Cementing Our Understanding of Concrete: Using Machine Learning Methods to Predict the Uniaxial Compressive Strength of Cement-Based Mixtures for Mining Applications

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Introduction

- Cement-based mixtures (e.g., shotcrete, grout, and backfill) are commonly used in the mining industry.
- For cement-based mixtures (like concrete), it is difficult to predict the uniaxial compressive strength (UCS) from just the mixing stage (e.g., the components of concrete).
- Predicting UCS before mixing saves resources such as money, time, and materials.
- Data exists, but there are currently no prediction tools available for the mining industry.

Research Question

Can machine learning techniques be used to accurately predict the uniaxial compressive strength of concrete?

Methods

- Using Python 3.11.3 with Jupyter Notebook, 4 different machine learning (ML) models were evaluated: Linear Regression (LR), Support Vector Regression (SVR), Gradient Boosting Regression (GBR), and Decision Trees (DT).
- The data was split into training and testing data in varying proportions to determine the best split for the models.
- The models were trained using the training data and then were evaluated with the testing data.

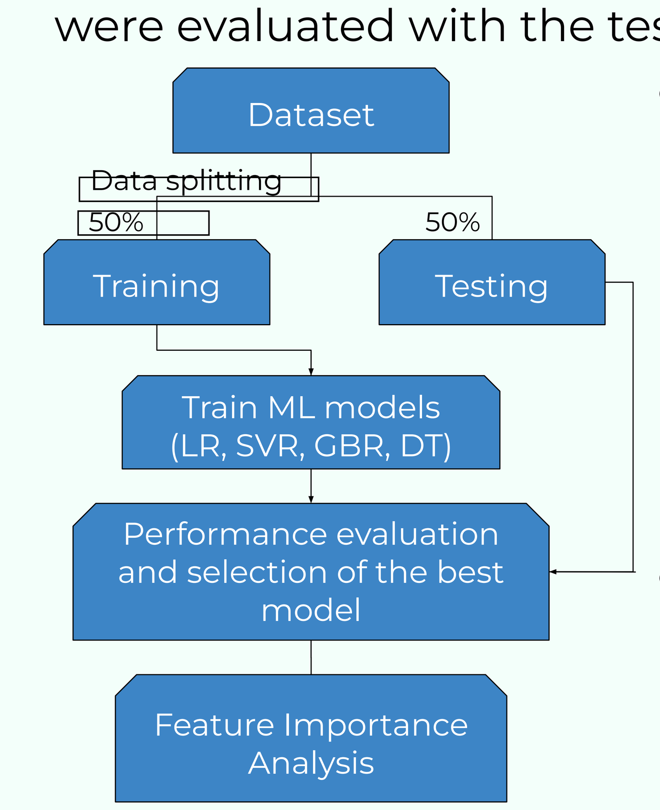

Figure 1: a tree diagram showing the steps of data processing and machine learning.

- The ratio of training to testing data that offered the best results was 50% training and 50% testing; that ratio was then used to determine the best model.
- The importance of each feature was also analyzed to see what component of concrete has the biggest impact in determining the UCS.

Results

Model Name	Training				Testing			
	R^2	MSE	RMSE	MAE	R^2	MSE	RMSE	MAE
Linear Regression	61.2%	103.769	10.187	8.172	61.2%	112.478	10.606	8.222
Support Vector Regression	82.5%	46.859	6.845	5.185	80.7%	55.898	7.476	5.560
Gradient Boosting Regression	**94.6%**	14.394	3.794	2.799	**93.0%**	20.260	4.501	3.260
Decision Trees	99.5%	1.417	1.191	0.091	79.7%	58.996	7.681	5.337

Table 1: four different machine learning models and their performance with the training and testing data. R^2 is the accuracy of the model (the closer to 100% the more accurate the model is).
MSE – mean squared error, RMSE – root mean squared error, MAE – mean absolute error.

- Gradient Boosting Regression has the highest accuracy (R^2) and lowest errors with the testing dataset.

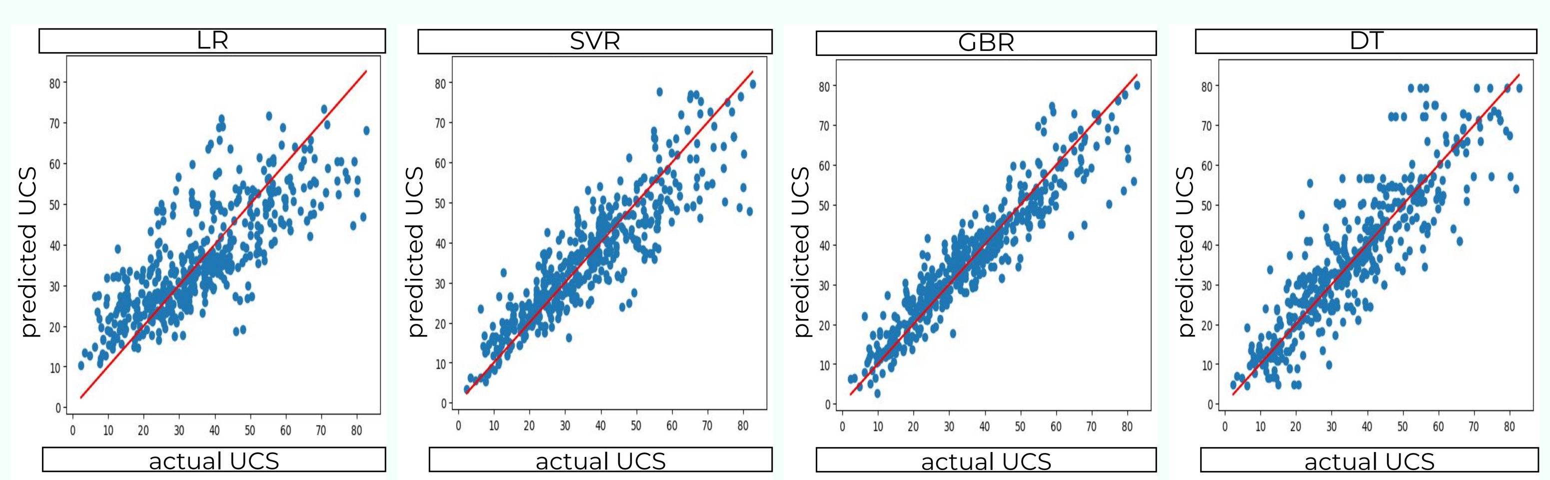

Figure 2.1-2.4: a visualization of the data in Table 1. The red line represents the slope of actual UCS over actual UCS which would be 100% accuracy.

- The visual representations show the accuracy by how close the blue dots mirror the slope of the red line.
- Gradient Boosting Regression (Figure 2.3) has the closest fit with the accuracy line.

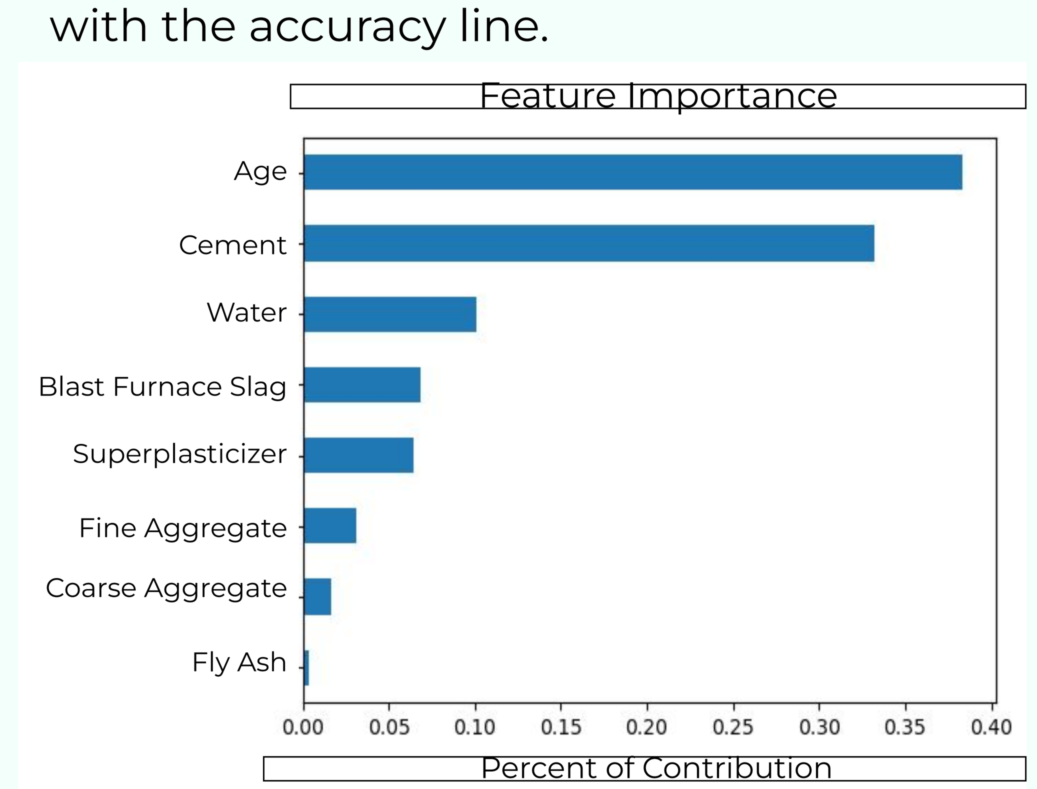

Figure 3: a graph that shows the variables (components of concrete) and how much they affect the final UCS.

- The most important feature when predicting UCS is age (the amount of time to cure and harden).
- Cement is also a prominent factor in determining UCS.

Conclusions

- The most accurate model is the Gradient Boosting Regression model with 50% training and 50% testing data.
- GBR uses complex decision trees so it is able to effectively model the intricate relationships between the many components.

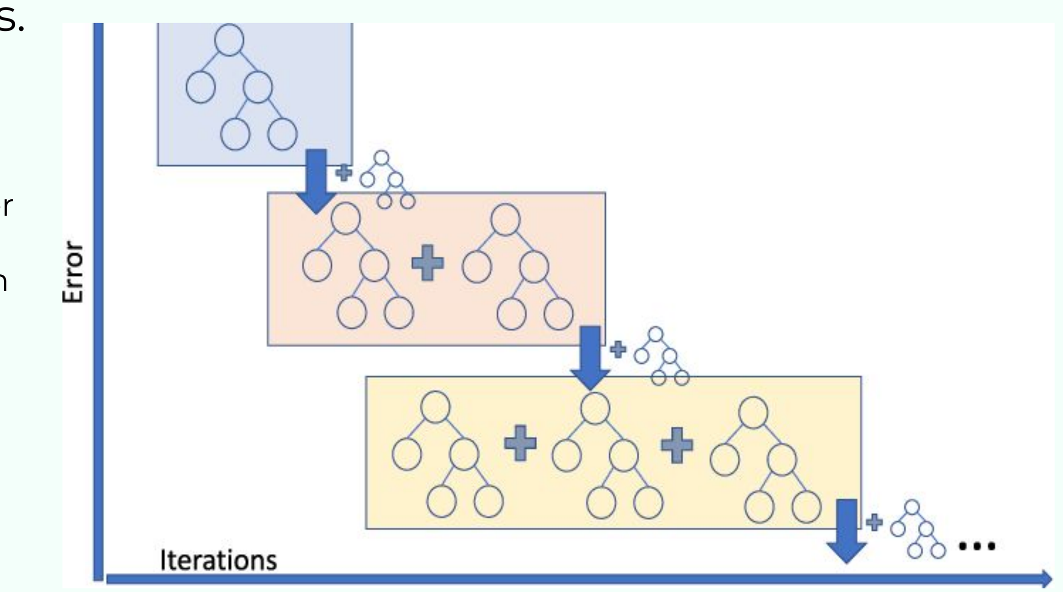

Figure 4: the inner workings of the GBR model which uses complex decision trees to make predictions (1).

- The most important factor in determining the UCS is age because the reaction between cement and water continues to strengthen the concrete over time (a 28 day sample will be stronger than a 3 day sample).
- Using machine learning, a relatively accurate model for predicting the UCS of concrete can be built.
- Predictions of UCS can be made, but not without error.
- Errors must be accounted for when using the predicted values.

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Literature Cited

1. Baturynska, I., & Martinsen, K. (2020). Prediction of geometry deviations in additive manufactured parts: comparison of linear regression with machine learning algorithms. *Journal of Intelligent Manufacturing, 32(1), 179–200*. https://doi.org/10.1007/s10845-020-01567-0