Surface Roughness Prediction using Machine Learning Algorithms while Turning under Different Lubrication Conditions

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Abstract. Lathe turning is one of the manufacturing sector's most basic and important operations. From small businesses to large corporations, optimising machining operations is a key priority. Cooling systems in machining have an important role in determining surface roughness. The machine learning model under discussion assesses the surface roughness of lathe turned surfaces for a variety of materials. To forecast surface roughness, the machine learning model is trained using machining parameters, material characteristics, tool properties, and cooling conditions such as dry, MQL, and hybrid nano particle mixed MQL. Mixing with appropriate nano particles such as copper, aluminium, etc. may significantly improve cooling system heat absorption. To create a data collection for training and testing the model, many standard journals and publications are used. Surface roughness varies with work parameter combinations. In MATLAB, a Gaussian Process Regression (GPR) method will be utilised to construct a model and predict surface roughness. To improve prediction outcomes and make the model more flexible, data from a variety of publications was included. Some characteristics were omitted in order to minimise data noise. Different statistical factors will be explored to predict surface roughness.

1. Introduction

Computer Numeric Control machines execute operations based on a computer software that interprets the operator's code. These machines do many workmanships, boring, boiling, knurling, chamfering, cutting and squatting. To get the desired result, accompanying the CNC machine with the appropriate machine tool is essential. Although there are a variety of choices, certain equipment are necessary, for example the turning tool, which can rapidly peel a large part of stock, the finishing tool that guarantees a precise finish. The operator provides machining parameters in the form of G-codes and M-codes. These codes have been manually produced and validated on a test part and processed to the CNC in early phases, but today these codes are created digitally on the basis of the tool paths specified by the user according to the CAD model of CAM software. These G-codes and M-codes direct the tool through the workpiece in order to accomplish the necessary job. All motions are carefully controlled by servo motors which minimise human intervention. The machine offers the operator with an interactive interface to pass the instructions before machining begins. The machine offers the greatest precision of the final products and is entirely dependent on passed input parameters and working circumstances. All human mistakes during the machining of these machines are removed and high precision components
are produced. The learning model of the machine under interest forecasts the surface roughness of the final product after processing (turning the pipe), based on several variables including machining parameters, properties, tooling properties and features of the cooling system. This model may be used in CNCs to forecast the ruggedness of the surface when the parameters are given as inputs before to processing. Based on anticipated outcomes, the input parameters may be adjusted to create the required component according to the specifications.

Surface ruggedness is linked to the texture of the surface, which may be measured from its ideal form by differences of the surface texture to the normal vector of the actual surface. When these variations are significant, the surface is called rough while the surface is smooth if they are minor. The quality of the surface finish may be regarded as a crucial criterion for turned components during machining. The cutting process is an essential step that substantially affects the quality of the surface of the generated component. Therefore, it is essential to choose optimal cutting settings to manage the desired surface quality. Operators usually utilise "trial and error" methods in industry in order to set up machine cutting settings to obtain desired surface roughness. Obviously, the 'trial and error' approach is not completely efficient or effective and obtaining the intended result is a time consuming repeated and empirical procedure. To address this issue, the machine learning model has been developed in order to decrease the waste of material and adjusting the machining settings before the operation. Various factors have been discovered that affect surface roughness in our research and assessment of several journals. The detected characteristics are shown in the tree diagram below figure 1.

Figure 1. Attributes for training

The parameters are some modifiable characteristics that affect the surface quality. The following factors are summarised based on the literature study carried out and conclusions from different machining manuals. Every aforementioned parameter has its own impact on the roughness of the workpiece's surface. Below is the impact of each parameter.

1.1. Machining Parameters:
1.1.1. Speed: The spindle speed fluctuation directly affects the surface roughness of the work piece. Hard materials such as titanium alloys may be machined at high speeds and low speed on soft materials such as aluminium. Unlike other factors, machining process speed and feed are interrelated. At low speed and high feed and low surface raw ness values, higher surface roughness values may be achieved i.e. greater surface finish at low feed and high speed. However, the material removal rate is modest in the second instance. The speed to be adjusted on a machine also depends on the cutting tool used to cut. Softer tools are intended for softer materials and should be spun to excellent surface finish at moderate speeds. When using tools with harder or higher speed carbide, greater speeds may be adjusted to provide excellent surface quality.
1.1.2. **Feed:** The length tool advances in the direction of cutting by one spindle revolution, termed feed (mm/revolution). Feed plays a crucial function in determining the machined product's surface quality. The connection between feed and speed is described above. If high feed is delivered at low speed, there is the potential of thread cutting on the machined surface, and too low feeds are not suggested when operating at high speeds, since the material removal rate (MRR) decreases significantly, which is not wanted either. The feed to be set on the machine also depends largely on the tool's nose radius. The amount of feed to be supplied should not be more than half the nose radius to guarantee a high surface finish, according to machine tool handbooks. The provision of high feeds for a dull instrument leads to unwanted chat markings.

1.1.3. **Depth of Cut:** Cut depth has a significant impact on the surface roughness when large cutting depths for the operation are provided. Due to the large amount of cut depth, the contact surface of the tool material raises the tension at the interface, resulting in poor surface quality.

1.2 **Material Properties:**

1.2.1. **Yield Strength and Tensile Strength:** The machinability of the workpiece is defined by the output and tensile strength of the workpiece material. These factors must be taken into account while selecting the tool and the kind of lubricants. The strength of the material determines the cutting forces provided and enables us to estimate the quantity of heat produced in the cutting area. Taking this into account and keeping in mind the thermal conductivity of the tool and workpiece, we may determine the necessary quantity of cooling and the kind of cooling to employ to produce a good surface quality.

1.2.2. **Hardness of workpiece:** In determining the surface roughness of the final result, the hardness of the workpiece influences several other characteristics. Machining characteristics such as speed rely directly on the hardness of the workpiece. Softer workpieces are preferable to turn at lower speeds and more hard work is recommended to turn at high speeds to guarantee excellent quality of the surface. Hardness of the part also affects some characteristics of the tool such as hardness of the tool and nose radius. The tool must be tougher than the workpiece to accomplish cutting and blunt tools must be used in order to anticipate a high surface quality.

1.3 **Tool Properties:**

1.3.1. **Tool coating and Rake angle:** The coating on a tool gives the thermal absorption capacity in the cutting area. The coating present on the tool absorbs considerable heat in the cutting zone and immediately reflects the surface roughness resulting from the heating removal. The rake angle determines the creation of the chip and minimises the potential for built-up edge development that also adds to surface roughness.

1.3.2. **Tool Hardness:** Hardness of the tool indirectly affects the surface roughness via influence of processing factors such as speed, feed and hardness of material. The hardness of the tool must always be greater than that of the workpiece. When high-speed tools (usually hard tools) are used for turning activities, it is provided for turning at high speeds. Hard tools for turning materials such as titanium alloys and hardened steel are typically utilised.

1.3.3. **Tool Nose Radius:** The nose radius of the cutting edge of the tool directly affects the feed rate for machining. The use of a blunt instrument and the provision of high feeds create discord. This is because the process of rubbing or sliding takes place instead of cutting owing to high radius and feeding. In accordance with the research carried out to determine an external connection between nose radius and feed rate, it is noted that the feed rate magnitude should not exceed half the magnitude of the nose radius for chat markings to be eliminated. The nose radius also defines the contact area between the tool and the workpiece that provides insight into the removal rate and heat that is produced.
1.4. Cooling Systems:
The friction between the workpiece and the tool generates heat. Many unfavourable consequences may ruin the surface quality of the workpiece when the heat produced is neglected. Here are several refrigeration systems for the research.

1.4.1. Dry: Dry turning is a turning technique where no coolant is provided during cutting. The surface ruggedness values of the final product compared to procedures using alternative cooling methods are substantially greater. Huge heat is produced and absorbed completely by the workpiece and the tool. This may lead to a tool failure or local welding on the tool part interface can occur if the temperature reaches a degree greater than the working part's melting point. Thermal conductivity values are taken as 0 W/m°2K in a dry lubrication system, with a weight ratio of 0.

1.4.2. Flooded cooling: The cooling system in which a coolant is inundated in the workpiece is termed flooded lubrication during turning operation. The coolant may be homogenous or water and oil emulsion. Water is generally utilised for non-corrosive work parts, and emulsions are used to communicate the coolant's heat absorption capacities. The coolant's thermal conductivity plays an essential role in heat absorption. Two basic and mixed fluids are examined for their thermal conductivity and the weight ratio depends on the composition of the mix. If no extra liquids containing nano particles are introduced, then it takes into consideration just the thermal conductivity of the base fluid and the mixing ratio is 1.

1.4.3. Minimum Quantity Lubrication (MQL): The main aim of MQL is to decrease the quantity of coolant required to lower the heat produced in the cutting zone effectively. One essential aspect of MQL to note is that the coolant is sprayed precisely at the cutting zone in the form of a mist, e.g. in the form of tiny atomized particles, sprayed at high pressure from a nozzle. Since they are atomized into tiny molecules, the capacity to absorb heat is enhanced. At the same time, since the workpiece does not inundate huge amounts of coolant, a lot of coolant is conserved. The refrigerant may be combined in the MQL tank with nanoparticles or other oils to enhance thermal absorption in the cutting area. To forecast the surface roughness, the thermal characteristics of the base fluid, nano-particles and the weight combination are taken into consideration. The MQL-assisted twisting of the cloth results in the highest surface quality, a minimum of surface ruggedness.

1.5 Prediction Using Machine Learning
Machine learning is an advanced technology in the artificial intelligence (AI) sector which needs to be taught via specific algorithms to provide huge amounts of pre-processed data sets to anticipate the requested answer. The data set that we offer is a collection of predictors that are independent variables and a set of response variables. In the model, various correlations are established between distinct predictors and the predictor seta and responses to train the model for correct results. The kind of connection between variable and learning techniques depends only on the type of algorithms used in the construction of the model. This sophisticated technology may be split into two subcategories, which are based on learning techniques:

1.5.1 Supervised Learning: This may be described as a machine learning method, defined by the usage of data sets labelled. These data sets are intended to train or “monitor” the algorithms in order to correctly categorise the data or to anticipate the replies. The model can evaluate its accuracy and learn over time using labelled inputs and outputs.

Classification: Using an algorithm, these issues typically divide test data into certain groups, like the separation of automobiles from motorbikes. In the real world, supervised learning algorithms may be used extensively to detect and segregate spam messages in your inbox in a different folder. All popular kinds of classification methods are linear classifiers, support vector machines (SVMs), random forest and decision-making trees.

Regression: Regression is a commonly used controlled technique of learning using an algorithm to analyse the connection between dependent and independent variables. The idea of regression models helps forecast numerical values on the basis of various data points, a company's sales projection based
on previous trends and statistics. Linear regression, Gaussian Process Regression (GPR), logistic Regression and polynomial regression are some of the prominent regression methods.

1.5.2 Un-Supervised Learning: This technique utilizes methods for machine learning to analyze and group unlabeled datasets. These algorithms are usually used to detect hidden patterns in data in order to classify data, to create clusters to better understand and visualize data and to determine the weight of the factors that influence the patterns of clusters. Since all these procedures are conducted with little human involvement, they are "unsupervised". Unsupervised learning models are used for three main tasks: clustering, association and dimensionality reduction:

- Clustering: This is an unlabeled data collection method based on their similarities and differences. For instance, K-means clustering algorithms put comparable data points into groups in which the K value is equal to group size and granularity. This method is of tremendous use for market segmentation, compression of images, etc.
- Association: This is another kind of unattended technique of learning that utilizes a certain set of instructions to discover connections between characteristics in a certain dataset. These techniques are often employed for the study and suggestion of market carts.
- Dimensionality reduction: This is a method of learning that has weight when the number of characteristics (or dimensions) of a given dataset is too large. It lowers the amount of data inputs to a computable size while maintaining data integrity. These procedures are frequently employed during the pre-processing phase of data. In the case of visual data, it is possible to utilize auto encoders to remove noise from visual information to enhance the quality of the image.

1.6 Gaussian Process Regression Algorithm:
The Gaussian Process Regression is best characterized as the idea that extends the distribution of numeric probability to the distribution of probability. Each observation provided as the input is considered as a curve. The larger the number of variables, the greater the function dimensionality. The size of the function determines the quality of the generated curve, which affects the quality of the medium function indirectly. In the notion of Gaussian Process Regression, the two fundamental functions are covariance and mean function.

Consider a training set \{(xi,yi); where i=1,2,...,n\}, where \(x_i \in \mathbb{R}^d\) and \(y_i \in \mathbb{R}\), drawn from an unknown distribution. A GPR model addresses the question of predicting the value of a new response variable \(y'\), given the new input vector \(x'\), and the training data. A linear regression model is of the form, \(y = f(x) \beta + \varepsilon\); here \(y\) is the response variable, \(x\) is the predictor variable and \(\varepsilon\) is the error or noise present in the data which has to be minimized. The GPR also deals with kernel functions and some base functions to establish empirical relationships to build the predicting model.

1.6.1 Covariance Function:
The covariance function is defined by a selected kernel function, which defines the degree of covariance between data points. In the case of GPR the smoothness of the generated curves is determined by the distribution functions. We can fit a probability distribution for a specific collection of data points by selecting distribution parameters that match the distribution's characteristics. We can fit all of the functions and find a mean function that smooths all functions. In addition to the mean function, we can also calculate the forecast confidence intervals.

Some important characteristics found in the research are given on the basis of the survey. The influence of Mr. Rajesh Kumar Bhushan [1] Impact of nose radius and processing parameters on surface roughness, wear and tool life during turning of AA7075/SiC composites was noticed in the works of Ms. Rajesh Kumar Bhushan [1]. Various insights have been noticed and the data set given in this study is used for model development. Devendra Singh, Vimanyu Chadha and Ranganath M Singari [2] researched and discussed the impact of nasal radius on surfacing ruggedness. Techniques such as RSM that allowed us to choose parameters were noticed. In their work, the experimental data provided helped create the
dataset. Similar work is being carried out by P. B. Patole & V.V. Kulkarni [5], whose main emphasis was parametric optimization using multi-response features to achieve the required surface quality. Md Rezaul Karim, Farhana Dilwar & Rifat Ahasan Siddique[3] examined variations in surface roughness for different machining settings and created a furious logic neural network model for surface roughness predictions. This model, however, predicts SiC-Alloy values that they utilised for testing. The methods utilised to construct the model were nonetheless observed and parametric optimization techniques described in their work are integrated into our research. Munish K. Gupta, P. K. Sood[4], has offered a method for optimising the process, evaluating variations in surface roughness of various lubrication systems, including mixed MQL nano powder. Variation in surface roughness has been found for different work factors. The impact on surface roughness of various nano-particles was clearly shown in its testing findings. The study was done on Ti6-Al4-V, which gave us a hard turning data set. Durmus Karayel[6] studied surface roughness variation values for the variation of processing parameters using aluminium alloy as the workpiece. The surface roughness was predicted using a model of artificial neural networks. References have been taken that helped us pick the algorithm for training. The ANFIS (Artificial Intelligence Fuzzy Inference System) model was developed for the prediction of surface roughness by R. Anil Raj1, M. Dev Anand2, K. Leo Dev Wins1 and A. S. Varadarajan[7]. Their study has shown how AI may be used successfully in process optimization. Besides these allusions, there are many more The following questions were discussed: G J Pavan Kumar[8], Goutam Devaraya Revankara*, Raviraj Shetty.b, Shricantha Srinivas Raoc, Vinayak Neelakanth Gaitonded[9], P. P. Shirpurkar, P. D. Kamble, S. R. Bobde, V. V. Patil[10], Neelesh Kumar Sahu et al [11], Mahdi S. Alajmi 1* and Abdullah M. Almeshalt [12]. Several writers have given different prediction models unique to their experimental material.

After a close study of all of the models stated in the journals we linked to, we can say that every model created was exclusively suitable and must be utilised, for this specific work material and performs well under those specific circumstances. Given this as a major issue, we have chosen to eliminate these limits and make the model more flexible by predicting the output based on the material and tooling characteristics, rather than by training it for a specific material. Data sets are thus gathered from several publications that have dealt with various materials. The material and tool characteristics which affect the roughness of the surface were discovered and given as input parameters.

2. Pre-Processing of raw data

The pre-processing of raw data includes several activities to eliminate ambiguity and data mismatch. Standardization of the data units is done at the first step for all accessible data. All spindle speed numbers in terms of cutting speed (m/min) are accessible. This is translated using conventional conversion equation to spindle speed (rpm). Likewise, the hardness levels of the tool and workpiece were a common job. The hardness values obtained were of various dimensions and had to be translated to the hardness of Brinell (BHN). A set of 500 values is carefully constructed based on necessary omissions and modifications, and the data are now divided into two sets: one for training and one for testing. We utilised around 400 test data points and 100 training observations. A certain number of observations were randomly selected from each journal and added to the test data set.

The next step is to train the model and visualise the data. The following speed is shown in Figure 2 on the x-axis and surface roughness on the y-axis. The image is produced by the first effort to observe the difference in surface roughness at different speeds of the spindle. A single data set with 27 observations is provided as an input. Although the distribution of the data points is unorganised, the slope can be examined, a simple implication can be drawn that the ruggedness of the terrain reduces as the speed increases. The slope is negatively affected by the distant data points. Which should be missed in order to enhance the slope precession. Once all variables are seen, the scene is prepared for constructing the model.
3. Regression Learner in MATLAB

Regression learner is a programme that is extensively used in the training of different regression models based on the pre-processed numerical data sets, as a major feature in current versions of MATLAB. The data must be pre-processed and loaded in the MATLAB workspace to be imported into the regression learner app when the training data is established. Once the data has been imported, the predictors and response variables must be determined based on the data type. After the pre process settings are established, a list of all true answers is shown. The plot of actual training data answers is shown in Figure 3 below. The surface ruggedness or response variable are displayed on the y-axis and the record number of all predictors is shown on the x-axis. Each record consists of every single observation predictor. The surface ruggedness value is shown in accordance with the relevant record. This plan is made before training. On the basis of the kind of training data, the type of algorithm is chosen. The method used for the data set training is Gaussian Regression. The model is suitable for medium to small data sets with several predictor factors. It also forecasts the exact answers for the kind of data we have.

![Figure 2. Initial Trials of Data Visualization.](image1)

![Figure 3. True responses for data visualization.](image2)

The pre-processed data are imported successfully and imported for training. The empirical relationships between various predictors and response variables were effectively established. Based on the average function produced, the data set values for the test prediction are given. This is done to assess the predictive accuracy and to examine the noise that misleads the model that deviates from the real values. The following figure 4 is shown with an x-axis record number and a y-axis surface roughness value.

The following figure 4 & 5 provides a short overview of the forecasts and their divergence from the actual answer. The forecast replies are yellow dots, while the actual answers are blue. The accuracy of the model may be assessed based on the proximity between the anticipated answers and the actual answers. The aforementioned model is trained using GPR algorithm and has 72 percent accuracy. To enhance accuracy, every genuine answer pair that is far apart is deemed to be incorrect forecasts and removed beyond the limits. This procedure is carried out by closely observing the data. We also looked to the remaining graph for the record numbers to be removed.

Trial predictions after noise reduction.

The noise on the data was eliminated based on different produced plots, such as a real versus expected response, a predicted vs actual plot and residual plots. This significantly impacted the model's accuracy, which increased the r-squared value by 95% from 0.75 to 0.95. The resulting plot is shown in Figure 5 below.
The projected answers in figure 6 are closer to the real answers, a significant improvement after noise removal. In figure 7, the r-squared value for the model is 0.95, suggesting a precision of 92 percent. The findings collected showing the precision of this model are shown in Figure 8.

The prediction limits are entirely based on the maximum and lower limit of values for the training of the model. These limits have their weight when setting the top or lower limits of the input parameters to forecast. The model is intended to forecast high precision, given that the inputs are intervals. The top and bottom limits of various input parameters are shown in Table 1 below.

![Figure 4. Trial predictions with noise](image1)

![Figure 5. True and predicted values post noise reduction.](image2)

| Attributes                        | Ranges            |
|-----------------------------------|-------------------|
| Speed (revolutions per minute)    | 223.68 - 3183.1   |
| Feed (mm/revolution)              | 0.04 - 0.4        |
| Depth of Cut (mm)                 | 0.2 - 2           |
| Yield Strength (MPa)              | 180-1000          |
| Tensile Strength (MPa)            | 210-1200          |
| Workpiece Hardness (BHN)          | 95-419            |
| Tool Coating                      | Yes/No            |
| Tool Hardness (BHN)               | 230-800           |
| Tool rake angle (degrees)         | 2-18              |
| Tool Nose Radius (mm)             | 0.2-1.2           |
| Base Thermal Conductivity (W/m^2.K)| 0 - 0.6          |
| Nano-Thermal Conductivity (W/m^2.K)| 0-0.2663       |
The anticipated vs the current figure is shown above, which provides a short sense of how near the predicted values are to the ideal forecast scenario. The real answers are on x-axis while the anticipated answers are on y-axis. The ideal instances lie on the slope of the diagonal 1. Since the model predicts 95% accurate values, most values are dispersed about the ideal line.

The model has now been trained and ready to predict the answers for fresh test data. A portion of the test data set is created by random observations from each data sub-set (approximately 4 values from each sub data set). Another portion of the data is filled with the noisy data set that is eliminated from the workout. The remaining portion is supposedly packed with inaccurate facts. This data collection comprising just predictors is given to the created model using the generated function in order to provide all these values in .csv format to the workstation, as is the training data. The results are ordered and the error percentage is computed. Table 2 in Figure 7 includes the replies, experimental results, and the error percentage that indicate a departure from the reply.

4. Predictions on new data:
The import data is submitted for forecast and the findings are presented in an excellent sheet in order to check each percentage mistake. The projected surface ruggedness values are acceptable if the error percentage can be observed closely, mostly around 5 to 8 percent. The model predicts that 95 percent of the outcomes will be acceptable. The model may also be modified for integration into an application, or the programme, for process optimization, can be integrated into CNCs described in the next chapter.

4.1. Model building using other ML algorithms
Many additional methods exist such as linear regression, polynomial regression, regression trees and vector support machines. There is a good opportunity both to utilise the techniques described above and
to construct a prediction model. A comprehensive research and analysis of many publications was carried out to choose an algorithm to construct the model. During our survey, we concluded that GRP was the suitable model for building the model for the following reasons.

- GRP is the best method for the development of small to medium-sized data sets including a large number of variables.
- GRP has a higher prediction accuracy than other models for data types utilised to forecast.

A table 3 containing r-squared values of model trained with different algorithms is presented for comparison of accuracy of prediction of different algorithms with that of GRP.

Table 2. Test data and results

| Machining Parameter | Work Piece Properties | Tool Properties | Cooling System | Residual Value(s) |
|---------------------|-----------------------|-----------------|----------------|------------------|
| Speed               | Feed                   | Depth of cut    | YIELD          | HSS/COAT/ROD/NURF| File Size           |
| 2268.17             | 0.16                   | 0.2             | 550            | 550              | 217k               |
| 1958.93             | 0.25                   | 0.2             | 550            | 550              | 217k               |
| 1958.94             | 0.2                    | 0.4             | 550            | 550              | 217k               |
| 1958.95             | 0.2                    | 0.5             | 550            | 550              | 217k               |
| 1958.96             | 0.2                    | 0.6             | 550            | 550              | 217k               |

A table 2 containing r-squared values of model trained with different algorithms is presented for comparison of accuracy of prediction of different algorithms with that of GRP.
Table 3. R-squared values of different training algorithms

| S. No. | ML Algorithm                              | R-squared value |
|--------|-------------------------------------------|-----------------|
| 1      | Gaussian Process Regression               | 0.95            |
| 2      | Linear Regression                         | 0.71            |
| 3      | Fine Tree                                 | 0.89            |
| 4      | Support Vector Machine (Linear)           | 0.69            |
| 5      | Support Vector Machine (Quadratic)        | 0.89            |
| 6      | Support Vector Machine (Cubic)            | 0.81            |

When we look at the R-squared values of several training methods, we may infer that GRP best fits the curve to predict the exact answers. The remaining r-squared values range between 0.70 and 0.90. GRP is therefore chosen to train the model to predict surface roughness levels as the right training method.

5. Conclusions

- A research is carried out focusing on the resultant surface ruggedness values and turning the lathe under various working circumstances. Various process factors have been identified and mentioned in the turning of lathes that affect the surface roughness of the turned workpiece.
- Different cooling methods have been examined, with a demonstrable impact on surface roughness. The findings and forecasts show that the surfaces under MQL are less harsh than any other cooling methods. Compared to other methods, MQL combined with nano particles provides increased surface quality.
- The model of surface ruggedness prediction is effectively constructed using a Gaussian regression learning model. The model can predict the surface ruggedness of the fresh test samples given with acceptable accuracy of 95%.
- The model will be evaluated with various test data sets and the anticipated outcomes will be correct. We noticed many writers offering prediction models tailored to certain workpieces and circumstances based on the literary survey conducted.
- The model developed has undergone widespread training where prediction characteristics played a vital role. The model can now correctly forecast the surface ruggedness of any workpiece under various working circumstances, providing the input variables fall within the specified predictor range.

References

[1] Bhushan, Rajesh. (2020). Impact of nose radius and machining parameters on surface roughness, tool wear and tool life during turning of AA7075/SiC composites for green manufacturing. *Mechanics of Advanced Materials and Modern Processes*. 6. 10.1186/s40759-020-00045-7.
[2] Singh, Devendra & Chadha, Vimanyu & Singari, Ranganath. (2016). Effect of Nose Radius on Surface Roughness During CNC Turning Using Response Surface Methodology. *International Journal of Recent Advances in Mechanical Engineering*. 5. 31-45. 10.14810/ijmech.2016.5203.
[3] Karim, Md & Dilwar, Farhana & Siddique, Rifat. (2019). Predictive Modeling of Surface Roughness in MQL assisted Turning of SiC-Al Alloy Composites using Artificial Neural Network and Adaptive Neuro Fuzzy Inference System. 5. 12-28.
[4] Gupta, Munish & Sood, P. (2017). Surface roughness measurements in NFMQL assisted turning of titanium alloys: An optimization approach. *Friction*. 5. 1-16. 10.1007/s40544-017-0141-2.
[5] Patole, P.B. & Kulkarni, V.V. (2017). Experimental investigation and optimization of cutting parameters with multi response characteristics in MQL turning of AISI 4340 using nano fluid. *Cogent Engineering*. 4. 10.1080/23311916.2017.1303956
[6] Karayel, Durmus. (2009). Prediction and control of surface roughness in CNC lathe using artificial neural network. *Journal of Materials Processing Technology*. 209. 3125-3137. 10.1016/j.jmatprotec.2008.07.023.

[7] Raj, R. & Anand, M. & Dev Wins, Leo & Varadarajan, A.s. (2016). ANFIS based Model for Surface Roughness Prediction for Hard Turning with Minimal Cutting Fluid Application. *Indian Journal of Science and Technology*. 9. 10.17485/ijst/2016/v9i13/90562.

[8] Ezeugwu, E. & Da Silva, Rosemar & Machado, Alisson & Bonney, J.. (2019). High Speed Turning of Ti-6Al-4V Alloy with Coated Carbide Tools in an Argon Enriched Environment.

[9] Machining of Ti-6Al-4V ELI Alloy: A brief review Anurag1, R kumar1, S Roy1, K K Joshi1, A K Sahoo1 and R K Das1. Published under licence by IOP Publishing Ltd. 2018 *IOP Conf. Ser.: Mater. Sci. Eng.* 390 012112

[10] Analysis of Surface Roughness and Hardness in Titanium Alloy Machining with Polycrystalline Diamond Tool under Different Lubricating Modes.

[11] Goutam Devaraya Revankara*, Raviraj Shettyb, Shrikantha Srinivas Raoc, Vinayak Neelakanth Gaitonded. P. P. Shirpurkar, P. D. Kamble, S. R. Bobde, V. V. Patil, 2014, Optimization of CNC Turning Process Parameters for Prediction of Surface Roughness by Taguchi Orthogonal Array, *International Journal of Engineering Research & Technology (IJERT) Volume 03, Issue 01* (January 2014),

[12] Prediction of surface roughness in turning of Ti-6Al-4V using cutting parameters, forces and tool vibration, Neelesh Kumar Sahu et al 2018 *IOP Conf. Ser.: Mater. Sci. Eng.* 346 012037.