A Comparative Analysis of Physics-Based and Machine Learning Models for Bouncing Ball Energy Dissipation

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Abstract

This study investigates energy loss in bouncing-ball collisions on different surfaces using both a physics-based exponential model and a machine-learning (linear regression) model. A golf ball was dropped from a height of 1.0 m onto wooden, carpeted, and cardboard surfaces, and rebound heights were measured experimentally. The coefficient of restitution and corresponding energy losses were calculated for each surface. A physics-based exponential decay model, assuming a constant coefficient of restitution, was used to predict the rebound heights, while a linear regression model was trained on experimental data which was collected. The performance of both models was evaluated using Mean Absolute Error (MAE) on a shared test dataset. The physics-based model achieved a lower MAE (5.38 cm) than the machine-learning model (7.08 cm), indicating a higher predictive accuracy for the physics model. However, increasing deviations were observed for softer surfaces and at higher bounce numbers, where real behaviour deviates from ideal conditions. These findings demonstrate that physics-based models perform best under ideal assumptions, while machine-learning models can adapt better to non-ideal situations. Both approaches have their own strengths and limitations, but when combined, they can provide a more robust framework for modelling complex real-world physical systems.

Keywords: Collisions, Energy, Rebound height, Linear regression, Bounce dynamics

1 Introduction

When an object collides with a surface, some part of its mechanical energy is lost due to deformation, sound and heat. 'Rebound height' is an important concept in physics. It is defined as the maximum height a bouncing object can reach after an impact. When a ball bounces up and down on a flat surface, the rebound height decreases with every bounce. In classical physics, this decrease happens in a very predictable way for most types of balls. The relationship between the maximum height reached by the ball on a particular bounce and the number of bounces that have occurred since the ball was released can be modelled using an exponential decay relationship given by the following equation 1:

$$y = hr^x \quad (1)$$

where y is the rebound height after the bounce number x, h is the height from which the ball was initially released, and r is the decay constant that depends on the physical characteristics of the ball used [1]. We also know that the gravitational potential energy of a ball is directly proportional to its height above the ground. So, the rebound height of the ball can be used to measure energy loss and to calculate the coefficient of restitution (COR), e, a physics concept that measures the elasticity of a collision. It is a number that lies between 0 and 1 (inclusive) and depends on the materials that the two colliding objects are made from. COR is a key factor in the design and analysis of collision systems. It allows designers and engineers to predict energy transfer, optimize performance, and enhance safety in various applications, such as sports design equipment, automobile safety, robotics and automation processes [2]. The physics-based model gives us a simple way to describe bouncing motion. In recent times, artificial intelligence (AI) and machine-learning (ML) techniques are being increasingly used to analyze physical systems by identifying trends/patterns from data. Unlike physics-based models, ML models do not depend on physical equations; instead, they tend to learn relationships from experimental measurements. While machine learning algorithms perform well in identifying patterns in large datasets with high accuracy, they can sometimes struggle and violate the underlying physical laws that govern the real world, such as conservation of energy and momentum. This is where the fusion of physics and machine learning becomes crucial, and researchers have just begun to explore the field of “AI + physics” [3]. That is why it is important to evaluate how the performance of such models compares to traditional physics-based approaches. In this study, the energy loss in bouncing ball collisions was investigated using both the physics-based traditional exponential decay model and a machine-learning regression model.

We hypothesized that the rebound height of the ball would decrease with every bounce due to energy dissipation, and while a machine-learning model may fit experimental data well, the physics-based model would provide more consistent and accurate predictions of rebound heights, and subsequently energy loss values across different conditions, especially for lower bounce numbers. To test the hypothesis, we collected data through experiments on the rebound height for a golf ball bouncing on three different surfaces: a carpeted floor (soft surface), a cardboard surface (moderately compliant), and a wooden floor (rigid). We performed all the experiments at home. The drops were performed on flat regions of each surface, away from any edge or joint, to maintain consistent impact conditions across trials. The accuracy and limitations of each modelling approach were then compared to assessing whether a data-driven ML model can predict bounce behaviour as effectively as a classical physics model.

2 Materials and Methods

A standard pressurized golf ball was used for all trials, and three impact surfaces - a carpeted floor, a cardboard surface, and a wooden floor. Rebound heights were measured using a vertical measuring scale (meter tape) placed within the frame of a smartphone camera. The smartphone used to capture each trial was capable of slow-motion video recording. A masking tape was used to mark the location from which the ball was being dropped each time. This ensured the same release position across each trial for all three surfaces. The data analysis was performed using spreadsheet software.

The ball was dropped from rest position at a fixed height of 1.00 m, measured from the bottom of the ball to the surface for all the trials. A smartphone camera was positioned at a fixed location perpendicular to the plane of motion. A vertical measuring scale was placed in the background within the camera frame to measure the rebound heights of the ball accurately. The position of the camera was kept constant throughout for all the trials. For each surface, namely, carpet, cardboard and wood, we conducted five trials. In each trial, the ball was released and allowed to bounce off the surface freely. The rebound heights of the ball after each bounce (h_1, h_2, h_3, h_4, h_5) were calculated by doing a frame-by-frame analysis of the captured slow-motion video. We continued the data collection until the rebound heights became too small to be measured effectively, with a minimum of three bounces recorded per trial. The coefficient of restitution for each impact of the ball on the surface was calculated using the rebound heights according to the physics equation 2 below [4], where h_0 = initial height of the release of the ball from the top of the surface = 1.00 m = 100 cms.

$$e_n = \sqrt{\frac{\text{Rebound height}}{\text{Initial height}}} = \frac{h_n}{h_{n-1}} \tag{2}$$

The percentage of energy that was lost due to each bounce was calculated as (1 - e_n^2) * 100. The descriptive statistics measurements - mean value, and standard deviation were calculated for each flat surface type to compare energy loss and collision elasticity under different surface type conditions.

To complement the physics-based analysis done previously, a simple machine-learning regression model was used to model rebound heights from the same data that was collected during the physical experiments. Machine learning was applied as a data-driven method to predict the next rebound height without assuming a physical equation explicitly. The goal was not to replace the classical physics model, but to compare the performance and limitations of an ML model with a classical physics-based approach in terms of predicting energy loss. The dataset used for machine-learning analysis consisted of the rebound heights measured previously from the five trials on three surfaces: carpet, cardboard, and wood. Each data point included the bounce number and the corresponding rebound height. A linear regression model was used for the ML analysis because it is simple, interpretable, efficient for smaller datasets, and less prone to overfitting than complex models [5]. Linear regression is a supervised machine learning algorithm that learns from a labelled dataset and maps the data points with the most optimized linear functions that can predict on new datasets [6]. The input variables to the machine-learning model were the bounce number, surface type, and the rebound height just before the bounce. The output variable was the rebound height after the bounce. Surface type was encoded as a categorical variable to allow the model to differentiate between different impact conditions. The model estimates a relationship between the input variable and rebound height by minimizing the difference between predicted and measured values. The dataset was split into a training and testing ratio of 70:30, allowing the model to predict with better accuracy. The performance of the model was then evaluated using the mean absolute error (MAE) between predicted and measured rebound heights. The MAE was calculated using the equation 3 below.

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |x_i - \hat{x}_i| \tag{3}$$

where N is the total number of data points,
x_i is the measured (experimental) value at data point i,
$\hat{x}_i$ is the predicted or calculated value at data point i,
and $|x_i - \hat{x}_i|$ represents the absolute error for data point i.

The ML analysis was done using Python libraries in Google Colab Notebook, and all model parameters were kept simple to ensure transparency. The rebound heights predicted by the ML model were then used to calculate the coefficient of restitution, and successively, the energy loss was calculated using the predicted rebound height from the ML model and the experimentally measured height immediately preceding the bounce. The energy loss estimates derived from the machine-learning model were then directly compared with those obtained from the physics-based model. This comparison allowed assessment of how well a data-driven model could capture bounce behaviour compared with physics principles.

3 Results

To test the hypothesis, the experiments were divided into two broad categories: the first using physics laws and the second using an Machine Learning model.

3.1 Physics-Based Experiments

Three experiments were conducted with a standard golf ball and three different surfaces, which are a carpeted floor, a cardboard surface, and a wooden floor. The rebound heights of the golf ball were measured during its impact on the three surfaces using the slow-motion camera of a smartphone. For each surface type, five trials were conducted. The initial dropping height of the ball was kept constant at 1.00 m (100 cm) for each trial. The coefficient of restitution was calculated, and the energy loss was quantified using the first bounce for each trial, as measurement uncertainty was observed in subsequent bounces due to decreasing rebound heights. The subsequent rebound heights were recorded to validate the exponential decay model and assess consistency in energy dissipation across impacts. Test 1 was for a carpeted floor. The first rebound height (h_1) ranged from 41 to 46 cm (Table 1). A rapid decrease was observed in the successive rebound heights with values ranging between 0.5 and 3 cm by the fourth bounce (Table 1). The fifth bounce could not be measured reliably due to the small rebound height. Hence, the analysis for the carpeted surface was restricted to the first four bounces. The numerical values for the coefficient of restitution of the first bounce (e_1) ranged between 0.64 and 0.68, with a mean value of 0.652 ± 0.018 (mean ± SD, n =5) (Table 1). The percentage energy loss during the first bounce varied between 53.76% and 59.04%, with a mean energy loss of 57.464% ± 2.357% (Table 1).

Initial dropping height $h_0 = 1.00$ m = 100 cm	Raw Data (Rebound Heights in cm)				Coefficient of Restitution				Energy Loss (%)
Trial No	h_1	h_2	h_3	h_4	e_1	e_2	e_3	e_4	$(1 - e_1^2) \times 100$
1	41	15	4	1	0.64	0.60	0.52	0.50	59.04
2	41	17	6	1	0.64	0.64	0.59	0.41	59.04
3	41	11	5	0.5	0.64	0.52	0.67	0.32	59.04
4	44	16	7	3	0.66	0.60	0.66	0.65	56.44
5	46	13	5	2	0.68	0.53	0.62	0.63	53.76
Mean (for e_1)					0.652	Mean Energy Loss (%)			57.464
Standard Deviation (for e_1)					0.018	Standard Deviation Energy Loss (%)			2.357

Table 1: Raw and derived data for carpeted surface. The initial drop height is 1.00 m. The raw data collected are the rebound heights of the ball after each bounce. The derived quantities are the coefficient of restitution and the percentage of energy loss from the first bounce for each of the five trials.

Test 2 was for a cardboard surface. The first rebound height (h_1) ranged from 43 to 54 cm (Table 2). A rapid decrease was observed in the successive rebound heights with values ranging between 1 and 3 cm by the third bounce (Table 2). The rebound heights after the third bounce were too small to be measured reliably, so the fourth and fifth bounces were therefore excluded from analysis. The numerical values for the coefficient of restitution of the first bounce (e_1) ranged between 0.66 and 0.73 with a mean value of 0.7 ± 0.03 (mean ± SD, n =5) (Table 2). The percentage energy loss during the first bounce varied between 46.71% and 56.44%, with a mean energy loss of 50.928% ± 4.19% (Table 2).

Initial dropping height $h_0 = 1.00$ m = 100 cm	Raw Data (Rebound Heights in cm)				Coefficient of Restitution				Energy Loss (%)
Trial No	h_1	h_2	h_3	h_4	e_1	e_2	e_3	e_4	$(1 - e_1^2) \times 100$
1	43	5	1	-	0.66	0.34	0.45	-	56.44
2	53	13	4	-	0.73	0.50	0.55	-	46.71
3	48	6	3	-	0.69	0.35	0.71	-	52.39
4	47	4	1	-	0.69	0.29	0.50	-	52.39
5	54	18	4	-	0.73	0.58	0.47	-	46.71
Mean (for e_1)					0.700	Mean Energy Loss (%)			50.928
Standard Deviation (for e_1)					0.03	Standard Deviation Energy Loss (%)			4.19

Table 2: Raw and derived data for cardboard surface. The initial drop height is 1.00 m. The raw data collected are the rebound heights of the ball after each bounce. The derived quantities are the coefficient of restitution and the percentage of energy loss from the first bounce for each of the five trials.

Test 3 was for the wooden floor. The first rebound height (h_1) ranged from 77 to 81 cm (Table 3). A consistent decreasing trend was observed in the successive rebound heights with values ranging between 6 and 20 cm by the fifth bounce (Table 3). The numerical value for the coefficient of restitution of the first bounce (e_1) remained consistently high, the values ranging between 0.88 and 0.91 with a mean value of 0.892 ± 0.013 (mean ± SD, n =5) (Table 3). This demonstrates that the variability between trials was low. For the successive rebounds, the coefficient of restitution (e_2 - e_5) remained relatively consistent, thereby indicating a stable rebound behavior over multiple impacts. The percentage energy loss during the first bounce varied between 17.19% and 22.56%, with a mean energy loss of 20.42% ± 2.331% (Table 3).

Initial dropping height $h_0 = 1.00$ m = 100 cm	Raw Data (Rebound Heights in cm)					Coefficient of Restitution					Energy Loss (%)
Trial No	h_1	h_2	h_3	h_4	h_5	e_1	e_2	e_3	e_4	e_5	$(1 - e_1^2) \times 100$
1	78	61	39	19	6	0.88	0.88	0.80	0.70	0.56	22.56
2	77	58	37	23	8	0.88	0.87	0.80	0.79	0.59	22.56
3	82	63	45	31	18	0.91	0.88	0.85	0.83	0.76	17.19
4	79	61	44	31	20	0.89	0.88	0.85	0.84	0.80	20.79
5	81	61	43	23	7	0.87	0.87	0.84	0.73	0.55	19.00
Mean (for e_1)						0.892	Mean Energy Loss (%)				20.420
Standard Deviation (for e_1)						0.013	Standard Deviation Energy Loss (%)				2.331

Table 3: Raw and derived data for the wooden surface. The initial drop height is 1.00 m. The raw data collected are the rebound heights of the ball after each bounce. The derived quantities are the coefficient of restitution and the percentage of energy loss from the first bounce for each of the five trials.

The wooden surface demonstrated the lowest mean energy loss compared to both the carpeted and cardboard surfaces, the carpeted floor being the highest (Table 4). The mean coefficient of restitution varied across surfaces, with the highest value observed for wood (e_1=0.892) and the lowest for carpet (e_1=0.652). The standard deviation of energy loss remained below 5% for all three surfaces. This shows consistent results across multiple trials.

Surface	**Mean (for e_1)**	**Standard Deviation (for e_1)**	**Mean Energy Loss (%)**	**Standard Deviation Energy Loss (%)**
Carpeted Floor	0.652	0.018	57.464	2.357
Cardboard	0.700	0.030	50.928	4.19
Wood	0.892	0.013	20.42	2.331

Table 4: Surface Comparison Table of Coefficient of Restitution and Energy Loss. The mean for e_1 is calculated. The other parameters calculated are the standard deviation for e_1 for each surface. The mean energy loss (%) from the first bounce and the standard deviation for the mean energy loss from the first bounce.

3.2 Machine Learning Model-Based Predictions

The same experimental data collected for physics-based experiments were used to set up the data table for the machine learning model prediction. It was observed that the prediction accuracy was highest for the wooden surface, while greater deviation between predicted and measured values was noticed for the carpeted and cardboard surfaces. The actual versus predicted rebound height plot for the wooden surface is shown in Figure 1 below to illustrate the performance of the machine learning model.

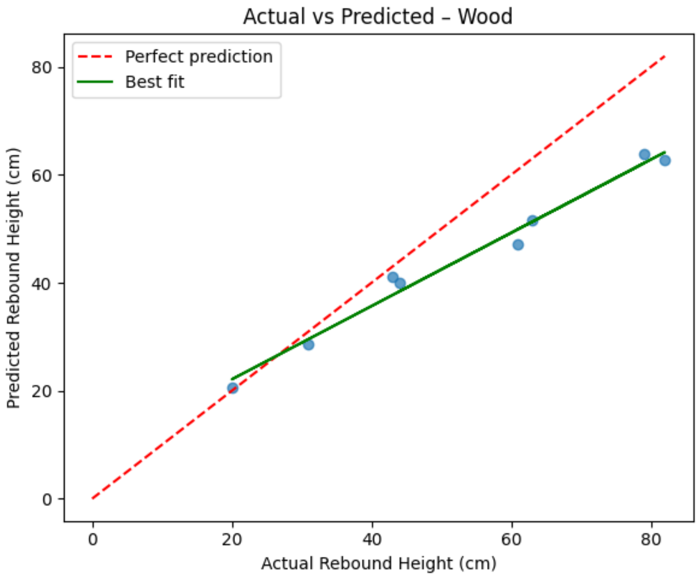

Figure 1: Comparison of machine-learning-predicted and experimentally measured rebound heights for the wooden surface. Each point represents an individual bounce event from the test dataset. The dashed line indicates perfect prediction (y = x), and the solid line shows the best-fit linear regression through the predicted values.

Our evaluation metrics are as follows:

- Mean Absolute Error (MAE): 8.63 cm
- Root Mean Square Error (RMSE): 10.93 cm
- Coefficient of Determination (R^2): 0.72
- Average Predicted e_1: 0.801, Average Energy Loss per Bounce: 35.9%

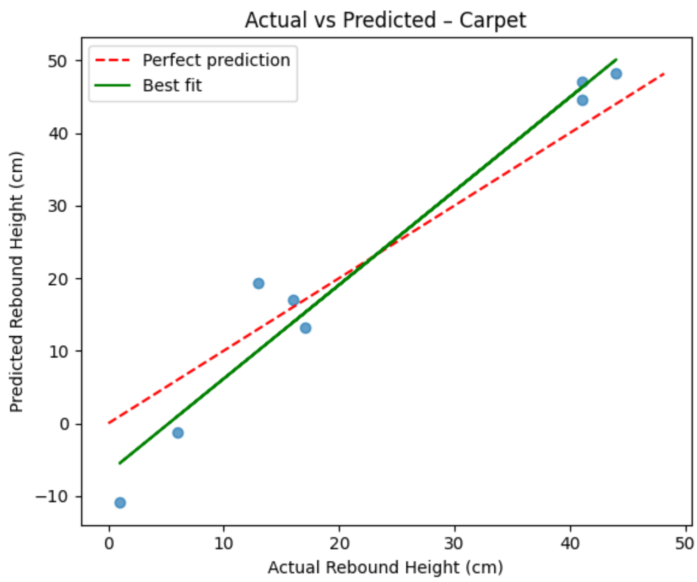

Figure 2: Comparison of machine-learning-predicted and experimentally measured rebound heights for the carpeted surface. Each point represents an individual bounce event from the test dataset. The dashed line indicates perfect prediction (y = x), and the solid line shows the best-fit linear regression through the predicted values.

Our evaluation metrics are as follows:

- Mean Absolute Error (MAE): 5.51 cm
- Root Mean Square Error (RMSE): 6.28 cm
- Coefficient of Determination (R^2): 0.85
- Average Predicted e_1: 0.647, Average Energy Loss per Bounce: 57.9%

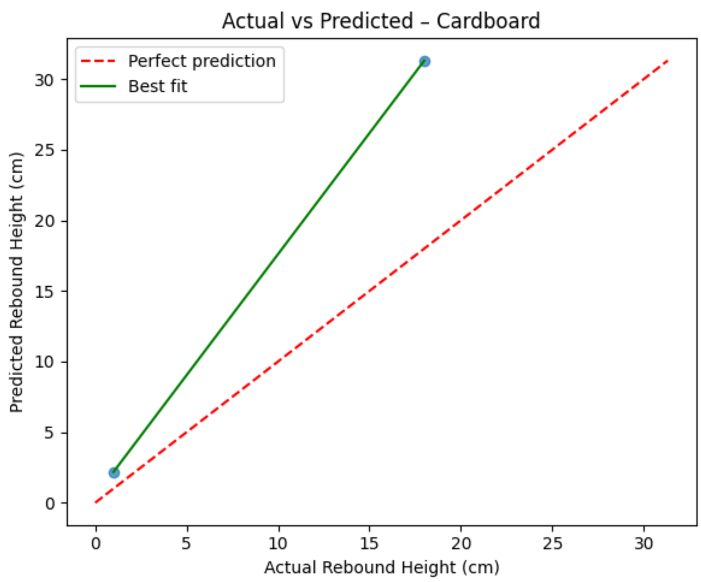

Figure 3: Comparison of machine-learning-predicted and experimentally measured rebound heights for the cardboard surface. Each point represents an individual bounce event from the test dataset. The dashed line indicates perfect prediction (y = x), and the solid line shows the best-fit linear regression through the predicted values.

Our evaluation metrics are as follows:

- Mean Absolute Error (MAE): 7.25 cm
- Root Mean Square Error (RMSE): 9.45 cm
- Coefficient of Determination (R^2): -0.24
- Average Predicted e_1: 0.750, Average Energy Loss per Bounce: 43.7%

The results of the cardboard and carpeted surfaces are summarized in Table 5 quantitatively. Table 5 below shows the predicted rebound height by the ML model, the actual measured height, the derived energy loss % calculated from the predicted rebound height, and the absolute error between predicted and measured rebound heights. A small number of negative rebound height predictions were produced by the machine-learning model; these were excluded from Table 5 as they are physically non-meaningful. The column values for the Energy loss percentage were derived from the machine-learning-predicted rebound heights, which were calculated using the experimentally measured height preceding each bounce.

The absolute error values were computed by taking the absolute difference between the predicted height and the actual height. The machine-learning model achieved a mean absolute error (MAE) of 7.08 cm on the test dataset, computed across all three surfaces.

Surface	Bounce Number	Actual Rebound Height (cms)	ML Predicted Rebound Height (cms)	Energy Loss from ML (%)	Absolute Error (cms)
Wood	2	61	47.06	39.67	13.94
Wood	3	43	41.09	32.65	1.91
Wood	5	20	20.70	33.23	0.70
Cardboard	3	1	2.18	45.48	1.18
Cardboard	2	18	31.31	42.01	13.31
Carpet	1	41	44.65	55.35	3.65
Carpet	2	17	13.14	67.95	3.86
Carpet	2	16	17.06	61.23	1.06

Table 5: Comparison of experimentally measured and machine-learning-predicted rebound heights for selected test-set bounce events, with the corresponding energy loss.

Table 6 shows the physics-based exponential decay predictions of rebound heights for each surface on the same test set data of Table 5. The predicted values are calculated using equation number 1, with h = 100 cms, the initial height of the drop of the ball. The simplified equation reduces to $h_n = 100r^n$, where h_n = rebound height after the n^{th} bounce. For each surface, the mean value of the coefficient of restitution for e_1 (Table 4) was used. In bouncing-ball collisions, the decay constant, r, is equal to the square of the coefficient of restitution, r = e_1^2, since rebound height is proportional to the square of the rebound velocity. The absolute error values were calculated by the absolute difference between the predicted rebound height and the actual height. The mean absolute error for the physics-based exponential model was calculated as 5.38 cms.

Surface	Bounce Number	Actual Rebound Height (cms)	Physics Predicted Rebound Height (cms)	Absolute Error (cms)
Wood	2	61	63.31	2.31
Wood	3	43	50.37	7.37
Wood	5	20	31.89	11.89
Cardboard	3	1	11.76	10.76
Cardboard	2	18	24.01	6.01
Carpet	1	41	42.54	1.54
Carpet	2	17	18.09	1.09
Carpet	2	16	18.09	2.09

Table 6: Physics-based exponential decay model predictions of rebound heights. The data was calculated for the same test-set bounce events, together with the corresponding absolute prediction error calculated relative to experimental measurements.

4 Discussion

This study aimed to compare a physics-based exponential decay model with a machine-learning (ML) regression model for predicting the rebound heights and the corresponding energy losses across three different surfaces, namely, wood, carpet, and cardboard. Our findings showed that the physics-based model had a lower mean absolute error (MAE = 5.38 cm) compared to the machine-learning model (MAE = 7.08 cm), indicating that, on average, the physics model provided more accurate predictions of the rebound heights across the test dataset.

The better performance of the physics-based model can be due to the relatively stable physical behaviour of the system, especially on rigid surfaces such as wood. The exponential decay model used for the physics-based predictions assumes a constant coefficient of restitution for a given surface, leading to a consistent fractional energy loss per bounce. This was well supported by the experimental data, where the measured coefficients of restitution showed low variability. This resulted in close alignment between predicted and observed rebound heights at early bounce numbers. But the physics-based model, however, showed increasing deviation at higher bounce numbers and on softer surfaces such as cardboard and carpet. In these cases, the assumption of a constant coefficient of restitution becomes less valid due to increased material deformation and energy dissipation mechanisms that vary across successive bounces. This limitation was particularly evident for cardboard, where the physics model overestimated rebound height at later bounces.

In contrast, the machine-learning model does not rely on explicit physical assumptions and instead learns patterns directly from experimental data. Although this allowed the ML model to adapt to non-ideal and surface-dependent behaviour, its predictive accuracy was limited by the relatively small dataset and the use of a simple linear regression model. These may have led to higher MAE for the ML approach, especially for later rebounds and highly dissipative surfaces. But, despite these, the ML model successfully captured the overall surface-dependent trends in energy loss and rebound behaviour, demonstrating its potential as a complementary tool to physics-based modelling. With a larger dataset and more advanced regression techniques, machine-learning approaches may offer improved performance, particularly in scenarios where physical assumptions break down.

5 Conclusion

The study examined the energy dissipation of a bouncing golf ball on surfaces of different compliances by analysing rebound heights and calculating the coefficient of restitution. The experimental results show that softer surfaces produced greater energy loss due to increased deformation and internal damping, thereby resulting in lower rebound heights. A physics-based exponential decay model, which assumes a constant coefficient of restitution, was able to predict the rebound behaviour with a comparatively higher accuracy. In contrast, the machine learning linear regression model captured general trends in the data but showed larger prediction errors, particularly when extrapolating outside the range of their training data. The comparison demonstrates an important distinction between the two modelling approaches. Physics-based models work best when scenarios behave ideally, relying on established physical laws. However, machine learning models may be less accurate in controlled conditions, but they are more flexible because they learn from actual data and can handle non-ideal behaviour. Overall, the results indicate that neither approach alone fully describes real collision behaviour. The most reliable understanding emerges from the integration of theoretical physics and data-driven methods. Such hybrid modelling can improve the prediction accuracy of complex, real-world collision behaviour, where ideal assumptions are rarely perfectly satisfied.

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