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# Prediction of shear capacity of steel channel sections using machine learning algorithms

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## Abstract

This study presents the application of popular machine learning algorithms in prediction of the shear resistance of steel channel sections using experimental and numerical data. Datasets of 108 results of stainless steel lipped channel sections and 238 results of carbon steel LiteSteel sections were gathered to train machine learning models including support vector regression (SVR), multi-layer perceptron (MLP), gradient boosting regressor (GBR), and extreme gradient boosting (XGB). The cross-validation with 10 folds has been conducted in the training process to avoid over-fitting. The optimal hyperparameter combinations for each machine learning model were found during the hyperparameter tuning process and four performance indicators were used to evaluate the performance of the trained models. The comparison results suggest that all four implemented machine learning models reliably predict the shear capacity of both stainless steel lipped channel sections and carbon steel LiteSteel sections while the implemented SVR algorithm is found to be the best performing model. Moreover, it is shown that the implemented machine learning models exceed the prediction accuracy of the available design equations in estimating the shear capacity of steel channel sections.

*Keywords:* Channel sections, Shear capacity, Design rules, Machine learning

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## 1. Introduction

Light gauge cold-formed steel elements have gained interest over heavier hot-rolled sections in recent times as cost effective, highly efficient structural solutions [1]. Szewczak et al. [2] reported that the use of thin-walled steel sections have reduced the steel consumption by up to 50%, construction time by up to 60% and construction costs by up to 25%, compared to conventional hot-rolled sections. Cold-formed lipped channel beams (LCBs) and LiteSteel beams (LSBs) are most utilised as primary and secondary load-carrying structural elements such as roof purlins, wall studs, steel framing, truss beams, and floor joists and bearers [1, 3–5].

Stainless steel is an evolving cold-forming material in the construction industry due to its outstanding material properties. Higher chromium content in stainless steel acts as a protective layer against oxidation and corrosion [6–8]. The unique characteristics that cold-formed stainless steel sections feature include corrosion resistance, fire and heat resistance, durability, good toughness and fatigue properties, high strength to weight ratio, simple fabrication and handling, and recyclability [4, 8]. The application of stainless steel in the construction industry has been increased with the improved insight of its advantages such as savings from corrosion-resistant coatings, reduced inspection frequency, maintenance, downtime and replacement costs, and a transition towards sustainability. However, stainless steel has become less popular in structural applications due to the high initial material cost of stainless steel structural components when compared to carbon steel. Therefore, the accurate prediction of resistance of stainless steel sections is of paramount importance.

Many research studies have been conducted to investigate the shear performance of cold-formed channel sections in the recent past, both experimentally and numerically. Keerthan and Mahendran [9, 10] performed experimental studies on the shear behaviour of carbon steel LSBs and LCBs, and the shear design equations have been proposed based on North American specifications [11]. Furthermore, Keerthan and Mahendran [1, 12, 13] developed finite element (FE) models to predict the non-linear shear behaviour of carbon steel channels, including their elastic buckling and ultimate shear capacities with precision. In addition, Pham and Hancock [14–17] conducted both experimental and numerical investigations on the shear response of plain and stiffened carbon steel channel sections. Since there was an absence of comprehensive investigations on the shear behaviour of cold-formed stainless

38 steel LCBs to date, Dissanayake et al. [18] performed a combined experi-  
39 mental and numerical study to predict the shear behaviour and strength of  
40 stainless steel LCBs. Dissanayake et al. [19] also conducted FE investigations  
41 to assess the shear and elastic shear buckling behaviours of the longitudinally  
42 stiffened stainless steel LCBs. Ishqy et al. [6] studied the effect of unrein-  
43 forced circular web openings on the shear behaviour of cold-formed stainless  
44 steel LCBs numerically. Moreover, Sonu and Singh [20, 21] examined the  
45 shear performance of lean duplex stainless steel rectangular hollow beams  
46 using FE analyses. These studies involve the modification of existing design  
47 rules considering the inelastic reserve capacity and strain hardening effect of  
48 stainless steel to enhance the shear capacity prediction accuracy of European  
49 standards for stainless steel [22] and the Direct Strength Method (DSM).

50 In recent years, the artificial intelligence methods, especially machine  
51 learning, have gained a lot of attention in civil engineering applications by  
52 offering viable solutions for complex problems such as prediction, classifi-  
53 cation and optimisation [23]. It is evident that the utilization of machine  
54 learning in civil engineering has fuelled many visions and hopes for future re-  
55 search and development [24–26]. The machine learning methods can perform  
56 exceptionally well in prediction the non-linear relationships among the inputs  
57 and outputs which are difficult to formulate otherwise and do not necessarily  
58 require large amount of data [24]. Also, the machine learning models are  
59 computationally efficient and at the same time can be expandable to provide  
60 robust predictions even with large amount of data. The application of ma-  
61 chine learning has been featured in numerous civil and structural engineering  
62 research publications [26–29].

63 The machine learning prediction models have been utilised in many civil  
64 and structural engineering research areas. Fonseca et al. [30] have investi-  
65 gated the possibility of employing experimental and numerical data to train  
66 an artificial neural network (ANN) to predict the patch load resistance. The  
67 ANN models have also been developed using finite element data to pre-  
68 dict the deflections for composite beams by Sakr and Sakla [31] and for  
69 steel-concrete composite bridges by Tadesse et al. [32]. A particle swarm  
70 optimization-based neural network was proposed to predict the failure of  
71 multi-storied reinforced concrete buildings by Chatterjee et al. [33]. Ab-  
72 dollahzadeh and Ghobadi [34] proposed a neural network model to predict  
73 the hysteretic behaviour of perforated steel plate shear walls. The neural  
74 network-based models were also developed using finite element data to esti-  
75 mate the stress concentration factors for multi-planar tubular joints by Chiew

76 et al. [35] and for welded joints by Dabiri et al. [36, 37]. The computational  
77 prediction models including genetic programming were developed using test  
78 results for moment-rotation behaviour of boltless steel connections by Shah  
79 et al. [38]. In another study, Bağcı [39] predicted the moment-curvature  
80 relationship of reinforced concrete sections using ANN. Jakubek [40] trained  
81 multi-layer perceptron and fuzzy weights neural network models to predict  
82 the load capacity of eccentrically loaded reinforced concrete columns. Nader-  
83 pour et al. [41] used different soft computing methods for the compressive  
84 strength prediction of FRP-confined reinforced concrete columns. Hadi [42]  
85 conducted optimization studies on concrete beams using back-propagation  
86 neural networks. The use of single and ensemble machine learning methods  
87 in prediction of long-term deflections of reinforced concrete beams were in-  
88 vestigated by Pham et al. [43]. Erdem [44] applied the ANNs to predict  
89 the moment capacity of reinforced concrete slabs in fire. McKinney and Ali  
90 [45] have employed supervised ANNs in spalling classification and failure pre-  
91 diction of high strength concrete columns subjected to fire. Also, a genetic  
92 algorithm optimized back-propagation neural network was developed for the  
93 determination of flexural capacity of postfire reinforced concrete beams by  
94 Cai et al. [46]. Moreover, Shen et al. [47] have proposed a new material  
95 design method for ultra-high strength stainless steel using machine learning  
96 algorithms. And Mu et al. [48] have devised an ensemble machine learn-  
97 ing model to predict the strain-induced martensite in austenitic steels. Vu  
98 et al. [49] have proposed an efficient framework based on the gradient tree  
99 boosting algorithms for the strength prediction of the concrete filled steel  
100 tubular columns. A gradient tree boosting model was also used by Truong  
101 et al. [50] to evaluate the safety of steel trusses through prediction of the  
102 load-carrying capacity and the displacement of the structure. Kim et al. [51]  
103 have assessed the efficiency of different machine learning models to predict  
104 and classify the load-carrying resistance of steel frames. It is of note that the  
105 most of these applications of machine learning models have outperformed the  
106 existing design methods in providing accurate predictions.

107 The use of machine learning prediction models in these particular appli-  
108 cation fields is explained by the availability of the large quantity of initial  
109 data on which the learning algorithm or the network is trained and most  
110 of the above applications provide reasonably easy access to large datasets,  
111 for example, through repeated laboratory experiments or computer mod-  
112 elling [52]. In addition, the application of machine learning models in civil  
113 engineering has dealt with structural health monitoring, damage detection

114 of structures, structural optimization, and structural parameter identifica-  
 115 tion. The structural health monitoring and material property modelling of  
 116 concrete have received significant attention in the recent past among these  
 117 machine learning applications in civil engineering [24]. The machine learning  
 118 algorithms have also been used to classify the failure modes of ultra-high  
 119 performance concrete beams [53]. Fig. 1 illustrates the typical workflow of  
 120 machine learning processes.

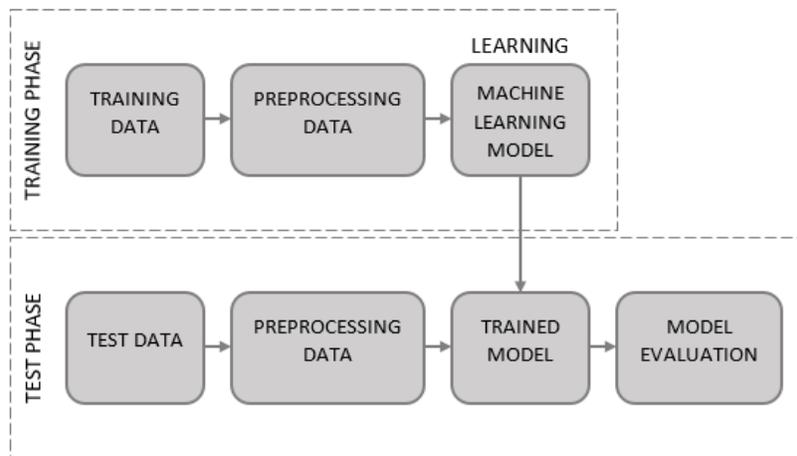


Figure 1: Typical workflow of machine learning processes.

121 In terms of tackling structural engineering problems, especially in or-  
 122 der to analyse the structural behaviours, data-driven approaches have been  
 123 used. To estimate material properties, researchers have established predic-  
 124 tive models which minimise the prediction error between the actual data  
 125 collected from experiments and models [54]. Machine learning applications  
 126 typically use classification and prediction to solve problems. As machine  
 127 learning enables training of algorithms and testing them based on available  
 128 datasets, the mastery of models, basic statistics and availability of reliable  
 129 data are essential to make most accurate predictions [25].

130 Although many past studies have utilised machine learning prediction  
 131 models for design and performance prediction of reinforced concrete and hot-  
 132 rolled steel structures, there are very few articles which focus on the applica-  
 133 tion of machine learning to predict the behaviour of cold-formed sections. In  
 134 particular, past studies have not attempted to investigate the application  
 135 of machine learning models in prediction of the shear strength of cold-formed

136 stainless steel and carbon steel channel sections. The accurate determination  
137 of section strengths plays vital role in planning and design of steel structures.  
138 The available machine learning models can be easily implemented to handle  
139 large number of data to make robust predictions. Therefore, considering the  
140 benefits of using machine learning prediction models in structural design,  
141 this research study aims to analyse the applicability of machine learning in  
142 prediction of the shear capacity of cold-formed stainless steel LCBs and car-  
143 bon steel LSBs to develop efficient machine learning prediction tools which  
144 will potentially help to lower the costs associated with experiments and FE  
145 simulations.

## 146 **2. The development of database**

147 A database of compiled results is required for the successful implemen-  
148 tation of machine learning algorithms. Hence, a literature survey has been  
149 undertaken to collect the results from experimental and FE studies on the  
150 shear capacity of cold-formed stainless steel and carbon steel beams. This  
151 section presents a brief review of experimental and FE modelling methods  
152 used herein followed by a summary of the collected database.

### 153 *2.1. Overview of experimental and FE analysis*

154 Dissanayake et al. [18] and Keerthan and Mahendran [9, 12] have in-  
155 vestigated the shear behaviour of cold-formed stainless steel LCBs and cold-  
156 formed carbon steel LSBs, respectively. The cross-sections of a LCB section  
157 and a LSB section are illustrated in Fig. 2. The aspect ratio, which is de-  
158 fined as the clear shear span ( $a$ ) divided by the clear web height ( $d_1$ ), governs  
159 the shear failure. It is considered that a shear dominant failure occurs when  
160 this ratio is equal to unity. For stainless steel LCB sections, Dissanayake et  
161 al.'s [18] test programme included aspect ratio of 1.0 while for LSB sections,  
162 Keerthan and Mahendran's [9] test programme included aspect ratio of 1.0  
163 and 1.5. Three-point loading test arrangement with two shear spans was  
164 used in both studies. The shear capacity was found from the peak load of  
165 the load-displacement response. More details about the three-point loading  
166 test programmes of cold-formed sections can be found from similar experi-  
167 mental studies [10, 15, 16, 55]. These experimental studies have been further  
168 extended using validated FE models.

169 Keerthan and Mahendran [12] and Dissanayake et al. [18] have developed  
170 non-linear FE models in the advanced FE modelling software, ABAQUS [56].

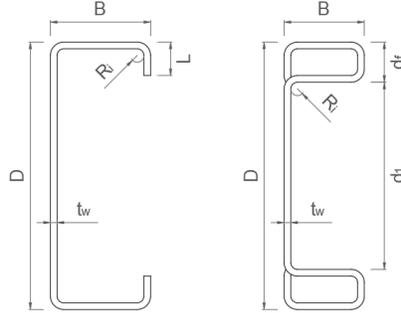


Figure 2: Cross-sections of LCB and LSB sections with key dimensions.

171 The developed FE models were validated against the experimental results in  
 172 terms of shear capacity, failure mode and load-displacement response. Sub-  
 173 sequently, parametric FE analysis was performed changing the dimensional  
 174 and mechanical parameters. The S4R shell elements available in ABAQUS  
 175 [56] element library were used to develop the FE model components of both  
 176 the steel channel section and the web side plates. The web side plates were  
 177 modelled with shell elements and a higher thickness value was assigned to  
 178 simulate the rigid body behaviour. These web side plates were connected  
 179 using tie constraints option. A mesh size of  $5 \text{ mm} \times 5 \text{ mm}$  was employed to  
 180 flat parts and a mesh size of  $1 \text{ mm} \times 5 \text{ mm}$  was employed to corner parts  
 181 of the channel sections. Meanwhile, a coarser mesh size was assigned to the  
 182 web side plates as the shear behaviour of the channel is not influenced by  
 183 the web side plates. Fig. 3 depicts the FE mesh and boundary conditions  
 184 employed in the FE models for LCBs.

185 The accurate material modelling of cold-formed carbon steel and stain-  
 186 less steel is required to obtain the actual behaviour from the FE model. The  
 187 stress-strain response of carbon steel was taken as a bi-linear model with per-  
 188 fect plasticity using nominal yield strength. However, stainless steel exhibits  
 189 a considerable degree of strain hardening as well as strength enhancements  
 190 due to cold-working. Therefore, the material model proposed by Arrayago et  
 191 al. [57], which is based on the modified Ramberg-Osgood model, was used.  
 192 The strength enhancements were assigned to the corner regions of the model  
 193 as per the Cruise and Gardner's [58] recommendations. Moreover, the initial  
 194 geometric imperfections were considered in the FE model superimposing the  
 195 critical elastic buckling analysis modes. An illustration of obtained FE shear  
 196 failure mode for LCB is also displayed in Fig. 3. For further details related

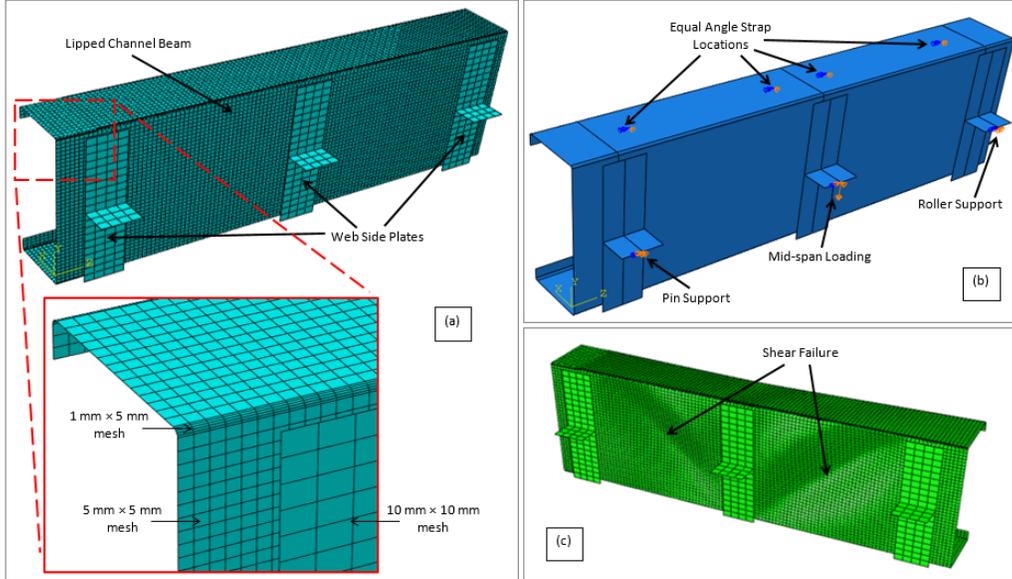


Figure 3: FE modelling of LCB section: (a) Mesh, (b) Boundary conditions, and (c) Failure mode.

197 to the FE modelling of cold-formed sections, similar numerical work can be  
 198 referred [1, 13, 14, 17, 19, 59–61].

## 199 2.2. Collected datasets

200 Dissanayake et al. [18] and Keerthan and Mahendran [9, 12] have gen-  
 201 erated a wide range of data using experimental and FE analysis methods  
 202 as described in the previous section. All the related data from their studies  
 203 were collated to form a database with input and output features. The details  
 204 of the collected data are discussed herein.

205 For cold-formed stainless steel LCB sections, 108 results were collected  
 206 in total from Dissanayake et al.'s [18] study. This includes 8 shear test  
 207 results and 100 numerical parametric study results. The dataset consists of  
 208 various geometric and material parameters as input features. The considered  
 209 geometric input features of stainless steel LCBs include web depth ( $D$ ), flange  
 210 width ( $B$ ), lip height ( $L$ ), and web thickness ( $t_w$ ). Also, aspect ratio ( $a/d_1$ )  
 211 and a slenderness measure of the web ( $d_1/t_w$ ) are taken into account. The  
 212 adopted material property features include the yield strength ( $f_y$ ) and the  
 213 ultimate strength ( $f_u$ ) of stainless steel. And, the output feature is the shear

214 strength ( $V$ ) of LCBs. Table 1 reports the key statistics of input and output  
 215 features of LCBs dataset.

Table 1: Key statistics of cold-formed stainless steel LCBs dataset

|            | #samples |     | $D$ (mm) | $B$ (mm) | $L$ (mm) | $t_w$ (mm) | $a/d_1$ | $d_1/t_w$ | $f_y$ (MPa) | $f_u$ (MPa) | $V$ (kN) |
|------------|----------|-----|----------|----------|----------|------------|---------|-----------|-------------|-------------|----------|
| Experiment | 8        | Min | 99.48    | 50.0     | 15.5     | 1.18       | 1.0     | 45.97     | 253.9       | 725.3       | 18.5     |
|            |          | Max | 200.98   | 75.5     | 16.5     | 1.99       | 1.0     | 163.55    | 253.9       | 725.3       | 47.1     |
| FE         | 100      | Min | 100.0    | 50.0     | 15.0     | 1.0        | 1.0     | 17.2      | 230.0       | 540.0       | 12.93    |
|            |          | Max | 250.0    | 75.0     | 15.0     | 5.0        | 1.0     | 244.0     | 500.0       | 700.0       | 356.07   |
| Overall    | 108      | Min | 99.48    | 50.0     | 15.0     | 1.0        | 1.0     | 17.2      | 230.0       | 540.0       | 12.93    |
|            |          | Max | 250.0    | 75.5     | 16.5     | 5.0        | 1.0     | 244.0     | 500.0       | 725.3       | 356.07   |

216 The gathered stainless steel LCBs dataset covers a range of parameters  
 217 that can be seen in practice. For an instance, the depth of the LCBs ranges  
 218 from 99.48 mm to 250 mm. The thickness of the LCBs is varying between  
 219 1 mm and 5 mm. The minimum and maximum values of the average yield  
 220 strength of the LCBs are 230 MPa and 500 MPa, respectively. Meanwhile,  
 221 the corresponding ultimate strength values range from 540 MPa to 725.3  
 222 MPa.

223 For cold-formed carbon steel LSB sections, 238 results were collected in  
 224 total including 25 shear test results and 213 parametric FE results from the  
 225 respective studies [9, 12]. Similar to the previously discussed LCBs dataset,  
 226 the considered geometric dimensions of LSBs include web depth ( $D$ ), flange  
 227 width ( $B$ ), clear web height ( $d_1$ ), and web thickness ( $t_w$ ). In addition, it con-  
 228 siders aspect ratio ( $a/d_1$ ) and a slenderness parameter of the web ( $d_1/t_w$ ).  
 229 The yield strength ( $f_y$ ) of carbon steel is the only material property con-  
 230 sidered. Similarly, the shear strength ( $V$ ) of LSBs is taken as the output  
 231 feature. The key statistics of input and output features of LSBs dataset are  
 232 summarised in Table 2.

233 As can be seen, Table 2 also demonstrates that the collated dataset covers  
 234 a full spectrum of practically used LSB sections in light gauge steel construc-  
 235 tion. For an instance, the depth of the LSBs ranges from 125 mm to 300  
 236 mm. The thickness of the LSBs is varying between 1.5 mm and 3 mm. The  
 237 minimum and maximum values of the average yield strength of the LSBs  
 238 from the collected data are 250 MPa and 459.7 MPa, respectively.

239 It is also of note that both the collected stainless steel and carbon steel  
 240 datasets cover the elastic and inelastic shear buckling, and shear yielding  
 241 failure behaviours. Furthermore, both datasets include a wide range of com-

Table 2: Key statistics of cold-formed carbon steel LSBs dataset

|            | #samples |     | $D$ (mm) | $B$ (mm) | $d_1$ (mm) | $t_w$ (mm) | $a/d_1$ | $d_1/t_w$ | $f_y$ (MPa) | $V$ (kN) |
|------------|----------|-----|----------|----------|------------|------------|---------|-----------|-------------|----------|
| Experiment | 25       | Min | 125.0    | 45.0     | 95.2       | 1.58       | 1.0     | 49.07     | 422.6       | 45.8     |
|            |          | Max | 300.0    | 75.0     | 262.3      | 2.51       | 1.6     | 133.14    | 459.7       | 143.7    |
| FE         | 213      | Min | 150.0    | 45.0     | 119.7      | 1.5        | 1.0     | 60.0      | 250.0       | 29.8     |
|            |          | Max | 300.0    | 75.0     | 260.8      | 3.0        | 1.5     | 163.0     | 450.0       | 173.0    |
| Overall    | 238      | Min | 125.0    | 45.0     | 95.2       | 1.5        | 1.0     | 49.07     | 250.0       | 29.8     |
|            |          | Max | 300.0    | 75.0     | 262.3      | 3.0        | 1.6     | 163.0     | 459.7       | 173.0    |

242 commercially available cross-sectional dimensions and material grades covering  
 243 a range of cross-section slenderness values and strengths. Therefore, the  
 244 collected database is found to be handy in developing machine learning al-  
 245 gorithms that could be more promising than the existing code provisions to  
 246 predict the shear capacities of stainless steel LCBs and carbon steel LSBs.

### 247 3. Review of design equations for cold-formed sections

248 The currently available design provisions for cold-formed sections are re-  
 249 viewed in this section. The shear design equations given in European stan-  
 250 dards for stainless steel, EN1993-1-4 [22] and the direct strength method  
 251 (DSM) shear provisions in North American specifications for cold-formed  
 252 steel members, AISI S100 [11] have been modified by Dissanayake et al. [18]  
 253 to enhance the shear resistance prediction accuracy of cold-formed stainless  
 254 steel LCBs. Also, Keerthan and Mahendran [12] have revised the DSM shear  
 255 design provisions in AISI S100 [11] considering the cold-formed carbon steel  
 256 LSBs. These proposed design provisions are found to be more accurate than  
 257 the codified design provisions. Therefore, the revised provisions were adopted  
 258 and would be used to compare and assess the prediction performance of the  
 259 machine learning models in Section 5.

#### 260 3.1. EN1993-1-4 shear design rules

European standards for stainless steel, EN1993-1-4 [22] provide a separate set of shear design equations which are to be referred together with European standards for plated steel elements, EN1993-1-5 [62]. Following these standards, the shear resistance of a section ( $V_{b,Rd}$ ) is taken as the summation of the shear buckling resistance of the section web ( $V_{bw,Rd}$ ) and the flange

contribution to the shear resistance of the section ( $V_{bf,Rd}$ ) as follows

$$V_{b,Rd} = V_{bw,Rd} + V_{bf,Rd} \leq \frac{\eta f_{yw} h_w t_w}{\sqrt{3} \gamma_{M1}}, \quad (1)$$

where  $f_{yw}$  is the yield strength of the section web,  $h_w$  is the web depth, and  $t_w$  is the web thickness.  $\gamma_{M1}$  is the partial safety factor and a value of  $\eta = 1.2$  is recommended. The shear buckling resistance of the section web ( $V_{bw,Rd}$ ) can be calculated as

$$V_{bw,Rd} = \frac{\chi_w f_{yw} h_w t_w}{\sqrt{3} \gamma_{M1}}, \quad (2)$$

where  $\chi_w$  is the shear buckling reduction factor of the web. EN1993-1-4 [22] provides a separate set of expressions for this shear buckling reduction factor ( $\chi_w$ ) of section webs with rigid end posts and they are expressed as follows

$$\chi_w = \eta \quad \text{for } \bar{\lambda}_w \leq \frac{0.65}{\eta}, \quad (3a)$$

$$\chi_w = \frac{0.65}{\bar{\lambda}_w} \quad \text{for } \frac{0.65}{\eta} < \bar{\lambda}_w < 0.65, \quad (3b)$$

$$\chi_w = \frac{1.56}{0.91 + \bar{\lambda}_w} \quad \text{for } \bar{\lambda}_w \geq 0.65, \quad (3c)$$

261 where  $\bar{\lambda}_w$  is the slenderness of the section web.

Following a number of experimental and numerical studies on cold-formed stainless steel LCBs, Dissanayake et al. [18] have proposed a modification to Eq. (3) to increase the prediction accuracy. These modified expressions are expressed as follows

$$\chi_w = 2.1 \quad \text{for } \bar{\lambda}_w \leq 0.12, \quad (4a)$$

$$\chi_w = \frac{0.839}{\bar{\lambda}_w^{0.433}} \quad \text{for } 0.12 < \bar{\lambda}_w < 0.667, \quad (4b)$$

$$\chi_w = \frac{1.797}{1.13 + \bar{\lambda}_w} \quad \text{for } \bar{\lambda}_w \geq 0.667. \quad (4c)$$

262

### 263 3.2. The direct strength method (DSM)

The DSM has been adopted in North American specifications for cold-formed steel members, AISI S100 [11]. The nominal shear strength of a

section ( $V_n$ ) with transverse web stiffeners are given as follows

$$\frac{V_n}{V_y} = 1 \quad \text{for } \lambda \leq 0.776, \quad (5a)$$

$$\frac{V_n}{V_y} = \left[ 1 - 0.15 \left( \frac{1}{\lambda^2} \right)^{0.4} \right] \left( \frac{1}{\lambda^2} \right)^{0.4} \quad \text{for } \lambda > 0.776, \quad (5b)$$

264 where  $\lambda$  is the section slenderness.

Dissanayake et al. [18] have also modified the DSM design equations given by Eq. (5) considering stainless steel LCBs. The modified DSM equations for the section nominal shear strength are expressed as follows

$$\frac{V_n}{V_y} = 2 \quad \text{for } \lambda \leq 0.122, \quad (6a)$$

$$\frac{V_n}{V_y} = \frac{0.795}{\lambda^{0.439}} \quad \text{for } 0.122 < \lambda \leq 0.592, \quad (6b)$$

$$\frac{V_n}{V_y} = \left[ 1 - 0.213 \left( \frac{1}{\lambda^2} \right)^{0.35} \right] \left( \frac{1}{\lambda^2} \right)^{0.35} \quad \text{for } \lambda > 0.592. \quad (6c)$$

265

In addition, extensive experimental and numerical investigations have been conducted by Keerthan and Mahendran [9, 12] on cold-formed carbon steel LSB sections. Based on these investigations, Keerthan and Mahendran [12] have revised the DSM shear design equations given by Eq. (5) aiming enhanced resistance predictions. The proposed DSM equations for the nominal shear strength of sections are stated as follows

$$\frac{V_n}{V_y} = 1 \quad \text{for } \lambda \leq 0.815, \quad (7a)$$

$$\frac{V_n}{V_y} = \left[ 1 - 0.15 \left( \frac{1}{\lambda^2} \right)^{0.5} \right] \left( \frac{1}{\lambda^2} \right)^{0.5} \quad \text{for } \lambda > 0.815. \quad (7b)$$

266

## 267 4. Machine learning algorithms

### 268 4.1. Overview

269 In this study, four well-known machine learning algorithms including sup-  
270 port vector machine (SVM), multi-layer perceptron (MLP), and gradient

271 boosting machine (GBM) are used to predict the shear capacities of stainless  
 272 LCBs and carbon steel LSBs. This section aims to provide a brief overview of  
 273 these models and the details of the implementation process of these models  
 274 in application to collected datasets.

#### 275 4.1.1. Support vector machine

276 SVMs are categorised as supervised learning algorithms and can be utilised  
 277 for classification and regression problems. Vapnik and his team [63, 64] have  
 278 immensely contributed to the development of SVMs in the last decades.  
 279 When applying these SVMs in solving regression related problems, it is  
 280 known as support vector regression (SVR).

281 The fundamental concept behind SVMs is the non-linear mapping of the  
 282 input vectors into a high dimensional feature space where the linear decision  
 283 surface is constructed. The generalisation ability of the learning machine is  
 284 ensured through the properties of the decision surface [64].

In other words, considering a set of training data  $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\} \subset \chi \times \mathbb{R}$ , the aim of  $\epsilon$ -SVR [63] is to predict a flat decision function,  $f(x)$  such that  $f(x)$  is only allowed to deviate from the actual data  $y_i$  in the range of  $(-\epsilon, \epsilon)$  for all the data in the training set [65]. For the case of linear decision function,  $f(x)$  this can be expressed as

$$f(x) = \langle \omega, x \rangle + b \quad \text{with} \quad \omega \in \chi, \quad b \in \mathbb{R}, \quad (8)$$

285 where  $\omega$  and  $b$  represent the weight and bias, respectively.

However, finding a decision function is not always possible as there could be data points in some datasets that are lying outside the feasible region [64, 65]. To address this issue, Cortes and Vapnik [64] have considered the “soft margin” loss function in SVMs and therefore slack variables  $\xi_i$  are introduced as illustrated in Fig. 4a. Then, setting the objective of flattening the decision function leads to the formulation of the optimisation problem that includes the slack variables  $\xi_i$  as follows [63]

$$\text{minimize} \quad \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^n (\xi_i), \quad (9a)$$

$$\text{subject to} \quad |y_i - \langle \omega, x \rangle - b| \leq \epsilon + \xi_i, \quad (9b)$$

$$\xi_i \geq 0, \quad (9c)$$

$$C > 0, \quad (9d)$$

286 where  $C$  determines both the flatness of the decision function  $f(x)$  and the  
 287 limit of the deviations that are larger than  $\epsilon$ .

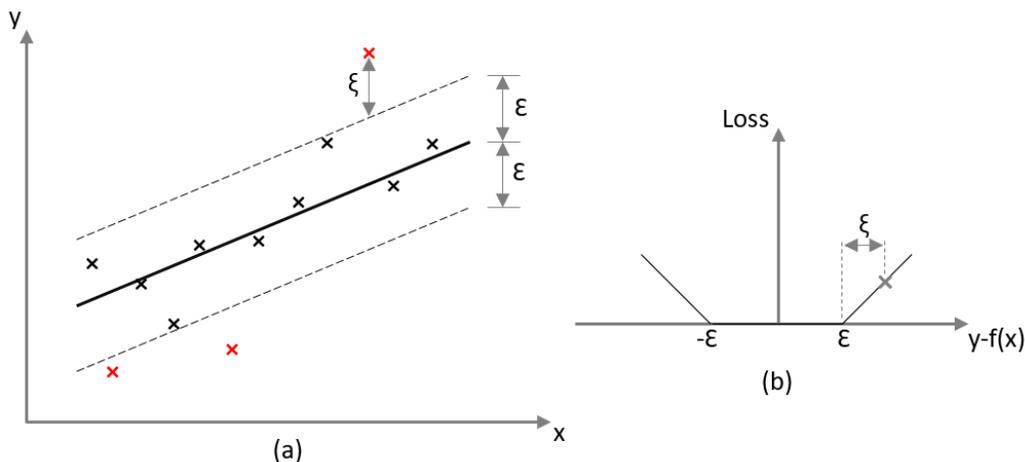


Figure 4: (a) “Soft margin” for linear SVM and (b)  $\epsilon$ -insensitive loss function.

Only the points which deviate more than  $\epsilon$  from the function contribute to the loss function in a linear fashion. This is known as  $\epsilon$ -insensitive loss function  $|\xi|_\epsilon$  [65] and this loss function which is illustrated in Fig. 4b is defined as

$$|\xi|_\epsilon = \begin{cases} 0 & \text{if } \xi \leq \epsilon, \\ \xi - \epsilon & \text{otherwise.} \end{cases} \quad (10)$$

288 Moreover, non-linear functions are introduced to SVM algorithms with  
 289 the help of a kernel function when the linear decision function is no longer  
 290 feasible. The kernel function defines the mapping of the training data from  
 291 a lower dimensional feature space to a higher dimensional feature space. To  
 292 achieve this, different types of kernel functions are employed [64, 65].

#### 293 4.1.2. Multi-layer perceptron

294 MLP network is a feed-forward artificial neural network (ANN) which  
 295 consists of layers of interconnected nodes. The layer with input features is  
 296 named as input layer followed by one or more hidden layers and finally an  
 297 output layer with one or more target outputs. Each layer consists of number  
 298 of nodes known as neurons. The neurons are interconnected between layers  
 299 [66]. The connection between two adjacent layers neurons are called weights

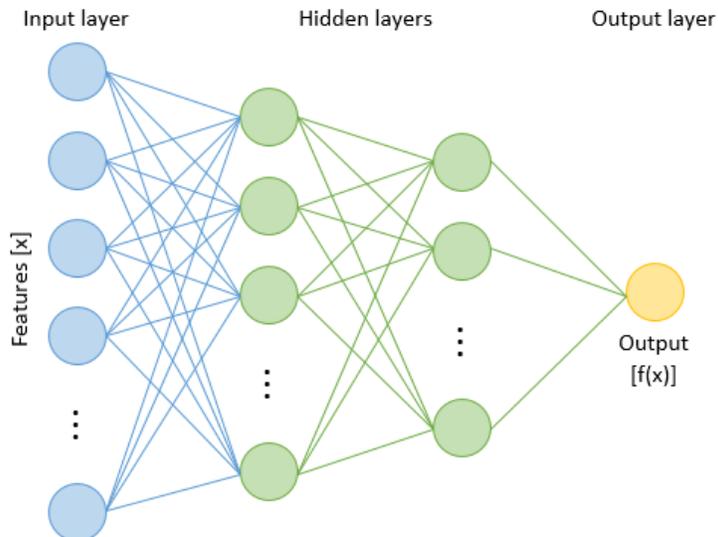


Figure 5: A multi-layer neural network with two hidden layers and a single output.

300 and biases are attached to each neuron. A multi-layer neural network with  
 301 two hidden layers and a single output is illustrated in Fig. 5.

The input layer consists all the input features and feeds them to the network. Each neuron in hidden layers sends an output signal to the next layer in the form of a weighted linear summation modified by a non-linear transfer function known as activation function [67]. The output  $a_i$  of the  $i^{th}$  neuron in a particular hidden layer passed on to the next layer is defined as follows

$$a_i = f \left( \sum_{j=1}^n (w_{ij} a_j + b_i) \right), \quad (11)$$

302 where  $f()$  is the activation function,  $w_{ij}$  is the weight between the  $j^{th}$  neuron  
 303 in the previous layer and  $i^{th}$  neuron in the current layer,  $a_j$  is the output of  
 304 the  $j^{th}$  neuron in the previous layer, and  $b_i$  is the bias of the  $i^{th}$  neuron in  
 305 the current layer.

306 There are many different types of activation functions available. These  
 307 includes linear, sigmoid, tanh and rectified linear units (ReLU) [67]. Fi-  
 308 nally, the output layer transforms the values received from hidden layers into  
 309 outputs.

310 MLP networks can be trained to learn the mapping function between the

311 input vector and the output vector using a set of training data. During the  
 312 training process, an output is first obtained based on the initially assumed  
 313 weights and biases when a training data set is presented to the network.  
 314 Then, the error signal is calculated comparing the difference between the  
 315 target and obtained outputs. This error signal is back-propagated through  
 316 the network, and weights and biases are adjusted to minimise the overall  
 317 error. A technique known as gradient descent is used to find the global  
 318 minimum point on the error surface during the iterative training process  
 319 [67].

#### 320 4.1.3. Gradient boosting machine

321 GBMs are the ensemble models combining weak, base-learners in a se-  
 322 quential manner to minimise the overall error of the whole ensemble. Fried-  
 323 man [68] has first developed these boosting method in 1999. In GBMs, de-  
 324 cision or regression trees are employed as base learners. During the learning  
 325 process, a new weak, base learner is added to the model at the each iteration  
 326 step. The new weak, base learner is trained to reduce the overall error of the  
 327 ensemble at that point [69]. The sequential adding of new base learners is  
 328 repeated until a desirable accuracy is achieved. This step by step addition  
 329 of decision trees to the ensemble model at the each iteration to reduce the  
 330 overall error to form a strong tree ensemble model is illustrated from Fig. 6.

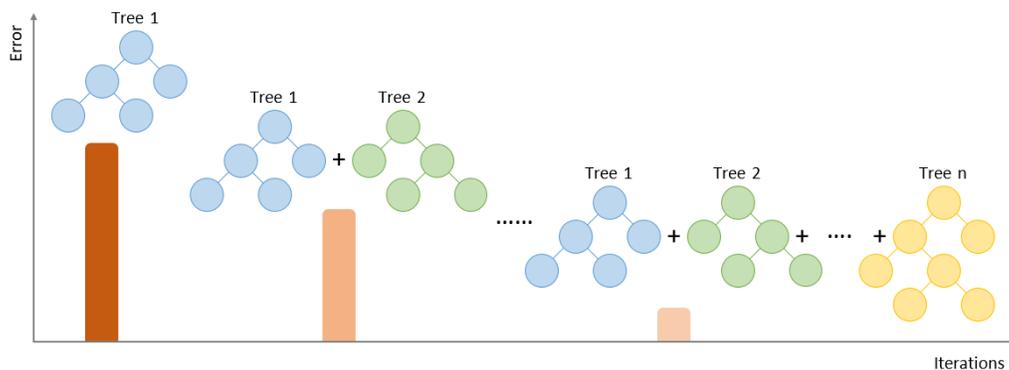


Figure 6: Gradient tree boosting machines.

In GBMs the error of the ensemble model is also known as the loss function. A number of loss functions are supported by GBMs and sometimes a case specific loss functions can be implemented [69]. Consider a vector

input  $x = \{x_1, x_2, \dots, x_n\}$  and its output  $y$ . The output is dependent of input through function  $f$ . The aim of GBM algorithm is to find an estimated function  $F(x)$  between inputs and the respective output such that the loss function  $\Psi(y, f)$  is minimised. This can be expressed as follows

$$F(x) = \arg \min_{f(x)} \Psi(y, f(x)). \quad (12)$$

In the ensemble model, the step-wise addition of the function in the iterative process for N number of iterations is given as

$$F_N(x) = \sum_{i=0}^N F_i(x), \quad (13)$$

331 where the initial estimation is  $F_0(x)$ .

332 When it comes to regression problems, gradient boosting regressor (GBR)  
333 and extreme gradient boosting (XGB) algorithms can be applied. The im-  
334 portance of XGB is that its high-scalability and at the same time, it performs  
335 more efficiently compared to other common boosting models [70].

#### 336 4.2. Model implementation

337 Four machine learning models including SVR, MLP, GBR, and XGB were  
338 implemented in Python for the shear resistance prediction of considered steel  
339 sections. The implementation has been expanded from the codes provided by  
340 Nguyen et al. [54] which was based on popular open source machine learning  
341 libraries including `scikit-learn` [71] and `XGBoost` [70]. The details of data  
342 pre-processing, cross-validation, and hyperparameter tuning are briefed in  
343 this section.

##### 344 4.2.1. Pre-processing of data

345 The pre-processing of data before it is being utilised for the training of a  
346 particular model is vital. One aspect of data pre-processing is to normalise  
347 the data into a uniform scale. The idea behind this is to avoid any domination  
348 and numerical difficulty associated with large numerals during the training  
349 phase of the model. In this study, all the input features were normalised to  
350 the scale of 0 to 1. Then, the normalised input features were used to train  
351 the models and the predicted outputs were transformed back to the original  
352 scale for testing.

353 *4.2.2. Cross-validation*

354 The traditional approaches of cross-validation sometimes lead to over-  
 355 fitting of the model in the training phase. The K-fold cross-validation method  
 356 has been introduced to overcome this problem. Kohavi [72] has shown that  
 357 choosing 10 number of folds provides the best results within a reasonable  
 358 time. This approach has also been used in a number of published works  
 359 [54, 73, 74]. Therefore, 10-fold cross-validation has been utilised in this study.

360 In the 10-fold cross-validation, the dataset is randomly divided into ten  
 361 folds with approximately equal size. Then, while keeping one fold as the test set,  
 362 the remaining nine folds are used for the training set. Once the first  
 363 training is finished, in the next round, another fold is used as the test set,  
 364 while remaining nine folds are used for the training. The process is repeated  
 365 ten times to ensure that each fold is considered as the test set for one time  
 366 and is contributed to the training set nine times. The final performance of  
 367 the model is reported by taking the mean of ten training and testing rounds.  
 368 This process of 10-fold cross-validation is illustrated in Fig. 7.

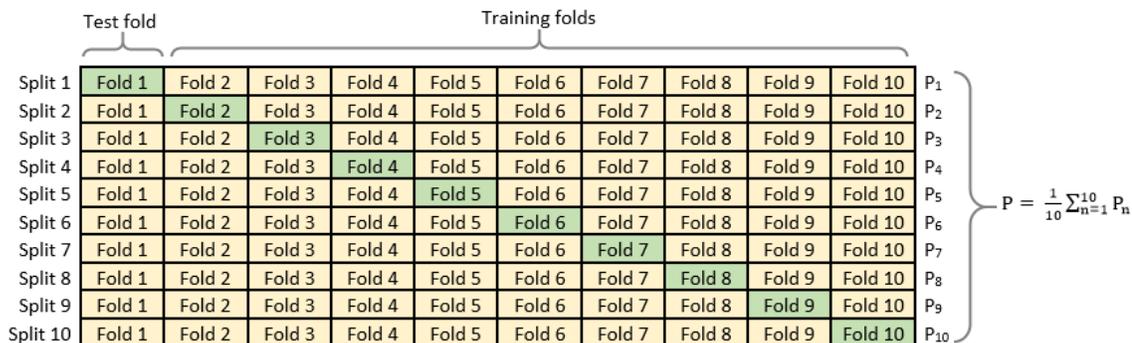


Figure 7: Cross-validation with ten folds.

369 *4.2.3. Hyperparameter tuning*

370 The performance of the most of the machine learning models is sensitive  
 371 to the values of their hyperparameters [75–77]. During the hyperparameter  
 372 tuning process, the optimal values for each hyperparameter are identified  
 373 through the implemented machine learning algorithms. First, a set of values  
 374 is predefined for each hyperparameter. Then, the values are assigned to  
 375 the each hyperparameter from the predefined sets to form different hyper-  
 376 parameter combinations. Thereafter, the machine learning model is trained

377 and evaluated for each of the hyperparameter combination, and the best  
378 performing combination is found during the tuning.

## 379 5. Prediction results and discussion

380 The performance of the developed machine learning models are evalu-  
381 ated using four performance indicators and then the performance of machine  
382 learning algorithms are compared with the currently available design equa-  
383 tions presented in Section 3.

### 384 5.1. Performance indicators

385 To evaluate the performance of different prediction approaches of shear  
386 capacity of steel channel sections including the implemented machine learn-  
387 ing algorithms and design equations, four performance indicators were incor-  
388 porated in this study. These four indicators are linear correlation coefficient  
389 (R), root mean square error (RMSE), mean absolute error (MAE), and mean  
390 absolute percentage error (MAPE).

To calculate the linear correlation coefficient R, the coefficient of deter-  
mination  $R^2$  shall be determined as follows

$$R^2 = 1 - \frac{\sum^n (y - \hat{y})^2}{\sum^n (y - \bar{y})^2}, \quad (14)$$

391 where  $y$  denotes the actual data and  $\hat{y}$  represents the predicted value.  $\bar{y}$   
392 corresponds to the mean value of the actual data and  $n$  is the size of the  
393 data sample. It is considered to be a good prediction, if the linear correlation  
394 coefficient R is closer to 1.

Other performance indicators RMSE, MAE, and MAPE can be deter-  
mined as follows

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum^n (y - \hat{y})^2}, \quad (15a)$$

$$\text{MAE} = \frac{1}{n} \sum^n |y - \hat{y}|, \quad (15b)$$

$$\text{MAPE} = \frac{1}{n} \sum^n \left| \frac{y - \hat{y}}{y} \right| \times 100. \quad (15c)$$

395 The lower values of RMSE, MAE, and MAPE suggest that the error is less,  
396 therefore a better prediction.

397 *5.2. Performance of the machine learning models*

398 *5.2.1. Cold-formed stainless steel LCBs*

399 Table 3 summarises the identified optimal combination of some hyperpa-  
 400 rameters during the hyperparameter tuning process for each machine learning  
 401 algorithm while Table 4 compares the performance of each algorithm using  
 402 four performance indicators discussed above for the cold-formed stainless  
 403 steel LCB sections. As can be seen from Table 4, all four algorithms demon-  
 404 strate good performances in prediction of shear capacity of stainless steel  
 405 LCBs and the implemented SVR machine learning model provides the best  
 406 performance among four algorithms in all indicators.

Table 3: Hyperparameter combinations of machine learning algorithms in prediction of shear capacity of stainless steel LCBs

| Method | Hyperparameter     |           |               |              |                   |
|--------|--------------------|-----------|---------------|--------------|-------------------|
| SVR    | kernel             | C         | epsilon       | gamma        | -                 |
|        | 'rbf'              | 600       | 0.01          | 0.1          | -                 |
| MLP    | hidden_layer_sizes | solver    | max_iter      | alpha        | -                 |
|        | (100,60)           | 'lbfgs'   | 900           | 0.0001       | -                 |
| GBR    | n_estimators       | max_depth | learning_rate | loss         | min_samples_split |
|        | 1000               | 10        | 0.1           | 'lad'        | 10                |
| XGB    | n_estimators       | max_depth | learning_rate | objective    | -                 |
|        | 1400               | 2         | 0.35          | 'reg:linear' | -                 |

Table 4: The performance of machine learning algorithms in prediction of shear capacity of stainless steel LCBs

| Method | R     | RMSE (kN) | MAE (kN) | MAPE (%) |
|--------|-------|-----------|----------|----------|
| SVR    | 0.999 | 2.76      | 2.32     | 4.03     |
| MLP    | 0.998 | 4.13      | 3.18     | 5.95     |
| GBR    | 0.997 | 5.53      | 4.19     | 4.47     |
| XGB    | 0.997 | 5.51      | 4.31     | 6.86     |

407 The experimental and FE shear capacities of stainless steel LCBs are  
 408 compared with the machine learning predictions for SVR and MLP models  
 409 in Figs. 8 and 9, respectively. It can be seen that the model predictions are  
 410 distributed closer to the actual data line and also the scatter of the predictions

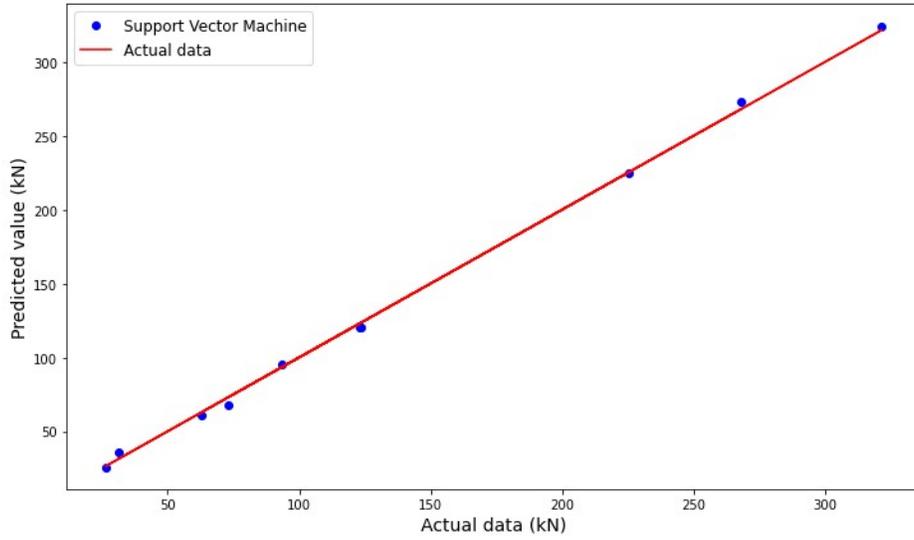


Figure 8: Performance of SVR model in prediction of shear capacity of stainless steel LCBs.

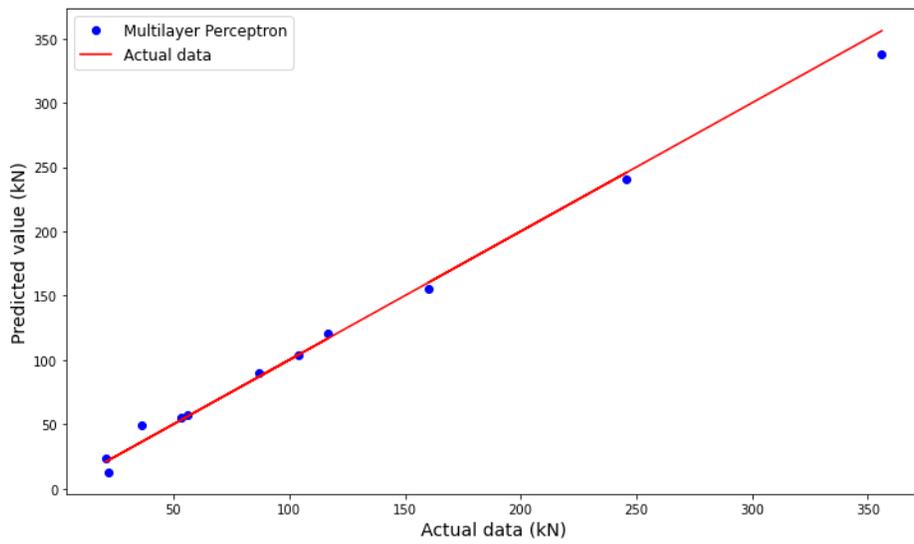


Figure 9: Performance of MLP model in prediction of shear capacity of stainless steel LCBs.

411 is very low. Therefore, the accuracy of machine learning predictions is further  
 412 evidenced from these comparisons.

413 The relative importance of each input feature on the shear strength of  
 414 the section was evaluated using the XGBoost library [70]. A higher value of  
 415 relative feature importance implies that the impact of the particular input  
 416 feature on the output is more significant. Fig. 10 illustrates the relative  
 417 importance of each input feature on the shear strength of stainless steel  
 418 LCB sections. From the figure, it can be observed that the input features  
 419 yield strength  $f_y$ , web thickness  $t_w$  and section depth  $D$  have a considerably  
 420 higher impact on the shear strength while yield strength  $f_y$  is being the most  
 421 dominant among all features. On the other hand, a relatively lower feature  
 422 importance can be seen from the features  $d_1/t_w$ , flange width  $B$  and lip  
 423 height  $L$ . Interestingly, the ultimate strength  $f_u$  and aspect ratio have the  
 424 least impact on the shear strength. There is no variation of aspect ratio in  
 425 the input data set could be the reason for the lower rank of the feature in  
 426 the relative importance. Also, the considered sections could have gained the  
 427 shear strength before reaching the ultimate stress and therefore, this could  
 428 result in ranking the ultimate strength  $f_u$  low.

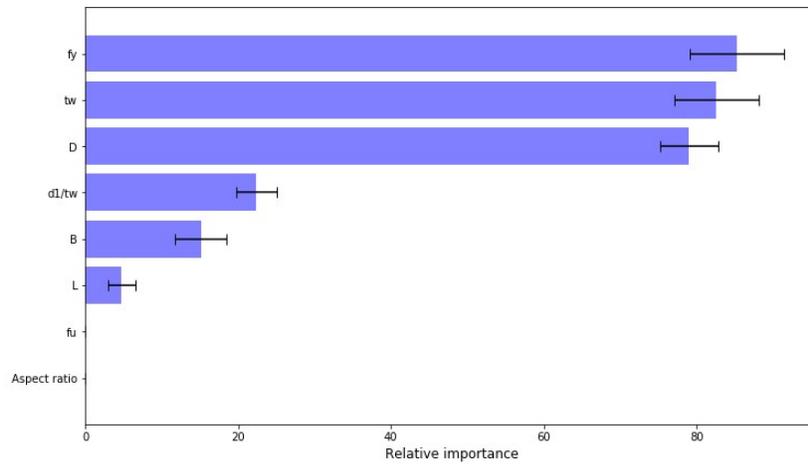


Figure 10: Relative importance of input features on the shear capacity of stainless steel LCBs.

### 429 5.2.2. Cold-formed carbon steel LSBs

430 The hyperparameter combinations which give the best predictions and the  
 431 performance indicators of four machine learning algorithms are summarised

432 for the cold-formed carbon steel LSBs in Tables 5 and 6, respectively. The  
 433 comparison results reported in Table 6 suggest that all four machine learning  
 434 models are able to perform well in prediction of shear capacity of carbon steel  
 435 LSBs as well. The implemented SVR model again offers the best agreement  
 436 considering the overall performance.

Table 5: Hyperparameter combinations of machine learning algorithms in prediction of shear capacity of carbon steel LSBs

| Method | Hyperparameter     |           |               |              |                   |
|--------|--------------------|-----------|---------------|--------------|-------------------|
| SVR    | kernel             | C         | epsilon       | gamma        | -                 |
|        | 'rbf'              | 600       | 0.01          | 0.3          | -                 |
| MLP    | hidden_layer_sizes | solver    | max_iter      | alpha        | -                 |
|        | (300,100)          | 'lbfgs'   | 350           | 0            | -                 |
| GBR    | n_estimators       | max_depth | learning_rate | loss         | min_samples_split |
|        | 1500               | 4         | 0.15          | 'huber'      | 6                 |
| XGB    | n_estimators       | max_depth | learning_rate | objective    | -                 |
|        | 800                | 2         | 0.15          | 'reg:linear' | -                 |

Table 6: The performance of machine learning algorithms in prediction of shear capacity of carbon steel LSBs

| Method | R     | RMSE (kN) | MAE (kN) | MAPE (%) |
|--------|-------|-----------|----------|----------|
| SVR    | 0.999 | 1.26      | 0.95     | 1.43     |
| MLP    | 0.998 | 1.65      | 1.05     | 1.39     |
| GBR    | 0.997 | 2.19      | 1.49     | 1.89     |
| XGB    | 0.996 | 2.06      | 1.35     | 1.74     |

437 Figs. 11 and 12 illustrate the comparison of experimental and FE shear  
 438 strengths of carbon steel LSBs with the machine learning predictions for  
 439 SVR and MLP algorithms, respectively. The distribution and lower scatter  
 440 of predictions demonstrate a good agreement with actual data.

441 Fig. 13 is produced to evaluate the relative importance of considered  
 442 input features on the shear strength of carbon steel LSB sections. The illus-  
 443 tration indicates that the feature yield strength  $f_y$  has the highest influence  
 444 on the shear strength of carbon steel LSBs which is a little less than twice of  
 445 the importance of the second most influencing feature web thickness  $t_w$ . In  
 446 contrast, the flange width  $B$  is found to be the feature with the least impact.

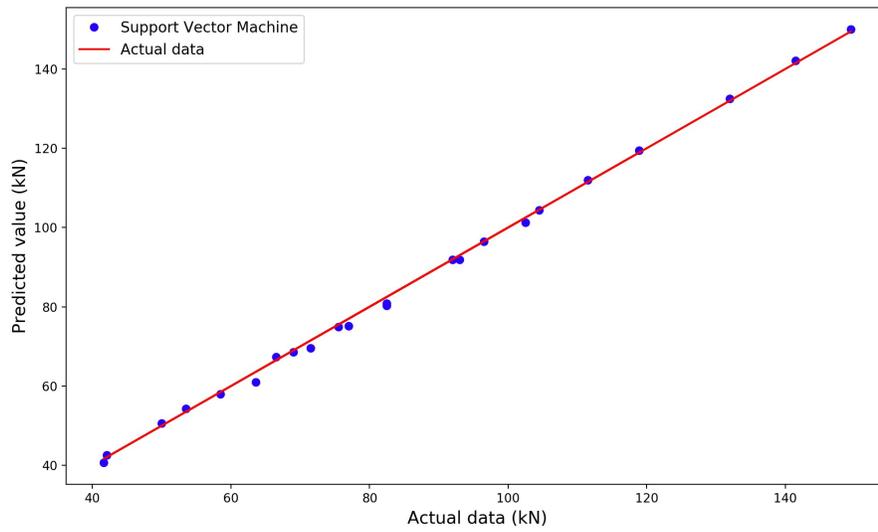


Figure 11: Performance of SVR model in prediction of shear capacity of carbon steel LSBs.

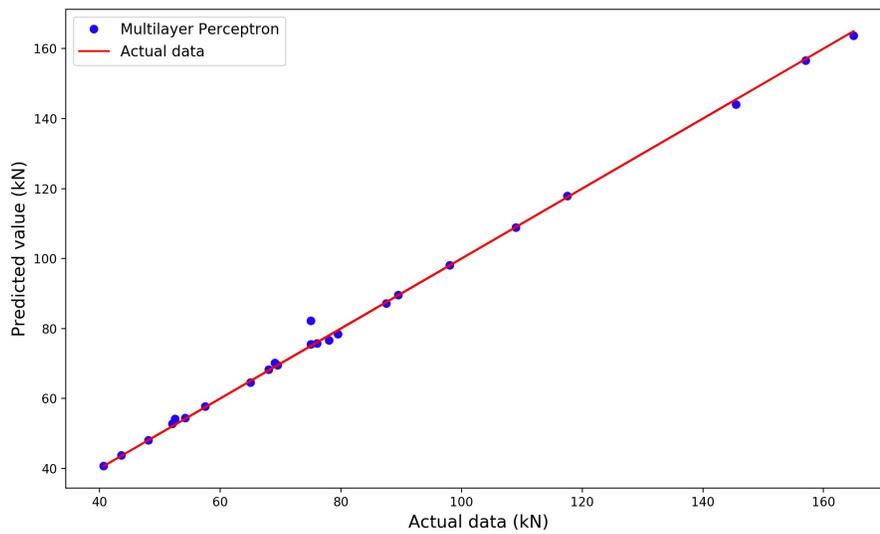


Figure 12: Performance of MLP model in prediction of shear capacity of carbon steel LSBs.

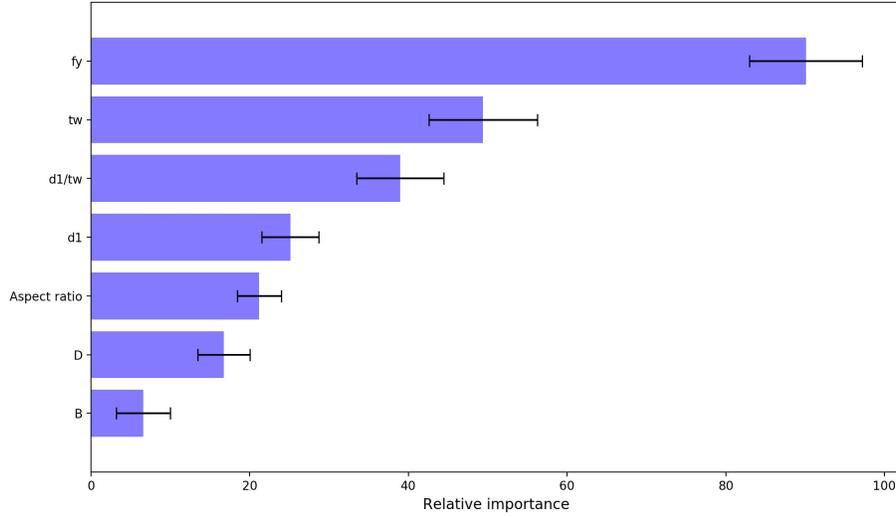


Figure 13: Relative importance of input features on the shear capacity of carbon steel LSBs.

447 *5.3. Performance of the design equations*

448 The performance of the design equations was also evaluated in prediction  
 449 of shear capacity of stainless steel LCBs and carbon steel LSBs using four  
 450 performance indicators. The modified shear design provisions for EN1993-1-  
 451 4 [22] in Eq. (4) and the proposed DSM shear design equations in Eqs. (6-7)  
 452 were incorporated herein.

453 Table 7 summarises the calculated performance indicators of these design  
 454 equations for both stainless steel and carbon steel databases considered in  
 455 this study. It can be observed that all four performance indicators provide  
 456 fairly satisfactory results in prediction of shear strength of LCBs and LSBs  
 457 using design equations.

Table 7: Performance of design equations in prediction of shear capacities of LCBs and LSBs

| Problem | Design equation | R     | RMSE (kN) | MAE (kN) | MAPE (%) |
|---------|-----------------|-------|-----------|----------|----------|
| LCB     | Eq. (4) [18]    | 0.998 | 3.78      | 2.85     | 3.56     |
|         | Eq. (6) [18]    | 0.998 | 4.16      | 3.29     | 4.28     |
| LSB     | Eq. (7) [12]    | 0.979 | 6.21      | 4.71     | 6.01     |

458 Furthermore, the experimental and FE shear capacities are compared  
 459 with the design equation predictions. Figs. 14-16 present the comparisons

460 for Eq. (4), Eq. (6), and Eq. (7). The predictions of the best performing  
 461 machine learning model which is SVR are also included in these comparisons.

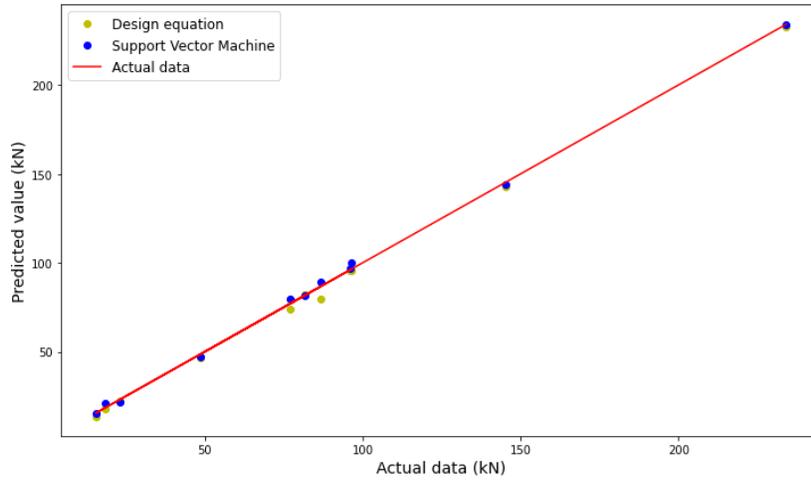


Figure 14: Comparison of the performance of Eq. (4) and SVR model in prediction of shear capacity of stainless steel LCBs.

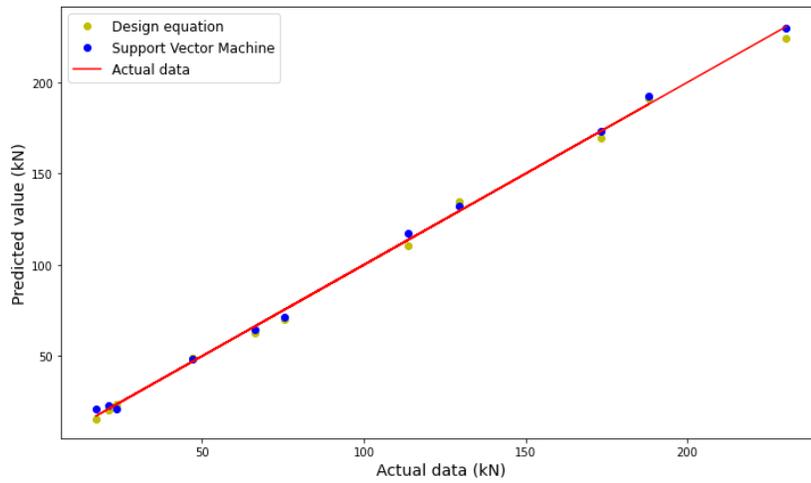


Figure 15: Comparison of the performance of Eq. (6) and SVR model in prediction of shear capacity of stainless steel LCBs.

462 It can be observed from Figs. 14 and 15 that the distribution and the  
 463 scatter of design equation predictions for stainless steel LCBs are marginally

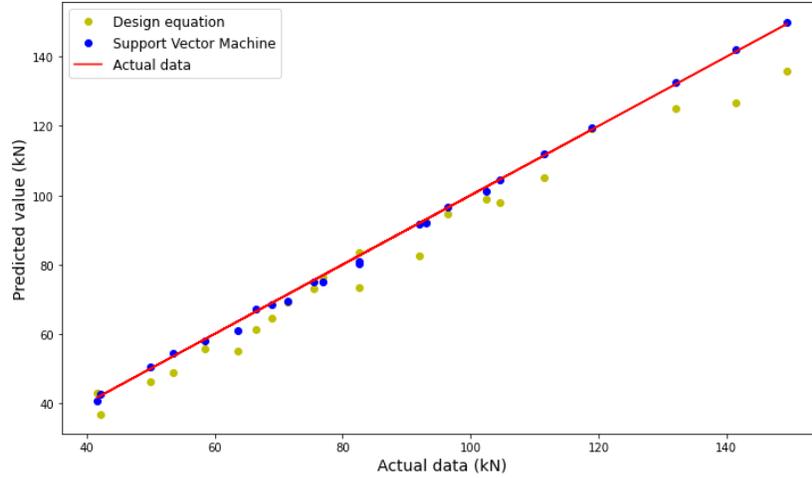


Figure 16: Comparison of the performance of Eq. (7) and SVR model in prediction of shear capacity of carbon steel LSBs.

464 equal to that of SVR model. However, the performance indicators are still  
 465 found to be better when machine learning models are used. Additionally,  
 466 Fig. 16 shows that the design equation predictions for carbon steel LSBs are  
 467 deviated away from the actual data line with a considerably higher scatter  
 468 than SVR model predictions. The design equation predictions appear to be  
 469 slightly conservative for LSBs.

470 Therefore, the comparison suggests that the implemented four machine  
 471 learning algorithms (SVR, MLP, GBR, and XGB) can be employed in accu-  
 472 rate prediction of the shear capacity of steel channel sections. Even though,  
 473 the existing design rules also seem to provide accurate predictions for the  
 474 shear capacity, the improvement of machine learning predictions compared  
 475 to the design rules can still be seen from the considered four performance  
 476 indicators. In contrast to the available experimental and numerical methods  
 477 which require greater deal of resources, the machine learning algorithms can  
 478 be easily implemented as a tool in the decision making process to help civil or  
 479 structural engineers. This study highlights the availability of machine learn-  
 480 ing as an efficient and powerful tool, which can be implemented for accurate  
 481 prediction of any section resistance of interest, given that adequate number  
 482 of previous data is available.

## 483 6. Concluding remarks

484 This study presents the application of popular machine learning algo-  
485 rithms in prediction of the shear resistance of steel channel sections. The ex-  
486 perimental and numerical results of three-point loading tests of cold-formed  
487 stainless steel LCBs and carbon steel LSBs are gathered from previous studies  
488 and then employed in training machine learning algorithms. Support vector  
489 regression, multi-layer perceptron, gradient boosting regressor, and extreme  
490 gradient boosting algorithms were implemented in the study to predict the  
491 shear capacity of steel channel sections using 108 results of LCBs and 238  
492 results of LSBs. During the implementation of algorithms, pre-processing  
493 of data, 10-fold cross-validation and hyperparameter tuning were performed.  
494 The optimal hyperparameter combinations for each machine learning model  
495 were found and the performance of the developed machine learning models  
496 were evaluated based on performance indicators including linear correlation  
497 coefficient, root mean square error, mean absolute error, and mean absolute  
498 percentage error. Then, the performance of machine learning algorithms were  
499 compared with the design equations predictions.

500 The developed SVR, MLP, GBR, and XGB machine learning models are  
501 efficient and predicted well the shear capacity of both stainless steel LCBs  
502 and carbon steel LSBs. The implemented SVR algorithm is proved to be  
503 the best performing model in this study. Moreover, the evaluated perfor-  
504 mance indicators for the design equations suggest fairly satisfactory results  
505 giving conservative predictions. The implemented machine learning algo-  
506 rithms are found to be performing better than the available design equations  
507 in prediction of the shear capacities of stainless steel LCBs and carbon steel  
508 LSBs. Therefore, this study highlights the applicability of machine learning  
509 algorithms to solve similar structural and civil engineering problems when  
510 carefully prepared data is present.

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