

PAPER 209 – APPLICATION OF SUPPORT VECTOR REGRESSION MODELLING FOR THE PREDICTION OF IMPACT ATTENUATION OF 3D PRINTED HIP PROTECTORS

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ABSTRACT

3D printed thermoplastic polyurethanes of different shore hardness were used to make hip protectors for the prevention of osteoporotic hip fracture, which was then tested. The result was used to develop a support vector regression model to estimate the effect of the protector shore hardness, shell thickness, and infill density on the impact attenuation capacity at different energy levels. The results from the model show that the impact attenuation ability of a hip protector is significantly dependent on the infill density of the hip protector and its shore hardness. Excellent agreement was found between the model results and test results.

KEYWORDS: 3D print, thermoplastic polyurethane; hip protector; impact attenuation; support vector regression; performance prediction.

1. INTRODUCTION

The enormous benefits of additive manufacturing over conventional manufacturing methods cannot be overemphasized (Parandoush and Lin, 2017). This benefit is due to its ability to significantly help in creating intricate part that would otherwise be very challenging to produce using other techniques, reduce the number of distinct parts needed for an assembly, reduce material waste, reduce the number of production steps and reduce the amount of inventory being held (Sendel et al., 2015).

Advancement has led to the application of 3D human body scan data to surface pad modeling to create custom-fit hip protectors, reportedly to have influenced adherence in a wearer test (Park and Lee, 2019). However, optimizing 3D printed hip protectors' mechanical performance requires careful study on the thickness of the printed intervention capable of restraining shock propagation to the vulnerable site in sideways fall, yet ensuring the protector aesthetic and fitness towards maintaining adherence (Holzer et al., 2009). Also, acquiring the impact attenuation data of a 3D printed hip protector is intensely demanding, from the making and remaking of a model, printing such model, to the biomechanical impact testing to acquire the force attenuation data. Most hip protector research has understandably not considered models fitting for impact attenuation because of the strain of the laboratory time and effort it represents in acquiring huge experimental data as seen in other fields where models are usually demanding enormous data (Van Der Ploeg et al., 2014). Consequently, test systems with subjective experimental models have been used in most studies to quantify various hip protectors' impact attenuation properties.

Moreso, artificial neural networks (ANN) have been demonstrated to predict composite plates' absorbed energy under low-velocity impact load due to their ability to efficiently learn the input-output relations of non-linear problems (Malik and Arif, 2013). However, the high generalization of performance and the ability to model non-linear relationships uniquely and globally make support vector regression (SVR) particularly appealing, justifying its growing adoption in various science and engineering fields (Üstün et al., 2007).

In this study, SVR has been chosen to develop a robust model with which a 3D printed hip protector's impact attenuation capability could be estimated. SVR expunges the difficulties of using linear functions in the high-dimensional feature space and ensures the transformation of optimization problems into dual convex quadratic programs (Roy et al., 2015). Support vector machines have been used extensively in computational biology to classify vectors derived from different features with great accuracy (Cohen and Widdows, 2013). Moreover, the use of SVR in performance prediction in biomechanical impact problems has not been reported in previous hip protectors optimization research. Therefore, there is an opportunity to explore the benefit of the reported performance edge of a promising statistical algorithm SVR over ANN (Akande et al., 2014)

2. METHODOLOGY

a. THE DATASET

ii. Experimental data acquisition

The proposed computational intelligence-based SVR model was developed using the experimental data derived from impact force attenuation testing of the 3D printed hip protectors using a biofidelic drop towers testing system (Yahaya et al., 2020). The hip protector (Figure 1) was modelled from the 3D surface geometry of the human hip scan, and the hip geometry data were applied to develop the inner surface of the hip protector in contact with the human body.

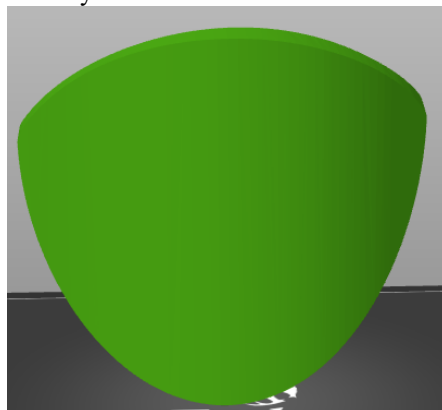


Fig. 1. The 3D printed hip protector.

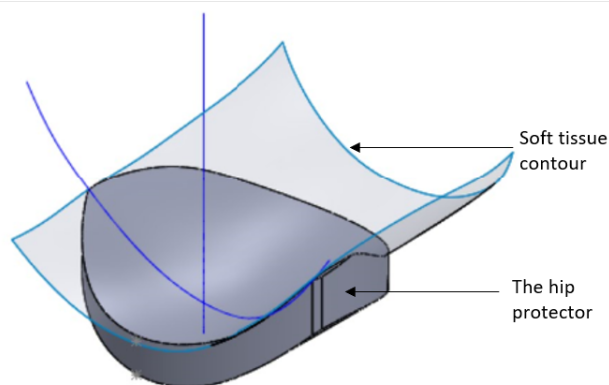


Fig. 2. The 3D printed hip protector modeled according to a hip surface geometry.

The outer surface was created with a shield-like shape projected to the inner surface at a thickness of 10.2 mm (Figure 2). It bears the dimension of the hip protector with the maximum height taken at the greater trochanter. When the cut was extruded to finalize the model, the protector's structural information conforming to the desired pad outline was extracted.

Three protectors of different shore hardness but having a similar characteristic and structural information were printed and subsequently subjected to drop towers impact test to measure each of the protectors' impact attenuation properties. An average of 5 impact tests was done per sample at different energy levels and recorded. The impact mass of 6.57 kg was dropped from heights of 300 mm and 400 mm, simulating impact to the sideways when a human falls to the ground. The forces were recorded first without the hip protecting pads and subsequently with the hip protectors in place. The attenuation rate was determined using the ratio of forces at the femoral neck when the soft tissue was not protected, termed the unprotected force, F_u , and F_p is the impact recorded at the same point when the hip protector was in place to protect the soft tissue.

iii. Description of dataset

Four descriptors, namely, pad thickness, impact energy, unprotected impact force, and maximum impact force, were used to train and test 18 experimentally acquired datasets in building a predictive model using SVR. Table 1 shows the training and testing dataset of the developed SVR model. To determine the impact force attenuation rate of the 3D printed hip protector, the above-mentioned descriptors were used to build the SVR model. The result of a statistical analysis of the acquired experimental data is also presented in Table 2. The mean, maximum, minimum, and standard deviation helps to describe the disparities in the dataset.

Additionally, Table 2 also shows the correlation of each of the descriptors and the target - impact force attenuation. The impact energy and maximum impact force are positively correlated with the target. However, the degree of correlation of the impact energy is higher than that of the correlation of the maximum impact force to the impact force attenuation rate. The pad shell thickness and infill density show a negative correlation to the target (impact force attenuation rate). These correlation results demonstrate the need to seek a nonlinear model to represent the descriptors' various effects since their degree of linear relationship is very weak and suggests a simple linear model cannot efficiently capture the existing relationship.

Table 1. Descriptor and target dataset.

Sample name	Impact attenuation	Shore hardness (%)	Shell thickness (L)	Infill density (%)	Impact energy (J)	Base impact force (N)	Impact force (N)
25_2L_85A	0.55	85	2	25	19.34	6,271.26	2,792.04
25_3L_85A	0.50	85	3	25	19.34	6,271.26	3,157.91
25_4L_85A	0.49	85	4	25	19.34	6,271.26	3,184.28
50_2L_85A	0.49	85	2	50	19.34	6,271.26	3,175.49
50_3L_85A	0.49	85	3	50	19.34	6,271.26	3,196.97
75_4L_85A	0.49	85	4	75	19.34	6,271.26	3,210.89
100_4L_85A	0.49	85	4	100	19.34	6,271.26	3,172.19
100_2L_95A	0.53	95	2	100	19.34	6,271.26	2,958.07
25_3L_95A	0.53	95	3	25	19.34	6,271.26	2,923.76
25_4L_95A	0.51	95	4	25	19.34	6,271.26	3,084.54
25_2L_75A	0.53	75	2	25	19.34	6,271.26	2,947.20
25_2L_85A_2	0.69	85	2	25	25.78	11,531.83	3,542.33
50_3L_85A_2	0.62	85	3	50	25.78	11,531.83	4,428.86
75_4L_85A_2	0.60	85	4	75	25.78	11,531.83	4,585.73
50_2L_95A	0.64	95	2	50	25.78	11,531.83	4,199.48
25_3L_95A_2	0.67	95	3	25	25.78	11,531.83	3,856.31
25_4L_95A_2	0.64	95	4	25	25.78	11,531.83	4,142.46
25_2L_75A	0.68	75	2	25	25.78	11,531.83	3,730.70

Table 2. Statistical analysis of the acquired dataset.

	Shore hardness	Shell thickness	Infill density (%)	Impact energy (J)	Maximum impact F_p (N)	Attenuation rate (%)
Mean	87.22	2.94	44.44	1.84	3,460.51	56
Maximum	95.00	4.00	100.00	25.78	4,585.73	69
Minimum	75.00	2.00	25.00	19.34	2,792.04	49
Standard deviation	6.29	0.85	25.76	3.14	543.01	7
R	7	-30	-30	93	68	

iv. Description of SVR computational intelligence technique

This study predicts 3D printed hip protectors' impact attenuation rate from the impact response value acquired from the dataset to train the SVR model. The main idea is to find a function $f(x, \alpha)$ (that predicts the impact attenuation based on SVM approach) that approximates the original dataset $(y_1, \dots, y_k)$ with the at most ε (margin) derivation from the actual obtained values y_i (impact attenuation based on biomechanical test). To construct the linear model $f(x)$ presented in Eq 1, the input dataset is mapped to a k-dimensional feature space with the aid of non-linear mapping function, and a soft margin concept was introduced by relaxing the ε deviation constrain to ensure the existence of the solution. The soft margin imposes a penalty cost using the slack variables ξ and ξ^* if the ε deviation setting is not met.

$$f(x) = w \cdot \phi(x) + b \quad 1$$

where w is the weight vector, $\phi(x)$ represents a set of non-linear transformation which maps the input vector to a higher dimensional feature space from a lower dimension and b is the bias constant (Salami et al., 2019).

The loss function that controls the ability of the SVR to estimate the impact attenuation is given by Eq. 2

$$L(y, f(x)) = \begin{cases} 0 & \text{if } |y - f(x)| \leq \varepsilon \\ |y - f(x)| - \varepsilon & \text{otherwise} \end{cases} \quad 2$$

by solving the primal optimization problem in Eq. 3, the optimal w can be obtained.

$$\text{Minimise } \frac{1}{2} ||w||^2 + C \sum_{i=1}^k [\xi_i + \xi_i^*] \quad 3$$

Subject to:

$$\begin{aligned} y_i - f(x) &\leq \varepsilon + \xi_i^* \\ f(x) - y_i &\leq \varepsilon + \xi_i^* \\ \xi_i \xi_i^* &\geq 0 \quad i = 1, \dots, k \end{aligned} \quad 4$$

where ξ_i and ξ_i^* are the non-negative slack variables that represent the magnitude of the soft margin outside the ε deviation and C is the regularization factor. The non-negative slack variable is assigned to each instance if the data is not linearly separable to avoid misclassification. It can be seen as the distance from the separating hyperplane if an instance is misclassified and $\|\omega\|^2$ is the Euclidian norm.

It is more effective to solve the primal problem by transforming it to a primal-dual setting with the inclusion of a non-linear mapping function known as the Kernel function, which is a dot product in some feature space described by Eq.5.

$$K(x, x_i) = \phi(x) \cdot \phi(x_i) \quad 5$$

Eq.6 is the reformulated solution of $f(x)$ obtained without directly operating $\phi(x)$ and calculating the weight vector w by using the kernel trick, $f(x)$ can be obtained.

$$f(x) = \sum_{i=1}^k (\alpha_i - \alpha_i^*) K(x, x_i) + b \quad 6$$

where k is the index of the data points, α_i and α_i^* are the Lagrangian multipliers which are greater than or equal to zero and must be less than C , and $K(x, x_i)$ is the result of the kernel function in Eq.6.

v. Description of the computational methodology

The SVR model's computational development was done using the training dataset, and the testing dataset with the aid of a test-set cross-validation technique was used to evaluate the accuracy of the generalization and predictive ability of the developed model. The computational methodology entails; data partitioning into training and testing datasets; selection of initial kernel parameters for a particular kernel function to create support vectors using the training dataset; estimation of the target in the testing dataset using the support vector and the testing dataset descriptors; evaluation of the model's estimation accuracy during the training and testing stage by comparing the impact attenuation of the 3D printed hip protector with the estimated values.

b. Optimal parameters search technique

To obtain the optimum kernel parameters, the test-set cross-validation optimization technique was employed. A computational efficient selection procedure for these optimized parameters requires multiple modelling iterations dependent on the nature and size of the dataset. This entails the initial selection of kernel parameters, deployment of test-set cross-validation technique, varying and altering kernel parameters combination for Kernel type in every run, identifying the model parameters' optimum values, and subsequently deploying them to train the final SVR algorithm. The optimum values were judged by the observed correlation coefficient (R^2) and the RMSE for each kernel parameters combination. The value of the kernel option characterizes the mapping of the kernel function in the transformation of the data to high-dimensional feature space. The hyper-parameter controls the choice of the hyperplane that ensures minimal error, the maximum allowed deviation of the estimated value from the actual target is controlled by the epsilon (ε). In contrast, the trade-off between the complexity of the model and the maximum allowed deviation of the target's estimated value from the experimental or actual value of the target is controlled by the regularisation factor or penalty factor, C .

c. Evaluation of the predictive capacity of the proposed SVR-based model

The statistical performance of the proposed SVR model was evaluated using the correlation coefficient (R^2), and the root means square error (RMSE) to determine the predictive and generalization capacity of the model. These parameters show the estimation quality of the model by revealing the associated error of estimation between the experimental and estimated values of impact force attenuation. Eq. **Error! Reference source not found.** shows the correlation coefficient and Eq. **Error! Reference source not found.** shows the RMSE, respectively.

$$R^2 = \frac{\sum_{i=1}^n (A_{r(\text{exp})} - A'_{r(\text{exp})})(A_{r(\text{est})} - A'_{r(\text{est})})}{\sqrt{\sum_{i=1}^n (A_{r(\text{exp})} - A'_{r(\text{exp})})^2 \sum_{i=1}^n (A_{r(\text{est})} - A'_{r(\text{est})})^2}} \quad (8)$$

$$RSME = \sqrt{\frac{1}{n} \sum_{i=1}^n (A_{r(\text{exp})} - A_{r(\text{est})})^2} \quad (9)$$

where $A_r(\text{exp})$ is experimental attenuation rate, $A'_r(\text{exp})$ is mean experimental attenuation rate, $A_r(\text{est})$ is estimated attenuation rate, $A'_r(\text{est})$ mean estimated attenuation rate.

3. RESULTS AND DISCUSSION

The identified optimum values of the model parameters deployed to train the final SVR algorithm are presented in Table 3.

Table 3. Optimum kernel parameters for the developed SVR-based model.

Kernel Function	Gaussian
Kernel scale	2.8284
Regularization factor	8
Gamma (G)	0.1250
Epsilon (ϵ)	9.7656×10^{-4}

The generalisation and predictive accuracy of the SVR model to estimate the impact attenuation of a 3D printed hip protector in a simulated sideways fall was evaluated. The model uses the pad's shore hardness, shell thickness, infill density, base impact force, maximum impact force and impact energy as input descriptors and the impact force attenuation as the target output. The impact force attenuation was either influenced by the input variables or is correlated with their data. The acquired support vectors during the training stage were utilized by the model to estimate the impact attenuation of the hip protecting pad in the testing dataset. Figures 3 and 4 present the correlation cross-plots for the training and testing datasets of the Gaussian kernel functions compared in terms of their estimation accuracy using the optimal SVR modelling parameters gotten from the search approach.

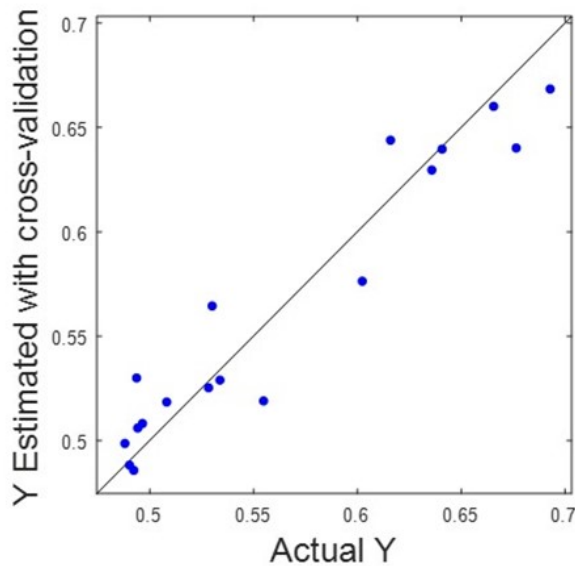


Fig. 3. Correlation cross-plot between experimental and estimated impact attenuation rate of 3D printed hip protectors for the training dataset.

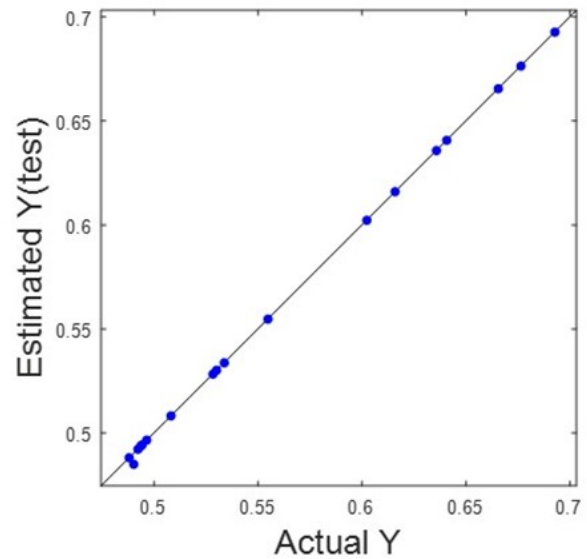


Fig. 4. Correlation cross-plot between experimental and estimated impact attenuation rate of 3D printed hip protectors for testing dataset.

There exists a close relationship between the experimental and estimated impact force attenuation of the training and testing dataset of the hip protector for the selected kernel type – Gaussian Kernel, The R^2 value of 91.5% (with RMSE = 0.0208) and 99.9% (with RMSE = 0.0012) obtained for the training and test sets respectively showed the proposed model is an excellent fit since it performed superbly in the phase that involved unseen data. The obtained RMSE values, which are measures of the proximity of the data points to the regression line, ranged from 0.0012 - 0.0208, indicating a good fit and showing that the developed model has good performance and can potentially be generalized. The implemented model produces results using the acquired support vectors that were in good agreement with the experiment result when only the descriptors were supplied to the model without the target. The measured impact attenuations were effectively tracked, as shown in Figure 5.

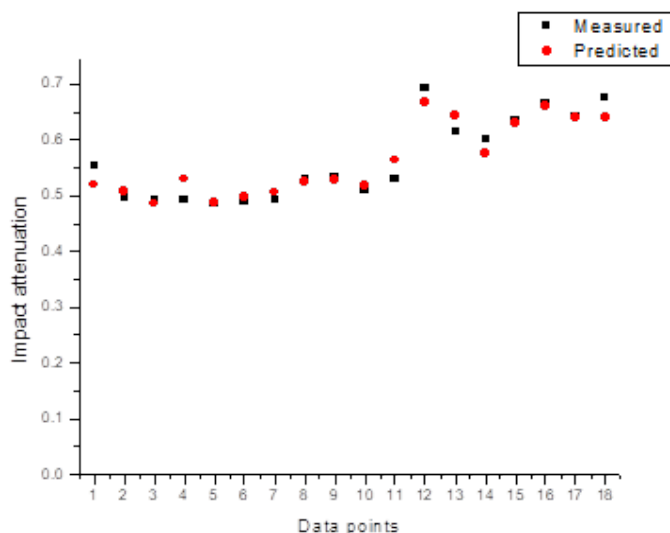


Fig. 5.Tracking of measured impact attenuation by SVR (Testing data).

4. CONCLUSION

This study has investigated the effect of shore hardness, infill density, and shell thickness on the impact attenuation of 3D printed TPU hip protectors using SVR. The impact attenuation of 3D printed hip protector has a highly non-linear dependency on the various factors that influence the material's stiffness, making it very difficult to model. Based on the result of the analysed data, the SVR-based model accurately estimated the impact attenuation of hip protector with an accuracy of over 99% and 0.002 based on R2 and RMSE between the experimentally obtained impact force attenuation and the corresponding estimated values. The proposed model help reduce the experimental cost of examining variability in design parameter yet quantify their performance. The results from the model demonstrate that SVR is viable in predicting the impact attenuation of 3D printed hip protectors. In addition, important new information is hereby provided regarding the influence of infill density and material shore hardness on the impact attenuation rate of a hip protector. This SVR model will find significant application in fracture prevention study because of its ability to predict novel hip protectors' impact attenuation capability

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