Analysis of Impact Attenuation in 3D Printed Hip Protectors: A Support Vector Regression Approach

S. A. Yahaya[1,2*], I. O. Muniru[1], S. Saminu[1], M. O. Ibitoye[1], T. M. Ajibola[1], L. J. Jilantikiri[1], Z. M.Ripin[2], M.I.Z. Ridzwan[2]

[1]Department of Biomedical Engineering, University of Ilorin, Ilorin, Nigeria.
[2]School of Mechanical Engineering, Universiti Sains Malaysia, Malaysia

ABSTRACT: This study examined the impact attenuation of 3D printed hip protectors using thermoplastic polyurethanes with different shore hardness values for preventing osteoporotic hip fractures. Rigorous testing at various energy levels were carried out to determine the protector's abilities to attenuate impact. Subsequently, the prediction of impact attenuation capacity based on key design parameters was achieved from developed Support Vector Regression (SVR) model generated from the data of the impact attenuation capabilities. The key design parameters were shell thickness, infill density and shore hardness. The results demonstrated a significant correlation between the impact attenuation ability and the infill density of the hip protectors with R^2 of 91% for the training set and 99% for the test set. The generated RMSE values are 0.0012 and 0.0208, respectively. Remarkably, the SVR model exhibited excellent agreement with the experimental test results, affirming the efficacy of SVR in the design of hip protectors to enhance protective performance and cut the cost of experimentation.

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

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I. INTRODUCTION

The significant advantages offered by additive manufacturing in contrast to traditional manufacturing methods cannot be overstated (Parandoush and Lin, 2017). This merit arises from its capability to effectively facilitate the production of intricate components that would pose considerable challenges using conventional methods. Additionally, it plays a crucial role in diminishing the quantity of distinct parts required for assembly, curbing material wastage, streamlining production steps, and minimizing inventory holdings (Sendel et al., 2015). The technique of additive manufacturing presents the benefit of uniting design flexibility with a diverse array of material options, thereby making a substantial contribution to the prevention of fractures (Parandoush and Lin, 2017).

The desire to improve adherence and performance of hip protectors has prompted clinicians, engineers, and product developers to continue to strive in making research findings in order to create new types of materials and design concepts. This desire is responsible for significant advancement in the design of impact protection interventions. A clear example of such technological progress is the creation of hip protector from conventional foams impregnated with shear thickening fluid, a concept that increases the energy absorption per displacement of a conventional foam (Haris et al., 2018).

Another advancement is creating the surface of the hip protecting pad using the 3D human body scan data to create custom-fit hip protectors, reportedly to have influenced adherence in a wearer test (Park and Lee, 2019). Optimizing 3D printed hip protector's 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). In this study, a thermoplastic polyurethane, TPU, was 3D printed to create a hip protector using the filament deposition method process. The design is intended to give the material the ability shunt impact force away from the greater trochanter in falls involving frail persons or absorb the impact (Cianferotti et al., 2015). Nevertheless, the process of obtaining the impact attenuation data for the 3D printed hip protector is very labor-intensive. It involves creating and remaking models, printing models, and biomechanical impact testing to obtain force attenuation data. However, if impact attenuation is being used as a fracture prevention approach, it is crucial to determine the effectiveness of any material.

As can be seen from other domains where models typically require massive amounts of data, most research on hip protectors has unsurprisingly not taken into account models fitting for impact attenuation due to the burden on laboratory time and effort involved in gathering huge experimental data (Van Der Ploeg et al., 2014). One such model is Artificial Neural Networks (ANN), which can effectively learn the input-

*Corresponding author: yahaya.say@unilorin.edu.ng
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output relations of non-linear problems, it has been demonstrated that ANN can forecast the absorbed energy of composite plates under low-velocity impact load (Malik and Arif, 2013). However, because of its sensitivity to training ratio, ANN can be easily prone to error in the event of abrupt changes in the training data. Additionally, if the model becomes stuck in a local minimum, it may have adverse effect on the capability of the developed model to predict outcomes (Zhang and Wang, 2008). Another alternative is the Support Vector Regression (SVR) which is reported to have a great generalization ability and the capacity to represent non-linear connections uniquely and globally, making it particularly appealing, justifying its growing adoption in various science and engineering fields (Üstün et al., 2007). Hence a SVR can be considered owing to the reported performance edge of a promising statistical algorithm SVR over ANN (Akande et al., 2014) or response surface methodology (RSM). Moreover, the use of SVR in performance prediction in biomechanical impact problems has not been reported in previous hip protector's optimization research. Also, when balanced learning and optimized decision-making are employed, the classification accuracy of ANN-based models is slightly influenced compared to SVR (Ren, 2012). Also, SVR offers a chance to test models that need less data

SVR was chosen as the most dependable model to create in order to evaluate the impact attenuation capacity of a 3D printed hip protector. SVR is the preferred approach for solving these kinds of problems because it can deal with difficulties involving linear functions in high-dimensional feature spaces and ensure that optimization problems become dual convex quadratic algorithms (Roy et al., 2015). In computational biology, support vector machines are frequently used to reliably classify vectors derived from a variety of features (Cohen and Widdows, 2013).

This offers an excellent opportunity to analyse the effects of material shore hardness and infill density on the impact attenuation capabilities of a customized 3D printed hip protector using data from laboratory tests. Developing a computational model that captures the non-linear relationship between hip protector properties and impact force attenuation is essential to save a significant amount of time and money. Since SVR has the potential to use non-linear kernels, it is a superior alternative for mimicking the non-linear response of the 3D printed hip pad.

kind of scenarios creates what is known as a multi-criteria decision-making problem. The central focus of this paper is to provide a framework that engineers and other stakeholders can use in selecting the most preferred wireless communication technologies based on more than one criterion to implement an excellent embedded device design. Some of the technologies reviewed in this work are Bluetooth, Long-Term Evolution (LTE), Z-wave, Classic WaveLAN, Wi-Fi and ZigBee. The selection of these technologies is based on their relevance and criteria for embedded device design such as Transmission Speed (TS), Security, Transmission Range (TR), Power Usage (PU), Development Cost (DC) and Development Complexity (DCOP). The multi-criteria method used in the selection of wireless communication technologies coupled with illustrative examples, and future work are extensively discussed in this paper.

II. MATERIALS AND METHODS

A. The dataset

I. Experimental data acquisition

The creation of the computational intelligence-driven Support Vector Regression (SVR) model was based on experimental data obtained through impact force attenuation tests conducted on 3D printed hip protectors. These tests utilized a biofidelic drop towers testing system, as detailed in the study by Yahaya et al. in 2020. The hip protector, illustrated as shown in Figure 1, was intricately crafted by replicating the surface geometry obtained from 3D scans of human hips. The inner surface of the hip protector was crafted to closely emulate the contours of the human body upon contact using the data of the hip geometry.

A protective shield-like configuration, projecting to the inner surface at a thickness of 10.2 mm, was crafted for the outer surface of the hip protector (Figure 2). This design embodies the dimensions of the hip protector, with the greatest height aligned with the greater trochanter. The finalization of the model involved extruding the specified cut, extracting the structural information of the protector. Through this process, the model achieved the desired pad outline, ensuring that the hip protector maintains its intended structural characteristics.

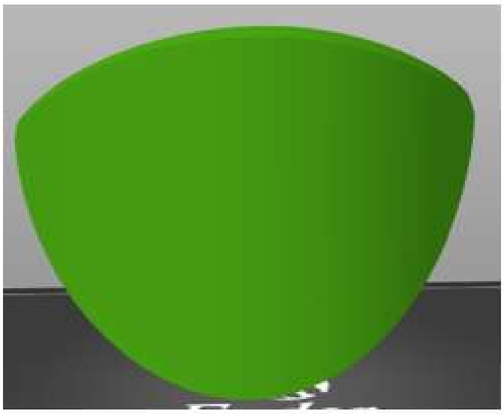

Figure 1. The 3D printed hip protector

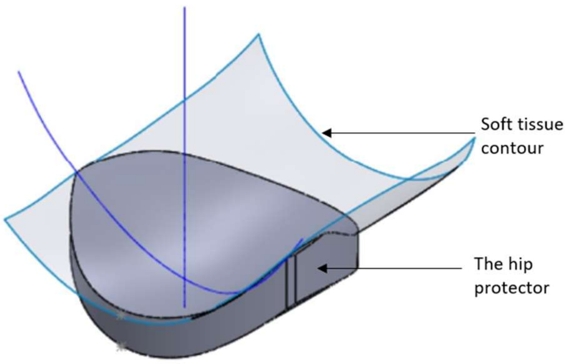

Figure 2. The hip protector

The procedure for producing the hip protector involved saving the file as a stereolithography (STL) file and utilizing the Prusa Slicer 2.3.0 software from Prusa Research, Czech, for slicing. The G-code was then generated by adjusting various settings. Employing the widely used 3D printing technique, Filament Deposition Modeling (FDM), the hip pad was produced. The Ender 3 Pro 3D printer, equipped with a 0.4 mm nozzle, executed the printing at a speed of 15 mm/s, with a nozzle temperature of 230 ^{O}C, and a layer thickness of 0.2 mm. The printing material is Thermoplastic Polyurethanes (TPU).

Three 3D printed hip protectors with different shore hardness levels but similar characteristics and structural details were used. These protectors were then put through rigorous drop tower impact testing in order to assess each one's unique impact attenuation capabilities. An average of five impact tests were performed on each sample, with the impact mass of 6.57 kg dropped from heights of 300 mm and 400 mm, at different energy levels. These experimental setups replicated the sideways impact that occurs when a person falls to the earth. The forces at the femoral neck were carefully recorded both with and without the hip guards in place (unprotected force, F_u; impact force, F_p).

The attenuation rate was established in order to measure the hip protectors' efficacy in reducing impact forces. By comparing the impact force recorded at the same location with the hip protector in place to the unprotected force (F_u), the ratio of forces at the femoral neck was obtained to determine this rate (F_p) as shown in Equation 1. Through the use of this methodology, a thorough evaluation of the hip protectors' ability to protect soft tissue during impacts was possible, yielding important information on how well they can attenuate impacts under various circumstances (Yahaya et al., 2020).

$$Impact\ Attenuation\ rate(\%) = 1 - \frac{F_p}{F_u} X\ 100\%. \quad (1)$$

II. Description of dataset

Four descriptors were taken into consideration for training and testing when building the predictive model with SVR, utilizing eighteen experimentally obtained datasets. These characteristics included maximum impact force, unprotected impact force, impact energy, and pad thickness. The foundation of the constructed SVR model is outlined in Table 1, which also includes details about the training and testing datasets. Using the previously described descriptors, the SVR model was specifically designed to evaluate the rate of attenuation of impact force of the 3D printed hip protector.

Table 2 presents the outcomes of a statistical analysis conducted on the experimental data obtained. This analysis included measures such as mean, maximum, minimum, and standard deviation, which served to elucidate the variations within the dataset. These statistical parameters contributed valuable insights into the overall characteristics of the experimental results, giving a thorough grasp of the 3D printed hip protector's impact attenuation capabilities in a variety of situations and environments.

Table 1. The target dataset and its descriptors

Run	Sample name	Impact attenuation	Shore hardness (%)	Shell thickness (L)	Infill density (%)	Impact energy (J)	Base impact force (N)	Impact force (N)
1	25_2L_85A	0.55	85	2	25	19.34	6,271.26	2,792.04
2	25_3L_85A	0.50	85	3	25	19.34	6,271.26	3,157.91
3	25_4L_85A	0.49	85	4	25	19.34	6,271.26	3,184.28
4	50_2L_85A	0.49	85	2	50	19.34	6,271.26	3,175.49
5	50_3L_85A	0.49	85	3	50	19.34	6,271.26	3,196.97
6	75_4L_85A	0.49	85	4	75	19.34	6,271.26	3,210.89
7	100_4L_85A	0.49	85	4	100	19.34	6,271.26	3,172.19
8	100_2L_95A	0.53	95	2	100	19.34	6,271.26	2,958.07
9	25_3L_95A	0.53	95	3	25	19.34	6,271.26	2,923.76
10	25_4L_95A	0.51	95	4	25	19.34	6,271.26	3,084.54
11	25_2L_75A	0.53	75	2	25	19.34	6,271.26	2,947.20
12	25_2L_85A_2	0.69	85	2	25	25.78	11,531.83	3,542.33
13	50_3L_85A_2	0.62	85	3	50	25.78	11,531.83	4,428.86
14	75_4L_85A_2	0.60	85	4	75	25.78	11,531.83	4,585.73
15	50_2L_95A	0.64	95	2	50	25.78	11,531.83	4,199.48
16	25_3L_95A_2	0.67	95	3	25	25.78	11,531.83	3,856.31
17	25_4L_95A_2	0.64	95	4	25	25.78	11,531.83	4,142.46
18	25_2L_75A	0.68	75	2	25	25.78	11,531.83	3,730.70

Table 2. statistical evaluation of the obtained data

	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	

III. SVR computational intelligence technique description

In order to estimate the impact attenuation rate of 3D printed hip protectors, this study uses a SVR model that is based on the impact response values that were obtained from the training dataset. The fundamental idea is to identify a function f (x, α) that, with a maximum deviation of ε (margin), approximates the original dataset $(y_1, \ldots, y_k)$ based on the impact attenuation values, y. that were determined by biomechanical experiments. A non-linear mapping function is used to map the input information to a k-dimensional feature space in order to build the linear model $f(x)$ in Equation 2. By introducing a soft margin idea, the deviation constraint, ε is relaxed, guaranteeing the availability of a solution. If the ε deviation setting is not satisfied, penalty costs are applied through slack variables ξ and ξ^*. The following represents the linear model:

$$f(x) = w \,.\, \phi(x) + b \tag{2}$$

where b is the bias constant, w is the weight vector, and $\phi(x)$ is a collection of non-linear transformations that translate the input vector to a higher dimensional feature space (Salami et al., 2019). Equation 3 provides the loss function, which governs the SVR's capacity to measure impact attenuation.

$$L\big(y, f(x)\big) = \begin{cases} 0 & \text{if } |y - f(x)| \le \varepsilon \\ |y - f(x)| - \varepsilon & \text{otherwise} \end{cases} \tag{3}$$

Equation 4's primal optimization problem can be solved to provide the ideal weight vector w, subject to the particular limitations given in Equation 5.

$$\text{Minimise } \frac{1}{2}||w||^2 + C\sum_{i=1}^{k}[\xi_i + \xi_i^*] \tag{4}$$

$$\begin{aligned} y_i - f(x) &\le \varepsilon + \xi_i^* \\ f(x) - y_i &\le \varepsilon + \xi_i^* \\ \xi_i\xi_i^* &\ge 0 \quad i = 1, \ldots, k \end{aligned} \tag{5}$$

To address the non-linearity of the data, the primal problem is effectively solved by transforming it into a primal-dual setting, utilizing the Kernel function, a non-linear mapping function. Equation 6 represents the Kernel function.

$$K(x, x_i) = \phi(x) \cdot \phi(x_i) \tag{6}$$

Thus, allows for the reformulation of the solution in Equation 7.

$$f(x) = \sum_{i=1}^{k}(\alpha_i - \alpha_i^*)K(x, x_i) + b \tag{7}$$

By applying the kernel method, the reformulated solution of f(x) is achieved without performing an operation directly on $\phi(x)$ and calculating the weight vector w. Equation 7 expresses f(x) as the product of the kernel function's output, $K(x, x_i)$ and the Lagrangian multipliers (α_i and α_i^*), along with the bias term b. The Lagrangian multipliers are subject to specific constraints and play a crucial role in the SVR's effectiveness in predicting impact attenuation.

IV. A synopsis of the computational approach

Using the training dataset, the SVR model was computationally developed. Its accuracy was evaluated using a test-set cross-validation technique with the testing dataset. There were multiple parts in the methodology: first, the data were divided into training and testing datasets. Subsequently, the training dataset was utilized to generate support vectors by selecting particular kernel parameters for a selected kernel function. Next, using the testing dataset's descriptors and support vectors, the SVR model predicted the target in the analysis.

The performance of the model was assessed both in the training and testing phases. This was accomplished by contrasting the estimated values obtained from the SVR model with the impact attenuation of the hip protection that was 3D printed. This procedure ensured the generated model's robustness in giving accurate estimates of effect attenuation across many scenarios and settings by methodically examining its accuracy, generality, and predictive capabilities.

B, *Optimal parameters search methodology*

The test-set cross-validation optimization technique was used to find the ideal kernel parameters, with the goals of robust modelling and computational efficiency. Several iterations were required for this process, depending on the amount and type of dataset. The first set of kernel parameters were chosen iteratively, the test-set cross-validation method was implemented, and the systematic variation of kernel parameter combinations for each run. The goal was to identify the optimum values for model parameters, which were subsequently utilized to train the final SVR algorithm. . For every combination of kernel parameters, the observed correlation coefficient (R^2) and the Root Mean Squared Error (RMSE) were assessed in order to determine the ideal values. The mapping of the kernel function in converting the data into a high-dimensional feature space was described by the value of the kernel option. The epsilon (ε) governed the maximum permitted departure of the estimated value from the actual target, while the hyper-parameter controlled the hyperplane selection, guaranteeing minimal error. Furthermore, the trade-off between the complexity of the model and the maximum allowable deviation of the predicted target value from the actual experimental or observed target value was controlled by the regularization factor, also known as the penalty factor and represented by the letter C. This comprehensive optimization process ensured that the SVR algorithm was fine-tuned with the most effective kernel parameters for accurate predictions and generalization across different scenarios

C. Evaluation of the prediction performance of the proposed SVR-based model.

In order to evaluate the predictive and generalization capacities of the suggested SVR model, its statistical performance was carefully evaluated using critical metrics including the correlation coefficient (R^2) and the RMSE. By presenting the related error between the estimated and experimental values of impact force attenuation, these parameters functioned as markers of the validity of the model's estimation. The correlation coefficient is shown in Equation 8, and the RMSE is shown in Eqn. 9

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

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

In these equations, $A_r(\exp)$ represents the experimental attenuation rate, $A'_r(\exp)$ denotes the mean experimental attenuation rate, $A_r(est)$ is the estimated attenuation rate, and $A'_r(est)$ stands for the mean estimated attenuation rate. These metrics collectively provide a comprehensive evaluation of the SVR model's performance by quantifying the accuracy and reliability of its predictions against the experimental data across multiple scenarios and conditions.

III. Results

The optimal values for the model parameters, identified through the test-set cross-validation optimization process, were utilized to train the final Support Vector Regression (SVR) algorithm. These optimal values are systematically summarized in Table 3, providing a clear reference for the specific configuration that enhances the SVR model's accuracy and effectiveness in predicting the impact attenuation rate of 3D printed hip protectors. The presented Table 3 serves as a crucial reference for replicability and transparency, ensuring that the adopted parameters are well-documented for future analysis and application of the SVR algorithm.

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 SVR model's generalization and predictive accuracy in calculating the impact attenuation of a 3D printed hip protector during a simulated sideways fall were evaluated. The impact force attenuation was the desired outcome of the model, which took into account a number of input characteristics such as the pad's shore hardness, shell thickness, infill density, base impact force, maximum impact force, and impact energy. The input factors affected the impact force attenuation or showed a correlation with their results. The SVR model found support vectors in the training phase, which were then used in the testing dataset to calculate the hip protector's impact attenuation. Correlation cross-plots for the training and testing datasets are shown in Figures 3 and 4, with an emphasis on the Gaussian kernel functions. The estimation accuracy attained with the best SVR modeling parameters found using the search strategy is shown graphically in these Figures. The cross-plots serve as valuable tools for evaluating how well the model can be generalized and accurately predicts impact force attenuation across different datasets, further affirming the robustness and reliability of the SVR model in this specific application.

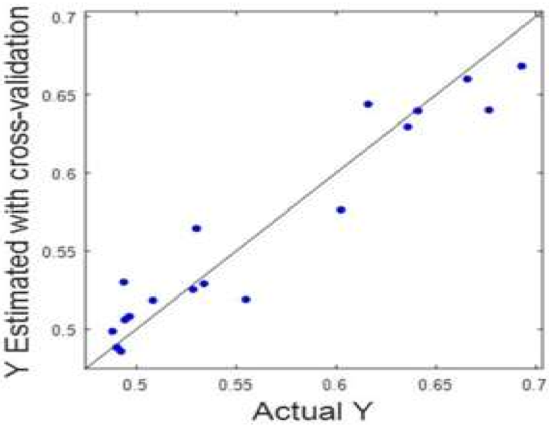

Figure 3. Cross-plot correlation analysis comparing the training dataset's experimental and projected impact attenuation rates for 3D printed hip protectors

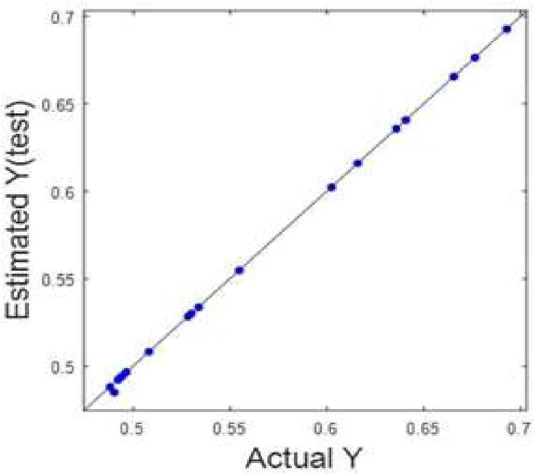

Figure 4. Correlation cross-plot for testing dataset: impact attenuation rate of 3D printed hip protection between estimated and experimental values

A strong correlation exists between the experimental and estimated impact force attenuation values for both the training and testing datasets of the hip protector, particularly for the selected Gaussian Kernel type. The obtained R^2 values of 91.5% (with RMSE = 0.0208) for the training set and 99.9% (with RMSE = 0.0012) for the test set underscore the excellence of the proposed model. This stellar performance on unseen data further validates the robustness of the model. The RMSE values, ranging from 0.0012 to 0.0208, signify the proximity of the data points to the regression line, indicating a highly accurate fit. These results collectively affirm that the developed model demonstrates exceptional performance and has the potential for effective generalization.

Moreover, the model successfully produced results in good agreement with the experimental data when only the descriptors were supplied to the model without the target. This is evident in the effective tracking of measured impact attenuations, as depicted in Figure 5. These findings collectively highlight the reliability and accuracy of the proposed SVR model in predicting impact force attenuation for 3D printed hip protectors, demonstrating its capability to yield consistent and precise estimations across different datasets and scenarios.

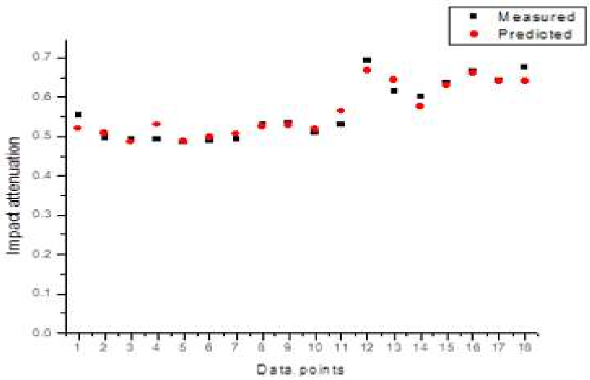

Figure 5. SVR's tracking of observed impact attenuation (Testing data)

IV. Discussion

This work describes the creation of an SVR model that was trained and evaluated to determine the rate of impact attenuation of a 3D printed hip protector at various residual impact energies. It also specifically looks into the impact attenuation effects of the hip pad's material shore hardness and infill density. The hip protector's attenuation rate was determined by a rigorous impact attenuation experiment using the drop impact tower testing equipment with anatomical femur; specifics are provided in (Yahaya et al., 2020). These experimental findings, as can be shown, agreed well with the outcomes attained during the model implementation phase. This indicates that the model can forecast the hip protector's impact force attenuation rate using acquired support vectors obtained from. Because there was a strong correlation between the experiment and the estimated values during the training and testing phases, the model performed well and could be generalized, as evidenced by the obtained R^2 values, which represent the correlation between the experimental and estimated impact attenuation rate and range from 91% to 99%. The generated RMSE values, which ranged from 0.0012 to 0.0208, further demonstrate the good fit and highlight how near the data point is to the regression line. This indicates even more how well the proposed model can forecast how different descriptor values will affect impact attenuation.

B. Z-wave

This is a wireless communication technology that supports interoperability especially at the application layer of the OSI model. Since embedded devices share information between hardware and software, the place of z-wave cannot be over emphasized in allowing hardware to interoperate with software. It has the capability of achieving data rate of 40 and 100 kbit/s providing cloud access through gateway (Z-wave bridge). They are embedded device protocols that are implemented on chips with frequency specification of sub-1 GHz band between 865 to 926 MHz routed through network architecture while the physical range covers up to 100 m. It functions more within low-power Radio Frequency Identification (RFID) communication with a reasonable support for home automation.

There is a special incentive to use SVR in predicting the impact response of a hip protector in order to optimize the impact force attenuation rate of the protector because it is well-supported in studying small-to-medium-sized problems (Vapnik, 1995) and can be done computationally to study the impact behaviour of materials (Malik and Arif, 2013). Because it eliminates the need to individually design and print several hip protector sizes for comparison, this designed model helps to optimize the 3D printed hip protector. The objective of every project is to minimize costs, and creating an optimal hip protection is no exception. The effect of every material behaviour under impact was captured by the established SVR model. The mechanism of impact attenuation tends to be different and Favour's reduced infill density for the materials of 85 percent and 75 percent shore A hardness, which are generally softer than the 95 percent shore A hardness TPU. This illustrates the significance of having less stiff material as hip protecting material. Much stiffer materials also function better, although doing so requires utilizing more material to create a rigid energy shunting intervention. This is in line with research by Robinovitch et al. (1995) about the suitability of stiffer materials for use as hip protectors.

Additionally, since the force required at the greater trochanter grows greatly with increasing shell thickness, it was found that increasing the pad's stiffness also negatively impacts the impact attenuation of the intervention manufactured with 75 percent and 85 percent shore hardness. On the other hand, the stiffer material with a 95% shore hardness increases impact attenuation due to the thickness of the shell. The material's increased cross-sectional area to withstand the shock is the cause of this increase. However, an unlimited increase in shell thickness would result in an unattractive, cumbersome hip protector that would eventually compromise adhesion (Holzer et al., 2009). Therefore, there is a need for a combination hip protector that would ensure both the benefits of the soft hip protectors as stated in the work of (Kannus et al., 1999; Robinovitch et al., 1995; van Schoor et al., 2003) and the greater protection of the hard hip protectors (Holzer et al., 2009). Consequently, research can be directed toward the development of structures that would provide remarkable energy absorption and shunting while maintaining an efficient balance between material use, efficacy, and appeal.

The claim that the SVR model is a crucial tool for creating an optimal clinical intervention—among them, the hip protector—is strengthened by the model's accuracy in robustly predicting the impact attenuation of the 3D printed hip protector in relation to the studied parameters of shore hardness, infill density, and shell thickness. Furthermore, the parameters of interest can be adjusted, and this SVR model can be used to accurately estimate the intervention's response.

V. CONCLUSION

By using the Support Vector Regression (SVR) technique, this study examined the complex relationship between the impact attenuation of 3D printed Thermoplastic Polyurethane (TPU) hip protectors and shore hardness, infill density, and shell thickness. The impact attenuation of these hip protectors displayed a highly non-linear dependence on factors influencing the material's stiffness, posing a significant challenge for accurate modelling. However, the SVR-based model, based on the analysed data, demonstrated exceptional accuracy in estimating hip protector impact attenuation, achieving over 99% accuracy and a minimal RMSE of 0.002, as indicated by the high R^2 value. This proposed model provides accurate performance quantification and is a useful tool for lowering the costs of conducting experiments to investigate the variability in design parameters. The findings support the feasibility of using SVR to forecast the impact attenuation of 3D printed hip protectors, which adds significant understanding to research on fracture prevention. Additionally, the study provides new insights into how material shore hardness and infill density affect the pace at which impacts are attenuated for hip protectors. Because of its resilience, the SVR model can be used to forecast how well-designed hip protectors will attenuate impacts, which can lead to important breakthroughs in the field of fracture prevention research.

AUTHOR CONTRIBUTIONS

S. A. Yahaya: conceptualisation, experiments design, methodology, and writing – original draft and editing **I. O. Muniru:** software, validation and data analysis. **S. Saminu:** study design, review and data analysis. **M. O. Ibitoye:** review and editing. **T. M. Ajibola:** review and editing. **L. J. Jilantikiri:** review and editing. **Z. M. Ripin:** supervision, writing – original draft, writing – review and editing. **M.I.Z. Ridzwan:** acquired funding, administered the project, and revised the manuscript.

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