Regression Analysis and Artificial Neural Network Approach to Predict of Surface Roughness in Milling Process

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Abstract

Surface roughness (Ra) has a significant influence on the fatigue strength, corrosion resistance, and aesthetic appeal of machine components. Ra is hence a crucial manufacturing process parameter. This study predicts Ra of aluminum alloy Al-7024 after milling. Regression analysis and artificial neural network (ANN) modeling approaches are suggested for predicting Ra values. For better surface roughness, the cutting parameter must be set properly. Spindle speed, feed rate, and depth of cut have been chosen as predictors. Through 31 study cases, regression and ANN were used to examine how these parameters affected Ra. The measurement of surface roughness, together with comprehensive Ra analysis and regression analysis. The findings of this investigation indicate that Ra was predicted by both the regression and ANN models. convergent results from model predictions are obtained. This convergence highlights the promising methodology used in this work to forecast Ra in the milling of Al-7024. The findings demonstrated that, in comparison to the regression model, which had an average variation from the actual values of roughly 1%, The surface roughness was accurately predicted by the ANN model.

Keywords: Prediction; Surface Roughness, Milling; Artificial Neural Networks and Regression Analysis.

1. Introduction

The current manufacturing process pays close attention to a machined part's surface roughness. The fatigue strength, corrosion resistance, and tribological qualities of machined components are influenced by the features of the machined surface. The surface finish created after machining determines the material quality. To provide safe turning operations, the machined surface must be controlled [1]. How closely a final product complies to requirements, such as size and surface quality, is what determines its quality [2]. Therefore, monitoring, and characterizing surface qualities are key components of production processes. Surface finish, surface texture, and surface roughness together define and identify the quality of a surface. One of the crucial aspects of a work piece's quality in the turning process is its surface roughness. A work item may need to be trashed or redone because the cutting circumstances have an influence on the quality of the surfaces. Numerous research has been done to forecast the value of roughness as a result [3]. The milling process modeling to forecast surface roughness is presented in this work. For greater surface roughness, the cutting parameter must be set properly. Unfortunately, the traditional approach of trial and error is time- and money-consuming. The goal of this research is to create a mathematical model utilizing artificial neural networks and regression analysis. Spindle speed, feed rate, and depth of cut are three separate predictors that can be used to determine surface roughness. The format of this essay is as follows: Prior research is then briefly reviewed. The results and predictions are then presented and examined. At the conclusion of the article, conclusions are drawn.

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2. Literature review

Hiba K. Hussein et al [4] (2022) In the milling process, Ra of Aluminum Al-7075 is anticipated and reduced. The formula for a conventional mathematical model must include Ra minimization. To estimate the least Ra value, a model is being developed to handle actual Ra experimental data from the milling process. For predicting the minimal Ra value, two model strategies are recommended: regression and artificial neural networks (ANN). The process parameters that were examined were cut speed, feed rate, and cut depth. Through 27 research cases, regression and ANN were utilized to examine how these factors affected Ra.

Saadat Ali Rizvi et al [5] (2021) investigated the effects of different machining input parameters, such as cutting speed (v c), feed rate (f), depth of cut, and nose radius (r), on output, i.e., surface roughness (Ra and R q), and metal removal rate (MRR), of the C40 steel using an artificial neural network (ANN) technique.

Jignesh G. Parmar et al (2012) [6] When end milling M.S. material with a carbide tool, the effects of different cutting settings on the surface roughness are explored experimentally. An artificial neural network (ANN) is used to ascertain how the surface roughness and the cutting input parameters are related (spindle speed, feed and depth of cut). The results of this study might be put to use in the workplace to make surface roughness prediction quicker and less expensive.

Yung-Chih Lin et al (2020) [7] offers surface roughness modeling for machined products based on machining vibration and cutting parameters (spindle speed, cutting depth, and feed rate). Prediction models were developed using multiple regression analysis and an artificial neural network (ANN) modeling approach.

Cheng-Hung Chen et al (2021) [8] To predict the surface roughness of the treated workpiece, a back propagation neural network (BPNN) was recommended. An ANOVA was used to analyze the effects of milling factors such as spindle speed, feed rate, cutting depth, and milling distance. The experimental results show that the root mean square error (RMSE) of the back propagation neural network is 0.008, which is much smaller than the 0.021 achieved by the traditional linear regression technique.

Acayaba and de Escalona [9] A multiple regression model was also developed to assess average surface roughness. It has two hidden layers with five neural connections each and a validity of 0.72 in terms of mean square error. The implication is that Artificial Neural Ne work has a better predictive ability.

Zain et al. [10] provide the Artificial Neural Network (ANN) model for predicting the performance measure in the machining process with the presumption that ANN is the major approach for assessing surface roughness. For surface roughness prediction using neural networks, a variety of processing parameters can be used [13–20].

Zerti et al. [11] utilized response surface approaches and artificial neural networks for output modeling. The parametric analysis method can be used to analyse data using a variety of statistical techniques. Input and output for neural networks that forecast additional processing parameters are both provided by surface roughness.

Thangarasu et al. [12], An artificial neural network was used to predict the side wear of cutting tools based on how the cutting force and surface roughness interact.

3. Methodology

Recently, two methods have been used on the aluminum alloy in comparison. The milling procedure produced the experimental results. ANOVA, regression analysis, and ANN models will all be employed for comparison and verification to predict better results. The ANN approach creates a correlation between system parameters by using their input and output variables. MATLAB has been used to create an ANN model using the back propagation approach. This investigation will show that both methods may accurately estimate surface roughness to a similar degree. Flow Chart Steps for Prediction of the surface roughness shown in figure (1).

- Steps for an artificial neural network model

The typical steps for creating neural networks to fix problems are:

1. Collect the data.
2. Establish a network.
3. Set the network up.
4. Set the weights and biases to zero.

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5. Train the network
6. Validate the network,
7. Run a network test.
8. ANN outcome

- ANOVA and regression analysis model steps

The following steps are included in the process to define a model of the process:

1. The following phases are included in the process to define a model of the process:
1. Deciding on the levels and the components that will be included in the process.
2. Randomly combining every potential component level in the experiment.
3. Using parametric analyses of variance to analyze the data gathered (ANOVA).
4. Creating a model for multiple regression.
5. Verifying the model's validity

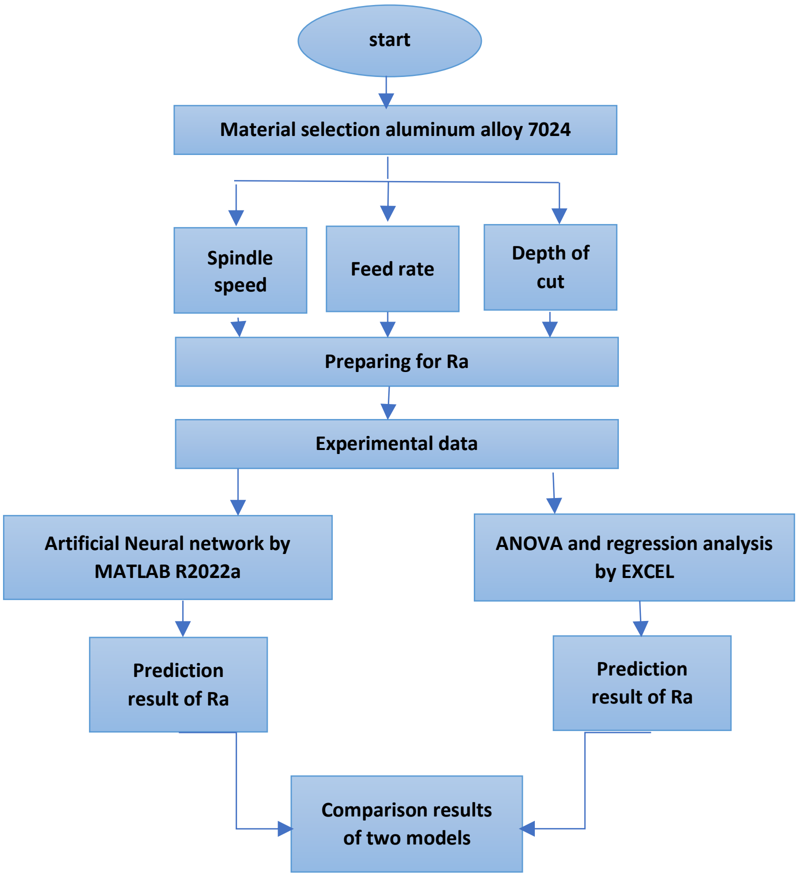

Figure 1: Flow Chart Steps for Surface Roughness Prediction

4. Experimental Work

The alloy of aluminum 7024 that will be machined is chosen. The AL work piece's measurements during the milling process were 100 mm by 150 mm by 3 mm. The alloy Al-7024's key chemical structure is listed in the table (1). The surface roughness value was calculated using a surface roughness tester. The input parameters [Spindle speed (rpm), feed rate (mm/rev), and depth of cut (mm)] were used to calculate the value of the surface roughness (Ra).

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Table 1: Chemical Composition of Aluminum 7024

Si%	Fe%	Cu%	Mn%	Mg%	Cr%	Ni%
0.163	0.422	2.14	0.216	1.55	0.090	0.012
Zn%	Ti%	Ga%	V%	Pb%	Other%	AL%
4.93	0.038	0.010	0.007	0.071	0.132	90.219

Each region has a variety of cutting circumstances, and depending on those variables, the surface roughness value will vary. After carrying out the experimental work, we used the 31 study cases provided in table (2) as the experimental data to determine the roughness for each region using the Pocket Surf tester. First, using case studies, regression analysis, and neural network models are used to compare and forecast results for surface roughness.

Table 2: Case Studies Information on the Impact of Cutting Parameters on Surface Finish

NO.	Spindle speed (rpm)	Feed rate (M m/min)	Depth of cut (mm)	Surface Roughness Ra (Mm)
1	1000	450	0.75	3
2	1000	600	0.25	4.1
3	1500	150	0.25	1.3
4	750	375	1.25	2.6
5	1500	525	1.25	3
6	1250	300	0.25	2.6
7	1000	300	0.25	3.1
8	1500	225	0.25	1.4
9	750	225	0.75	2.6
10	750	150	0.75	1.7
11	750	525	0.75	4
12	1000	600	0.75	4
13	1250	150	1.25	1.7
14	1000	375	0.75	2.6
15	1250	300	0.75	2.5
16	1000	225	0.75	2.4
17	1500	300	0.75	2.1
18	1000	525	0.75	3.9
19	1250	225	0.25	2.1
20	1000	150	0.75	1.9
21	1250	375	0.75	2.5
22	1000	150	0.25	1.6
23	1000	225	1.25	2.7
24	750	225	1.25	2.5
25	1250	450	0.75	2.2
26	1500	300	0.25	2.3
27	750	450	0.25	4.8
28	1250	600	0.75	2.6
29	750	525	0.25	4.5
30	1250	225	1.25	2.4

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NO.	Spindle speed (rpm)	Feed rate (M m/min)	Depth of cut (mm)	Surface Roughness Ra (Mm)
31	1250	150	0.75	1.7

4.1 ANOVA and Regression Analysis Model

The relationship between surface roughness and a few chosen machining factors is predicted using regression analysis. The research considered both the direct impacts of these factors as well as the results of their interactions [13]. The experiment's input data and surface roughness reading values are shown in Table (2). The Excel software is used to determine the constants for the multiple linear regression equation. The regression model was fed experimental input data (Speed, Feed rate, and Depth of cut) and the associated output data (Experimental roughness data). Surface Roughness and Regression Output are shown in Figure (2) and the results of the multiple linear regression model are shown in Table 3.

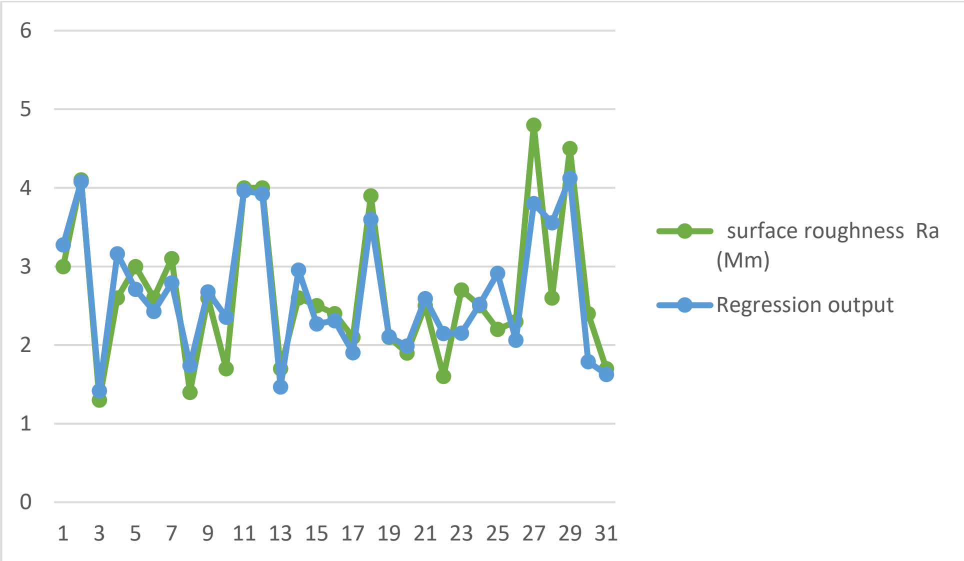

Figure 2: Regression Output and Surface Roughness

Table 3: Summary Output

Regression Statistics	
Multiple R	0.889416598
R Square	0.791061884
Adjusted R Square	0.767846538
Standard Error	0.437155277
Observations	31

ANOVA

	df	SS	MS	F	Significance F
Regression	3	19.535656	6.511885	34.07495531	2.52723E-09
Residual	27	5.159827869	0.191105		
Total	30	24.69548387			

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	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	3.045925358	0.468253807	6.50486	5.65838E-07	2.085147907	4.006702808	2.085147907	4.006702808
Spindle speed (rpm)	-0.001461319	0.000318229	-4.59204	9.11554E-05	-0.002114271	-0.000808368	-0.002114271	-0.000808368
Feed rate (M m/min)	0.004290492	0.000531455	8.073108	1.12881E-08	0.003200037	0.005380947	0.003200037	0.005380947
Depth of cut (mm)	-0.317431496	0.224100141	-1.41647	0.168072212	-0.777247004	0.142384011	-0.777247004	0.142384011

4.2 Prediction of Surface Roughness Using Artificial Neural Network (ANN)

ANN is crucial because it can address nonlinear problems [14]. Additionally, ANN is used in this work to forecast the surface roughness using the MATLAB R2022a tool. The supplied ANN model has multiple layers, and the data were processed in the hidden levels of these layers. Cutting speed, feed rate, and depth of cut are provided to the network together with the desired output, surface roughness, during the training phase of an ANN. The weights are initially created randomly, and then changed using the back propagation process to reach a desired performance level [15-16]. The mentioned ANN model's network is trained using 31 trials. The network demonstrated effective training and learning to forecast the surface roughness output value for testing and validation. Figure (3) displays the neural network architecture, Figure (4) displays the neural network training results, and Figure (5) displays the error curve for the optimized neural network over the training, validation, and test data.

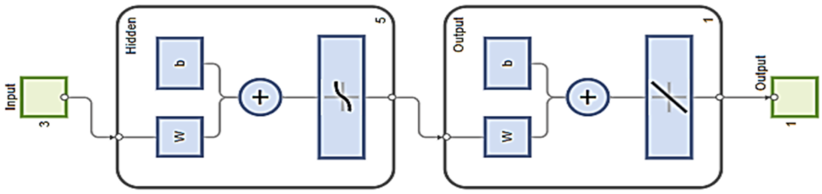

Figure 3: Neural Network Architecture

Figure (6) displays the Training State Plot. It is evident from Figure (7) below, The Curve for Correlation Among the Factors and Following the Regression Pattern, that most of the predicted and experimental values closely match each other on the regression line during the training phase, achieving R=0.995 in training values. Regression was found to be 0.982 in total values performance, which is an excellent result. Regression was found to be 0.972 and 0.994 in validation and testing, respectively. The occurrence of some real values that are not totally consistent with the predicted ones can often be attributed to a variety of sources. These elements might be the outcome of errors in experimental results brought on by the environment, tools, and observations. The neural network model won't lead to a coincidence between expected and actual values, and the residuals won't be both negative and positive. The performance of the given network depended on the quantity of the mean square in proportion to the increase in the number of epochs, with the best validation performance in Figure (5) above being 0.11387 at epoch number 6. Table 4 provides an overview of the neural network model.

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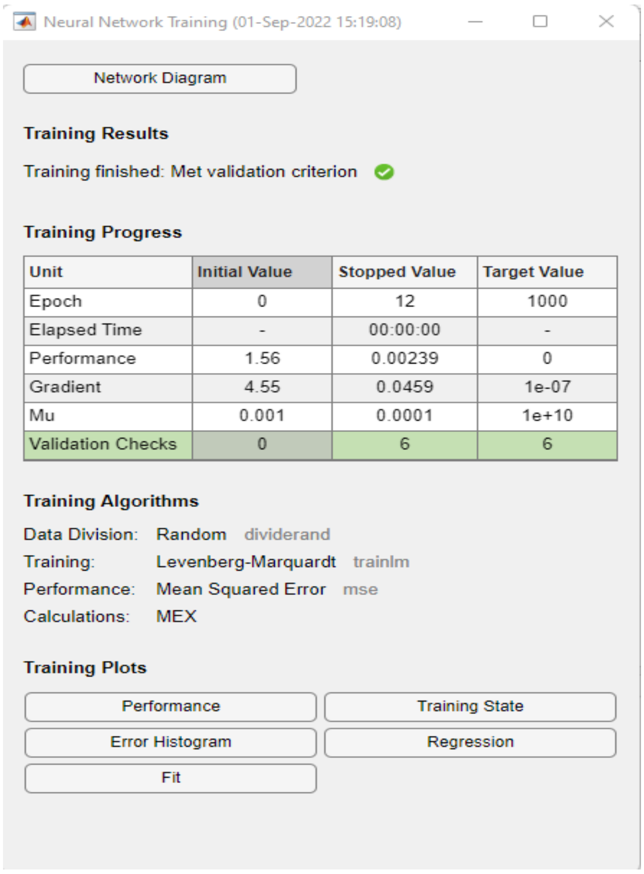

Figure 4: Neural Network training results

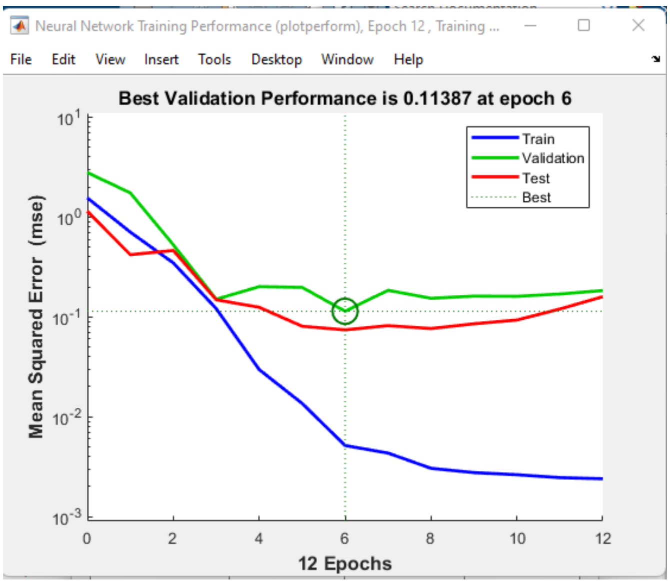

Figure 5: Error Curve for Optimized Neural Network over the Training, Validation, and Test Data

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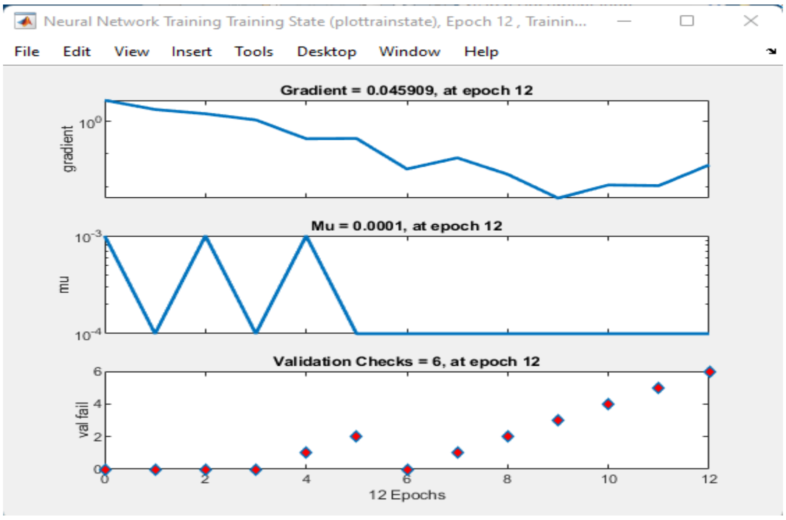

Figure 6: Training State Plot

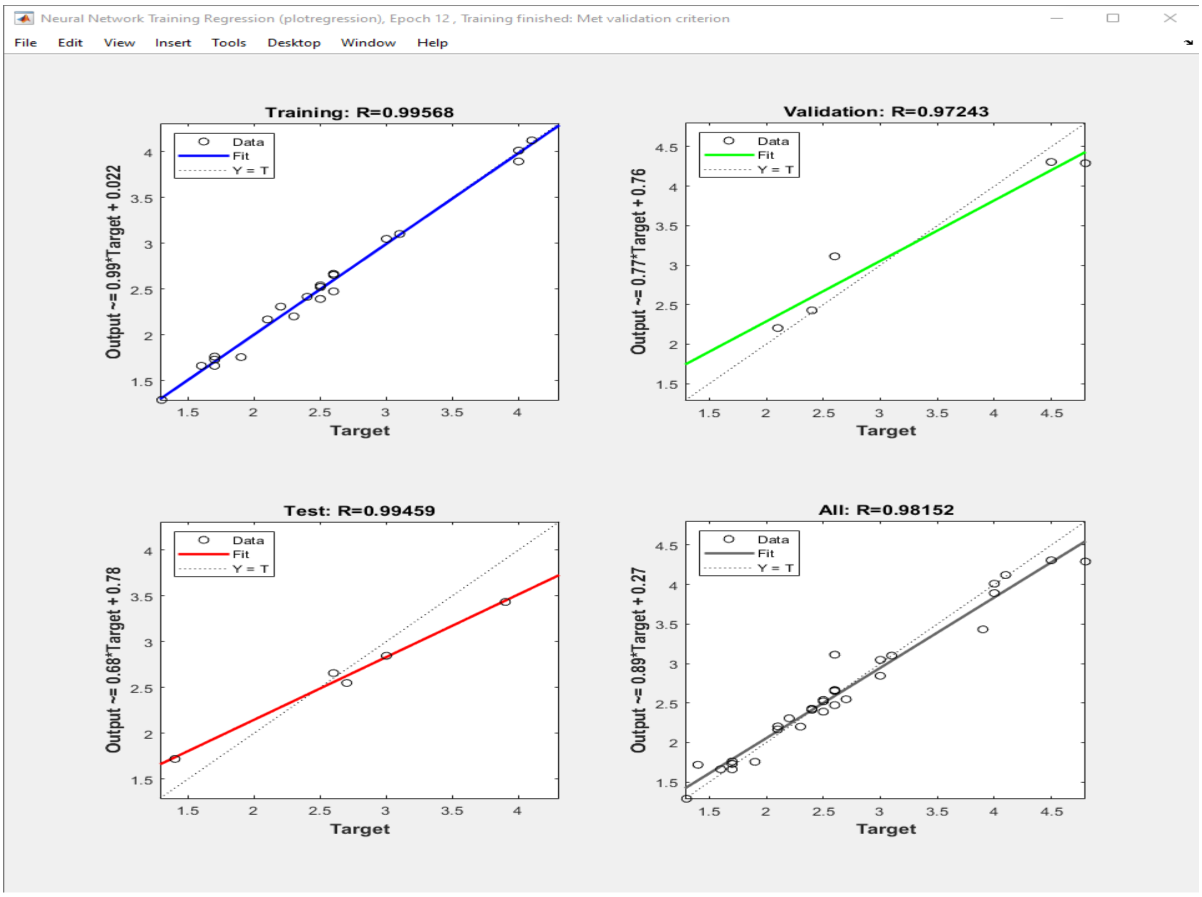

Figure 7: The Regression Pattern and the Curve for Correlation Among the Factors

Table 4: Summary of Neural Network Model

ANN Type	Multi-layer feed forward back propagation neural network
Input Layer	Three neurons (Spindle speed(rpm), Feed rate (M m/min), Depth of cut(mm))
Output Layer	One neuron (Ra)

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Hidden Layer	5
Data Division	Training data: 70% Validation data: 15% Test data 15%
Learning Algorithm	Levenberg Marquardt (LM)
Epoch	12
Activation Function	Tangent sigmoid (tansig)
Evaluate ANN Performance	Mean square error (MSE)= performance = 0.0338

5. Discuss Results of Two Models

The outcome of data forecasting for the following two years using two models—ANN and regression analysis—is shown in Table 5. Less of a fraction of Ra's original data and the outcomes of the predictions were off. This study looked at the effects of three factors and could predict (Ra) values. The original Ra data and the Surface Roughness Using Artificial Neural Network Prediction result are shown in Figure (8). Comparison of the Original Ra Data with the Prediction by ANN and Prediction by Regression Analysis is shown in Figure (9). The findings demonstrated that, in comparison to the regression model, which had an average variation from the actual values of roughly 1%, the ANN model estimated surface roughness with a high degree of accuracy.

Table 5: The Result of Forecasting Data for the Next Two Years

NO.	Spindle speed (rpm)	Feed rate (M m/min)	Depth of cut (mm)	surface roughness Ra (Mm)	Predicted surface roughness by ANN	ERROR	Regression output	ERROR
1	1000	450	0.75	3	2.8	0.2	3.3	-0.3
2	1000	600	0.25	4.1	4.1	0.0	4.1	0.0
3	1500	150	0.25	1.3	1.3	0.0	1.4	-0.1
4	750	375	1.25	2.6	2.7	-0.1	3.2	-0.6
5	1500	525	1.25	3	3.0	0.0	2.7	0.3
6	1250	300	0.25	2.6	2.7	-0.1	2.4	0.2
7	1000	300	0.25	3.1	3.1	0.0	2.8	0.3
8	1500	225	0.25	1.4	1.7	-0.3	1.7	-0.3
9	750	225	0.75	2.6	2.5	0.1	2.7	-0.1
10	750	150	0.75	1.7	1.8	-0.1	2.4	-0.7
11	750	525	0.75	4	4.0	0.0	4.0	0.0
12	1000	600	0.75	4	3.9	0.1	3.9	0.1
13	1250	150	1.25	1.7	1.7	0.0	1.5	0.2
14	1000	375	0.75	2.6	2.7	-0.1	3.0	-0.4
15	1250	300	0.75	2.5	2.5	0.0	2.3	0.2
16	1000	225	0.75	2.4	2.4	0.0	2.3	0.1
17	1500	300	0.75	2.1	2.2	-0.1	1.9	0.2
18	1000	525	0.75	3.9	3.4	0.5	3.6	0.3
19	1250	225	0.25	2.1	2.2	-0.1	2.1	0.0
20	1000	150	0.75	1.9	1.8	0.1	2.0	-0.1
21	1250	375	0.75	2.5	2.4	0.1	2.6	-0.1
22	1000	150	0.25	1.6	1.7	-0.1	2.1	-0.5
23	1000	225	1.25	2.7	2.5	0.2	2.2	0.5
24	750	225	1.25	2.5	2.5	0.0	2.5	0.0

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NO.	Spindle speed (rpm)	Feed rate (M m/min)	Depth of cut (mm)	surface roughness Ra (Mm)	Predicted surface roughness by ANN	ERROR	Regression output	ERROR
25	1250	450	0.75	2.2	2.3	-0.1	2.9	-0.7
26	1500	300	0.25	2.3	2.2	0.1	2.1	0.2
27	750	450	0.25	4.8	4.3	0.5	3.8	1.0
28	1250	600	0.75	2.6	3.1	-0.5	3.6	-1.0
29	750	525	0.25	4.5	4.3	0.2	4.1	0.4
30	1250	225	1.25	2.4	2.4	0.0	1.8	0.6
31	1250	150	0.75	1.7	1.7	0.0	1.6	0.1

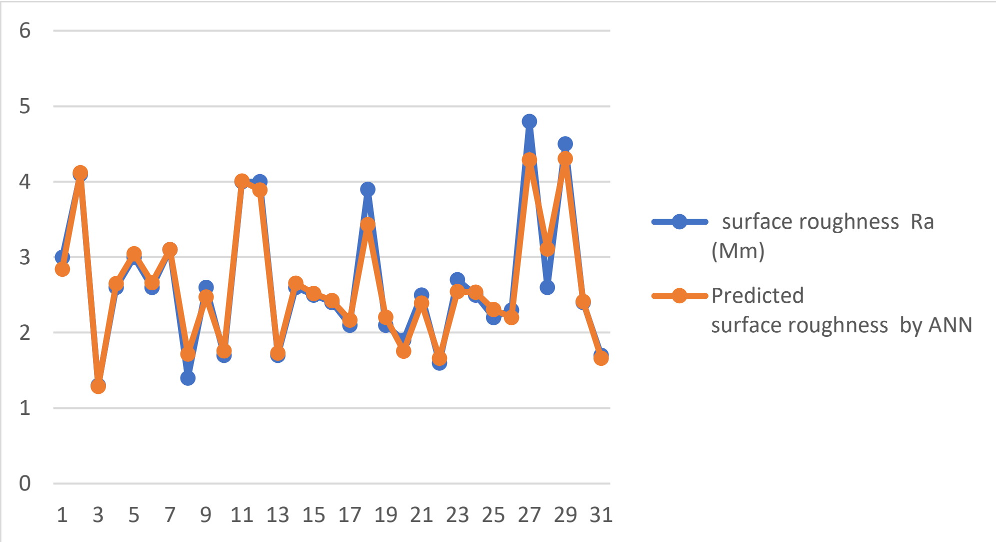

Figure 8: The Original Data of Ra and Prediction Result of Surface Roughness Using Artificial Neural Network

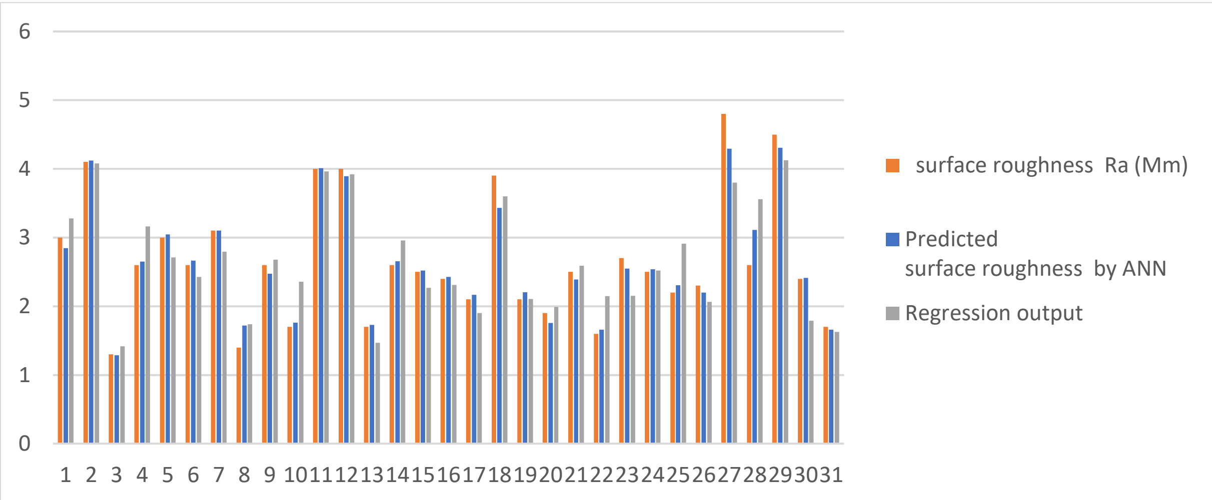

Figure 9: Comparing Between Original Ra Data with The Results of The Predication by ANN and The Predication by Regression Analysis

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6. Conclusions

Regression analysis and an artificial neural network were utilized in the current study to assess the surface roughness of the alloy made of 7024 aluminums. When surface roughness was estimated using a regression model, it was discovered that there was a disparity of about between the value obtained using NN and the value with a satisfactory estimation. It is discovered that both models lowered the experimental data's minimum surface roughness value by around 0.987%. In reducing surface roughness, very comparable outcomes were obtained. Overall, it can be said that when ANN and regression are used to estimate the lowest surface roughness, similar results are obtained. Regression and artificial neural networks both offered promising ways to predict how surface roughness will behave in response to changing machining process parameters. Due to its simplicity and capacity to predict the behavior of the nonlinear system, NN may really be seen as a potent instrument to estimate surface roughness value with these fair results.

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