development process, in involves processes such as data preparation, data pre-processing, features selection, features scaling, data partitioning, and evaluation of the model performance. R-squared value and correlation between the predicted displacement value and actual displacement value is used to evaluate the performance of the model. Predictive machine learning model is highly recommended to be used in civil engineering field as the computational is much more efficient compared to conventional testing method.

Keywords: Fiber Reinforced Polymer, PYTHON, R-squared

Corresponding author: nickholas@uthm.edu.my

1. Introduction

Beam deflection are issues that always concern to engineer especially in buildings construction. RC beams are commonly used in construction, including buildings construction. The properties of beam materials, includes concrete that has good compressive strength but poor in tensile [1], and also steel reinforcement bar that has good tensile strength but poor in compressive. Beam deflection induced by several factors such as length of beam not supported, young's modulus of beam, amount of force applied, and size of beam cross section.

In reinforced concrete beam reinforcement, fiber reinforced polymer (FRP) is often employed. Carbon fiber reinforced polymer (CFRP), glass fiber reinforced polymer (GFRP), and basalt fiber reinforced polymer are some of the most prevalent FRP reinforcements utilised in civil engineering (BFRP). These FRP reinforcements are commonly utilised as reinforcement because they are more corrosion resistant and can be prestressed during strengthening, thus reducing deflection.[2]

The aim of this study is to develop a machine learning model base on the reinforced concrete beam wih FRP reinforcement historical data. Conventional beams deflection prediction method is always consumed a greater amount of time. In conventional method, the beams specimen needs to prepare before the testing. The predicted value also may be interrupted by human error during testing and also machine faulty.

Introduction of machine learning in construction industries has brought a significant impact. In machine learning, the system explore the construction and study of algorithm from provided historical data [1]. In this study, parameters such as beam width (b), beam depth (d), beam length (L), FRP Young's modulus (Efrp), steel young's modulus (E), ratio of reinforcement (Pf%), bonded length, applied load (Pu), and concrete strength (Fu) are assigned as input. Beam displacement is assigned as the outputs to train the algorithm. Machine learning able to learn from a large set of data and build correlation of input and output [3].

2. Literature Review

2.1 Externally Reinforced Concrete Beam with FRP Reinforcement

Due to the bending moment of the beam, the effective depth of the FRP strips changes in flexural behavior for beam prestressed with unbonded FRP strips. The prestressed bonded FRP laminate considerably increased the serviceability of the externally bonded FRP laminate. Finally, the reinforcing of the FRP bars near the surface has enhanced the cracking stress of the beam, resulting in reduced beam deflection. This is due to the fact that cracking causes deflection.

2.2 Ductility of Beam

For the ductility of beam, the addition of strengthening materials may increase the possibility of the beam to fail in brittle modes [4]. Beams with width to thickness ratio greater than 20, the failure is caused by plate end debonding. For beam with width to thickness ratio does not exceed 20, it failed by separation of plate end and concrete cover. Whereas for beam with no strengthening plate, it failed caused by yielding of steel bars and crushing of concrete.

2.3 Bond Slip Relationship

For bond slip relationship, study by [5], shows the correlation between concrete strength, rebar diameter, bonded length, concrete cover thickness, bonding stress level, and stirrups, with mean bond stress. Theincrement of these parameters size has decreased the mean bond stress of the beam.

2.4 Span to Depth Ratio

For span to depth ratio, RC beam with high span to depth ratio mostly will experienced debonding failure at sections of high bending moment [6]. Two modes of failure are noticed, which is intermediate concrete debonding for span to depth ratio 3.5 to 7.0. For span to depth ratio 1.5 to 3.0, it failed by concrete cover separation.

2.5 Machine Learning

Machine learning is divided into three categories of algorithm, supervised learning, unsupervised learning, and reinforced learning. In supervised learning, the model is trained to understand the data description. In supervised learning, it able to define the data according to their description and distinguish the data from others[7]. For unsupervised learning, the algorithm labels the raw data. The algorithm classified the data into groups according to their description [8]. Reinforced learning is the behavioral study of machine learning. The systems learn the relationship between the successful event and the sequence of the event, then it will solve the problem [9].

3. Materials and Methods

The Workflow for machine learning development process is started with established data set from three previous study. Next, the data is sort out in a table and save in Microsoft excel. Then, the data sets is pre-processed to check for missing data, clean the data, selects independent features which are highly correlated with the dependent feature. Multiple linear regression model algorithm is used to train 80% of the data sets and remaining 20% as test set. The model is evaluated from the OLS regression result obtained and the difference between predicted value and actual value.

3.1 Workflow of Methodology

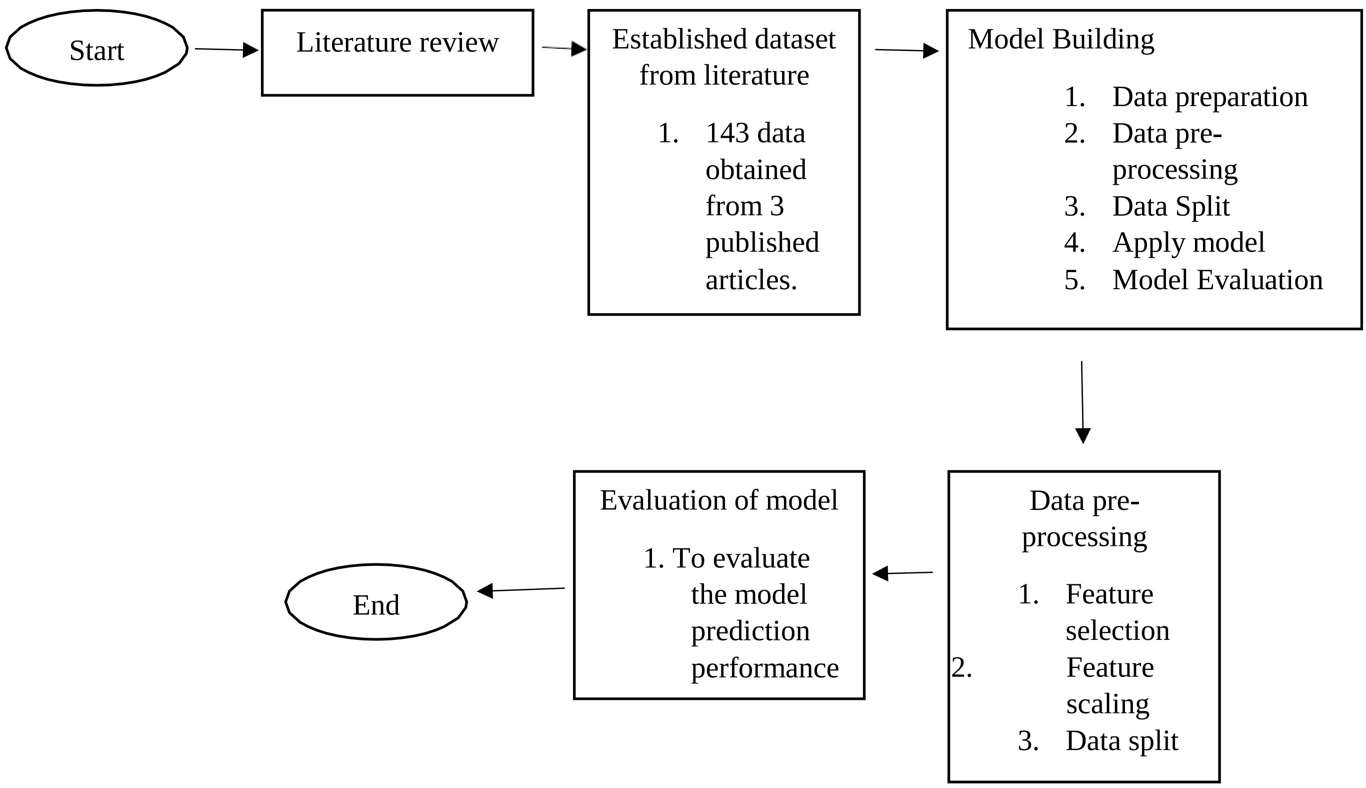


Figure 1: The workflow for methodology

3.2 Table of Data

Table 1: Test result for GFRP beam [10]

b (mm)	d (mm)	L (mm)	E (Gpa)	E,frp(Gpa)	Pf%	Pu (KN)	Fc (KNm)	Bonded length (mm)	Type of FRP	Disp. (mm)
170	416	990	200	42	1.7	25	28	50	GFRP	3.3
170	416	990	200	39	1.7	25	30	50	GFRP	3.4
170	416	990	200	41	1.7	25	28.5	50	GFRP	3.9
170	416	990	200	40	1.14	25	31.5	50	GFRP	3.8
170	416	990	200	41.5	1.14	25	32	50	GFRP	4.5
170	416	990	200	39.5	1.14	25	33	50	GFRP	4.6
170	416	990	200	42	1.14	25	57.5	50	GFRP	3.51
300	1088	990	200	51.9	1.24	25	49.3	50	GFRP	12
300	1106	990	200	144	0.46	25	38.7	50	CFRP	10
300	501	990	200	37.9	1.71	25	39.9	50	GFRP	13.1
300	502	990	200	37.9	1.71	25	41.2	50	GFRP	15.3
300	497	990	200	41.1	2.12	25	66.4	50	GFRP	14.2

Table 2: Test result of studied FRP beams [11]

b (mm)	d (mm)	L (mm)	E (Gpa)	E,frp(Gpa)	Pf%	Pu (KN)	Fc (KNm)	Bonded length (mm)	Type of FRP	Disp. (mm)
350	350	5000	200	168	2.9	120.9	23.3	4150	CFRP	166.7
350	350	5000	200	53	2.9	174.7	23.3	4150	BFRP	51.18
350	350	5000	200	53	2.9	155.5	23.3	4150	BFRP	150.68
350	350	5000	200	53	2.9	121.8	23.3	4150	BFRP	40.25
350	350	5000	200	53	2.9	185.2	23.3	4150	BFRP	97.38
350	350	5000	200	53	2.9	179.2	23.3	4150	BFRP	129.72
350	350	5000	200	53	2.9	194.8	23.3	4150	BFRP	92.66
350	350	5000	200	53	2.9	181	23.3	4150	BFRP	119.5
350	350	5000	200	53	2.9	109.2	23.3	4150	BFRP	94.3

3.4 Workflow of Machine Learning Building Process

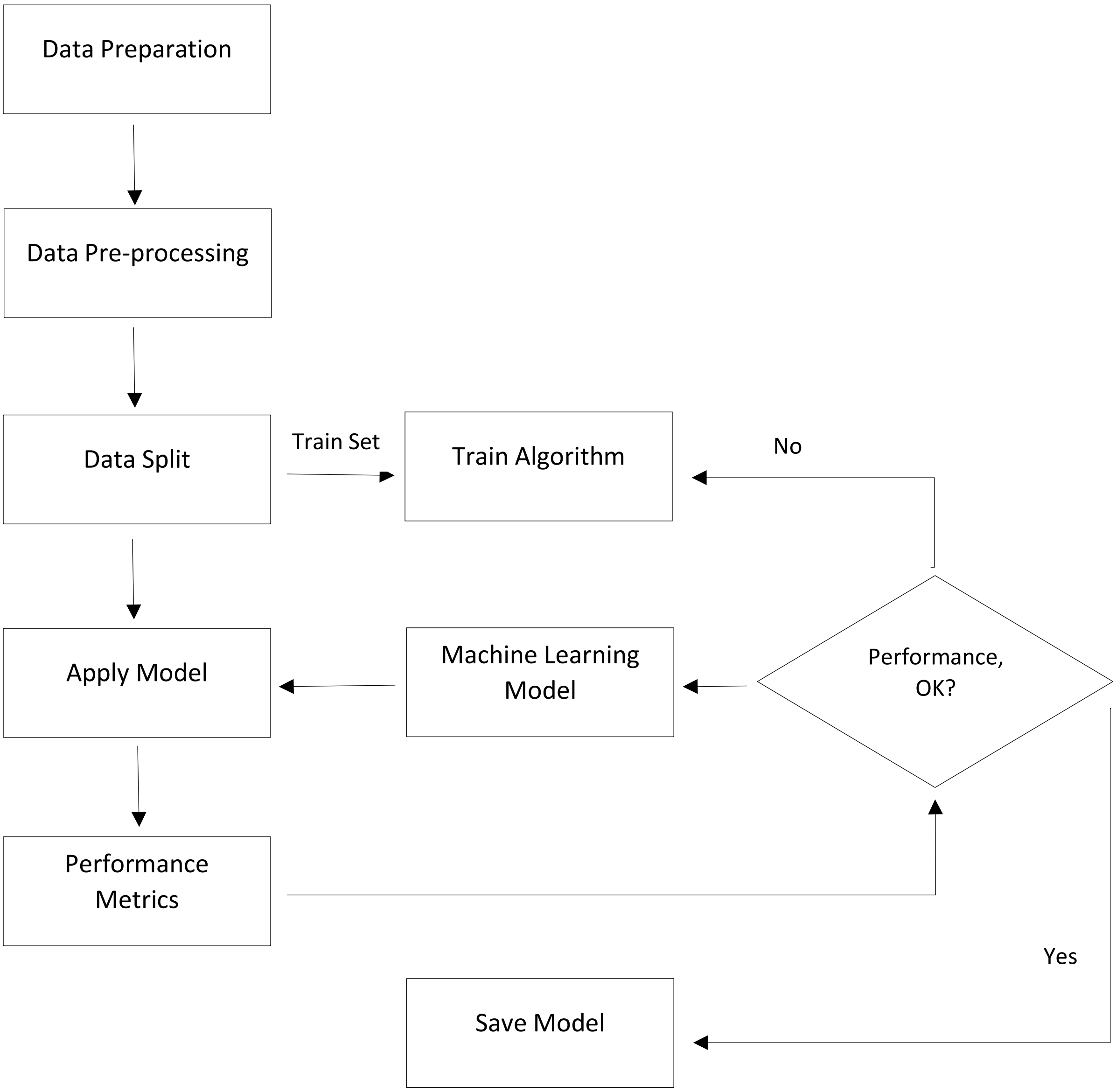


Figure 2: The workflow for machine learning building process

3.4 Linear regression model.

Multiple Linear regression is used in doing regression on a target variable based on the independent variables obtained from the data set. The algorithm then obtained the correlation between the independent variables and the dependent variable.

$$y = \beta 0 + \beta 2X2 + \beta 3X3 + \cdots + \beta pXp + e \qquad Eq. 1$$

4. Results and Discussion

4.1 Data Exploration

4.1.2 Univariate Analysis

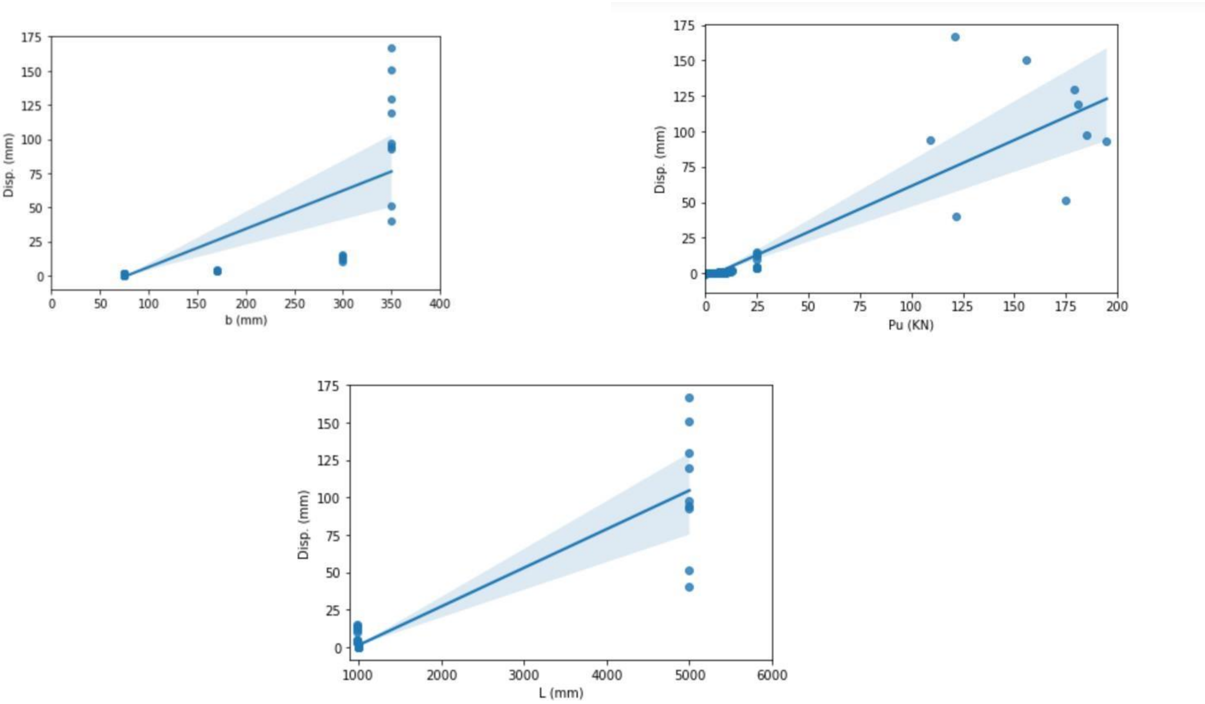
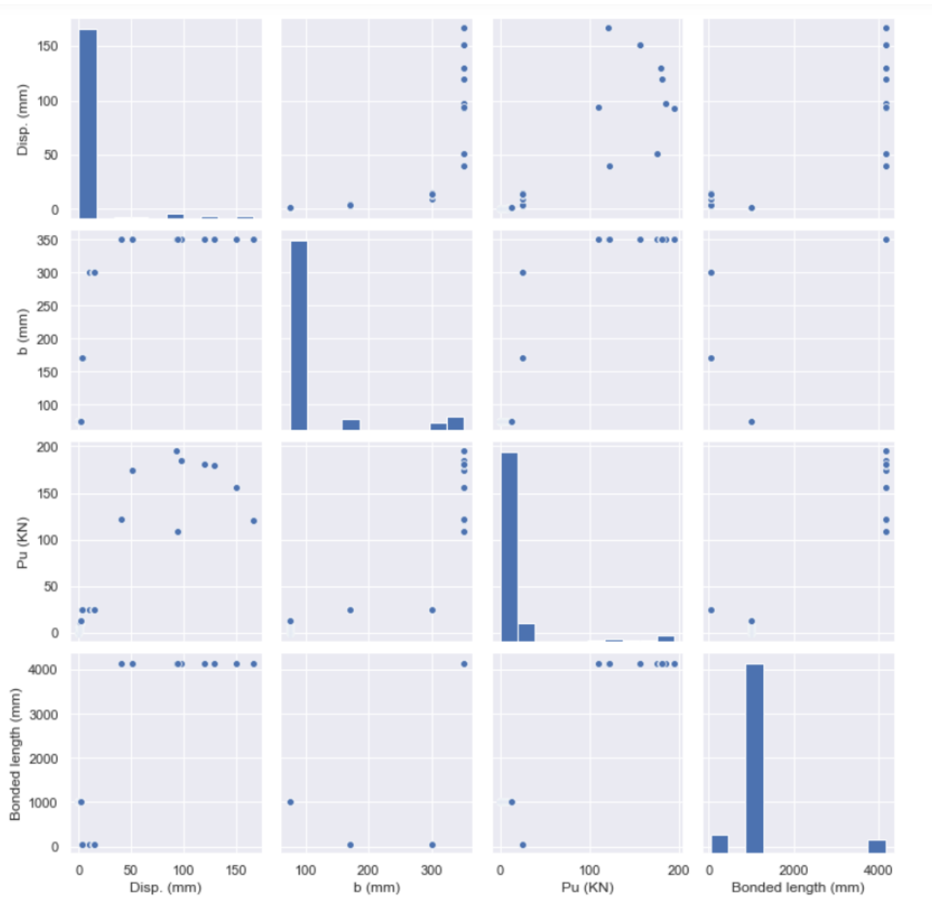


Figure 3: Regression plot beam displacement against b (mm), Pu (KN), and L (mm)

The studied variables are beam beam displacement against beam width (b), beam displacement against load applied (Pu), and beam displacement against beam length (L). For all of these three analyses, it shows that the beam displacement is increased when the values of the studied variables also increased. This result is supported by the increasing trend of the blue regressionline on the regression plot

4.1.2 Multivariate Analysis

Multivariate analysis is an analysis process to understand the interactions between more than 2 variables which is the input variables and output variable. In this study, multivariate analysis is done by using pair plot function, to study the relationship between input variables, b (mm), Pu (KN), and bonded length with the output variable, Disp. (mm).



4.2 Removing Outliers

2.Determine outliers

```
In [74]: sns.boxplot(x=data["Disp.  (mm)"])
Out[74]: <matplotlib.axes._subplots.AxesSubplot at 0x18ff8c0982(
```

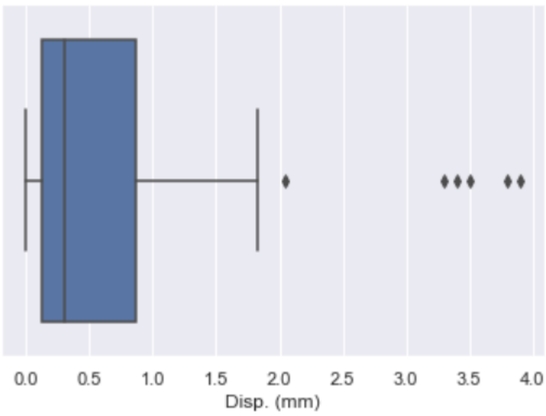


Figure 4: The boxplot of the beam displacement data

Figure 5: The value for Q1, mean, and Q3 for beam displacement data.

```
In [199]: data.describe()
```

Out[199]:

	d (mm)	L (mm)	E,frp(Gpa)	Pf%	Pu (KN)	Fc (KNm)	Bonded length (mm)	Type of FRP_GFRP	Type of FRP_PC	Disp. (mm)
count	127.000000	127.000000	127.000000	127.000000	127.000000	127.000000	127.000000	127.000000	127.000000	127.000000
mean	160.472441	999.606299	76.429134	0.939921	6.722362	20.594488	962.598425	0.039370	0.275591	0.613228
std	51.934915	1.952440	87.897932	0.611147	5.134448	3.705280	185.481838	0.195244	0.448581	0.774291
min	150.000000	990.000000	0.000000	0.000000	0.000000	20.000000	50.000000	0.000000	0.000000	0.000000
25%	150.000000	1000.000000	0.000000	0.000000	2.980000	20.000000	1000.000000	0.000000	0.000000	0.120000
50%	150.000000	1000.000000	24.500000	1.070000	6.260000	20.000000	1000.000000	0.000000	0.000000	0.300000
75%	150.000000	1000.000000	200.000000	1.490000	9.240000	20.000000	1000.000000	0.000000	1.000000	0.860000
max	416.000000	1000.000000	200.000000	1.700000	25.000000	57.500000	1000.000000	1.000000	1.000000	3.900000

Outliers in the beam displacement data are identified using boxplot analysis. The first quartile (Q1), median (the vertical line in the center of the box), and third quartile are all shown in the boxplot. Aside from that, the boxplot displays the data's lower and upper boundaries. The first quartile of the beam displacement data is 0.12 mm, and the third quartile is 0.86 mm, according to the boxplot analysis. The data has a mean value of 0.30 mm. The original is equivalent to 143 data and was removed up to 127 data remaining, means 16 data was removed. The 16 data is removed because it is considered as ouliers that lies beyond the upper limit.

4.3 Feature Selection

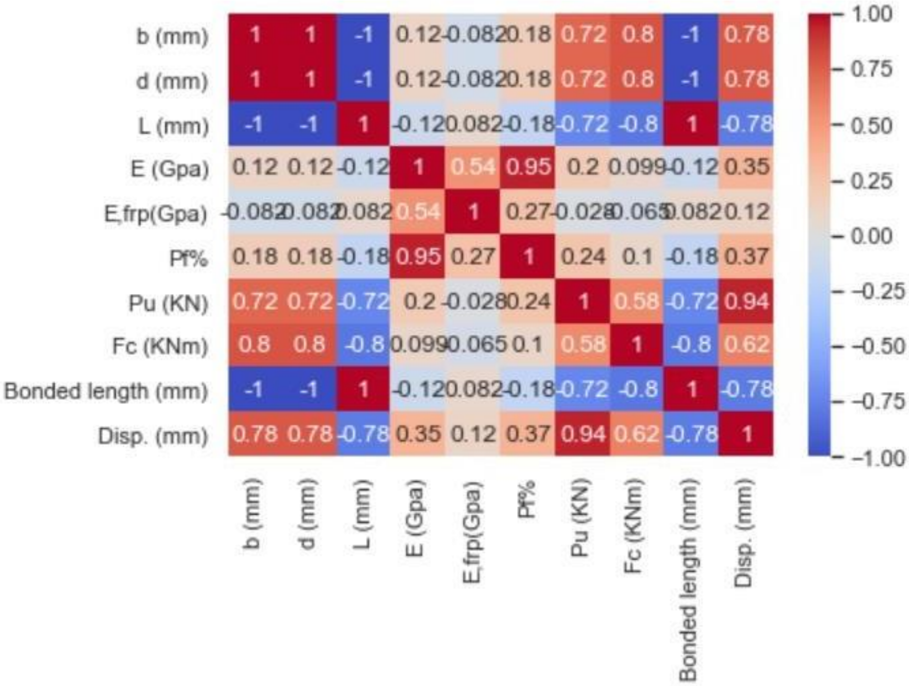


Figure 5: The heatmap correlation between the variables

```
Out[122]: b  (mm)                 0.779281
          d  (mm)                 0.779281
          L  (mm)                 0.779281
          Pf%                     0.366932
          Pu  (KN)                0.940490
          Fc  (KNm)               0.615720
          Bonded length  (mm)     0.779281
          Disp.  (mm)             1.000000
          Name: Disp.  (mm), dtype: float64
```

Figure 7: The value of targeted correlation of the chosen variables

The correlation between the variables is determined using a heatmap. The variables used in this analysis are those with a target correlation value of more than 0.3. Beam width (b), beam depth (d), reinforcement ratio (Pf percent), load applied (Pu), concrete strength (Fc), and bonded length are the variables selected from the analysis. Because it has a positive value, the study concludes that beam breadth (b), beam depth (d), reinforcement ratio (Pf percent), load applied (Pu), and concrete strength (Fc) are positively associated. Because it has a negative value, beam length (L) and bonded length (L) are negatively connected.

4.4 Handling Categorical Variable

Handling categorical variable

```
In [38]: data = pd.get_dummies(data,drop_first=True)
         data.head(10)
```

Out[38]:

	b (mm)	d (mm)	L (mm)	E (Gpa)	E,frp(Gpa)	Pf%	Pu (KN)	Fc (KNm)	Bonded length (mm)	Disp. (mm)	Type of FRP_GFRP	Type of FRP_PC	Type of FRP_RC
0	170	416	990	200	42.0	1.70	25.00	28.0	50	3.30	1	0	0
1	170	416	990	200	39.0	1.70	25.00	30.0	50	3.40	1	0	0
2	170	416	990	200	41.0	1.70	25.00	28.5	50	3.90	1	0	0
3	170	416	990	200	40.0	1.14	25.00	31.5	50	3.80	1	0	0
6	170	416	990	200	42.0	1.14	25.00	57.5	50	3.51	1	0	0
21	75	150	1000	0	0.0	0.00	0.00	20.0	1000	0.00	0	1	0
22	75	150	1000	0	0.0	0.00	0.30	20.0	1000	0.00	0	1	0
23	75	150	1000	0	0.0	0.00	0.60	20.0	1000	0.01	0	1	0
24	75	150	1000	0	0.0	0.00	0.89	20.0	1000	0.02	0	1	0
25	75	150	1000	0	0.0	0.00	1.19	20.0	1000	0.03	0	1	0

Figure 8: Categorical variable is changed to numeric form.

The type of the FRP column is changed to numeric form to start with the machine learning process, which is to develop multiple linear regression models. This is because the text data will be misinterpreted by the model algorithm. The get dummies functionality is used to convert the data. This feature creates a variable indication with the numbers 0 and 1 labelled on it. The number 0 denotes false, indicating that it does not reflect the FRP type. True indicates that the value represents the kind of FRP.

4.5 Model Performance Evaluation

Out[56]:

OLS Regression Results

Dep. Variable:	Disp. (mm)	**R-squared:**	0.947
Model:	OLS	**Adj. R-squared:**	0.943
Method:	Least Squares	**F-statistic:**	277.2
Date:	Tue, 22 Jun 2021	**Prob (F-statistic):**	1.78e-57
Time:	12:00:40	**Log-Likelihood:**	33.512
No. Observations:	101	**AIC:**	-53.02
Df Residuals:	94	**BIC:**	-34.72
Df Model:	6		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.5988	0.018	33.295	0.000	0.563	0.634
x1	0.0393	0.008	4.958	0.000	0.024	0.055
x2	0.0393	0.008	4.958	0.000	0.024	0.055
x3	-0.0393	0.008	-4.958	0.000	-0.055	-0.024
x4	-0.1069	0.090	-1.183	0.240	-0.286	0.073
x5	-0.5142	0.255	-2.016	0.047	-1.020	-0.008
x6	0.5710	0.026	21.642	0.000	0.519	0.623
x7	-0.0397	0.036	-1.106	0.272	-0.111	0.032
x8	-0.0393	0.008	-4.958	0.000	-0.055	-0.024
x9	0.0393	0.008	4.958	0.000	0.024	0.055
x10	-0.6948	0.291	-2.390	0.019	-1.272	-0.118

Omnibus:	9.074	**Durbin-Watson:**	2.024
Prob(Omnibus):	0.011	**Jarque-Bera (JB):**	9.069
Skew:	0.721	**Prob(JB):**	0.0107
Kurtosis:	3.276	**Cond. No.**	4.99e+20

` **Figure 9: The OLS regression result for the model**

Table 3: Comparison between predicted beam displacement and actual beam displacementvalue

Predicted Displacement (mm)	Actual Displacement (mm)
-0.325067	0.02
0.348888	0.19
1.305945	2.05
0.207489	0.18
-0.017314	0.00
0.440681	0.32
1.080176	1.22
0.248406	0.15
-0.357445	0.01
1.014304	1.10

4.2 Discussion

Figure 4.1 shows the OLS regression result for the model. The percentage of variance in the dependent variable relative to the independent variables is calculated using the R-squared value, which is also known as the coefficient of determination. The R-squared value ranged from 0 to 1, with 1 indicating that the model is good and 0 indicating that the model is not. This model has an R-squared score of 0.947, indicating that it is a decent model. Two observations are made for the regression coefficient. A positive correlation exists between b (x1), d (x2), Pu(x6), and the type of FRP, GFRP (x9). It may be deduced that as these factors rise, the mean value of beam displacement rises as well. The negative value is the second point to notice. The negative correlation between L (x3), Efrp (x4), Pf percent (x5), Fc (x7), bonded length (x8), and kind of FRP, PC (x10) and beam displacement suggests that as the independent factors grow, the dependent variable, beam displacement, decreases. The P>|t| value comes next. E,frp (x4) equals 0.240, and Fc (x7) equals 0.272, both of which are greater than 0.05. This means that the variables have no bearing on the dependent variable, beam displacement. The coefficient value of the other eight independent variables is less than 0.05, indicating that they are significant in relationto the dependent variable.

Table 3 shows the correlation matrix determines the relationship between the expected and actual value, and this graphic also depicts the number of strongly linked data pairings. This study's anticipated and actual values are highly associated, with a correlation score of 0.96788. This value is getting close to 1, which is the highest value or one that indicates a strong association.

5. Conclusion

The main objectives To develope a machine learning model based on reinforced beam deflection historical data is achieved. The machine learning model was created using 143 sets of beam deflection data. The information was gathered from three published journals. Data gathering, data exploration, outliers' determination, feature selection, feature scaling, data segmentation, and model performance evaluation are all part of the model development process. Recommendation for a better study in the future is to Predict reinforced concrete deflection by using other algorithm such as artificial neural network, Compare the results between different models, thus to obtained a better model, The study should use a greater amount of historical data as it can increase the performance of the model.

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