# **Predicting Steel Strength: A Regression-based Approach**

Steel is one of the most ubiquitous materials in modern society. Its mass production was one of the primary drivers of the First Industrial Revolution. It’s relative affordability and high strength has made it feasible to build big and strong without breaking the bank.

It is primarily Iron with a mix of other elements known as alloying elements. Combining different alloying elements can result in widely varied properties and as such, depending on the application, an appropriate alloying composition can be chosen. Metallurgists could find use in having a rough idea of the strength of a grade of steel prior to it being manufactured. In this project, I create a regression model that estimates the strength of a grade of steel solely based on its alloying elements.

Steel is a polycrystalline material, meaning it’s made of multiple crystals. Crystals are groups of atoms which have a repeating fundamental structure, known as a unit cell.

Polycrystalline materials are a group of bonded crystals that all point in different directions as it can be seen below:

Chart

Description automatically generated

A black and white drawing of a polycrystalline

Description automatically generated with low confidence

In a metallurgical setting, crystals are commonly referred to as grains. Each enclosed area in the figure below is one grain of steel.

Diagram

Description automatically generated

Adding elements to Iron can change the size and shape of these grains while also resulting in the creation of new phases. The addition of alloying elements can also stretch or compress the crystal lattice of the steel which can provide some benefit. All these tweaks can result in improved strength.

# 1.0 Data

Steel chemistry data was collected from the machine learning data repository

Graphical user interface, text, application, table

Description automatically generated[Kaggle](https://www.kaggle.com/datasets/rohannemade/mechanical-properties-of-low-alloy-steels?resource=download). It consists of 915 samples of steel each with its respective steel chemistry and strength parameters. An example of the dataset is shown below:

# 2.0 Data Cleaning

Various features needed to be dropped, Alloy code wasn't useful in this context, neither was Carbon equivalent (Ceq). Columns were then renamed. 0.2% Proof Stress is another name for Yield strength and was renamed as such.

There were no null values however there was one unusually high strength property observation which was dropped. Additionally, the temperatures the samples were pulled ranged from 27ºC to 650ªC. A cut-off of 450ºC was chosen since most steel applications don't reach temperatures that high. 450ºC is still unusually high for a typical engineering application, however I couldn't risk removing too much data.

# 3.0 EDA

Table

Description automatically generatedThe first step of EDA was to look for general patterns in the data therefore a heatmap was created as shown below:

Temperature is negatively correlated with both Yield and Tensile strength which is expected. The higher the temperature, the weaker a metal gets. Correlations between the other strength variables are all expected as well but the main goal is to find relationships between the elements and strength!

The elements that stick out the most are Vanadium (v), Molybdenum (mo), Nickel (ni) and Manganese (mn). Surprisingly, Carbon doesn't have a huge role to play in determining strength. There are no elements that contribute negatively to steel strength in a significant way.

The following scatterplots show the relationship between the Yield strength and the weight percent of each element in that sample of steel.

The strength variable, Yield strength, was chosen to be the target variable in this project since it is one of the most important strength parameters and is widely used. It is the value of the applied stress (tension) to the material that would result in permanent deformation. One would want to avoid a low-tensile strength steel in an application that requires strength.

Chart, scatter chart

Description automatically generated

# 4.0 Preprocessing

The remaining data was split into training and test sets and the X datasets were transformed using a Standard Scaler.

# 5.0 Modelling

Table

Description automatically generatedPyCaret is a low-code machine learning library that automates the model selection process. It scores various models using k-fold cross-validation and returns a ranked list of the best models. Using this library, the top 3 models were chosen. The models were put into an ensemble Voting Regressor which returns the weighted average each model’s predictions. The top 10 models are shown below:

The CatBoost Regressor, Light Gradient Boosting Machine and Extra Trees Regressor were chosen to be input into the Voting Regressor.

## Explaining Models

The CatBoost Regressor (CAT) is a relatively new machine learning model. This model is an evolution of decision trees and gradient boosting and is best at working with categorical data. In this instance it works well with numeric values as well!

LightGBM (LGBM) and XGBoost are similar models. Where they differ is how their trees grow. In LGBM trees are grown vertically or leaf-wise. XGBoost leaves are grown level-wise. This distinction results in LGBM being faster, but it does tend to overfit.

A picture containing diagram

Description automatically generated

Diagram

Description automatically generated

Extra Trees (XT) models are also an ensemble decision tree model like Random Forests. The differentiating factor is that decision trees in an XT model are trained on the entire dataset unlike the decision trees in Random Forests that are trained on bootstrapped samples. Nodes are also split randomly unlike in Random Forests where they are split optimally according to a selection criterion. Since there is no heavy calculation required when splitting, XT are much faster.

## 5.2 Feature Importance

Here are the feature importance graphs for each of the regressors.

**Chart, scatter chart

Description automatically generatedCatBoost Regressor (CAT):**

**Extra Trees (XT):**

Chart, scatter chart

Description automatically generated

**Light Gradient Boosting Machine (LGBM):**

Chart, scatter chart

Description automatically generated

There are a few elements that are commonly major contributors in these 3 models, Vanadium (v), Manganese (mn) and Nickel (ni). Temperature is also a major contributor. An interesting finding is that XT and CAT rely heavily on the top 3 or 4 elements to make their decision. On the other hand, LGBM takes a more democratic approach and weighs the information of the other elements as well. Vanadium weight is also quite high in XT and CAT but has second to last importance in LGBM. These models are taking quite a different approach. Temperature has the highest feature importance in the LGBM model and therefore its contribution should be limited since temperatures that reach 450ºC aren’t common in engineering settings.

As it can be seen, Vanadium is the element which contributes most to Yield strength in XT and CAT. Most samples didn't contain this element as it can be seen in the histogram below:

A picture containing text, screenshot, line, plot

Description automatically generated

Vanadium (v), Nickel (ni) and Manganese (mn) all contribute to increased strength in these samples. They reduce the grain size of the steel and/or form new phases in the steel matrix that reduce movement of dislocations [1][2][3].

Temperature plays a crucial role in reducing Yield strength. An increase in temperature makes the movement of dislocations in most metals much easier since atoms are physically moving more. This ease of dislocation movement in higher temperatures causes most metals to show less resistance to stress.

## 5.3 Hyperparameter Tuning

Table

Description automatically generated Here are the metrics of the untuned and tuned models trained on the training set, and tested on the training set, validation set, test set and cross-validated on the entire dataset.

The untuned CAT was chosen to be included in the final Voting Regressor model since it performed better than the untuned regressor. Both the tuned LGBM and XT performed better than their untuned counterparts. They all tended to overfit on the training sets, but still performed admirably on the other sets.

# 6.0 Final Model

Text

Description automatically generatedAs mentioned above, a Voting Regressor was chosen to combine all models. In this meta-model, a weighted average of each model's predictions is used to form a final prediction. The algorithm is shown below:

The most accurate weights for the Cat Boost Regressor, Light Gradient Boosting Machine and Extra Trees Regressor had optimum weights of 0.7, 0.1 and 0.2 respectively. The final metrics table is shown below:

Table

Description automatically generated

# 7.0 Conclusion

This model does do quite a good job in predicting steel strength. Surprisingly, data on the samples' microstructure resulting from its heat treatment was not needed in this analysis. A limitation to this model is that the data is probably representative of a certain set of steel samples and may not be generalizable to other steel with different chemistries and heat treatments. Additionally, the inclusion of temperature in this analysis might not be useful in most cases however the regressor that weighed temperature most heavily, LGBM, has the lowest weightage in the final model.

# 8.0 Sources

[1] Applications of vanadium in the steel industry. (2021). Vanadium, 267–332. https://doi.org/10.1016/b978-0-12-818898-9.00011-5

[2] Applications of vanadium in the steel industry. (2021). Vanadium, 267–332. https://doi.org/10.1016/b978-0-12-818898-9.00011-5

[3] Kaar, S., Krizan, D., Schneider, R., Béal, C., Sommitsch, C. (2019). Effect of manganese on the structure-properties relationship of cold rolled AHSS treated by a quenching and partitioning process. Metals, 9(10), 1122. https://doi.org/10.3390/met9101122