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Supervised machine learning algorithms to optimize the Ultimate Tensile Strength of friction stir welded aluminum alloy

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ABSTRACT

In this study, two supervised machine learning algorithms i.e. supervised machine learning regression and supervised machine learning classification model have been used for predicting the Ultimate Tensile Strength (MPa) and Weld joint efficiency of Friction Stir Welded joint. The results showed that Polynomial regression model yields better result than other supervised machine learning regression model and Decision Tree (Both Gini Index and Information Gain criterion), Artificial Neural Network classification models gave better classification result than K-Nearest Neighbor classification model.

Keywords: Artificial Intelligence; Machine Learning; Friction Stir Welding; Tensile Strength

1. INTRODUCTION

Machine Learning can be considered as a subset of artificial intelligence where available information and data are being learned by some algorithms. The history of the development of machine learning dates back to 1950 when the Turing test was created by Alan Turing in order to verify the intelligence of the computer system [1]. In 1952 the first learning-based computer program was developed by Arthur Samuel [2]. The first neural network i.e. the perception model was created for computers by Frank Rosenblatt in 1957 with the main objective of simulating the thought process of humans. In 1967, basic pattern recognition activities for computers were carried out by a designed nearest neighbor algorithm. Machine learning algorithms are divided into four categories i.e. supervised machine learning algorithm, unsupervised machine learning algorithm, semi-supervised machine learning algorithm, and reinforcement machine learning algorithm [3-5]. Supervised machine learning algorithm finds application in predicting the future, unseen or unavailable data based on the available dataset [6-7]. The supervised machine

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learning algorithm is further subdivided into two types i.e. regression model and classification model [8-9].

Supervised machine learning algorithms are finding various applications in the manufacturing and materials industries. Supervised machine learning algorithms are being used for predicting the material properties such as fracture strength, tensile strength, elongation percentage, and also the hardness of the given material [10-13].

The present research work focuses on the implementation of supervised machine learning regression algorithms such as polynomial regression, support vector regression, decision tree regression, random forest regression as well as an artificial neural network is used for predicting the Ultimate Tensile Strength of friction stir welded similar AA2024-T3 aluminum alloy and supervised machine learning classification algorithms such as K-nearest neighbors, decision tree classifier with Gini Index and Information Gain as criteria for classifying the joint having weld strength efficiency greater 70 percent of the base metal.

2. MATERIAL AND METHODS

Similar AA2024-T3 aluminum alloy plates of dimension 200 X 100 X 3.5mm were mounted on a vertical milling machine in order to be butt welded by the Friction Stir Welding process by using a tapered pin profile tool steel (HSS) [14]. The experimental dataset consists of 27 data which is fetched from the work of Hussein et al. [14] and is further converted to CSV (Comma Separated Values) file for importing purposes during the execution of Python codes. The dataset consists of Tool Shoulder Diameter (mm), Tool Rotational Speed (rpm), Tool Traverse Speed (mm/min), Number of weld passes, and Tool Tilt Angle as input parameters while the Ultimate Tensile Strength (UTS) is an output parameter. The Python libraries which are imported for constructing and executing the Machine Learning algorithms were Numpy, Matplotlib, Seaborn, Pandas, Tensorflow, and Keras. Figure 1 shows the hierarchy of the experimental procedure subjected to the CSV dataset.

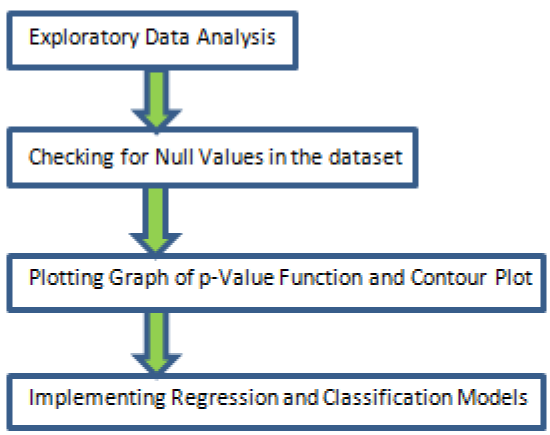

Figure 1: Various operations subjected to the imported dataset

The dataset is subjected to Machine Learning Classification Models. For the Machine Learning classification modeling, the output of the given dataset is classified as 0 if the UTS is less than 70% of the reference value and as 1 if UTS is greater than or equal to 70 % of the reference value and at last it is subjected to three classifier models i.e. K- Nearest Neighbors, Decision Tree with Gini Index and Information Gain as criteria and Neural Network classification model.

3. RESULTS AND DISCUSSION

3.1 Exploratory Data Analysis

At this stage, we have explored the relation the features shared with the target variable. Accordingly, the features were dropped which have no relation with the target variable. From Table 1 we can see the data's distribution and judge whether we need to normalize our data or not. We also get other statistics using the table.

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Table 1: Statistical model of the experimental dataset

	Shoulder Diameter (mm)	Rotational Speed (rpm)	Traverse Speed (mm/min)	Tilt Angle	Passes	UTS (Mpa)
count	27.000000	27.000000	27.000000	27.00000	27.00000	27.000000
mean	14.000000	1033.333333	58.666667	2.00000	2.00000	249.666667
std	1.664101	292.206460	16.751579	0.83205	0.83205	69.089685
min	12.000000	700.000000	40.000000	1.00000	1.00000	95.000000
25%	12.000000	700.000000	40.000000	1.00000	1.00000	217.500000
50%	14.000000	1000.000000	56.000000	2.00000	2.00000	245.000000
75%	16.000000	1400.000000	80.000000	3.00000	3.00000	304.500000
max	16.000000	1400.000000	80.000000	3.00000	3.00000	361.000000

3.2 Checking Null Values

The check_null( ) function is used to check the number of null values in the dataset. The null values are replaced by mean.

3.3 Plotting Graph of p-Value Function and Contour Plot

The plot_graph_pvalue function plots a line plot between given variables and prints the p-value and Pearson values. The contour_plot function plots a contour plot for the given variables. Figure 2 shows the plot against the shoulder diameter (mm) and UTS (MPa). The obtained p-value and Pearson value for the given parameters is 0.50151 and 0.135 respectively.

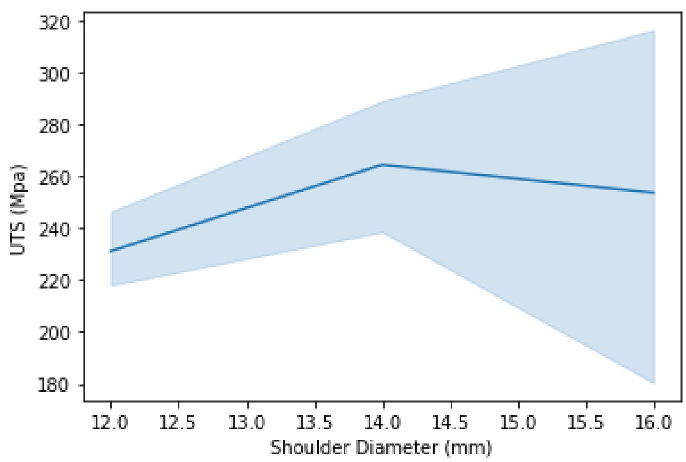

Figure 2. Relationship between UTS (MPa) and Shoulder Diameter (mm)

From the p-value and Pearson value, we can clearly interpret that shoulder diameter is highly correlated with UTS. From the graph, we can see the Pearson's predictions come to life as we see the UTS values start to drop with increasing shoulder diameter after 14 mm. Figure 3 shows the contour plot of shoulder diameter and UTS.

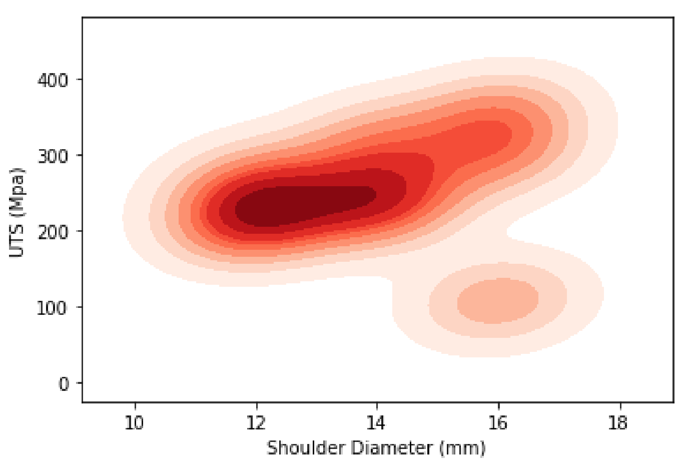

Figure 3. Contour Plot between UTS (MPa) and Shoulder diameter (mm)

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Figure 4 shows the plot against the Tool Rotational Speed (rpm) and UTS (MPa). The obtained p-value and Pearson value for the given parameters is 0.00034 and 0.638 respectively. Figure 5 shows the contour plot between Tool Rotational Speed (rpm) and UTS (MPa).

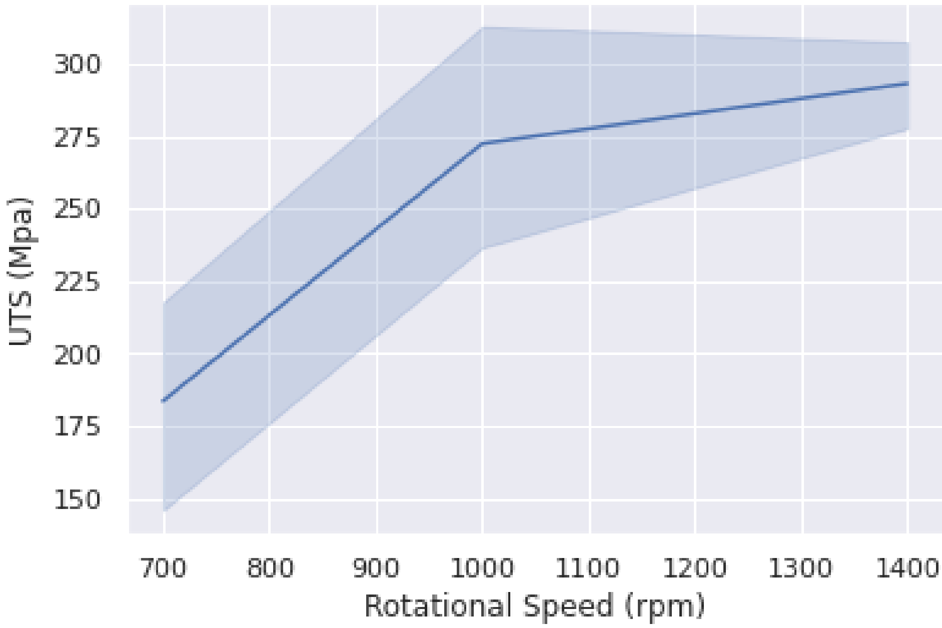

Figure 4. Relationship between UTS (MPa) and Tool Rotational Speed (rpm)

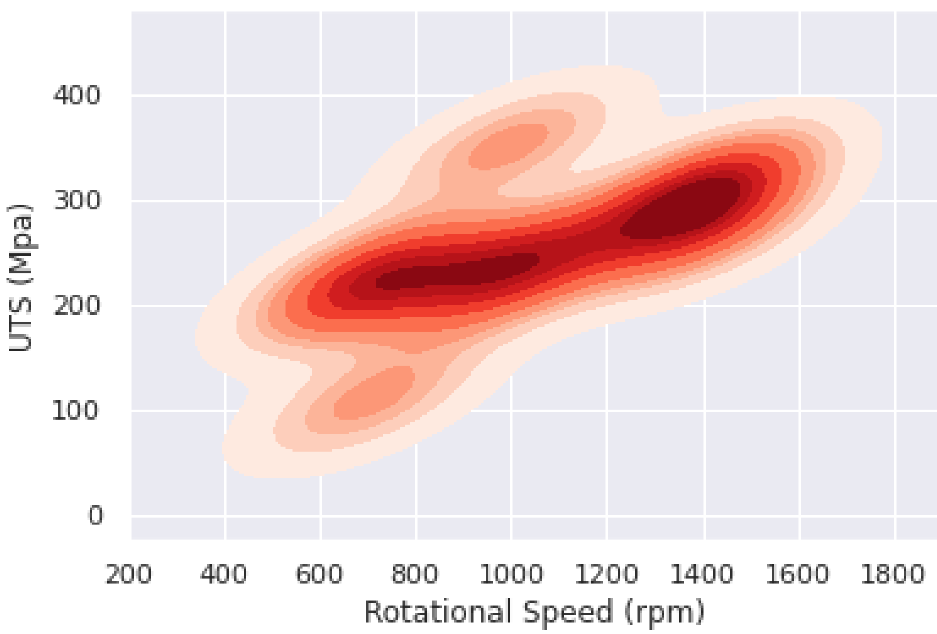

Figure 5. Contour Plot between UTS (MPa) and Tool Rotational Speed (rpm)

From the graph depicted in Figure 4 it is observed that the UTS increases after tool rotational speed of 1000 rpm. Figure 6 shows the plot against the Tool Travel Speed (mm/min) and UTS (MPa). The obtained p-value and Pearson value for the given parameters is 0.00045 and 0.628 respectively. Figure 7 shows the contour plot between Tool Traverse Speed (mm/min) and UTS (MPa).

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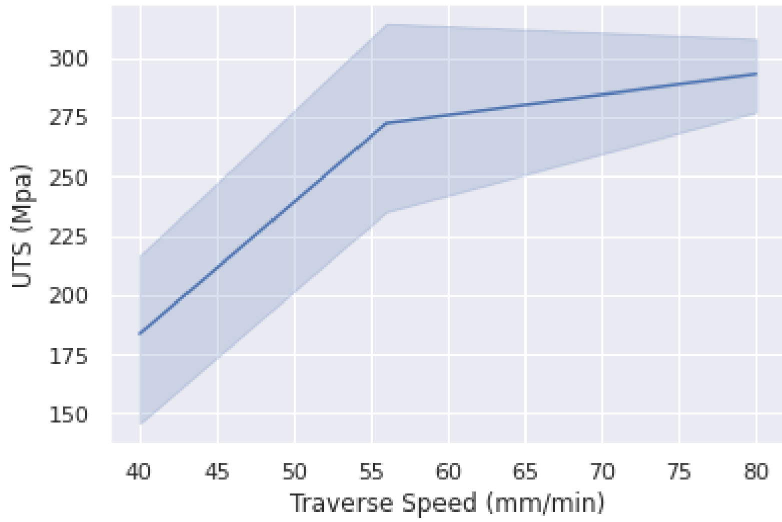

Figure 6. Relationship between UTS (MPa) and Tool Traverse Speed (mm/min)

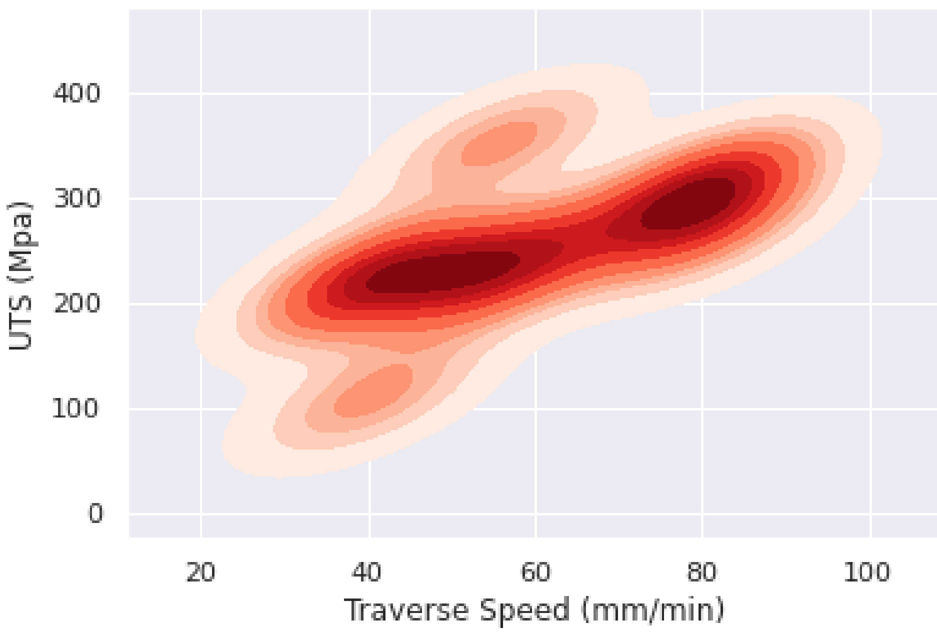

Figure 7. Contour Plot between UTS (MPa) and Tool Traverse Speed (mm/min)

From the graph shown in Figure 6 it is observed that the UTS continue to increase after traverse speed greater than 55 mm/min. Figure 8 shows the plot against the Tilt Angle and UTS (MPa). The obtained p-value and Pearson value for the given parameters is 0.34943 and 0.187 respectively. Figure 9 shows the contour plot between Tilt Angle and UTS (MPa).

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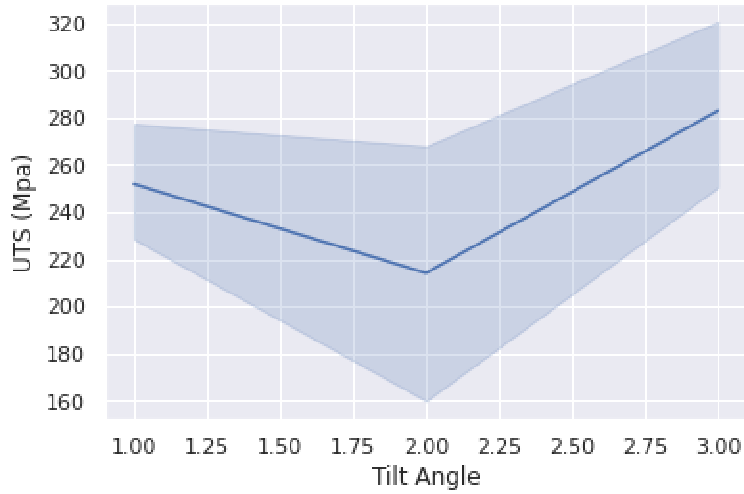

Figure 8. Relationship between UTS (MPa) and Tool Tilt Angle

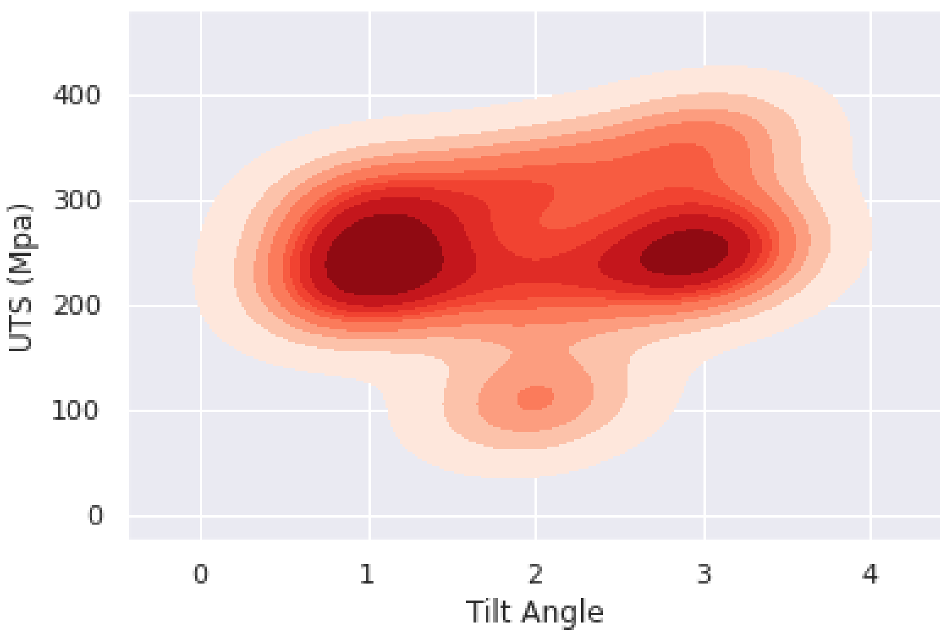

Figure 9. Contour Plot between UTS (MPa) and Tool Tilt Angle

From the graph shown in Figure 8 it is observed that UTS continues to decrease with increase in Tool Tile angle upto 2 degree but after 2 degree, UTS starts increasing. Figure 10 shows the plot against the number of weld passes and UTS (MPa). The obtained p-value and Pearson value for the given parameters is 0.63737 and 0.095 respectively. Figure 11 shows the contour plot between number of weld passes and UTS (MPa).

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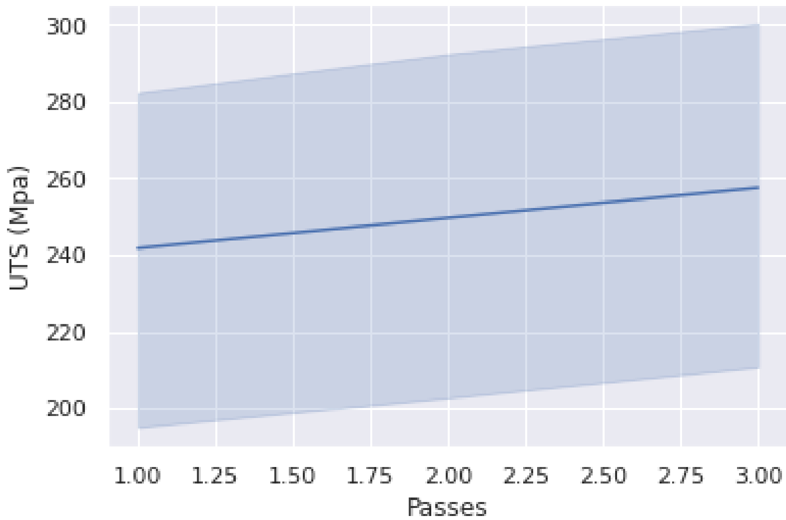

Figure 10. Relationship between UTS (MPa) and Number of passes

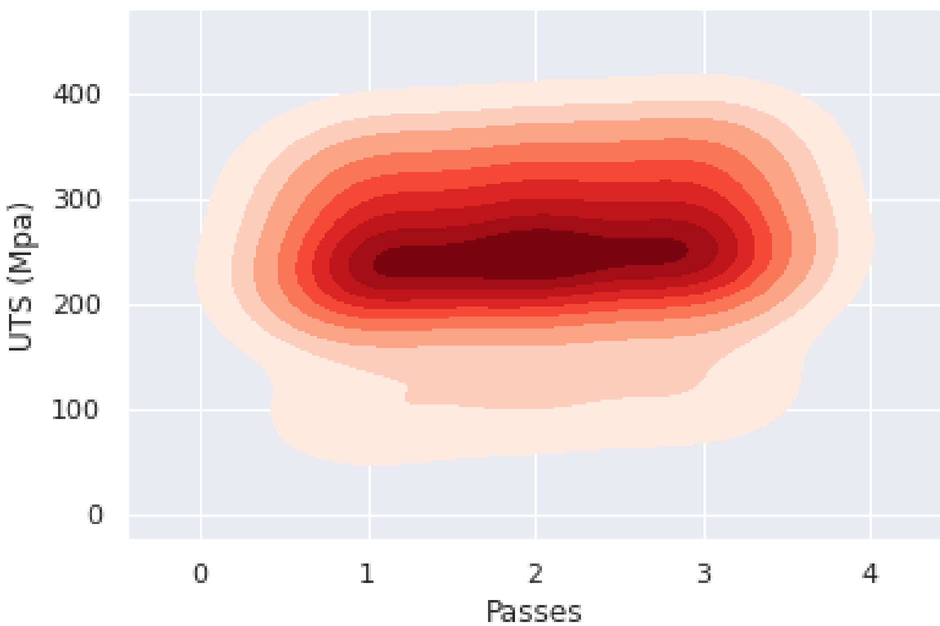

Figure 11. Contour Plot between UTS (MPa) and Number of passes

Figure 12 shows the correlation heat map.

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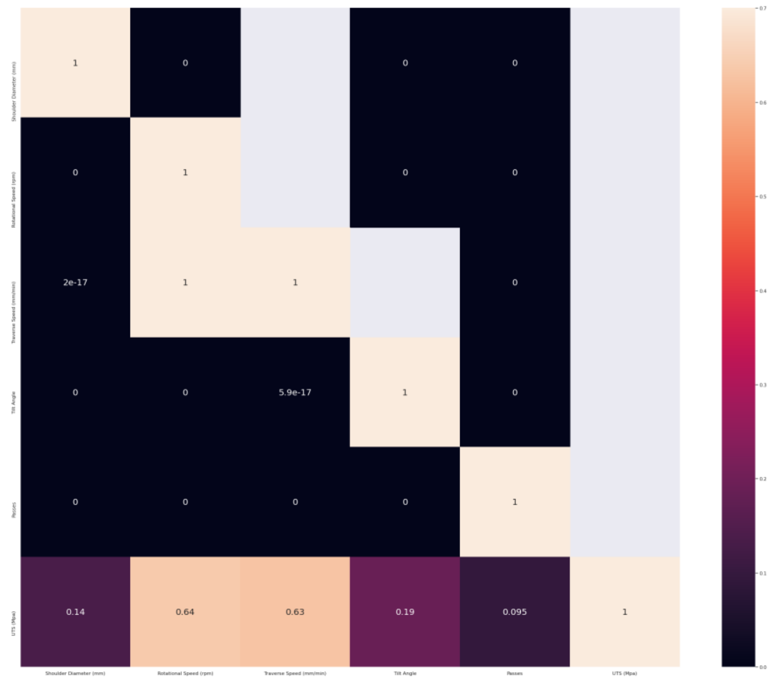

Figure 12. Correlation Heat map

Figure 13 shows the correlation plot with response variable using bar graph. From the plot analysis, we conclude that all input parameters have some relation with UTS. So, we will not be dropping them from the dataset.

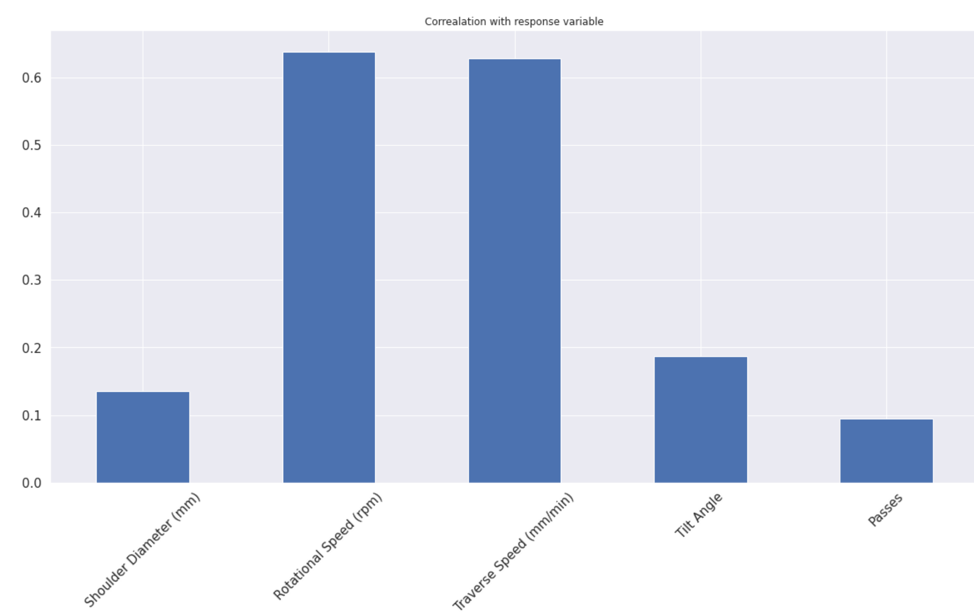

Figure 13. Response variable plot

3.4 Implementation of Supervised Machine Learning Regression Models

Firstly, the dataset is split after that we decide whether to normalize or not. From the statistics shown in the Table 2, we will decide whether or not to normalize the dataset.

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Table 2. Statistical Data Analysis

	Shoulder Diameter (mm)	Rotational Speed (rpm)	Traverse Speed (mm/min)	Tilt Angle	Passes	UTS (Mpa)
count	27.000000	27.000000	27.000000	27.00000	27.00000	27.000000
mean	14.000000	1033.333333	58.666667	2.00000	2.00000	249.666667
std	1.664101	292.206460	16.751579	0.83205	0.83205	69.089685
min	12.000000	700.000000	40.000000	1.00000	1.00000	95.000000
25%	12.000000	700.000000	40.000000	1.00000	1.00000	217.500000
50%	14.000000	1000.000000	56.000000	2.00000	2.00000	245.000000
75%	16.000000	1400.000000	80.000000	3.00000	3.00000	304.500000
max	16.000000	1400.000000	80.000000	3.00000	3.00000	361.000000

Since the range of Travel speed is larger than that of other variables, we will be normalizing the data.

The get_score_regression function will give Mean Absolute Error, Mean Squared Error, and R squared error to analyze the model's performance. The Polynomial regression, Decision Tree regression, Random Forest regression, Support Vector Regression and Neural Network regression models were implemented and the one which performs the best was selected. Table 3 shows the model analysis of the regression models implemented on the dataset.

Table 3. Mean Absolute Error, Mean Square Error and Coefficient of determination

	Model	Mean Absolute Error	MSE	R2
0	Polynomial Regression	0.029136	0.001868	0.998428
1	SVR	0.453090	0.554425	0.533566
2	Decision Tree Regressor	0.129469	0.019894	0.983263
3	Random Forest Regressor	0.293354	0.146900	0.876414
4	DNN	1.082620	2.339795	-2.860712

Figure 14 shows the model performance of the Neural Network Regressor model.

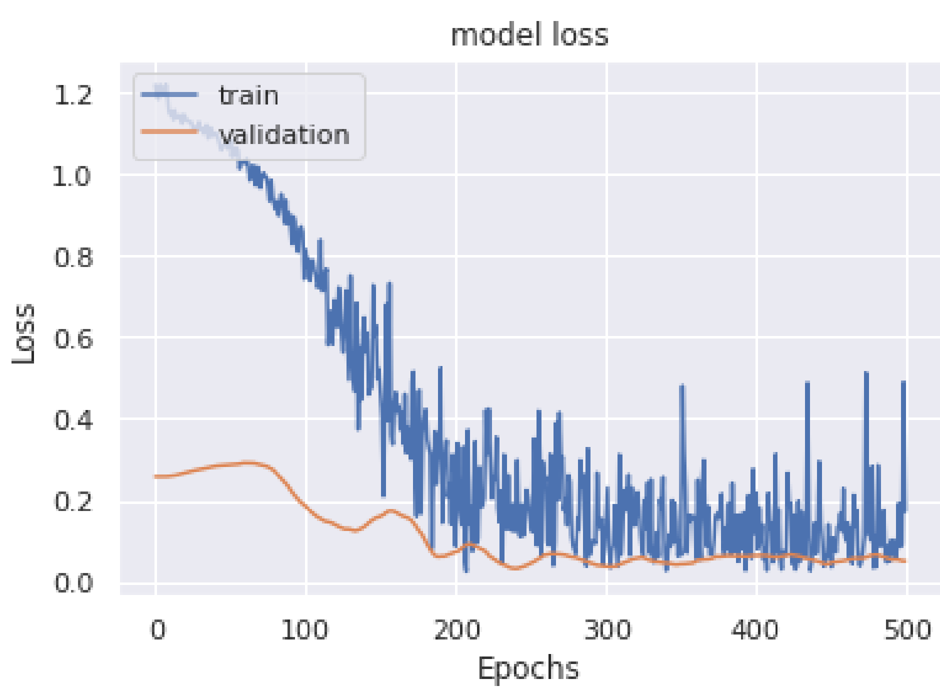

Figure 14. Variation of loss function with number of epochs

Figure 15 and Figure 16 shows the model performance in terms of Mean Square Error (MSE) and Mean Absolute Error (MAE).

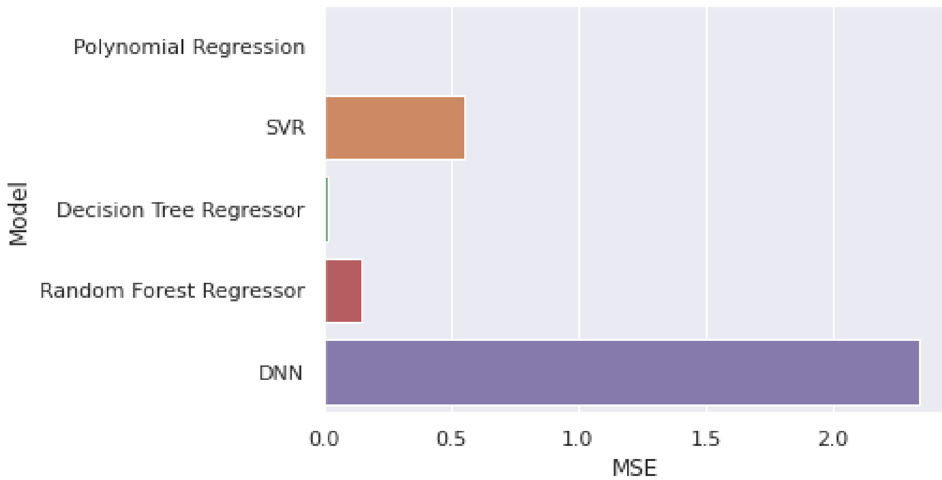

Figure 15. Representation of MSE of each Machine Learning regression models

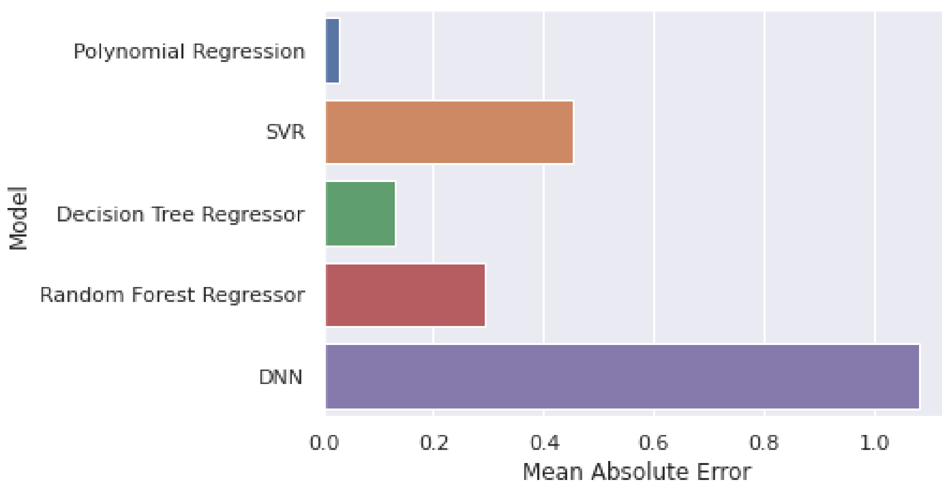

Figure 16. Representation of Mean Absolute Error of each Machine Learning Regression Models

From Figure 15 and 16 it can be clearly interpreted that the Polynomial Regression model and Decision Tree are a better fit than other models while on the basis of Mean absolute error, we can see that the Polynomial Regression model outperforms all other models.

3.5 Implementation of Supervised Machine Learning Classification Models

K-nearest Neighbors, Decision Tree Classifier (with Gini Index and Information Gain as Criterions), and Neural Network classification models were subjected to the dataset. The accuracy of the models for classification is shown in the Table 4. It is observed that Artificial Neural Network, Decision Tree classifier (Gini Index) and Decision tree classifier (Information gain as criterion) results better accuracy.

Table 4. F1 Accuracy of Machine Learning Classification models

KNN	0.89
Decision Tree Classifier	1.00
Decision Tree Classifer(Information Gain)	1.00
ANN	1.00

Figure 17 shows the performance of training and testing set while implementing Neural Network classification model.

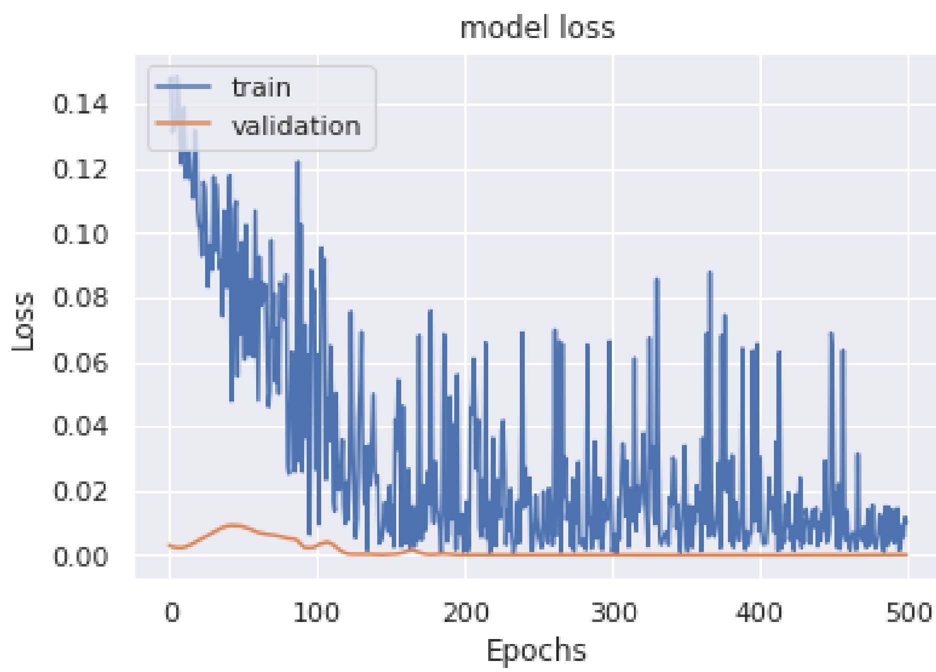

Figure 17. Training and testing set model performance

Figure 18 shows the plot of F1-accuracy of each classification models.

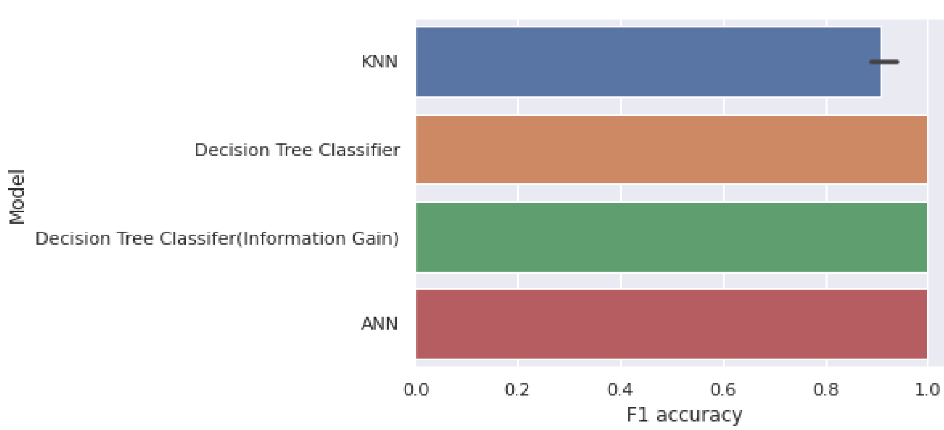

Figure 18. F1-accuracy of Machine learning classification models

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4. CONCLUSION

From the obtained results, we can see that Decision Tree Regressor and Polynomial Regressor outperform all other regressor models. As a classifier, Artificial Neural Network, Decision Tree (Gini Index) and Decision Tree (Information Gain) outperform the K-Nearest Neighbor model. In both the case, the Deep Learning model could have given a much better performance had there not been lack of data.

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Conflict of Interest:

The authors declare that there are no conflicts of interests.

Data and materials availability

All data associated with this study are present in the paper.

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