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Development of Property Prediction Model for Hot Strip Mill Using Machine Learning Algorithms

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Abstract: Producing machine learning models to capture and comprehend the relationship between variables and mechanical properties of hot-rolled steels was the goal of this effort. Mechanical Property are impacted by a variety of variables throughout the process. The innovation that has been presented would significantly alter this process. Metrics of accuracy that are utilised in the process of evaluating the effectiveness of machine learning models. To deal with complexity and uncertainty, a number of machine learning models have been created for the ultimate tensile strength, yield strength, and elongation as functions of chemical elements and thermo-mechanical variables. Machine learning techniques such as multiple linear regression, random forest model, gradient boosting model and XGBoost are used to predict mechanical properties of hot rolled steel by specifying processing parameters such as chemical composition and various thermo mechanical variables. By changing one variable while holding the other variables constant, the models were utilised to interpret trends. Spearheaded a high-impact initiative at JSW Steel to create a cutting-edge property prediction model for their hot strip mill, enhancing operational efficiency and product quality.

Keywords: Machine Learning Models, Hot Strip Mill, Chemical Composition, Rolling Processing Parameters, Mechanical Properties

1. Introduction

A large share of the global annual steel production is made up of hot-rolled strips and plates. More than 6 million tonnes of steel can be produced annually in a modern hot-strip factory. The hot rolling process's capacity to effectively manufacture huge quantities of product at attractive prices is its most appealing feature. Even yet, there is opportunity for further process and product improvement. As the continuously-cast slab is reduced to its final thickness in the range 1.2-22.0mm, hot rolling is generally performed at a temperature higher than that at which the austenite recrystallizes. The thermo-mechanical processing parameters, chemical composition, and heat-treatment all have an impact on the mechanical properties of steel. It would be preferable to establish a link between mechanical properties and controlling variables. Many studies have used linear regression equations to represent patterns between variables [1], however such approaches are time-consuming relationship's previous assumption, are linear or pseudo-linear, and are not sufficiently adaptable to capture the data's complexity. Machine Learning models are artificial intelligence technique suited in these instances and are capable of dealing with complex difficulties. Their adaptability allows them to grasp complex correlations in data. Controlling compositional and process parameters is crucial for improving and controlling properties. Various steel grades have different mechanical properties because of steel chemical variations and manufacturing processes. Traditional methods for determining mechanical properties include destructive testing, which is expensive, time-consuming, and ineffective. [2].

Temperature is a crucial Parameter in the hot strip rolling process because it affects the mechanical Properties and microstructure development of the finished products as well as accuracy in strip size and load distribution within the stands. In order to take into account how the morphology of the microstructure affects the mechanical properties, two important process parameters—for example, the exit temperature from the finishing mill and the coiling temperature—are added into the model for the structure-property correlations. [3]

2. Literature Survey

QianXie [4] Proposed DNN model to predict the mechanical properties of hot-rolled steel plate based on its Chemical composition and Rolling processing parameters data for real-world, advanced steel. Manufacturing Plant data with 27 input characteristics and 4 target features variables and 11,101 data points from the 'hot-rolling process' were collected.

N. Sandhya [5] presented approach to develop several machine learning algorithms for predicting steel tensile strength and find the method with the highest prediction accuracy. The developed regression-based models' random forest, SVM, ANN, decision tree, linear regression, K-Nearest Neighbor, and ensemble approach (boosting) predicted tensile strength values with 96.3%, 95%, 94%, 90%, 89%, 93.6% and 95% accuracy. N. S. Reddy [6] developed neural network model for prediction of mechanical properties and analysis of hot rolled steel strip. The results showed that the model can be used to examine the impact of individual inputs (coil target temperature and finish rolling temperature) on output parameters (mechanical properties), which is extremely difficult to performexperimentally. ChaovaratJunpradub [7] proffered a solution which predicts Predict the Mechanical Properties of Hot Rolled Steel Sheets using Mathematical Modeling. To accomplish adequate process control, the regression equation must be properly modelled in order for the quality parameters of yield strength, tensile strength, and elongation to be reliably anticipated and managed. YongjunLan [3] has projected a technique for predictingmechanical propertiesconsiders not only the normal composition, grain diameter, and volume fraction of ferrite, but also process parameters such as the finishing exit temperature and coiling temperature to quantify the influence of ferrite and pearlite morphology on mechanical properties.

NopponJiratthanakul [8] recommended an approach of Prediction of the Mechanical Properties of Hot-Rolled Low Carbon SteelStrips in Correlation to Chemical Compositions and Rolling Conditions.

The empirical formulae for estimating the mechanical properties of steel strip were produced using multiple regression analysis and were correlated to chemical compositions, coiling and finishing temperatures, along with thickness and width of strip. D. F. Sokolov [9] implemented Model to predict the microstructure and mechanical properties of steels produced in accordance with specified hot deformation and fast cooling regimes, an integrated mathematical physically based model is constructed. Mehmet SiracOzerdem [10] used Artificial Neural Network approach to predict mechanicalproperties of hot rolled, nonresulfurized, AISI 10xx series carbon steel bars. The capacity of a neural network to reliably anticipate the output of unseen test data is the primary quality measure.

ZHI-WEI XU [11] presented an approach for Mechanical Properties Prediction for Hot Rolled Alloy Steel Using Convolutional Neural Network. The suggested CNN model's hot rolled steel mechanical property prediction accuracy has significantly increased. I. Mohanty [2] proposed a neural network-based model For the purpose of forecasting YS, UTS, and % elongation of hot rolled IF steels. The level 3 system of the HSM has been connected with this model, and an online prediction system has been created.

HeungNam Han [12] implemented a computational model to simulate the deformation, temperature, and phase transformation behaviour of strip on a run-out table (ROT) in a hot strip mill in both the thickness and width directions. Wei gang Li [13] developedPrediction model for mechanical properties of hot rolled strips by deep learning. To describe the complicated relationship between the contributing elements, the one-dimensional numerical data were transformed into two-dimensional data. Following that, a new convolutional network was presented to construct a prediction model of hot-rolled strip tensile strength, and an improved inception module was included into this network to extract features from different scales.

3. Hot Strip Mill

A hot strip mill has reheat furnaces at the beginning, a roughing mill, a finishing mill, a run out table with accelerated cooling, and a coiler at the end. Chemical composition, coiling temperature, reheating temperature, reheating duration, total reduction ratio of finishing rolling, and coil thickness are all factors that affect the development of microstructure during processing.

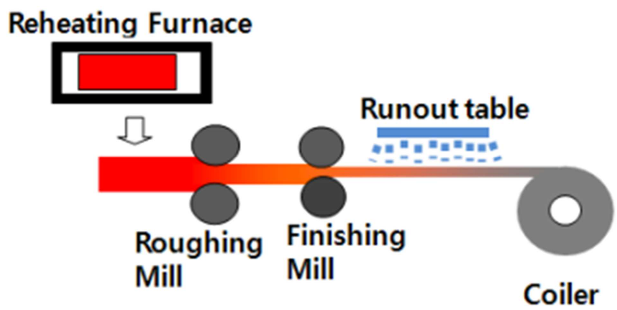


Figure 1. *Hot rolling process.*

Reheating Furnace

The slabs are heated to 1100 - 1200°C in the reheating furnaces, resulting in completely annealed coarse austenite with a low defect density. The slab's temperature is practically uniform. The reheating temperature and duration impact grain size, and some chemical segregation related with the solidification microstructure is homogenized.

Roughing Mill

The heated slabs are rolled to an intermediate thickness between 60 and 150 mm in a roughing mill. Full recrystallization takes place in this step due to the roughing mill's lengthy rolling stand intervals and high temperature. There is also a chance for dynamic recrystallization to take place during deformation because of the high temperature (1050–1150 °C), the relatively slow strain rate (10 s-1), and the huge strains (0.4–0.6).

Recovery, Recrystallization and Microalloying

Recovery and recrystallization can occur during and after deformation, respectively, and are referred to as dynamic and static processes.

Finishing Mill

The ferrite grain size and mechanical Properties are heavily influenced by the finish-rolling temperature. It is determined by the chemical composition of the steel as well as the mechanical properties required. The deformation is characterised as "recrystallized controlled rolling" when TFR >Tnr [14]. Recrystallization and grain growth result in equiaxed austenite grains. Pancaked austenite grains with deformation bands and distorted annealing twins are created for TFR< Tnr [15].

Coiling

The coiling temperature has a significant impact on the microstructure scale, encompassing ferritie grain size and morphology, pearlite interlamellar spacing, pearlite lamellar thickness, and grain boundary cementite thickness. TFR and cooling rate at the runout table can be varied to manage Tc. A low Tc is in the 550-650°C range and is related with a rapid cooling rate, resulting in increased super cooling and fine ferrite [16]. Low cooling rates are associated with high Tc, resulting in a coarse microstructure.

4. Problem Statement

The work proposed in this paper addressses the following issue:

To predict the mechanical properties of any material in advance material science and engineering, researchers, manufacturers, and practitioners of material science and engineering have traditionally depended on traditional testing methods that take time, money, and personnel. In the case of steels, a Universal Tensile Testing Machine (UTM) is used to test steels and determine mechanical properties such as tensile strength, yield strength, Percent Elongation and so on. However, when the material must be evaluated at high temperatures, it takes longer to determine the material's properties. The major goal of this research is to develop several data science approaches or algorithms and demonstrate which algorithm properly predicts mechanical properties such as Ultimate tensile strength, Yield Strength, Perecentage Elongation.

5. Data Collection and Visualization

The data is collected from JSW Steel Ltd. Vijayanagar Works, Toranagallu, Karnataka, India.

Table 1. *Statistics of Dataset used.*

Number of Variables	30
Number of Rows	40964
Variable Types	Numerical:28 Categorical: 2

The dataset contains 30 variables divided as features and target variables. Target variables consists of mechanical properties need to be predicted. The Dataset is then further divided into 28 numerical and 2 categorical features as shown in table 1.

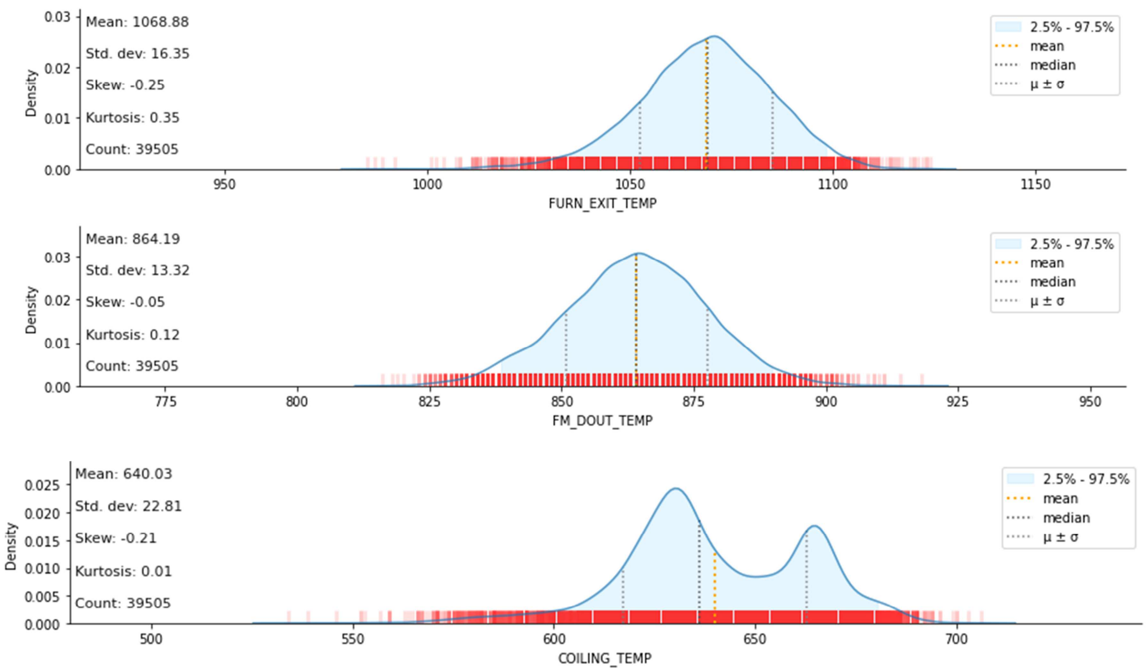


Figure 2. *Distribution of temperatures during hot strip rolling.*

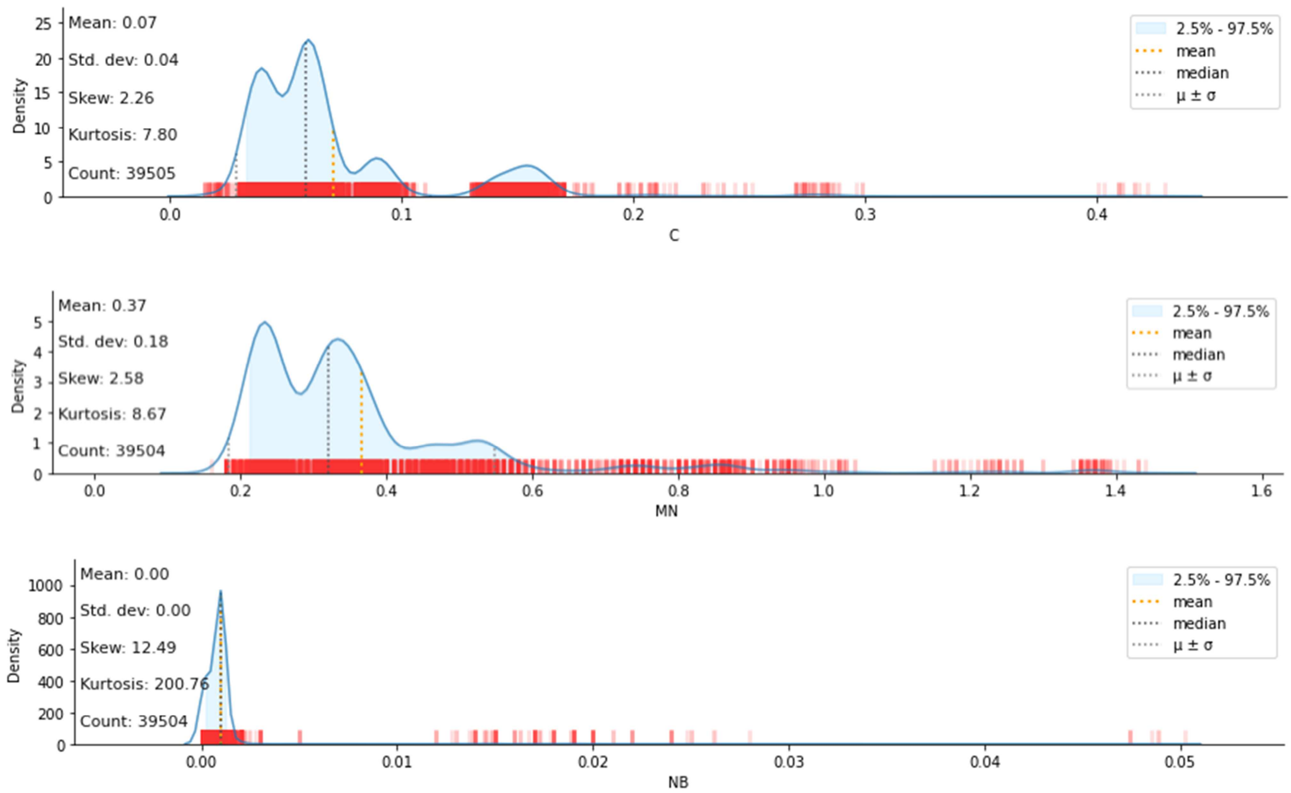


Figure 3. *Distribution of alloying elements during hot strip rolling.*

Figure 2 and 3 shows the distribution of temperatures and alloying element during hot strip rolling respectively. Distribution plot used for analysis of each and every feature in dataset provides the information regarding mean, standard deviation, skewness, and count.

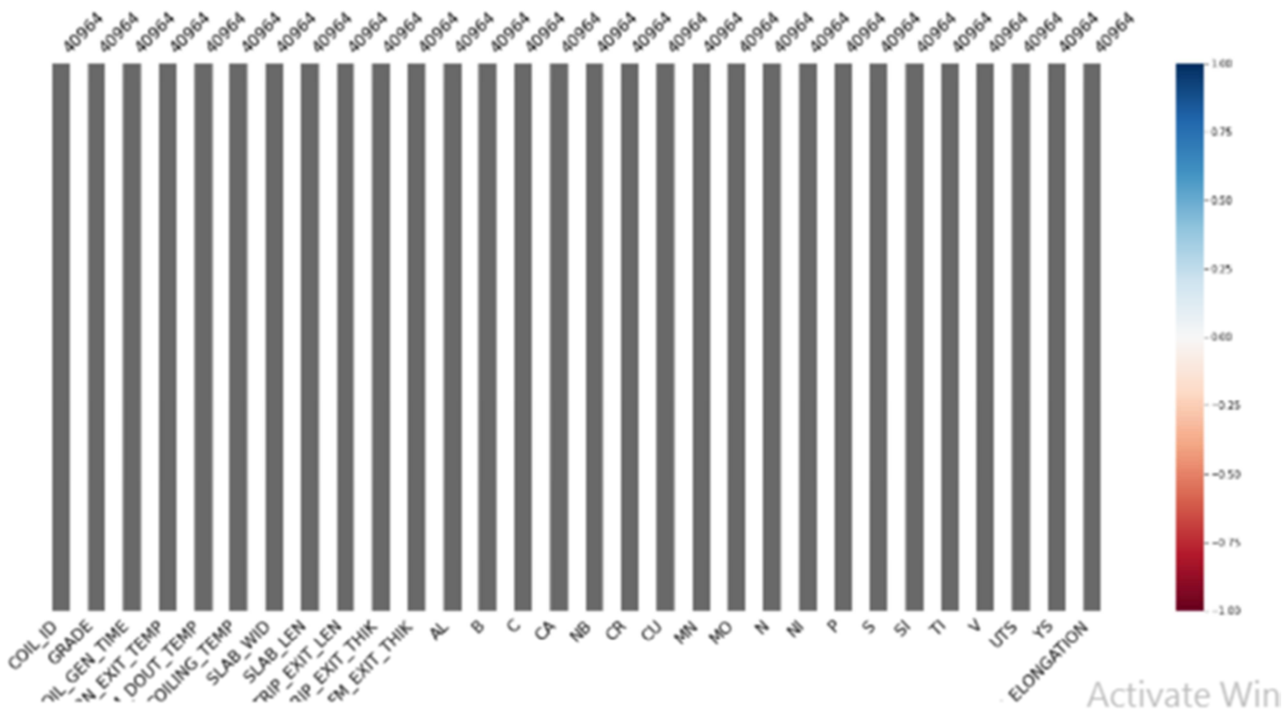


Figure 4. *Missing Data Analysis.*

The above visualization of missing data analysis clearly shows that there is no missing values present in dataset.

Correlation analysis

Pearson correlation coefficient used for analysis of correlation between features and target variables. Correlation coefficient value 1 indicates two variables are highly positively correlated.-1 and 0 indicates two variables highly negatively correlated and not related respectively.

Effect of alloying element on Mechanical properties using Pearson correlation coefficient.

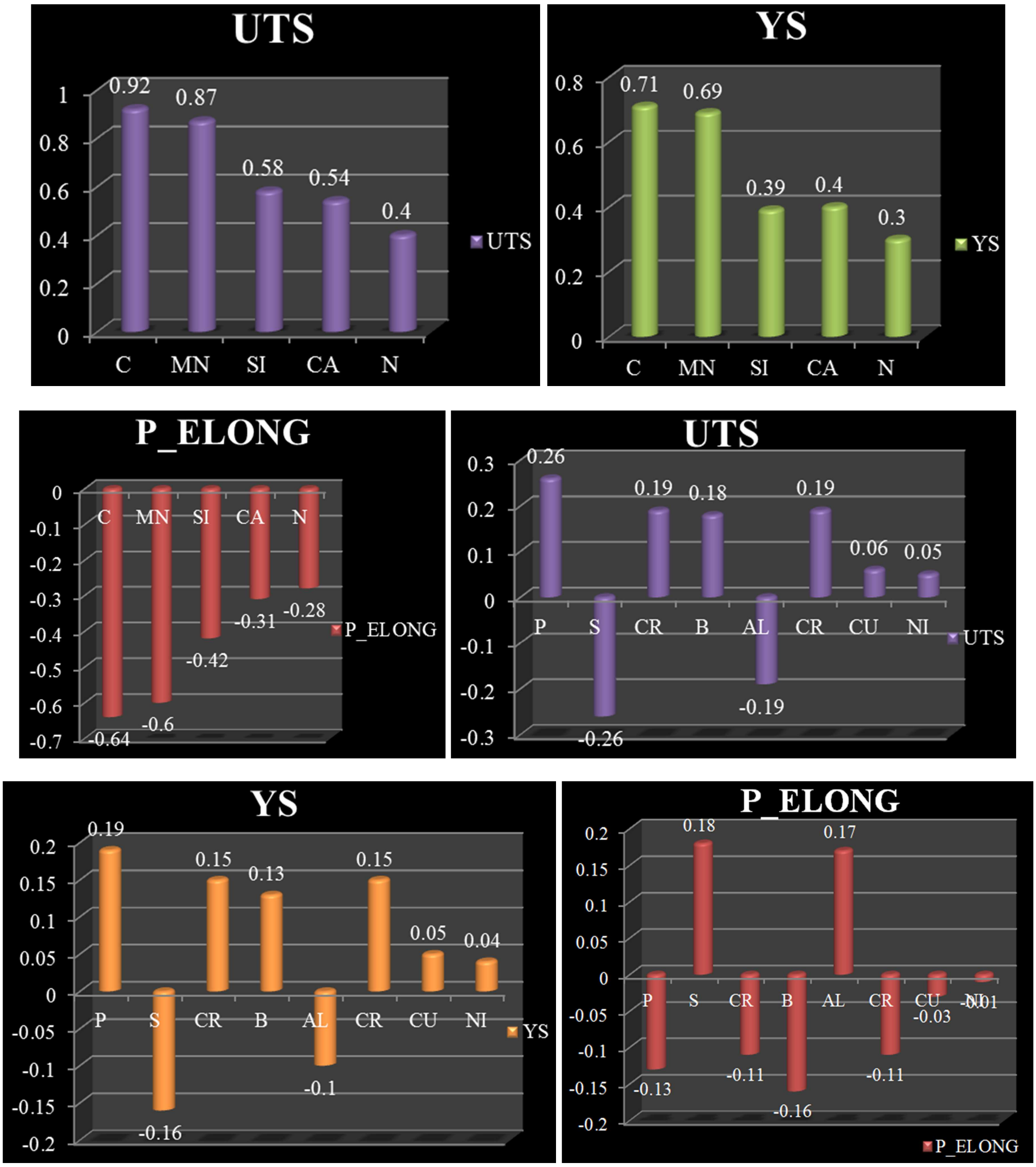


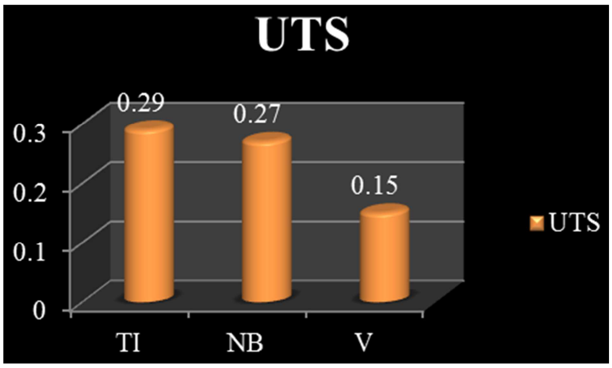
Figure 5. *Effect of alloying elements on Mechanical properties.*

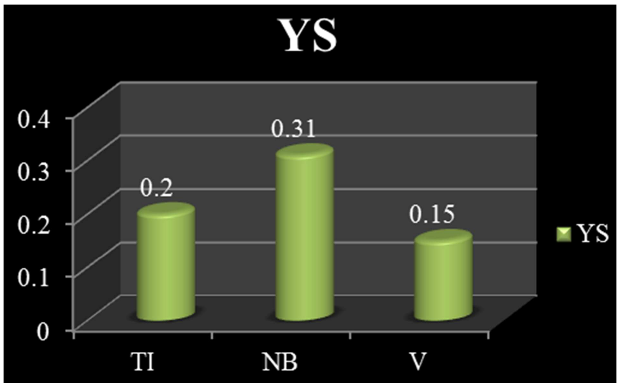
Figure 5 shows the effect of alloying elements on mechanical Properties, C, MN, SI, CA, N shows positive correlation w.r.t Ultimate Tensile Strength and yield strength. Negatively correlated w.r.t Percentage Elongation. Aluminum and Sulphur Shows negative correlation w.r.t ultimate tensile strength and yield strength but positively correlated with Percentage Elongation. It's interesting to see that the yield strength is less carbon sensitive than the final tensile strength. Manganese not only has a significant impact on the austenite's stability but also strengthens solid solutions. Silicon enhances tensile strength, most likely as a result of the solid solution strengthening.

Effect of Micro alloying element on Mechanical properties using Pearson correlation coefficient.

NB, TI and V shows positive correlation with ultimate tensile strength and yield strength but negatively correlated with the Percentage elongation as shown in Figure 6. Nb, Ti and V carbonitrides assist refine austenite grain size during hot rolling by pinning the grain boundaries and retarding recrystallisation. Nb is the most efficient micro alloying addition for suppressing recrystallisation.

Small quantities of titanium are occasionally added to niobium microalloyed steels to pin the austenite grain boundaries. It is vital to remember each of the micro alloys are distinct and hence are used depending upon appropriateness of the process route and ultimate product. For traditional hot strip rolling, niobium functions primarily as a grain refiner, vanadium primarily as a precipitation hardener, and titanium's influence is intermediate. As a result, niobium has the capacity to create high strengths while also boosting toughness.





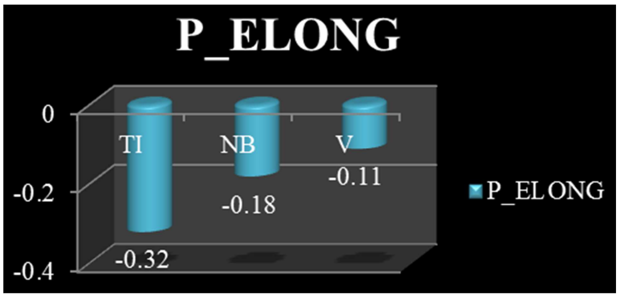
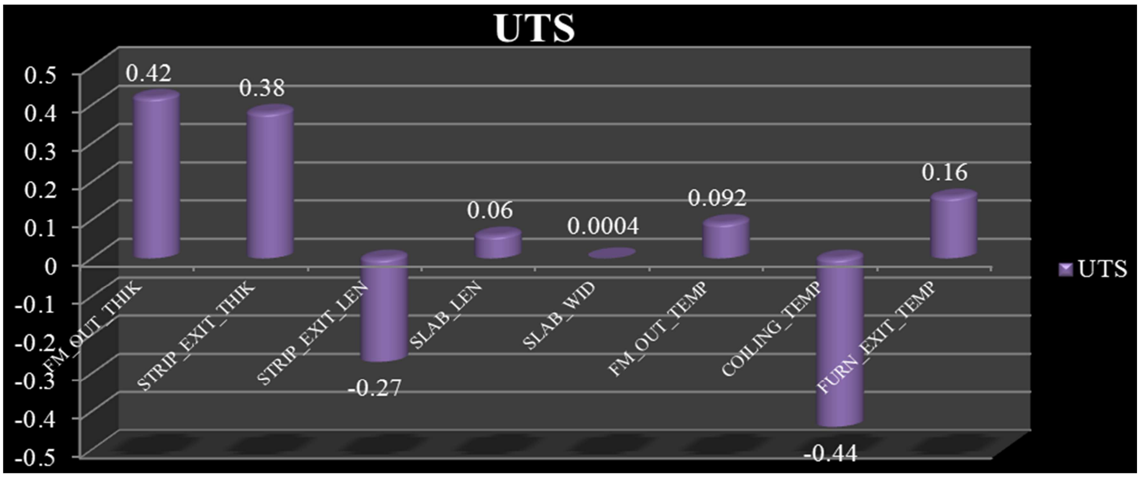
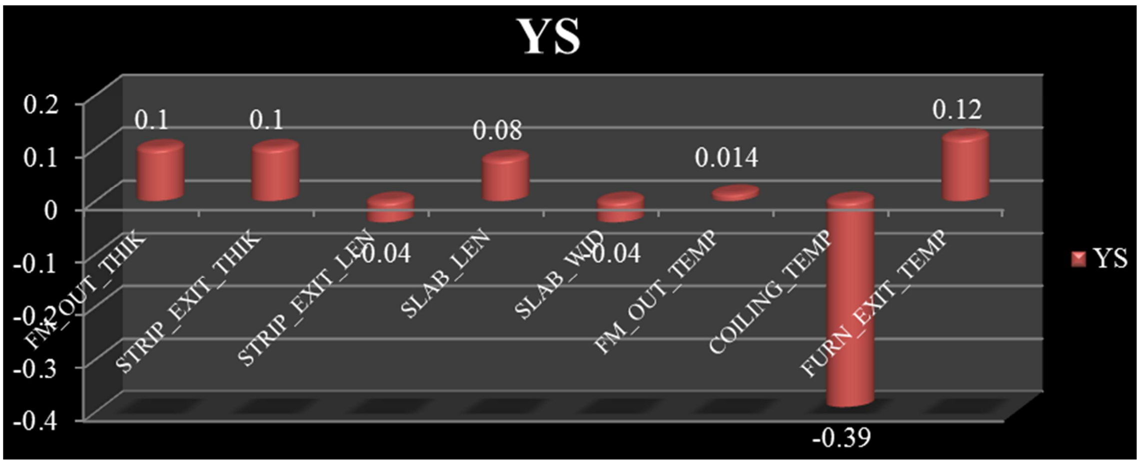


Figure 6. *Effect of Micro alloying elements on Mechanical properties.*

6. Effect of Rolling Process Parameters on Mechanical Properties





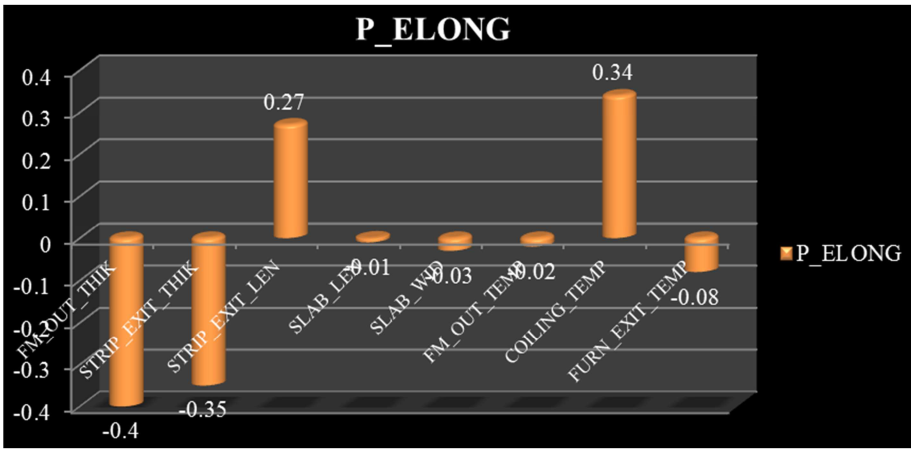


Figure 7. *Effect of on rolling process parameters on Mechanical properties.*

FM_out_temp and furn_exit_temp shows positive correlation w.r.t Ultimate tensile strength and Yield strength but negatively correlated with percentage elongation. Impact of coiling temperature on mechanical properties is as shown in figure. Coiling temp is negatively correlated w.r.t Ultimate Tensile Strength and Yield Strength. Positively correlated w.r.t Percentage elongation. This is to be expected since the finish roll temperature (850-910C) effects a variety of parameters such as the volume percentage of proeutectoid ferrite, the grain size of ferrite and the texture generated during rolling, the precipitation of different carbides, and so on. While the coil target temperature is in the (570-650C) range, it is substantially lower than the eutectoid temperature, resulting in less change in microstructure and hence less variance in properties.

7. Proposed System

The entire process of the proposed system has been classified into phases for ease of operations.

The first phase consists of Feature selection method.

We are aware that having a machine learning model with too many features leads to problems like the "curse of dimensionality" and necessitates the use of additional memory, processing time, and power. We utilise feature selection strategies on our Feature Engineering processes to try to eliminate less valuable features from our datasets.

Several factors lead to the usage of feature selection techniques: shortened training durations, simpler to understand models, avoidance of the dimensionality curse, and improved generalisation by eliminating over fitting (reduction of variance).

BorutaShap package

The Boruta feature selection technique and the Shapley values are combined in the BorutaShap wrapper feature selection approach. This combination has shown to be faster and create a higher-quality feature subset than the original Permutation Importance technique. In addition to offering a superior subset of features, this approach can also deliver the most precise and reliable global feature rankings, which can be applied to model inference. BorutaShap gives the user the option to use any Tree Based learner as the basis model in the feature selection process, in contrast to the original R package, which restricts the user to a Random Forest model.

Steps:

1) Creating shadow features
2) Rank the features using a feature importance metric
3) Create a threshold using the maximum importance score
4) Attributes importance < threshold
'Unimportant'
5) Attributes importance > threshold
'Important'
6) Repeat the procedure until an importance has been assigned for each feature

Feature Selection using BorutaShap for Ultimate Tensile strength Prediction

13 attributes confirmed important :['FM_DOUT_TEMP', 'STRIP_EXIT_LEN', 'C', 'NB', 'COILING_TEMP', 'MN', 'P', 'TI', 'CR', 'SI', 'FM_EXIT_THIK', 'GRADE', 'N']

Feature Selection using BorutaShap for Yield strength Prediction

15 attributes confirmed important:['STRIP_EXIT_LEN','S','SI','TI','FM_EXIT_THIK ', 'AL', 'NB', 'FM_DOUT_TEMP', 'GRADE', 'MN','STRIP_EXIT_THIK','CR','COILING_TEMP', 'C', 'N']

Feature Selection using BorutaShap for Percentage Elongation Prediction

10attributes confirmed important: ['S', 'FM_DOUT_TEMP', 'TI', 'FM_EXIT_THIK', 'GRADE','SI','COILING_TEMP','STRIP_EXIT_LEN', 'MN', 'C'].

The next and the Second phase is model building with selected Features.

Multiple Linear Regression

Given that there are several independent variables, multiple linear regression is an extension of simple linear regression. By fitting the optimal linear connection, it employs two or more independent variables to predict a dependent variable. It has one dependent variable (Y), the value to be predicted, and two or more independent variables (X). As a result, it is a method for quantitative response prediction employing a variety of features.

Build machine learning Model using Scikitlearn python Library on a sample data set. And then calculate the RMSE. This will give us the model error.

Random Forest Model

Random Forest Regression methods are a type of Machine Learning technique that employs the usage of numerous random decision trees, each of which has been trained on a sample of data. The usage of several trees offers the algorithm stability and decreases variance. Because of its capacity to operate effectively with large and diverse datasets, the random forest regression technique is a commonly used model. The RMSE of a model determines its absolute fit to the data. In other words, it displays how near the actual data points are to the expected values of the model. A low RMSE number implies a better fit and is an excellent metric for measuring the accuracy of the model's predictions.

Gradient Boosting Model

Gradient boosting is one of the ensemble techniques that combines many weak models to improve overall performance. The fundamental concept is to transfer the desired results from the prior models to the new model in order to reduce mistakes. This is another boosting algorithm. It offers a great deal of versatility, can optimise on many loss functions, and offers a number of hyper parameter tuning possibilities, make the function fit highly adaptable. Model performance checked using RMSE score.

XG-BOOST Model

The gradient boosting technique has been scaled and improved, and the eXtreme Gradient Boosting (XGBoost) was created for effectiveness, computational speed, and model performance. It belongs to the Distributed Machine Learning Community and is an open-source library. XGBoost is an ideal combination of software and hardware capabilities created to improve current boosting methods accurately and quickly. Build machine learning Model using Scikitlearn python Library on a Given data set. And then calculate the RMSE score for model performance analysis.

Evaluation metrics for regression models

The regression model seeks to fit a line that results in the least difference between actual and predicted values (measured values). There are three error metrics (Cost Function) that are commonly used for evaluating and reporting the performance of a regression model; they are: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE). In all cases, the goal is to estimate the difference between the predicted values and the actual values.

8. Model Evaluation and Result

The last and most crucial phase comprises of model evaluation and discovering really considerable results.

There are many hyper-parameters for each model, therefore experimenting with different combinations and comparing the outcomes is a good technique to determine the best set of hyper-parameters. A list of required hyper-parameters is used by Grid Search to analyse all possible combinations, and it then reports which combination has the highest accuracy. Accuracy metrics used to evaluate the performance of machine learning models.

Table 2. *Model Comparison for Ultimate Tensile Strength Prediction.*

Machine learning Models	MAE	MSE	RMSE
MLR	8.64	158.88	12.60
RF	7.63	132.32	11.50
GBM	8.51	148.33	12.17
XGBOOST	7.87	134.71	11.60

Table 3. *Model Comparison for Yield Strength Prediction.*

Machine learning Models	MAE	MSE	RMSE
MLR	12.70	309.59	17.59
RF	10.80	236.14	15.36
GBM	12.06	270.25	16.44
XGBOOST	11.41	244.64	15.64

Table 4. *Model Comparison for Percentage Elongation Prediction.*

Machine learning Models	MAE	MSE	RMSE
MLR	2.58	12.11	3.48
RF	2.32	9.76	3.12
GBM	2.42	10.45	3.23
XGBOOST	2.30	9.71	3.11

Based on Accuracy metrics scores as shown in Table 2, Table 3 and Table 4 respectively. select best model for Ultimate tensile strength Prediction, yield strength Prediction and Percentage elongation Prediction.

For Tensile Strength Prediction Random forest model shows best result, Cost function Value (error matrix value) i.e MAE, MSE and RMSE is less compare to all other models. For Yield Strength Prediction also Random forest model shows best result, cost function value is less compare to all other models. For Percentage elongation prediction, XGBOOST model shows good results with least value of cost function. The Main Aim of Machine Learning Model is to reduce the value of Cost function so that the performance of machine learning model is enhanced.

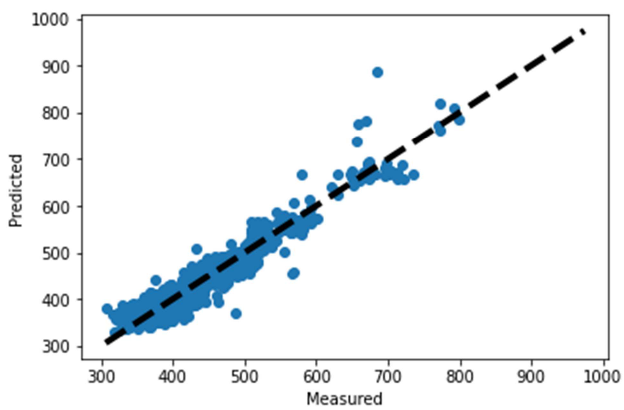


Figure 8. *Predicted VS Measured Values.*

9. Conclusion and Future Scope

Machine learning and analytics will undoubtedly have an impact on present material sciences by exaggerating accuracy and reliability in estimating mechanical properties utilising vast ensembles of datasets from various material databases and by employing various data science methods. In this paper, 4 different algorithms were applied to the dataset, and the most accurate model was determined. The proposed innovation will be a game changer for the traditional method of conducting tensile tests on steel using a Universal Tensile Test machine (UTM). For UTS and YS prediction Random Forest Model is selected based on Accuracy Scores. similary for Percentage Elongation XGBOOST model is selected.

The Machine Learning Algorithms, which save time and money, predict mechanical properties of Hot Rolled Steel, such as Ultimate tensile strength, yield Strength and Pecentage Elongation using Chemical Composition of Hot Rolled steel and Rolling Process Parameters.

In the future, this research will be expanded to predict other mechanical Properties such as work hardening, Hardness, impact toughness and so on.

Conflicts of Interest

The author(s) declare no conflict of interest.

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