

# Artificial Intelligence in Prediction of Shear Beams Strength

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- **Traditional Methods Calculating The Shear Strength of Beams.**
- **AI and ML Methods:**
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  2. Elastic Net.
  3. Stochastic Gradient Descent.
  4. Multilayer Perceptron.
  5. Ensemble Learning.
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- **Results & Conclusion.**
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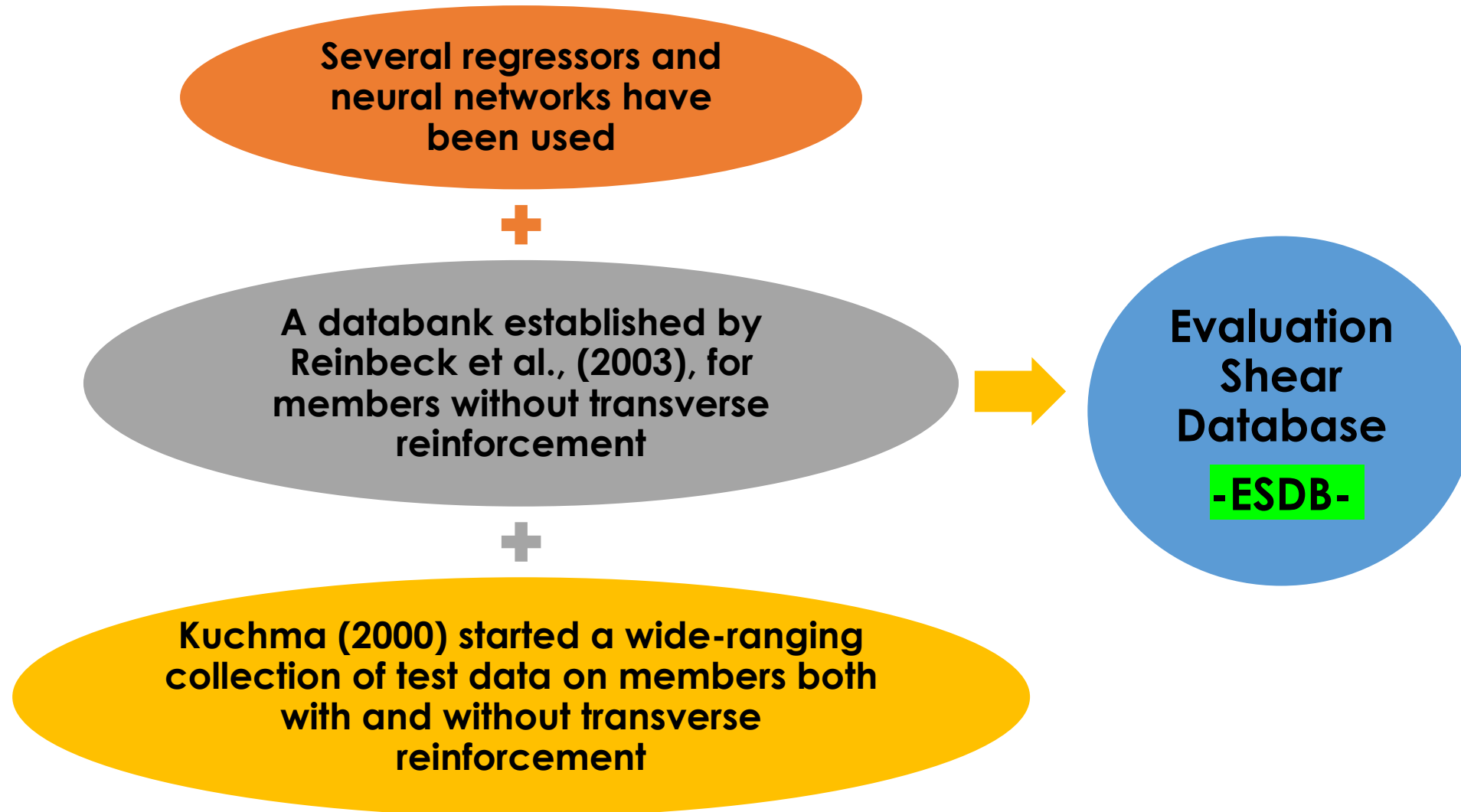
**Artificial intelligence  
“AI” has big  
contributions to  
problem-solving in  
multiple fields.**

**The shear strength of the  
beam is an important  
factor to have safe  
buildings.**

**Calculating of those  
values is done usually  
using approximate  
methods [1].**

**AI methods proved to  
give reliable results in  
multiple fields when  
used with enough  
training data [2].**

**Multiple artificial  
intelligence and  
machine learning  
techniques have been  
used to predict the  
shear beam strength.**

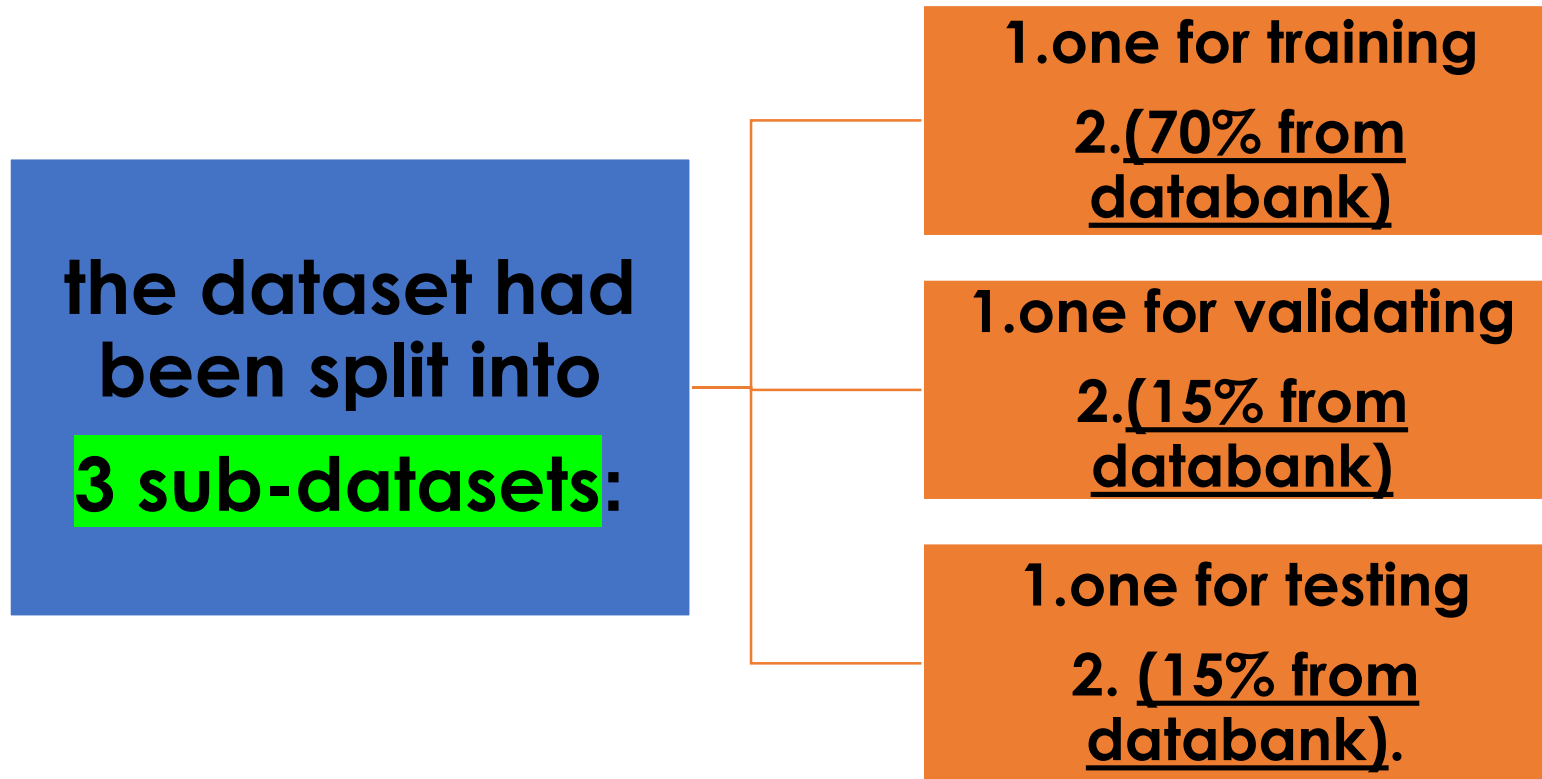


**The shear strength of RC beams without shear reinforcement is of interest to this research in order to :**

**1- acquire a better understanding of the shear behavior of RC beams.**

**2- contribution of concrete to the shear strength of RC beams.**

We have used the collection shear databank (**Evaluation Shear Database -ESDB-**) from [3] to form our dataset.



The parameters taken into account :

**b, h, a/d, ps, fsy, ftk, As2, fsy2, Asw, sw, fyw, Vu**







- To make comparisons between different tests and code equations **table (3)**, it was necessary to convert strength values determined on different control specimens to standardized and unique strength values.

Table.3: Conversion factors of concrete compressive strengths of different specimens.

Specimen strength	Relational equation	Specimen type and size, mm
$f_{c,cyl}$	$f_{1c,cyl} = 0.95 f_{c,cyl}$	Cylinder $\phi 150$ X H300
$f_{c,cube}$	$f_{1c,cube} = 0.75 f_{c,cube}$	Cube 150 X 150
$f_{c,cyl,100/300}$	$f_{c,cyl} = 1.05 f_{c,cyl,100/300}$	Cylinder $\phi 100$ X H300
$f_{c,cyl,70/150}$	$f_{c,cyl} = (1.0/1.06) f_{c,cyl,70/150}$	Cylinder $\phi 70$ X H150
$f_{c,cyl,120/360}$	$f_{c,cyl} = (1.0/0.95) f_{c,cyl,120/360}$	Cylinder $\phi 120$ X H360
$f_{c,cyl,100/200}$	$f_{c,cyl} = (0.92/0.95) f_{c,cyl,100/200}$	Cylinder $\phi 100$ X H200
$f_{c,cube200}$	$f_{c,cube} = 1.05 f_{c,cube200}$	Cube 200 X 200
$f_{c,cube100}$	$f_{c,cube} = 0.90 f_{c,cube100}$	Cube 100 X 100

A dozen AI and ML techniques:



to find the best solution from multiple aspects like accuracy, and speed, and the number of outliers.

A.Tikhonov Regularization.

A.Elastic Net.

A.Stochastic Gradient Descent.

A.Multilayer Perceptron.

A.Ensemble Learning.

A.Stacking Regressors.

A.Voting Regressor.

A.Histogram-based Gradient Boosting Regression Tree.

The Tikhonov regularization method is a powerful alternative for regularization of nonlinear system identification problems

We got a validation result of **66%** which is not good enough

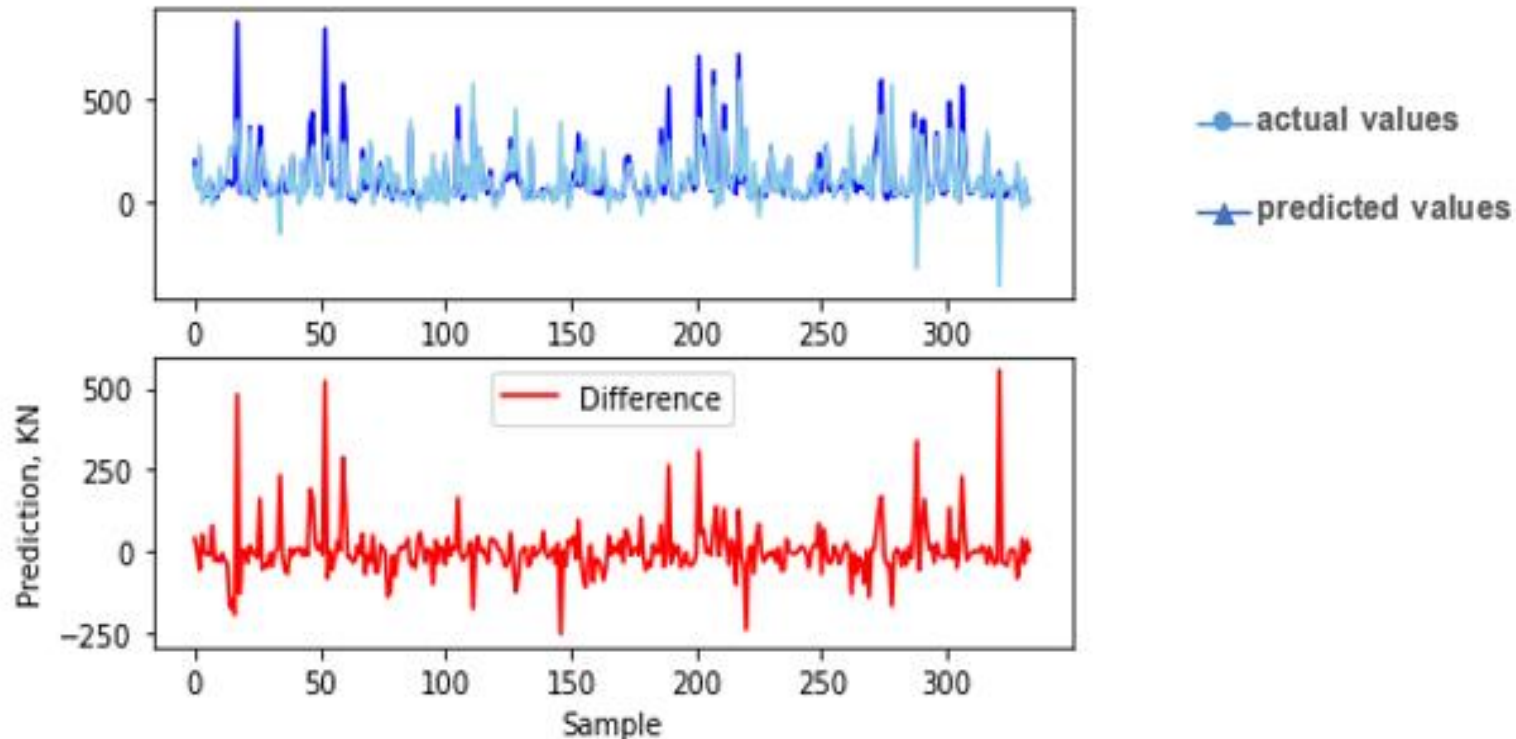


Fig 1. Ridge regression results.

## B. ELASTIC NET

Elastic Net combines:

- Tikhonov regularization
- With LASSO regression

Our model was able to get worse results at **63%**.

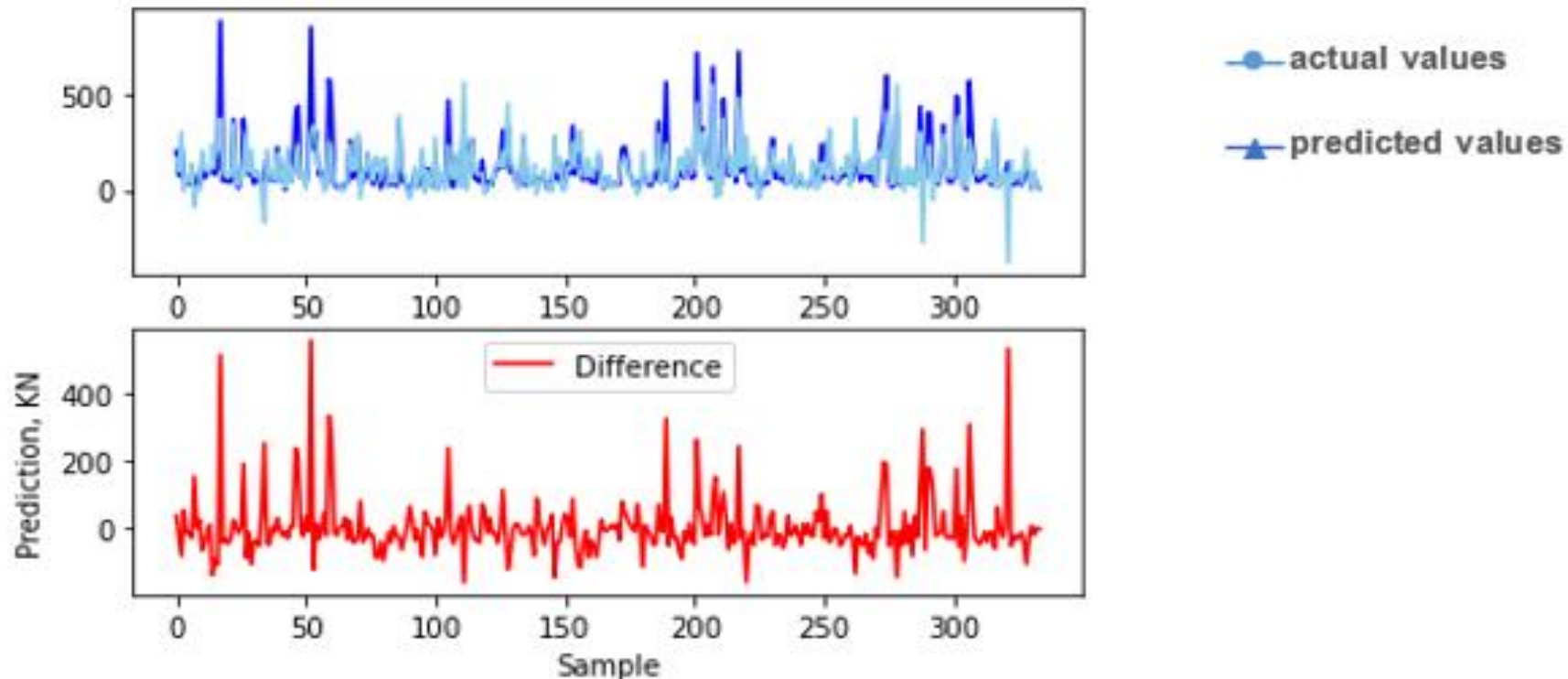


Fig. 2. The elastic net regression result.

## C. STOCHASTIC GRADIENT DESCENT

SGD is an iterative method for optimizing an object function



it is a form of stochastic approximation of gradient descent optimization



In our tests, it got the result of **68%**, slightly better than Tikhonov regularization.

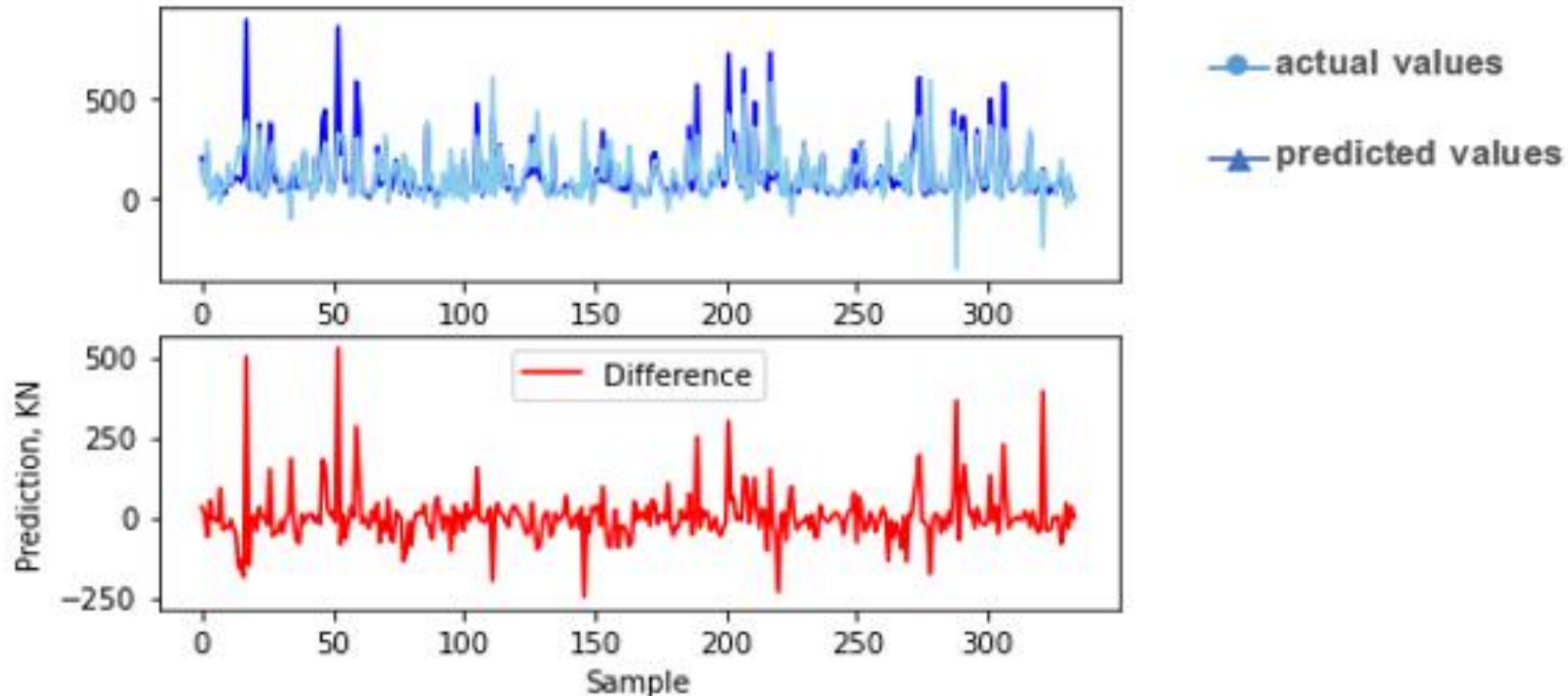


Fig. 3. SGD regression result

## D. MULTILAYER PERCEPTRON

MLP for short proved to be very good in understanding the relationship between the input and output

The MLP consists of three or more layers (an input and an output layer with one or more hidden layers).

After building our regressor based on MLP we had a result of **89%**.

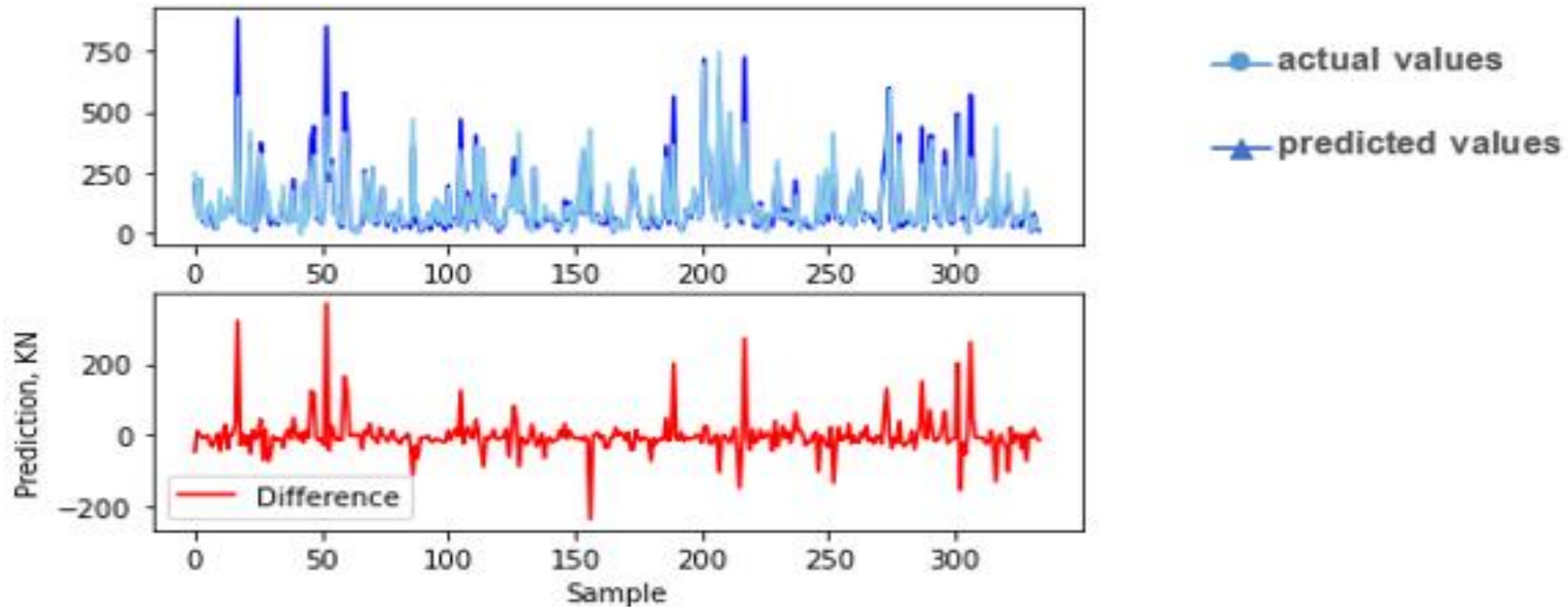


Fig. 4. MLP regression result

## E. ENSEMBLE LEARNING

- An ensemble is itself a supervised learning algorithm because it can be trained and then used to make predictions.
- Empirically, ensembles tend to yield better results when there is significant diversity among the models.
- a result of this method **90%** is obtained which is better than MLP by 1%.

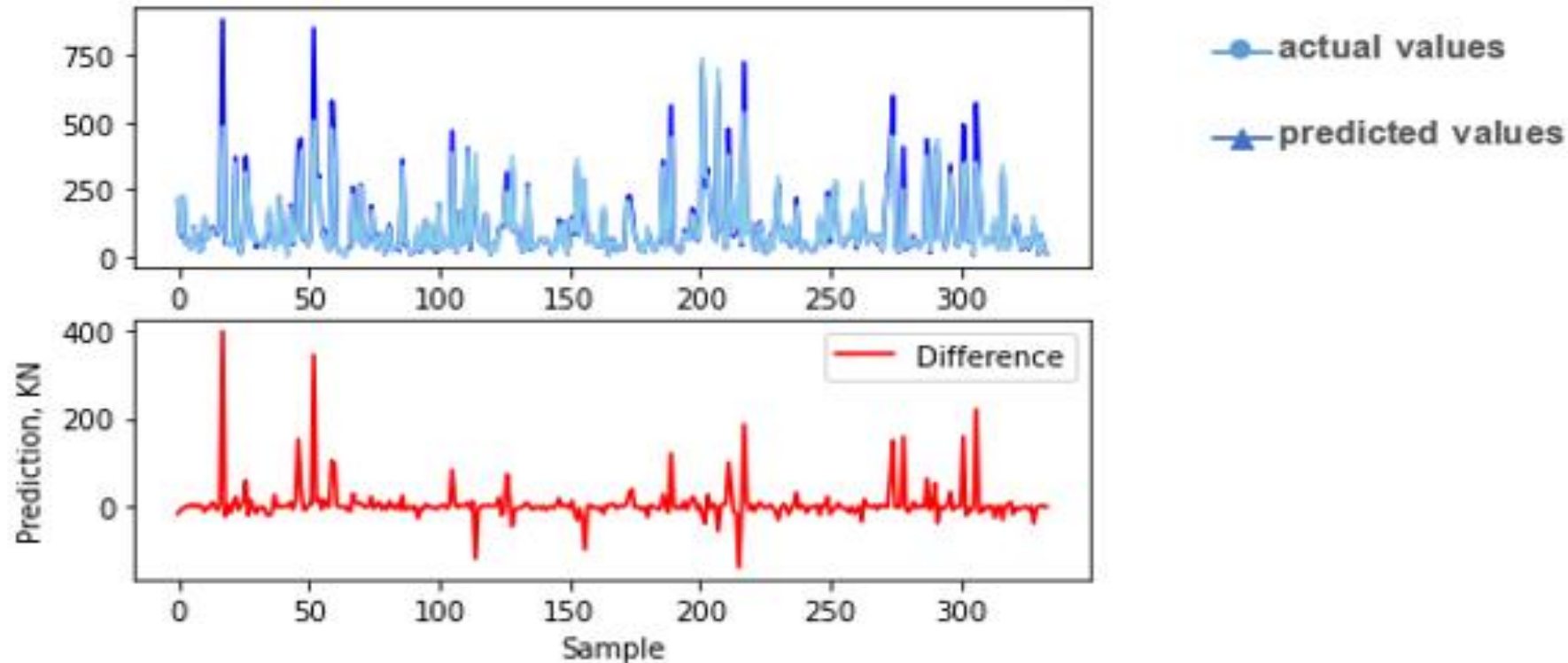


Fig. 5. Randomized decision trees results.

## F. STACKING REGRESSORS

Stacking allows to use of the strength of each estimator by using their output as the input of a final estimator [8].

after testing we found that the extra complication yielded a result of **69%**.

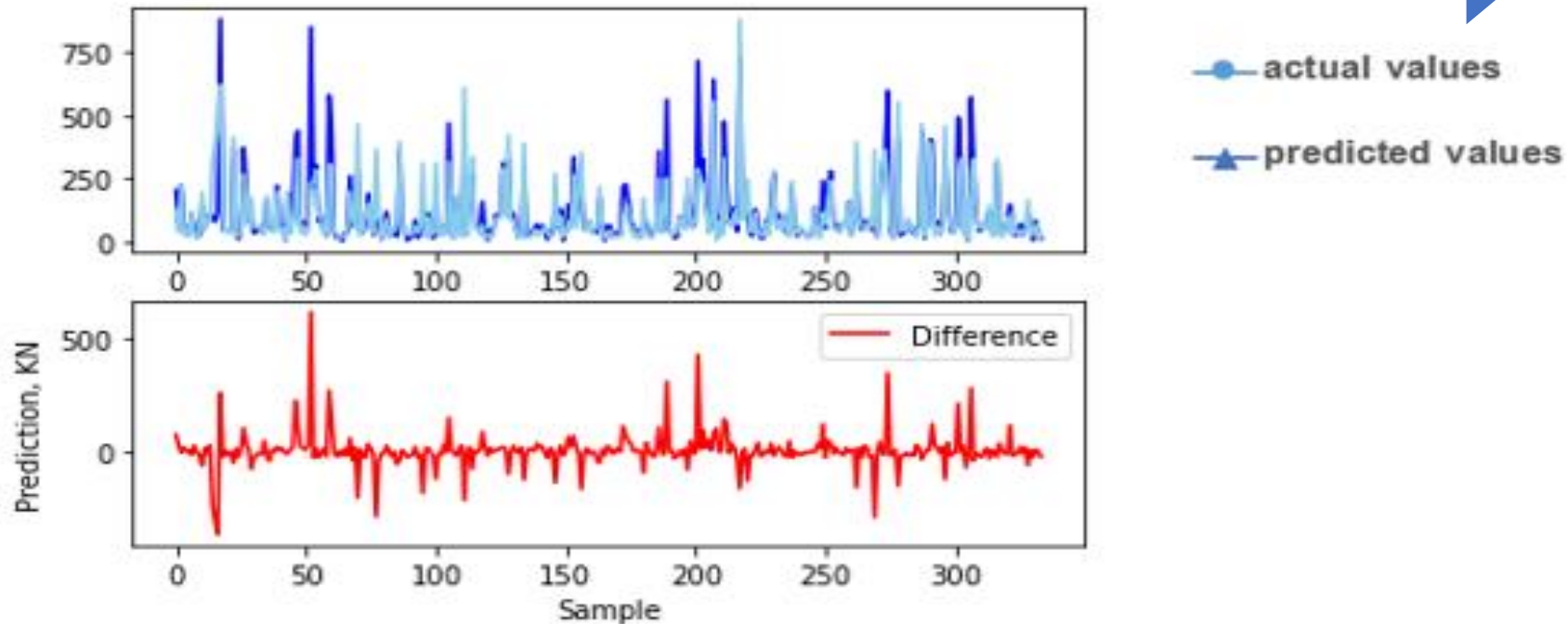


Fig. 6. Result of stacking multiple regressors.



# G. VOTING REGRESSOR

Voting Regressor did not take time in training as the stacking regressor yet.

it averages the individual predictions to form a final prediction [9].

it gets a result of **85%** but without any use of neural networks

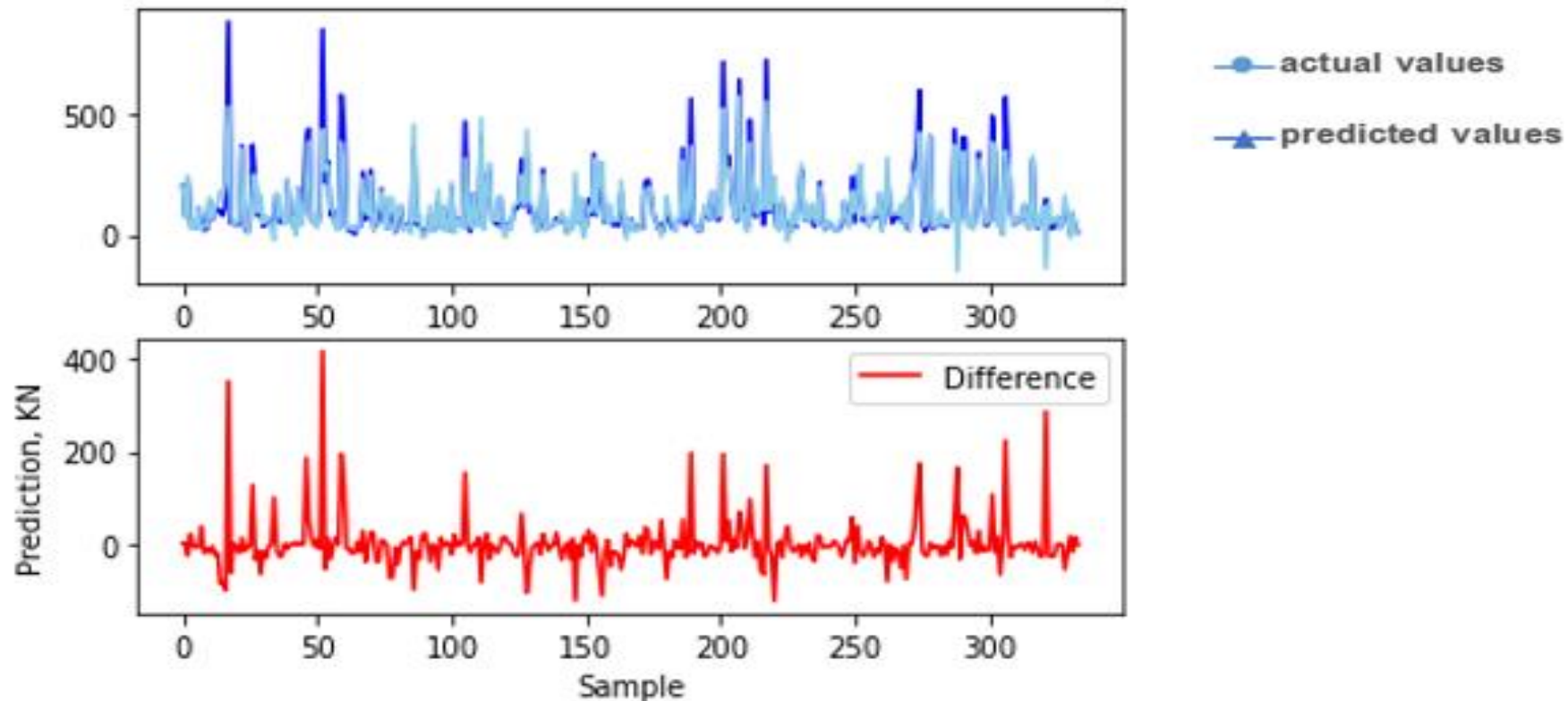


Fig. 7. Result of a voting regressor.

**Gradient boosting is one of the most powerful techniques for building predictive models**

**Hypothesis boosting was the idea of filtering observations, focusing on developing new weak learners**

**Gradient boosting is typically used with decision trees (especially CART trees) of a fixed size as base learners**

## H. HISTOGRAM-BASED GRADIENT BOOSTING REGRESSION TREE

An unprecedented **96%** was acquired using histogram-based gradient boosting regression trees.

also the outliers are smaller in quantity and value.

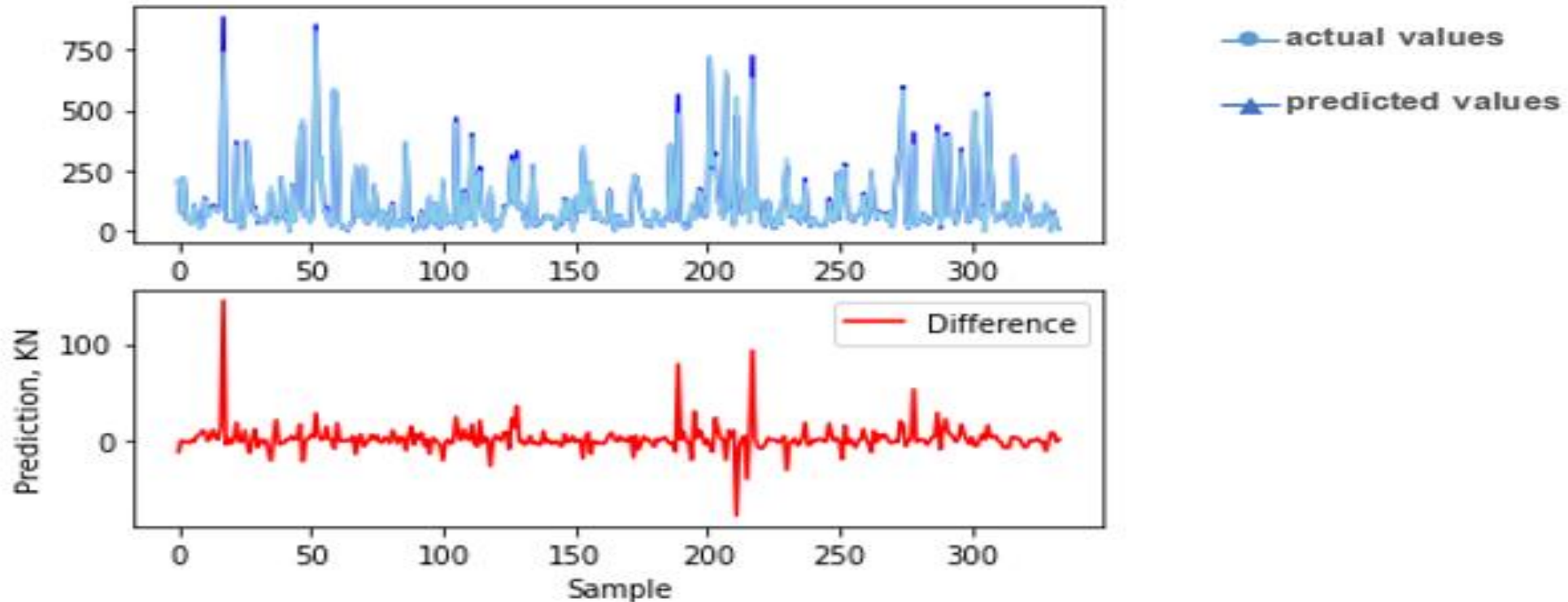


Fig. 8. Result of Histogram-Based Gradient Boosting Regression Tree.

- **Table (4)** shows training, test, and validation results for multiple machine learning and artificial intelligence methods.

Table .4:  
Multiple  
algorithms  
scores.

Algorithm	Training Accuracy	Test Accuracy	Validation Accuracy
<b>A- Ridge</b>	0.73	0.63	<b>0.66</b>
<b>B- Elastic Net</b>	0.68	0.58	<b>0.63</b>
<b>C- SGD Regressor</b>	0.73	0.64	<b>0.68</b>
<b>D- MLP Regressor</b>	0.90	0.85	<b>0.89</b>
<b>E- Extra Trees Regressor</b>	0.99	0.90	<b>0.90</b>
<b>F- Ridge+Linear SVR+Random Forest Regressor</b>	0.76	0.65	<b>0.69</b>
<b>G- Voting Regressor</b>	0.91	0.83	<b>0.85</b>
<b>H- Hist-Gradient Boosting Regressor</b>	0.97	0.98	<b>0.96</b>

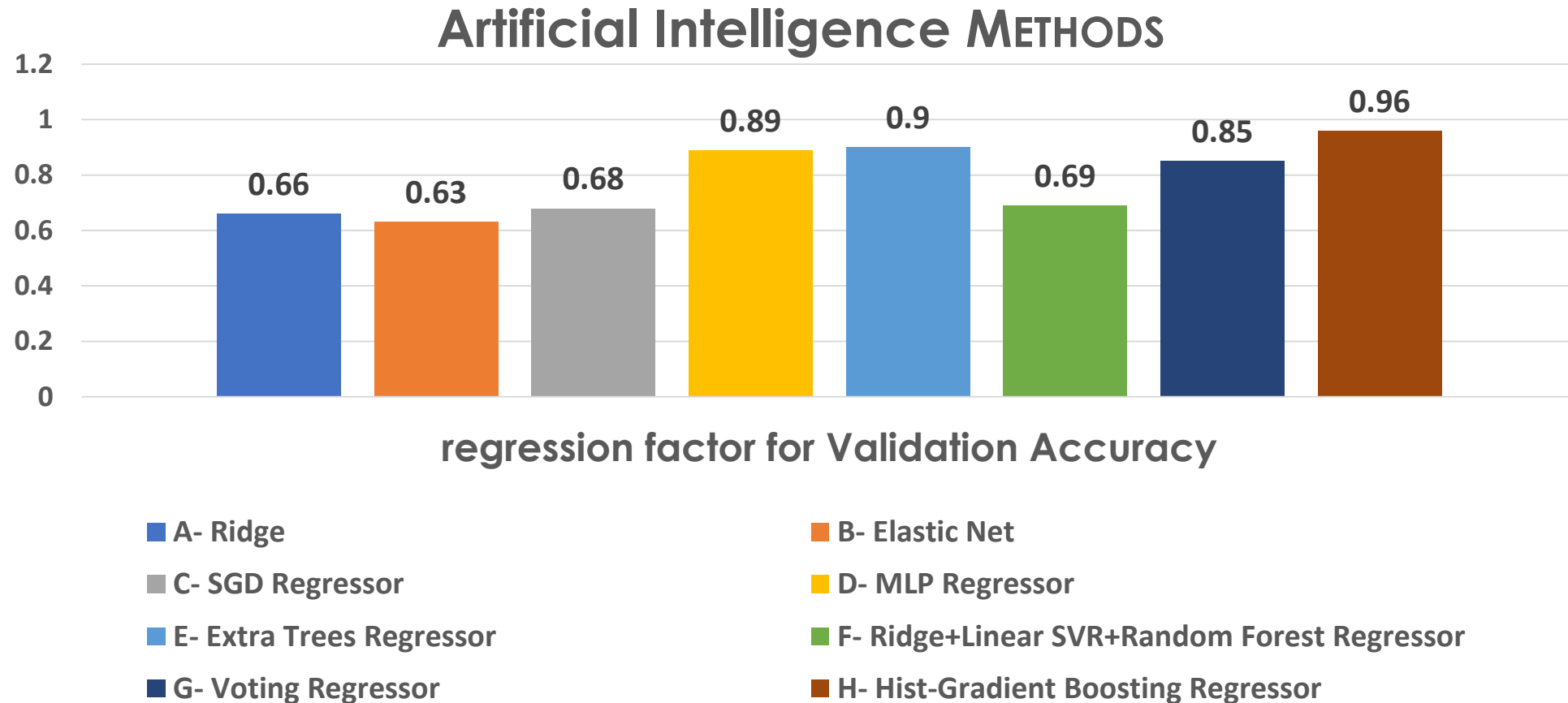


Fig. 9. Result of regression factor for Validation Accuracy of AI Methods

- **The histogram-based gradient boosting regression** gave the **best results** with the smallest number of outliers, and the highest accuracy compared to other artificial intelligence and machine learning methods.

1. A total of 8 techniques has been evaluated for solving the problem of beam strength prediction, The techniques were applied on data collection shear databank (**ESDB database**).
2. Root mean squared error was used to evaluate the predicted values.
3. the comparison metric was the validation accuracy, which uses unseen data for evaluation.
4. Histogram Gradient boosting regressor a machine learning technique has outperformed the best in class predictor namely the MLP neural network.
5. It is an indicator that the nature of this problem could be solved with far simpler architectures than neural networks.
6. Developing new models and experimenting with different setups and configurations has been conducted to explore the usage of AI in the field of beam strength prediction.

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