PREDICTION OF SURFACE ROUGHNESS USING MACHINE LEARNING & DEEP LEARNING

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ABSTRACT

The prediction of surface roughness is an important task in the field of manufacturing and engineering. Traditional methods for predicting surface roughness have relied on empirical models and experimental data, which can be time-consuming and costly. In recent years, machine learning and deep learning techniques have shown promise in predicting surface roughness with high accuracy and efficiency. The proposed model uses a combination of input features such as cutting parameters and workpiece material properties, along with the use of various machine learning algorithms, such as Non-linear, Simple Regression, polynomial Regression, Multilinear Regression to predict surface roughness

MACHINE LEARNING:

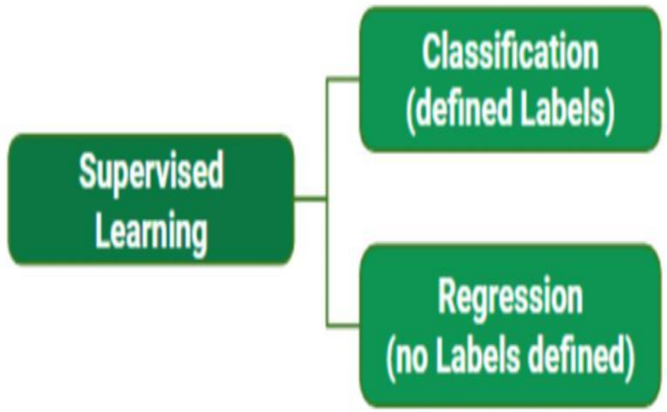
Machine learning (ML) is a type of artificial intelligence (AI) that allows software applications to become more accurate at predicting outcomes without being explicitly programmed to do so.

There are three basic approaches:

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

Supervised learning is Again of Two Types :

- 1.Classification
- 2.Regression



- classification refers to a predictive modeling problem where a class label is predicted for a given example of input data Examples are detecting spam emails.

- Regression is a technique for investigating the relationship between independent variables or features and a dependent variable or outcome. It's used as a method for predictive modelling in machine learning, in which an algorithm is used to predict continuous outcomes.

DEEP LEARNING:

Deep learning is a subset of Machine Learning and it drives many artificial intelligence(AI) applications that imitates the way humans gain certain types of knowledge. neural networks have one or more layers of processing elements. The arrangement of neurons in each layer is entirely dependent on the user, hence they have the ability to represent a large range of output and input patterns.

DEEP LEARNING METHODS:

1. Learning rate decay
2. Transfer learning
3. Training from scratch
4. Dropout

LITERATURE REVIEW

The terms surface finish and surface roughness are used very widely in industry and are generally used to quantify the smoothness of a surface finish. In machining of parts, surface quality is one of the most specified customer requirements where major indication of surface quality on machined parts is surface roughness. It is one of the most important measures in finish cutting (turning, milling, drilling, etc.) operations.Roughness average **(**Ra) is universally recognized and the most used international parameter of roughness.

A considerable amount of studies has investigated the general effects of the speed, feed, depth of cut, nose radius and others on the surface roughness. Factors effecting roughness that major investigators studied are the Speed, feed, depth of cut. A popularly used model for estimating the surface roughness value is as follows [1] (Groover 1996, p. 634 and Boothroyd and Knight 1989, p. 166):

Ri =f2/32r 1

Where Ri = ideal arithmetic average (AA) surface roughness (in. or mm), f2= feed (in./rev or mm/rev),

and *r* = cutter nose radius (in. or mm). The above model assumed a relatively large nose radius and slow feed. For a zero nose radius and a relatively large feed, the following model is recommended (Boothroyd and Knight 1989, p. 168)

Ri =f/4(cot α+cotβ) 2

where α and β is the major and end cutting edge angle, respectively.

Shaw (1984) [3] presented a case when the feed lies between the above two. Denoting the peak-to-valley roughness by Rth, then

$$\frac{\mathbf{f}}{\mathbf{r}} = \sqrt{\frac{\mathbf{2R_{th}}}{\mathbf{r}} - \left(\frac{\mathbf{R_{th}}}{\mathbf{r}}\right)^{\mathbf{2}}} + \boldsymbol{sin\beta} + \left(\frac{\boldsymbol{R_{th}}}{\boldsymbol{r}} - \mathbf{1} + \boldsymbol{cos\beta}\right)\boldsymbol{cot\beta} \qquad 3$$

General Electric [4] developed charts to modify the estimate on Rq or the root mean square (RMS) surface roughness values in turning. In addition to feeds and tool nose radius, the chart presented a modifier rai or actual-to-ideal surface roughness ratio based on the cutting speeds and the work piece material group (ductile, cast iron or free machining). Groover (1996) [1] provided an overview of this method as shown in Equation (4).

Although a qualitative analysis of such machining variables as speed, feed and depth of cut (DOC) on the surface roughness has been widely available in the literature, few comprehensive predictive models have been developed. In this thesis, models will be developed based on metal cutting experiments of factorial designs, and it will include the feed rate, tool nose radius, spindle speed and depth of cut.

Jiao (2004) utilized a similar adaptive neural network to create a prediction model using spindle speed, feed rate, and depth of cut. While limited in scope, this study did illustrate some advantages of such a system over regression modelling of complex systems such as turning.[5] Abburi and Dixit (2006) did a similar study, comparing the use of a standard neural network system to that of a combined neural network and fuzzy-sets system. The prediction systems created in this study confirmed that the combination of fuzzy logic and neural networks is more capable and manageable than neural networks alone.

This research features the following contributions. First, it applies the factorial experimentation approach to design several rounds of experiments following the sequential experimentation strategy. The impact of each individual factor and factor interactions on surface roughness are clearly examined with a reasonably small amount of time and cost. Second, with the improved accuracy of today's machine tools and surface roughness measuring devices and the increased computing power of today's computers and software, the research is able to include more parameters simultaneously with more accurate experimental data. Third, this research is able to use the computational neural networks (CNN) in addition to the RA method in developing the empirical models for surface roughness prediction. These two methods have been recently termed data mining techniques [6] (Witten and Frank 2016). The work of Jang (2006) appears to be the only research in the literature contributed to the application of CNN in surface roughness study, but they focused on the development of a surface roughness measuring system. They did not compare the CNN results with the RA method. Also, they did not apply the fractional factorial experimentation method for design and analysis of the experiment. Therefore, although a number of factors were included in their study, they were not able to examine and identify which factors and factor interactions were important. Fourth, the research presented uses additional experimental data and a rigorous procedure to check and compare the goodness of fit of the models developed by the RA and CNN methods and that of Equation (1). Fifth, instead of grouping the work piece materials into three groups as used in GE or otherwise in many other studies, this research attempts to quantify the material based on its hardness value.

EXPERMENTATION AND RESULT

USING MACHINE LEARNING ALGORITHMS

- Importing Necessary Libraries For the consistent Data such as NumPy, Pandas, Matplotlib ,Sklearn.
- Loading ,visualization and describing the data as shown in Below Figure.

Import Necessary Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

1. Data Preparation (Loading the data & Visualizing the data)

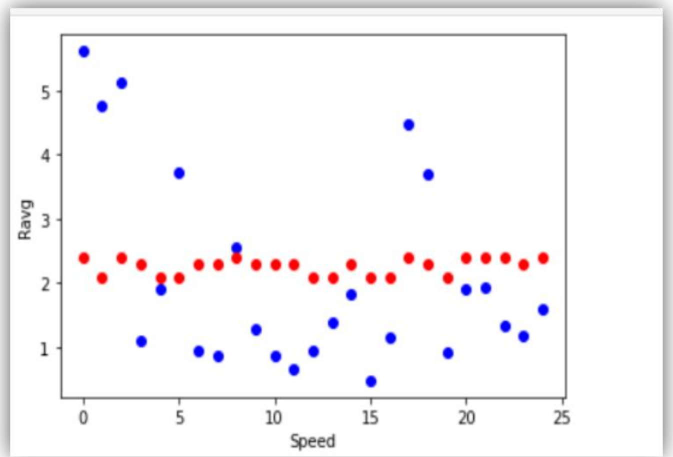
```
d1 = pd.read_excel("My Mtech&1.xlsx")
d1.head()
```

	Speed	Feed	Depth_of_cut	Nose_Radius	Ravg
0	88	0.05	0.2	0.0	4.63
1	88	0.07	0.2	0.0	3.68
2	88	0.10	0.2	0.0	2.75
3	150	0.05	0.2	0.0	4.86
4	150	0.07	0.2	0.0	4.38

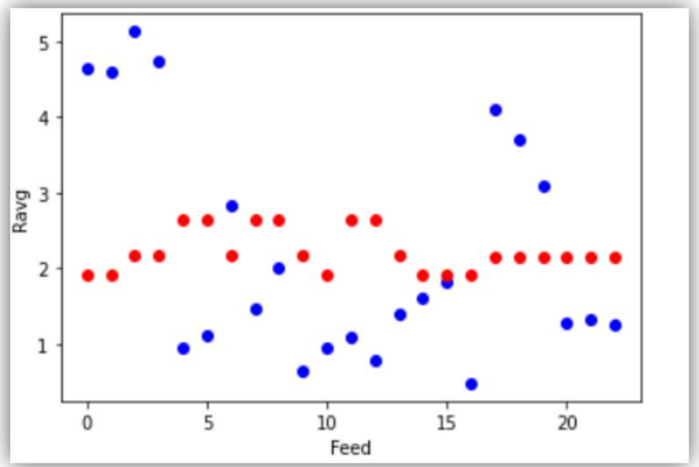
```
d1.describe()
```

	Speed	Feed	Depth_of_cut	Nose_Radius	Ravg
count	108.000000	108.000000	108.000000	108.000000	108.000000
mean	162.666667	0.070000	0.304167	0.266667	2.219722
std	67.051103	0.018796	0.075929	0.206438	1.374795
min	88.000000	0.050000	0.200000	0.000000	0.470000
25%	88.000000	0.057500	0.237500	0.000000	1.140000
50%	150.000000	0.065000	0.300000	0.300000	1.685000
75%	250.000000	0.077500	0.381250	0.500000	2.995000
max	250.000000	0.100000	0.400000	0.500000	5.610000

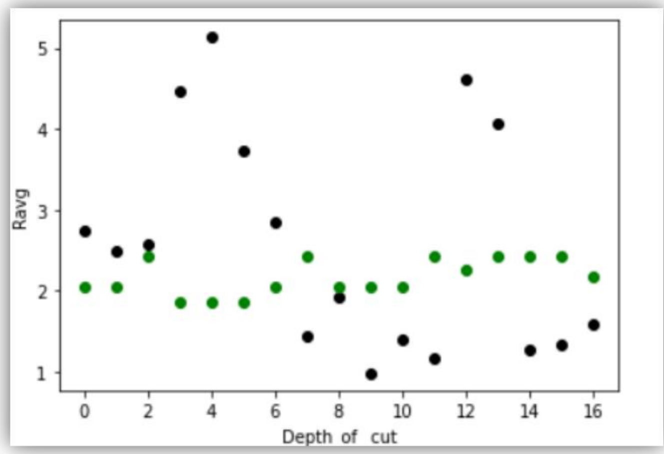
- Visualize the data and understand the trend between features and Labels.
- With the Help of Polynomial Regression We can Testing and Training the data.
- The graph Between Speed, Feed, Depth of cut and Ravg should be plotted.



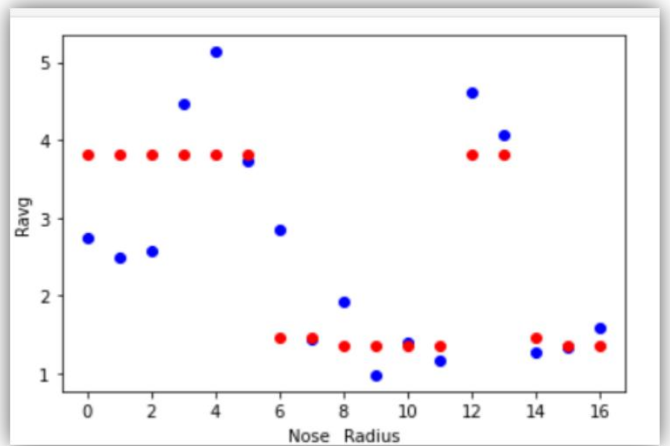
Speed vs Ravg



Feed vs Ravg



Depth of Cut vs Ravg



Nose Radius vs Ravg

- **Mean absolute error:** It is the mean of the absolute value of the errors. This is the easiest of the metrics to understand since it's just average error.
- **Mean Squared Error (MSE):** Mean Squared Error (MSE) is the mean of the squared error. It's more popular than Mean absolute error because the focus is geared more towards large errors. This is due to the squared term exponentially increasing larger errors in comparison to smaller ones.
- **R-squared or (R2 score):** It is a popular metric for accuracy of your model. It represents how close the data are to the fitted regression line. The higher the R-squared, the better the model fits your data. Best possible score is 1.0 and it can be negative (because the model can be arbitrarily worse).
- The Below is the Experimental Observations Between the Polynomial Regression and the Multi Linear Regression.

In [127…

```
from sklearn.metrics import mean_squared_error,r2_score
print ("MSE:",mean_squared_error(out4test,out4pred))
print ("R2 score",r2_score(out4test,out4pred))
```

```
MSE: 0.5767181041606722
R2 score 0.6702804220687646
```

In [41]:

```
inp1test = np.asanyarray(test[["Feed","Depth_of _cut","Nose _Radius"]])
out1test = np.asanyarray(test[["Speed"]])
out1pred = reg.predict(inp1test)
from sklearn.metrics import mean_squared_error,r2_score
print ("MSE:",mean_squared_error (out1test,out1pred))
print ("R2 Score:",r2_score(out1test,out1pred))
```

```
MSE: 5292.210180196411
R2 Score: -0.14921102411895704
```

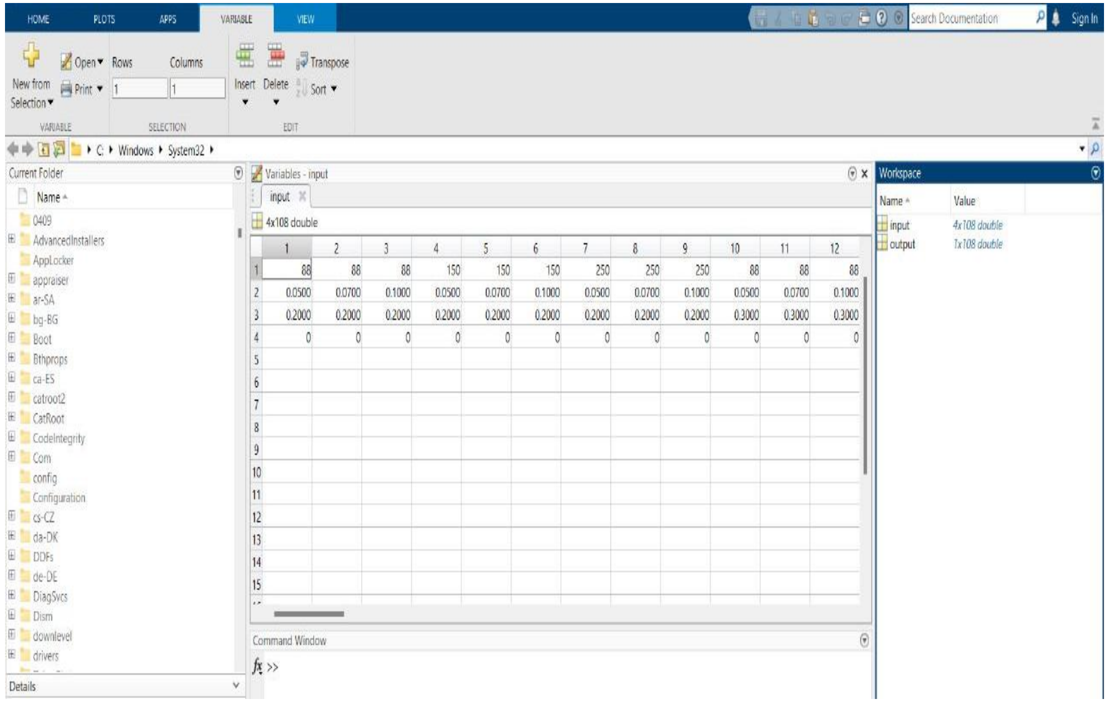
From the above two regressions we can conclude that polynomial regression has the efficient R2 score.

DEEP LEARNING PROCESS OVERVIEW

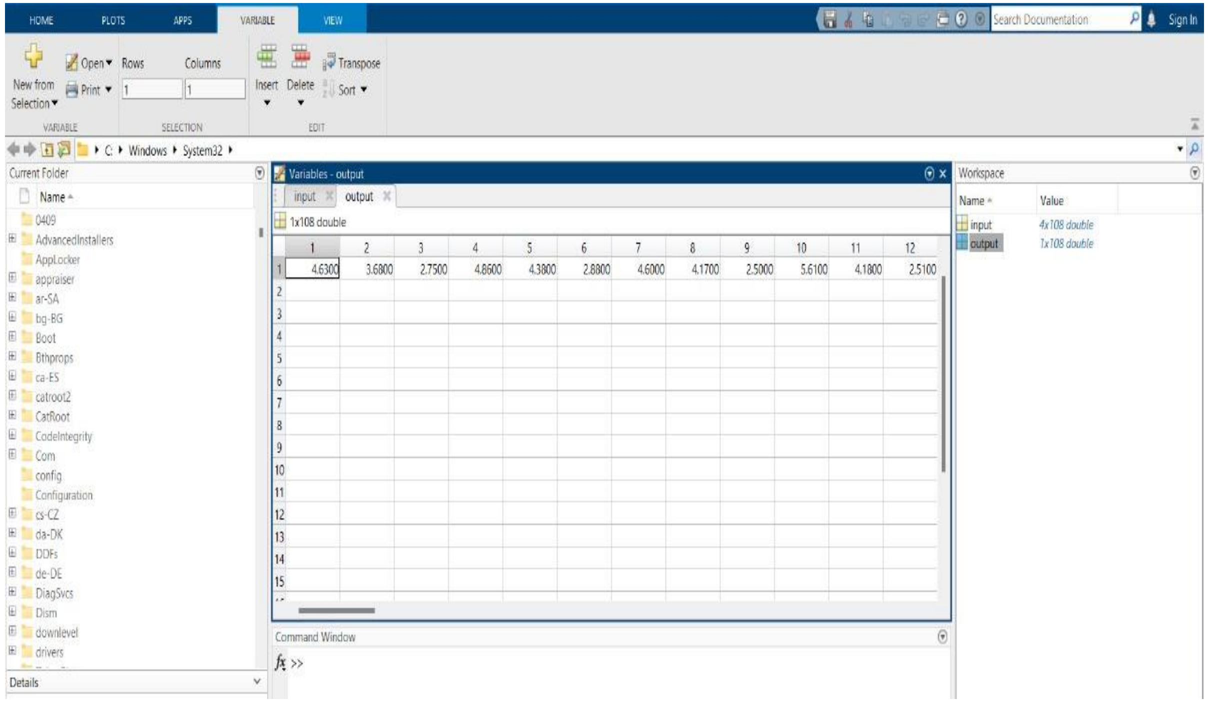
In order to use deep learning we need a platform, we have chosen MATLAB (R2020a)
1.arranging data and importing it to the matlab
2.Under MATLAB we execute “nntool” which is neural network tool
3.Arranging data to neural network that is imported as input and output
4.
Here we are importing the experimental surface roughness data

Input data consists of speed , feed , depth of cut , nose radius
Target data consists of arithmetic data (Ra) from the experimented data that is performed

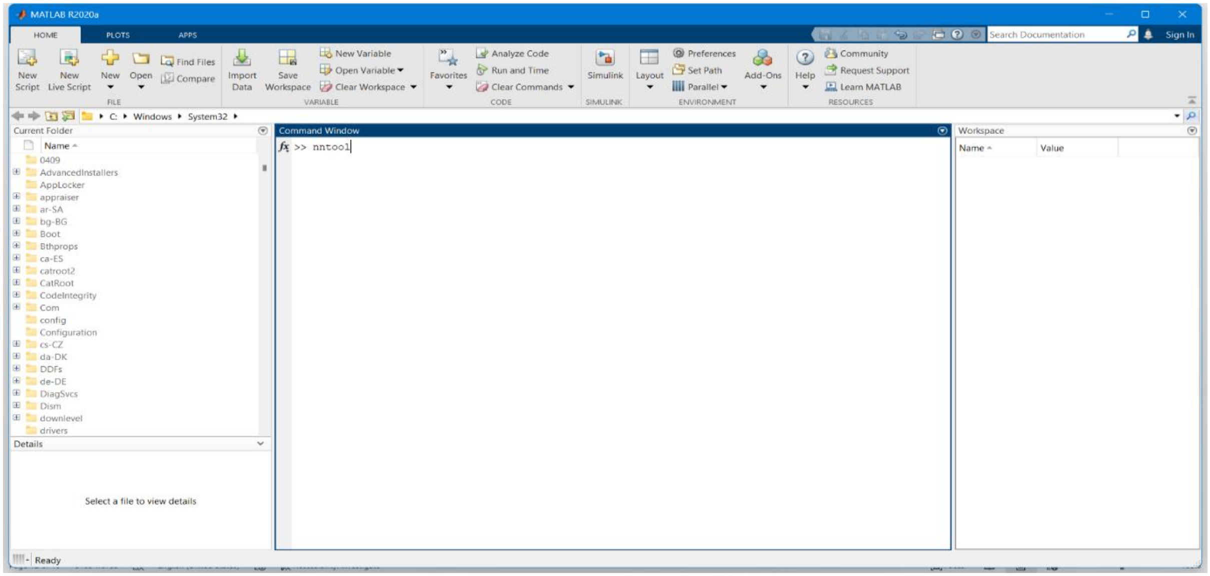
1.Importing Input Data

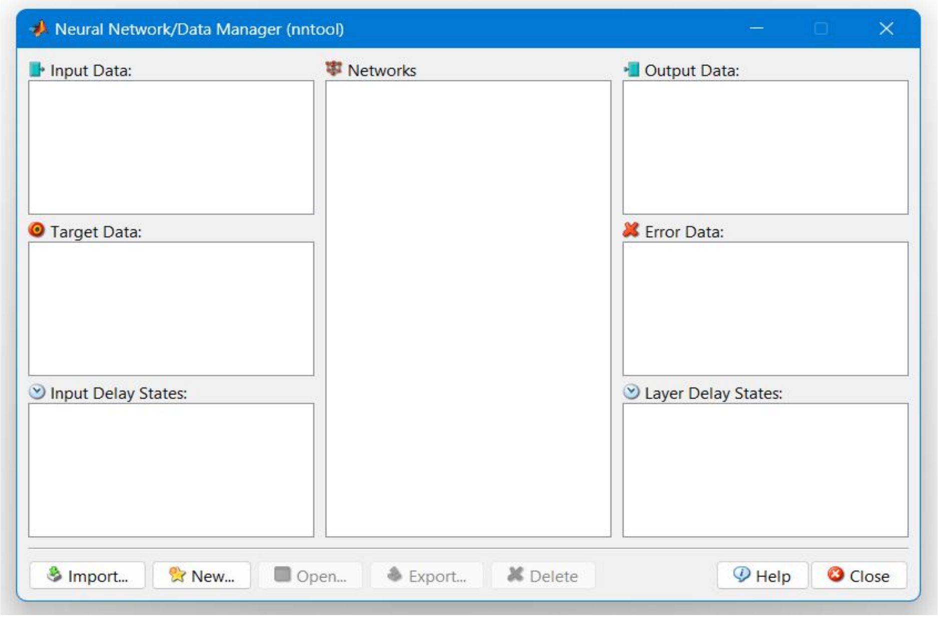


2.Importing Target Data

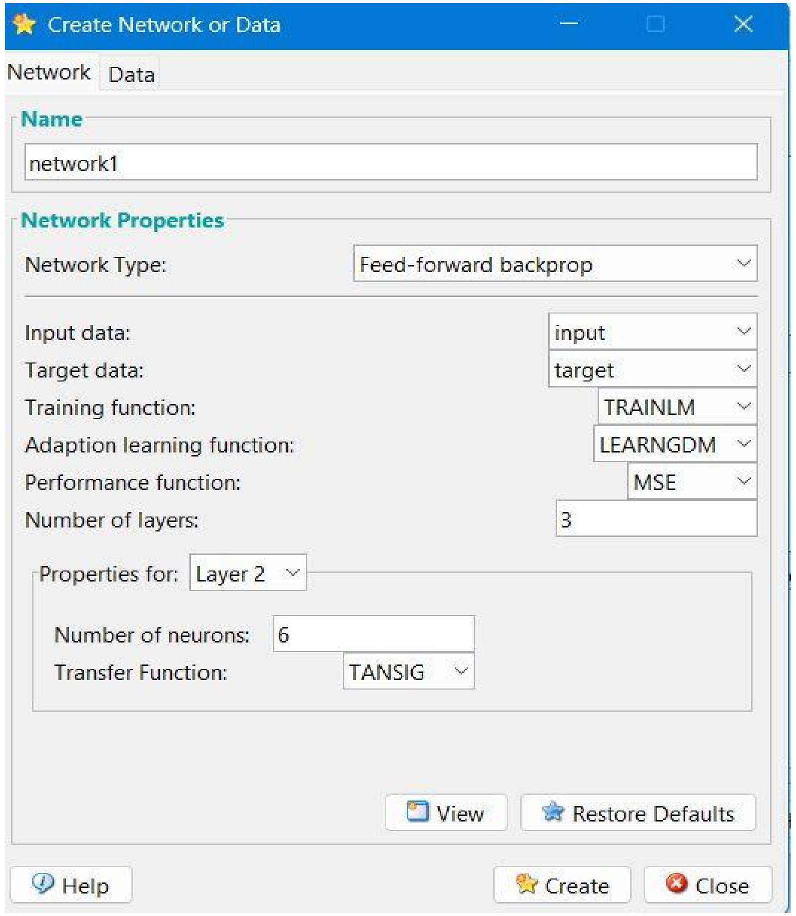


3.Executing nntool where neural network, data manager pop up



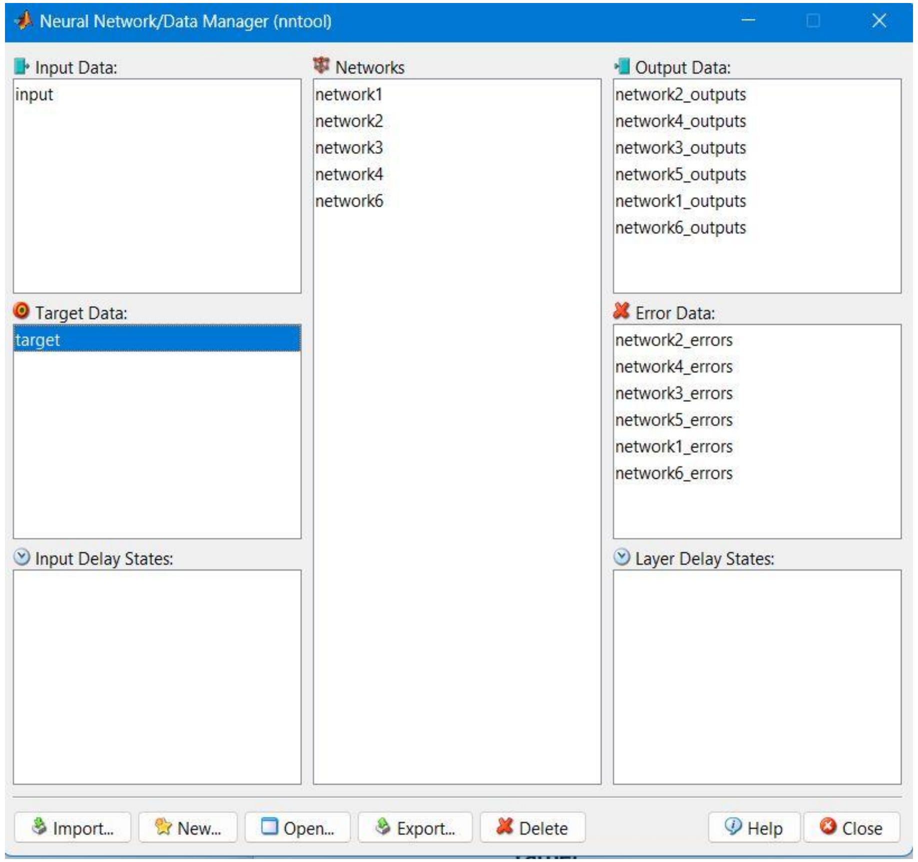


4.Creating new network

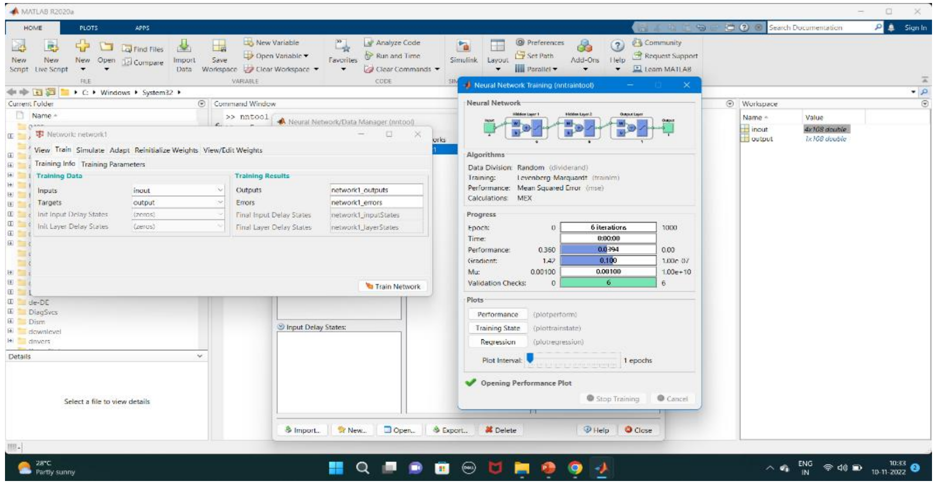


Feed forward backprop
Feed forward distributed time delay
Feed forward time delay
Generalized regression
Hopfield

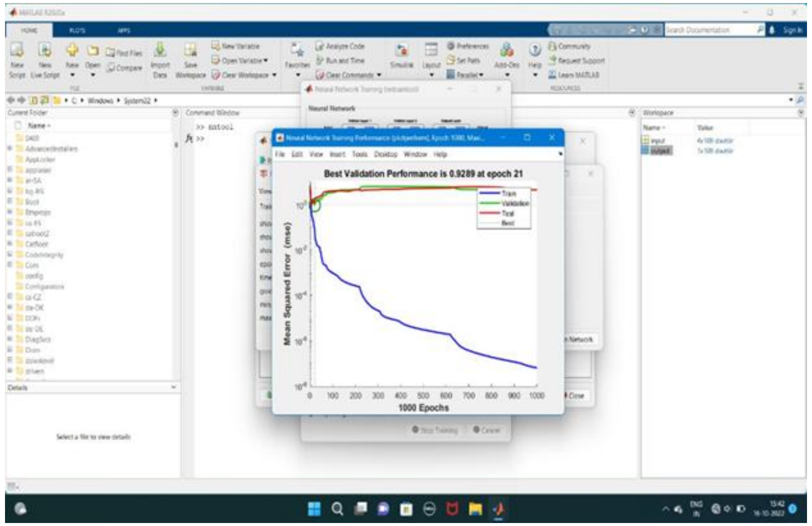
5.Created networks



6.Training the data

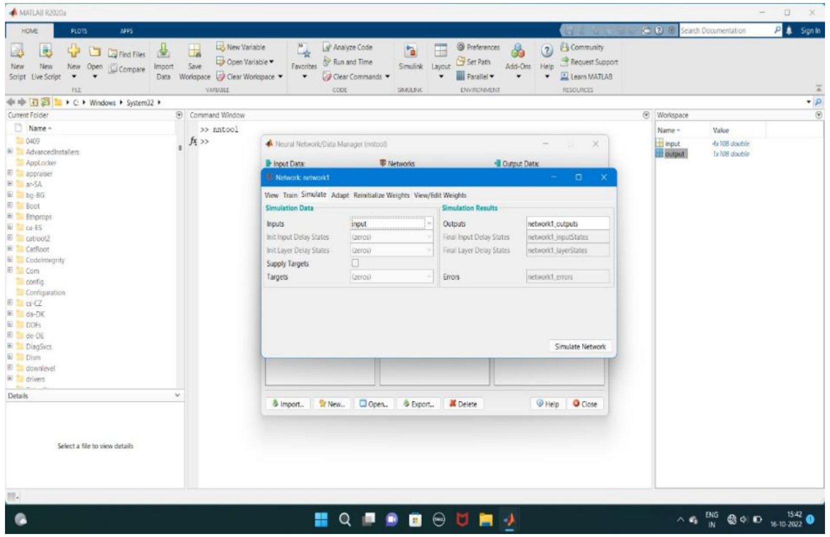


7.Performance of data



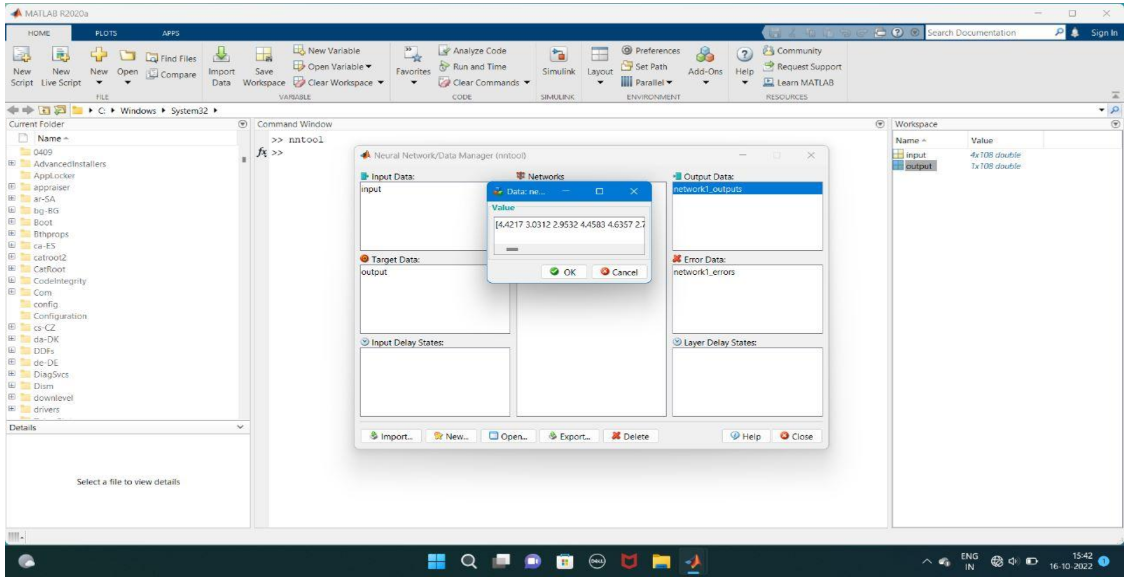
To know how well our data we can see there that the graphs will be there

8.Simulating the data



After that we need to simulate the data that is training the data with the same input data without target data

9.Export the output data comparing it with the actual values



After simulating data the output data of the network will be appeared on the network output box

After that we need to extract he data and compare it with the actual data and we need to calulate the percentage of error with that data

REFERENCES :

1.Groover, M. P. (1996),Fundamentals of Modern Manufacturing, Prentice Hall, Upper Saddle River, NJ

2.Boothroyd, G. and Knight, W. A. (1989) Fundamentals of Machining and Machine Tool ,Marcel Dekker, New York.

3.Shaw, M. C. (1984) Metal Cutting Principles, Oxford University Press, New York

4.General Electric,Surface Finish. Machining Development Service, Publication A-5, General Electric Company, Schenectady, NY

5. N.R.. Abburi and U.S. Dixit, 2006, A knowledge-based system for the prediction of surface roughness in turning process, *Robotics and CIM*, Vol. 22/4, pp. 363-372..

6.Witten and Frank 2001, Data Mining: Practical Machine Learning Tools and Techniques (Second Edition Morgan) Kaufmann, June 2016, 525 pages Paper.