Cold-Formed Steel Built-Up Column Strength Prediction and Failure Mode Classification

This repository provides machine learning models to predict the **axial strength** and classify the **failure mode** of Cold-Formed Steel (CFS) built-up columns. The implemented models include:

- 1. MLP (Multilayer Perceptron) for Regression and Classification
- 2. **XGBoost** for Regression
- 3. Random Forest (RF) for Classification

Once the ML models (provided in GitHub repository) are trained using Jupyter Notebook, users can utilise these models for new data prediction and classification. Creating an account on **Google Colaboratory** is recommended. The GitHub repository includes a direct link to Google Colab, allowing users to run the provided notebooks directly in their own Colab account. The training process takes only a few seconds as the hyperparameters of the ML models have already been found, and the trained models can be reused multiple times for other predictions.

Additionally, users can interpret the results of the ML models using SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) to understand which parameters drive the model's predictions. These tools provide valuable insights into the decision-making process of the models.

To summarise, the provided ML models consist of three key steps:

- **1**-Training the model: Train the model on the provided dataset.
- **2**-Prediction for new instances: Use the trained model to predict outcomes for new data.
- 3- Interpretation of results: Analyse and interpret the model outputs using SHAP or LIME to identify influential features.

The input features for each ML model are discussed below.

1. MLP (Regression and Classification)

The **MLP** models use the following features for both regression and classification tasks:

```
new_data = {
  'L': [1500],
                                # Length (mm)
  't': [1.5],
                                # Thickness of the section (mm)
  'h': [179],
                                # Height of single section (mm)
                                # Flange of single section (mm)
  'b': [67],
  'KL_r': [29.39],
                                # non-dimensional member slenderness
  'P_y': [418.5],
                                # Yield strength (kN)
  'A': [930],
                                # Cross-sectional area (mm²)
  'P<sub>ne</sub>': [393.62],
                                # Global Buckling Strength (kN)
  'P<sub>(crl_s,crd_s)</sub>': [47.74]
                                # Sectional Buckling Strength (kN)
```

2. XGBoost (Regression)

The **XGBoost** regression model uses the following features:

```
new_data = {
  'L': [1500],
                              # Length (mm)
  't': [1.5],
                              # Thickness (mm)
  'h': [175],
                              # Height of single section (mm)
                              # Flange of single section (mm)
  'b': [65],
  'KL_r': [25.27],
                              # non-dimensional slenderness
  F_y: [450],
                              # Yield stress (MPa)
  '\lambda_c': [0.38],
                              # Global Slenderness
  '\lambda_{(le-d)}': [2.36],
                               # Sectional Slenderness (max. of local or distortional)
  'A': [988]
                              # Cross-sectional area (mm²)
```

3. Random Forest (Classification)

For the **RF regression** model uses the following features:

```
\label{eq:new_data} \begin{tabular}{lll} new_data &= & & & \\ L': [1500], & \# Length (mm) \\ 't': [1.5], & \# Thickness (mm) \\ 'h': [175], & \# Height of single section(mm) \\ 'b': [65], & \# Flange of single section(mm) \\ 'F_y': [450], & \# Yield stress (MPa) \\ '\lambda_c': [0.38], & \# Global Slenderness \\ '\lambda_{(le-d)}': [2.36] & \# Sectional Slenderness (max. of local or distortional) \\ \end{tabular}
```

* The values inside the square brackets are examples of inputting the features

Note:

When using both regression and classification models, it is recommended that new input features fall within the range of the 5th to 95th percentiles of the data used to train the machine learning (ML) models. Predictions made by these models may be inaccurate if the input features lie outside the range of most of the training data. The table below lists the 5th and 95th percentiles for the input features.

Table: Ranges of input features based on 5th and 95th percentiles of training data.

Feature Name	Abbreviation	From	То
Length (mm)	L	300.00	3200
Thickness (mm)	t	0.75	2.50
Height of single section (mm)	h	50.00	180.00
Flange of the single section (mm)	b	32.00	138.00
Member slenderness	KL/r	6.00	128.00
Area (mm²)	A	300.00	2351.00
Yielding stress (MPa)	F_{y}	280.00	618.70
Yielding strength (kN)	$\mathbf{P}_{\mathbf{y}}$	132.00	844.00
Global slenderness	λ_{c}	0.12	2.10
Sectional slenderness	$\lambda_{(le,d)}$	0.48	3.33
(max. of local or distortional)			
Global buckling strength (kN)	Pne	47.00	757.56
Sectional buckling strength (kN)	$P_{crl,crd}$	26.47	953.86
(min. of critical local or distortional buckling)			

Estimation of Sectional and Global Buckling Strength Features

CUFSM, an Open-source software (Li and Schafer 2013), can be used to estimate a CFS section's sectional (local or distortional) buckling stress. Additionally, the software can provide the nominal area, radius of gyration, and other sectional properties. The software is available at the following link:

https://www.ce.jhu.edu/cufsm/downloads/

The section's global strength can be estimated using the following equations recommended in the North American Specification for the Design of Cold-formed Steel Structural Members (AISI S100-16 2020).

The nominal global column strength is calculated as follows:

For
$$\lambda_{\rm c} \leq 1.5$$
;
$$P_{ne} = \left(0.658^{\lambda_{\rm c}^2}\right) P_y$$
For $\lambda_{\rm c} > 1.5$;
$$P_{ne} = \left(\frac{0.877}{\lambda_{\rm c}^2}\right) P_y$$

$$\lambda_c \text{ is global slenderness };
$$\lambda_c = \left(\frac{P_v}{P_{cre}}\right)^{0.5}$$$$

Flexural buckling strength;
$$P_{cre} = \frac{\pi^2 E A}{\left(\frac{KL}{r_o}\right)^2}$$

Modified slenderness ratio;
$$\left(\frac{KL}{r}\right)^2 = \left(\frac{KL}{r_0}\right)^2 + \left(\frac{a}{r_0}\right)^2$$

Fastener spacing limit;
$$\frac{a}{r_i} \le \frac{1}{2} \left(\frac{KL}{r_o} \right)$$

 P_{cre} = least of the applicable elastic flexural and flexural-tortional buckling stress:

Where A is the gross area and P_{ne} and P_y are the global compressive and yield strength of the member, respectively; (KL/r_o) is the overall slenderness ratio of the entire built-up section about the minor axis; (KL/r)m is the modified slenderness ratio; a is the fastener spacing; r_i is the minimum radius of gyration of a single section; K is the effective length factors for flexural buckling. L is the unbraced lengths of the member for flexural and flexural-torsional buckling, respectively; E is the modulus of elasticity. For the modified slenderness method, the (KL/r_o) shall be replaced by the term $(KL/r)_m$ to account for the effect of intermediate screw spacing (a) in the elastic global buckling stress of built-up section. Where $\lambda_{le} = (P_{ne}/P_{crl})^{0.5}$ and $\lambda_d = (P_y/P_{crd})^{0.5}$ are local-global, and distortional slenderness of the sections; P_{crl} and P_{crd} are critical elastic local and distortional buckling loads, respectively.

References:

American Iron and Steel Institute (AISI). (2020). *North American Specification for the Design of Cold-Formed Steel Structural Members*, AISI S100-16 (2020), with Supplement 2. Washington, D.C.

Li, Z., and B. W. Schafer. 2013. "Constrained Finite Strip Method for Thin-Walled Members with General End Boundary Conditions." *J. Eng. Mech.* 139 (11): 1566–1576. https://doi.org/10.1061/(asce)em.1943-7889.0000591.