Surface Roughness Prediction with Machine Learning

Wenhe Zhang*
School of Mechanical Engineering, University of Jinan, Jinan 250022, China
*Corresponding author’s e-mail: 1901110384@pku.edu.cn

Abstract. Surface roughness is an exceedingly essential index to measure the quality of materials. For manufacturing and production, it is very significant yet difficult to precisely measure the surface roughness of materials. Based on input features including the rational speed, feed and depth of cutting, we managed to predict the surface roughness with machine learning models, based on a real-world dataset collected in the laboratory. The process and results are discussed in this paper. We demonstrate that the neural network can achieve a better prediction performance, compared with other baseline models. This insight will be of great help to the manufacture industry.

1. Introduction
If a prediction method can be used to predict the surface roughness of the material with minimal error for different tool depths, spindle speeds, and feed rates when using turning and milling materials, it will bring a great convenience to subsequent production and manufacturing. The smaller the error, the more beneficial it is to manufacturing. Accurate roughness prediction will bring great economic benefits, and the performance and life of parts produced can also be well guaranteed. In 2018, the number of new product development projects for manufacturing enterprises above designated size reached 55 million, an increase of 56.3% over 2013. Digitization, intelligence, automation equipment and high-end information and electronic products have become new growth points. The numbers of electronic vehicles, smart devices, industrial robots, and civilian drones reached 1.202 million, 1.34 billion, 183,000 sets and 3.088 million, respectively. These new product developments also have high requirements for surface roughness, which shows the importance of prediction [1].

We first introduce the basic concepts and measurement methods of surface roughness. Surface Roughness refers to the three-dimensionality and spacing of the surface micro-geometry. The cutting surface roughness has a great influence on the use and life of the parts. How to establish an accurate surface roughness prediction model, improve processing efficiency, and reduce processing costs has become the goal pursued by both domestic and foreign researchers.

Secondly, we must understand the evaluation parameters of surface roughness and its measurement methods. The surface roughness parameters can be divided into 3 categories:

1. Parameters related to the characteristics of the height direction, such as the arithmetic mean deviation of the contour Ra, the maximum height of the contour Ry and the ten-point height of the microscopic unevenness Rz, etc.;

2. Parameters related to the spacing characteristics, such as the average spacing Sm of the microscopic unevenness of the profile and the average single-peak spacing S of the profile;

3. Features related to shape characteristics.

As for the measurement methods of surface roughness, there are various methods. From the late 1920s to the 1930s, some experts in Germany, the United States, and the United Kingdom designed...
and manufactured profile recorders and profile meters. At the same time, they also produced light
section microscopes and interference microscopes to measure surface microscopic unevenness using
optical methods. The instrument created conditions for quantitative evaluation of surface roughness
numerically. Since the 1930s, researchers have studied the quantitative evaluation parameters of
surface roughness. For example, Abbott in the United States proposed to use the depth from the peak
of the surface profile and the support length rate curve to characterize the surface roughness.

For Al6061, there have been corresponding predictions before, but there is no in-depth prediction,
that is, to minimize the prediction error of roughness. This paper will use the machine learning models
to predict the surface roughness, and discuss the predicted value and main axis in depth. The
relationship between the speed, the depth of the tool and the feed rate can improve the accuracy of
prediction and reduce the error, which is used to further improve the research of this material.

After measuring the data of Al6061 in the laboratory, we conducted research on a data set
containing the rational speed, feed, depth of cutting and corresponding surface roughness, and had the
following findings:

1. When the rational speed and feed are constant, as the depth of cutting increases, the roughness
gradually increases;
2. When the depth of cutting and feed are constant, as the rational speed increases, the roughness
gradually decreases;
3. When the depth of cutting and rational speed are constant, the roughness gradually increases as
the feed rate increases.

Based on this real-world dataset, we further predict the surface roughness with machine learning
models. The models involved in this paper include the Linear Regression, Decision Tree, Random
Forest and Neural Network. We find that the neural network can achieve a better prediction
performance, compared with other models.

2. Related Work

In this part, we cover the related work shortly, especially those using machine learning and deep
learning models, which have also been proven effective in the surface roughness prediction problems
and other problems [2-22]. Wang and Chen et al. [21] used probability theory and regression analysis
principle. Shi, Chen and Liu [21] used second-order response method and reaction method to establish
the predictive model. Li et al. [21] used artificial neural network methods. Liu [15] used the BP neural
network for the face gear, by comparing the predicted value of the model with the test value. The
model can accurately describe the grinding depth, wheel speed and work piece feed. The influence of
speed on the surface roughness of face gear grinding, the prediction maximum relative error is 9.1%
[15]. In actual operation, the spindle speed is too large to bring unavoidable disturbance, Chang and
Xiong [16] found that the Bayesian neural network can effectively predict the surface roughness of the
spindle speed disturbance, and the prediction error is within 7% [16]. The Taguchi analysis method
[22] is also used and can obtain the optimal solution with a small number of experiments. In addition,
there are many other prediction models, such as genetic algorithm, particle swarm algorithm and
neural network methods.

Wang et al. [9] used multiple linear regression analysis, and used the F-value test for evaluating
model parameters, which proved that both the model and the parameters are highly significant. The
maximum error is 8.9%, which verifies the effectiveness of the surface roughness prediction model. It
provides a theoretical basis for TC4 titanium Alloy processing.

Taking the bearing ring as the research object, through the ultrasonic rolling extrusion test, the test
results were analyzed by mathematical statistics, and the influence of the ultrasonic rolling extrusion
bearing ring was studied in [10]. Then the ultrasonic rolling extrusion test was carried out, and the
response surface and BP neural network model were established. The comparison between the two
model test results and the predicted results showed that the established bearing ring The relative error
of the surface roughness BP neural network model is controlled at about 4.5%, and the maximum error
does not exceed 5.06%.
3. Dataset

The use of sections to divide the text of the paper is optional and left as a decision for the author. Where the author wishes to divide the paper into sections the formatting shown in table 2 should be used. We use a self-collected real-world datasets collected in the laboratory. The source of the dataset is the result of laboratory determination of Al6061.

The data contains 4 columns and 48 rows. The columns include the rational speed, feed, depth of cutting and surface roughness, and a total of 48 records. The data range and distribution are shown in Figure 1-4 for the four columns, respectively. From Figure 1-3, we may find that the rational speed, feed and depth of cutting are discrete values, but in Figure 4, we find that the surface roughness is continuous.

![Figure 1. The data distribution of the rational speed.](image-url)
Figure 2. The data distribution of the feed.

Figure 3. The data distribution of the depth of cutting.
In this paper, we are dealing with a regression problem. Based on the input features including the rational speed, feed and depth of cutting, the surface roughness value is expected as the output. Before entering the machine learning models, we first show the relationship between the input features with the surface roughness in Figure 5-7, respectively.

Figure 4. The data distribution of the surface roughness.

Figure 5. The relationship between the rational speed and the surface roughness.
Figure 6. The relationship between the feed and the surface roughness.

Figure 7. The relationship between the depth of cutting and surface roughness.

From Figure 5-7, we find that:

1. When the rational speed and feed are constant, as the depth of cutting increases, the roughness gradually increases;
2. When the depth of cutting and feed are constant, as the rational speed increases, the roughness gradually decreases;
3. When the depth of cutting and rational speed are constant, the roughness gradually increases as the feed rate increases.
4. Models
Note that as a general principle, for large tables font sizes can be reduced to make the table fit on a page or fit to the width of the text.

Positioning tables
In this paper, we compare the performance of four machine learning models, including one deep learning model, i.e., the deep neural network.

4.1. Machine Learning Models
The three shallow machine learning models we use include:

(1) Linear Regression: This model models the input features and the output value with a linear relationship, which can be expressed as a linear equation. The weights and the bias are treated as the model parameters and should be fit from the training data and then applied to the testing data.

(2) Decision Tree: A tree structure is built for processing different input features in decision tree. And each data sample would be categorized into a leaf node, which has the corresponding class and probabilities for all the possible classes. The data is used to train the tree structure as well as the conditions used in the nodes.

(3) Random Forest: Random Forest uses the ensemble method of Bagging (bootstrap aggregation). In Bagging, a random forest will train multiple classifiers independently, and each classifier is trained based on a subset. Finally, the prediction results of different classifiers will use the majority rule to derive the final classification results. Compared with a certain classifier, the ensemble model is not easy to make mistakes on a single sample.

4.2. Deep Learning Models
The neural network model we use contains one input layer, five hidden layer and one output layer. We use 100 neurons in each hidden layer, and relu as the activation function in the hidden layer.

5. Experiments

6. Conclusion

5.1. Settings
The models are implemented with Python 3.7, using scikit-learn as the machine learning package. We use the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) as evaluation metrics.

5.2. Results
The models we compare are summarized in Table 1. The results are obtained through a five-fold cross validation. And we calculate the mean and standard deviation of different folds and show them in Table 1.

| 1.1. Model Name   | 1.2. MAE             | 1.3. RMSE             |
|-------------------|----------------------|-----------------------|
| 1.4. Linear regression | 1.5. 0.0251(0.00611) | 1.6. 0.0306(0.00771) |
| 1.7. Decision Tree | 1.8. 0.0287(0.00540) | 1.9. 0.0348(0.00672) |
| 1.10. Random Forest | 1.11. 0.0158(0.00511) | 1.12. 0.0237(0.00450) |
| 1.13. Neural Network | 1.14. 0.0123(0.00279) | 1.15. 0.0151(0.00770) |

From Table 1, we find that the neural network performs the best. Many previous studies also believe that neural network is the best prediction model, but the research materials are different, so
some studies will have their own best prediction model conclusion. Furthermore, in order to directly show the predicted values of different models, we give a specific prediction result of different models in Figure 8.

6. Conclusion
In conclusion, in this paper, we predict the surface roughness of Al6061 based on machine learning. We use linear regression, random forest and decision tree, etc. It seems that neural network is the best choice to predict. Although at present, we can predict the surface roughness through the collected data and corresponding models, the amount of data collected is limited, which cannot be guaranteed in practice. In the case of a large amount of data, there are unreasonable prediction values. Now the amount of data collected by the researchers is not enough very likely. So in the future we should collect more data to improve our work. If possible, many new parameters can be introduced to correct the predicted value.

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