



# Prediction of Mechanical Properties of Metal through Machine Learning Approach

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## ABSTRACT

Metals are synthetic substances which have mechanical properties like tensile strength, yield strength, hardness and elongation. The main objective of this project is to implement different machine learning algorithms for anticipating steel mechanical properties. Integrating machine learning techniques in material science and engineering helps manufacturers, designers, analysts and students in understanding the determination disclosure and advancement of materials utilized for various applications. Machine Learning algorithms help to find out the properties of the material without performing any experiments manually. Based on alloy chemical properties like chemical composition of carbon, sectional size and temperature mechanical properties of the metal have been predicted. The metal which is considered for prediction is steel. To predict the mechanical properties of steel machine learning algorithms have been used. Machine Learning handles programmed algorithms which takes input and analyzes to predict output. When the new data is inserted to the existing data then the algorithms learn and predict the output with good accuracy. In this research the algorithms implemented for prediction of steel mechanical properties are Random Forest, Decision Tree, Naive Bayes and Logistic Regression. Results obtained from various algorithms are compared to know the efficiency of best algorithm.

**Key words:** Decision Tree, Elongation, Hardness, Logistic Regression, Machine Learning, Random Forest, Tensile Strength, Yield Strength.

## 1. INTRODUCTION

The research here is useful for the prediction of mechanical properties of steel based on the chemical composition like carbon content, sectional size, and temperature for various steel standards. Carbon content plays a vital role in most of

the steel alloy. In case the sum of carbon substance raises at that point solidness and toughness progresses holding capacity. Generally most of the steel contains fewer amounts of carbon percent that is 0.35. Steel metal capacity expresses the typical sectional size for a particular material. As the capacity number raises then the sectional size of the material decreases. In most of the steel mill areas temperature measurements have been made. While making steel, record the temperature to get the chosen mechanical properties.

Steel has different type of standards like ASTM-American Society for Testing Materials, SAE-Society for Automotive Engineering, EN-British Standards, and JIS. In our research ASTM, SAE, EN standards are taken into consideration. Along with the standards, chemical properties of steel like carbon, sectional size, and temperature are considered to predict the steel mechanical properties like tensile strength, yield strength, elongation. Tensile Strength of the metal should be in the range of 420 to 500 MPa. Yield Strength should be within the limit of 350 to 400 MPa. The range for elongation is 18 to 25.

Zhi-wei, Xu.et.al[1] proposed a convolutional neural network model for predicting the hot rolled alloy steel mechanical properties based on the chemical composition using the two dimensional data images. Raghuram Karthik Desu[2] used the steel named austenitic stainless at the different temperatures to measure the tensile strength, yield strength and elongation of a metal using the artificial neural network model. Gauri Mahalle[3] implemented artificial neural network approach for predicting the inconel alloy steel and validated the results by using various testing methodologies. Alexei S. Bondar[4] predicted the alloy depending on the chemical composition using neural network approach by considering the different types of steel. Ping-yi chou[5] implemented artificial neural network to optimize the taguchi swarm optimized particles involved seven non linear benchmark functions to increase the speed capacity. Vladimir Tarasov[6] used fuzzy logic interface system for mapping the yield strength with the chemical composition of the material like a356 alloy and error rate is predicted using the membership functions of fuzzy. Weifang Zhang[7] implemented a method for predicting the mechanical properties of 5A106 alloy in the natural sea water by keeping it for twelve days and observed whether there are any micro fracture occurred in the sea due to increase of tensile strength. N.D. Ghetiya[8]

implemented artificial neural network by considering welding parameters like friction stir welding and tool rotational speed by calculating tensile strength. Yidiz sahin[9]proposed artificial neural networks for the optimization of tensile strength by adding calcium carbonate and polypropylene homopolymer by using the taguchi experimental design. Javier Nieves[10] implemented the prediction of tensile strength using the bayesian network by differentiating with the real foundry system. L.A.Dobrzanski[11]proposed neural network approach for classification of metals based on the parameters tensile strength, hardness and grain size with the three alloys namely aluminum, magnesium and zinc.

## 2. STANDARDS OF STEEL

In world there are many types of steel standards available. Some of the standards of steel are ASTM(American Society for Testing Materials), SAE (Society of Automotive Engineering), and EN (European Standard). ASTM selection structure for the use of metals contains an alphabet followed by number. SAE system has a basic four digit system. EN standard contains an alphabet followed by number starting with zero and can extend up to five digits. In every standard, steels are classified into four classes namely carbon, alloy, tool and stainless steels. ASTM standards are mostly used for construction of bridges, buildings, parking, and landing of boats. SAE is mainly used in software applications and safety engineering. EN standards are used in railway vehicles and fire conservation system.

## 3. RELATED WORK

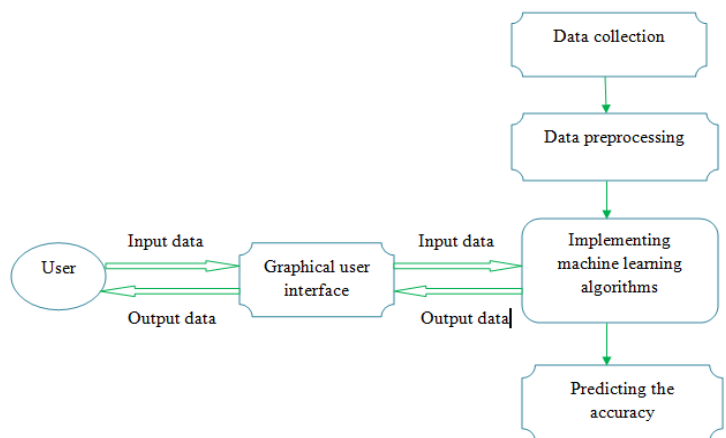
Steel contains important mechanical properties like tensile strength, yield strength and elongation. Oneof the basic traditional test conducted is uniaxial tensile test which is done for many reasons. In engineering applications, tests of tensile are used to select materials. To assure quality in the materials tensile properties are used. When making strides, modern materials estimation of ductile properties is included so that unmistakable materials can be related. In steel material, the protection across the load is a function of a cross section and mechanical properties. To figure out the mechanical properties of steel like tensile strength, yield strength, and elongation tensile test is performed.Yield Strength of a substance gives the stress when deformation exceeds the limit of plastic. Yield Strength is permanent when deformation is higher and results to stress. Yield Strength of a material is measured in Pascal.The results obtained are plotted on a curve called stress-strain curve.To identify the points from this curve is bit difficult.

The Yield Strength of the material is identified at the point where stress is deviated from original point of the curve. Tensile strength is the highest point plotted on the stress-strain curve after the test has been performed.If the temperature varies then the tensile strength of a material varies proportion to it. Elongation is the point to which a substance may be developed or shorten before it shatter.It plays an important role during the manufacturing process and measures the amount of bending and shaping a material without any breaks.In traditional process manpower and time required are more. So in this project the proposed

method integrates with the machine learning algorithms which reduces manpower, time and improves the efficiency.

## 4. PROPOSED METHOD

The proposed approach will remove lot of manpower and time and finds a better way for prediction of steel mechanical properties using the machine learning algorithms. Machine Learning algorithms are combined with the material sciences. Here algorithms like Random Forest, Decision Trees, Naive Bayes, and Logistic Regression are used. The dataset required for this research is collected from the standards resources. In this paper, different standards are taken into consideration along with the carbon content, sectional size and temperature. In Machine Learning algorithms supervised methods are used for prediction as it can be trained with both input and output values. This approach will give better results to predict tensile strength, yield strength and elongation of steel with different standards.



**Figure1:**System Architecture for Prediction

Data Collection: The “Steel Prediction” dataset is collected from various sources and merged together with different parameters. It consists of seven attributes namely standards, carbon content, thickness, temperature, tensile strength, yield strength, elongation. In the above attributes four are independent variables (standards, carbon content, thickness, temperature) and three are dependent variables(tensile strength, yield strength, elongation).

Data Preprocessing: The second stage after collection of data is the preprocessing of data. The missing values are handled using the nan function. After filling the missing values split the dataset into two categories training set and testing set.In training set the algorithm will be able to learn the behavior of the system and predicts the output using testing samples. It is the process of preparing data for analysis by removing data that is incorrect, incomplete, duplicate, and irrelevant and it also includes standardizing dataset by correcting mistakes such as empty fields, missing values using. After cleaning the dataset validate the accuracy.

## 5. MACHINE LEARNING ALGORITHMS

Machine Learning Algorithms perform mathematical and logical operations to get better results even with the extreme size of data. In machine learning algorithm the data will be divided into two classes namely training and testing. In the training part 70% of the data is considered and remaining 30% is used for testing. In this research the implemented algorithms are Random Forest Regression, Decision Tree, Naive Bayes, and Logistic Regression.

### 5.1 Random Forest Regression

Random Forest is a method which produces multiple numbers of decision trees. In this data samples are divided into various subsamples. The prediction of the model can be calculated with each decision tree produced. If the predicted output of first iteration is incorrect then the samples are iterated and added to the next iteration and gives the correct output. It produces by building the decision trees at training time and generates the output of the class. Random Forest Regressor is mainly used to control overfitting and improve the accuracy. Random forest regressor can be represented as

$$\text{RandomForestRegressor}(n\_estimators=10, \text{random\_state}=10) \quad (1)$$

*n\_estimators*: the number of trees present in the forest  
*random\_state*: it is used to get the best split at each iteration of the sample when the trees are constructed.

`Fit(train_features,train_labels)`

*train\_features*: select the features from the dataset to train the model.

*train\_labels*: select the labels from the selected features.

To calculate the errors the formula can be given as:

$$me = 100 * ((\text{predicted\_testsample}) / \text{testsample})^2 \text{accuracy\_sample} = 100 - np.mean(me) \quad (3)$$

The accuracy is calculated with the mean absolute error at each and every step of iteration.

It gives the accurate results with the large database and can manage thousands of variables without any missing values. Random Forest is an efficient method to preserve the accuracy even when the data is missing.

In this project to improve the accuracy we have implemented adaboost classifier.

### 5.2 Decision Tree Classifier

Extra Tree Classifier is one of the advancement classifier of decision tree. In the extra tree classifier decision trees are constructed from the original training dataset. Here large number of unpruned decision trees are created during the training phase. Extra Tree is an altogether machine learning algorithm that combines the predictions from many decision trees. For every node, features are extracted with the random function by splitting the data. The prediction in this algorithm is calculated from the decision tree by averaging the test samples. Here there are two parameters to be considered while implementing the algorithm. One is number of sample size for splitting the data and the other is number of trees required. In the training set the available data is used to build stump. The best split to form the root node is identified in the number of features selected to train the model. The depth of the tree to form stump is one. The computational power required for the decision trees is very low.

### 5.3 Naive Bayes

Naive Bayes is one of the easy and fastest machine learning algorithms for the multi class prediction. The training data required is very less in this algorithm. It is classified based on the naive condition. The probability distribution used is Gaussian, the outcome of this model gives high performance. Here mean and variance are estimated using the maximum likelihood function. The number of training splits required is less. The computational power required is very low and can be implemented effectively.

### 5.4 Logistic Regression

Logistic Regression is one of the supervised machine learning algorithm. The class considered here is multinomial and the solver is saga. To the small amount of dataset the solver saga is used. The Computational power required is very low and can be implemented effectively.

## 6. EXPERIMENT AND EVALUATION

In this section the performance of mechanical properties tensile, yield and elongation of steel have been evaluated using the machine learning algorithm. Efficiency of the developed model has evaluated by validating predictions on the test data. The error rate is calculated using the Mean Square Error (MSE) and Mean Absolute Error (MAE). The mean square error is calculated by measuring the average of the square of the difference between the true value and the predicted value. The value of the calculated result must lies between 0 to 1 as the error rate must be low it is measured in terms of degrees. Mean Absolute Error is the difference between actual value and the predicted value. It takes the average of each and every record present in the dataset and gives the result.

### 6.1 Random Forest

Random Forest algorithm consists of different parameters. In this graph x axis represents predicted value and y axis represent actual value. In first step error rate of the system

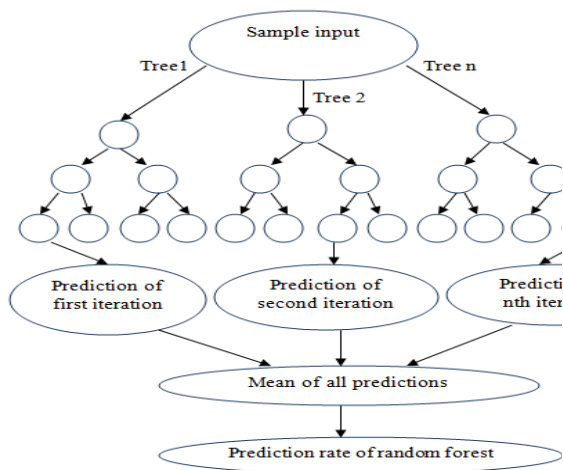


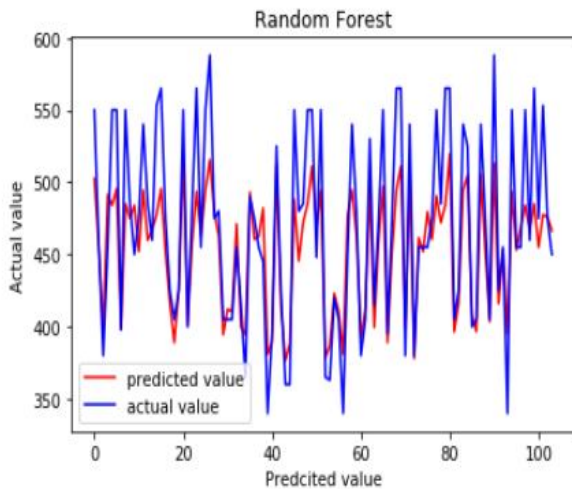
Figure 2: Random Forest

is calculated using the mean absolute error. Formulae used to calculate error rate is  

$$\text{Error\_rate} = 100 * (\text{Predicted value} - \text{Actual value}) / \text{Actual value} \quad (4)$$

In second step the accuracy of the system is calculated using the formulae  

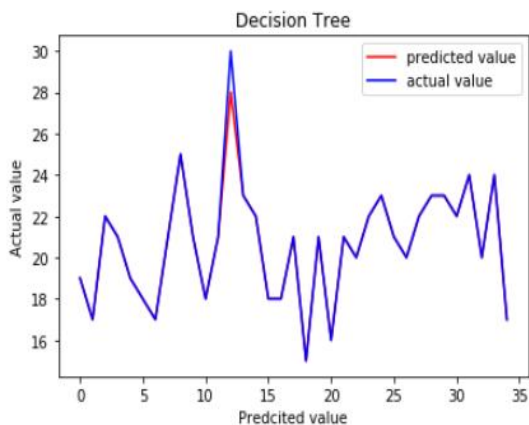
$$\text{Accuracy} = 100 - \text{mean}(\text{Error\_rate}) \quad (5)$$
 The accuracy obtained during the experiment is 90% which improved the performance of the system. This statistical analysis proves that our system is well trained and obtained good results.



**Figure 3:**Graph Plotted between Predicted value and Actual value

### 6.2 Decision Tree

In this graph x axis represents iterations and y axis represent accuracy. For calculating the accuracy the data is stumbled and splitted into folds as k-1/k into training data set and evaluated on test data as 1/k splits. The accuracy obtained during the experiment is 96% which improved the performance of the system. This statistical analysis proves that our system is well trained and obtained good results.



**Figure 4:**Graph Plotted between Iterations and Accuracy

### 6.3 Naive Bayes

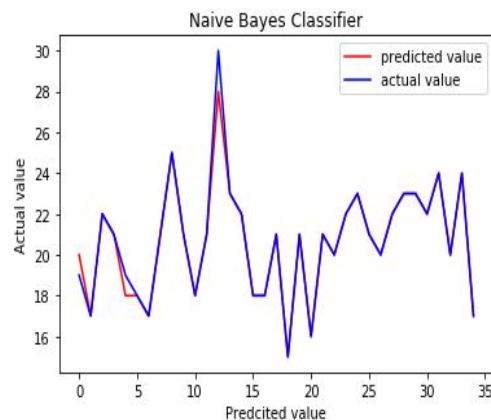
Naive Bayes is one of the supervised machine learning algorithms. In this algorithm conditional independence of each and every feature is identified using the Gaussian naive bayes approach. The likelihood of the features are estimated using the equation

$$p(x|y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp\left(-\frac{(x-\mu_y)^2}{2\sigma_y^2}\right) \quad (6)$$

In this algorithm accuracy is calculated using the accuracy score function. The formulae used to calculate accuracy score is

$$\text{Accuracy\_score} = \text{number of matching sample} / \text{total number of samples} \quad (7)$$

The accuracy obtained by using this formula is 93%. The below graph shows the results

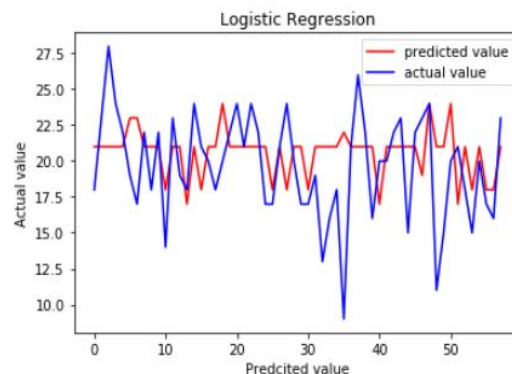


**Figure 5:**Graph Plotted between Predicted and Experimental values

### 6.4 Logistic Regression

Logistic Regression is machine learning algorithm which consists of single class and multi class. In this graph X axis represents predicted value and y axis represents the actual value. The result obtained is calculated using the formulae 
$$\text{Accuracy} = \text{average}(\text{true\_values} * (\text{1pred\_values}) + (\text{1 true\_values}) * \text{pred\_values}) \quad (8)$$

By calculating accuracy using this formula the result obtained is 90%.



**Figure 6:**Graph Plotted between Predicted value and Actual value

## 7. CONCLUSION

The research here ensures that Machine Learning techniques will benefit in terms of accuracy and firmness for predicting the mechanical properties of steel metal. The dataset here is implemented with different machine learning algorithms like Random Forest, Decision Tree, Naive Bayes and Logistic Regression to achieve the good performance. Here 70% of the data is used for training and 30% data is used for testing. The results obtained are validated with the test data to ensure the results obtained are correct. The implemented algorithms gave better results for predicting tensile strength, yield strength and elongation of steel. The accuracy obtained here is more than 90% for different machine learning algorithms. The work presented here can be future enhanced for different metals with their input processing parameters and can predict the mechanical properties of other metals. It plays an important role in many of the applications which removes lot of manpower and time.

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