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# Efficient Prediction of Surface Roughness Using Decision Tree

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**ABSTRACT:** *Surface roughness is a parameter which determines the quality of machined product. Now a days the general manufacturing problem can be described as the attainment of a predefined product quality with given equipment, cost and time constraints. So in recent years, a lot of extensive research work has been carried out for achieving predefined surface quality of machined product to eliminate wastage of over machining. Response surface methodology is used initially for prediction of surface roughness of machined part. After the introduction of artificial intelligent techniques many predictive model based on AI was developed by researchers because artificial intelligence technique is compatible with computer system and various microcontrollers. Researchers used fuzzy logic, artificial neural network, adaptive neuro-fuzzy inference system, genetic algorithm to develop predictive model for predicting surface roughness of different materials. Many researchers have developed ANN based predictive model because ANN outperforms other data mining techniques in certain scenarios like robustness and high learning accuracy of neural network. In this research work a new predictive model is proposed which is based on Decision tree. ANN and ANFIS are known as black box model in which only outcome of these predictive models are comprehensible but the same doesn't hold true for understanding the internal operations. Decision tree is known as white box model because it provides a clear view of what is happening inside the model in the view of tree like structure. As use of decision tree held in the prediction of cancer that means it is very efficient method for prediction. At the end of this research work comparison of results obtained by ANN based model and Decision tree model will be carried out and a prediction methodology for roughness is introduced using decision tree along with ANN.*

***Keywords:*** *ANN, CNC, Decision tree.*

## I. INTRODUCTION

There is a demand of high strength material of light weight material for increasing application in aerospace industries. These properties are fulfilled by aluminium alloys as they are having high strength weight ratio. 7000 series of aluminium alloy has highest strength so 7075 T6 alloy is taken for our study. For fabrication of structures and equipment of aircraft metal cutting process is used. One of the major conventional metal cutting processes which used frequently is the milling process. There is a rotating cutter used for removal of material in the milling process. The purpose of milling operation is to obtain great accuracy with minimum use of available resources. Nowadays it is achievement for industry to attain predefined quality of surface roughness. Roughness is defined as the vertical deviation of real surface from ideal surface. Which surface has more deviation is known as rough surface. Surface roughness plays vital role in machining. There are many factors which make roughness a key factor of machining. These factors are described below.

1. Precision: The precision that is required on mating surfaces, such as seals, fittings, gaskets, dies and tools. For example, gages and ball bearings require very smooth surfaces, whereas surfaces for brake drums and gaskets can be quite rough.
2. Frictional consideration: It is the effect of roughness on wear, lubrication and friction.
3. Fatigue and Notch Sensitivity: The rougher the surface, the shorter the fatigue life.
4. Electrical and Thermal contact resistance: the rougher the surface, the higher the resistance will be.
5. Corrosion Resistance: The rougher the surface, the greater the possibility of entrapped corrosive media.
6. Subsequent Processing: They may be performed, such as coating and painting, in which a certain amount of roughness helps in improved bonding.
7. Appearance: For attractive appearance lower the roughness.
8. Cost: The finer the finish, the higher the cost.

High surface roughness is responsible for reducing the fatigue life of structural members of aircraft [SURATCHAI et al. 2008]. It is the acrimony present on the surface of airplane which acts as minute notches. These minutes notches are responsible to the increase in stress concentration on surface. As we know pressure is change with height from earth. Due to this pressure differences held during the flight of plane. The outer structure of aircraft undergoes a huge amount of fluctuating stress. Due to such conditions failure may occur in the earliest if roughness is not maintained up to predefined limit.

## II. LITERATURE REVIEW

Various literatures are reviewed to see the capability of ANN and others predictive techniques in order to the modelling of machining process. Following table reflects the comparative view of all predictive methods used for prediction of surface roughness

| S.N | Paper title | Author and published year | Implemen-tation | Machining parameters | Model/ Technique | Remarks |
|---|---|---|---|---|---|---|
| 1 | Novel machine learning based models for estimating minimum surface roughness value in the end milling process. | SaroshHashmi et.al. (2014) | CNC end milling machine | a) cutting speed b) feed rate c) radial rake angle | a) Model tree b) SMO-SVM | Predictive model based on model tree gave minimum value of roughness upto 0.182µm. |
| 2 | Predictive modelling and optimization of machining parameters to minimize surface roughness using ANN coupled with GA | Girish Kant and Sangwan (2015) | CNC milling machine | a) depth of cut b)cutting speed c) feed rate | a) ANN b) GA | 4.11% mean relative error achieved. |
| 3 | Predictive modelling for power consumption in machining using AI techniques. | Girish Kant and Sangwan (2015) | CNC milling machine | a) depth of cut b)cutting speed c) feed rate | a) ANN b) GA | 1.79% mean absolute error achieved. |
| 4 | Surface roughness prediction using ANN in hard turning of AISI H13 steel with minimal fluid application. | B. Anuja Beatrice et.al. (2014) | CNC lathe machine | a) feed rate b) cutting speed c) depth of cut | ANN | Accuracy achieved upto 95.96%. |
| 5 | Prediction of surface roughness in the end milling using ANN. | AzlanMohdZain et.al. (2010) | CNC end milling machine | a) rake angle b) feed rate c) cutting speed | ANN | Predicted result depends upon configuration of neural network and no. of training data set. They found 3-1-1 config. Gave best result with 24 data set. |
| 6 | Optimal selection of process parameters in CNC end milling of AL 7075-T6 aluminium alloy using a Taguchi-Fuzzy approach | Thakur paramjit and R.Rajesh (2014) | CNC end milling machine | a) cutting speed b) depth of cut c) feed rate d) nose radius | Taguchi-Fuzzy | A3B1C3D2 combination gave optimum result with surface roughness 0.14µm. |
| 7 | Optimization of machining parameters to minimize surface roughness using integrated ANN-GA approach. | Sachin saxena et.al. (2015) | CNC lathe machine | a) cutting force b) cutting speed c) feed rate d) depth of cut | a) SVR b) ANN | Mean error obtained by SVR is 1.86 where as ANN gave 1.749 mean error. |
| 8 | Prediction and control of surface roughness in CNC lathe using ANN. | DurmusKarayel (2009) | CNC lathe machine | a) depth of cut b)cutting speed c)feed rate | ANN | The predicted result is extremely close to measured result. |
| 9 | Neural network process modelling for turning of steel parts using conventional and wiper inserts. | TugrulOzel et.al. (2009) | CNC lathe machine | a)nose radius b)depth of cut c) feed rate d) cutting speed | ANN | With conventional insert roughness of 0.26µm obtained while from wiper insert 0.22µm roughness obtained. |
| 10 | Prediction of surface roughness of freeform surfaces using ANN. | Rajesh.M and R.Manu (2014) | CNC ball end milling machine | a) feed rate b) depth of cut c) step over | ANN | Accuracy upto 96.37% achieved. |
| 11 | Grey fuzzy multiobjective optimization of process parameters for CNC turning of GFRO/Epoxy composites. | HariVasudevan et.al. (2014) | CNC lathe machine | a) nose radius b)cutting speed c)feed rate d)depth of cut | a) Fuzzy logic b) Taguchi | Combination of 0.8mm tool nose radius, 120 m/min cutting speed, 0.05 mm/rev feed rate and 1.6 mm depth of cut gave optimum value. |
| 12 | Integration of fuzzy logic with RSM for thrust force | B.Suresh and | CNC | a) spindle speed b) feed rate | a) Fuzzy logic b) RSM | 9.77% of average |

| | | | | | | |
|---|---|---|---|---|---|---|
| | and surface roughness modelling of drilling on titanium alloy. | N.Baskar (2013) | milling machine | | | deviation obtained in thrust force. |
| 13 | Simulation of surface milling of hardened AISI340 steel with minimal fluid application using ANN. | Leo Dev Wins et.al. (2012) | CNC milling machine | a) pressure at fluid injector<br>b) frequency of pulsing<br>c) quantity of cutting fluid | ANN | 0.011% standard error obtained and mean error achieved 0.93% with 3-6-6-1 architecture of neural network. |
| 14 | Artificial intelligence based surface roughness prediction modelling for 3D end milling. | Hossain and Ahmad (2012) | CNC end milling machine | a) spindle speed<br>b) feed rate<br>c) radial depth of cut<br>d) axial depth of cut<br>e) cutter axis inclination angle | a) ANN<br>b) ANFIS<br>c) RSM | ANFIS gave best result as MAPE is 0.003014% obtained while in ANN this is 0.0314% and in RSM 27.72% obtained. But ANN gave better result in testing of data. |
| 15 | Fuzzy rule based for predicting machining performance for SNtr carbide in milling titanium ally (Ti-6Al-4v). | Mohd Adnan et.al. (2012) | CNC milling machine | a) cutting speed<br>b) feed rate<br>c) radial rake angle | Fuzzy logic | 0.9845 correlation value obtained between real experiment and fuzzy rule based prediction. |
| 16 | A fuzzy logic based model to predict surface roughness of a machined surface in glass milling operation using CBN grinding tool. | M. Hamdi et.al. (2012) | CNC milling machine | a) lubricant pressure<br>b)feed rate<br>c)spindle speed<br>d)depth of cut | Fuzzy logic | 93.103% accuracy achieved. |
| 17 | Surface roughness prediction model using ANN and ANFIS. | S. Hari Krishna et.al (2011) | CNC lathe machine | a) cutting speed<br>b) feed rate<br>c) depth of cut | a) ANN<br>b)ANFIS | ANFIS gave 3.39% testing error where as ANN gave 3.868 % testing error. |
| 18 | Investigation into the effect of cutting conditions on surface roughness in turning of free machining steel by ANN model. | J.P Davim et.al. (2008) | CNC lathe machine | a) depth of cut<br>b) cutting speed<br>c) feed rate | ANN | Combination of low feed rate and high cutting speed gave minimal surface roughness. |
| 19 | Prtediction of minimum surface roughness in end milling mold parts using neural network and GA. | HasanOktem et.al. (2006) | CNC end milling machine | a) cutting speed<br>b) feed rate<br>c) axial depth of cut<br>d) radial d.o.c<br>e) machining tolerance | a) ANN<br>b) GA | Error reduced upto 1.33% by the integration of GA with ANN. |
| 20 | Approach to optimization of cutting conditions by using ANN. | FranciCus and UrosZuper (2006) | CNC lathe machine | a) feed rate<br>b) cutting speed<br>c) tool life<br>d) cost of production<br>e) depth of cut<br>f) time of production | ANN | It gives the idea about where use of ANN is economically beneficial for us. |
| 21 | Predictive modelling of surface roughness and tool wear in hard turning using regression and neural networks. | Ozel and Karpat (2005) | CNC lathe machine | a) cutting force<br>b) cutting speed<br>c) feed rate<br>d) depth of cut<br>e)cutting tool | a) ANN<br>b) Regression model | Average rms error was found 5.4 for prediction of roughness while 2.1 rmserror was found for prediction of tool flank wear. |
| 22 | Prediction of surface roughness in CNC face milling using neural networks and Taguchi's design of experiments. | P.G. Benardos et.al. (2002) | CNC face milling machine | a) depth of cut<br>b) feed rate per tooth<br>c) cutting speed<br>d) tool wear<br>e) cutting fluid | a) ANN<br>b) Taguchi's method | Mean square error upto 1.86% can be achieved in the prediction of surface roughness consistently. |

After detailed literature survey it has been observed that most of the researchers working in the field of development of predictive model for surface roughness of a machined surface. But they have mostly focused on the RSM approach, fuzzy logic, artificial neural network, ANFIS and genetic algorithm; which are the various AI techniques used for machine learning except RSM. From this survey researchers have formulated some problem and the research gap is found to be as follows

- All predicted models are black box models i.e. what processes are happening inside the process are unseen and untouchable. There are no any understanding bridge between input and output.
- Result obtained ANN based predictive model always varies as shown in table 1. They depend upon number of layers and number of nodes on intermediate layer so optimum number of layer and intermediate node is very essential for good prediction and this is obtained by trial and error method.
- A white box predictive model is much needed for reliability of predictive model and decision tree is well known white box model technique. None of researchers worked on it for prediction of surface roughness and we know that use of decision tree takes place in prediction of cancer.

## III. EXPERIMENTATION

Experiments were conducted on EMCO 250 concept MILL with help of carbide cutting tool.to study the effect of cutting parameters on surface roughness. Following picture of experimental set-up is shown below.


### 3.1. Selection of input parameters with their levels

Spindle speed, depth of cut and feed rate is taken as the input parameters for the machining process with three levels which are given in tabular form.

| **Input parameter** | **Level 1** | **Level 2** | **Level 3** |
|---|---|---|---|
| Spindle speed (rpm) | 1400 | 1600 | 1800 |
| Feed rate (mm/min) | 560 | 640 | 720 |
| Depth of cut(mm) | 0.5 | 0.75 | 1 |

## IV. DESIGN OF EXPERIMENT

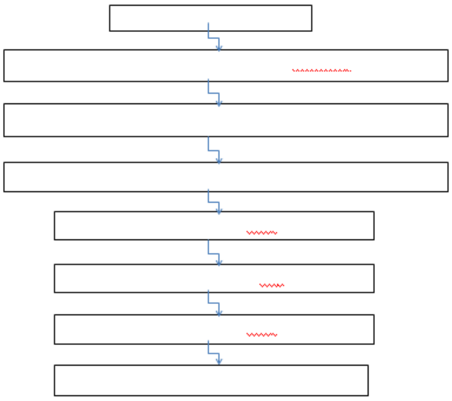
Design of experiment is carried by L27 Taguchi orthogonal array method. The surface roughness which is output of experiment is measured with the help of TESA-Rugosurf 10G surface roughness tester machine with cut off length 0.8 mm. all experimental run with output value is shown in tabular form below.

| **S. No** | **Spindle Speed (RPM)** | **Feed (mm/min)** | **Depth of cut (mm)** | **Roughness(µm)** | | |
|---|---|---|---|---|---|---|
| | | | | **Ra** | **Rq** | **RSm** |
| **i.** | 1400 | 560 | 0.5 | 1.818 | 2.199 | 64 |
| **ii.** | 1400 | 640 | 0.5 | 1.965 | 2.418 | 170 |
| **iii.** | 1400 | 720 | 0.5 | 1.74 | 2.147 | 237 |
| **iv.** | 1600 | 560 | 0.5 | 1.544 | 1.921 | 150 |
| **v.** | 1600 | 640 | 0.5 | 1.115 | 1.408 | 101 |
| **vi.** | 1600 | 720 | 0.5 | 1.562 | 2.006 | 169 |
| **vii.** | 1800 | 560 | 0.5 | 1.206 | 1.499 | 120 |
| **viii.** | 1800 | 640 | 0.5 | 1.47 | 1.84 | 218 |
| **ix.** | 1800 | 720 | 0.5 | 1.935 | 2.357 | 290 |
| **x.** | 1400 | 560 | 0.75 | 2.453 | 3.101 | 177 |
| **xi.** | 1400 | 640 | 0.75 | 1.936 | 2.277 | 453 |
| **xii.** | 1400 | 720 | 0.75 | 2.418 | 2.694 | 323 |
| **xiii.** | 1600 | 560 | 0.75 | 2.136 | 2.821 | 202 |
| **xiv.** | 1600 | 640 | 0.75 | 1.782 | 2.159 | 147 |
| **xv.** | 1600 | 720 | 0.75 | 1.943 | 2.256 | 197 |
| **xvi.** | 1800 | 560 | 0.75 | 1.487 | 1.758 | 187 |
| **xvii.** | 1800 | 640 | 0.75 | 1.653 | 2.167 | 183 |
| **xviii.** | 1800 | 720 | 0.75 | 1.196 | 1.455 | 114 |
| **xix.** | 1400 | 560 | 1 | 0.835 | 1.047 | 72 |
| **xx.** | 1400 | 640 | 1 | 1.71 | 2.049 | 151 |
| **xxi.** | 1400 | 720 | 1 | 2.095 | 2.425 | 294 |
| **xxii.** | 1600 | 560 | 1 | 2.081 | 2.499 | 233 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **xxiii.** | 1600 | 640 | 1 | 1.119 | 1.38 | 84 |
| **xxiv.** | 1600 | 720 | 1 | 1.798 | 1.998 | 307 |
| **xxv.** | 1800 | 560 | 1 | 1.093 | 1.395 | 143 |
| **xxvi.** | 1800 | 640 | 1 | 2.921 | 3.505 | 300 |
| **xxvii.** | 1800 | 720 | 1 | 2.054 | 2.379 | 193 |

## V. RESULTS OBTAINED THROUGH ANN

Here we are going to explain the implementation technique adopted for development of ANN based predictive model. We manually write the script for neural network. We develop separate neural network for $R_{a,}$ $R_q$and $RS_m$using Command line functions. Flow chart of implementation of neural network is also given below.



➢ **key points of our neural network**:

- We take 2000 loops of network to create best network for our dataset.
- Feed forward neural network method is used.
- Tan-sigmoid transfer function is used in each hidden layer of network.
- Linear transfer function is used in output layer.
- Levenberg-Marquardt algorithm is used for the training of network.
- We take 80% data for training, 10% for validating and 10% for testing of network.After selection of network we have to predict the value of input variable. For retrieval of output variable following script is written manually.

### 5.1 Analysis of result obtained by ANN

In this section we analyze the model by evaluating mean square error to decide accuracy of ANN based predictive model. Predicted result from ANN is compared to experimental result. We analyze the result separately for Ra, Rq and RSm in tabular form. These comparisons are given below.

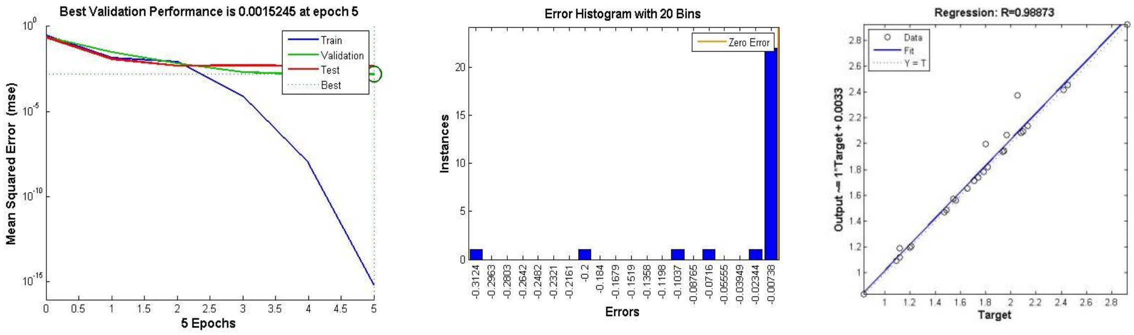
#### 5.1.1 Analysis of predicted value of Ra by ANN.

- Mean error percentage of sample in predictive Ra model obtained **is 0.91769%.**
- Mean accuracy percentage of sample in predictive Ra model obtained is **99.08231%.**
- Performance i.e. means square error of predictive Ra model obtained is **6.862986e-04.**
- Accuracy of predictive model is **99.93%.**
- Number of hidden layer in this neural network is **15.**

| s.no | Spindle Speed(rpm) | Feed (mm/min) | D.O.C (mm) | Measured Ra(μm) | Predicted Ra (μm) | Error% | Accuracy% |
|---|---|---|---|---|---|---|---|
| 1 | 1400 | 560 | 0.5 | 1.818 | 1.818 | 2.6302e-07 | 100 |
| 2 | 1400 | 640 | 0.5 | 1.965 | 2.0671 | 3.4969 | 96.503 |
| 3 | 1400 | 720 | 0.5 | 1.74 | 1.74 | 9.2389e-08 | 100 |
| 4 | 1600 | 560 | 0.5 | 1.544 | 1.5716 | 0.94645 | 99.054 |
| 5 | 1600 | 640 | 0.5 | 1.115 | 1.1923 | 2.6462 | 97.354 |
| 6 | 1600 | 720 | 0.5 | 1.562 | 1.562 | 4.3094e-07 | 100 |
| 7 | 1800 | 560 | 0.5 | 1.206 | 1.206 | 8.3672e-07 | 100 |
| 8 | 1800 | 640 | 0.5 | 1.47 | 1.47 | 4.5179e-07 | 100 |
| 9 | 1800 | 720 | 0.5 | 1.935 | 1.935 | 1.6976e-06 | 100 |
| 10 | 1400 | 560 | 0.75 | 2.453 | 2.453 | 2.9227e-06 | 100 |
| 11 | 1400 | 640 | 0.75 | 1.936 | 1.936 | 2.1046e-07 | 100 |
| 12 | 1400 | 720 | 0.75 | 2.418 | 2.418 | 4.5804e-07 | 100 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 13 | 1600 | 560 | 0.75 | 2.136 | 2.1354 | 0.02198 | 99.978 |
| 14 | 1600 | 640 | 0.75 | 1.782 | 1.782 | 7.294e-07 | 100 |
| 15 | 1600 | 720 | 0.75 | 1.943 | 1.943 | 6.9481e-07 | 100 |
| 16 | 1800 | 560 | 0.75 | 1.487 | 1.487 | 1.7576e-06 | 100 |
| 17 | 1800 | 640 | 0.75 | 1.653 | 1.653 | 2.6116e-06 | 100 |
| 18 | 1800 | 720 | 0.75 | 1.196 | 1.196 | 1.1339e-06 | 100 |
| 19 | 1400 | 560 | 1 | 0.835 | 0.835 | 2.3066e-06 | 100 |
| 20 | 1400 | 640 | 1 | 1.71 | 1.71 | 7.2951e-06 | 100 |
| 21 | 1400 | 720 | 1 | 2.095 | 2.095 | 5.5678e-06 | 100 |
| 22 | 1600 | 560 | 1 | 2.081 | 2.081 | 1.8234e-06 | 100 |
| 23 | 1600 | 640 | 1 | 1.119 | 1.119 | 3.2064e-06 | 100 |
| 24 | 1600 | 720 | 1 | 1.798 | 1.9936 | 6.6961 | 93.304 |
| 25 | 1800 | 560 | 1 | 1.093 | 1.093 | 2.2626e-06 | 100 |
| 26 | 1800 | 640 | 1 | 2.921 | 2.921 | 3.2381e-07 | 100 |
| 27 | 1800 | 720 | 1 | 2.054 | 2.3744 | 10.97 | 89.03 |

➢ **Performance, error histogram and regression plot of neural network for Ra.**

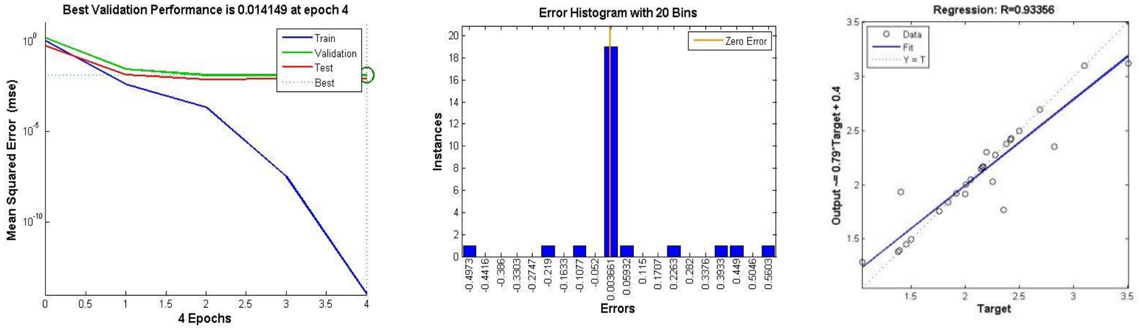



### 5.1.2 Analysis of predicted value of Rq by ANN.

- Mean error percentage of sample in predictive Rq model obtained is **2.7717%.**
- Mean accuracy percentage of sample in predictive Rq model obtained is **97.23%.**
- Performance i.e. means square error of predictive Rq model obtained is**3.368465e-03.**
- Accuracy of predictive model is **99.66%.**
- Number of hidden layer in this neural network is **17.**

| s.no | Spindle Speed(rpm) | Feed (mm/min) | D.O.C (mm) | Measured Rq(μm) | Predicted Rq (μm) | Error% | Accuracy% |
|---|---|---|---|---|---|---|---|
| **1** | 1400 | 560 | 0.5 | 2.199 | 2.2994 | 2.8646 | 97.135 |
| **2** | 1400 | 640 | 0.5 | 2.418 | 2.418 | 7.001e-06 | 100 |
| **3** | 1400 | 720 | 0.5 | 2.147 | 2.147 | 4.3371e-06 | 100 |
| **4** | 1600 | 560 | 0.5 | 1.921 | 1.921 | 3.1275e-05 | 100 |
| **5** | 1600 | 640 | 0.5 | 1.408 | 1.9331 | 14.983 | 85.017 |
| **6** | 1600 | 720 | 0.5 | 2.006 | 2.006 | 1.1186e-07 | 100 |
| **7** | 1800 | 560 | 0.5 | 1.499 | 1.499 | 7.208e-06 | 100 |
| **8** | 1800 | 640 | 0.5 | 1.84 | 1.84 | 1.8223e-06 | 100 |
| **9** | 1800 | 720 | 0.5 | 2.357 | 1.7689 | 16.78 | 83.22 |
| **10** | 1400 | 560 | 0.75 | 3.101 | 3.101 | 2.1257e-06 | 100 |
| **11** | 1400 | 640 | 0.75 | 2.277 | 2.277 | 2.1732e-05 | 100 |
| **12** | 1400 | 720 | 0.75 | 2.694 | 2.694 | 1.7048e-06 | 100 |
| **13** | 1600 | 560 | 0.75 | 2.821 | 2.3552 | 13.291 | 86.709 |
| **14** | 1600 | 640 | 0.75 | 2.159 | 2.159 | 6.2561e-06 | 100 |
| **15** | 1600 | 720 | 0.75 | 2.256 | 2.028 | 6.5044 | 93.496 |
| **16** | 1800 | 560 | 0.75 | 1.758 | 1.758 | 3.6405e-06 | 100 |
| **17** | 1800 | 640 | 0.75 | 2.167 | 2.167 | 8.5419e-06 | 100 |
| **18** | 1800 | 720 | 0.75 | 1.455 | 1.455 | 8.623e-07 | 100 |
| **19** | 1400 | 560 | 1 | 1.047 | 1.2895 | 6.9197 | 93.08 |
| **20** | 1400 | 640 | 1 | 2.049 | 2.049 | 6.0755e-07 | 100 |
| **21** | 1400 | 720 | 1 | 2.425 | 2.425 | 5.4954e-07 | 100 |
| **22** | 1600 | 560 | 1 | 2.499 | 2.499 | 5.894e-06 | 100 |
| **23** | 1600 | 640 | 1 | 1.38 | 1.38 | 3.8951e-06 | 100 |
| **24** | 1600 | 720 | 1 | 1.998 | 1.913 | 2.426 | 97.574 |
| **25** | 1800 | 560 | 1 | 1.395 | 1.395 | 1.2569e-05 | 100 |
| **26** | 1800 | 640 | 1 | 3.505 | 3.117 | 11.069 | 88.931 |
| **27** | 1800 | 720 | 1 | 2.379 | 2.379 | 5.2843e-07 | 100 |

➢ **Performance, error histogram and regression plot of neural network for Rq.**

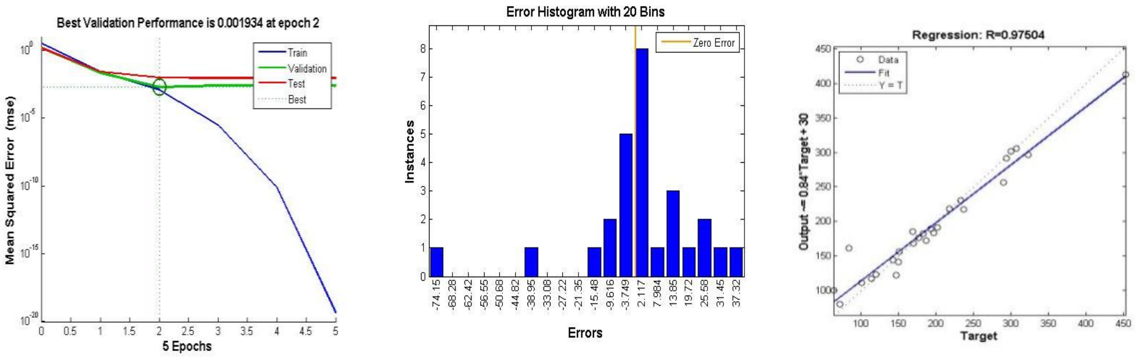



### 5.1.3 Analysis of predicted value of RSm by ANN.

- Mean error percentage of sample in predictive RSm model obtained is **3.02909%.**
- Mean accuracy percentage of sample in predictive RSm model obtained is **96.971%.**
- Performance i.e. means square error of predictive RSm model obtained **2.320221e-03.**
- Accuracy of predictive model is **99.76%.**
- Number of hidden layer in this neural network is **19.**

| s.no | Spindle Speed(rpm) | Feed (mm/min) | D.O.C (mm) | Measured RSm(µm) | Predicted RSm (µm) | Error% | Accuracy% |
|---|---|---|---|---|---|---|---|
| **1** | 1400 | 560 | 0.5 | 64 | 100.31 | 8.0157 | 91.984 |
| **2** | 1400 | 640 | 0.5 | 170 | 168.01 | 0.43944 | 99.561 |
| **3** | 1400 | 720 | 0.5 | 237 | 217.78 | 4.2424 | 95.758 |
| **4** | 1600 | 560 | 0.5 | 150 | 141.47 | 1.8824 | 98.118 |
| **5** | 1600 | 640 | 0.5 | 101 | 110.82 | 2.1671 | 97.833 |
| **6** | 1600 | 720 | 0.5 | 169 | 185.26 | 3.5903 | 96.41 |
| **7** | 1800 | 560 | 0.5 | 120 | 123.28 | 0.72508 | 99.275 |
| **8** | 1800 | 640 | 0.5 | 218 | 218.15 | 0.034 | 99.966 |
| **9** | 1800 | 720 | 0.5 | 290 | 256.16 | 7.4701 | 92.53 |
| **10** | 1400 | 560 | 0.75 | 177 | 176.21 | 0.17462 | 99.825 |
| **11** | 1400 | 640 | 0.75 | 453 | 412.75 | 8.8853 | 91.115 |
| **12** | 1400 | 720 | 0.75 | 323 | 296.48 | 5.8546 | 94.145 |
| **13** | 1600 | 560 | 0.75 | 202 | 190.84 | 2.4631 | 97.537 |
| **14** | 1600 | 640 | 0.75 | 147 | 121.81 | 5.5613 | 94.439 |
| **15** | 1600 | 720 | 0.75 | 197 | 183.01 | 3.0884 | 96.912 |
| **16** | 1800 | 560 | 0.75 | 187 | 172.63 | 3.1713 | 96.829 |
| **17** | 1800 | 640 | 0.75 | 183 | 182.06 | 0.20839 | 99.792 |
| **18** | 1800 | 720 | 0.75 | 114 | 116.68 | 0.59086 | 99.409 |
| **19** | 1400 | 560 | 1 | 72 | 80.364 | 1.8464 | 98.154 |
| **20** | 1400 | 640 | 1 | 151 | 156.53 | 1.221 | 98.779 |
| **21** | 1400 | 720 | 1 | 294 | 291.47 | 0.55756 | 99.442 |
| **22** | 1600 | 560 | 1 | 233 | 229.95 | 0.67417 | 99.326 |
| **23** | 1600 | 640 | 1 | 84 | 161.08 | 17.016 | 82.984 |
| **24** | 1600 | 720 | 1 | 307 | 305.36 | 0.36124 | 99.639 |
| **25** | 1800 | 560 | 1 | 143 | 144.1 | 0.2425 | 99.757 |
| **26** | 1800 | 640 | 1 | 300 | 302.04 | 0.44926 | 99.551 |
| **27** | 1800 | 720 | 1 | 193 | 189.14 | 0.85298 | 99.147 |

➢ **Performance, error histogram and regression plot of neural network for Rsm.**



## VI. RESULTS OBTAINED THROUGH DT

Here we are going to explain the implementation technique adopted for development of DT based predictive model. We use CART algorithm for development of predictive model. Regression model as well as classification model is generated with the help of CART algorithm. Manual script is written for development of both the models.

In **classification tree** we classify the decision (output) in 'YES' or 'NO'. Which output is desirable we put them in YES & we put undesirable output in NO. Three classification trees are generated for Ra, Rq and RSm separately.

In **regression tree** decision or output is a numeric value. In this model we have to interpret that this output value has relevance or not for our work. Three regression trees is generated for Ra, Rq and RSm separately.

➢ **key points of our Decision tree**:

- Mean square error is taken as performance measure of decision tree.
- Accuracy of decision tree depends upon accuracy of classification of data in decision tree.

We perform Normalisation and de-normalisation technique for development of RSm regression decision tree. These techniques are known as pre-processing and post-processing. These techniques are used for increasing accuracy of model.

### 6.1 Analysis of Result Obtained By DT

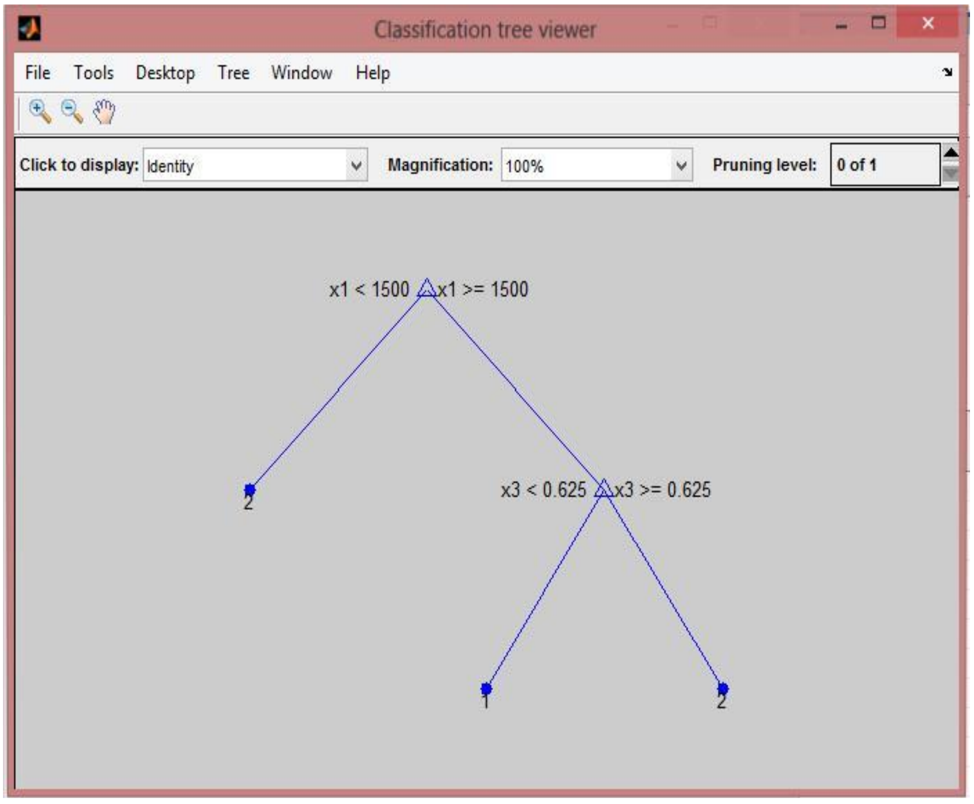
In this section we analyze the model (Classification model and Regression model) by evaluating mean square error to decide accuracy of DT based predictive model. Predicted result from DT is compared to experimental result. We analyze the result separately for Ra, Rq and RSm obtained by classification and regression model in tabular form. These comparisons are given below.

#### 6.1.1 Analysis of predicted value of Ra by classification DT.

- Mean square error of model is **0.2222.**
- Percentage accuracy of model is **77.7778%.**
- In classification table threshold value is taken as 1.6 microns. Smaller than and equal to 1.6 microns is classified as 1 otherwise classified as 2.

| s.no | Spindle Speed(rpm) | Feed (mm/min) | D.O.C (mm) | Measured Ra classification | Predicted Ra classification |
|---|---|---|---|---|---|
| **1** | 1400 | 560 | 0.5 | 2 | 2 |
| **2** | 1400 | 640 | 0.5 | 2 | 2 |
| **3** | 1400 | 720 | 0.5 | 2 | 2 |
| **4** | 1600 | 560 | 0.5 | 1 | 1 |
| **5** | 1600 | 640 | 0.5 | 1 | 1 |
| **6** | 1600 | 720 | 0.5 | 1 | 1 |
| **7** | 1800 | 560 | 0.5 | 1 | 1 |
| **8** | 1800 | 640 | 0.5 | 1 | 1 |
| **9** | 1800 | 720 | 0.5 | 2 | 1 |
| **10** | 1400 | 560 | 0.75 | 2 | 2 |
| **11** | 1400 | 640 | 0.75 | 2 | 2 |
| **12** | 1400 | 720 | 0.75 | 2 | 2 |
| **13** | 1600 | 560 | 0.75 | 2 | 2 |
| **14** | 1600 | 640 | 0.75 | 2 | 2 |
| **15** | 1600 | 720 | 0.75 | 2 | 2 |
| **16** | 1800 | 560 | 0.75 | 1 | 2 |
| **17** | 1800 | 640 | 0.75 | 2 | 2 |
| **18** | 1800 | 720 | 0.75 | 1 | 2 |
| **19** | 1400 | 560 | 1 | 1 | 2 |
| **20** | 1400 | 640 | 1 | 2 | 2 |
| **21** | 1400 | 720 | 1 | 2 | 2 |
| **22** | 1600 | 560 | 1 | 2 | 2 |
| **23** | 1600 | 640 | 1 | 1 | 2 |
| **24** | 1600 | 720 | 1 | 2 | 2 |
| **25** | 1800 | 560 | 1 | 1 | 2 |
| **26** | 1800 | 640 | 1 | 2 | 2 |
| **27** | 1800 | 720 | 1 | 2 | 2 |

➤ **Classification decision tree for Ra.**

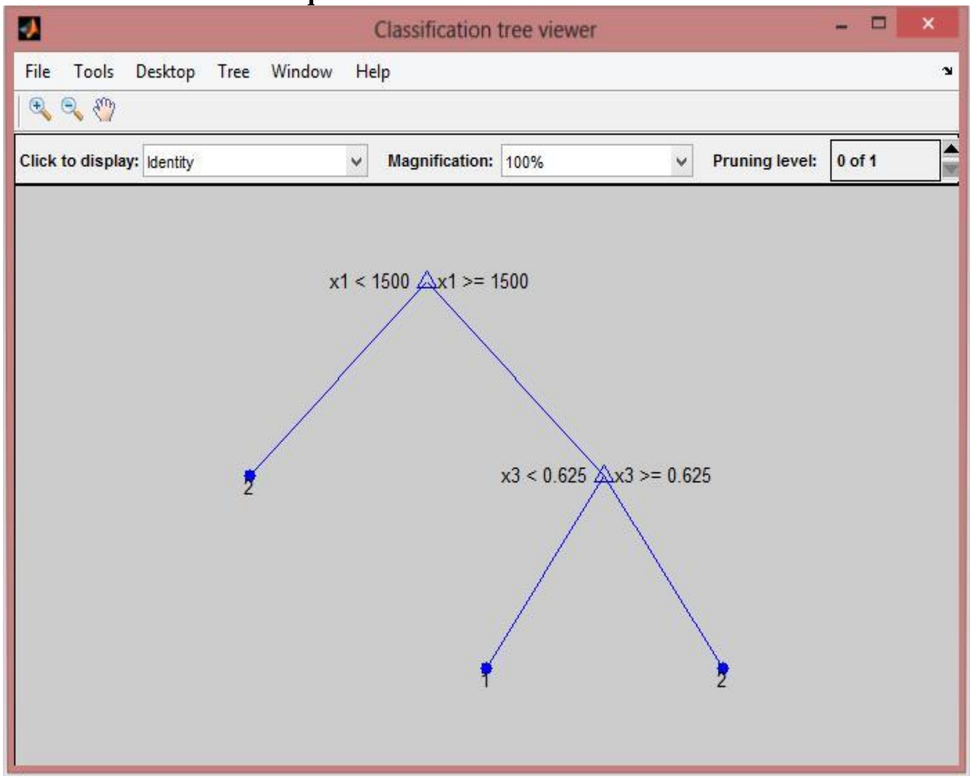



### 6.1.2 Analysis of predicted value of Rq by classification DT.

- Mean square error of model is **0.2963.**
- Percentage accuracy of model is **70.3704%.**
- In classification table threshold value is taken as 2.109 microns. Smaller than and equal to 2.109 microns is classified as 1 otherwise classified as 2.

| s.no | Spindle Speed(rpm) | Feed (mm/min) | D.O.C (mm) | Measured Rq classification | Predicted Rq classification |
|---|---|---|---|---|---|
| **1** | 1400 | 560 | 0.5 | 2 | 2 |
| **2** | 1400 | 640 | 0.5 | 2 | 2 |
| **3** | 1400 | 720 | 0.5 | 2 | 2 |
| **4** | 1600 | 560 | 0.5 | 1 | 1 |
| **5** | 1600 | 640 | 0.5 | 1 | 1 |
| **6** | 1600 | 720 | 0.5 | 1 | 1 |
| **7** | 1800 | 560 | 0.5 | 1 | 1 |
| **8** | 1800 | 640 | 0.5 | 1 | 1 |
| **9** | 1800 | 720 | 0.5 | 2 | 1 |
| **10** | 1400 | 560 | 0.75 | 2 | 2 |
| **11** | 1400 | 640 | 0.75 | 2 | 2 |
| **12** | 1400 | 720 | 0.75 | 2 | 2 |
| **13** | 1600 | 560 | 0.75 | 2 | 2 |
| **14** | 1600 | 640 | 0.75 | 2 | 2 |
| **15** | 1600 | 720 | 0.75 | 2 | 2 |
| **16** | 1800 | 560 | 0.75 | 1 | 2 |
| **17** | 1800 | 640 | 0.75 | 2 | 2 |
| **18** | 1800 | 720 | 0.75 | 1 | 2 |
| **19** | 1400 | 560 | 1 | 1 | 2 |
| **20** | 1400 | 640 | 1 | 1 | 2 |
| **21** | 1400 | 720 | 1 | 2 | 2 |
| **22** | 1600 | 560 | 1 | 2 | 2 |
| **23** | 1600 | 640 | 1 | 1 | 2 |
| **24** | 1600 | 720 | 1 | 1 | 2 |
| **25** | 1800 | 560 | 1 | 1 | 2 |
| **26** | 1800 | 640 | 1 | 2 | 2 |
| **27** | 1800 | 720 | 1 | 2 | 2 |

➢ **Classification decision tree for Rq.**

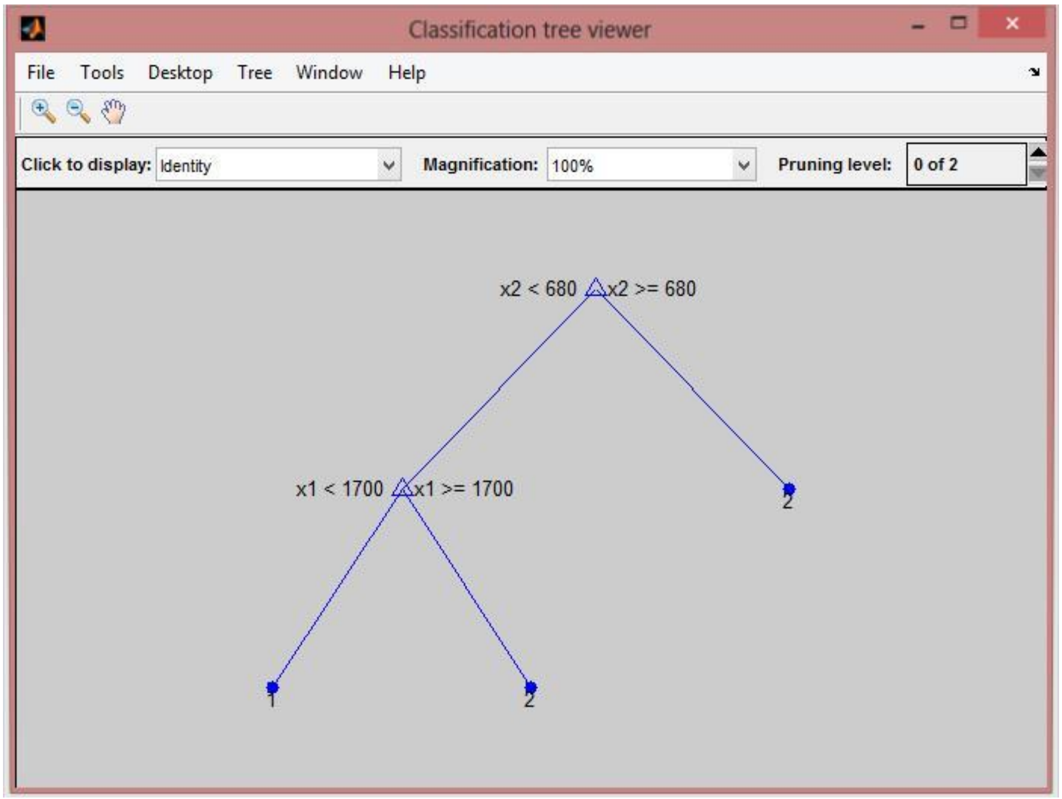



### 6.1.3 Analysis of predicted value of RSm by classification DT.

- Mean square error of model is **0.2593.**
- Percentage accuracy of model is **74.0741%.**
- In classification table threshold value is taken as 183 microns. Smaller than and equal to 183 microns is classified as 1otherwiseclassified as 2.

| s.no | Spindle Speed(rpm) | Feed (mm/min) | D.O.C (mm) | Measured RSm classification | Predicted RSm classification |
|---|---|---|---|---|---|
| **1** | 1400 | 560 | 0.5 | 1 | 1 |
| **2** | 1400 | 640 | 0.5 | 1 | 1 |
| **3** | 1400 | 720 | 0.5 | 2 | 2 |
| **4** | 1600 | 560 | 0.5 | 1 | 1 |
| **5** | 1600 | 640 | 0.5 | 1 | 1 |
| **6** | 1600 | 720 | 0.5 | 1 | 2 |
| **7** | 1800 | 560 | 0.5 | 1 | 2 |
| **8** | 1800 | 640 | 0.5 | 2 | 2 |
| **9** | 1800 | 720 | 0.5 | 2 | 2 |
| **10** | 1400 | 560 | 0.75 | 1 | 1 |
| **11** | 1400 | 640 | 0.75 | 2 | 1 |
| **12** | 1400 | 720 | 0.75 | 2 | 2 |
| **13** | 1600 | 560 | 0.75 | 2 | 1 |
| **14** | 1600 | 640 | 0.75 | 1 | 1 |
| **15** | 1600 | 720 | 0.75 | 2 | 2 |
| **16** | 1800 | 560 | 0.75 | 2 | 2 |
| **17** | 1800 | 640 | 0.75 | 2 | 2 |
| **18** | 1800 | 720 | 0.75 | 1 | 2 |
| **19** | 1400 | 560 | 1 | 1 | 1 |
| **20** | 1400 | 640 | 1 | 1 | 1 |
| **21** | 1400 | 720 | 1 | 2 | 2 |
| **22** | 1600 | 560 | 1 | 2 | 1 |
| **23** | 1600 | 640 | 1 | 1 | 1 |
| **24** | 1600 | 720 | 1 | 2 | 2 |
| **25** | 1800 | 560 | 1 | 1 | 2 |
| **26** | 1800 | 640 | 1 | 2 | 2 |
| **27** | 1800 | 720 | 1 | 2 | 2 |

➢ **Classification decision tree for RSm.**

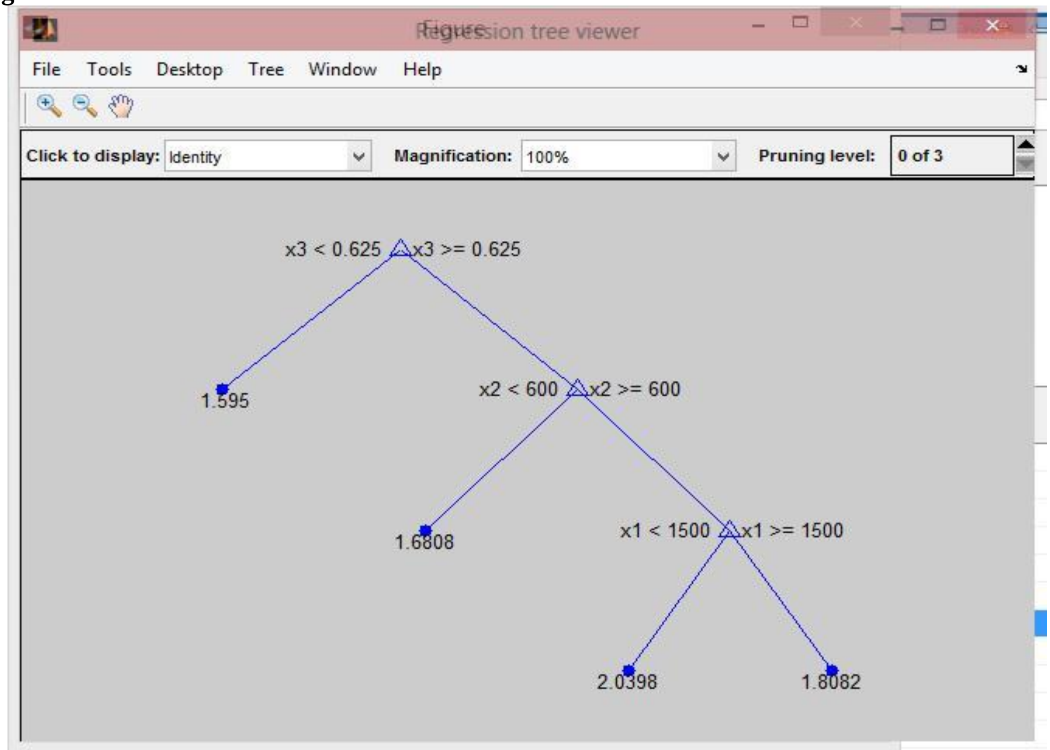



### 6.1.4 Analysis of predicted value of Ra by regression DT.

- Mean square error of model is **0.1942.**
- Percentage accuracy of model is **80.5793%.**
- Regression decision tree gives only four decisions which is**1.5950, 1.6808, 1.8082** and **2.0398.**

| s.no | Spindle Speed(rpm) | Feed (mm/min) | D.O.C (mm) | Measured Ra (microns) | Predicted Ra (microns) |
|---|---|---|---|---|---|
| **1** | 1400 | 560 | 0.5 | 1.818 | 1.5950 |
| **2** | 1400 | 640 | 0.5 | 1.965 | 1.5950 |
| **3** | 1400 | 720 | 0.5 | 1.74 | 1.5950 |
| **4** | 1600 | 560 | 0.5 | 1.544 | 1.5950 |
| **5** | 1600 | 640 | 0.5 | 1.115 | 1.5950 |
| **6** | 1600 | 720 | 0.5 | 1.562 | 1.5950 |
| **7** | 1800 | 560 | 0.5 | 1.206 | 1.5950 |
| **8** | 1800 | 640 | 0.5 | 1.47 | 1.5950 |
| **9** | 1800 | 720 | 0.5 | 1.935 | 1.5950 |
| **10** | 1400 | 560 | 0.75 | 2.453 | 1.6808 |
| **11** | 1400 | 640 | 0.75 | 1.936 | 2.0398 |
| **12** | 1400 | 720 | 0.75 | 2.418 | 2.0398 |
| **13** | 1600 | 560 | 0.75 | 2.136 | 1.6808 |
| **14** | 1600 | 640 | 0.75 | 1.782 | 1.8082 |
| **15** | 1600 | 720 | 0.75 | 1.943 | 1.8082 |
| **16** | 1800 | 560 | 0.75 | 1.487 | 1.6808 |
| **17** | 1800 | 640 | 0.75 | 1.653 | 1.8082 |
| **18** | 1800 | 720 | 0.75 | 1.196 | 1.8082 |
| **19** | 1400 | 560 | 1 | 0.835 | 1.6808 |
| **20** | 1400 | 640 | 1 | 1.71 | 2.0398 |
| **21** | 1400 | 720 | 1 | 2.095 | 2.0398 |
| **22** | 1600 | 560 | 1 | 2.081 | 1.6808 |
| **23** | 1600 | 640 | 1 | 1.119 | 1.8082 |
| **24** | 1600 | 720 | 1 | 1.798 | 1.8082 |
| **25** | 1800 | 560 | 1 | 1.093 | 1.6808 |
| **26** | 1800 | 640 | 1 | 2.921 | 1.8082 |
| **27** | 1800 | 720 | 1 | 2.054 | 1.8082 |

➢ **Regression decision tree for Ra.**

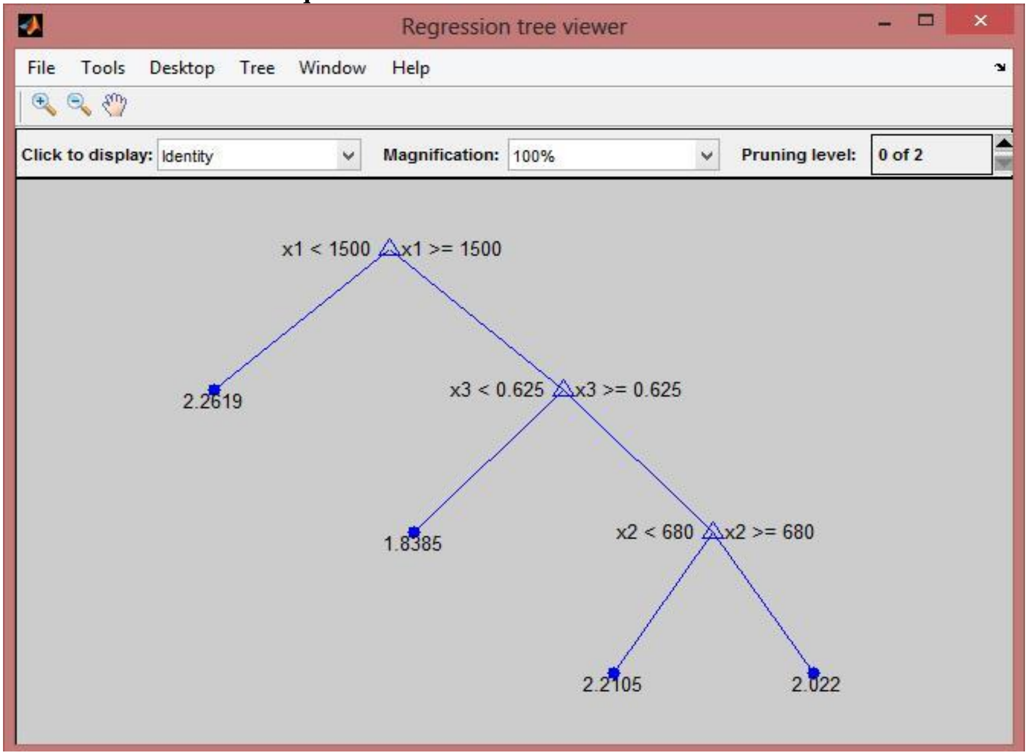



### 6.1.5 Analysis of predicted value of Rq by regression DT.

- Mean square error of model is **0.2698.**
- Percentage accuracy of model is **73.0194%.**
- Regression decision tree gives only four decisions which are**1.8385, 2.022, 2.2105**and **2.2619.**

| s.no | Spindle Speed (rpm) | Feed (mm/min) | D.O.C (mm) | Measured Rq (microns) | Predicted Rq (microns) |
|---|---|---|---|---|---|
| **1** | 1400 | 560 | 0.5 | 2.199 | 2.2619 |
| **2** | 1400 | 640 | 0.5 | 2.418 | 2.2619 |
| **3** | 1400 | 720 | 0.5 | 2.147 | 2.2619 |
| **4** | 1600 | 560 | 0.5 | 1.921 | 1.8385 |
| **5** | 1600 | 640 | 0.5 | 1.408 | 1.8385 |
| **6** | 1600 | 720 | 0.5 | 2.006 | 1.8385 |
| **7** | 1800 | 560 | 0.5 | 1.499 | 1.8385 |
| **8** | 1800 | 640 | 0.5 | 1.84 | 1.8385 |
| **9** | 1800 | 720 | 0.5 | 2.357 | 1.8385 |
| **10** | 1400 | 560 | 0.75 | 3.101 | 2.2619 |
| **11** | 1400 | 640 | 0.75 | 2.277 | 2.2619 |
| **12** | 1400 | 720 | 0.75 | 2.694 | 2.2619 |
| **13** | 1600 | 560 | 0.75 | 2.821 | 2.2105 |
| **14** | 1600 | 640 | 0.75 | 2.159 | 2.2105 |
| **15** | 1600 | 720 | 0.75 | 2.256 | 2.0220 |
| **16** | 1800 | 560 | 0.75 | 1.758 | 2.2105 |
| **17** | 1800 | 640 | 0.75 | 2.167 | 2.2105 |
| **18** | 1800 | 720 | 0.75 | 1.455 | 2.0220 |
| **19** | 1400 | 560 | 1 | 1.047 | 2.2619 |
| **20** | 1400 | 640 | 1 | 2.049 | 2.2619 |
| **21** | 1400 | 720 | 1 | 2.425 | 2.2619 |
| **22** | 1600 | 560 | 1 | 2.499 | 2.2105 |
| **23** | 1600 | 640 | 1 | 1.38 | 2.2105 |
| **24** | 1600 | 720 | 1 | 1.998 | 2.0220 |
| **25** | 1800 | 560 | 1 | 1.395 | 2.2105 |
| **26** | 1800 | 640 | 1 | 3.505 | 2.2105 |
| **27** | 1800 | 720 | 1 | 2.379 | 2.0220 |

➢ **Regression decision tree for Rq.**

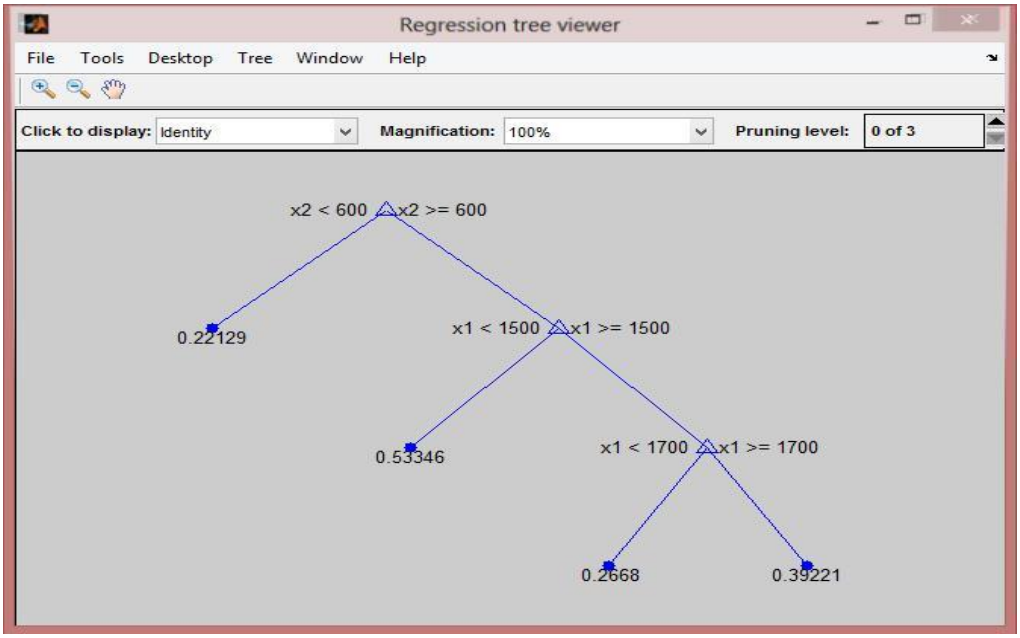



**7.1.6 Analysis of predicted value of RSm by regression DT.**

- Mean square error of model is **0.0354.**
- Percentage accuracy of model is **96.4596%.**
- Regression decision tree gives only four decisions which are **149.7778, 167.5000, 216.3333** and**271.3333.**
- In this decision tree; value at tree nodes denotes normalised value.

| s.no | Spindle Speed(rpm) | Feed (mm/min) | D.O.C (mm) | Measured RSm (microns) | Predicted RSm (microns) |
|---|---|---|---|---|---|
| **1** | 1400 | 560 | 0.5 | 64 | 149.7778 |
| **2** | 1400 | 640 | 0.5 | 170 | 271.3333 |
| **3** | 1400 | 720 | 0.5 | 237 | 271.3333 |
| **4** | 1600 | 560 | 0.5 | 150 | 149.7778 |
| **5** | 1600 | 640 | 0.5 | 101 | 167.5000 |
| **6** | 1600 | 720 | 0.5 | 169 | 167.5000 |
| **7** | 1800 | 560 | 0.5 | 120 | 149.7778 |
| **8** | 1800 | 640 | 0.5 | 218 | 216.3333 |
| **9** | 1800 | 720 | 0.5 | 290 | 216.3333 |
| **10** | 1400 | 560 | 0.75 | 177 | 149.7778 |
| **11** | 1400 | 640 | 0.75 | 453 | 271.3333 |
| **12** | 1400 | 720 | 0.75 | 323 | 271.3333 |
| **13** | 1600 | 560 | 0.75 | 202 | 149.7778 |
| **14** | 1600 | 640 | 0.75 | 147 | 167.5000 |
| **15** | 1600 | 720 | 0.75 | 197 | 167.5000 |
| **16** | 1800 | 560 | 0.75 | 187 | 149.7778 |
| **17** | 1800 | 640 | 0.75 | 183 | 216.3333 |
| **18** | 1800 | 720 | 0.75 | 114 | 216.3333 |
| **19** | 1400 | 560 | 1 | 72 | 149.7778 |
| **20** | 1400 | 640 | 1 | 151 | 271.3333 |
| **21** | 1400 | 720 | 1 | 294 | 271.3333 |
| **22** | 1600 | 560 | 1 | 233 | 149.7778 |
| **23** | 1600 | 640 | 1 | 84 | 167.5000 |
| **24** | 1600 | 720 | 1 | 307 | 167.5000 |
| **25** | 1800 | 560 | 1 | 143 | 149.7778 |
| **26** | 1800 | 640 | 1 | 300 | 216.3333 |
| **27** | 1800 | 720 | 1 | 193 | 216.3333 |

- **Regression decision tree for RSm.**




### 6.2 Comparison Of Results

A glimpse of the model accuracy of all developed predictive model is concluded below in form of tabular form.

**Table:** Comparative study on model accuracy of various techniques.

| Roughness / Model | **Ra** | **Rq** | **RSm** |
|---|---|---|---|
| **ANN** | 99.93% | 99.96% | 99.76% |
| **Classification DT** | 77.78% | 70.34% | 74.07% |
| **Regression DT** | 80.58% | 73.02% | 96.46% |

## VII. CONCLUSION AND SCOPE FOR FUTURE WORK

Overall the research study reveals that the predictive model based on different machine learning techniques pursue different mean square error for the same sets of data. This study concludes that the results obtained through ANN based predictive model is much better than results obtained through DT based predictive model for given sets of data. Even in DT based predictive model; regression tree gives more reliable result than classification tree for same set of data. There are some important facts observed during this research work which is given below.

**A)** ANN based model gives the best predicted values. This shows that ANN is a very powerful tool for prediction even for small samples of data.

**B)** DT based predictive model gives little bit less accuracy than ANN. This held because of size of data set. Accuracy of DT based upon size of sample data set; if size of data set is large we get better accuracy. For most of the cases DT gives best result for large size of data sets but we have only 27 data sets. Due to this reason we get less accuracy through DT based model than ANN.

**C)** It has been proved that DT requires large size of data to get more accurate result. There is a very large application of DT in field of development for predictive model like in Medical field, Electrical field due to its characteristics of being white box model. There are ample sets of sample data available in those fields where as in Mechanical field size of sample set is constrained by economy and time. What is held in prediction of output is comprehensible that's why it is known as white box model and due to this characteristics use of DT is preferred over other methods.

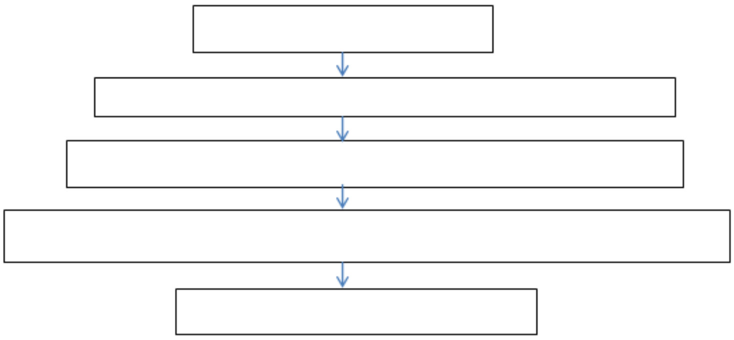
**D)** In some observations, the output of predictive model based on DT is very close to output of predictive model based on ANN.

**E)** Accuracy of ANN doesn't depend upon size and type of sample data set.

**F)** If there is need of predefined value of surface roughness then in that case we have to use both the techniques i.e. DT and ANN for quick and most reliable prediction of input parameters. At first predefined value is put in classification tree and after that we get input parameters. Further these input parameters are verified through ANN for predefined value of roughness. In such cases use of only ANN takes a lot of time as it goes though hit and trial process for selection of input parameters.

- **Strategy to use ANN and DT as predictive model**

A methodology is concluded from our research work to how to use ANN and DT for development of predictive model; which is given below in the form of flow chart:



### 6.1 Scope for the Future Work

On the basis of this report some area have been identified for future work in the field of development of predictive model for manufacturing work; which are given below-

- For effective use of ANN and DT techniques in manufacturing industry; it is desirable to integrate both the techniques to obtain best result in minimum possible time. Hence there is scope to conduct research for integration. Integration can be carried out by in phases or multiple studies.
- Development of database for all the materials which are used in machining process can be done for CAPP.
- By using these two techniques another predictive models can be developed considering other parameters like nose radius, tool wear, machining tolerance etc.
- Different work-piece material can be taken for development of predictive model.

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