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ORIGINAL PAPER

Machine Learning-Based Erosion Behavior of Silicon Carbide Reinforced Polymer Composites

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Abstract

The machine learning methodology is gaining immense exposure as a potential methodology for solving and modelling the machining behaviour of advanced materials. The present paper deals with the application of machining learning approach in analyzing and predicting the effect of reinforced silicon carbide (SiC) particle size on the erosion behaviour of silicon carbide reinforced polymer composites. L_{27} orthogonal array was designed based on Taguchi's methodology to execute the experiments. Support vector machine (SVM) and multi-linear regression (MLR) approach were coupled with Taguchi's methodology to validate obtained optimized response characteristics. These machine learning-based SVM and MLR models are adopted to analyze the absurdity among obtained experimental results and predicted response. Out of 27 experimental runs based on experimental design, 19 experimental runs were selected for training models whereas 08 models were selected for the testing phase. Impingement angle, workpiece reinforcement, standoff distance and slurry pressure were used as input process parameters, whereas material loss was observed as response characteristics. The kernel functions, i.e. Pearson VII based universal kernel (PUK) and radial based function (RBF) kernel were used with machine learning models to obtain the best performing machine learning approach in predicting erosion behaviour of polymer composites.

Keywords Erosion · Polymer composites · Machine learning · Multi linear regression · Support vector machine · Silicon carbide

1 Introduction

The silicon carbide (SiC) reinforced polymer composite materials are widely used in those areas where climatic conditions play a significant role in influencing the performance of materials [1, 2]. These areas are subjected to constant attack of abrasive slurry particles which diminishes the strength of materials by degrading material's upper surface in operating conditions. The erosion on the surface of components assembled in marine and aerospace application degrades surface by causing wear [3]. During the erosion phenomenon, the impact of abrasive particles initiates tiny cracks over the material surface, which leads to substantial material loss. The presence of solid erosion particles in the environment causes surface degradation of the component of aircraft made up of polymeric materials [4]. The surface damage due to erosion has emerged as a severe problem for the component's performance in dusty and slurry environment [5]. The presence of dust particles in air roots surface degradation of the component's surface assembled in aircraft [4] which results in costly maintenance as well as security risks [6]. Erosion of surface mainly occurs in industrial applications where components made from polymers are used because of high stiffness and specific strength [7]. The SiC reinforced polymer matrix composites have gained immense popularity as industrial material due to improved strength [8]. As far as glass fibre-based composites are concerned, the erosion phenomenon consists of matrix removal, fibre breaking and debonding of reinforcement from matrix [9]. The degradation in surface material depends upon several factors like nature of erodent particles, impingement angle, impact velocity etc. The fiber orientation significantly influences the erosion of fibrous composites as the unidirectional fiber orientation shows semi ductile erosion behavior [8]. In

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Table 1 Process parameters at different levels

Sr. no.	Process parameters	Designation	Level 1	Level 2	Level3
1	Abrasive Erodent (Type)	A	River	Beach	Desert
2	Impingement Angle (°)	B	30	60	90
3	W. R. Size (mesh)	C	400	320	220
4	Standoff Distance (mm)	D	10	15	20
5	Slurry Pressure (bar)	E	3	4	5

comparison, the graphite/fiber polymer composite exhibits brittle erosion behavior, and aramid fiber polymer composite exhibits quasi ductile behavior [10]. Another study shows that with an increase in glass fiber reinforcement, the ductile erosion behavior changes into brittle erosion behavior [11]. The small particle size (less than two μm) shows the minimal effect on erosion loss, but an increase in particle size significantly increases the erosion loss from the composite surface [12]. The erosion loss in the fibrous composites can be reduced by reinforcing treated fibers. The treatment in the fibers increases the interfacial strength, which improves the erosion resistance [13]. Also, the impact at the angle of 90° shows lesser erosion loss as compared to erosion loss at 30° [14].

From last few decades, various optimization techniques like an artificial neural network [15], particle swarm optimization [16], genetic algorithm [17], grey relational analysis [18] etc. were adopted by researchers for the optimization of various engineering processes. But in recent years, the application of machine learning approaches has emerged as a potential contender for the modelling and validation of experimentation results. Ushasta et al. [19] used a support vector machine coupled with particle swarm optimization for modelling of EDM response parameters. Guangwei et al. [20] estimated the height of the online workpiece during reciprocated TW-EDM by using support vector machine and concluded that the SVM method reduced the estimation error as well as machining time significantly. Guofeng et al. [21] compared Gaussian mixture regression (GMR) with radius basis function, multiple linear regression and neural network for tool wear prediction. They concluded that GMR based model produces the best result in comparison. Sun et al. [22] implemented a support vector machine to carry out multi-classification of tool conditions and concluded that the SVM approach effectively performs multi-classification of tool wear and improved productivity.

2 Experimental Design and Planning

The glass fibers and silicon carbide particles reinforced polymer composites were prepared by hand layup method [1]. The variable sizes of SiC particles were used as reinforcement to analyze the effect of particle size on the erosion characteristics of the composite, as shown in Table 1. The mixture of Araldite epoxy resin and hardener in the ratio of 5:4 was used as matrix. The epoxy adhesive cures at temperature ranges from 68 °F (20 °C) to 356 °F (180 °C) with no release of volatile constituents. ASTM G76 standard was adopted for the analysis of erosion behaviour using in house fabricated abrasive erosion test setup. The line diagram for abrasive erosion setup is presented in Fig. 1. The parameters were studied at three levels to analyze the non-uniform behaviour of input process parameters. Taguchi's methodology based L_{27} orthogonal array was used to analyze parametric combination. Each experiment was performed with three repetitions to validate the erosion loss during experimentation. Depending upon required response characteristics, lower the better S/N ratio criteria [23–25] is preferred and calculated using Eq. (1) as follows:

$$\eta_{ij} = -10\log\left\{\frac{1}{n}\sum_{i=1}^{n} y_{ij}^{2}\right\} \tag{1}$$

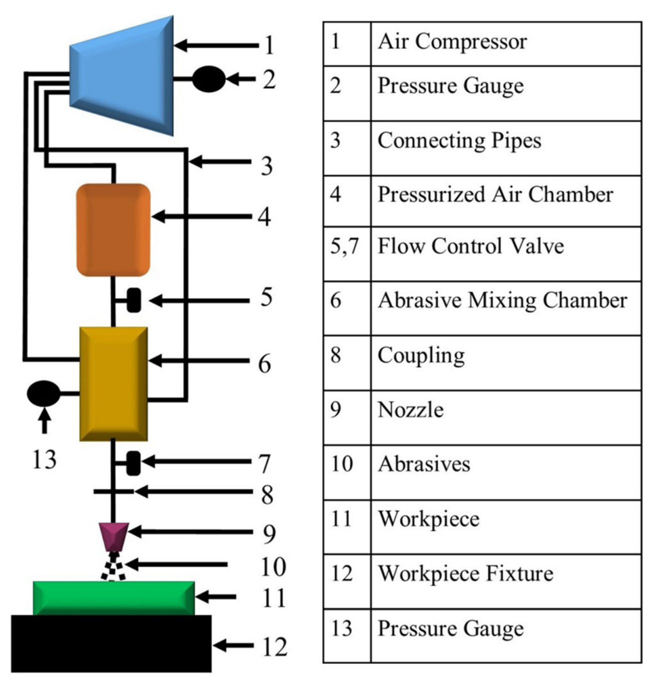

Fig. 1 Line diagram for erosion setup [1]

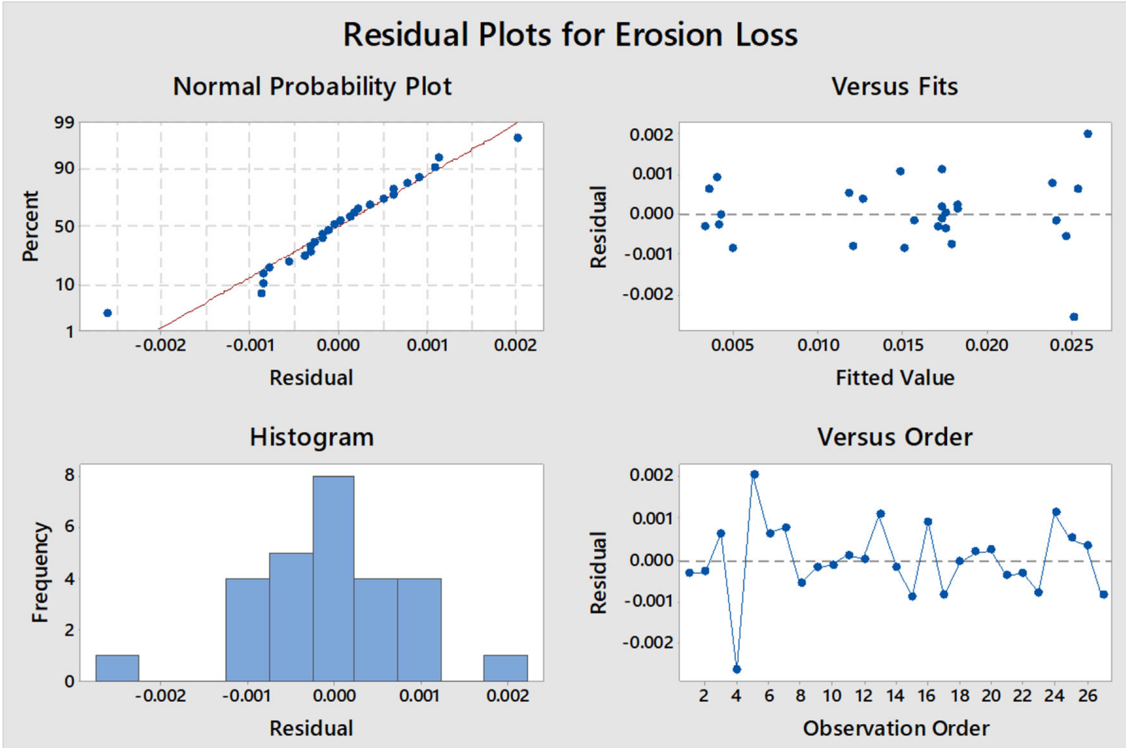

Fig. 2 Residual plots for erosion loss

Here y_{ij} is the i^{th} experiment at j^{th} test and n is the total number of tests.

The impact angles (β) for the present test were varied from 30° to 90°. The erodent particles in the form of different types of sands from different locations, i.e. river, beach and desert were used for the experimentation. The high-pressure erodent slurry comes out through nozzle and strikes the specimen each time continuously for four minutes. The average erosion loss from three replications was recorded for each specimen. The variance in initial and final weight of specimens was termed as weight loss. The several test settings engaged for erosion test are presented in Table 1.

3 Taguchi's Methodology

The experimental results for a signal to noise ratio with corresponding erosion loss are plotted in Figs. 2 and 3. The signal dominating the noise value corresponds to the higher S/N ratio to generate healthier quality characteristics. Therefore, the parametric setting where the S/N ratio comes out as supreme value, the specimen will show high resistance to erosion. In Fig. 3, the optimal conditions for minimum erosion loss are $A_2B_1C_1D_1E_1$. For numeral and classification terms, the optimal values are found to be abrasive erodent, beach sand; impingement angle, 30°; workpiece reinforcement size, 400 mesh; standoff distance, 10 mm and slurry pressure, 3 bar. The analysis of variance (ANOVA) was used to identify the parameters which affect the erosion loss significantly. The ANOVA for erosion loss is shown in Table 2. The ANOVA indicates that erosion loss is affected substantially by workpiece reinforcement size (44.85%) followed by standoff distance (28.59%), impingement angle (15.70%) abrasive erodent (9.22%) and slurry pressure (1.40%). The error associated with the experimental results was found to be 0.28%.

4 Support Vector Machine (SVM)

SVM is resultant of algebraic learning model and grounded on the optimal partition of modules for cataloguing problem. For

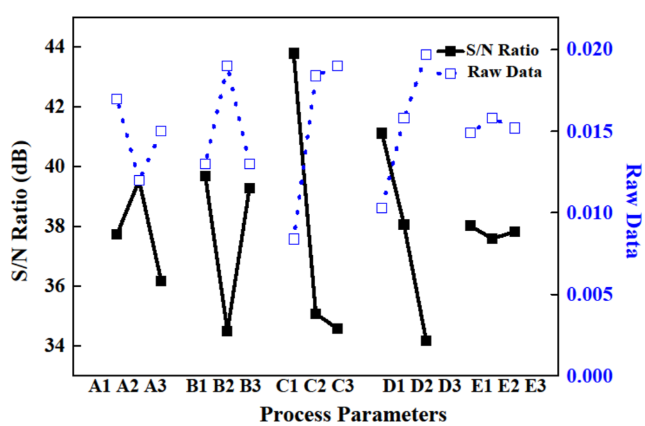

Fig. 3 S/N ratio and raw data plots

Table 2 ANOVA for Erosion Loss

Source	DF	SS	MS	F Value	*P* Value	% C
Abrasive erodent	2	0.000131	0.000066	53.36	0.000	9.22
Impingement angle	2	0.000223	0.000112	90.36	0.000	15.70
W. R. size	2	0.000637	0.000318	258.81	0.000	44.85
Standoff distance	2	0.000406	0.000203	164.82	0.000	28.59
Slurry pressure	2	0.000004	0.000002	1.42	0.270	1.40
Error	16	0.000020	0.000001			
Total	26	0.001420				

two-class cataloguing problem, SVM picks a classifier which has smallest simplification miscalculation from unlimited quantity of linear classifier or fixed higher boundary to error which is attained from organizational menace minimisation. Thus supreme margin between two classes could be attained from the designated hyperplane and accumulation of distances of the hyperplane from the adjacent point of two groups [26]. Additional planned model is ε-Support vector regression (SVR) by giving an opportunity ε-insensitive damage function [27]. This damage function permits the indication of superiority to be used for regression concerns where verge is categorized as the aggregate of the partings of the hyperplane from the adjacent purpose of the two classes. The purpose of the SVR is to determine a function having at highest ε deviation from the real target vectors for all given information data and must be as level as could sensibly expect [28]. Vapnik [29] presented the impression of kernel function for non-linear support vector regression.

4.1 Kernel Functions

In the analysis through machine learning, the term kernel is generally referred to as a technique used to solve the non-linear problem using the linear classifier. There are various kernel functions associated with the SVM. By adjusting the kernel parameters, the optimal kernel function can be obtained. In the present research, three kernel functions are used for the analysis, i.e. radial basis kernel, Pearson kernel and polynomial kernel.

4.1.1 Radial Basis Kernel (RBK)

In SVM, the most commonly used kernel function is the radial basis kernel (RBK). The RBK for two samples as feature vector viz. x and y can be expressed as

$$K(x,y) = \exp\left(\frac{\|x-y\|^2}{2\sigma^2}\right) \tag{2}$$

Here $\|x-y\|^2$ is square of the Euclidean distance between feature factors.

4.1.2 Pearson Kernel (PUK)

PUK is universal kernel function usually used for the SVM for its flexibility and high adaptability. The PUK functions can also be used to replace other kernel functions [30].

Table 3 Characteristics of the data used for model development and validation

Range	Impingement angle	Workpiece R. size	SOD	Slurry pressure	Erosion loss
	Training data set				
Mean	58.4211	308.4211	15.0000	4.0000	0.0156
Standard Deviation	25.4434	76.6857	4.0825	0.8165	0.0075
Minimum	30.0000	220.0000	10.0000	3.0000	0.0029
Maximum	90.0000	400.0000	20.0000	5.0000	0.0280
Confidence Level (95.0%)	12.2633	36.9613	1.9677	0.3935	0.0036
	Testing data set				
Mean	63.7500	325.0000	15.0000	4.0000	0.0146
Standard Deviation	25.0357	74.6420	4.6291	0.9258	0.0076
Minimum	30.0000	220.0000	10.0000	3.0000	0.0038
Maximum	90.0000	400.0000	20.0000	5.0000	0.0241
Confidence Level (95.0%)	20.9304	62.4023	3.8700	0.7740	0.0064

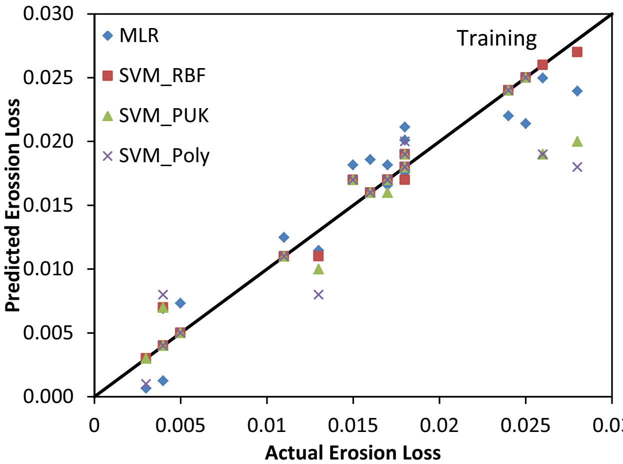

Fig. 4 Agreement plot among actual and predicted values using MLR and SVM based models using the training data set

4.1.3 Polynomial Kernel (POLY)

The POLY kernels are used in SVM to represent the similarity of feature vector over polynomial of the actual parameter. It can be represented as

$$K(x, y) = \langle \phi(x), \phi(y) \rangle \quad (3)$$

4.2 Multilinear Regression: (MLR)

Multiple regression (MLR) is also applied on more than one predictor parameters. The general equation of the MLR model is as follow:

$$E = c_0 + c_1 x_1 \;\; c_2 x_2 + \ldots\ldots\ldots\ldots\ldots c_n {x_n}^n \quad (4)$$

where E = dependent variable, x_1.,x_2, x_3,….,x_n = independent variables.

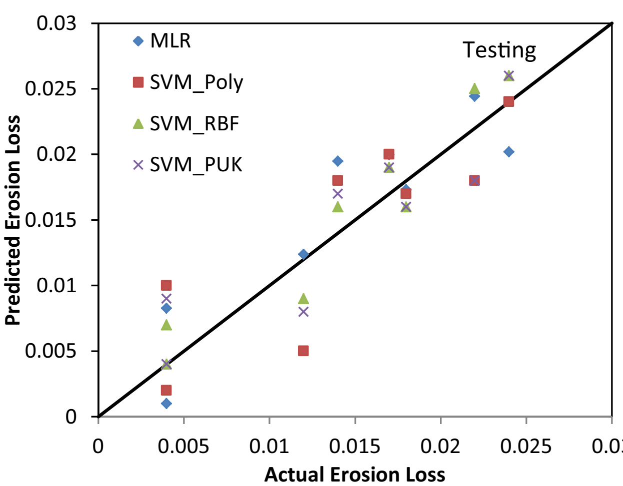

Fig. 5 Agreement plot among actual and predicted values using MLR and SVM based models using the testing data set

Table 4 Performance evaluation parameters using training and testing data sets

Techniques	CC	RMSE	MAE	SI
	Training data set			
MLR	0.950096	0.002284	0.001994	0.146117
SVM_RBF	0.990524	0.001026	0.000526	0.065635
SVM_PUK	0.938489	0.002685	0.001316	0.171783
SVM_Poly	0.901313	0.003269	0.001737	0.209107
	Testing data set			
MLR	0.902072	0.003301	0.002881	0.22962
SVM_RBF	0.838722	0.004047	0.003375	0.281503
SVM_PUK	**0.95972**	**0.002318**	**0.002125**	**0.16128**
SVM_Poly	0.897396	0.003122	0.00275	0.217217

4.3 Performance Assessment Parameters

For the model performance assessment, four statistical parameters Coefficient of correlation (CC), root mean square error (RMSE), mean absolute error (MAE) and scattering index (SI) were used. The above-mentioned assessment parameters can be calculated by the equations as follow:

$$CC = \frac{a\sum AZ - (\sum A)(\sum Z)}{\sqrt{a(\sum A)^2 - (\sum Z)^2}\sqrt{a(\sum A - \sum Z)^2}} \quad (5)$$

$$RMSE = \sqrt{\frac{1}{a}\left(\sum_{i=1}^{a}(A - Z)^2\right.} \quad (6)$$

$$MAE = \frac{1}{a}|A - Z| \quad (7)$$

$$SI = \frac{RMSE}{\overline{A}} \quad (8)$$

where A = Observed, Z = Predicted, $\overline{A}$ = mean observed, a= number of observations.

4.4 Data Set

Total 27 observations from solid particle erosion of SiC reinforced polymer composites are used for model development and validation. The entire data set was splitting into two different groups. The process of splitting is arbitrary. A larger group (70% observations) is considered as training data set for models development, and the remaining group is considered as testing data set for the model validation. Four independent variables, namely as impingement angle (IA), workpiece r. size (WR), SOD and slurry pressure (SP) were considered as inputs. In contrast, Erosion Loss is considered as a target for model development and validation. Characteristics of the data

Table 5 Single-factor ANOVA results

Source of variation	F	*P* value	F crit	Difference among groups
Between MLR and Actual	0.070069	0.795094	4.60011	Insignificant
Between SVM_Poly and Actual	0.001081	0.974235	4.60011	Insignificant
Between SVM_RBF and Actual	0.05036	0.825681	4.60011	Insignificant
Between SVM_PUK and Actual	0.004681	0.946422	4.60011	Insignificant

used for model development and validation are listed in Table 3.

5 Result and Discussions

The MLR is the empirical equation developed by least square technique to drive regression coefficients using the training data set. XLSTAT software is used for the development of MLR based model.

$$E = -0.07002 + 0.00091\ IA + 0.00039\ WR + 0.00262\ SOD - 0.00543\ SP - 0.000075\ IA^2 - 0.0000007\ WR^2 - 0.00006\ SOD^2 + 0.00072\ SP^2 \quad (9)$$

Figures 4 and 5 provide agreement plots between actual and predicted erosion of polymer composites by MLR and SVM based models for training and testing stages, respectively. Forecast values from MLR and SVM based models are by the actual values. Results of test data set Table 4 indicate that the performance of SVM_PUK based model is best among other kernel-based SVM and MLR approaches. Pearson VII kernel function works better than polynomial or radial basis kernel functions. Correlation coefficient values of 0.9597, MAE as 0.00212, RMSE as 0.002318 and SI as 0.16128 were achieved by Pearson VII kernel function based SVM model. This model suggests a better performance in comparison to the MLR based model. It also works better than polynomial and radial basis kernel function based model for the prediction of erosion loss. MLR based model achieved the correlation coefficient value of 0.902072 (RMSE = 0.003301). Single-factor ANOVA results (Table 5) suggest that there is an insignificant variation among actual and predicted values using MLR and SVM based models. A performance plot is shown in Fig. 6 using the testing data set. It can be noted out from this figure that predicted values provided by SVM_PUK based model were found to follow the same patterns of actual values with minimum deviation.

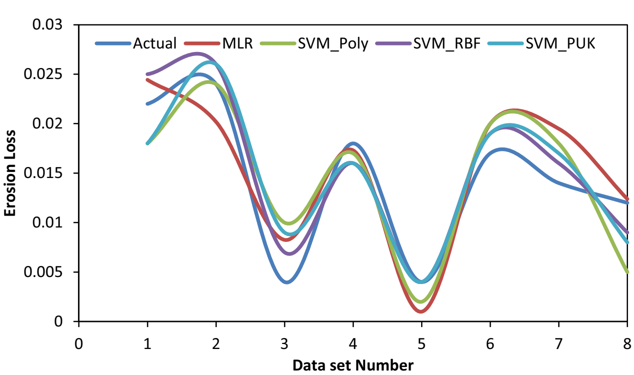

Fig. 6 Performance plot among actual and predicted values using MLR and SVM based models using testing data set

6 Conclusions

The investigation was based on the adopting multi-linear regression and support vector machine-based models in predicting erosion behavior of SiC reinforced polymer composites. Out of the detailed investigation, the following key conclusions can be drawn:

- Taguchi's analysis produces workpiece reinforcement size as key dominating factor in the erosion behavior of the SiC reinforced PMC followed by standoff distance, impingement angle, erodent nature and slurry pressure.
- The optimum conditions for minimum erosion loss are obtained as $A_2B_1C_1D_1E_1$. The optimal values are found to be abrasive erodent, beach sand; impingement angle, 30°; workpiece reinforcement size, 400 mesh; standoff distance, 10 mm and slurry pressure, 3 bar.
- Taguchi is coupled with machine learning for the testing and training of the experimental data.
- The comparative analysis shows that SVM_PUK based model approach works better (CC = 0.95972, RMSE = 0.002318) as compared to other kernel described above function based SVM models for this data set.
- The additional conclusive remark is that the MLR based model is superior to the radial basis kernel function and polynomial kernel function based SVM models.

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