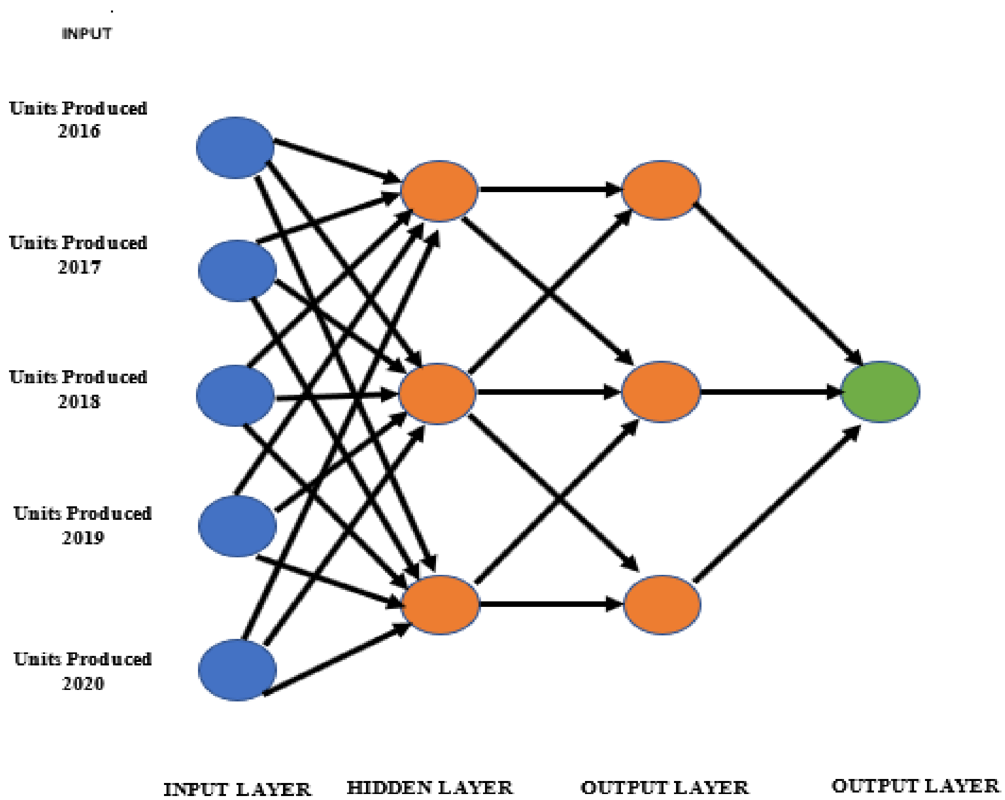

Figure 1: Architecture of the Neural Network

2.5 Training of Artificial Neural Network

During the course of setting up the neural network for training, the data was arranged into input and output variables. The number of neurons used was twelve (12), it enabled the weight (w) and the bias (b) of each neuron to be adjusted to suit the best size of the network. Figure 2 shows the structure of the artificial neural network with the input and output variable

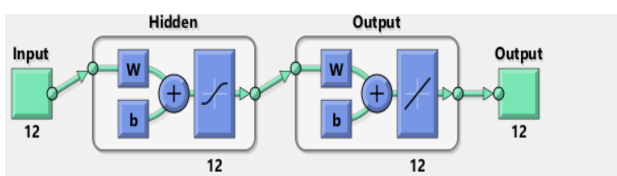

Figure 2: Structure of the Artificial Neural Network with the Input and Output Variable

3. RESULTS AND DISCUSSION

3.1 Simple Linear Regression Analysis of Defective Rotary Shouldered Connections

The result obtained from the simple linear analysis carried out on the defects on Rotary Shouldered Connections during machining from quality control records (as shown in Table 1) of the Manufacturing Company are given below

From Equation (3), the values of β have been obtained

$\beta = \frac{795.2278}{4507.5092}$

= 0.1764

From Equation (2), α was calculated and is presented in Equation (8)

$\alpha = 8.2982 - (0.1764 \times 27.2807)$

= 3.4859

From Equation (1), the linear regression model becomes

$$\hat{Y} = 3.4859 + 0.1764X \quad (8)$$

From Equation (7), the mean squared error is calculated as

$\frac{495.63366}{57}$

= 8.6953

From the simple linear regression analysis carried out, the results showed a regression coefficient of 0.1764, a regression constant of 3.4859, and a mean squared error 8.6953.

3.2 Analysis Artificial Neural Network Results

From Figure 2, the artificial neural network best validation performance is observed to be 49.0927 at epoch 3.

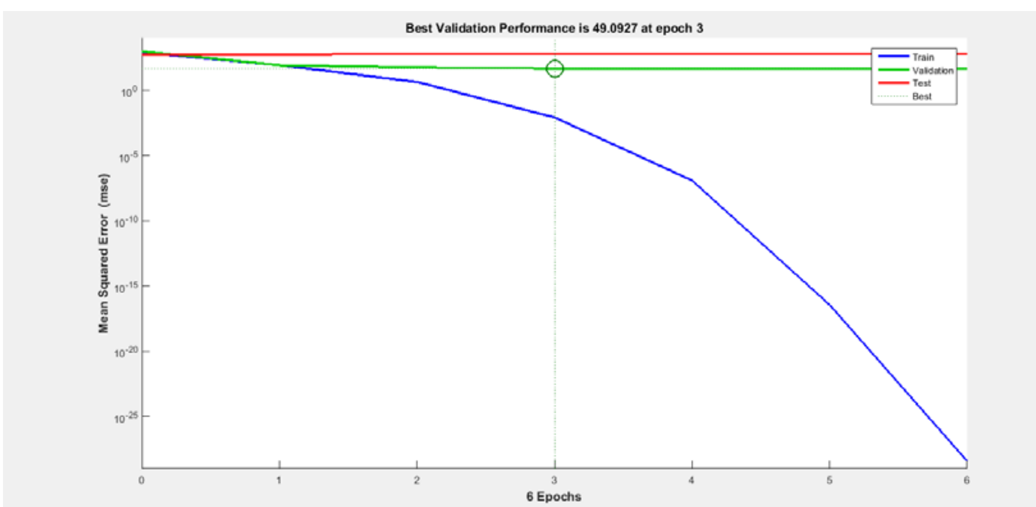

Figure 2: Neural Network Best Validation Performance (Combined Dataset)

The regression models readily allow inference on the significance of explanatory variables and expected predictive capability. From Figure 4.22, the regression of the artificial neural network during is 0.99995, -0.29869 during testing and -0.69351 during validation. The average regression of the combined dataset is observed to be -0.42665 which is a moderate regression coefficient value (Patrick *et al.* 2018). The adaptation of regression in Artificial Neural Network helps to increase the prediction therefore making the system linear (Kuang, *et al.* 2021; Aasi & Mishra, 2021 and Mas & Ahlfeld, 2007).

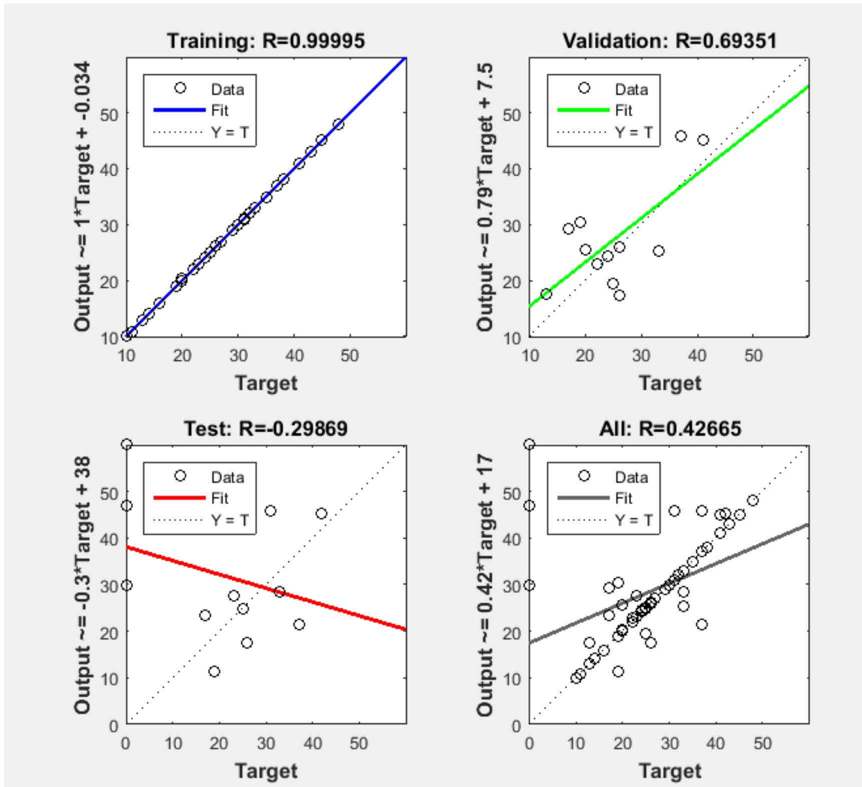

Figure 3: Neural Network Regression

From the histogram error in Figure 4, the total error range is divided into 20 smaller bins. At the mid of the plot, we have a bin corresponding to the error of $-1.457e^{-16}$ and the height of that bin for training dataset lies between 45 and 45. It was also observed that the errors were high during the training process but then reduced significantly during testing. The result show that the more the bins the better the prediction which is line with the study of Heinrich (2021), if too few bins are chosen, the rank histogram is likely to miss miscalibrations; if too many are chosen, even perfectly calibrated forecast systems can yield rank histograms that do not appear uniform, thereby improving on the performance of the model (Rahman, *et al.* 2021).

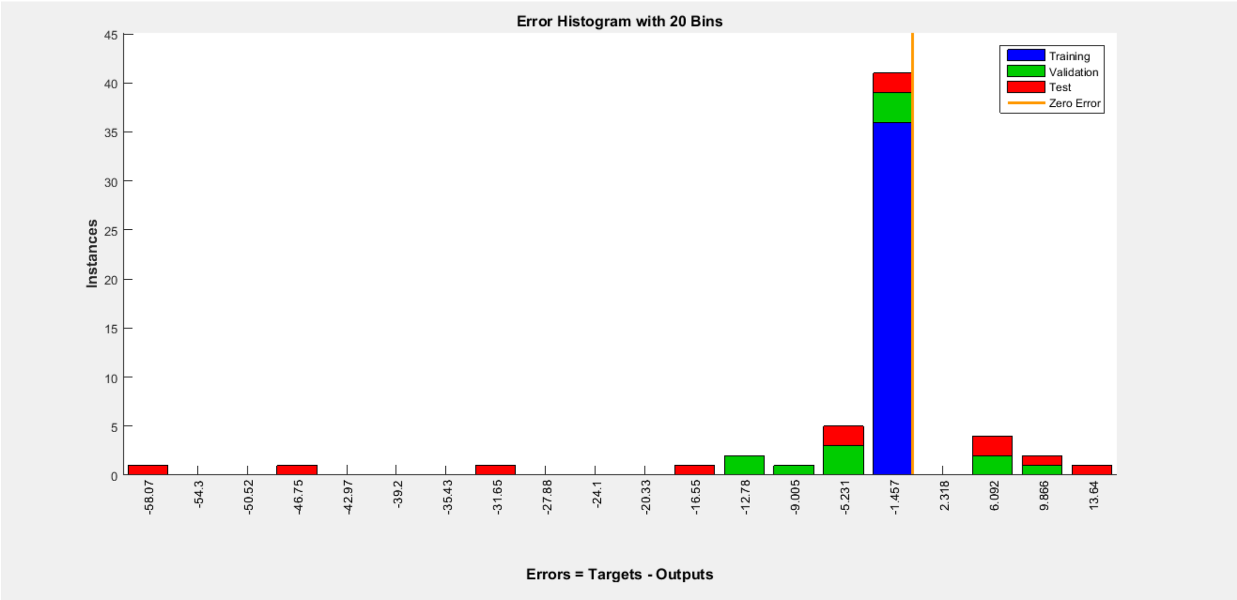

Figure 4: Neural Network Error Histogram

Based on the data, Artificial Neural Network training state was deployed to learn the dataset for the prediction. From Figure 5, the gradient of the artificial neural network is observed to be $2.1092e^{-13}$ at epoch 6 during training, $1e^{-9}$ during testing at epoch sting at epoch 6 and 0 upon validation check at epoch 6. The output obtained on the dataset depicts that the result obtained is line with the following work on Novák & Lehký (2006) that an efficiency training of a dataset helps to prepare the dataset for effective prediction.

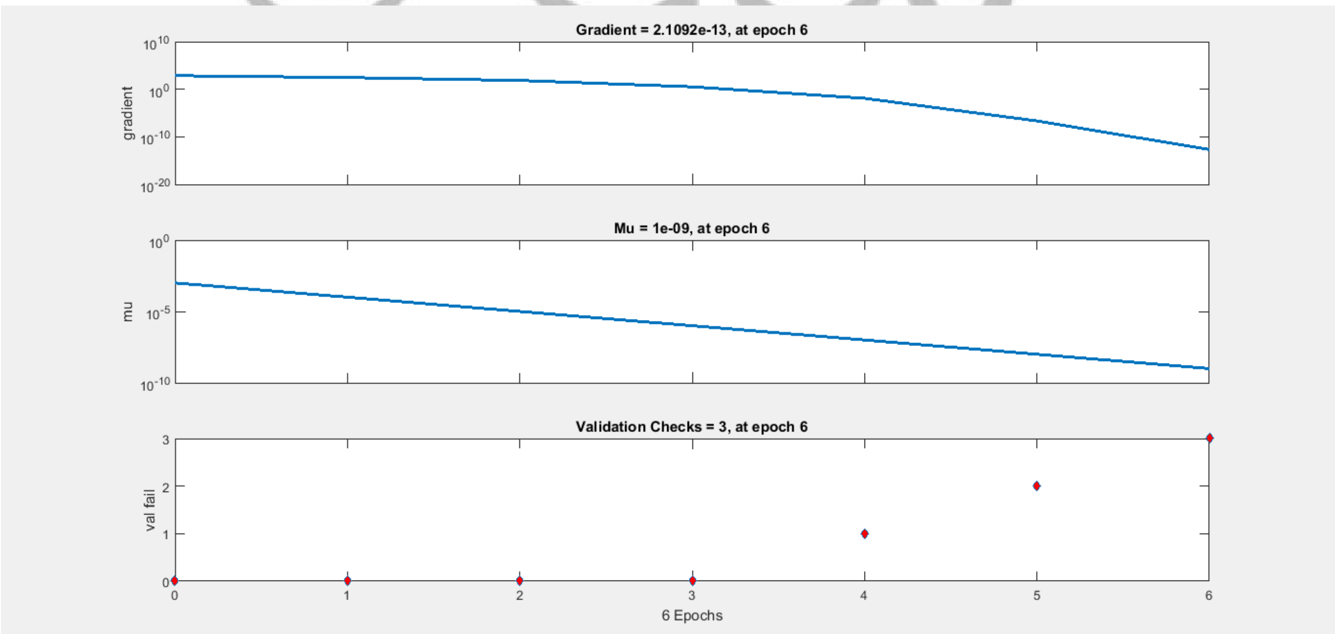

Figure 5: Neural Network Training State (Combined Dataset)

3.3 Comparison of the Simple Linear Regression and Artificial Neural Network Results

To ascertain the difference between the simple linear regression result and the artificial neural network result, the regression coefficient of the Simple Linear Regression is compared to that of the artificial neural network. The regression obtained using the simple linear regression and ANN was 0.1764 and 0.42665.

Hence, the percentage difference can be calculated as

$$\frac{0.1764}{0.42665} \times 100$$

$$= 0.4134 \times 100$$

= 41.34%

As such, it can be said that artificial neural network has been able to minimize the defects of the rotary shouldered connections up to 41.34%.

Also, from the analysis, the mean square error of the artificial neural network is 0.00860542, when compared to the mean square error (8.6953) from the data of the simple linear regression, shows a closer value to the line of best fit. Furthermore, the mean square obtained when ANN was applied to the data were minimal to that of statistical, which shows that the ANN was an improve tool for prediction because it makes use of hybridized method for optimization, which is in line with the study of Quiza *et al.* (2007), that Artificial Neural Network model produce a better and accurate prediction for Rotary Shouldered Connections.

4. CONCLUSION

From the analysis carried out on minimizing the defects of rotary shouldered connections, the simple linear regression approach gave a regression coefficient of 0.1764, while the artificial neural network gave a regression coefficient of 0.42665. Also, the artificial neural network gave a mean square error of 0.00860542 which is closer to the line of best fit when compared to that of simple linear regression which is 6.73386.

In comparison of the two approaches, it is noted that the effectiveness of artificial network in minimizing defects cannot be overemphasized, as it has been seen to be able to minimize the defects of the rotary shouldered connections up to 41.34%.

From the detailed analysis carried out, it is recommended that:

i. Further study should incorporate a larger dataset as it will improve the accuracy of the model.
ii. The result be compared with that of other machining learning tools such as Random Forest and Support Vector Machine.

This research has shown that control of defects in production process can be achieved by the application of artificial neural network and Ishikawa diagram which enumerates the causes of the defects. The introduction of ANN shows that it can enhance production with less minimal error.

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