Prediction of Fire Resistance of Fiber-Reinforced Polymer-Strengthened Concrete Beams Using Machine Learning Techniques

Cesar Malenab

Agenda

- Introduction
- Methodology
- Results and Discussion
- Conclusion

Introduction

Structural Retrofitting

Structural retrofitting is the process of modifying existing buildings or structures to improve their performance, safety, functionality, or sustainability.

Commonly applied to:

- Old buildings
- Construction mistakes
- Earthquake damages

Fiber-Reinforced Polymer (FRP)

FRP composite materials are composed of high-strength continuous fibers, such as glass, carbon, or steel wires, embedded in a polymer matrix.

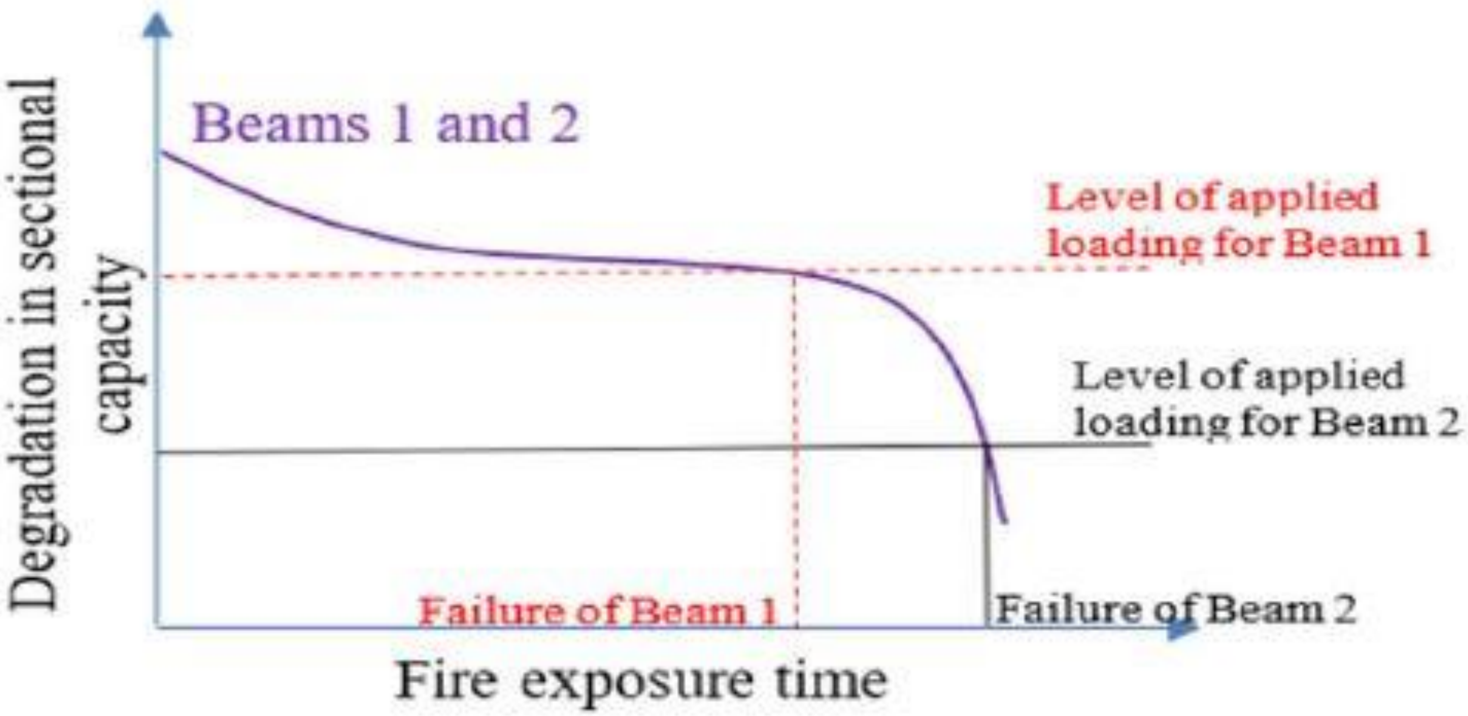
- Low labor and installation cost
- Lesser time to complete
- Minimum service disruption

FRP-strengthened concrete beams

One of the major disadvantages of FRP is its poor performance when subjected to elevated temperatures as its continued capability to sustain design loads can easily diminish at rapidly increasing temperatures.

Moreover, adhesion failure between concrete members and FRP is likely due to its exposure to the external environment unless insulation devices are rendered to protect it.

Fire Resistance



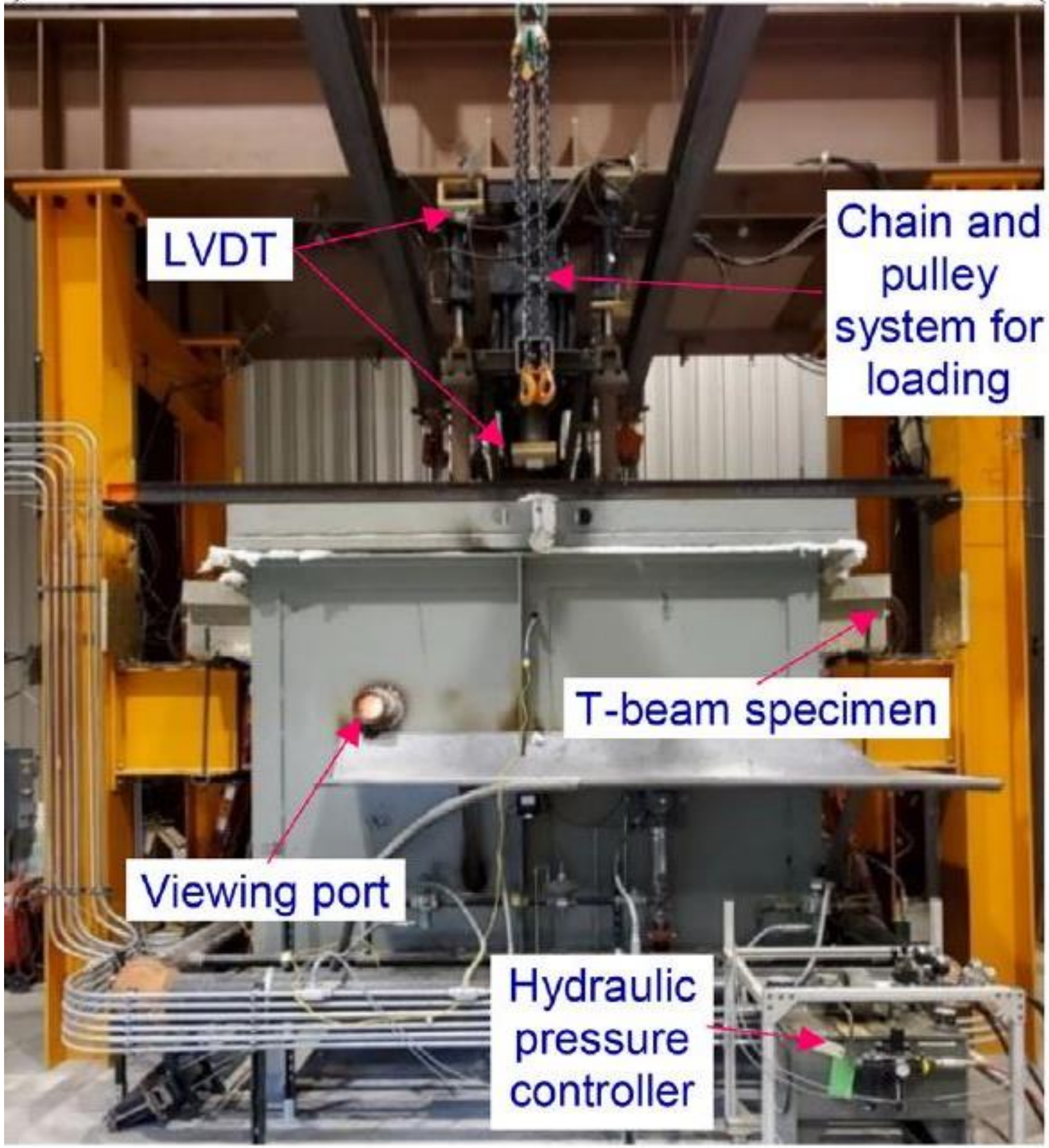
Fire resistance is defined as the duration for which a structural member sustains the applied loading under fire exposure.

Currently, there is limited understanding of the performance of FRP-strengthened concrete members under structural loading and fire conditions, which hinders widespread use in building applications.

Approaches for evaluating fire resistance:

Full scale fire test

An experimental method that involves creating concrete beam specimens at the laboratory subjected to constant loading and elevated temperatures using a fire chamber.

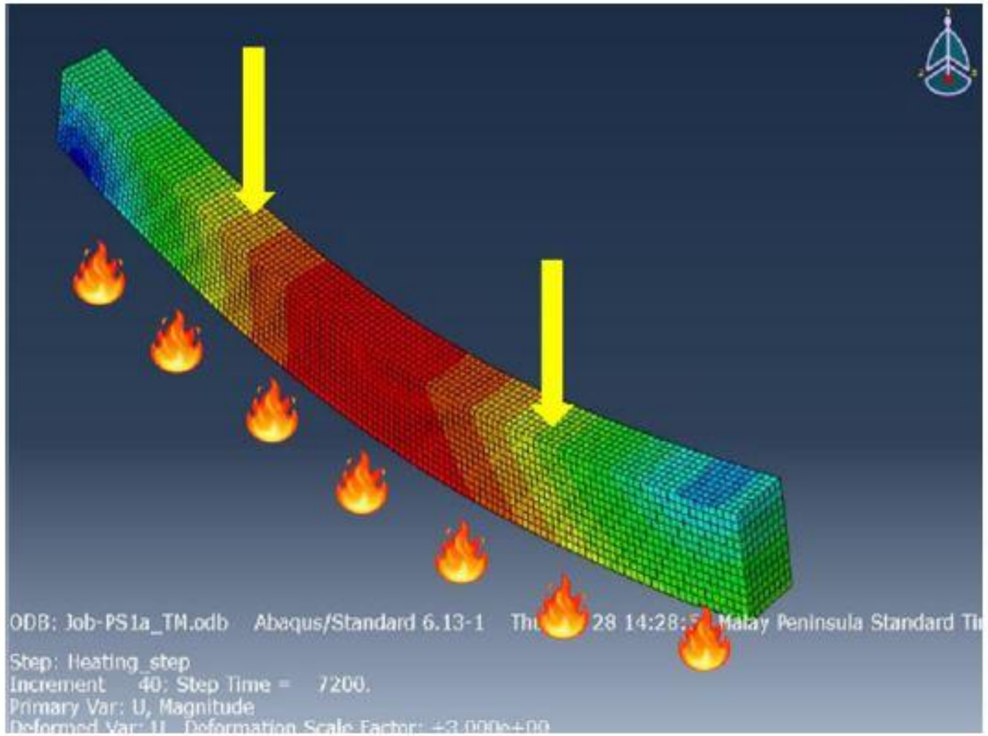


Approaches for evaluating fire resistance:

Numerical modeling

Development of a finite element model using ABAQUS or ANSYS programs.

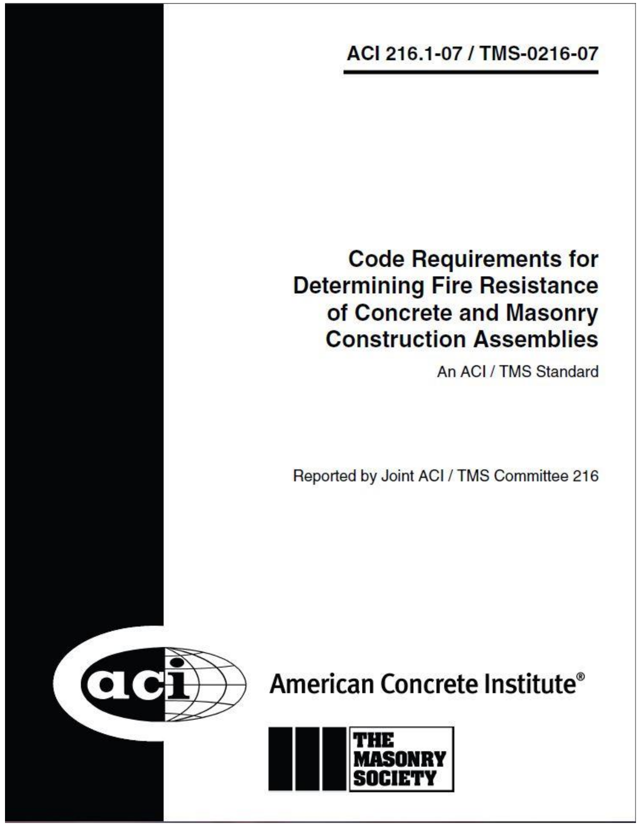
To be able to make simulations, a mesh consisting of up to millions of small elements that together form the shape of the structure needs to be created. Calculations are made for every single element. Combining the individual results gives us the final result of the structure.



Approaches for evaluating fire resistance:

Prescriptive Approaches

Set of regularizations that govern the design, construction, and alteration of structures.


ACI 216.1-07 / TMS-0216-07

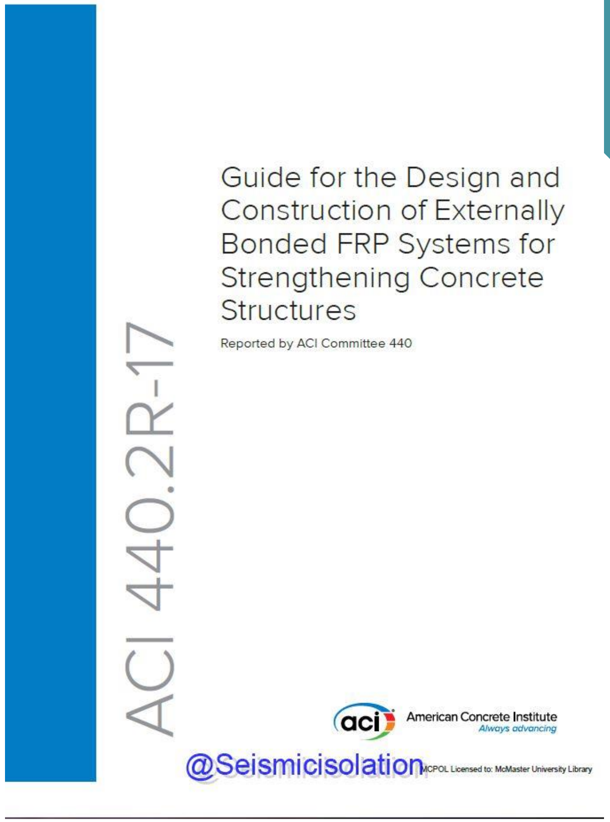
Code Requirements for Determining Fire Resistance of Concrete and Masonry Construction Assemblies

An ACI / TMS Standard

Reported by Joint ACI / TMS Committee 216

aci American Concrete Institute®

THE MASONRY SOCIETY


ACI 440.2R-17

Guide for the Design and Construction of Externally Bonded FRP Systems for Strengthening Concrete Structures

Reported by ACI Committee 440

aci American Concrete Institute Always advancing

@Seismicisolation

Research Novelty

The oversimplification and infeasibility of existing methodologies in determining the fire performance of FRP-strengthened concrete beams call for a more pragmatic approach such as the use of machine learning (ML) algorithms and artificial intelligence (AI).

ML-based approaches can significantly include all parameters influencing the performance of FRP-strengthened members which can easily be retrained as new data becomes available.

Methodology

Dataset

- From the paper "Dataset on fire resistance analysis of FRP-strengthened concrete beams" published last January 2024.
- Contains 21,434 data with 50 experimental data compiled from various literature and supplemented with 21,384 data points from numerical modeling.
- Composed of geometric, material, and loading parameters which total to 15 features that can be used to predict fire resistance.

Data Preprocessing

The dataset is largely clean, though a few discrepancies were present, such as beam lengths denoted in varying units, duplicate beam names, and negative values for insulation thickness.

Performed standard scaling where each feature has a mean of 0 and standard deviation of 1.

Machine Learning Models

- Linear Regression with ElasticNet Regularization
- Support Vector Regressor
- Random Forest
- Extreme Gradient Boosting
- Deep Neural Networks

Performance Metrics

- Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{n}}$$

- Mean Absolute Error (MAE)

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \widehat{y_i}|}{n}$$

- Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{\sum_{i=1}^{n}(y_i - \overline{y_i})^2}$$

Training and Hyperparameter Tuning

- 80-20 train-test-split
- RandomizedSearchCV
  - five-fold cross-validation
  - 100 combinations of hyperparameters
- Manual tuning of hyperparameters for DNN
  - 17 models studied

Results

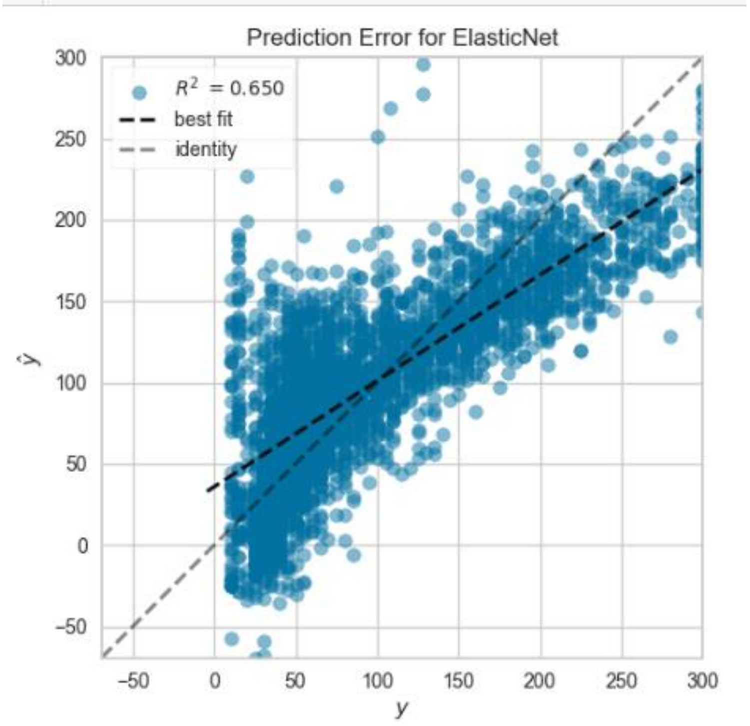
Linear Regression

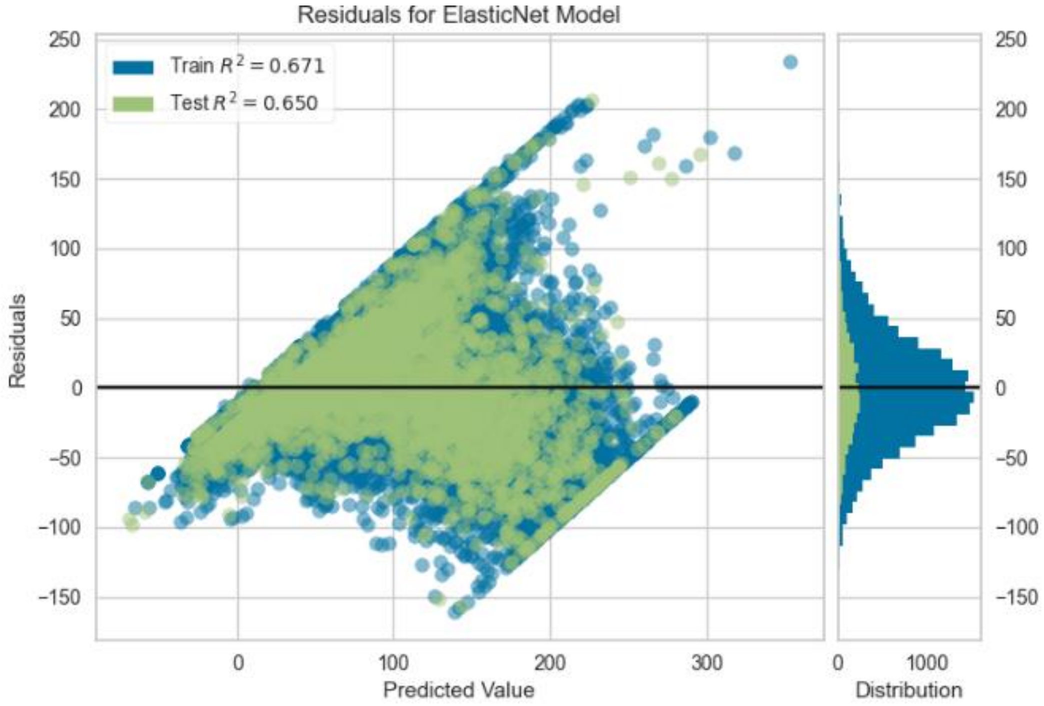
Hyperparameter	Range	Value
Regularization Parameter	[0.1, 1, 5, 10, 50, 100]	0.1
Mixing Parameter	[0.1, 0.5, 0.7, 0.95, 0.99, 1]	1

Linear Regression

Metric	Value
RMSE	44.10
MAE	33.77
R^2	0.65

Linear Regression





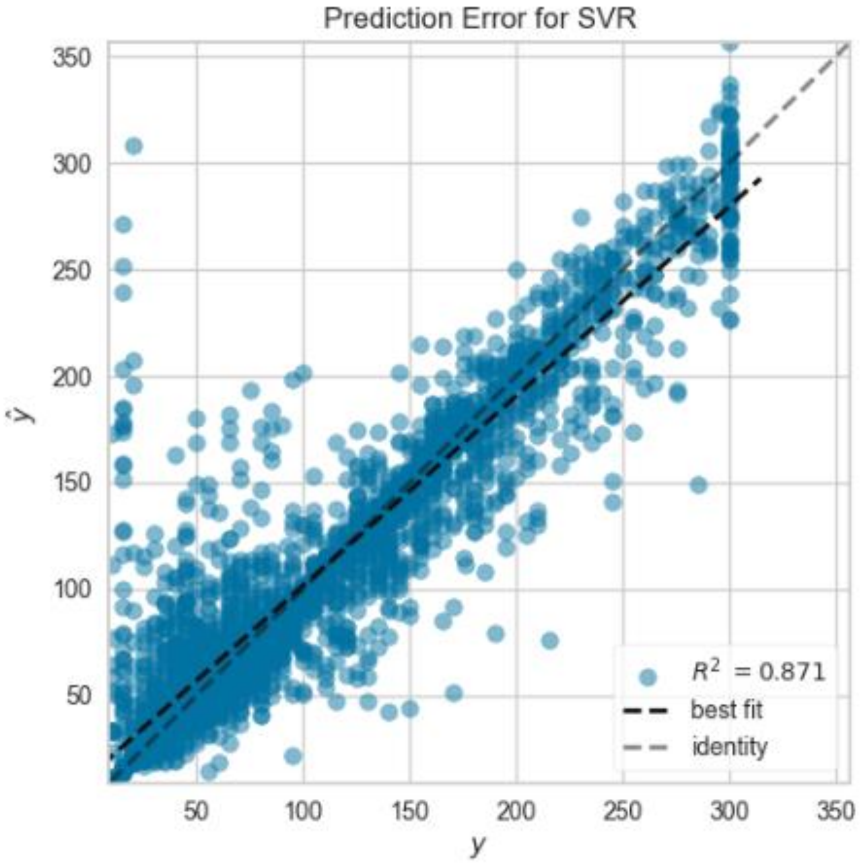
Support Vector Regressor

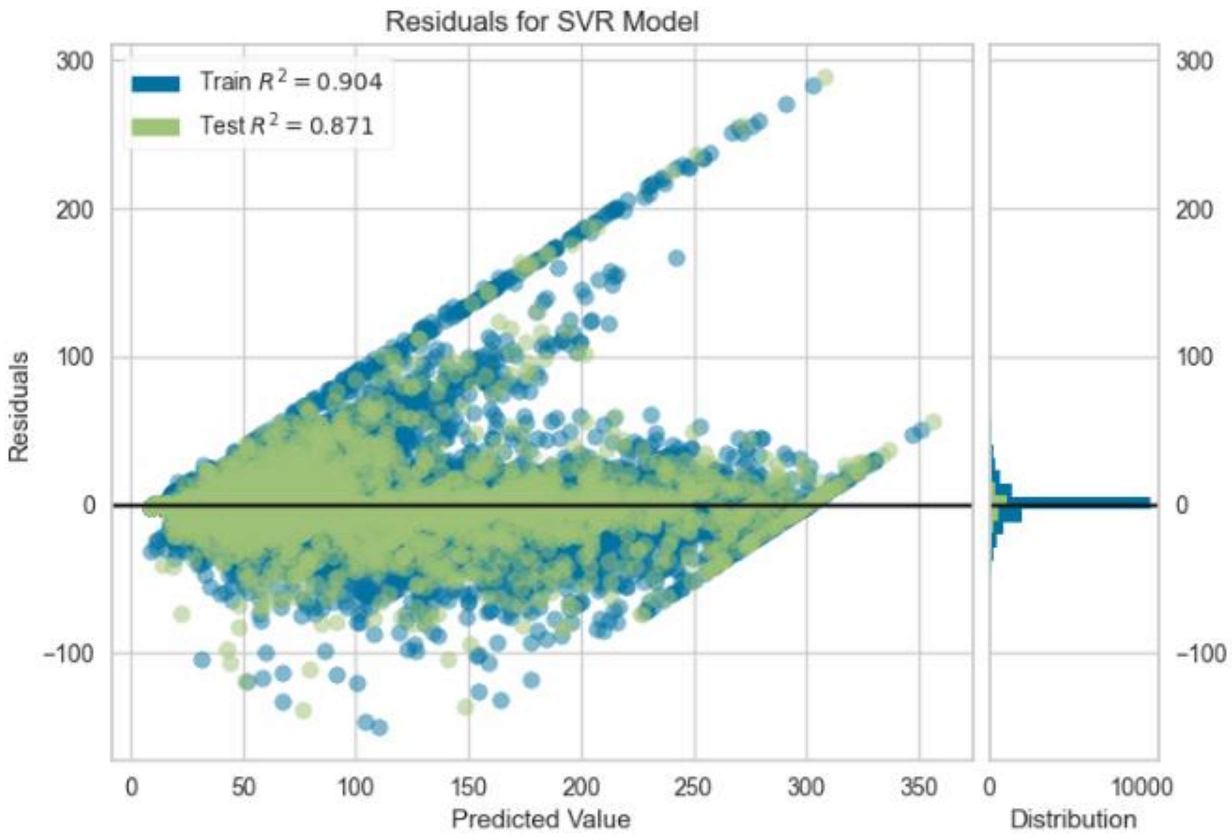
Hyperparameter	Range	Value
Kernel	['linear', 'poly', 'rbf', 'sigmoid']	Radial Basis Function
C	[0.5, 1, 5, 10, 15, 100, 500, 1000]	1000
degree	[2,3,4,5]	-
gamma	['scale', 'auto']	auto
epsilon	[0.1, 0.5, 1]	1

Support Vector Regressor

Metric	Value
RMSE	26.49
MAE	14.71
R^2	0.871

Support Vector Regressor





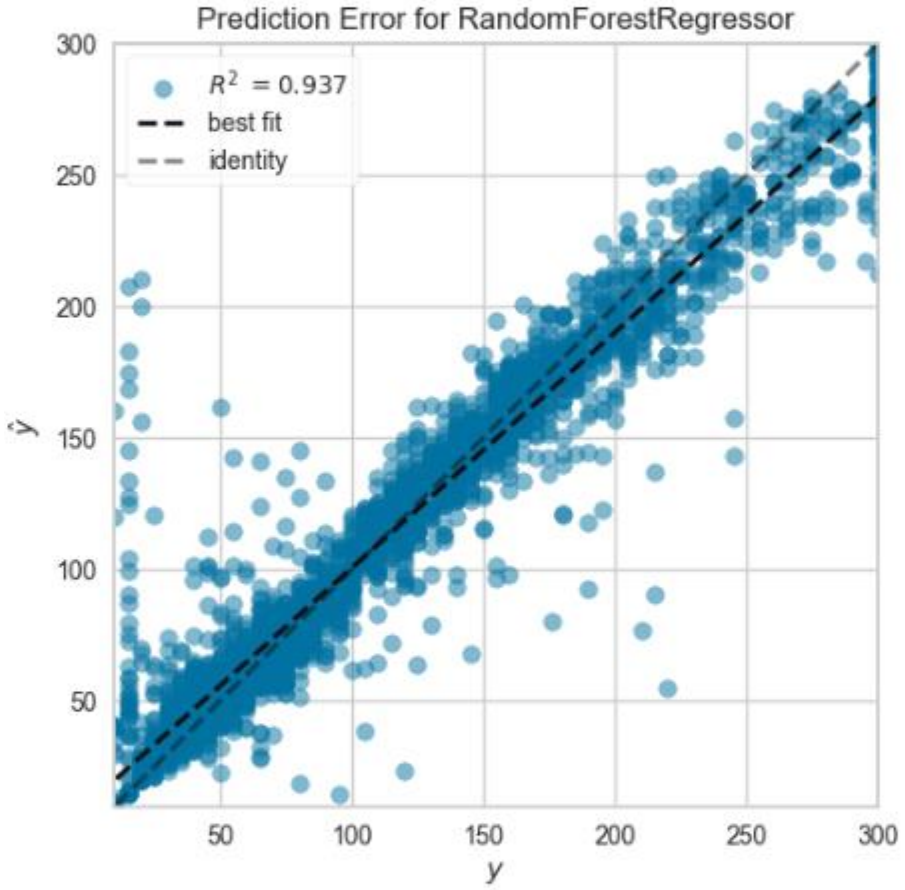
Random Forest

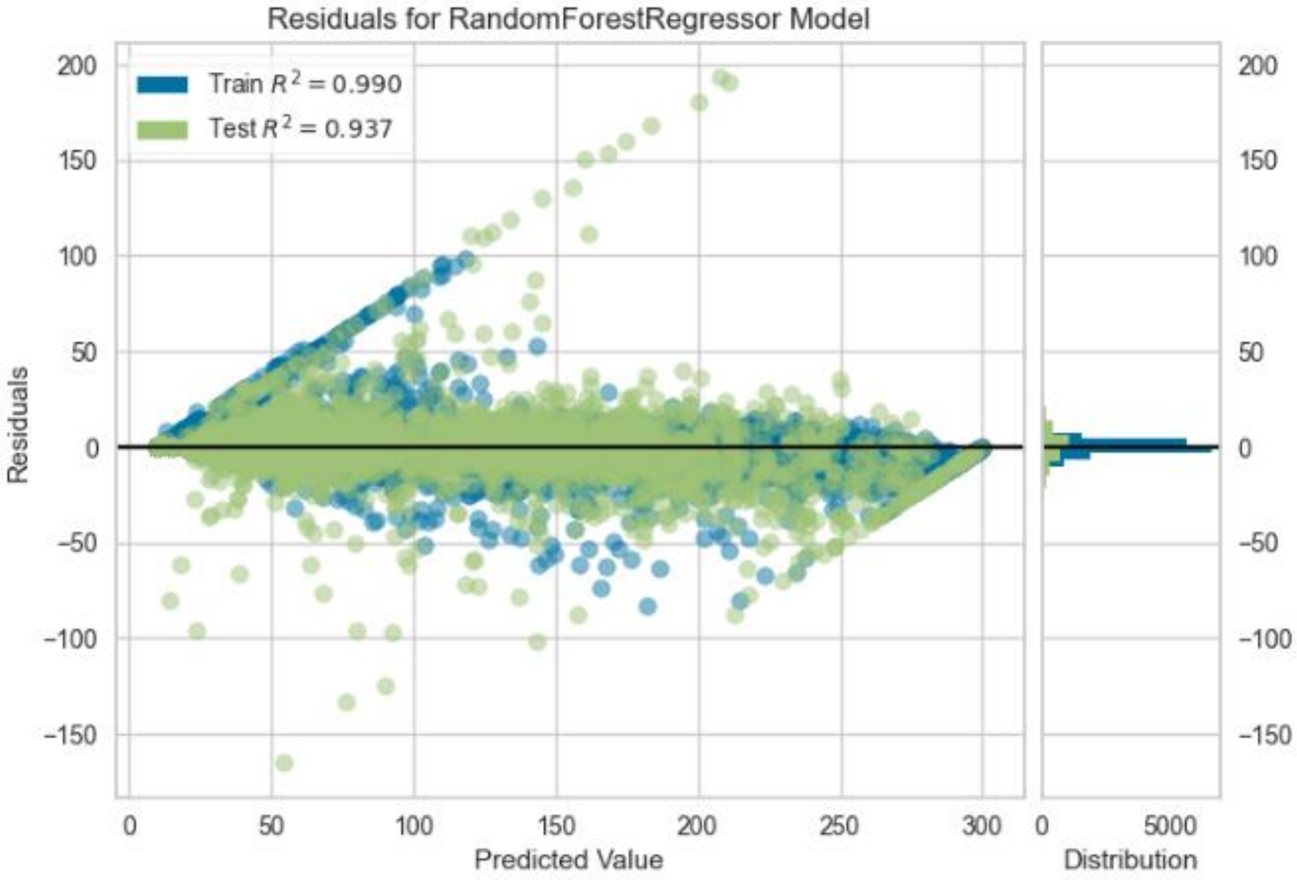
Hyperparameter	Range	Value
Number of trees	[100, 200, 300, 500, 1000]	300
Maximum depth of tree	[0.33, 0.66, 0.75, 0.99, None]	None
Minimum Sample Split	[2, 5, 8, 10, 12, 14]	2
Maximum fraction of observation	[10, 50, 100, None]	0.99
Maximum number of features	[2, 6, 8, 10, 12, 15]	5

Random Forest

Metric	Value
RMSE	18.58
MAE	10.33
R^2	0.937

Random Forest





Extreme Gradient Boosting

Hyperparameter	Range	Value
Number of Trees	50 to 500	400
Maximum depth of tree	3 to 8	7
Learning Rate	0.01 to 0.3	0.1
Maximum fraction of observations	0.5 to 1.0	0.95
Maximum fraction of features	0.5 to 1.0	0.8

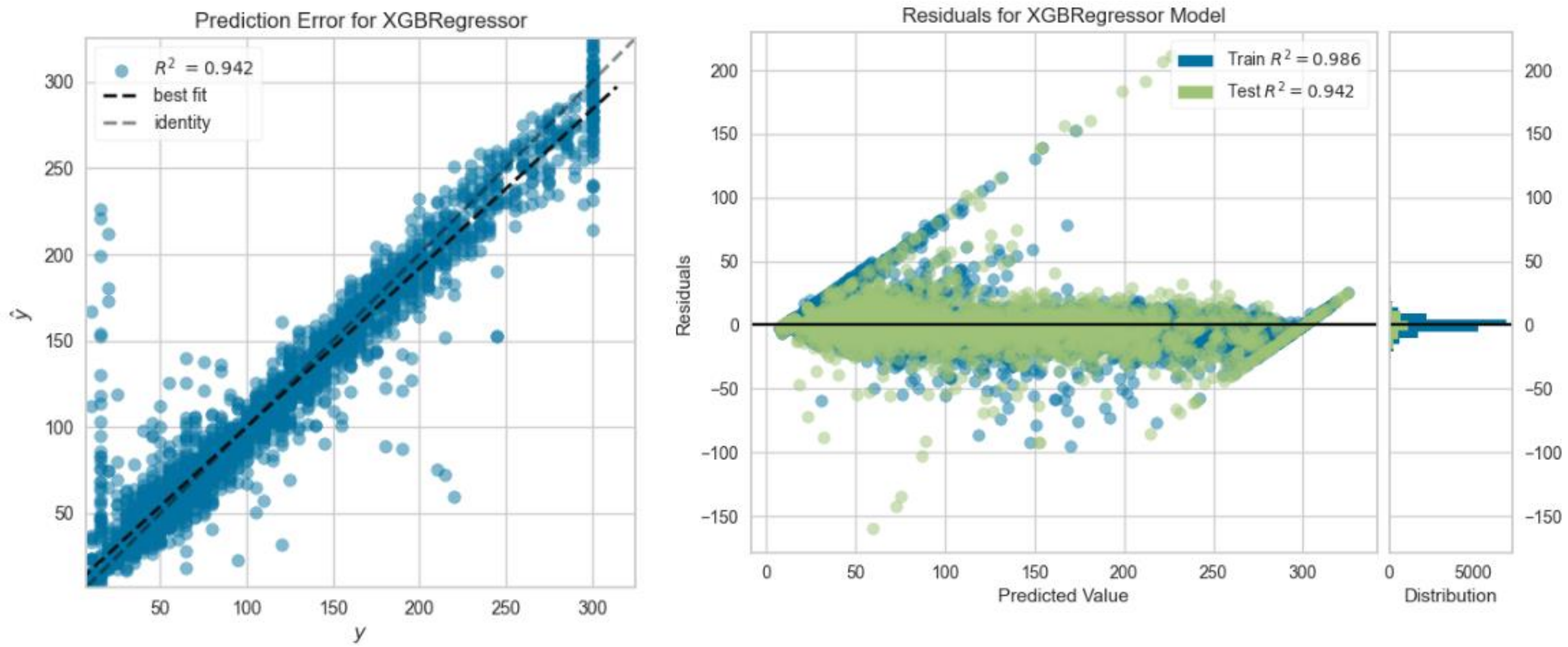
Extreme Gradient Boosting

Hyperparameter	Range	Value
Minimum split loss	1 to 9	5
L1 regularization	0 to 5	3
L2 regularization	0 to 5	4

Extreme Gradient Boosting

Metric	Value
RMSE	17.82
MAE	9.87
R^2	0.942

Extreme Gradient Boosting



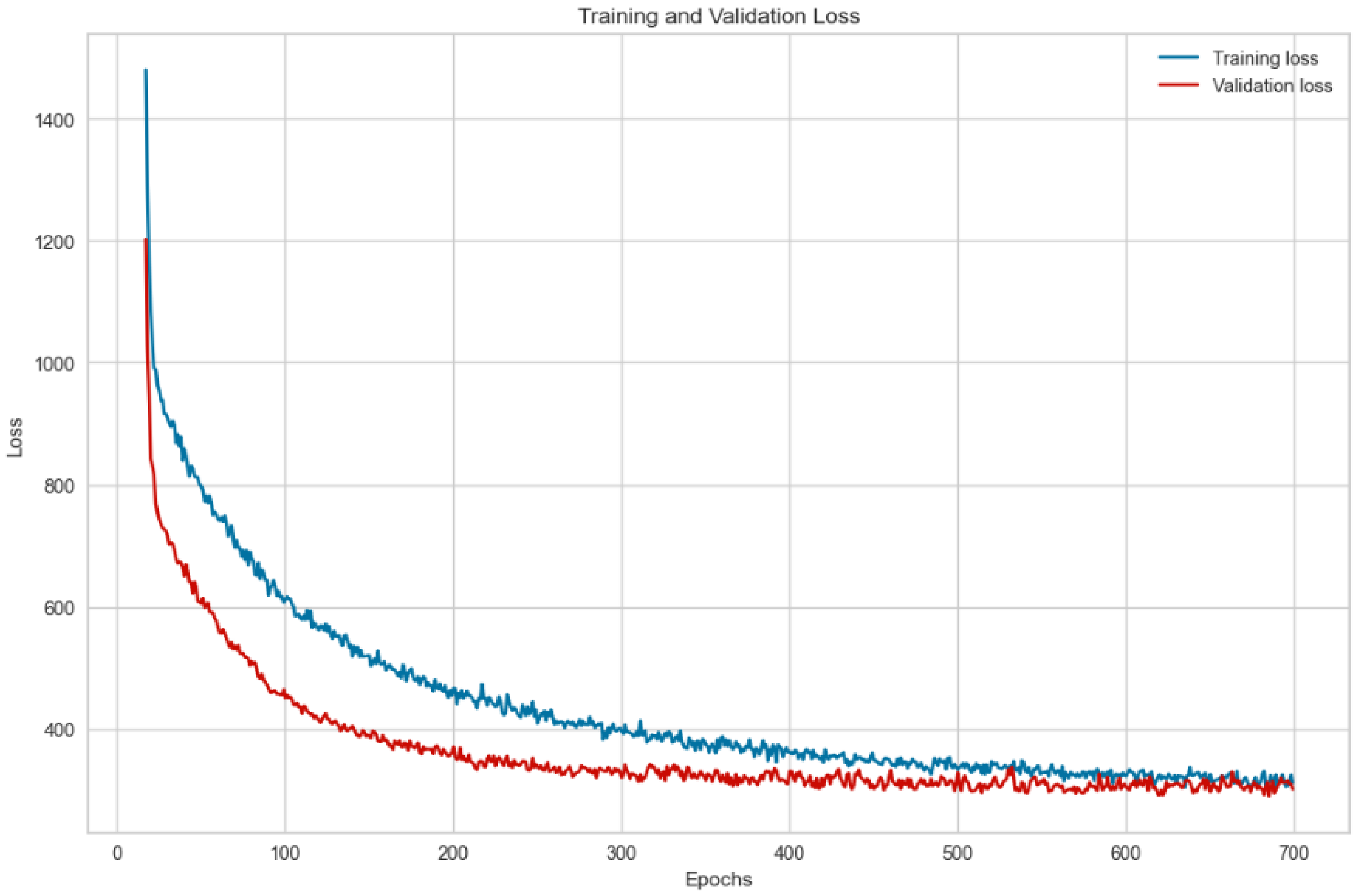
Deep Neural Networks

Hyperparameter	Range	Value
Input size	-	15
Output size	-	1
Hidden layers	2 to 6, 50 to 300 neurons	[200, 300, 200]
Activation Function	ReLU, Tanh, Sigmoid, SeLU, ELU	ReLU
Initialization Method	Uniform, Xavier, He, Lecun	He

Deep Neural Networks

Hyperparameter	Range	Value
Dropout	0.2 to 0.5	0.25
Batch Normalization	True, False	True
Learning Rate	0.1, 0.01, 0.001	0.001
Epoch	100 to 2500	700
Optimizer	Adam	Adam
Batch Size	32 to 1024	512

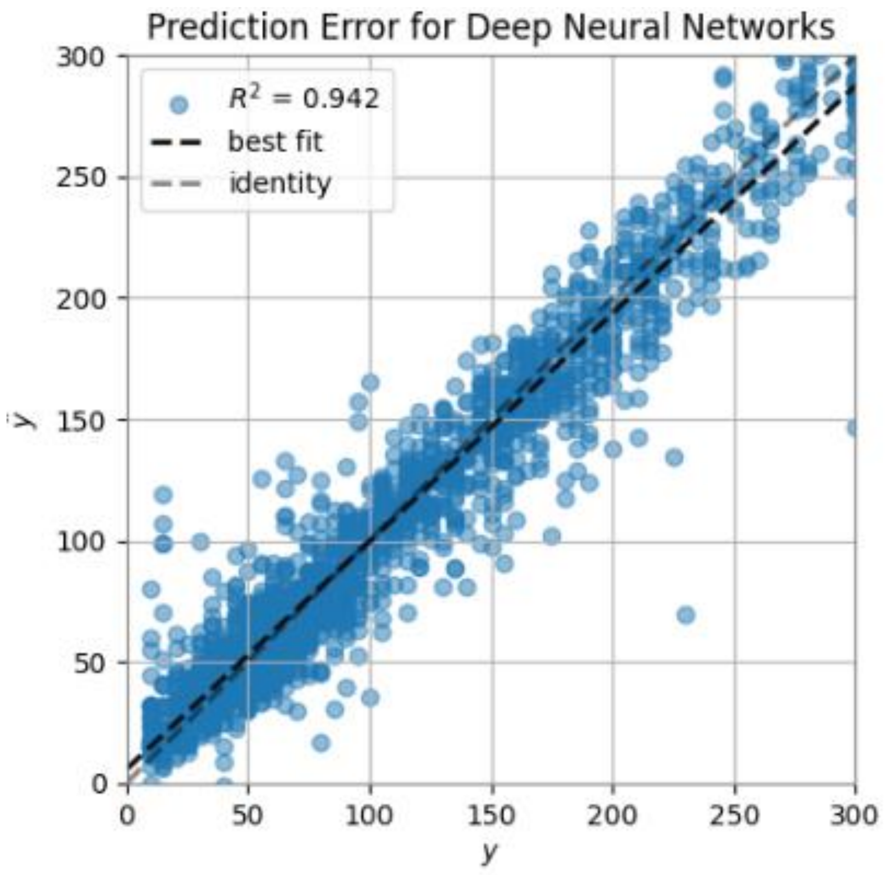
Deep Neural Networks

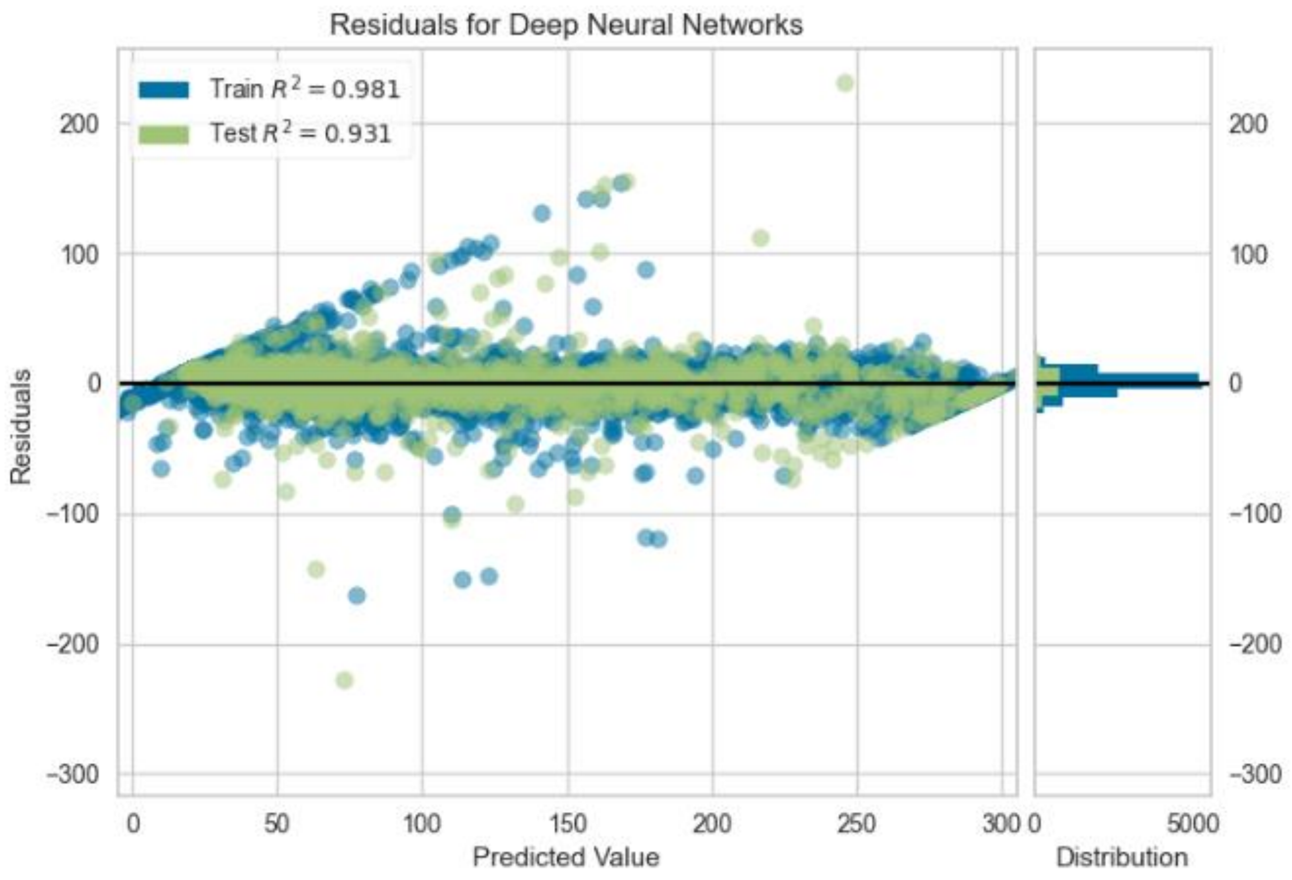


Deep Neural Networks

Metric	Value
RMSE	17.66
MAE	12.15
R^2	0.942

Deep Neural Networks

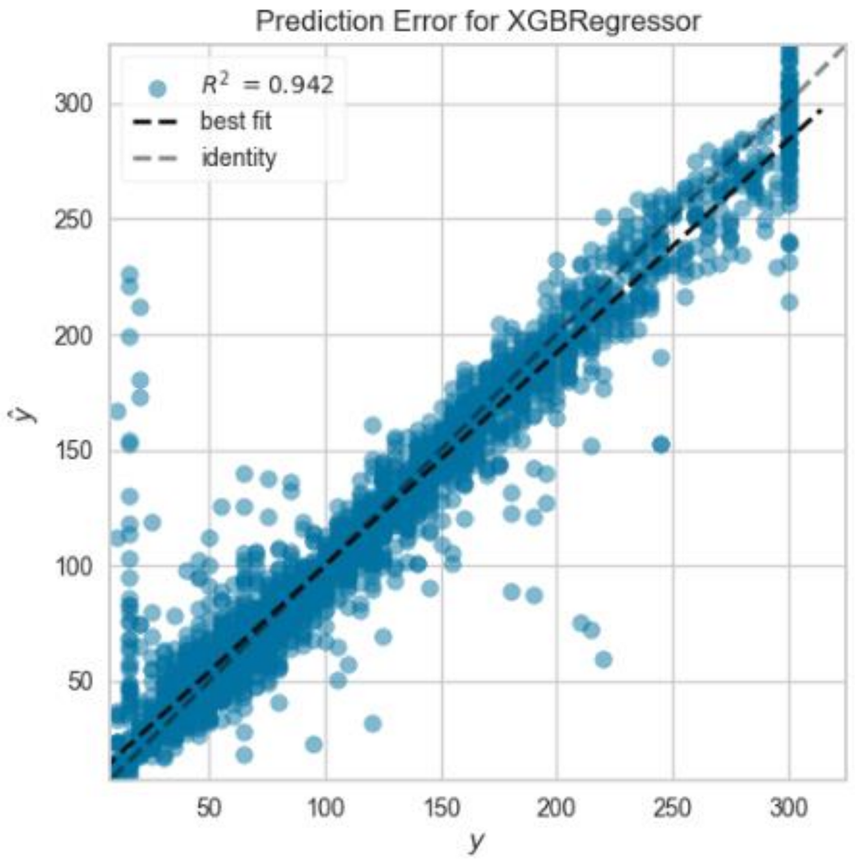


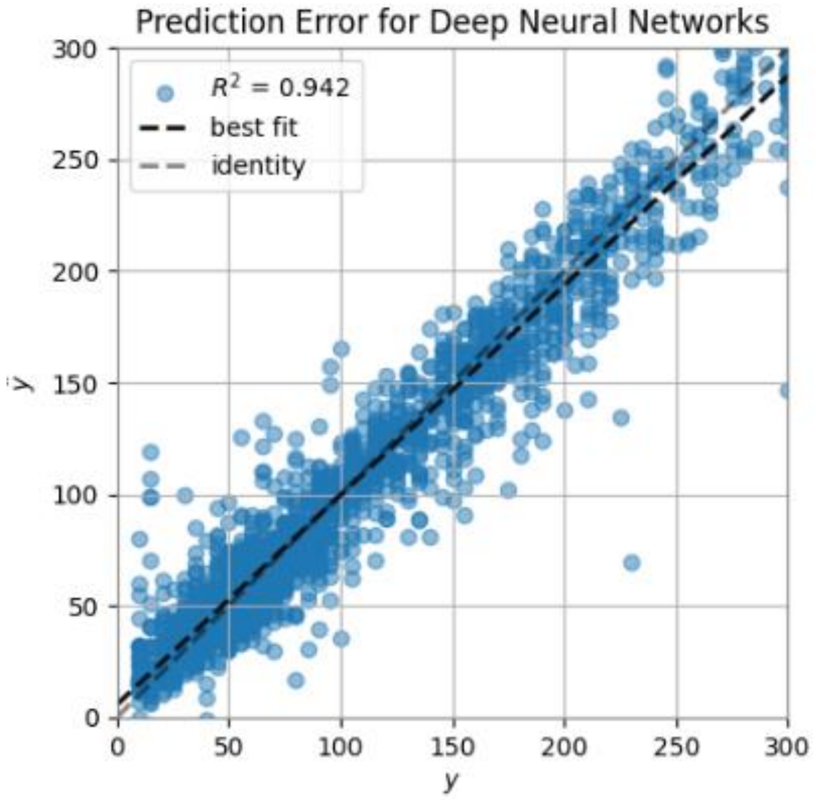


XGBoost vs Deep Neural Networks

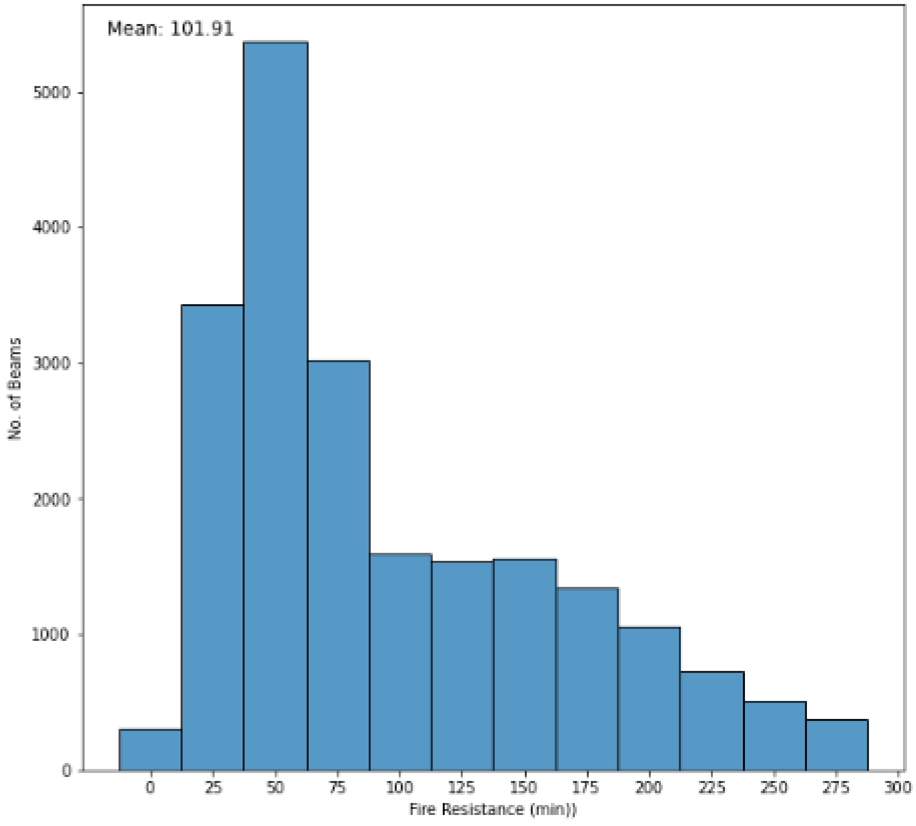
Metric	XGBoost	DNN
RMSE	17.82	**17.66**
MAE	**9.87**	12.15
R^2	0.942	0.942

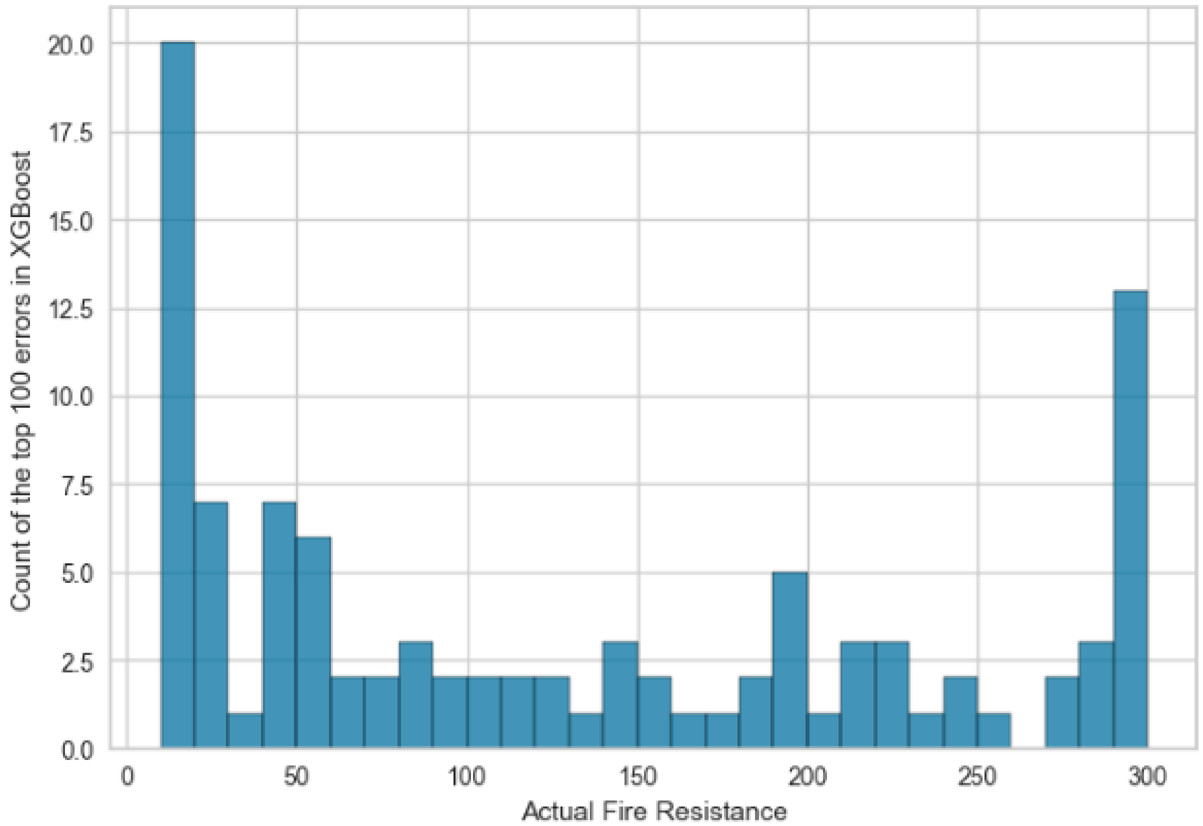
XGBoost and DNN performance



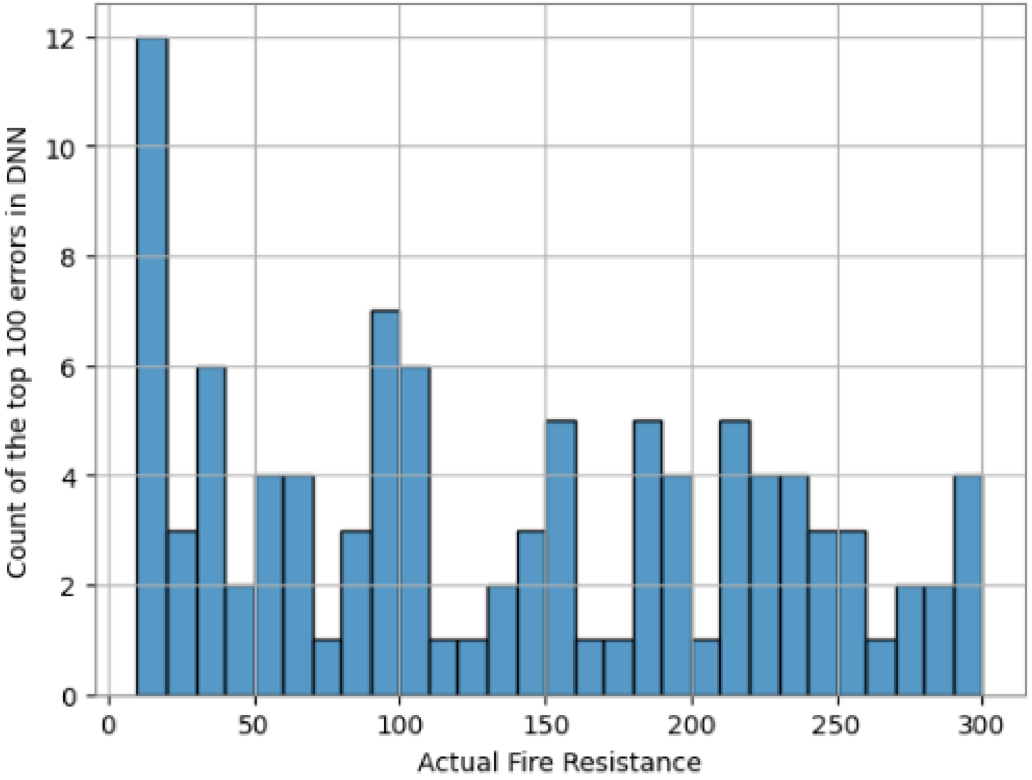


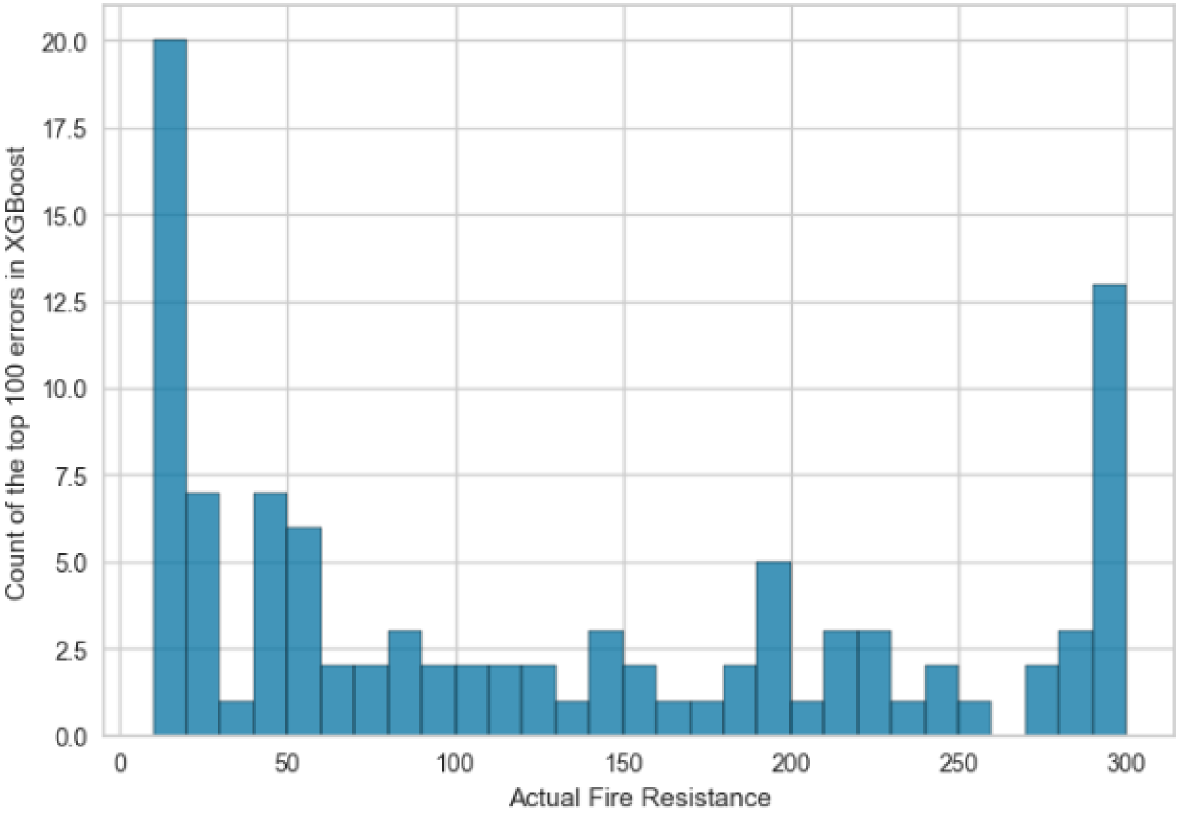
Top 100 data points with the highest prediction errors for XGBoost



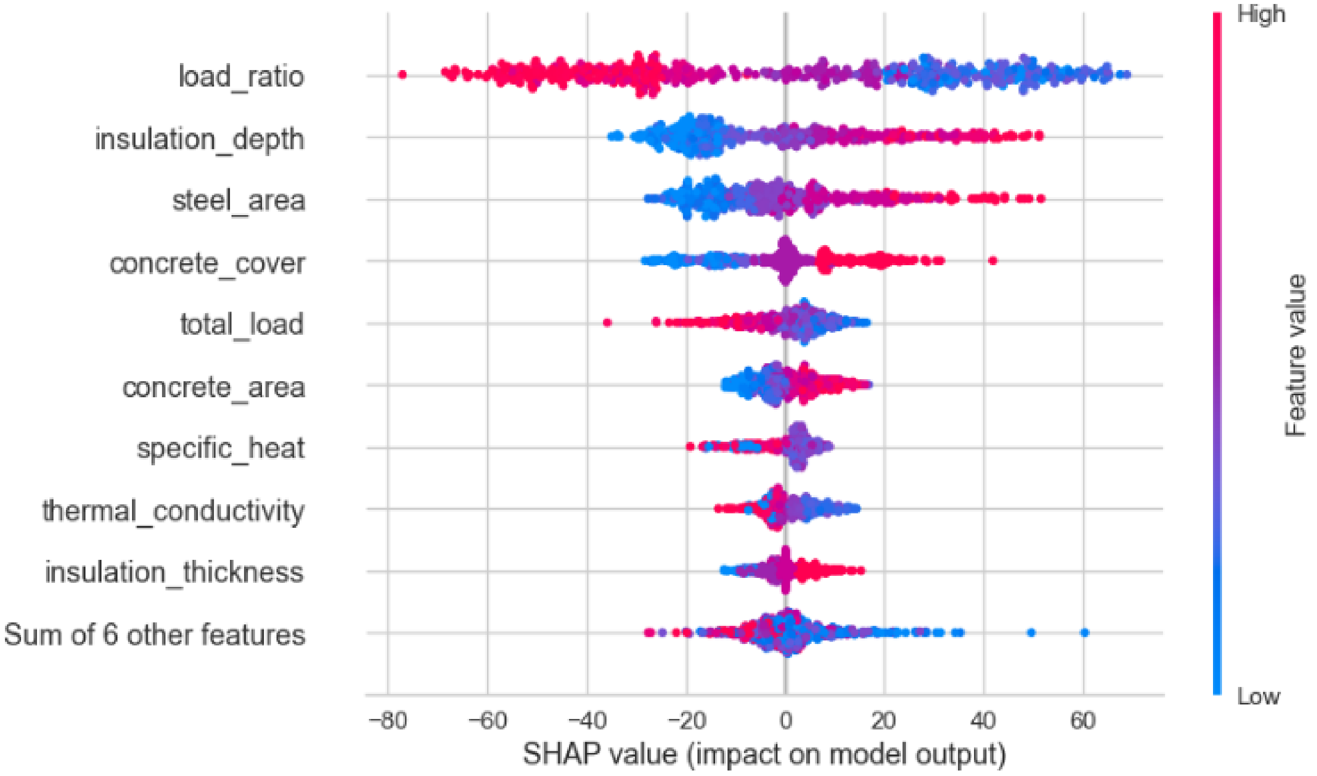


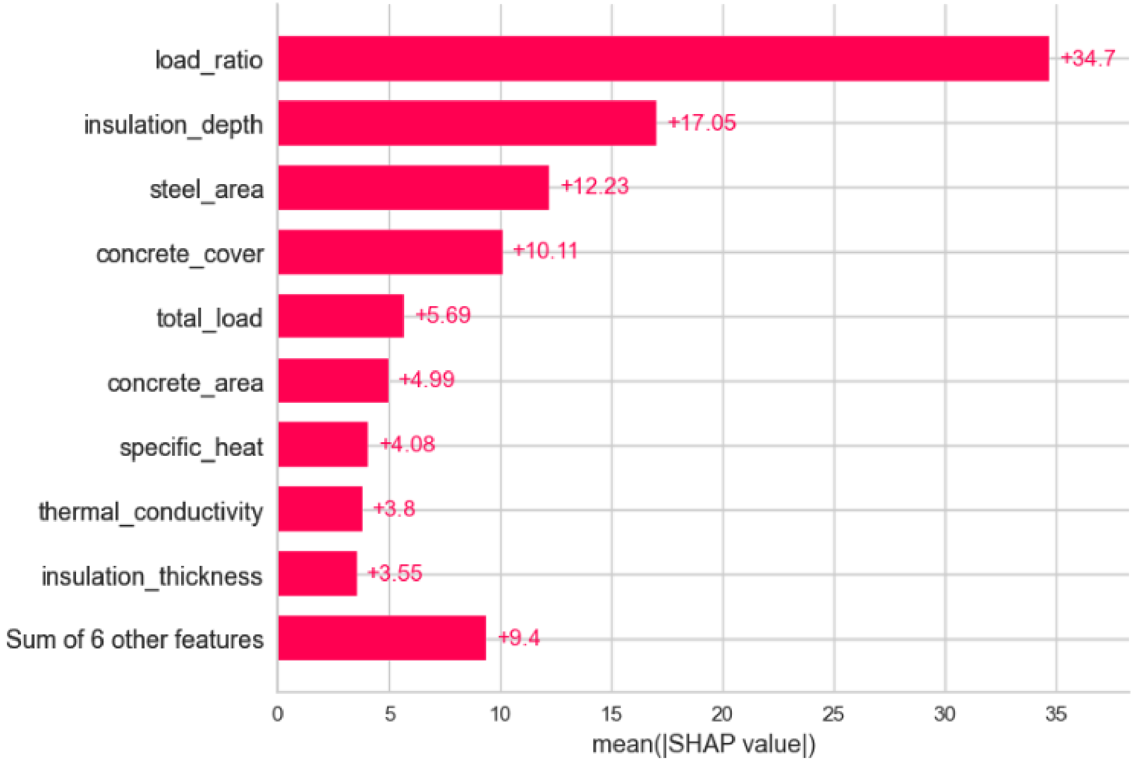
Top 100 data points with the highest prediction errors for DNN and XGBoost



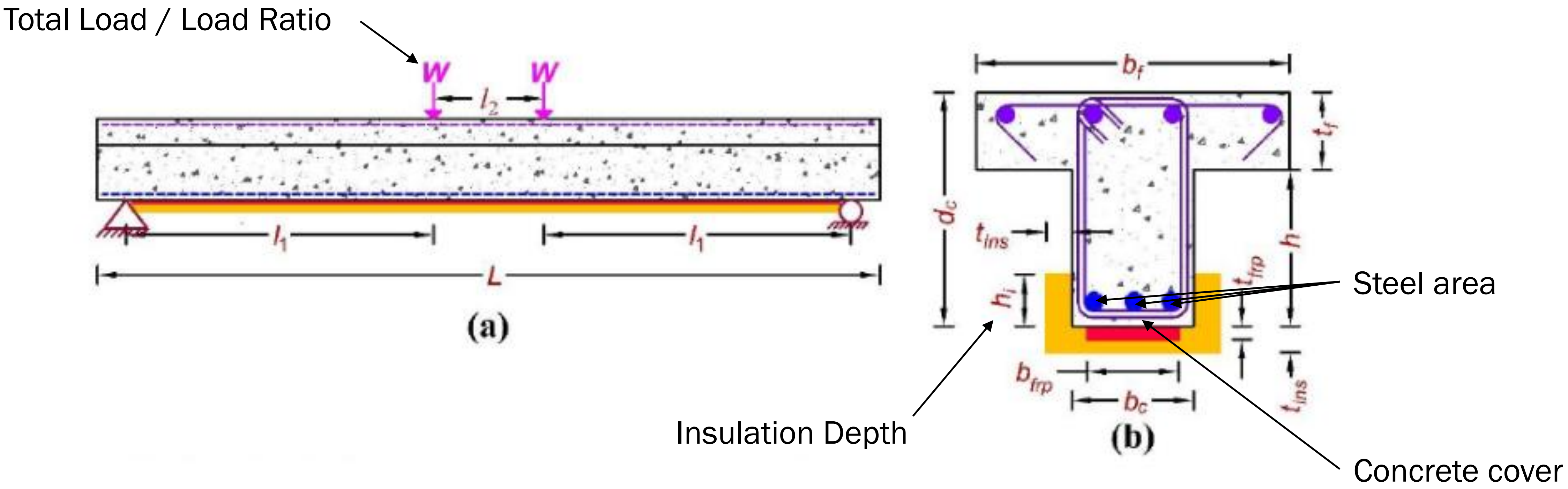


Feature Importance





Feature Importance



Top 5 DNN prediction errors with fire resistance between 95 to 105 minutes

Beam Name	Features			DNN Prediction	
	Insulation Depth	Load Ratio	Actual Fire Resistance	Fire Resistance	Absolute Difference
I3_B4464	76	69.93	95	180.28	85.28
I2_B2453	0	59.65	100	24.23	75.67
I3_B4463	76	57.39	100	166.55	66.55
I5_B3087	0	71.80	95	42.31	52.69
I4_B1236	25	71.25	105	59.59	45.41

Conclusion

Conclusion

- Extreme Gradient Boosting demonstrates strong performance in overall fire resistance prediction, while Deep Neural Networks excel particularly in capturing extreme values of fire resistance.
- Key factors influencing fire resistance are load ratio, insulation depth, steel area, concrete cover, and total load.
- This paper emphasizes the potential of ML models to address highly nonlinear problems in classical engineering domains where conventional knowledge-based approaches may prove impractical or unfeasible.

Thank you!