

**PROJECT**

Axial Capacity Prediction of Circular Concrete Filled Stainless Steel Tubular Columns Using Machine Learning Algorithms

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# ABSTRACT

Concrete-filled steel tubular (CFST) columns are quite omnipresent in the construction of Civil Structures owing to their great axial capacity and having advantages of both building materials i.e. concrete and steel negating each other’s downside. Nowadays Concrete-filled stainless-steel tubular (CFSST) columns are preferred over traditional concrete-filled steel tubular (CFST) columns given their superior corrosion resistance. While extensive experimental and numerical research has been conducted to assess the behavior of CFSST columns under various loading conditions, accurately predicting their axial capacity remains challenging. The distinct properties of stainless steel compared to carbon steel render the existing design code equations for conventional CFST columns unreliable for predicting the strength of the CFSST columns. To address this issue, the Machine Learning (ML) approach has been used. In Structural Engineering the use of Artificial Intelligence (AI) has gained some popularity in academia nowadays to circumvent the limitations of the existing design philosophies.

The main aim of this study is to leverage the ML techniques, to overcome the limitations of traditional prediction methods and provide a more reliable solution to estimating the axial capacity of CFSST columns. To achieve this, a comprehensive dataset comprising 422 circular and rectangular CFSST columns has been meticulously compiled from the existing literature about the experimental studies done in the past. This extensive dataset serves as the foundation for developing robust ML models capable of accurately forecasting CFSST column performance.

The accuracy of the model is evaluated using a range of performance metrics to ensure a comprehensive assessment. These metrics include coefficient of determination (R2), root mean square error (RMSE), mean absolute error (MAE), Nash-Sutcliffe Model (NSE), and Index of Agreement (d).

Mention the ML algorithms used and point out the findings i.e. the best one based on the accuracy metrics mentioned above like RMSE, R2 etc.

To demonstrate the validity and exceptional performance of the top-performing \_\_\_\_\_\_\_\_\_\_\_\_ machine learning model, the predictions/results are then compared against the prediction from the most commonly and widely used design codes around the world.

# TABLE OF CONTENTS

[ABSTRACT 2](#_heading=h.1ksv4uv)

[TABLE OF CONTENTS 3](#_heading=h.44sinio)

[LIST OF FIGURES 4](#_heading=h.2jxsxqh)

[LIST OF TABLES 5](#_heading=h.z337ya)

[NOTATIONS 6](#_heading=h.3j2qqm3)

[LIST OF ABBREVIATIONS 7](#_heading=h.1y810tw)

[CHAPTER 1: INTRODUCTION 9](#_heading=h.2xcytpi)

[Background 9](#_heading=h.1ci93xb)

[Comparison between CFSST and Conventional CFST 9](#_heading=h.3whwml4)

[Literature Review 11](#_heading=h.qsh70q)

[Research Gap 13](#_heading=h.3as4poj)

[Objectives 14](#_heading=h.1pxezwc)

[Methodology 14](#_heading=h.49x2ik5)

[CHAPTER 2: DATABASE FOR CFSST COLUMN AXIAL CAPACITY PREDICTION 15](#_heading=h.2p2csry)

[CHAPTER 3: DEVELOPMENT OF MACHINE LEARNING MODELS 19](#_heading=h.3o7alnk)

[CHAPTER 4: COMPARISON OF PREDICTIONS FROM DIFFERENT ML MODELS 20](#_heading=h.23ckvvd)

[CHAPTER 5: COMPARISON OF RESULTS WITH EXISTING DESIGN CODE EQUATIONS 21](#_heading=h.ihv636)

[Model performance vs Design Code Prediction 23](#_heading=h.32hioqz)

[CHAPTER 6: CONCLUSION 24](#_heading=h.1hmsyys)

[CHAPTER 6: FUTURE RECOMMENDATION 25](#_heading=h.41mghml)

[REFERENCES 26](#_heading=h.2grqrue)

[Database: 27](#_heading=h.1rvwp1q)

# LIST OF FIGURES

[Figure 1: Correlation matrix for Rectangular CFSST columns 10](#_heading=h.2s8eyo1)

[*Figure 2: Correlation matrix for Circular CFSST columns.* 11](#_heading=h.17dp8vu)

[*Figure 3: Histograms for parameters of Rectangular CFSST columns.* 12](#_heading=h.3rdcrjn)

[*Figure 4: Histograms for parameters of Circular CFSST columns.* 12](#_heading=h.26in1rg)

# LIST OF TABLES

[Table 1: Table of Comparison between CFST and CFSST 10](#_heading=h.2bn6wsx)

[Table 2: Mean and Standard Deviation for Input Parameters 15](#_heading=h.147n2zr)

# NOTATIONS

| D | Diameter of the Circular Column |
| --- | --- |
|  | Thickness of Stainless-Steel Tube |
|  | Height of the Rectangular Column |
|  | Width of the Rectangular Column |
| L | Length of the Specimen |
|  | Modulus of Elasticity of Stainless Steel |
| Ec | Modulus of Elasticity of Concrete |
|  | Cylindrical Compressive Strength of Concrete |
|  | Ultimate Strength of Stainless Steel |
|  | 0.2% Proof Stress of Stainless Steel |
|  | Strain-Hardening Exponent |
| As | Area of Cross-section of Steel Tube |
| Ac | Area of Concrete Core |
|  |  |
|  |  |
|  |  |

# LIST OF ABBREVIATIONS

| AISC | American Institute of Steel Construction |
| --- | --- |
| CSA | Canadian Standards Association |
| EC | Eurocode |
| CFSST | Concrete Filled Stainless Steel Tubular |
| CFST | Concrete Filled Steel Tubular |
| RMSE | Root Mean Square Error |
| R | Pearson Correlation Coefficient |
| R2 | Coefficient of Determination |
| R-2 | Adjusted R2 |
| MAE | Mean Absolute Error |
| MAPE | Mean Absolute Percentage Error |
| NSE | Nash-Sutcliffe Model Error |
| MSE | Mean Square Error |
| CoV | Coefficient of variation |
| XGBoost | Extreme Gradient Boosting |
| LightGBM | Light Gradient Boosting Machine |
| CatBoost | Categorical Gradient Boosting |
| GA-BPNN | Genetic Algorithm Back-Propagation Neural Network |
| RBFNN | Radial Basis Function Neural Network |
| GPR | Gaussian process regression |
| MLR | Multiple Linear Regression |
| GTB | Gradient Tree Boosting |
| RF | Random Forest |
| SVM | Support Vector Machines |
| DT | Decision Tree |
| DL | Deep Learning |
| CART | Classification And Regression Tree |
| AdaBoost | Adaptive Boosting |
| GB | Gradient Boosting |
| NN | Neural Network |
| ARF | Additive Random Forests |
| ANN | Artificial Neural Networks |
| SHAP | SHapley Additive exPlanations |

# CHAPTER 1: INTRODUCTION

## Background

Stainless steel has seen increasing adoption in the construction industry in recent years, driven by enhanced performance characteristics like superior durability [1], corrosion resistance [2], and fire resistance [3] compared to traditional carbon steel. It also provides greater strength-to-weight ratios, allowing for more efficient structural designs [4].

But costs associated have been the biggest challenges in its wider adoption. However, the engineering community came up with an innovative approach to offset its higher initial cost by filling the hollow tube with concrete to take advantage of both materials compensating for each other’s weaknesses [5].

The resulting composite system is called Concrete-Filled Stainless-Steel Tubes (CFSST). This technique offers several benefits:

* Increased load-bearing capacity
* Reduced overall production costs.
* Composite action of steel and concrete

This composite approach allows designers to leverage the superior properties of stainless steel while mitigating some of the cost concerns, especially as an axially loaded compression member, potentially expanding its applicability in construction projects.

While CFSST columns may have a higher upfront cost, they offer substantial advantages when considering the total life cycle expenses of a project. This long-term perspective reveals their cost-effectiveness over time, potentially outweighing the initial investment. Also, CFSST can be designed with smaller cross-sections while maintaining equivalent or superior strength. This feature allows for more efficient use of space within structures. These combined attributes make CFSST columns an attractive option for architects and engineers seeking to balance structural performance, long-term cost-effectiveness, and design aesthetics in their projects [6].

## Comparison between CFSST and Conventional CFST

Conventional Concrete-Filled Steel Tubular (CFST) Columns have been widely used in construction due to their balance of strength, cost-effectiveness, and ease of fabrication for quite some time now and have proved their usefulness, especially in high-rise buildings, industrial facilities, especially in high seismic zones, where the composite behavior of steel and concrete provides excellent load-bearing capacity and ductility. However, they require regular maintenance to prevent corrosion in harsher environments and the application of CFST columns has been limited to regions with moderate conditions.

To solve this problem, engineers explored the use of stainless steel instead of carbon steel, therefore Concrete-Filled Stainless-Steel Tube (CFSST) Columns. The table below gives a comparison highlighting their properties, advantages, disadvantages, and typical applications:

*Table 1:* Table of Comparison between CFST and CFSST

| **Aspect** | **Concrete-Filled Steel Tube (CFST)** | **Concrete-Filled Stainless-Steel Tube (CFSST)** |
| --- | --- | --- |
| **Material Composition** | Carbon steel tube filled with concrete | Stainless steel tube filled with concrete |
| **Corrosion Resistance** | Moderate; needs additional protection (e.g., coatings) | High; stainless steel provides excellent corrosion resistance |
| **Cost** | Generally lower than CFSST | Higher due to stainless steel material costs |
| **Strength and Ductility** | High strength with good ductility | Higher strength and enhanced ductility due to stainless steel |
| **Fire Resistance** | Improved fire resistance due to concrete infill but lower than CFSST | Enhanced fire resistance as stainless-steel resists oxidation and thermal degradation better |
| **Load-bearing Capacity** | High axial and flexural strength | Typically, higher than CFST due to the higher yield strength of stainless steel |
| **Durability** | Susceptible to corrosion if not protected | Highly durable in harsh environments (marine, industrial) due to corrosion resistance |
| **Maintenance Requirements** | Regular maintenance to prevent corrosion | Low maintenance due to the inherent corrosion resistance of stainless steel |
| **Aesthetic Appeal** | Requires finishing or painting for aesthetics | Stainless steel offers a modern, polished appearance; often used in visible structures |
| **Environmental Impact** | Lower environmental impact than stainless steel | Higher due to the energy-intensive production of stainless steel |
| **Thermal Conductivity** | Higher thermal conductivity than stainless steel | Lower thermal conductivity, potentially improving fire performance |
| **Common Applications** | Bridges, industrial buildings, seismic applications | Marine structures, high-end buildings, coastal bridges, corrosive environments |
| **Life Cycle** | Shorter life cycle in corrosive environments | Longer life cycle with reduced need for repairs/replacement |
| **Sustainability** | Easier to recycle but requires a protective coating | Stainless steel is highly recyclable and durable but more resource-intensive |

Stainless steel basically fixes most of the flaws of steel as a material and it can clearly be seen from the comparison there are so many advantages of using it over conventional CFST Columns. Therefore, CFSST is now increasingly used in specialized applications where durability and corrosion resistance are essential, such as in marine and coastal environments, high-end architectural projects, and infrastructure in industrial or pollutive areas.

## Literature Review

Over the last two decades, the exceptional performance of Concrete Filled Stainless Steel Tubular (CFSST) columns has sparked significant interest in the research community, leading to many experimental and numerical studies [5], [7], [8], [9]. This has led to our comprehensive understanding of Concrete-Filled Stainless-Steel Tubular (CFSST) columns. Key findings from the following studies are:

1. **Uy et al. [6]:** Uy et al. tested 117 short and slender CFSST columns, showing that existing design codes like AS 5100 [10], AISC 360-16 [11], DBJ/T [12] and EC4 [13] generally provide conservative estimates for axial capacities for both short and slender columns.
2. **He and Zhao [14]:** He and Zhao examined 18 circular CFSST specimens under partial and full loading, concluding that current design standards (EC4 and AISC 360-16) yield conservative results compared to experimental data.
3. **Lam and Gardner [15]:** Lam and Gardner's study on circular and square CFSST sections with concrete strengths ranging from 30 to 100 MPa showed that code provisions, especially for circular columns, were overly conservative.
4. **Young and Ellobody [16]:** Young and Ellobody's experiments on high-strength cold-formed stainless steel tubes with concrete with compressive strength ranging from 40 to 80 MPa demonstrated that code equations' accuracy varied depending on specimen type but still were quite conservative.
5. **Dai et al. [17]:** Dai et al.'s study on 18 CFSST columns comprising 9 having an austenitic shell and 9 with duplex stainless-steel shell under compression revealed that both European and Chinese codes underestimated axial resistance, leading them to propose and develop new analytical methods for strength prediction for both austenitic and duplex CFSST columns.
6. **Guo et al. [18] and Li et al [19]:** Proposed new formulations to more accurately estimate the axial load-carrying capacity of stainless-steel tubular stub columns, addressing the limitations of existing design codes.

On the machine learning front, there has been extensive development in academia to explore the application of data-driven approaches for the strength prediction of conventional CFST Columns [20], [21], [22], [23] [24]. Various machine learning algorithms were employed to analyze and predict axial capacity using the available dataset. The algorithms tested most included:

* Back-propagation neural network (BPNN)
* Radial basis function neural network (RBFNN)
* Gaussian process regressor (GPR)
* Multiple linear regression (MLR)

Their performance was then evaluated against established design codes, specifically AISC-360 and EC-4. It was noted based on the multiple error evaluation criteria like coefficient of determination (R2), root mean square error (RMSE), etc. that data-driven approaches, especially advanced algorithms like GPR predicted the axial capacity with much better accuracy than existing design standards. In addition to this Vu et al. [22], Lee et al. [23], Ngo et al. [25] explored the use of advanced ML algorithms like gradient tree boosting (GTB), categorical gradient boosting (CATBoost), Additive Random Forests (ARF), and Artificial Neural Networks (ANNs) for predicting CFST axial capacity. The following tables highlight the performance metrics and accuracy scores of different ML models tested in each study.

| **Cakiroglu et al. [20]** | | | | |
| --- | --- | --- | --- | --- |
| **ML Model Parameter** | **RMSE (kN)** | **R2** | **MAPE (%)** | **MAE (kN)** |
| **XGBoost** | 93.4 | 0.986 | 4.3 | 74.5 |
| **LightGBM** | 198.1 | 0.935 | 7.2 | 141.3 |
| **Random Forest** | 148.9 | 0.963 | 3.4 | 80.7 |
| **CatBoost** | 193.1 | 0.938 | 7.8 | 157.4 |
| **Best Model** | **XGBoost** | | | |

| **Hou & Zhou [21]** | | | | | | |
| --- | --- | --- | --- | --- | --- | --- |
| **ML Model  Parameter** | **R2** | **MAE (kN)** | **RMSE (kN)** | **MAPE (%)** | **MEAN** | **COV** |
| **GA-BPNN** | 0.983 | 178.39 | 306.856 | 9.98 | 0.999 | 0.148 |
| **RBFNN** | 0.977 | 200.29 | 346.641 | 10.34 | 1.001 | 0.139 |
| **GPR** | 0.986 | 136.55 | 270.308 | 6.99 | 0.996 | 0.097 |
| **MLR** | 0.954 | 254.18 | 486.357 | 21.80 | 0.880 | 0.676 |
| **Best Model** | **GPR** | | | | | |

| **Viet Vu et. al. [22]** | | | |
| --- | --- | --- | --- |
| **ML Model  Parameter** | **MSE (kN)** | **R2** | **R-2** |
| **GTB** | 0.00000453 | 0.9989 | 0.9989 |
| **RF** | 0.00023600 | 0.9711 | 0.9696 |
| **SVM** | 0.00023800 | 0.9650 | 0.9632 |
| **DT** | 0.00025000 | 0.9635 | 0.9616 |
| **DL** | 0.00007520 | 0.9884 | 0.9878 |
| **Best Model** | **GTB** | | |

| **S. Lee et al. [23]** | | | | |
| --- | --- | --- | --- | --- |
| **ML Model  Parameter** | **R2** | **MSE (kN)** | **RMSE (kN)** | **MAE (kN)** |
| **CatBoost** | 0.981 | 43428.23 | 190.032 | 98.119 |
| **CART** | 0.920 | 162416.92 | 362.688 | 152.579 |
| **AdaBoost** | 0.950 | 126628.76 | 316.854 | 208.387 |
| **GB** | 0.966 | 61777.21 | 226.751 | 100.316 |
| **RF** | 0.957 | 128965.34 | 312.323 | 158.732 |
| **XGBoost** | 0.976 | 49058.14 | 202.280 | 105.445 |
| **LightGB** | 0.962 | 66739.86 | 240.303 | 118.770 |
| **NN** | 0.949 | 203086.50 | 361.436 | 190.276 |
| **SVM** | 0.911 | 157703.82 | 338.940 | 186.258 |
| **Best Model** | **CatBoost** | | | |

| **Tri Ngo et at. [24]** | | | |
| --- | --- | --- | --- |
| **ML Model  Parameter** | **R** | **MAE (kN)** | **MAPE (%)** |
| **ARF** | 0.98 | 211.31 | 6.39 |
| **ANN** | 0.98 | 610.44 | 40.26 |
| **Best Model** | **ARF** | | |

These studies conclude that Machine Learning can be looked at as an effective alternative approach and may offer a valuable complement or alternative to existing design code calculations, potentially leading to more efficient and reliable structural designs.

## Research Gap

De Carvalho et al. [26] and V-Linh Tran et al. [27] have explored this approach for CFSST in the past. De Carvalho et al. used ANN and Random Forest algorithms to develop the machine learning model. However, there are a few downsides to his study, the biggest of which is that his data set only comprises a circular section, and data points have been taken from the numerical study instead of real experimental data. This is not wrong per se but can be subjected to the modeling inaccuracies associated with Finite Element Modeling. V-Linh Tran on the other hand used multiple machine-learning algorithms like RF, KNN AdaBoost, GNRT, and XGBoost trained on the 142 data samples of circular CFSST Columns. He found that XGBoost provides the best accuracy based on the R2 measurement.

Both studies were limited by the number of data points and the lack of diversity in the dataset on which the model has been trained. These two studies typically focus only on circular sections, leading to a narrow dataset that lacks diversity in cross-sectional shapes which is not exactly representative of a variety of the configurations used in practice. To address these limitations, our study expands upon prior work by incorporating a broader variety of CFFST column sections, including both rectangular and circular shapes, and by increasing the dataset to 422 data points. This comprehensive dataset allows for more accurate and generalizable ML predictions of column strength across various section geometries.

In addition to this, the current state of research reveals a significant gap in the field of Concrete-Filled Stainless-Steel Tubular (CFSST) columns:

1. It can be noted across all the aforementioned different studies that the applicability of the various proposed analytical models for the prediction of the axial strength of CFSST requires different input parameters that vary quite widely based on the geometric shape and the grade of the material used.
2. Extensive machine learning (ML) studies have been conducted on Concrete-Filled Steel Tubular (CFST) columns. However, there is a notable absence of data-driven prediction models specifically tailored for CFSST columns in the existing literature.
3. Previous research has highlighted limitations in the current codified equations for CFSST columns:
   1. These equations tend to produce overly conservative estimates.
   2. They often fail to accurately predict the axial capacity of CFSST columns.
4. A critical shortcoming in applying conventional CFST column equations to CFSST columns is that it does not account for the strain-hardening behavior of stainless steel. This omission is particularly significant as strain hardening is a crucial component affecting the performance of CFSST columns.

So, to come up with the one-size-fits-all approach for strength prediction of CFFST Columns that accurately addresses these inconsistencies and uncertainties, and applies to a wide range of configurations, the data-driven approach based on a large amount of the open experimental database is explored in this study.

## Objectives

This research aims to create a robust model that improves prediction accuracy and addresses limitations in existing design equations for Concrete-Filled Stainless-Steel Tubular (CFSST) columns. The study's key objectives are:

* **Database Development:** Compile a comprehensive database from available literature to serve as a foundation for the analysis.
* **Parameter Identification:** Determine the most influential factors affecting the axial capacity of CFSST columns.
* **Development of the Machine Learning Models:** Mention all the ML models being tested in this study.
* **Model Comparison:** Evaluate the accuracy of newly developed Machine Learning (ML) models against current design codes using metrics like RMSE, R2, etc.
* **Result Interpretation:** Utilize Shapley Additive exPlanations (SHAP) to elucidate the relationship between input parameters and predicted outcomes.

By addressing these objectives, the study aims to provide a more accurate and practical approach to CFSST column design and analysis, bridging the gap between theoretical models and real-world applications. Using ML models, it is possible to avoid, costly and time-consuming experimental work.

## Methodology

Please discuss briefly ML its theories, and workings, and describe the algorithms explored in this study.

Also, describe the accuracy metric employed in the study and describe them briefly.

# CHAPTER 2: DATABASE FOR CFSST COLUMN AXIAL CAPACITY PREDICTION

A reliable database is essential for developing dependable prediction models and identifying the key factors that influence prediction accuracy. A comprehensive dataset was compiled from multiple peer-reviewed journals and open dissertation papers describing their experimental findings based on the studies conducted in the past. In this project, a total of 422 data points has been gathered and are evenly divided between circular and rectangular Concrete-Filled Stainless-Steel Tubular (CFSST) columns, with 211 datasets for each type. This extensive compilation serves as the foundation for the study's analysis and model development.

This study aims to develop a reliable machine learning (ML) model for predicting the axial capacity of Concrete-Filled Stainless-Steel Tubular (CFSST) columns using a data-driven approach. The model's output is the axial compression capacity (N\_Test) measured in kilonewtons (kN), while the input parameters include:

1. Column length (L, mm)
2. Tube thickness (t, mm)
3. Stainless steel proof stress (f0.2, MPa)
4. Stainless steel ultimate strength (fu, MPa)
5. Stainless steel elastic modulus (Eo, MPa)
6. Strain hardening component (n)
7. Concrete compressive strength (f’c, MPa)
8. Column diameter (D, mm) for circular sections
9. Cross-section width (B, mm) and height (H, mm) for rectangular sections

| **Input** | **Circular Columns** | | **Rectangular Columns** | |
| --- | --- | --- | --- | --- |
|  | **Mean** | **SD** | **Mean** | **SD** |
| *D (mm)* | 134.2 | 68.7 | - | - |
| *t (mm)* | 3.5 | 2.2 | 3.8 | 2.0 |
| *H (mm)* | - | - | 120.9 | 41.5 |
| *B (mm)* | - | - | 124.7 | 44.5 |
| *L (mm)* | 399.9 | 205.5 | 377.6 | 122.6 |
| *L/B* | - | - | 3.2 | 0.8 |
| *L/D* | 3 | 0.5 | - | - |
| *E*o (MPa) | 196780.3 | 7491.6 | 199730.0 | 6793.5 |
| *f*0.2 (MPa) | 324.5 | 72.2 | 433.1 | 101.1 |
| *f*u (MPa) | 692.0 | 58.9 | 674.7 | 120.9 |
| *n* | 6.0 | 1.7 | 6.3 | 2.0 |
| *f*c*’ (*MPa*)* | 52.1 | 29.1 | 48.0 | 20.6 |

*Table 2: Mean and Standard Deviation for Input Parameters*

To Move forward with the development of the data-driven strength prediction ML models for CFSST columns it is imperative to identify the feature’s importance. Therefore, a correlation analysis is done on the dataset. As of now, previous studies involving data-driven approaches for strength prediction have indicated a high degree of significance of the sectional properties like D, B, t, L, etc. on the axial capacity of the specimen.

Correlation analysis is a statistical method that quantifies the relationship between two variables. The Pearson correlation coefficient (r) indicates the strength and direction of this relationship, with values near 1 suggesting a strong positive correlation, those close to 0 indicating a weak correlation, and values approaching -1 signifying a strong negative correlation.

*Figures 1* *and 2* represent the correlation between multiple parameters for circular and rectangular sections in the form of a correlation matrix (heatmap).

* **For circular sections:** Thickness (t) is the most influential dimension, with a correlation coefficient (r-value) of 0.85. Diameter (D) and length (L) follow as the second most important features, both with r values of 0.84.
* **For rectangular sections:** Thickness (t) again proves to be the dominant feature, giving a correlation coefficient of 0.86. Height (H) and width (B) rank as the second and third most significant parameters, with r values of 0.73 and 0.66, respectively.

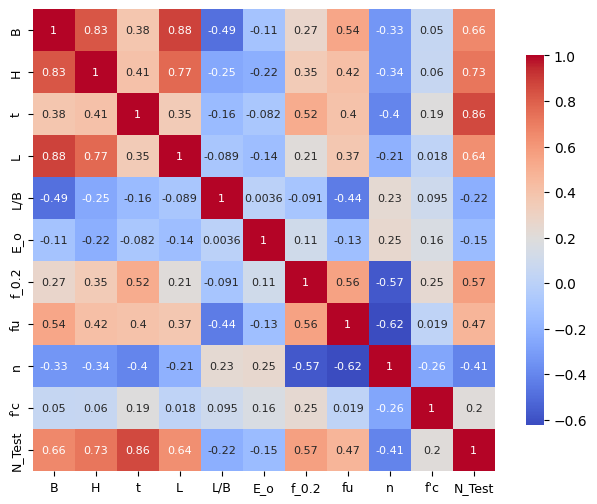
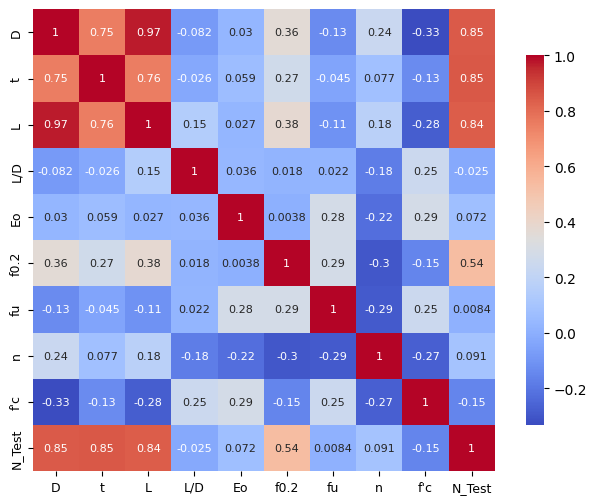
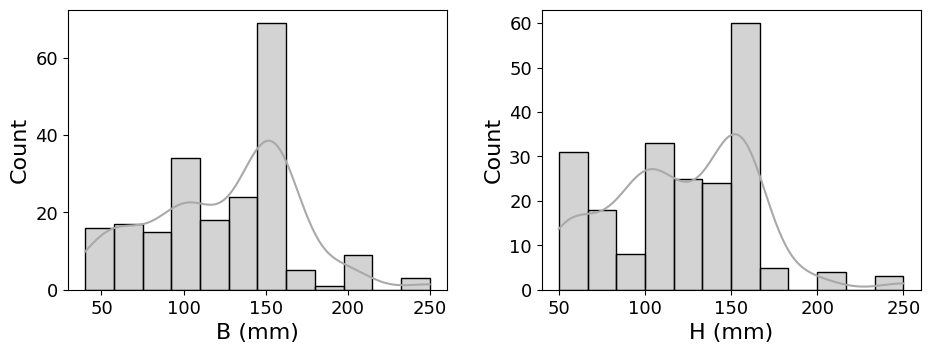
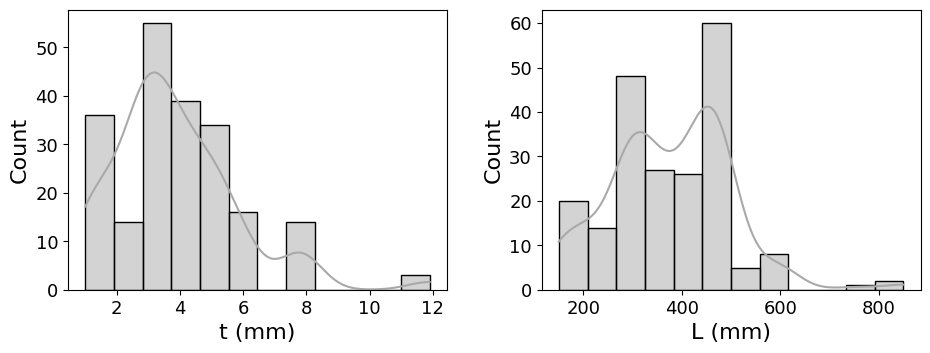


Figure 1: Correlation matrix for Rectangular CFSST columns

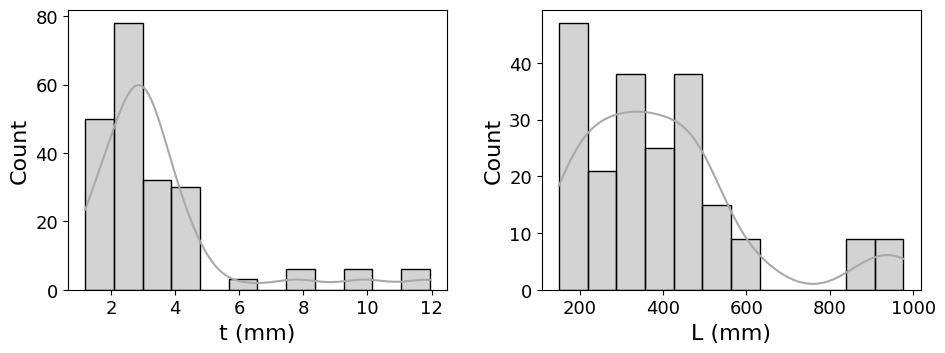
*Figure 2: Correlation matrix for Circular CFSST columns.*

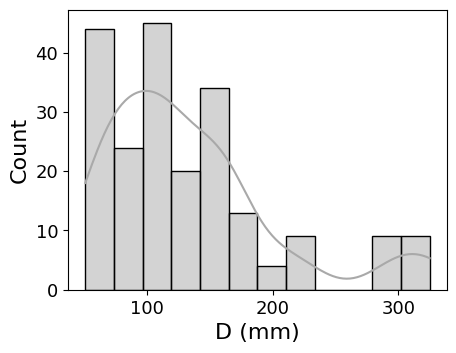
To further visualize the distribution of these highly correlated features, histogram plots were developed and are presented in Figures 3 and 4.





*Figure 3: Histograms for parameters of Rectangular CFSST columns.*





*Figure 4: Histograms for parameters of Circular CFSST columns.*

# CHAPTER 3: DEVELOPMENT OF MACHINE LEARNING MODELS

*Why they are correlated*

*Why those models did not work?*

*Explain by the means of math involved the algorithms*

*Stratify the data preprocessing.*

*Curve Underfitting vs overfitting for different models or hyperparameter tunings*

# CHAPTER 4: COMPARISON OF PREDICTIONS FROM DIFFERENT ML MODELS

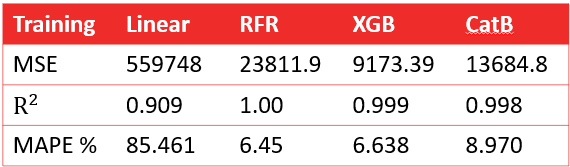
For this project we decided to create Linear Regression, Random Forest Regression, XGBoost, and CatBoost models to handle both our Rectangular and Circular datasets which resulted in the construction of 8 models. We evaluated the performance of these models based on 3 error metrics and the use of plots representing the predicted axial capacities of the testing set for each model.

The 3 error metrics used in our project were:

(1)

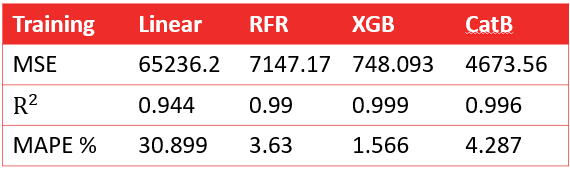
(2)

(3)

The 3 error metrics displayed above were used to determine model accuracy along with if a model was underfitting or overfitting. Although we did place a primary focus on the R squared value for our grid search results. This decision was made because the R squared metric is the easiest to compare between models, especially since our rectangular dataset and circular dataset contain different features and a different number of features. Applying these error metrics to the best results of our grid searches we obtained the following results for our model training and testing.

# 

Table \_ Error Results for the Circular Models Training



# 

# 

# 

Table \_ Error Results for the Rectangular Models Training

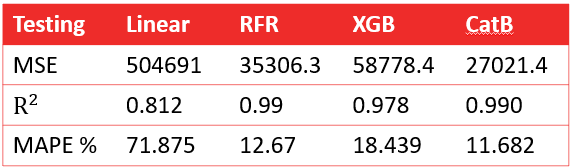


Table \_ Error Results for the Circular Models Testing

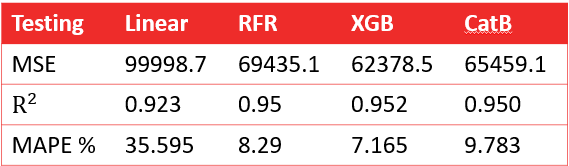


Table \_ Error Results for the Rectangular Models Testing

From the results listed in the tables above we determined that the top performing models for the circular dataset were the Catboost and the Random Forest Regressor. For the rectangular data set it was not as obvious however we decided that the XGBoost and the Random Forest Regressor did the best job in minimizing the change in magnitude of the error between training and testing.

Along with the error metrics we mentioned that we also generated plots based on the predicted axial capacity for the testing set for each of the models. These plots will be displayed below.

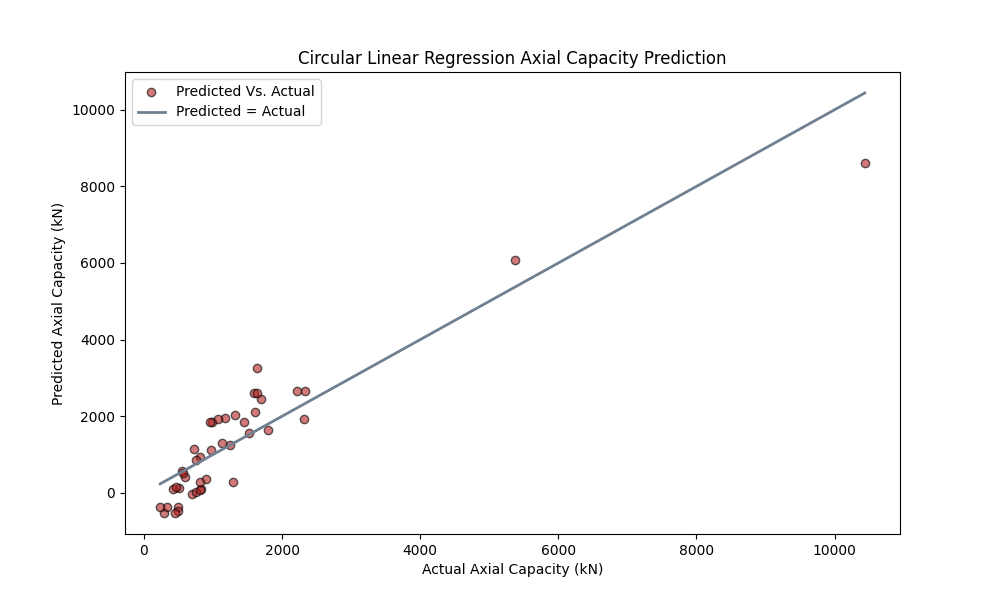


Figure \_ Results of the Circular Linear Regression Model

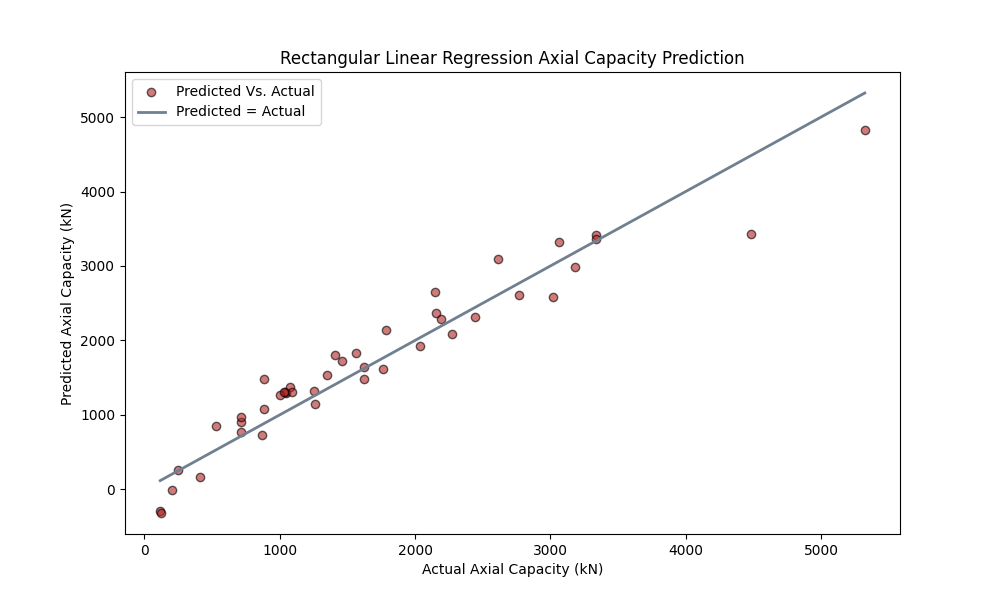


Figure \_ Results of the Rectangular Linear Regression Model

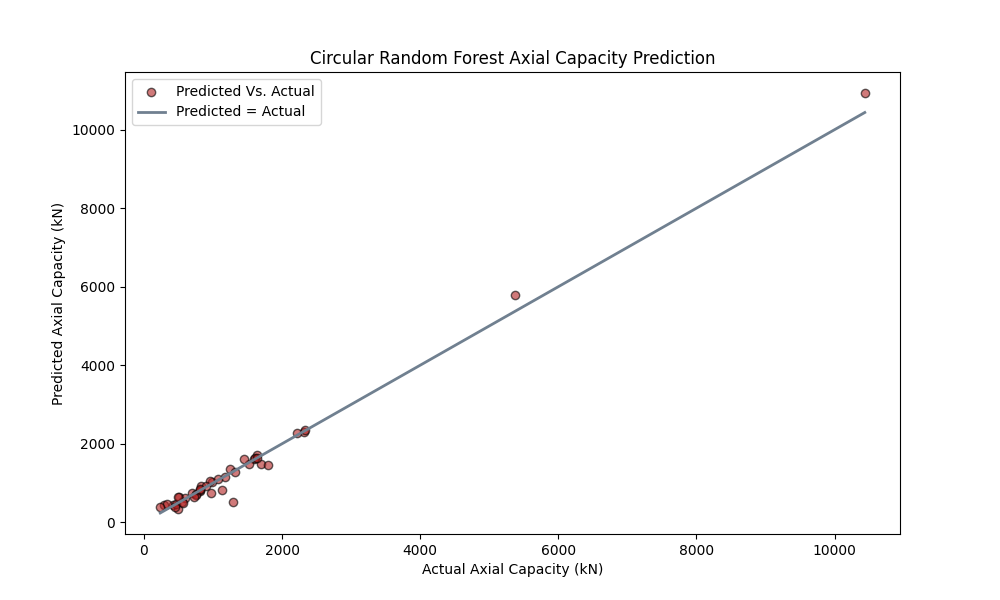


Figure \_ Results of the Circular Random Forest Regressor Model

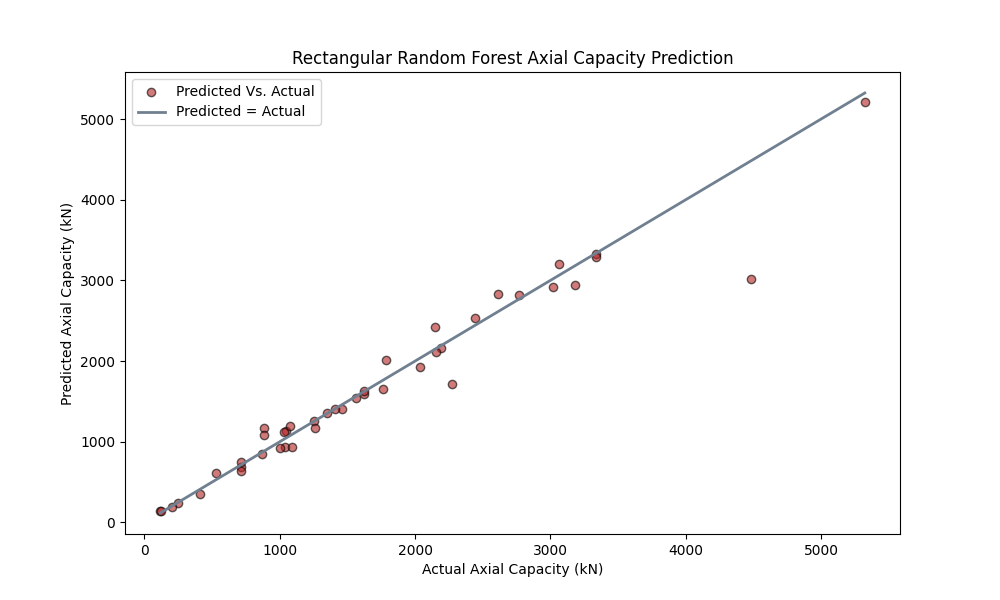


Figure \_ Results of the Rectangular Random Forest Regression Model

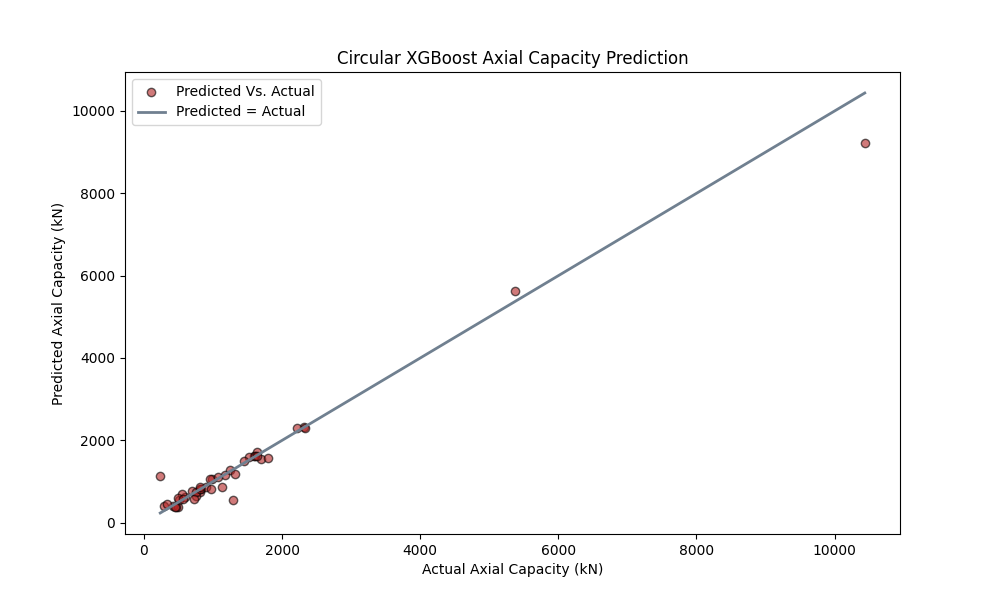


Figure \_ Results of the Circular XGBoost Model

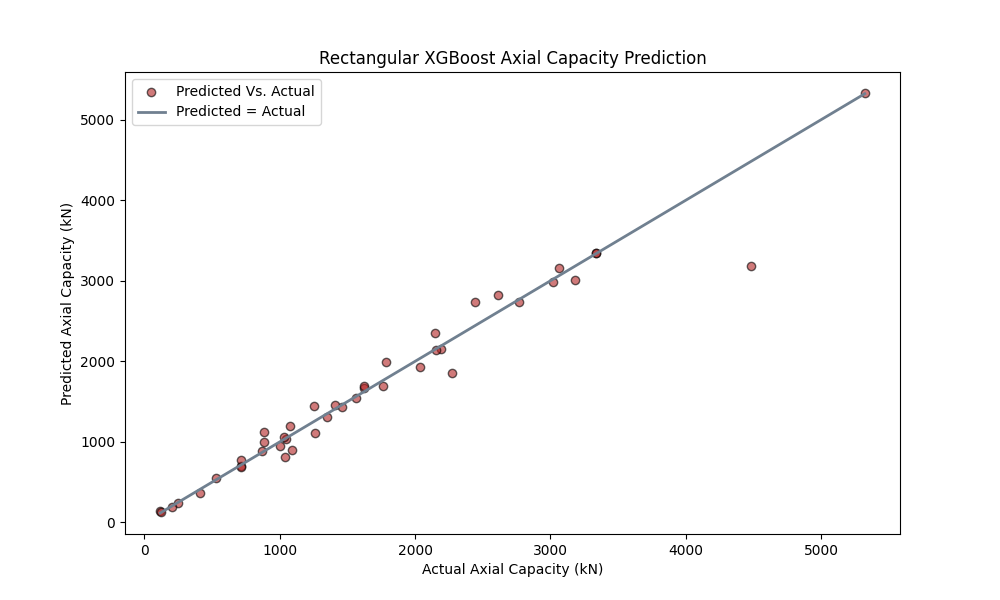


Figure \_ Results of the Rectangular XGBoost Model

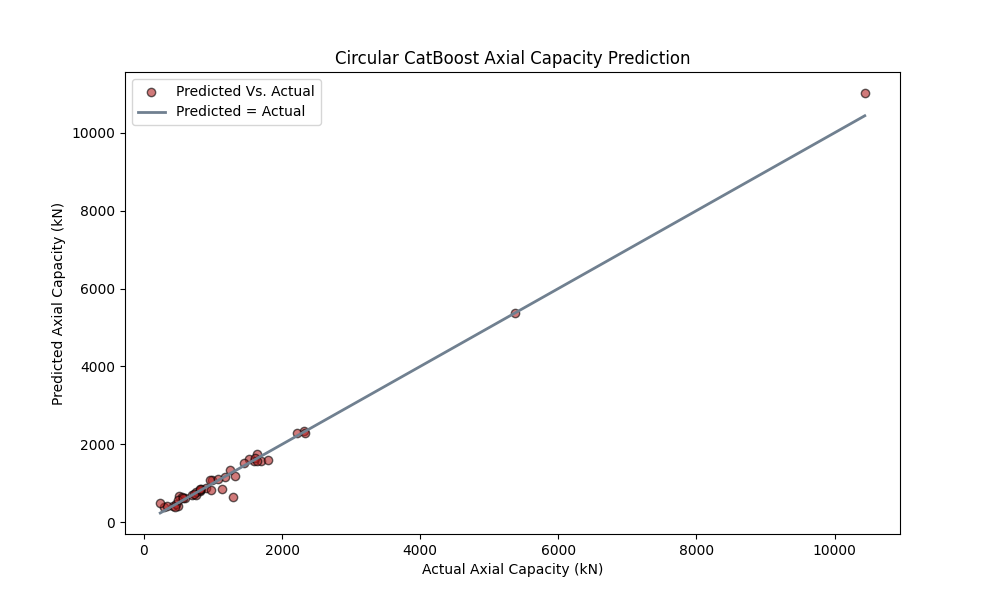


Figure \_ Results of the Circular CatBoost Model

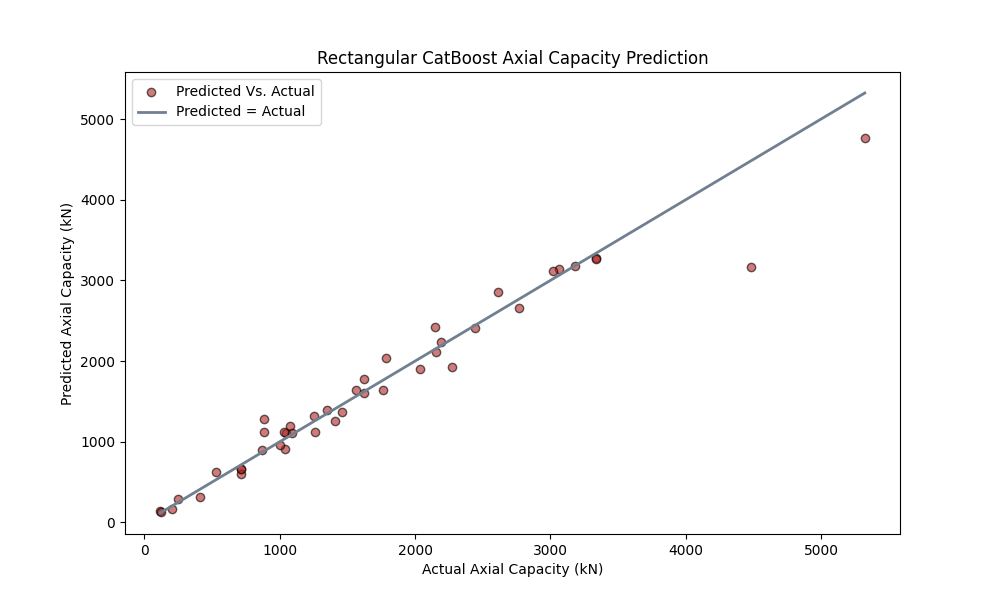


Figure \_ Results of the Rectangular CatBoost Model

Looking at the plots above we have the x-axis set to display the actual axial capacity while the y-axis represents the model's predicted axial capacity. There is also a x = y line running through the middle of each plot, this line would represent a perfect fit but we are also using this line to help determine the best fitting model. Since we are using these models to predict the strength of columns we also need to take into account safety concerns. This means we would much rather have a model that underpredicts the axial capacity rather than overpredict the overall strength. Taking this into consideration we now look at the figure \_, \_, \_, and \_. These plots represent the circular and rectangular Random Forest Regressor models, the rectangular XGBoost and the circular CatBoost. Looking back at our error metric results these 4 models represent the top 2 performing models for each of the rectangular and the circular dataset. Using both the error metric results and the visualized final predictions of the models we can see that for the Rectangular Data set the XGBoost model was our best performing model and for the Circular Data set it was the CatBoost model as they both minimize the magnitude and the number of overpredictions seen in their respective figures. Overall we can say that the Circular CatBoost was our best model of the 8, it minimized change in error between the training and testing set while also providing one of the best fits for the plot.

Next we will look at each dataset individually, starting with the rectangular data set. Ranking the 4 models from best to worst we get that the XGBoost, Random Forest Regressor, CatBoost and then the Linear Regression, the worst model being the Linear Regression was expected since it is the least computationally powerful and it is not capable of considering the non linear portions of our dataset. That being said it was mostly used as a baseline in order to compare it to our more complex and computationally powerful models. The next model is the CatBoost which is surprising as it was our best performing model when applying it to the circular dataset, the lack in performance of this model has been attributed to it being slightly too simple when looking at the hyperparameters applied for the grid search. We believe that slight adjustments to the grid search intervals could have allowed the model to perform slightly better and it could have even been our best performing model. Now looking at the remaining 2, as mentioned above the Random Forest Regressor and the XGBoost where very similar in results we believe this to be because they are our 2 most complex models in terms of parameter setup. We believe that since the rectangular dataset contains an extra highly correlated feature it responded best to our more complex models which happened to be the Random Forest Regressor and the XGBoost.

Lastly there are the models trained using the circular dataset. Just like with the rectangular dataset the Linear Regression model is the worst performing for the same reasons and it was once again used as a baseline to compare model performance. Now looking at the remaining three models we see an inverse in performance with the XGBoost now in the third place spot and the CatBoost as our top performer. Comparing the dataset there are only 4 features in the circular dataset with correlation above a value of 0.4, compared to the 6 found within the rectangular dataset. Because of this we believe the slightly less complex model in the CatBoost was able to perform best for the circular dataset.

# CHAPTER 5: COMPARISON OF RESULTS WITH EXISTING DESIGN CODE EQUATIONS

To further evaluate the Circular Catboost models’s accuracy, its results were compared against three established design code provisions:

* AISC 360-16 [11]:

For Compact Sections:

For Noncompact Sections:

where,

*λ* = Section's slenderness ratio is equivalent to the proportion of diameter to thickness.

*NuAIS* = axial compressive strength of CFSST column.

Np= Plastic Strength of the Composite Section

Ny = Yield Strength of the Composite Section

* Eurocode 4 [13]:

where,

coefficients of the CFST column which represents the confinement effect.

*Le* = Effective length of the CFST column;

*Es* = Elastic Modulus of the Exterior Steel tube;

*Ec* = Elastic Modulus of Concrete;

*Is* = Second Moments of Area of the Exterior Steel tube;

*NuEC* = axial compressive strength of CFSST column.

*Ncr* = Critical Compressive Strength of the Column based on Euler Buckling strength

* CSA S16-19 [28]:

where,

*Cfs* = Sustained Axial Load

*Cf* = Total Load on the Column

*NuCs* = axial compressive strength of CFSST column.

= Resistance Factor

= 0.85 – 0.0015f′c > 0.73

*Le* = Effective length of the CFST column

*Is* = Moments of Inertia of the Exterior Steel tube

*Ic* = Moments of Inertia of the Concrete

*n = 1.80*

For the purposes of calculating the accurate capacities, the resistance factors have been taken as 1, to rule out any intended conservatism from the picture.

It's important to note that since there are no specific codes for stainless steel, equations for conventional CFST columns were applied.

As discussed in the [Introduction](#_heading=h.4i7ojhp) chapter the code equations generally yield less accurate results for several reasons:

* **Input Restrictions:** Many codes have limitations on input values, particularly for material strengths.
* **Exclusion of High-Strength Materials:** Some codes, such as EC4, do not account for high-strength materials in their equations.
* **Steel Yield Strength Limitations:** In some codes, the maximum steel yield strength (fy) is capped at 460 MPa.

## Model performance vs Design Code Prediction

Compare the results using the MAE R2 etc and summarize

# CHAPTER 6: CONCLUSION

Github:

# CHAPTER 6: FUTURE RECOMMENDATION

It can be seen from the results that the developed ML models were able to achieve great accuracy but it's important to acknowledge its limitations and areas for future improvement:

* The study focuses solely on concentrically loaded short and medium-height columns subjected to the availability of the dataset.
* Parameters like residual stresses, imperfections, and confinement of concrete were not incorporated into the ML models.

Future Recommendations:

* Develop experimentally validated numerical models covering a broader range of parameters to enrich the current dataset.
* Include large cross-sectional sizes and slender columns to enhance the database for ML-based axial capacity prediction.
* Create more comprehensive models that account for previously omitted factors and a wider variety of loading conditions.

These limitations highlight the need for continued research to develop more robust and versatile models for accurate axial capacity prediction in CFSST columns. Future studies should aim to address these gaps, ultimately leading to more reliable and widely applicable prediction tools for structural engineering applications.

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