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STUDY ON PERFORMANCE OF MACHINE LEARNING MODELS IN PREDICTING SURFACE ROUGHNESS WHEN TURNING HARDENED AISI 4340 STEEL USING CERMET CUTTING TOOL

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ABSTRACT

This study investigates the effectiveness of machine learning models in predicting surface roughness (Ra parameter) during the hard turning of AISI 4340 steel using CERMET cutting tools, an area with limited prior research. The experiments were conducted on a CNC lathe under dry conditions, with surface roughness measured using a profilometer. The Taguchi design of experiments was utilized to structure the data, incorporating factors such as cutting speed, feed rate, and depth of cut. Three machine learning algorithms-Linear Regression (LR), Random Forest (RF), and Support Vector Regression (SVR)-were employed to develop predictive models. The models' performance was evaluated using the root mean square error (RMSE) and R-squared (R^2) metrics. The RF model demonstrated superior predictive accuracy with an RMSE of 0.0758 µm and an R^2 value of 0.9814 for the testing dataset. The performance of the LR model (RMSE = 0.0783 µm, R^2 = 0.9791) and the SVR model (RMSE = 0.0779 µm, R^2 = 0.9798) were close to that of the RF model. Overall, all the algorithms demonstrated good potential for model development in this study.

Keywords: ra parameter, linear regression, random forest, support vector regression, Taguchi.

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INTRODUCTION

Surface roughness in metal cutting significantly influences mechanical properties such as fatigue strength and corrosion resistance, and its control minimizes secondary finishing operations, reducing production costs and enhancing manufacturing efficiency. As a measurable quality criterion, surface roughness ensures parts meet specified tolerances and standards, optimizing performance and appearance in metal cutting operations [1].

Surface roughness is typically measured using contact or non-contact methods. Contact methods involve using a profilometer with a stylus that traces the surface profile, recording deviations to calculate parameters like Ra (average roughness) and Rz (average maximum height) [2]. Non-contact methods include optical techniques such as laser scanning, interferometry, and confocal microscopy, which measure surface roughness without physically touching the surface, suitable for delicate or sensitive materials. Each method has its advantages depending on the required precision, material characteristics, and application needs, providing essential data for optimizing cutting parameters and ensuring desired surface quality in metal cutting processes [3].

Hard turning is a precision machining process used to cut hardened materials typically above 45 HRC, offering an alternative to traditional grinding for finishing operations. It involves using single-point cutting tools made from materials like cubic boron nitride (CBN), ceramics, and carbide, each with specific advantages and challenges. CBN tools are renowned for their exceptional hardness, thermal stability, and wear resistance, making them highly effective in cutting very hard materials such as hardened steel and cast irons. They maintain sharp cutting edges and exhibit resilience against impact loads and sudden changes in cutting conditions, minimizing the risk of tool failure. Ceramics, such as silicon nitride or alumina-based tools, offer extreme hardness and wear resistance but can be brittle, prone to chipping, or fracture under high-impact loads. Carbide tools, tougher than ceramics, may struggle with maintaining edge sharpness and wear resistance when cutting very hard materials above 55 HRC, leading to accelerated tool wear and potential dimensional inaccuracies [4-7].

To enhance the performance of these cutting tools in hard turning, advanced coatings are often applied. Coating materials deposited on carbide tools improve hardness, lubricity, and thermal resistance, addressing specific challenges associated with machining hardened materials. The selection of coated carbide tools in hard turning requires careful consideration of cutting parameters (speed, feed rate, depth of cut), cooling strategies, and part geometry to optimize machining efficiency and achieve desired surface finishes and dimensional accuracies [6,8-12]. Continuous advancements in tool materials, coatings, and machining techniques further enhance the effectiveness and reliability of hard-turning processes, providing manufacturers with versatile solutions for high-precision machining of hardened materials in various industries [13].

Machine learning is a branch of artificial intelligence that enables computer systems to learn from data and improve their performance over time without being explicitly programmed. It involves algorithms and

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statistical models that analyze large datasets to recognize patterns, make predictions, or generate insights. Supervised learning tasks involve training models on labeled data to predict outcomes, such as classifying images or forecasting sales. Unsupervised learning identifies patterns in unlabeled data, like clustering similar customer behavior. Reinforcement learning uses feedback from the environment to learn actions that maximize rewards, applicable in areas like autonomous driving or game playing [14-16].

Machine learning is employed in predicting surface roughness in hard turning by analyzing historical data on cutting parameters (such as speed, feed rate, and depth of cut), tool characteristics, and environmental conditions. Supervised learning models, like regression or neural networks, are trained on labeled datasets to learn patterns and correlations between these inputs and surface roughness metrics (e.g., Ra or Rz). Feature engineering is critical to extract relevant features impacting roughness, enabling the model to accurately predict surface quality. Once trained, the model facilitates real-time optimization of cutting parameters, suggesting adjustments to achieve desired surface finishes and improving manufacturing efficiency while reducing costs associated with scrap and rework. Continuous updating with new data ensures the model adapts to evolving machining conditions, supporting ongoing process refinement and enhanced quality control in hard-turning operations [17-21].

Cheng *et al*. [22] utilized a machine learning technique to predict surface roughness when cutting nickel alloy Haynes 230 material. In this study, a novel hybrid kernel extreme learning machine model with radial basis function (RBF) kernel (Gaussian kernel) and arc-cosine kernel function was proposed to predict surface roughness. The whale optimization algorithm was also introduced to improve the prediction accuracy. Taking the mean absolute error (MAE) as the quantification indicator, the machine learning models that resulted in this study were compared one to another. The study concluded that the hybrid model was successfully predicting the surface roughness. The surface roughness and tool wear from the testing dataset were also verified by experiment. The hybrid model showed better results compared to the other machine learning models such as Support Vector Regression (SVR), Gaussian Process Regression (GPR), and Light Gradient Boosting Machine (LightGBM).

In turning tool steel with a hardness of 220HB with coated carbide tools, Motta *et al*. [23] collected 92 experiments. In their work, models for the prediction of surface roughness were developed using Random Forest (RF) and GPR machine learning algorithms. The root mean square error (RMSE) was used as the quantification indicator. The result of the study showed that GPR performed better and more consistently than RF for training sets representing 67 to 90% of datasets. Moreover, when trained with 80% of the dataset, both models were capable of providing surface roughness prediction with RMSE lower than 0.4 μm on the remaining 20% of datasets.

Dubey *et al*. [24] studied the surface roughness resulting from the turning of AISI 304 which is supported by minimum quantity lubrication (MQL) technique. The cutting fluid for MQL was enriched with alumina nanoparticles of two different average particle sizes of 30 and 40 nanometers. The experiment for measuring surface roughness as a response variable was carried out with a Box-Behnken design. There were 27 surface roughness data resulting from each experiment of cutting fluid usage (particle sizes of 30 and 40 nanometers). Two-thirds (2/3) of those 27 surface roughness data were randomly selected by the program as the training dataset for developing SVR, RF, and Linear Regression (LR) machine learning models. For evaluating the accuracy of the predicted surface roughness values, the coefficient of determination (R^2), mean absolute percentage error (MAPE), and mean square error (MSE) were used. The result of the study showed that RF outperformed the other two models in both cutting fluids.

To the best of our knowledge, studies on predicting surface roughness under the hard turning process using ceramic metal (CERMET) cutting tools are very limited. Therefore, we are conducting this research to address this gap and provide valuable insights.

MATERIALS AND METHODS

A CNC lathe machine tool with a spindle speed maximum of 5000 rpm and power of 9.5 kW motor is used for the turning experiment. Annealed bars of AISI 4340 with a hardness number of 50 HRC and dimensions of ∅ 80 mm x 300 mm are used as workpieces. For the cutting tool, the uncoated CERMET with the designation product code SNMG120408-QM5015 from Sandvik Coromant is used. The turning experiment is carried out under dry conditions.

For the design of the experiment, the Taguchi design is adopted with factors and levels as shown in Table-1. Process parameters in this experiment are cutting speed (v), feed (f), and depth of cut (a) while the response is surface roughness in the Ra parameter. For measuring the surface roughness, a portable profilometer Mitutoyo SJ 210 with a stylus angle of 60o and radius of 2 μm is used. Sampling and evaluation length are set according to ISO 4288:1998 and a Gaussian filter is used [2].

Table-1. Factors and levels of Taguchi design of experiment.

Factors	Symbols	Units	Levels		
Cutting speed	*v*	m/min	70	100	140
Feed	*f*	mm/rev	0.1	0.15	0.2
Depth of cut	*a*	mm	0.1	0.15	0.2

There are 3 (three) algorithms are used to generate machine learning models for predicting surface roughness in this study, i.e. Linear Regression (LR), Random Forest (RF), and Support Vector Regression (SVR). The tool for model development in this study is

Jupyter Notebook bundled with Anaconda package version 1.9.12, and the programming language used is Python 3.0.

The LR is chosen due to its simplicity and interpretability. It provides a clear mathematical relationship between input features (such as cutting speed, feed rate, and depth of cut) and surface roughness, allowing for straightforward understanding and communication of how each factor influences the outcome. This transparency is beneficial for process optimization and decision-making in metal cutting [25].

The RF offers high predictive accuracy and robustness to overfitting due to its ensemble nature, where multiple decision trees are built on random subsets of data and features. This robustness makes it effective in handling complex, non-linear relationships between input variables and surface roughness. Additionally, Random Forest can handle many input variables and provides insights into feature importance, helping identify key factors influencing surface roughness in the metal-cutting process [26, 27].

The SVR is highly flexible due to its ability to use kernel functions to capture non-linear relationships between input variables and surface roughness. SVR is effective in scenarios where the relationship between variables is complex and not well-represented by linear models. Its precision in fitting the data within a specified margin of tolerance allows for accurate predictions of surface roughness, making it suitable for applications requiring high precision in the metal-cutting process [25].

The performance of LR, RF, and SVR models in this study is evaluated in terms of root mean square error (RMSE) metric and R^2 score. The RMSE is the normalized distance between the vector of predicted values and the vector of observed values. This metric is mathematically given by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad \# \ldots 1$$

Where n is the sample size, $\hat{y}_i$ is a predicted value, and y_i is the corresponding observed value. The smaller the value of RMSE, the higher the accuracy of the predictor. Known as the coefficient of determination, the R^2 score indicates the percentage of the response variable variation that is explained by a regression model. A higher score of R2 is preferred to show the better regression model fits the data.

RESULTS AND DISCUSSIONS

The measurement of surface roughness in the Ra parameter resulting from the turning experiment is shown in Table-2. The data was used as the training and testing datasets for developing the machine learning models as described in the following section.

Table-2. Taguchi L27 design with the results of surface roughness measurement.

No	*v*	*f*	*a*	Ra	No	*v*	*f*	*a*	Ra
	m/min	mm/rev	mm	μm		m/min	mm/rev	mm	μm
1	70	0.1	0.1	0.981	15	100	0.15	0.2	1.844
2	70	0.1	0.1	1.105	16	100	0.2	0.1	2.487
3	70	0.1	0.1	0.981	17	100	0.2	0.1	2.741
4	70	0.15	0.15	1.823	18	100	0.2	0.1	2.402
5	70	0.15	0.15	1.867	19	140	0.1	0.2	0.434
6	70	0.15	0.15	1.823	20	140	0.1	0.2	0.443
7	70	0.2	0.2	2.710	21	140	0.1	0.2	0.442
8	70	0.2	0.2	2.462	22	140	0.15	0.1	1.586
9	70	0.2	0.2	2.462	23	140	0.15	0.1	1.681
10	100	0.1	0.15	0.910	24	140	0.15	0.1	1.618
11	100	0.1	0.15	0.926	25	140	0.2	0.15	2.229
12	100	0.1	0.15	0.926	26	140	0.2	0.15	2.098
13	100	0.15	0.2	1.590	27	140	0.2	0.15	2.359
14	100	0.15	0.2	1.622					

Development of Models and Surface Roughness Prediction

There are 3 (three) machine learning models developed for predicting surface roughness in this study. About 80% of the data in Table-2 were randomly picked by the program for model development (training dataset), and the model was validated using the remaining data (testing dataset). The construction of the model uses using supervised learning method in which cutting speed (v), feed (f), and depth of cut (a) are used as the input variables and the response is surface roughness (Ra). Due to the unit differences of the input variables, a standard scalar was applied for both datasets for minimizing the errors. Moreover, the underfitting or overfitting was checked by GridSearch cross-validation using a K-fold number.

The three models are successfully developed and validated. The models were then used to predict the values of surface roughness for all 27 cutting conditions in Table-2. Some cutting conditions for run numbers 2, 8, 11, 14, 17, 20, 22, and 26 were then selected to represent the models, and the values of Ra prediction resulting from the models were plotted and presented in Figure-1. As a reference of comparison, the values of Ra experiment with the same run numbers were also plotted in Figure-1.

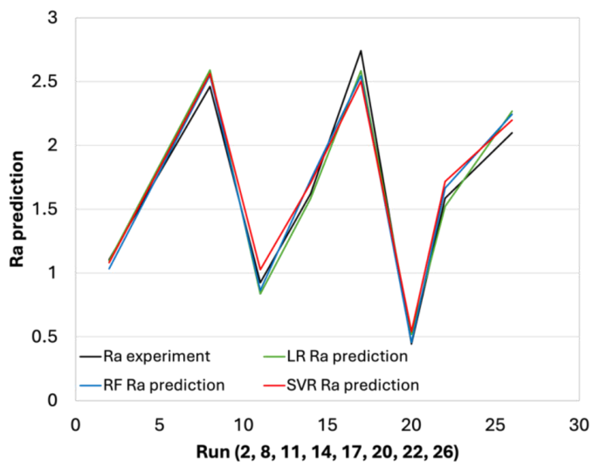

Figure-1.

From Figure-1, the plots of Ra prediction resulted from the models (LR, RF, SVR), and the plots of the Ra experiment show a good agreement with one another, and the plots are almost identical. This fact indicates that the results of the prediction are close to the results of the experiment, meaning that the accuracy of the prediction resulting from the models is good and reliable.

Performance of Models

The accuracy of prediction of surface roughness values provided by the models is assessed by two indicators, i.e. RMSE dan R^2. The scores of RMSE and R2 for each model in both training and testing are given in Table-3.

As per the performance metrics in Table-3 are concerned, the lowest value of RMSE is provided by the RF model for both training and testing. In the case of the R^2 score, the RF value has the highest scores for both training and testing. These facts prove the outstanding of the RF model in predicting the surface roughness in this study. In the case of the LR and the SVM models, their performance can be said, to be very close or almost identical.

Table-3. Performance metrics of models.

Model/Performance Metrics	Training		Testing	
	R-Squared	RMSE	R-Squared	RMSE
LR	0.9744	0.1157	0.9737	0.0900
RF	0.9837	0.0923	0.9814	0.0758
SVR	0.9787	0.1056	0.9636	0.1060

Further analysis of the performance of models, and the quality of Ra prediction provided by the LR model, the RF model, and the SVR model are visualized in Figures 2, 3, and 4, respectively. The graphs in those figures present the scatter and line plots of the Ra experiment versus the corresponding Ra prediction resulting from the models. A red color line plot in the figures is a line corresponding to the equality between predicted and observed (experiment) Ra values. In addition, in each figure, the average RMSE value of prediction and experiment, and the R2 score of the corresponding line for each model are listed.

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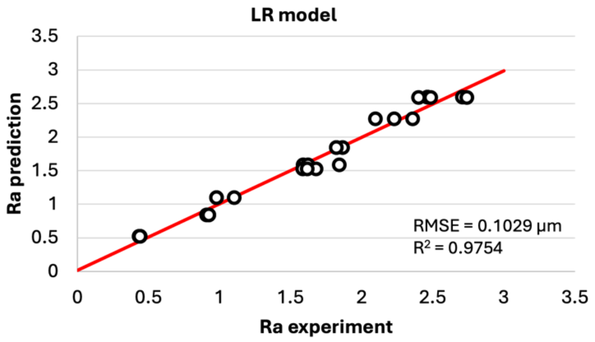

Figure-2. Plot for visualizing the quality of Ra prediction resulting from the LR model versus Ra experiment.

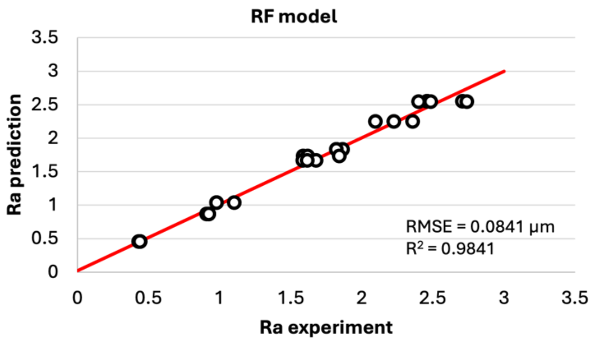

Figure-3. Plot for visualizing the quality of Ra prediction resulting from the RF model versus Ra experiment.

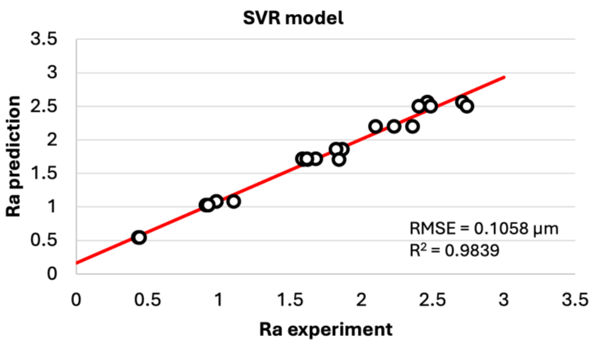

Figure-4. Plot for visualizing the quality of Ra prediction resulting from the SVR model versus Ra experiment.

From the RMSE and R^2 scores in Figures 2, 3, and 4, the lowest RMSE = 0.0841 μm is provided by the RF model, and the highest score of R^2 = 0.9841 is also provided by the RF model (see Figure-3). This is to confirm the previous results shown in Table-3 that the RF model provides better prediction of surface roughness than the LR and the SVR models. For the LR and the SVR models in Figures 2 and 4, when the score of R2 is concerned, the score of R^2 = 0.9839 resulted by the SVR model (Figure-4) is higher than R^2 = 0.9754 resulted by the LR model (Figure-2). A higher score of R^2 showed by the SVR model indicates that more variability can be explained by the regression model and thus, the better the regression model fits the data. Yet, the error value of RMSE = 1029 μm resulting from the LR model is slightly lower than the RMSE = 1058 μm of the SVR model. These results show the closeness of quality between the LR model and the SVR model in predicting the surface roughness values in this study.

CONCLUSIONS

This study successfully evaluated the effectiveness of machine learning models in predicting surface roughness (Ra parameter) during the hard turning of AISI 4340 steel using CERMET cutting tools. Among the three models tested-Linear Regression (LR), Random Forest (RF), and Support Vector Regression (SVR)-the Random Forest model demonstrated the highest predictive accuracy, achieving an RMSE of 0.0758 μm and an R^2 value of 0.9814. This indicates its superior capability in modeling the relationship between cutting parameters and surface roughness.

The Linear Regression and Support Vector Regression models also performed well, with the LR model recording an RMSE of 0.0783 μm and an R^2 of 0.9791, and the SVR model achieving an RMSE of 0.0779 μm and an R^2 of 0.9798. These close performance metrics suggest that both LR and SVR are also reliable for surface roughness prediction, highlighting the robustness of machine learning approaches in this context.

The findings underscore the significant potential of machine learning models in optimizing machining parameters to enhance surface quality, leading to improved product quality and production efficiency. Despite these promising results, the study also points out the limited prior research in this area, suggesting a need for further studies to validate and refine these models under varied conditions and with different materials.

Finally, this research has demonstrated that machine learning models, particularly the Random Forest model, are highly effective in predicting surface roughness during the hard turning of AISI 4340 steel using CERMET tools, paving the way for future advancements in machining processes through optimized parameter selection.

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