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Original Article

Cutting force estimation in turning of AISI 1117 free-cutting steel using machine learning algorithms

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ABSTRACT

This research investigates how effectively machine learning algorithms can predict cutting forces during machining, offering a practical alternative to conventional experimental and numerical methods. The experiments included turning AISI 1117 steel with a cemented carbide insert on a CNC lathe while changing the cutting speed, feed rate, and depth of cut in a planned way. Cutting force data was collected using a Kistler 9257B dynamometer and used to train and test several regression-based machine learning models. These included cubic support vector machine (SVM), gaussian process regression (GPR), various forms of linear regression, decision trees, and ensemble techniques. Two modelling scenarios were analysed: one using cutting speed and feed rate as input variables, and the other using depth of cut as a third input. In the two-variable case, cubic SVM showed the best performance (R^2=0.93, root mean squared error [RMSE]=19.57), while GPR with a Matern 5/2 kernel achieved the highest accuracy in the three-variable model (R^2=0.99, RMSE<40). Model performance was assessed using metrics such as R^2, RMSE, mean squared error, and mean absolute error, with R^2 and RMSE being most effective for comparisons. The findings indicate that while cubic SVM is suitable for simpler, lower-dimensional data, GPR performs better in capturing complex, non-linear relationships among multiple variables.

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INTRODUCTION

This study aims to evaluate which learning algorithm provides the most accurate predictions using machine learning (ML) methods and to compare the algorithms that produce the best findings.

The finite element method has been the leading numerical methodology in this field for a long time. Recently, ML and artificial intelligence have become significant methodologies for handling engineering difficulties. The advantage of predictive or learning methodologies is in the ability to reduce the resolution times of problems that are difficult to address using the finite element method, enabling faster solution acquisition. Finite element software can integrate learning or predictive methodologies, either in conjunction to minimise solution time or separately to attain the solution. When precise modelling approaches and assumptions are used, numerical solution methods, such as the finite el-

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ement method, produce results that closely correspond to experimental data. Artificial intelligence or ML systems can use the finite element method to reproduce data. Concurrently, it can reduce the time and financial resources spent on studies by obtaining data that is inaccessible through experimental methods.

ML is a specialised field in artificial intelligence that involves creating models and algorithms to analyse current data using mathematical and statistical techniques. These models are then used to generate predictions about unknown data based on the patterns and insights derived from the analysis. The primary objective of ML is to provide precise estimations. Nevertheless, comprehending the prediction functions and linking them to a particular probability model may present challenges [1].

Machining processes, fundamental to manufacturing procedures, generate outputs including cutting forces, temperature, surface roughness, tool wear, and tool vibrations, all of which directly influence production quality. Researchers have increasingly utilised ML and artificial intelligence algorithms in recent years to predict and optimise these outputs. Researchers have conducted and continue to develop numerous studies in this field. While some researchers have evaluated the performance of individual ML algorithms, others have focused on hybrid approaches by combining multiple algorithms to achieve higher accuracy. These efforts contribute significantly to making manufacturing processes more efficient, predictable, and automated.

For instance, in a study focusing on the turning process of AISI 4340 alloy steel, gaussian process regression (GPR) was employed to predict cutting forces. The results showed that GPR was better than other methods like support vector machines (SVM) and artificial neural networks (ANN), with a mean absolute percentage error of 5.12% and a high coefficient of determination (R^2=0.9843). Moreover, the GPR model exhibited the shortest training time, completing in just 0.35087 seconds. These findings suggest that GPR can be effectively utilised by process engineers to estimate cutting forces prior to production, aiding in resource optimisation and the design of experiments aimed at achieving desired product quality [2].

Kumar et al. [3] did a study comparing different ML algorithms to predict cutting forces in turning operations using cutting fluids that are enriched with hybrid nanofluids. Their results emphasised the importance of fluid-based process parameters for enhancing prediction accuracy. Mikołajczyk et al. [4] suggested a method that compares multiple linear regression (MLR), SVM, and ANN to predict cutting forces when turning materials, using a large set of experiments with various tool shapes, feed rates, and cutting speeds. Their work involved an extensive experimental dataset covering different combinations of tool geometry, feed rate, and cutting speed. The results demonstrated that ANN models outperformed MLR and SVM in terms of prediction error and robustness across various machining conditions.

In their study, George et al. [5] employed ML algorithms to identify the most effective parameters for removing metal. They found that neural networks and ML are valuable resources for engineers, but their implementation in industrial settings requires innovative approaches to gather applicable data. Kant and Sangwan [6] employed ANN and support vector regression models to identify the optimal processing parameters. As a result, it was found that ANN produced more accurate results than the reinforcement learning model, and the learning methods used were very similar to the experimental findings. Yang et al. [7] employed the supported vector machine method to handle difficult-to-machine materials, namely AISI 304. In their work on optimising cutting settings, they discovered that the SVM method achieved a high level of accuracy.

Recent advancements in machining have demonstrated the growing relevance of ML for optimising cutting processes and predicting performance metrics, such as surface roughness, cutting forces, and tool wear. Dehghanpour Abyaneh et al. [8] investigated the grinding of UNS S34700 stainless steel under different coolant conditions using a hybrid modelling framework combining GPR, ANN, and genetic algorithms. Their models achieved high predictive accuracy (R^2≈0.98), showing that ML can effectively model complex grinding dynamics. Similarly, Hernández-González et al. [9] applied ANN to analyse the dry, high-speed turning of AISI 1045 steel, revealing that moderate cutting speeds minimise specific energy consumption and cutting forces while emphasising the role of optimal parameter selection. In another recent study, Das et al. [10] used multiple ML techniques—including polynomial regression, Random Forest, Gradient Boosting, and AdaBoost—to predict tool wear, cutting forces, and surface roughness during the tough turning of AISI D6 steel with an AlTiSiN-coated tool. Their models, particularly polynomial regression, achieved R^2 values above 0.90 and were coupled with metaheuristic optimisation to determine the optimal machining parameters. Pawanr and Gupta [11] investigated the dry turning of SDSS-2507 super duplex stainless steel using textured tools and applied ML to estimate mean roughness depth (Rz), validating the effect of feed rate and the efficacy of tool surface modifications under challenging machining conditions. Jouini et al. [12] studied dry and Cryo+MQL-assisted high-speed turning of hardened AISI 4340 and found that the feed rate was the most important factor affecting cutting forces and surface quality, while tool life was more affected by cutting speed, as demonstrated by Grey Relational Analysis. Sudarsan et al. [13] sought to improve the production process parameters in the CNC machining of aluminium alloy 7071 using the L27 orthogonal array developed by Taguchi and response surface methodology. Nevertheless, they did not intend to employ ML algorithms in their studies.

Numerous studies have focused on enhancing surface quality within the manufacturing sector. Recent studies have increasingly concentrated on enhancing surface integrity using roller burnishing, especially for aluminium alloys such as Al6061-T6. Somatkar, et al. [14] conducted an extensive assessment of process parameters—including burnishing speed, feed rate, and number of passes—and their effects on surface roughness, microhardness, and residual stresses. The authors reiterated the importance of modelling tools, such as ANN and response surface methodologies, for optimising surface properties and accurately predicting results.

Dwivedi et al. [15] established a comprehensive modelling and optimisation framework for Al6061-T6, illustrating that enhanced surface smoothness and improved roundness may be achieved by precise modulation of penetration depth and burnished pressure. Their experimental methodology, utilising statistical methods, confirmed the efficacy of their predictive model, which is pertinent to machine learning-driven process control systems.

Somatkar et al. [16] conducted a comparative study examining the impact of lubrication conditions—dry versus nanofluid minimum quantity lubrication (MQL)—on surface quality. The results show that nanofluid MQL markedly improves microhardness and diminishes surface roughness in comparison to dry burnishing. These findings underline the importance of thermal and tribological parameters in surface integrity and pave the way for data-driven modelling of lubrication techniques in roller burnishing.

Beyond conventional experimental approaches, machine learning (ML) techniques have been increasingly applied to finite element simulation studies, particularly parameter estimation and surrogate modelling. This trend reflects the growing need to reduce the computational costs associated with traditional physics-based simulations in manufacturing. Hashemitaheri et al. [17] created SVR and GPR models that use data from finite element simulations to predict cutting forces and maximum tool temperatures during orthogonal machining. Their study demonstrated that ML models, particularly SVR, can match the predictive accuracy of numerical methods while enabling near real-time predictions. In the same way, Klippel et al. [18] suggested a ML system based on 2,500 virtual experiments using SPH to predict cutting and feed forces when machining Ti6Al4V. The model incorporated tool geometry variables such as rake angle, clearance angle, and cutting-edge radius, providing a fast and efficient alternative to SPH simulations. Although the ML model slightly underpredicted certain trends when compared with physical experiments, it proved highly effective for interpolating across a wide design space. These studies collectively highlight the synergy between physics-based simulations and data-driven models, where ML serves not only as a surrogate for rapid prediction but also as a tool for identifying trends and generalising simulation results for complex machining processes.

These studies collectively illustrate that ML-driven modelling achieves high predictive accuracy for machining outputs. Key parameters, including feed rate, cutting speed, and depth of cut, remain significant determinants of machining results. Enhancements in tool design, such as coatings and textures, provide quantifiable performance advantages when combined with ML. Furthermore, contemporary machining strategies increasingly integrate sustainability metrics, such as energy efficiency, by highlighting ML's contribution to performance prediction and optimising smart, sustainable manufacturing.

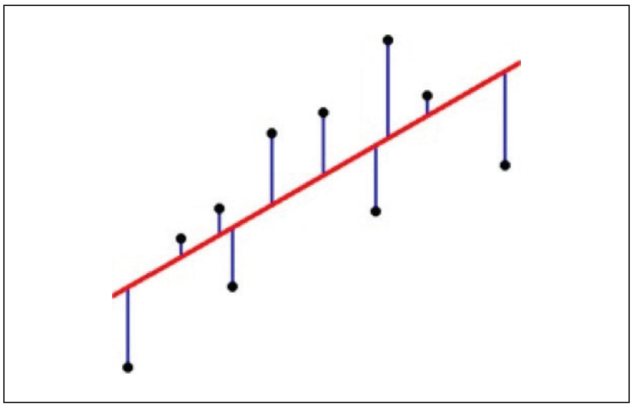

Figure 1. Visualising errors in regression. The vertical lines represent the error in our regression model, which is squared and summed to make our SSE [23].

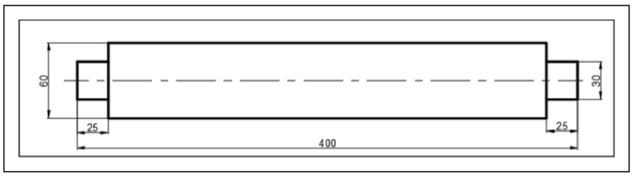

Figure 2. The workpiece used in the experiments [24].

Evaluation Criteria of Learning Algorithms

Once the experimental data has been transmitted to the regression learning algorithm in Matlab software, all learning algorithms may be executed concurrently, and the most optimal prediction method can be chosen. Estimation involves two crucial steps: data preparation and model comparison. The parameters used to evaluate and contrast models include accuracy, speed, resilience, scalability, and interpretability. R2, mean square error (MSE), root mean squared error (RMSE), and mean absolute error (MAE) are key performance measures used in the evaluation of ANN and ML techniques [19].

The coefficient R^2, which represents the explanatory coefficient of the model, is directly related to its predictive ability. The model's performance inversely correlates with the error metrics MSE, RMSE, and MAE. According to Jierula et al. [20], low values of MSE, RMSE, and mean absolute error MAE imply a high level of performance. Out of these performance indicators, R^2 is the coefficient used to determine the accuracy of the model. The coefficient's high value suggests a strong predictive link. According to Wang et al. [21], low values of MSE, RMSE, and MAE imply strong performance, with the level of performance being inversely proportional to the results of these error measures. For instance, when the RMSE is zero, it indicates a high level of performance [22].

Several regression models depend on distance metrics to determine convergence towards the optimal result. Determining the ideal result requires a quantitative analysis based on specific criteria. The often-employed metrics include the MAE, the MSE, or the square RMSE. MAE measures the absolute deviation of the predicted values (entries of the dataset) from the actual values in a

Table 1. Experimental cutting parameters [24]

Experiment number	Cutting speed (m/min.)	Cutting depth (mm)	Feed rate (mm/rev)
1	50	1-2	0.1
2			0.15
3			0.2
4			0.25
5			0.3
6	75	1-2	0.1
7			0.15
8			0.2
9			0.25
10			0.3
11	100	1-2	0.1
12			0.15
13			0.2
14			0.25
15			0.3
16	125	1-2	0.1
17			0.15
18			0.2
19			0.25
20			0.3
21	150	1-2	0.1
22			0.15
23			0.2
24			0.25
25			0.3

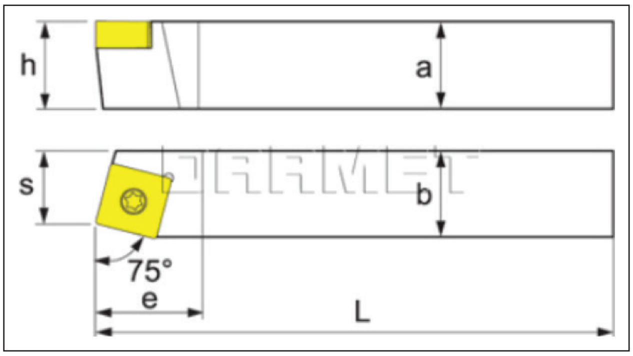

Figure 3. Schematic drawing of the cutting tool and tool holder used in the experiments [24].

regression problem. It is calculated by taking the average of the absolute differences between the predicted and actual values. When calculating negative errors, the absolute value of the distances is employed to ensure accuracy. Figure 1 accurately illustrates this scenario. Equation 1 displays the computation of MAE [23].

Table 2. Tool holder dimensions [24]

Parameter	Dimension (mm)
a	25
b	25
L	150
h	25
s	22
e	25

Table 3. Specifications of the JOHNFORD T35 CNC lathe

X axis	250 mm
Y axis	600 mm
Power	10 kW
Revolution speed	4000 dev/dak.
Hydraulic chuck diameter	250 mm
Precision	0.001 mm
Turret tool capacity	12

Table 4. Technical specifications of the Kistler 9257B dynamometer [24]

Force Range	-5…10 kN
Response	<0.01N
Sensitivity	
Fx, Fy	-7.5 pC/N
Fz	-3.5 pC/N
Linearity	1% FSO
Hysteresis	0.5% FSO
Natural frequency	3.5 kHz
Operating temperature	0…70°C
Capacitance	220 pF
Insulation resistance at 20°C	1013 Ω
Ground insulation	>108 Ω
Protection class	IP 67
Weight	7.5 kg

$$MAE = \frac{1}{n}\sum_{i=1}^{N}\left|y_i^{real} - y_i^{prediction}\right| \quad (1)$$

An alternative approach is to calculate the square of the distance, resulting in positive values. As the projected values approach the real values, the MSE decreases. The MSE, is calculated by taking the average of the squared errors of the model, as shown in Equation 2.

$$MSE = \frac{1}{n}\sum_{i=1}^{N}(y_i^{real} - y_i^{prediction})^2 \quad (2)$$

RMSE is a mathematical metric that calculates the square root of the MSE and converts it back to the original unit of measurement. RMSE quantifies the dispersion of predicting errors (Equation 3).

$$RMSE = \sqrt{MSE} \quad (3)$$

In this study, all parameters were evaluated, and the ML algorithms used were closer to the prediction.

MATERIAL AND METHOD

Workpiece

The experimental tests conducted in the laboratories of Gazi University, Faculty of Technology, utilised a workpiece with a diameter of 60 mm and a length of 400 mm. [24]. The workpiece material is AISI 1117 steel. The material's surface was initially machined with a depth of cut of 1 mm in case of hardening of the outer surface layer. The dimensions of the workpiece are illustrated in Figure 2. Experimental cutting parameters are given in Table 1.

Cutting Tool and Tool Holder

The cutting tool used in the experiments is a cemented carbide SCMW 12 M508-12F insert, compliant with ISO 1832 standards and without a chip breaker. It features a rake angle of 0° and a clearance angle of 7°. The tool holder is of type SSBCR 25 25 M12 with a 75° lead angle, suitable for the insert geometry. Figure 3 provides a schematic representation of the tool and holder, while Table 2 provides the dimensional specifications.

Experimental Setup

The experiments were conducted at the CNC Workshop of Gazi University, Faculty of Technical Education, using the JOHNFORD T35 CNC turning machine. The main specifications of the lathe are presented in Table 3 [24]. The cutting forces in the experiments were measured using a Kistler 9257B-type dynamometer, as seen in Figure 4. The technical features of this dynamometer are shown in Table 4. During the cutting process, signals produced by the tool were transmitted to a computer using an amplifier and transformed into actual force values using the Dynoware software package [24].

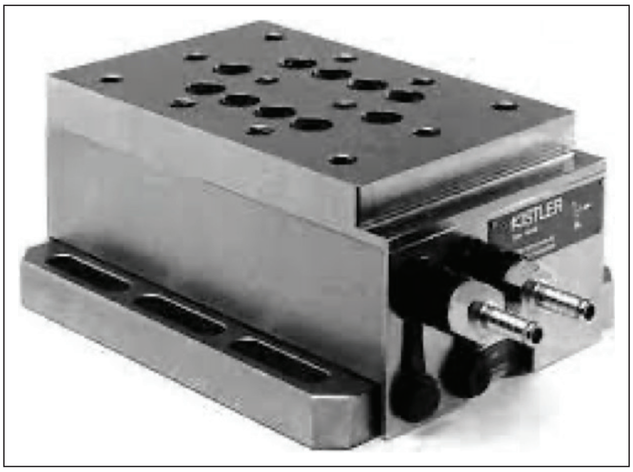

Figure 4. Kistler 9257B dynamometer [24].

Estimation of Cutting Forces by Learning Method

This part emphasises the prediction of cutting forces through the analysis of variations in cutting speed, feed rate,

Table 5. Comparison of learning algorithms in Matlab regression

Algorithms Used	RMSE	R^2	MSE	MAE
Linear regression (interactions linear)	23,441	0.91	549.48	18,607
Linear regression (linear)	22,089	0.9	48.93	18,642
Linear regression (robust linear)	22,358	0.91	499.89	18,716
Stepwise linear regression	22,089	0.91	487.93	18,642
Tree (medium tree)	74,713	0	5582.1	63,092
Tree (coarse tree)	74,713	0	5582.1	63,092
Tree (fine tree)	51,269	0.53	2628.5	45,503
SVM (linear SVM)	22,478	0.91	505.28	18,837
SVM (medium gaussian SVM)	33.09	0.79	1149.8	29,176
SVM (cubic SVM)	19,573	0.93	383.1	16,658
SVM (coarse gaussian SVM)	30,644	0.83	939.03	26,287
SVM (fine gaussian SVM)	73,152	0.04	5351.3	61,087
Gaussian process regression (squared exponential GPR)	22,013	0.91	484.57	18,652
Gaussian process regression (matern 5/2 GPR)	22,932	0.91	525.85	19,386
Gaussian process regression (rational quadratic GPR)	22,839	0.91	521.63	19,266
Gaussian process regression (exponential GPR)	22,561	0.91	509.14	19,988
Ensemble (boosted trees)	50,841	0.54	2584.8	44,141
Ensemble (bagged trees)	60,588	0.34	3670.9	51,621

SVM: Support vector machine; GPR: Gaussian process regression; RMSE: Root mean squared error; MSE: Mean square error; MAE: Mean absolute error.

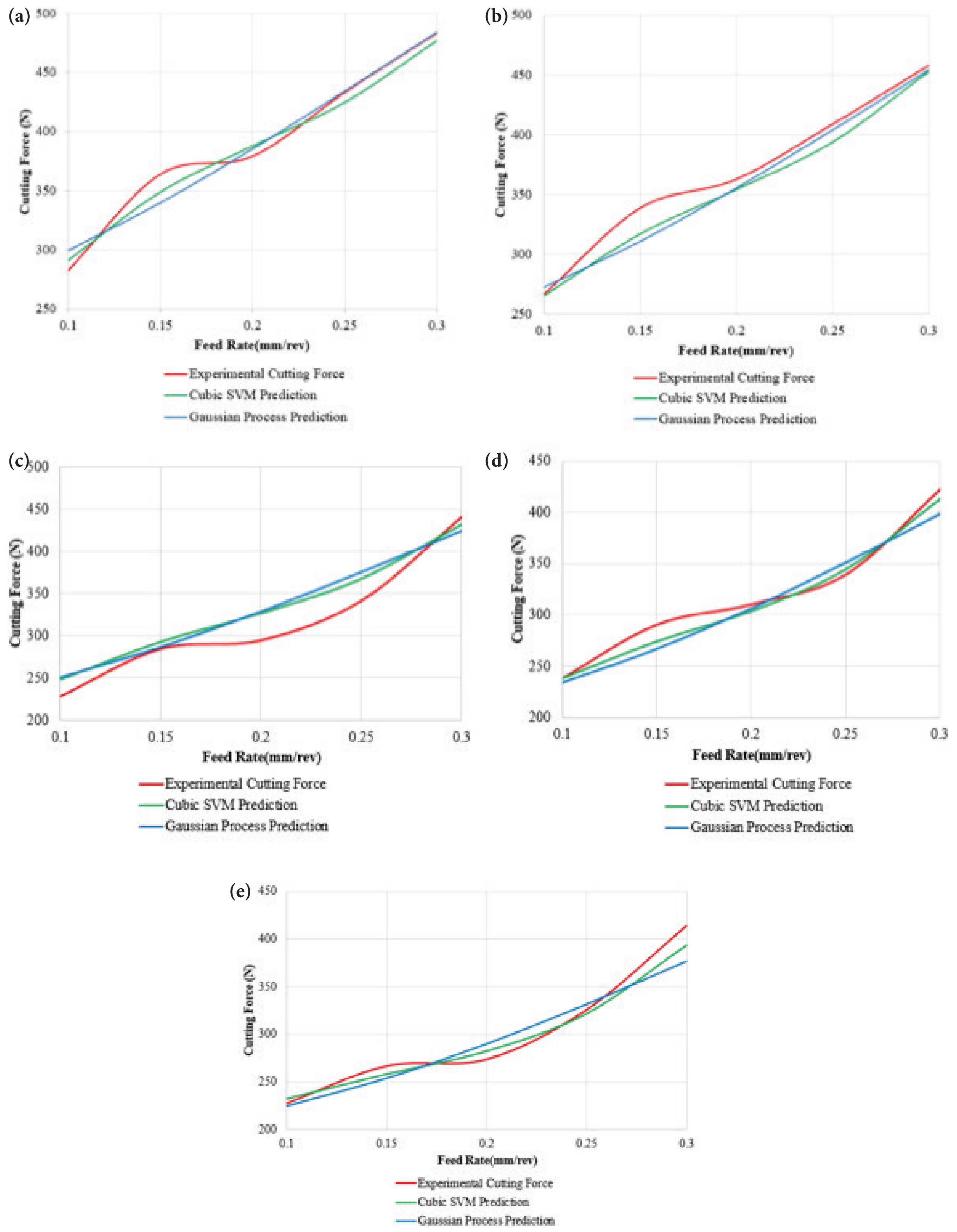

Figure 5. Feed rate & cutting force for the cutting speed of **(a)** 50 m/min **(b)** 75 m/min **(c)** 100 m/min **(d)** 125 m/min **(e)** 150 m/min.

and depth of cut. The depth of cut was initially maintained constant, but the feed rate and cutting speed were treated as independent variables. Subsequently, depth of cut was incorporated as a third independent variable in addition to the initial two. The prediction models were evaluated to determine which method most precisely mirrored the experimental

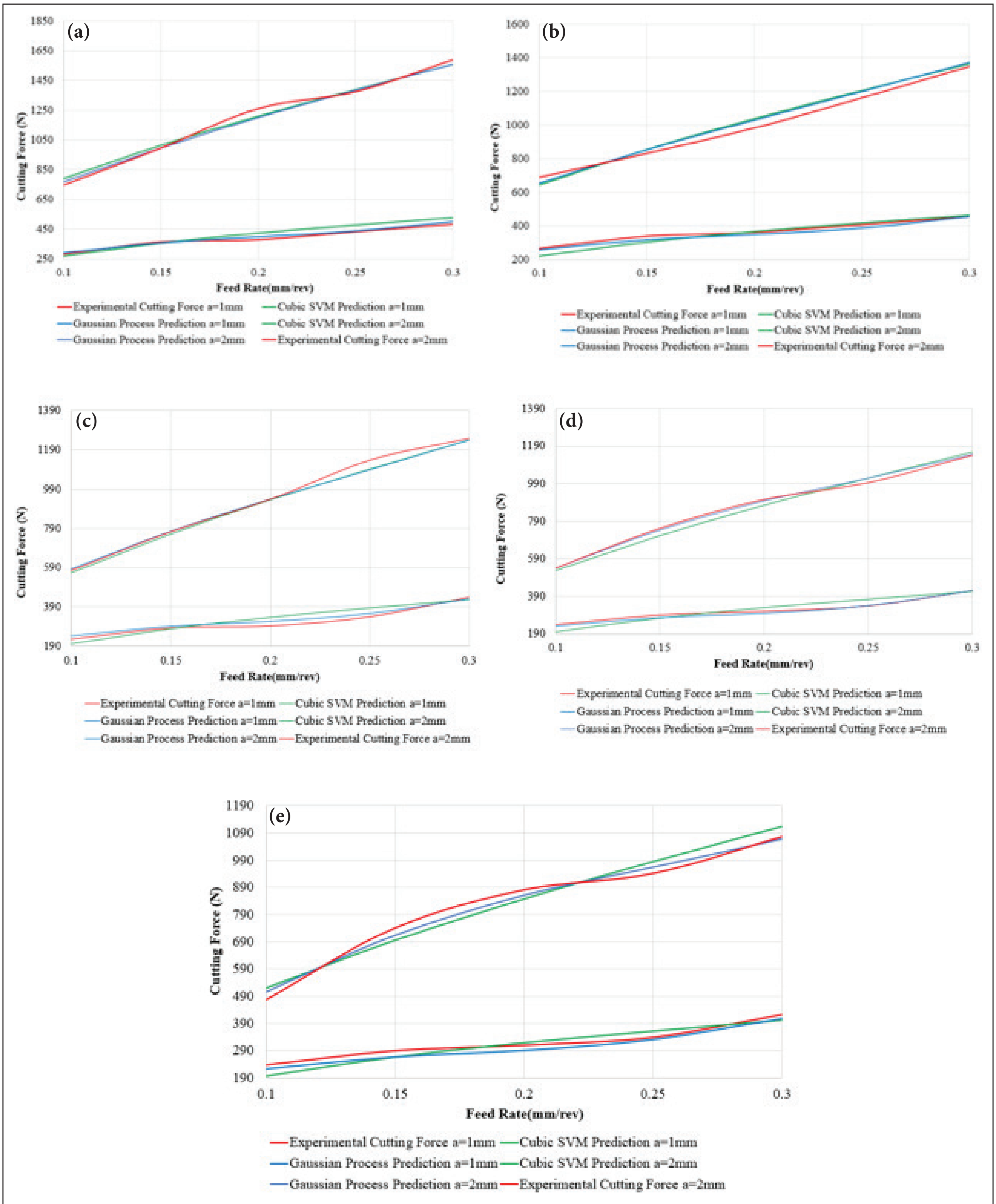

Figure 6. Feed rate & cutting force for various cutting speeds and depths of cuts **(a)** 50 m/min **(b)** 75 m/min **(c)** 100 m/min **(d)** 125 m/min **(e)** 150 m/min.

cutting forces, the dependent variable. The aim is to estimate cutting forces using only independent variables and to see if ML techniques produce more accurate results by comparing the predicted cutting force to experimentally acquired values. The efficacy of the learning algorithms was assessed utilising R^2, RMSE, MSE, and MAE, as previously mentioned.

Hyperparameter Tuning and Cross-Validation Methods

The success of ML algorithms depends not only on the choice of the model but also on the selection of appropriate hyperparameter values and model validation strategies. In this study, regression-based learning algorithms were implemented using MATLAB's Regression Learner interface, which provides

Table 6. Comparison between experimental and predicted cutting force results

Cutting speed (m/min)	Feed rate (mm/rev)	Experimental cutting force (N)	Cubic SVM prediction	Gaussian process prediction	Cubic SVM prediction error rate	Gaussian process prediction error rate
50	0.1	283	291.5	299.6	3.02	5.87
50	0.15	364	349.0	339.7	-4.12	-6.66
50	0.2	379	387.7	385.2	2.28	1.63
50	0.25	433	424.5	433.9	-1.97	0.20
50	0.3	483	476.5	483.5	-1.34	0.10
75	0.1	267	265.7	272.7	-0.49	2.14
75	0.15	339	317.3	311.1	-6.39	-8.24
75	0.2	363	354.4	355.4	-2.37	-2.09
75	0.25	409	393.9	403.8	-3.68	-1.28
75	0.3	458	453.0	453.8	-1.10	-0.93
100	0.1	229	248.4	250.5	8.46	9.40
100	0.15	285	292.8	286.4	2.74	0.49
100	0.2	295	327.0	328.7	10.83	11.44
100	0.25	342	367.8	375.7	7.55	9.87
100	0.3	441	432.5	425.1	-1.94	-3.60
125	0.1	238	237.9	234.3	-0.04	-1.56
125	0.15	290	273.8	267.0	-5.60	-7.93
125	0.2	310	303.6	306.6	-2.07	-1.10
125	0.25	339	344.4	351.3	1.60	3.64
125	0.3	422	413.3	399.1	-2.06	-5.43
150	0.1	228	232.5	224.8	1.99	-1.40
150	0.15	267	258.4	253.9	-3.20	-4.91
150	0.2	274	282.6	290.1	3.14	5.87
150	0.25	326	322.0	331.8	-1.22	1.77
150	0.3	414	393.8	377.0	-4.89	-8.94

SVM: Support vector machine.

automated tools for testing multiple hyperparameter configurations and selecting the optimal model setup. Specifically, the study explored and compared different kernel functions and associated parameter values for cubic SVM and GPR.

Although the hyperparameter tuning was not conducted manually by the user, the automated configuration and selection process provided by the Regression Learner interface was effectively meant to enhance model performance. In the case of SVM, kernel types such as linear, cubic, and Gaussian were evaluated, while for GPR, various kernel functions, including squared exponential, rational quadratic, and Matern 5/2, were tested.

Model performance was assessed using a cross-validation approach. The MATLAB Regression Learner applies 5-fold cross-validation by default, which objectively evaluates the generalisability of the model. In this method, the training dataset is divided into five equal parts, each serving as a test set in turn, and the average performance metrics are calculated and compared.

Results of the Estimation Utilizing two Independent Variables

This section presents a constant cutting depth of 1 mm. The cutting speed and feed rate are considered as independent variables, whereas the cutting force is regarded as the dependent variable. Regression and learning techniques from MATLAB are employed for analysis.

The review of Tables 5 and 6 and Figure 5 shows how well different ML algorithms predict cutting forces using two factors: cutting speed and feed rate. The cubic SVM was the most accurate of all the algorithms tested, with an R^2 value of 0.93 and the lowest RMSE of 19.57, outperforming both linear regression and tree-based models. The cubic SVM showed the best accuracy of all the algorithms tested, with an R^2 value of 0.93 and the lowest RMSE of 19.57, outperforming linear regression and tree-based models.

The prediction errors presented in Table 6 demonstrate that Cubic SVM consistently achieves errors below 10%, especially at both lower and higher cutting speeds.

Table 7. Learning algorithms and validation with Matlab regression

Algorithms used	RMSE	R^2	MSE	MAE
Linear regression (interactions linear)	46.92	0.99	2201.8	35,146
Linear regression (linear)	121.24	0.9	14699	95,669
Linear regression (robust linear)	125.55	0.9	15763	98,627
Stepwise linear regression	49,256	0.98	2426.1	36,959
Tree (medium tree)	210.43	0.71	44282	153.34
Tree (coarse tree)	390.13	0	343.35	343.35
Tree (fine tree)	164.63	0.82	27102	112.88
SVM (linear SVM)	142.58	0.87	20329	105.99
SVM (medium gaussian SVM)	105.38	0.93	11105	69,801
SVM (cubic SVM)	51,572	0.98	2659.7	40,816
SVM (coarse gaussian SVM)	168.22	0.81	28299	114.84
SVM (fine gaussian SVM)	363.17	0.13	131890	316.04
Gaussian process regression (squared exponential GPR)	43,163	0.99	1863.1	34,137
Gaussian process regression (matern 5/2 GPR)	39,782	0.99	1582.6	32,321
Gaussian process regression (rational quadratic GPR)	43,316	0.99	1859	34,112
Gaussian process regression (exponential GPR)	75,386	0.96	5683	49,352
Ensemble (boosted trees)	151.55	0.85	22968	99,037
Ensemble (bagged trees)	278.71	0.49	77680	243.28

SVM: Support vector machine; RMSE: Root mean squared error; MSE: Mean square error; MAE: Mean absolute error.

Figures 6a–e illustrate a linear increase in cutting force with respect to feed rate, with a steeper slope observed at higher cutting speeds, thereby confirming the impact of feed rate on force generation.

Trend Analysis Across Cutting Speeds

Figure 5 illustrates the correlation between feed rate and cutting force at various cutting speeds (50, 75, 100, 125, and 150 m/min). In all instances, the cutting force exhibits a linear rise with the feed rate, which is consistent with expected machining behaviour. The rate of increase is more obvious at higher cutting speeds, suggesting that feed rate significantly influences cutting force at increased speeds.

Model Performance Observation

At lower cutting speeds (like 50 m/min, Figure 5a, both models provide similar results, with Cubic SVM slightly performing better than GPR in terms of error (as shown in the first five rows of Table 6). At medium speeds (75–100 m/min, Figures 5b, Figure 5c, GPR shows more reliable results, especially when cubic SVM tends to overestimate or underestimate (for example, at 100 m/min and 0.2 mm/rev, Cubic SVM has an error of 10.83% while GPR has 11.44%). At higher speeds (125–150 m/min, Figures 5 (d and e)), both models provide reliable predictions, but GPR is better at handling small changes in the force response.

Error Rate Evaluation

Table 6 indicates that Cubic SVM consistently achieves a prediction error below 10%, demonstrating optimal performance at both very low and very high cutting speeds. GPR predictions demonstrate increased stability under different conditions, particularly at mid-range feed rates (e.g., 0.2–0.3 mm/rev). The most unfavourable prediction scenarios (e.g., 100 m/min at 0.2 mm/rev) demonstrate the sensitivity of Cubic SVM to particular input interactions, whereas GPR exhibits relative robustness.

Estimation Results Using Three Independent Variables

This part concentrates on predicting cutting forces by analysing variations in cutting speed, feed rate, and depth of cut. By incorporating the depth of cut as a third independent variable, several regression approaches are utilised to choose the ML strategy that achieves the greatest prediction accuracy.

As depth of cut is introduced as a third variable, Table 7 and Figures 6a through 6e reveal a shift in algorithm performance. GPR, using the Matern 5/2 kernel, performed better than Cubic SVM, reaching an R^2 of 0.99 and a low RMSE of 39.78. The figures demonstrate that even under more complex conditions, GPR offers more stable predictions. Tables 8, 9 further confirms this trend: while Cubic SVM's error rates range from 5% to 10%, GPR's prediction errors mostly stay under 4% for a depth of 1 mm and often below 3% for 2 mm depth, highlighting its robustness in higher-dimensional data environments. These tabular and graphical findings collectively demonstrate that cubic SVM is effective for simpler, two-variable models, whereas GPR provides more accurate and consistent predictions when dealing with three-variable, nonlinear machining scenarios.

Table 8. Result comparison for three parameters

Cutting speed (m/min)	Feed rate (mm/rev)	Experimental cutting force a=1mm (N)	Cubic SVM prediction a=1mm (N)	Gaussian process prediction a=1mm (N)	Cubic SVM prediction error rate	Gaussian process prediction error rate
50	0.1	283	269.4	289.2	-4.81	2.19
50	0.15	364	356.7	356.4	-2.01	-2.09
50	0.2	379	423.5	396.6	11.74	4.64
50	0.25	433	477.5	436.0	10.28	0.69
50	0.3	483	526.3	499.1	8.96	3.33
75	0.1	267	222.5	261.7	-16.67	-1.99
75	0.15	339	304.3	318.7	-10.24	-5.99
75	0.2	363	366.4	350.0	0.94	-3.58
75	0.25	409	416.4	387.6	1.81	-5.23
75	0.3	458	462.2	455.0	0.92	-0.66
100	0.1	229	204.4	242.8	-10.74	6.03
100	0.15	285	281.4	291.5	-1.26	2.28
100	0.2	295	339.6	317.2	15.12	7.53
100	0.25	342	386.5	356.9	13.01	4.36
100	0.3	441	429.8	432.3	-2.54	-1.97
125	0.1	238	200.5	233.3	-15.76	-1.97
125	0.15	290	273.6	278.0	-5.66	-4.14
125	0.2	310	328.5	300.4	5.97	-3.10
125	0.25	339	373.0	340.0	10.03	0.29
125	0.3	422	414.7	418.6	-1.73	-0.81
150	0.1	228	196.3	222.4	-13.90	-2.46
150	0.15	267	266.1	266.9	-0.34	-0.04
150	0.2	274	318.6	290.4	16.28	5.99
150	0.25	326	361.3	330.8	10.83	1.47
150	0.3	414	402.1	408.5	-2.87	-1.33

SVM: Support vector machine.

CONCLUSION

This study finds that ML methods, especially cubic SVM and GPR, are very promising for accurately predicting cutting forces in machining. The cubic SVM demonstrated superior performance with cutting speed and feed rate as the sole inputs, attaining a high R^2 and low RMSE. Incorporating depth of cut as a third factor improved the performance of GPR, particularly when using the Matern 5/2 kernel, making it more accurate and reliable than all other methods. Along with these two models, we also looked at different algorithms, such as several kinds of linear regression, decision trees (fine, medium, and coarse), and ensemble methods (boosted and bagged trees). These models typically exhibited reduced performance, especially in their ability to capture nonlinear and multivariable interactions. This study's results align with previous research by Kumar et al. [3] and Chen and Jeng [25], both of which highlighted the advantages of SVM and GPR models in machining applications.

The study indicates that the quantity and nature of independent variables significantly affect the generalisation capabilities and predictive accuracy of ML models. Models such as Cubic SVM demonstrate effective performance in low-dimensional settings characterised by stable variable interactions. As the number of input variables increases and their interactions grow more complex, particularly regarding the depth of cut, results projection becomes more difficult, necessitating the use of more adaptable and robust algorithms like GPR. This highlights the necessity of aligning model complexity with data structure in manufacturing contexts. This study identifies optimal models for predicting cutting force and contributes to the advancement of manufacturing science through computational intelligence.

Data Availability Statement

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

Table 9. Result comparison for three parameters

Cutting speed (m/min)	Feed rate (mm/rev)	Experimental cutting force a=2mm (N)	Cubic SVM prediction a=2mm (N)	Gaussian process prediction a=2mm (N)	Cubic SVM prediction error rate	Gaussian process prediction error rate
50	0.1	745	789.7	767.2	9.49	3.58
50	0.15	993	1012.3	993.7	9.57	3.62
50	0.2	1260	1209.0	1200.9	9.68	3.65
50	0.25	1373	1387.5	1385.5	9.60	3.61
50	0.3	1586	1555.5	1557.3	9.58	3.66
75	0.1	691	646.4	655.8	9.60	3.68
75	0.15	832	856.0	852.4	8.95	3.69
75	0.2	983	1040.4	1030.2	8.63	3.46
75	0.25	1163	1207.5	1200.8	8.67	3.35
75	0.3	1348	1364.8	1371.0	8.71	3.09
100	0.1	574	563.5	582.4	8.73	3.06
100	0.15	772	760.8	773.9	8.21	2.95
100	0.2	937	933.7	936.8	8.12	2.96
100	0.25	1137	1090.1	1087.1	7.90	2.73
100	0.3	1248	1237.4	1238.0	7.76	2.68
125	0.1	540	526.4	539.2	7.62	2.59
125	0.15	752	712.1	741.7	6.28	2.48
125	0.2	905	874.3	896.0	5.78	2.15
125	0.25	996	1020.6	1018.6	5.78	1.86
125	0.3	1141	1158.8	1143.8	5.75	1.81
150	0.1	476	520.6	504.9	5.49	1.69
150	0.15	740	695.4	713.3	3.49	1.36
150	0.2	880	847.6	861.3	3.21	1.27
150	0.25	940	984.7	964.6	2.85	1.13
150	0.3	1076	1114.3	1069.3	2.89	1.14

SVM: Support vector machine.

Author's Contributions

Kadir Özdemir: Conception, Materials, Design, Data Processing, Supervision, Analysis and Interpretation, Literature Review, Writer, Critical Review.

Ulvi Şeker: Conception, Materials, Data Collection and Processing, Interpretation, Literature Review, Writer, Critical Review.

Mustafa Cemal Çakır: Conception, Materials, Design, Supervision, Analysis and Interpretation, Literature Review, Writer, Critical Review.

Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Statement on the Use of Artificial Intelligence

Artificial intelligence was not used in the preparation of the article.

Ethics

There are no ethical issues with the publication of this manuscript.

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