SEMARAK ILMU PUBLISHING

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Developing Blast Prediction Model for Composition 4 (C4) Explosive using Support Vector Machine (SVM)

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ARTICLE INFO

Article history:
Received 13 February 2026
Received in revised form 22 April 2026
Accepted 30 May 2026
Available online 8 June 2026

Keywords:
Support Vector Machine (SVM) regression; composition 4 (C4); blast prediction model; k-fold cross validation; radial base function

ABSTRACT

The Kingery-Bulmash equation has been widely adopted as an explosion prediction model comprising of empirical data for detonation parameters. Theoretically, support vector machine (SVM) is one of the machine learning components that fit small datasets and can generate models with higher accuracy. This study was conducted to develop an explosive prediction model for Composition 4 (C4) using the SVM regression method with explosives weighing in the range from 0.1 to 1.0 kg in burst surface explosion conditions. The experiment was conducted to identify four parameters, namely peak pressure, arrival time, inclined pressure, and reflection pressure, at distances of 0.5 to 5.0 m. The dataset gain was used to develop the prediction model using linear, radial base and polynomial kernel functions. The accuracy for each model was determined using mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE). The optimisation was conducted using search grid analysis to identify the best configuration for penalty factor (C), epsilon, (ε) and gamma (γ). K-fold cross-validation was used to validate the prediction accuracy. The research focuses on the prediction of blasts, and the model shows significant results with 89% accuracy. The radial basis function (RBF) kernel has better fitting for the dataset and produces a higher accuracy prediction algorithm than linear and polynomial kernel functions.

1. Introduction

The semi-empirical blast prediction model, like the Kingery and Bulmash methods, was one of the reliable results developed from experimental trials and allowed simplified equations and charts to define the relationships between blast variables [1]. The variability of the explosion was inherent uncertainty around the charge's size, shape, position, and material [2]. Various explosive prediction models were created by several experiments that included a machine-learning technique. The artificial neural networks (ANN) were used to predict blast loading in an inside setting, and different parameters were applied to describe blast loading in a confined space with an accuracy of 81% [3]. While decision trees model method was used to identify the peak particle velocity and ground vibration amplitude to both the explosive charge weight per delay and distance from the blast. This

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https://doi.org/10.37934/journal.60.5.115126

research replaced the blasting pattern and was primarily based on conventional methods that utilize various empirical equations using decision trees, and the accuracy was 80.5% [4]. Hybrid artificial neural networks and particle swarm optimisation algorithm prediction was used to predict air blast overpressure in quarry blasting.

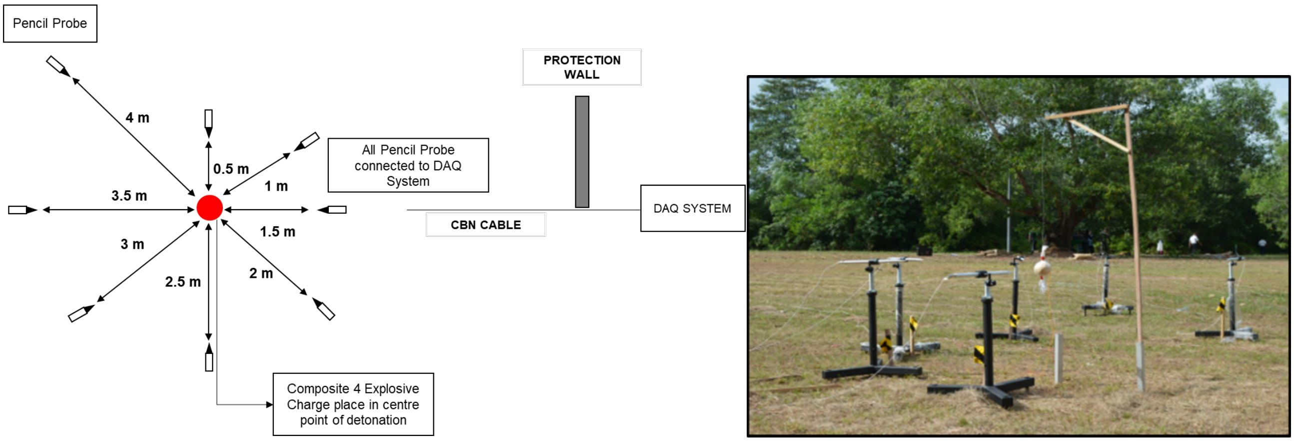
Furthermore, accurate and efficient modelling of blast loads remains a challenge. Blast loadings occur in an extremely short period but with very high intensity, resulting in different structural reactions [5]. All of these are typical of the circumstances in which explosions occur and are disregarded, and machine learning seems a prominent and alternative method to develop a blast prediction model. A deterministic model is used to analyse each distinct input combination of outputs to generate probability distributions that allow the risk of occurrences to be understood and utilised in the decision-making process using machine learning analysis [6]. This computational analysis of explosive occurrences is now carried out primarily with deterministic methods, which yield a single solution to a well-defined problem [7,8]. The optimisation process between several parameters increases the model's predicted accuracy and discovers the correlations between several input variables [9]. The explosive blast prediction model to determine the expected impact of an explosion through machine learning techniques for increased prediction accuracy of actual explosion blasts.

This research aims to create a blast prediction model using Support Vector Machines (SVM) by utilizing the inherent heterogeneity in blast wave parameters from nominally identical explosives. Experimental observations of reflected pressure-time histories from a series of carefully monitored small-scale blast tests will be used to address this subject. To determine whether it is possible to produce dependable, highly consistent, repeatable results that match predictions remarkably well or whether there is, in fact, some inherent variability in the blast waves produced from nominally identical high explosive events, data fitting techniques will be used to obtain positive phase pressure and impulse parameters. Furthermore, the model of choice needs to be quick in executing each distinct scenario so that the time needed to build a thorough grasp of the threat is not unachievable. The blast prediction model developed using a Support Vector Machine (SVM) seem like key for identify the correlation between existing military and commercial explosives by developing blast prediction models. The blast prediction model using machine learning will improve the drawback faced in semi-empirical methods developed from experimental trials and reduce the time of computations [10]. Python-based software develops an intense prediction model for C4 explosives in Malaysian context using SVM and instance capability to predict the peak pressure, time of arrival, incident pressure, and reflection.

2. Methodology

2.1 Blast Measuring Systems

The pencil probes made from piezoelectrical material was connected to data acquisition (DAQ) systems, were used to record blasting parameters, and placed out of shockwave distance, as shown in Figures 1a and b. During the explosive inducement, the shockwave is distorted with high frequencies and hits the pencil probe tip placed in several locations according to the experiment requirements [11]. The pencil probe tip should be pointed to the blasting direction and aligned to the incoming air blast to record accurate measurement overpressure and to prevent wave reflection and amplification. The experiment was conducted 1.0 meters from the ground in free space condition. The pencil probe was placed at 0.5 to 5 meters in radial arrangement.



(a) (b)

Fig. 1. (a)The schematic diagram for the experiment with pencil probe sensors placed in radial arrangement and (b) The arrangement of pencil probe sensors in radial arrangement

During the field test, the probe will produce a voltage as output generated by impact propagation of wave on quartz material inside the sensor, and the voltage signal will be transferred to the DAQ system. The blast transducers were built using acceleration-compensated quartz sensing elements, and embedded ICP microelectronics in pencil probe aid in driving the blasting signal over lengthy cables with increased stability and endurance. The Series 137B quartz pencil probes have a swift microsecond response time and a resonant frequency above 400kHz. This system will receive the voltage signal and transform its explosive blasting parameters. The blasting characteristics such as pressure, arrival time, positive pressure time, negative pressure, and positive impulse can be identified using this method. The placement of the probe should consider the factor minimizing the interference flow of shock waves. The expansion also slightly releases preload quartz material, which can be resolved by tight wrap black electrical tape around sensors. The flat and hard surface was a suitable platform to avoid blast ground shocks that could disturb the measurement accuracy. The data obtained was used to analyse the combination of the kernel as in peak pressure value, time of arrival, and inclined and reflective pressure. The surface burst explosion produces propagation of shock wave overpressure, which increases the peak overpressure from the detonation point to several distances.

2.2 Support Vector Machine (SVM)

The SVM method implements linear epsilon-insensitive SVM (ε-SVM) and the set of training data includes predictor variables and observed response values [12]. The penalty factor *C* is the box constraint. This positive numeric value controls the penalty imposed on observations outside the epsilon margin (ε) and helps to prevent over fitting (regularization) which determines the trade-off between the flatness of $f(x)$ and the amount up to which deviations larger than ε are tolerated as Eq. (1) [13].

$$f(x) = \sum_{i}^{n} (\alpha_i^* + a_i) K\,(x, xi) + B \tag{1}$$

where, $(\alpha_i^*, a_i) \geq 0$ represents the Lagrange multiplier, $K(x, x_i)$ represents the kernel function and *B* represents the bias term.

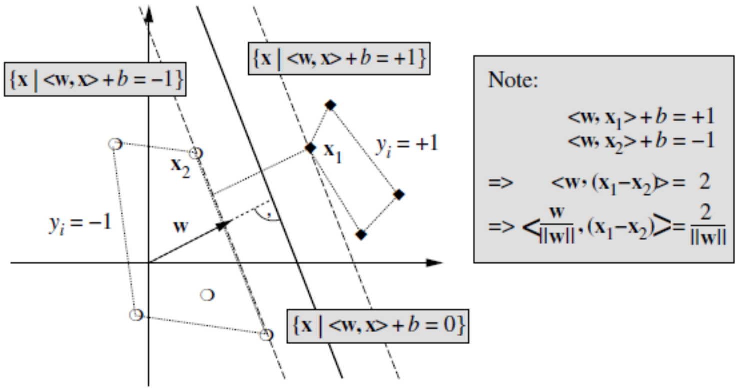


Fig. 2. SVM the linear line divide into two group data [14]

2.3 Kernel

The SVM depends on hyperplane parameters such as penalty factor, epsilon, and gamma value to determine the efficiency and accuracy of each model [15]. The mathematical function used to transform the input dataset according to the function form and widely used kernel functions such as linear, polynomial, sigmoid, and radial basis functions (RBF) [16]. This kernel technique is usually applied for finding hyperplane by turning nonlinear data by projecting the input data into a high dimensional feature space and for identifying separation boundaries [17]. Figure 3 shows kernel function method applied to produce prediction model.

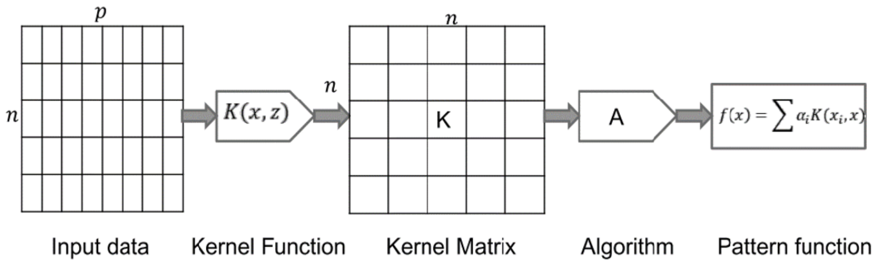


Fig. 3. Prediction model based on kernel function on SVM [18]

The kernel function for Linear can derive Eq. (6), Polynomial Function as Eq. (7), sigmoid function as Eq. (8) and RBF as Eq. (9)[19]

$$k(x_i, x_j) = (x_i * x_j) \tag{2}$$

$$k(x_i, x_j) = (1 + x_i * x_j) \tag{3}$$

$$k(x_i, x_j) = \tanh(\propto x^T y + c) \tag{4}$$

$$k(x_i, x_j) = e^{\frac{(-\gamma |x_i - x_j|^2}{2\sigma^2})} \tag{5}$$

The penalty factor values an enlarged feature space, and it controls the trade-off between smooth decision boundaries to determine the classifying training points correctly as shown in Eq. (6) [20]

$$= min\frac{1}{2}\ ||w||^2 + C\sum_{i=1}^{N} \epsilon_i \tag{6}$$

2.4 Data Analysis

The experiment data were tabulated according to 0.1 kg to 1 kg, and four other blasting parameters were recorded. The peak overpressure, arrival time, incident pressure and reflective pressure readings for spherical and hemispherical shapes data were collected and tabulated in table format [21].The raw dataset was cleaned manually using Microsoft Excel and then generalised into comma-separated values (csv) format according to the weight of the explosive with a four-parameter. The Python program was coded using NumPy module to identify R^2 value for three different kernels, which used analysis, using a combination of hyperplanes. The Python program used optimization by tuning the hyperplane using the Grid Search method for all kernel functions. The process was repeated to identify the best prediction model using experiment data. The analysis was continued by using k-fold cross-validation analysis using developed code with NumPy module for determining overall prediction value. The flow chart in Figure 4 expresses how this study was executed to generate a blasting prediction model explosive.

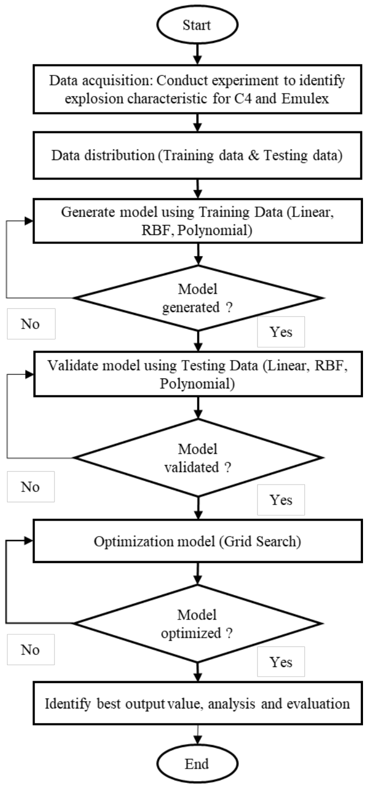


Fig. 4. The flowchart for research methodology

2.5 Coefficient of Determination for Different Kernel Function

The analysis used experiment dataset which divided randomly into two groups comprising 80% of training data and 20% of testing data. The prediction model was created using training data and the fit according to three different kernel types: linear, polynomial and RBF. The equation as shown Eq. (7), Eq. (8) and Eq. (9) [22].

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y}) \tag{7}$$

$$\mathrm{MAE} = \frac{|(y_i - \bar{y}|}{n} \tag{8}$$

$$\mathrm{RMSE} = \sqrt[2]{\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})} \tag{9}$$

where $\bar{y}$ is mean value of y value. While the R^2 also known as coefficient will determination on how the prediction model able to produce prediction value compared to original dataset. The accuracy was draw in range between 0 to 1 and the value close to 1 indicated the more accurate the model fit [22]. A penalty factor value must be higher to fit on algorithm [23]. The error on prediction was measured by using Mean Absolute Error (MAE) function as Eq. (10), and Mean Square Error indicated the average difference between actual and prediction values by squaring the difference between these two values.

$$R^2 = \frac{\sum(\hat{y}_i - \bar{y})^2}{\sum(y_i - \bar{y})^2} \tag{10}$$

where $\bar{y}$ is mean value of y and $\hat{y}$ is prediction value MSE measure based on data is scaled or not and identify residual error and on other hand, R^2 indicated standardised which indicated variance fraction variable captured by regression model. While the testing data was used for testing the prediction model, the result will be indicated by MSE and R^2. The MSE indicated the relative error during prediction; the lowest MSE will provide a better prediction. The higher R^2 value indicates better prediction results when the value is closest to value 1.

2.6 Grid Search Algorithm

The normality test is a mathematical method to test if the data is normally distributed [24]. This procedure is applied to consider the distribution of all the independent variables and the dependent variable of the research. Researchers should standardise the data to become normal if it is not to obtain more accurate and way higher reliability results. Since the sample size is less than 50, Shapiro-Wilk test is appropriate to be used. If the p-value from the software output is higher relative to α, we fail to reject the null hypothesis and consequently come out with the conclusion that the data is expected otherwise, the data is not normal. The Grid Search Algorithm method was used to determine model evaluation indexes and the repetition of the possible combination of all hyperplane parameters. The grid search will set parameters to train the model and select the optimal model accuracy. Generally, the grid search algorithm will use the appropriate value approximately on the logarithmic scale, such as 0.001, 0.01, 0.1, 1, 10, 100, and 1000[25]. This step will identify the best setting for generating a higher coefficient determination value. It was also able to identify the accuracy and reliability of the models, but it consumes time to generate computation results.

2.7 The k-fold Cross Validation

The k-fold cross-validation is one of the most well-known methods to verify prediction models using the overall dataset. The dataset is randomly divided into K groups, and K–1 group is the training dataset while the remaining 1 group is the test dataset. The prediction model train used the training data set and the test set to evaluate the trained model. This process repeatedly evaluates the model training performance of each group and generates average performance from all groups expressed as an indicator. The K value is typically set to five or ten to get more reliable accuracy on the prediction model. This study uses k = 10 as the selected value for conducting cross-validation. The hemispherical and spherical shape C4 explosive was identified by k-fold cross-validation, which was conducted to determine the overall accuracy value.

2.8 Comparison with TM5 – 1300

The TM 5 – 1300 publication describes procedures for determining the blast effects of an explosion, as well as approaches for designing reinforced concrete structures subjected to blast stresses. The distinctive properties of an incident blast wave have been defined, which focused on formulating explosive to equivalent TNT explosive charges, with overpressure being the primary parameter. This standard was examined using TNT, Pentaerythritol Tetranitrate (PETN) and Ammonium Nitrate Fuel Oil (ANFO). The research was carried out with consideration for three parameters, which are overpressure, length, and impulse of the positive blast wave phase. The conventional weapons (CONWEP) simulation was a product of this research, which was developed using a combination of methods to represent these blast wave parameters. The SVM prediction model, which was created using Python-based program results, was compared with the TM 5-1300 chart, which is widely used as a significant guideline for explosion impact. The comparison focuses on the Z value, which is determined using the equation in Eq 3. The accuracy of both tool values of explosives was used to compare 0.50 kg and 1.00 kg.

3. Results

3.1 Coefficient of Determination for Different Kernel Function

Table 1 shows the coefficient of determination for peak pressure, time arrival, incident pressure and reflective pressure for linear, RBF and Polynomial kernels.

Table 1
The mean R^2 value on blasting parameter using different kernel function

Type of Kernel	Prediction Parameter			
	Peak Pressure	Time Arrival	Incident Pressure	Reflective Pressure
	Cylindrical Shape			
Linear	0.526	0.966	0.765	0.736
RBF	0.623	0.974	0.963	0.791
Polynomial	0.014	0.769	0.040	0.158
	Spherical Shape			
Linear	0.461	0.971	0.651	0.631
RBF	0.748	0.972	0.982	0.890
Polynomial	0.385	0.766	0.027	0.094

The RBF kernel model indicated the higher R^2 value dataset followed by a linear function. In comparison, the polynomial function shows a high error value and could be more ideal as an explosive dataset. The overall result indicated that the RBF was a reliable kernel, and the RBF model was used for the next stage of the optimisation step.

Table 2
The R^2 value on blasting parameter using RBF kernel function

Parameter	Hyperplane Parameter			
Type of Kernel	Penalty Factor, C	Epsilon, ε	Gamma, γ	R^2
		Cylindrical		
Peak Pressure	1000.000	1.000	1.000	0.943
Time Arrival	1000.000	1.000	0.100	0.911
Incident Pressure	1000.000	0.100	0.010	0.916
Reflective Pressure	100.000	0.100	0.100	0.791
		Spherical		
Peak Pressure	1000.000	1.000	1.000	0.910
Time Arrival	1000.000	1.000	0.010	0.990
Incident Pressure	100.000	0.100	0.100	0.770
Reflective Pressure	1000.000	1.000	0.010	0.913

The hyperplane tuning using the Grid Search Algorithm identifies the best R^2 value RBF kernel for hemispherical and spherical. The analysis hyperplane parameter will be used for k-fold cross-validation analysis.

3.2 The k-Fold Cross Validation Analysis

While the Table 3 shows the analysis of the dataset for hemispherical and spherical-shaped C4 explosives to determine the overall accuracy value.

Table 3
The R^2,MSE,RMSE and MAE was determine using k-fold cross validation method for cylindrical and spherical shape

Parameter	Kernel	Result Analysis				
		R^2	K-Fold	MSE	RMSE	MAE
			Cylindrical Shape			
Peak Pressure	RBF	0.997	0.893	0.608	0.726	0.351
Time Arrival	RBF	0.994	0.990	0.584	0.099	0.057
Incident Pressure	RBF	0.985	0.830	0.103	0.211	0.163
Reflective Pressure	RBF	0.982	0.892	0.219	0.312	0.170
			Spherical Shape			
Peak Pressure	RBF	0.998	0.892	0.454	0.615	0.305
Time Arrival	RBF	0.999	0.997	1.618	0.061	0.025
Incident Pressure	RBF	0.985	0.786	0.267	0.397	0.324
Reflective Pressure	RBF	0.999	0.876	0.042	0.164	0.116

The *k*-cross-validation, as shown in Table 3, indicated R^2 low value compared to R^2 the value in Table 3, and it clearly exposes how best the entire dataset was fit to the model. The k-fold cross-validation value will measure the mean of k = 10-fold, which has been done before this. The optimisation model did not indicate the overall performance and the R^2 value, which only used 20 % of the dataset to produce the result. The peak pressure R^2 for both shapes indicated almost 89%, which indicated the RBF kernel was perfectly fit and able to generate higher accuracy, along with a low MSE value of less than 60.8%. The analysis using the Python-based platform for the C4 explosive prediction model indicated that the RBF kernel function shows the higher R^2 and lowest MSE value overall. The RBF function fits the dataset pattern and optimisation penalty factor, and epsilon and gamma parameters generate a more realisable prediction model.

3.4 Comparison with TM5 – 1300

Tables 4 to 7 show the comparison between the SVM prediction method with TM 5 -1300, which is used to validate the accuracy of the peak pressure, time arrival, incident pressure and reflective pressure.

Table 4
Comparison graph for peak pressure parameter

Distance (m)	Weight of Explosive					
	0.5 (kg)			1 (kg)		
	TM 5-1300	SVM Model	Difference (%)	TM 5-1300	SVM Model	Difference (%)
1.000	965.300	990.780	-2.570	1620.325	1627.000	-0.410
2.000	199.955	209.460	-4.530	330.960	350.040	-5.760
3.000	89.635	92.110	-2.680	137.900	144.840	-5.030
4.000	62.055	55.480	11.850	96.530	81.910	15.140
5.000	48.265	40.450	19.320	68.950	56.900	17.470

The difference in peak pressure parameters between the RBF model and the TM 5-1300 varies from 0.40 to 19.30 %, as shown in Table 4. The difference increased linearly with the distance of explosive and reduced when the explosive weight increased.

Table 5
Comparison graph for time arrival parameter

Distance (m)	Weight of Explosive					
	0.5 (kg)			1 (kg)		
	TM 5 -1300	SVM Model	Difference (%)	TM 5-1300	SVM Model	Difference (%)
1.000	0.500	0.530	-6.000	0.400	0.440	-10.000
2.000	200	1.930	3.500	1.300	1.500	-15.380
3.000	3.300	3.700	-12.120	2.900	3.310	-14.130
4.000	3.600	4.000	-11.110	3.300	3.800	-15.150
5.000	3.800	4.400	-15.780	3.600	4.000	-11.110

The difference time parameter between the SVM model and the TM 5-1300 varies from 3.5 to 15.78 %, as shown in Table 5. The difference was increased linearly with the distance explosive for 0.5 kg, and the difference value in the range between 10.00 to 15.15 % for the difference was reduced when the weight of the explosive increased.

Table 6
Comparison graph for incident pressure parameter

Distance (m)	Weight of Explosive					
	0.5 (kg)			1 (kg)		
	TM 5-1300	SVM Model	Difference (%)	TM 5-1300	SVM Model	Difference (%)
1.000	137.900	157.340	-14.090	172.375	218.180	-26.570
2.000	96.530	103.320	-7.030	137.900	157.470	-14.190
3.000	62.0550	69.834	-12.530	131.005	109.770	16.200
4.000	62.0550	54.003	12.970	82.740	82.470	0.320
5.000	55.160	45.420	17.650	68.950	71.780	-4.100

Table 6 shows that the incident pressure parameter difference between the SVM model and the TM 5-1300 in varies from 4.00 to 26.50 %. The difference was increased slightly with distance explosive for weight 0.50 kg, and the difference was reduced when for 1.00 kg explosive.

Table 7
Comparison graph for reflective pressure parameter

Distance (m)	Weight of Explosive (kg)					
	0.5 (kg)			1 (kg)		
	TM 5-1300	SVM Model	Difference (%)	TM 5-1300	SVM Model	Difference (%)
1.000	655.025	751.040	-14.650	1041.145	1249.410	-20.00
2.000	252.290	241.325	4.340	358.540	412.880	-15.15
3.000	151.690	162.090	-6.850	241.325	270.820	-12.22
4.000	124.110	119.280	3.890	206.850	194.390	6.02
5.000	137.900	120.740	12.440	151.690	170.470	-12.38

Table 7 shows that the adequate pressure difference between the SVM model and the TM 5-1300 was varying from 3.00 to 20.00 %. The difference was increased slightly with distance explosive for weight 0.50 kg, and the difference was increased for 1.00 kg explosive. The difference between Table 4, Table 5, Table 6, and Table 7 is due to TM 5-1300 mainly using a compilation of blast experiments, while the SVM model only uses the sample of an explosion to generate the result. The SVM function was tuned for the experiment to generate a prediction model by using penalty factor, epsilon and gamma, which were used in the overall data set which generated the prediction value.

4. Conclusions

To summarise the conclusion, this research is focused on producing a prediction model for C4 explosives using the SVM method. Generally, experiments show that the RBF kernel function has a better prediction model for C4 explosion. The best generalisation and robustness achieved between accuracy attained with minimum errors to predict unseen database input dataset. The accuracy and minimum error prediction model depend on SVM kernels, which can be achieved through optimisation with a combination of penalty factor, epsilon, and gamma. The analysis using the Python-based platform shows the ability to train and create an algorithm with fast processing time and compile it as the actual application. The explosive blasting prediction was modal for C4 and developed in Malaysia using a machine learning method with realisable and conservative predictions.

From the theoretical point of view, the blast wave will propagate symmetrical and regular shapes; however, the field measurement shows the complexity of the periodic trends in real-time. The machine learning base models can produce models and corresponding overpressure peak estimates that are strongly sensitive to input parameters and could result in conservative predictions of blast explosive parameters. The model significantly shows positive results with a prediction of more than 89% compared to actual value gain through the experiment and blasting prediction model in Malaysian context, which can be adopted for future research and explosive technology development.

Acknowledgement
This research is fully supported by FRGS grant, FGRS/1/2020/TK0/UPNM/02/1. The authors fully acknowledged Ministry Higher Education (MOHE) and National Defence University of Malaysia (UPNM) for the approved fund which makes this important research viable and effective.

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