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The Accuracy and Error of Ground Penetrating Radar System with Machine Learning Support Vector Regression Technique

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ABSTRACT

Ground penetrating radar (GPR) is a non-destructive evaluation technique which involve knowledge of electromagnetic theory. Basically, there are three types of radar systems that are often applied in radar applications such as Monostatic, Bistatic, and Multi-static radar. Besides, in order to detect and locate the underground object, various technique has been implemented to cater issues in GPR such as clutter issues, inaccuracy in detect and locate the target object, signal loss, properties of soil and etc. In this paper, machine learning (ML) with support vector regression (SVR) is applied in GPR system using copper plat as buried object. Evaluation and validation on this method was carried out in term of S-Parameter and operating frequency. The scope of this work focuses on data analysis for the accuracy of object detection, validation graph and the error signal processing of Machine Learning in GPR system. The result of the experiment was shows low error, the validation point fit to hyperplane line (validation graph). Therefore, the output that expected for this research is validate the low false alarm rate of machine learning in GPR system.

1. Introduction

Ground penetrating radar (GPR) is a high-resolution geo-physic method for near-surface tools [1-2]. Nowadays, ground penetrating radar (GPR) systems are widely used in many fields to make tasks easier [3] for example medical field, AI, Civil field and etc. Besides, the GPR system is still facing some issues regarding accuracy of localization and clarity of image signal process due to soil properties, clutter, coupling effect between transmitters and etc. To eliminate this unwanted signal or noise from the GPR system, several learning techniques and algorithms are used, such as machine learning technique [4-7]. Machine learning (ML) has been widely employed in various fields to produce better outcome results and improve the quality of signal interpretation.

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Many application areas greatly benefit from machine learning techniques, such as breast cancer detection, tumour detection, especially application in medical imaging [8-9], voice and face [10], recognition [10-11] and computer vision. Machine learning is able to construct algorithms and models that can learn to make decisions from data. Machine learning algorithms generally categories to supervised learning and unsupervised learning [12].

Supervised learning algorithms learn classification or regression tasks from label data, while unsupervised learning algorithms focus on classifying the sample sets into different groups (i.e., clusters) with unlabelled data [13]. Therefore, machine learning may be used to GPR systems to increase localization accuracy, eliminate clutter, and provide superior signal images [15-16].

To eliminate noise, certain algorithms are used in GPR systems such as k-neighbor (KNN) classifier [17-18], hidden Markov models (HMMs) [19-21], HOG [22] and etc. Support vector regression (SVR) is built from the concept of support vector machine (SVM). SVM is a supervised learning algorithm that can be learned from label data. SVM learning is one of the machine learning techniques, compared to the others machine learning, SVM is very powerful at recognizing subtle patterns in complex datasets and some research was apply on ground penetrating radar on time delay and detection of debonding [23-25]. SVM is widely used in recognizing handwriting [26], recognize fraudulent credit cards [27], recognize voice or speech recognition [28], also recognize face [29] and etc.

1.1 Key of Machine Learning

Nowadays, several engineering fields are focusing on bid data analysis. Therefore, analysing data and developing an algorithm is critical to obtaining an accurate result. In addition, machine learning techniques are appropriate for self-study and decision-making based on data. In this research study, three main points of machine learning may be concluded. First, has some underlying pattern to be learning to improve a better output or make the prediction of output more accurate. Second the program was not easy definite, so machine learning was required. Last, must have one or more input data and data for learning form. Machine learning can be said in the form of AI that enables the system to learn from data rather than through explicit programming. Therefore, machine learning is not a simple process and needs a lot of data for the system to analysis [30]. Figure 1 shows the regular flow of machine learning based on the research of GPR system. First of all, the database is collected from the GPR system. Then process the machine learning technique with the algorithms for classification purpose or regression with the smart machine learning technique it can study and make a decision. As the result, a better skill or result by the machine learning technique. For our research GPR system can make an improvement of the accuracy by removing the clutter or unwanted signal [31].

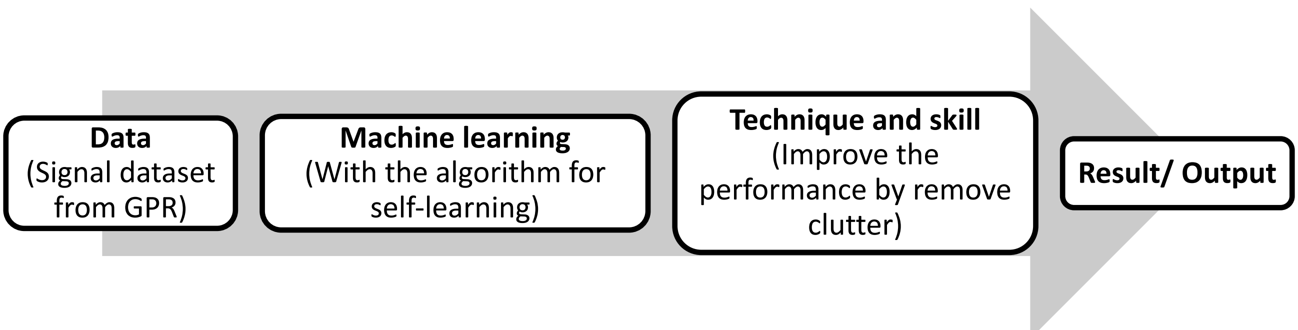


Fig. 1. Flow of the machine learning

1.2 Support Vector Regression

The support vector machine (SVM) is supervised learning for clustering and regression. Therefore, the SVM model is a powerful method for building a classifier. The main function is making a decision boundary between two classes for the prediction of the feature vectors. This decision boundary is known as hyperplane. The theoretical formula based on the hyperplane of SVR [32] is shown as below. Hyperplane is a decision boundary to predict continuous output that suitable for Ground Penetrating Radar. The points that are close to hyperplane are Support Vector. This is a required line that shows the predicted output of the algorithm [33]. The basic theory experiment of the SVM is shown in Figure 2.

The training dataset: $(x_1, y_1), \ldots (x_n, y_n)$; $x_i \in R^d$; $y_i \in$ (-1, +1)

where x_i is a feature of vector and y_i is the class label (negative is the lower part line, positive is higher part line) the dataset from the first (x_1, y_1) to (x_n, y_n).

The optimal of hyperplane: $wx^T + b = 0$

where w is a weight vector, x is the input feature vector, and b is the bias.

The training set: $wx_i{}^T + b \geq +1$ if $y_i = 1$, $wx_i{}^T + b \leq -1$ if $y_i = -1$.

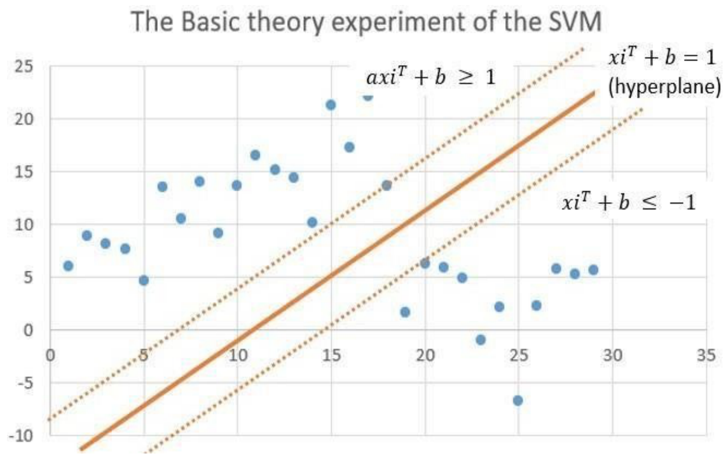


Fig. 2. Basic theory experiment of the SVM [32]

2. Methodology

2.1 Ground Penetrating Radar

Nowadays, ground penetrating radar (GPR) systems are widely used in many fields to make the task easier. GPR helps a lot in a variety of application areas, such as security military [33-35] locating of the pipe and cable [37], concrete or building structure [38-39] and etc. The modal GPR theory is to detect the reflected signal from the subsurface structure. Figure 3 depicts an example of an experiment modal GPR system using monostatic radar, with the transmitter and receiver located in the same location (shown as a brown box in the modal). The incident wave will be transmitted to underground from the red box, and the dispersed wave will be received at the GPR modal. The signal will be received and shown at the vector network analyzer. The input parameters of slotted bowtie antenna, operating frequency is 1.00GHz – 3.0GHz, gain is 9dB, type of soil: sand and polarization is in linear form. The output parameter is s11-parameter (input and output port1).

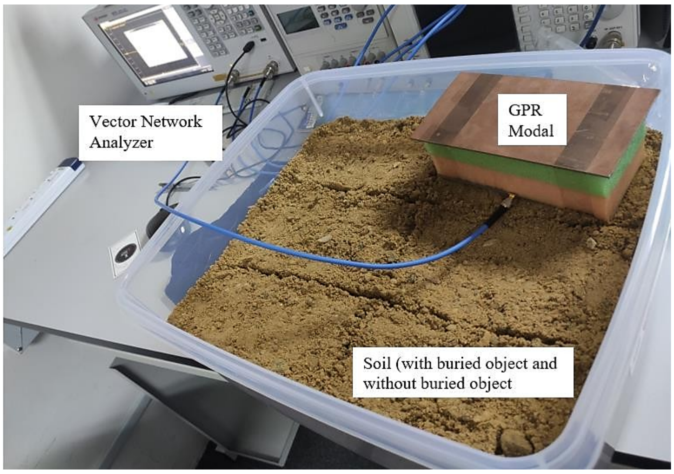


Fig. 3. Experiment modal of the GPR System

2.2 Input and Output Parameter

The input parameters include frequency of the GPR, transmitter, S11 LogMag and type of soil. The frequency is about 1-3Hz, sand as type of soil and the transmitter is directional antenna – slotted bowtie antenna and mono-static antenna. S11 shows output and input signal at port 1 with 10dB. Table 1 shows the parameter of input and output.

The buried object on the was focus on copper because most of the cable underground was copper. First of all, the data was taken without buried objects to make a comparison. After that, the item was buried and measured again. Figure 4 depicts the buried items (copper plate) for GPR system testing.

Table 1
Parameter of input and output

Input and output	Unit	Type
Frequency	1-3GHz	
Type of soil	Sand	
Transmitter	Directional antenna	Slotted bowtie antenna
S11 LogMag	10dB	
Ref	0.000dB	
Output	S11-parameter (dB)	

Fig. 4. The buried object

2.3 Data From GPR

First, the experimental land was separated into sections to guarantee that the measurement of the signal between sections is clear. To begin the GPR system localization experiment, the land without any buried objects must be measured and compared to the object that is present. The measurement was based on several sections. Furthermore, the object has been buried and make the measurement of the signal. Repeat the experiment numerous times and record the results to ensure machine learning can learn more accurately from the data. In the planning of signal data measurement, 6 sets of repeating datasets of 12 times must be recorded for SVM regression responder and predictor. Figure 5 shows the modal of the experimental object placed and the experimental land that is divided into six parts.

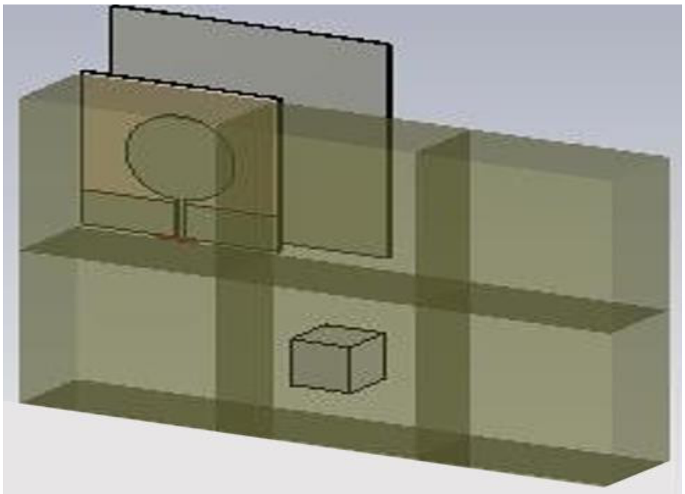


Fig. 5. The experiment modal for the land divided (modal)

2.4 Simulation Experiment

Firstly, the group of datasets collected from the GPR system and analysis by network analyzer that convert signal to data. Also import all the data into MATLAB to analysis data. The simulation data is divided into training data sets and testing data sets. Training data is used to learn data from the dataset. The purpose of testing data is to assess the performance of the algorithm training. Use the method of cross-validation to determine respond and predictor. After that, trained the data with SVR. In this study 12 sets of data have been collected per part and have been trained by SVR. Therefore, 12 sets of the RMSE result have been produced. Select the lowest RMSE value and train the SVR validation of prediction and actual plot modalities as an output. Lastly, the error result and the validation modal will show the support vector regression (SVR) is validated for ground penetrating radar (GPR). Figure 6 shows the flow of the simulation experiment.

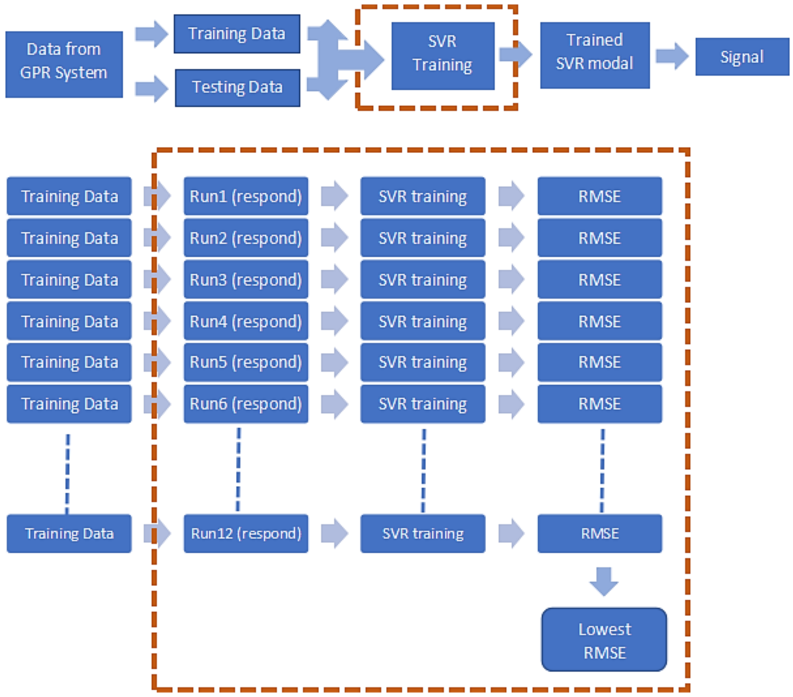


Fig. 6. Flow of the simulation experiment

3. Results

Root mean square error (RMSE) is used for measuring the prediction error of the modal in predicting output. Mean square error is used for measuring the quality of estimator. The value of mean square error which always positive and closer to 0 are more perfect. Mean absolute error is a term for measuring how close the prediction is to the output signal and is all the absolute error. The standard deviation of predicted error is defined as the root mean square error (RMSE). The lower the RMSE, the better the fit of the data concentration on the hyperplane. Table 2 to Table 7 shows the value result RMSE, MSE and MAE of the experiment and Table 4 shows the error of the buried object (copper). Figure 7 shows the result RMSE, MSE and MAE of the GPR after SVR training. Even though the RMSE of buried object is the highest among the perfect RMSE (without buried object) but still in the category of low false alarm rate.

Table 2
RMSE, MSE and MAE without object

Formatted Data	RMSE	MSE	MAE
1	0.52377	0.27433	0.36664
2	0.23235	0.053986	0.18262
3	0.19926	0.039706	0.13883
4	0.18943	0.035884	0.15142
5	0.28749	0.08265	0.16563
6	0.15773	0.02488	0.12871
7	0.18162	0.032987	0.14186
8	0.13843	0.019163	0.10376
9	0.27472	0.075473	0.21869
10	0.14046	0.019729	0.1041
11	0.25701	0.066056	0.21597
12	0.26069	0.067957	0.18574
	Data 8		
mode	0.13843	0.019163	0.10376

Table 3
RMSE, MSE and MAE without object

Formatted Data	RMSE	MSE	MAE
1	0.41521	0.1724	0.33198
2	0.18261	0.033345	0.1563
3	0.31786	0.10103	0.23683
4	0.44317	0.1964	0.21405
5	0.34848	0.12144	0.28543
6	0.15889	0.025247	0.13388
7	0.17657	0.031178	0.15532
8	0.20352	0.041419	0.18099
9	0.2576	0.066359	0.22918
10	0.21511	0.046273	0.15809
11	0.75785	0.57433	0.32603
12	0.31821	0.10126	0.18116
	Data 6		
mode	0.15889	0.025247	0.13388

Table 4
RMSE, MSE and MAE with object

Formatted Data	RMSE	MSE	MAE
1	0.40028	0.16022	0.25971
2	0.57254	0.3278	0.41516
3	0.56438	0.31852	0.39114
4	0.54965	0.30212	0.3341
5	0.45099	0.20339	0.35407
6	0.60708	0.36855	0.36304
7	0.50527	0.25529	0.36336
8	3.6901	13.617	1.8999
9	0.34054	0.11587	0.25569
10	0.32826	0.10776	0.29176
11	0.46638	0.21751	0.24487
12	0.33985	0.1155	0.24862
	Data 10		
Mode	0.32826	0.10776	0.29176

Table 5
RMSE, MSE and MAE without object

Formatted Data	RMSE	MSE	MAE
1	0.88224	0.77835	0.50808
2	0.5106	0.26071	0.31234
3	0.74571	0.55608	0.32356
4	0.31067	0.096516	0.27415
5	0.19606	0.038441	0.15958
6	0.12187	0.014852	0.091757
7	0.27699	0.076724	0.18118
8	0.18047	0.03257	0.14014
9	0.1961	0.038455	0.14729
10	0.19739	0.038963	0.14509
11	0.59513	0.35418	0.40746
12	0.17579	0.030902	0.12594
	Data 6		
mode	0.12187	0.014852	0.091757

Table 6
RMSE, MSE and MAE without object

Formatted Data	RMSE	MSE	MAE
1	0.3339	0.11149	0.26611
2	0.36394	0.13245	0.27035
3	0.38205	0.14596	0.28166
4	0.28166	0.09987	0.27982
5	0.36124	0.13049	0.25721
6	0.43867	0.19243	0.32256
7	0.21508	0.046261	0.17317
8	0.37986	0.14429	0.30716
9	2.6216	6.873	0.98651
10	0.56588	0.32022	0.40119
11	0.54678	0.29897	0.35239
12	0.59361	0.35238	0.38317
	Data 7		
mode	0.21508	0.046261	0.17317

Table 7
RMSE, MSE and MAE without object

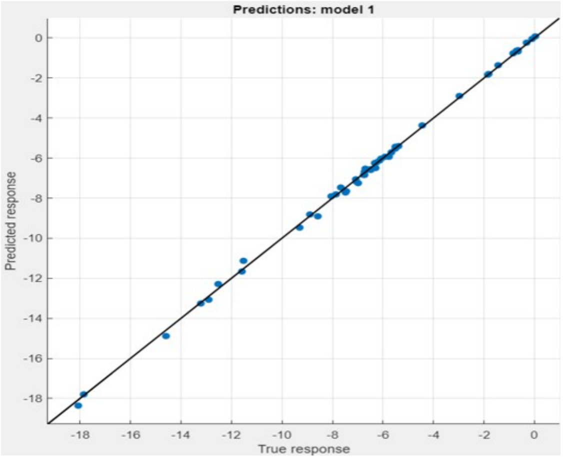
Formatted Data	RMSE	MSE	MAE
1	0.26178	0.068531	0.19525
2	0.54292	0.29476	0.41944
3	0.24568	0.06036	0.20381
4	0.20968	0.043967	0.16033
5	0.46746	0.21852	0.24944
6	0.29868	0.089212	0.25341
7	0.18865	0.035588	0.14852
8	0.52289	0.27341	0.2906
9	0.22674	0.051411	0.16335
10	0.30167	0.091006	0.25914
11	0.66051	0.43627	0.50929
12	0.26091	0.068076	0.21345
	Data 7		
mode	0.18865	0.035588	0.14852

DATA 1	DATA 3	DATA 5
RMSE 0.13843 MSE 0.019163 MAE 0.10376	RMSE 0.32826 MSE 0.10776 MAE 0.29176	RMSE 0.21508 MSE 0.046261 MAE 0.17317
DATA 2	**DATA 4**	**DATA 6**
RMSE 0.15889 MSE 0.025247 MAE 0.13388	RMSE 0.12187 MSE 0.014852 MAE 0.091757	RMSE 0.18865 MSE 0.035588 MAE 0.14852

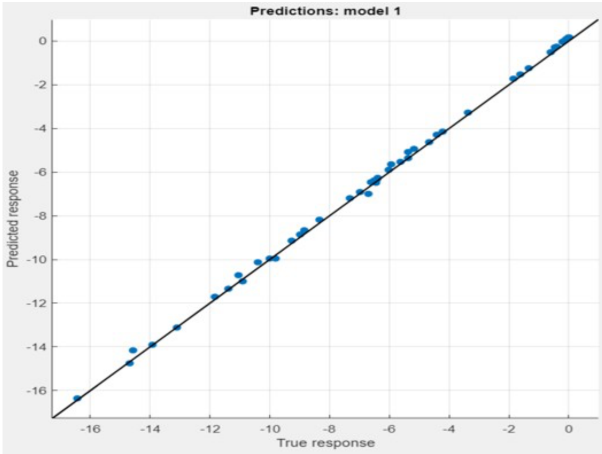
Fig. 7. The result RMSE, MSE and MAE of the GPR after SVR training

The lower the RMSE number, the closer the data point is to the hyperplane and the more accurately the model predicts the response. Therefore, the simulation segment with the lowest RMSE value was chosen to create more fit data points to the hyperplane. Figure 8 shows the data point is very near to the hyperplane which is the best fit line. At the DATA PART 3 even some of the points are not lie the line but most of the data point is near or lie on the best fit line. As a result, SVR can provide more validate signals for GPR systems based on the validation data point.

DATA PART 1



DATA PART 2



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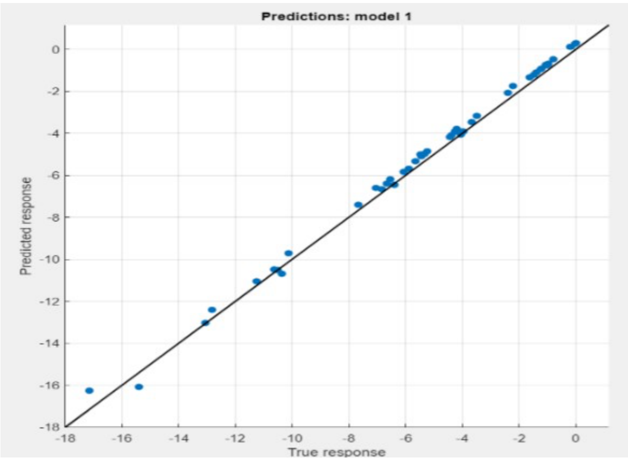
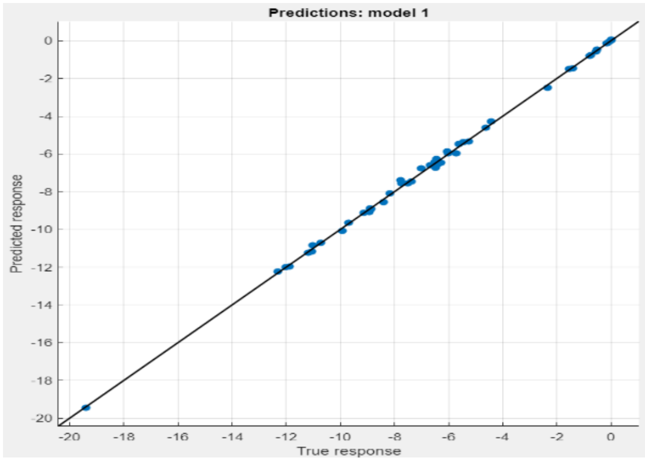
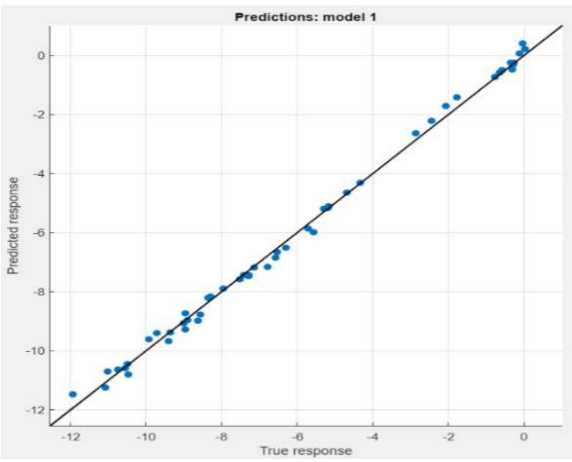


DATA PART 4



DATA PART 5



DATA PART 6

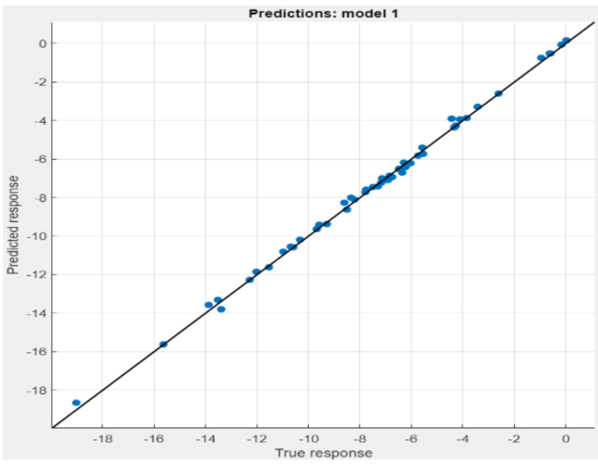


Fig. 8. The validation hyperplane of the GPR result for SVR

The frequency detective 1GHz to 1.5GHz. The object detection was determined by signal fluctuation. The depth of the object can be determined from the frequency of the GPR. High frequency for shallow depth and low frequency for deeper depth. Therefore, because the shallow depth object was located, a high frequency of roughly 1-3GHz was used in this experiment. Based on the result in Figure 9, the signal of copper after SVR is only slightly different, but the result after SVR (yellow line) shows that the signal fluctuation is relatively high. Therefore, the detection of the object is more clearly demonstrated by the signal. As a result, the signal of and the signal after SVR are more reliable.

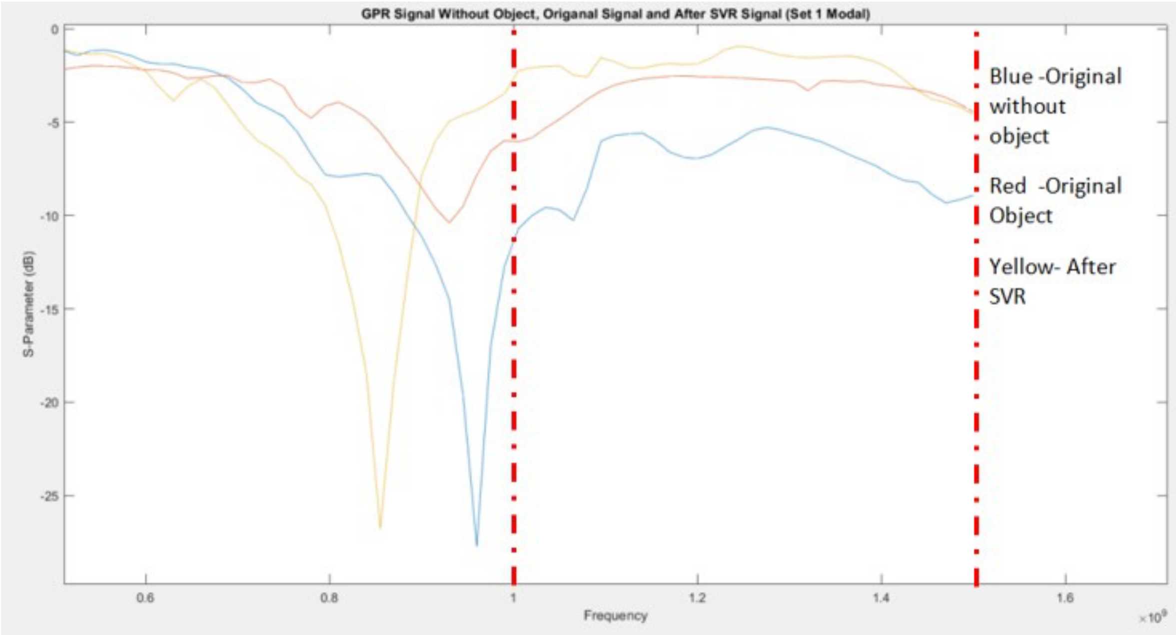


Fig. 9. The validation

4. Conclusions

As a result, machine learning support vector machine (SVM) with support vector regression (SVR) is preferable to ground penetrating radar (GPR) for classification and regression with two reasons. The first explanation is that the root mean square error is low (RMSE). Low RMSE can produce more validated signal graphs that lessen noise and unwanted signal. The second reason is because most of the data points are fitted to a hyperplane, which allows the model to anticipate the reaction more accurately. As a result of the low RMSE and best fit line, the machine learning support vector regression is suited for GPR system regression and SVM is suitable for GPR system classification.

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