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Towards Intelligent Physics Experiments: A Physics-Informed KNN Approach for Projectile Motion Reconstruction Using Tracker Video Analysis in Python

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ABSTRACT

This study develops a Physics-Informed K-Nearest Neighbors (KNN) approach to reconstruct projectile motion based on experimental data using Tracker video analysis and Python. This study is motivated by the limitations of idealized physical models in representing real experimental conditions, which are influenced by air resistance, measurement noise, and data uncertainty. The research method comprises three main stages: acquisition of parabolic motion data using Tracker, theoretical modeling based on kinematic equations, and trajectory reconstruction using KNN. The results show that Physics-Informed KNN produces trajectories that are closer to the observed data compared to pure physics models. Horizontal motion exhibits the characteristics of uniform linear motion (ULM), while vertical motion forms a parabolic pattern consistent with uniformly accelerated linear motion (UALM). Error analysis indicates that the best performance is achieved at K = 2 with the minimum RMSE value. Based on the experimental dataset analyzed, the integration of machine learning and physical principles shows potential for improving the accuracy of dynamic system reconstruction under realistic experimental conditions.

Keywords: Physics-Informed KNN; Projectile Motion; Tracker Video Analysis; Computational Physics; Trajectory Reconstruction.

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Menuju Eksperimen Fisika Cerdas: Pendekatan KNN Berbasis Fisika untuk Rekonstruksi Gerak Peluru Menggunakan Analisis Video Tracker dalam Python

ABSTRAK

Penelitian ini bertujuan mengembangkan pendekatan Physics-Informed K-Nearest Neighbors (KNN) dalam merekonstruksi gerak parabola berdasarkan data eksperimen yang diperoleh melalui analisis video menggunakan perangkat lunak Tracker dan bahasa pemrograman Python. Pengembangan metode ini didasarkan pada keterbatasan model fisika ideal dalam menggambarkan kondisi eksperimen nyata yang dipengaruhi oleh hambatan udara, derau pengukuran, serta ketidakpastian data. Metode penelitian meliputi tiga tahapan utama, yaitu akuisisi data gerak parabola menggunakan Tracker, pemodelan teoritis berdasarkan persamaan kinematika, dan rekonstruksi lintasan menggunakan algoritma KNN. Hasil penelitian menunjukkan bahwa pendekatan Physics-Informed KNN mampu menghasilkan rekonstruksi lintasan yang lebih akurat dan lebih mendekati data observasi dibandingkan model fisika konvensional. Analisis gerak menunjukkan bahwa komponen horizontal mengikuti karakteristik gerak lurus beraturan (GLB), sedangkan komponen vertikal mengikuti pola gerak lurus berubah beraturan (GLBB) yang membentuk lintasan parabola. Evaluasi kinerja menggunakan Root Mean Square Error (RMSE) menunjukkan bahwa nilai K = 2 memberikan hasil terbaik dengan tingkat kesalahan terendah. Temuan ini menunjukkan bahwa integrasi pembelajaran mesin dengan prinsip-prinsip fisika berpotensi meningkatkan akurasi rekonstruksi sistem dinamis serta memberikan pendekatan yang lebih adaptif terhadap kondisi eksperimen nyata.

Kata kunci: *Physics-Informed KNN; Gerak Parabola; Analisis Video Tracker; Fisika Komputasi; Rekonstruksi Lintasan.*

INTRODUCTION

Recent advances in artificial intelligence and computational methods have created new opportunities for enhancing the analysis and modeling of physical systems. In experimental physics, real-world measurements are often affected by noise, uncertainty, and deviations from idealized theoretical assumptions, making accurate reconstruction of physical phenomena a challenging task. To address these limitations, researchers have increasingly explored the integration of data-driven approaches with established physical laws. Among these developments, physics-informed machine learning (PIML) has attracted considerable attention because it embeds physical constraints into machine learning models, thereby improving prediction reliability, model stability, and interpretability (Haywood-alexander et al., 2025; Kalesh et al., 2025; Y. Wu et al., 2024). Previous studies have demonstrated the applicability of PIML in areas such as fluid dynamics, robotic systems, and nonlinear dynamical processes, where incorporating physical knowledge helps improve model performance and generalization, particularly when available data are limited (Kontolati et al., 2024; Li, 2024; Moon et al., 2025; Zapf et al., 2022). Alongside these developments, advances in video-based tracking technologies have enabled more accurate acquisition of kinematic data from real physical experiments. Tools such as Tracker facilitate the extraction of object trajectories directly from experimental observations, providing data that more closely reflect actual physical conditions. However, trajectory measurements obtained from video analysis remain susceptible to tracking errors, environmental disturbances, and measurement noise. Recent studies suggest that combining tracking data with machine learning techniques can improve trajectory estimation and robustness compared with conventional analytical approaches (Floch & Kossa, 2023; Jiang et al., 2021; R. Wu et al., 2023). Furthermore, incorporating physical constraints into the learning process can produce trajectory reconstructions that remain consistent with the underlying laws of motion (Jiang et al., 2021; Kardamaki et al., 2026).

Despite the growing adoption of physics-informed approaches, existing studies are still largely dominated by computationally intensive models such as deep learning and physics-informed neural networks (PINNs) (Moon et al., 2025; Ryck, 2024). Although these methods often achieve high predictive performance, they typically require substantial computational resources and may offer limited interpretability. In contrast, classical machine learning methods such as K-Nearest Neighbors (KNN) provide a simpler and more transparent alternative. As a non-parametric method, KNN has demonstrated the ability to capture nonlinear relationships in physical systems while maintaining competitive predictive performance on experimental datasets (Demidova, 2021; Lytridis et al., 2020; Pulgar et al., 2019). Previous studies have also shown its effectiveness for time-series prediction and dynamic system reconstruction (Iaousse et al., 2023; Lytridis et al., 2020; Paramasivam et al., 2023).

However, the application of physics-informed KNN using empirical data extracted from experimental video analysis remains relatively unexplored, particularly in fundamental physics experiments such as projectile motion. Most existing studies rely on simulation data or idealized theoretical models, which may not adequately represent real experimental conditions characterized by measurement uncertainty and noise. This gap highlights the need for lightweight, interpretable, and experimentally grounded approaches that integrate physical knowledge with data-driven learning.

Therefore, this study proposes a physics-informed KNN framework that utilizes empirical trajectory data obtained from Tracker video analysis to reconstruct projectile motion. The proposed approach combines the consistency of kinematic principles with the flexibility of machine learning, enabling adaptation to experimental deviations while preserving physical plausibility. In addition, this research develops a Python-based smart physics experimental framework that integrates data extraction, modeling, and evaluation processes. Through this approach, the study aims to demonstrate the potential of a lightweight and interpretable hybrid method for trajectory reconstruction and to provide a replicable framework that can be extended to other physical phenomena.

METHOD

Research Design

This study employed a data-driven quantitative experimental approach that integrated video analysis using Tracker for kinematic data extraction, physics-based projectile motion modeling as the theoretical framework, and machine learning through the K-Nearest Neighbors (KNN) algorithm for trajectory reconstruction. The experiment was conducted indoors at a height of 3 m above the floor surface. A ball with a mass of 1 kg was manually launched to generate projectile motion. The motion was recorded using a digital camera with a spatial resolution of 634 × 480 pixels and a frame rate of 30.0 fps. The camera was positioned 2 m from the plane of motion and aligned perpendicular to the trajectory plane to minimize perspective distortion and ensure accurate kinematic measurements.

The recorded video was analyzed using Tracker to obtain the horizontal and vertical position coordinates of the projectile over time. A total of 100 trajectory data points were extracted from the video and used in the subsequent analysis. This number was selected to provide sufficient temporal resolution for representing the projectile trajectory while maintaining computational efficiency during the KNN modeling process. The extracted coordinates were calibrated using a reference scale within the experimental setup and then preprocessed to remove inconsistencies and prepare the dataset for machine learning analysis.

The research workflow consisted of three main stages: (1) experimental data acquisition through video recording and trajectory extraction, (2) physical modeling and data preprocessing based on projectile motion principles, and (3) trajectory reconstruction using a physics-informed KNN framework. In the final stage, physical constraints derived from kinematic equations were incorporated into the learning process to ensure that the reconstructed trajectories remained consistent with the underlying laws of motion while adapting to experimental deviations and measurement noise.

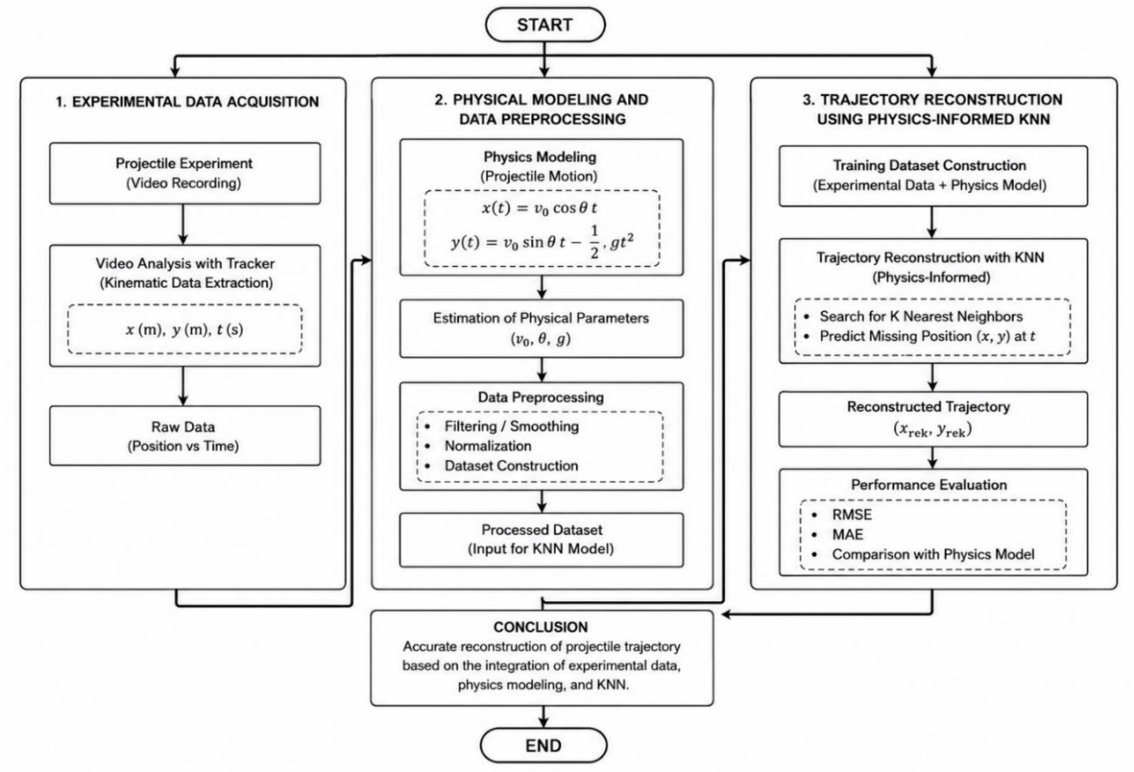


Figure 1. Flowchart of Physics-Informed KNN-Based Projectile Trajectory Reconstruction

Data Collection with a Tracker

The experiment was conducted by recording the parabolic motion of an object using a camera. The video was then analyzed using Tracker software to obtain the following data: horizontal position x(t), vertical position y(t), and time t. The data was exported in a numerical format (CSV) for further processing in Python.

A Physics Model of Parabolic Motion

Parabolic motion follows the equations of two-dimensional kinematics:

$$x(t) = v_0 \cos\theta\, t \qquad (1)$$

$$y(t) = v_0 \sin\theta\, t - \tfrac{1}{2} g t^2 \qquad (2)$$

v_0 is the initial velocity, θ is the elevation angle, and g is the acceleration due to gravity. This equation is used as a physical constraint in the physics-informed approach, both for validating and constraining model predictions. In the physics-informed machine learning approach, the equations of motion are incorporated into the loss function so that the model not only learns from the data but also adheres to the fundamental laws of physics governing the system (Seo, 2024; W. Zhang, 2024). This approach has proven effective in improving the accuracy of predictions and addressing differential problems in dynamic systems because the model is guided by the relevant physical equations (Harmening & Peitzmann, 2024).

Two-dimensional kinematic equations are used to ensure that the predicted trajectory continues to follow the physical characteristics of projectile motion, namely horizontal motion at a constant velocity and vertical motion influenced by gravity. Incorporating the laws of physics into the learning model makes the trajectory reconstruction process more stable, especially when the experimental data contains noise or is limited in quantity. The physics-informed neural networks (PINNs) approach can improve prediction performance in various motion and dynamics systems, including projectile trajectories, equations of motion, and nonlinear mechanical systems (Chiha et al., 2024; Hou et al., 2024). A physics-based approach is also capable of ensuring that the predicted results are consistent with the laws of conservation and the differential equations underlying physical phenomena (Z. Zhang et al., 2024).

Model K-Nearest Neighbors (KNN)

The K-Nearest Neighbor (KNN) method is used to reconstruct trajectories based on data proximity. The distance between data points is calculated using Euclidean distance because it effectively measures the degree of similarity between data points in a multidimensional space (Abror et al., 2025; Janjua et al., 2024). The Euclidean distance formula is written as follows:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{N} \left(x_{ik} - x_{jk}\right)^2} \qquad (4)$$

where x_i and x_j are the two data points being compared, and N denotes the number of features. In trajectory reconstruction and time-series analysis, this method works by identifying a number of nearest neighbors that share the most similar characteristics with the target data. The use of Euclidean distance in the KNN algorithm is effective for prediction and reconstruction because it preserves the main patterns of the data and reduces the influence of noise (Fatima et al., 2024; Jian et al., 2024). In the KNN method, position values are predicted by calculating the average of the K nearest neighbors obtained from the minimum distance search process. The prediction equation is written as follows:

$$\hat{y} = \frac{1}{K} \sum_{i=1}^{K} y_i \qquad (5)$$

where $\hat{y}$ is the predicted value and yi is the value of the i-th nearest neighbor. This approach allows the model to reconstruct the motion trajectory or experimental signal based on local patterns in the previous data. The more optimal the choice of K, the more stable the predicted results will be, as the influence of fluctuations in the experimental data can be minimized (Souza et al., 2020). The KNN approach has also been widely applied to signal reconstruction, dynamic systems, and experimental data modeling because it is simple to implement yet yields good accuracy (Jeong et al., 2024).

Integration of Physics-Informed KNN

The KNN model was modified using a physics-informed approach by employing a parabolic trajectory constraint as a reference model, adjusting predictions to ensure they do not deviate from physical patterns, and conducting error-based evaluations such as deviations from the theoretical model. This approach ensures that the prediction results are not only numerically accurate but also physically valid.

Model Evaluation

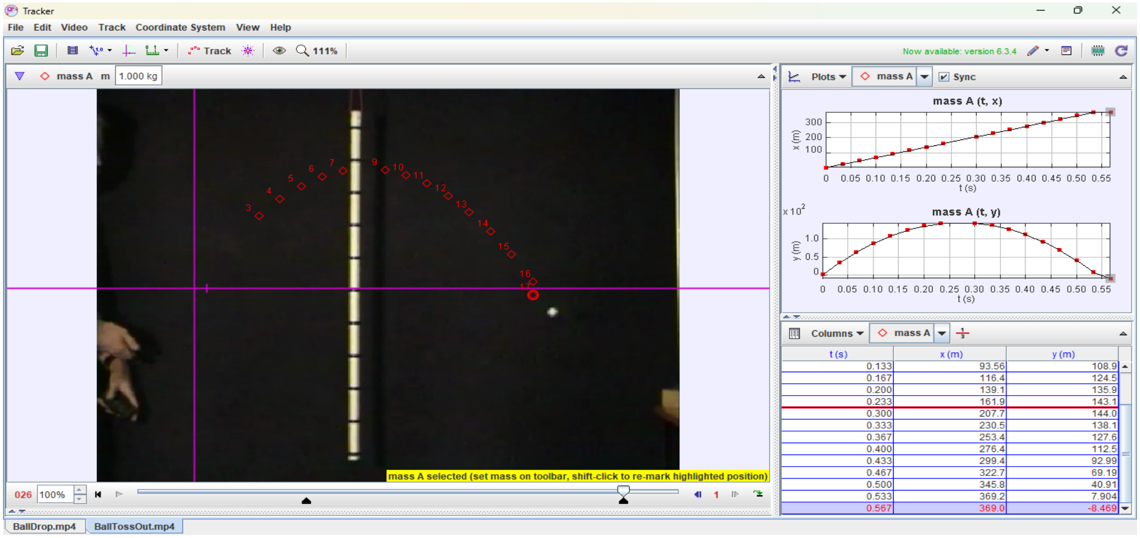
Model performance was evaluated using several statistical metrics, namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). These three parameters are commonly used in the evaluation of machine learning and reconstruction models because they effectively represent the level of prediction error and the model's ability to capture patterns in the actual data (Aich et al., 2024; Rainio, 2024). The MAE is used to measure the average absolute difference between predicted and actual data, while the RMSE penalizes large errors and is therefore sensitive to data outliers. The coefficient of determination (R^2) indicates the proportion of variation in the data; a value close to 1 indicates excellent model performance (Adil & Ahmed, 2023; Rainio, 2024). The RMSE equation used in this study is written as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \qquad (6)$$

where y_i represents the actual data, $\hat{y}_i$ represents the model's predicted data, and N denotes the number of data points. RMSE is widely used in the evaluation of data reconstruction models and dynamic systems because it quantifies the model's average deviation from the reference data. The smaller the RMSE value, the better the model's performance in representing the observed physical phenomena (Rainio, 2024). Reconstruction and physics-informed machine learning also show that the combination of the RMSE and R^2 metrics is highly effective in evaluating model accuracy on experimental data containing noise (Fatima et al., 2024; Hakkak et al., 2026).

RESULT AND DISCUSSION

A ball is thrown so that it follows a parabolic trajectory and is recorded using a video camera. Figure 2 shows the process of analyzing parabolic motion using Tracker video analysis software. Video analysis methods such as this are considered effective for teaching and analyzing kinematics because they provide a quantitative and accurate visualization of motion (Renika et al., 2024). Tracker-based analysis allows motion parameters such as displacement, velocity, and acceleration to be calculated directly from experimental video data (Zahran et al., 2024). The use of the Tracker can significantly improve students' analytical skills and their understanding of kinematic concepts (Karima et al., 2023; Mardiyah & Subali, 2024).



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t (s)	x (m)	y (m)
0.133	93.56	108.9
0.167	116.4	124.5
0.200	139.1	135.9
0.233	161.9	143.1
0.300	207.7	144.0
0.333	230.5	138.1
0.367	253.4	127.6
0.400	276.4	112.5
0.433	299.4	92.99
0.467	322.7	69.19
0.500	345.8	40.91
0.533	369.2	7.904
0.567	369.0	-8.469

Figure 2. Analysis of Parabolic Motion Using Video-Based Tracker Software: An Experiment

Table 1 shows that the optimal value of the K parameter in the KNN method is K = 2 for both the X and Y positions. This indicates that the model performs best when using the two nearest neighbors in the process of predicting the projectile. The study utilized a total of 100 experimental data points obtained from video analysis using Tracker. Based on the evaluation results, the RMSE values obtained were 0.2729 for the X position and 0.2847 for the Y position, while the MAE values were 0.2168 and 0.2269, respectively. These relatively small error values indicate that the model's prediction results are very close to the actual experimental data, making the model's accuracy very good.

Table 1. Cross-Validation Results and Evaluation of the KNN Model

Parameter	X Position	Y Position
Optimal K	2	2
Total Data	100	100
RMSE Before	0.2729	0.2847
RMSE After	0.2729	0.2847
MAE Before	0.2168	0.2269
MAE After	0.2168	0.2269
R^2 Before	0.9994	0.9930
R^2 After	0.9994	0.9930
Improvement	0.00%	0.00%

The R^2 values of 0.9994 for the X position and 0.9930 for the Y position indicate that the KNN model is capable of representing the patterns of projectile motion with a very high degree of accuracy. The evaluation values before and after reconstruction show the same results, indicating no improvement or decline in model performance (improvement = 0.00%). This indicates that the KNN model is already in an optimal and stable state for reconstructing motion trajectories based on experimental data. The KNN reconstruction results closely match the observed data, demonstrating that this method effectively preserves the primary observed patterns (Renika et al., 2024).

The evaluation results indicate that the Physics-Informed KNN model achieved very low prediction errors, with RMSE values of 0.2729 for the X position and 0.2847 for the Y position, accompanied by MAE values below 0.23 and R^2 values exceeding 0.99. These results demonstrate that the reconstructed trajectories closely follow the experimental observations. The small RMSE values can be explained by the nature of projectile motion data itself. The trajectory recorded by Tracker exhibits a smooth and continuous temporal pattern, where consecutive positions are highly correlated. Under such conditions, neighboring observations contain very similar kinematic information, allowing the KNN algorithm to estimate positions accurately using local data structures. Because the prediction is based on nearby experimental points rather than a global mathematical approximation, deviations between predicted and observed positions remain small. This explains why the reconstruction error is minimal and why the R^2 values approach unity. Similar findings have been reported in machine-learning-based reconstruction studies, where local learning algorithms effectively preserve physical patterns while minimizing prediction errors in noisy experimental datasets (Hakkak et al., 2026; Xie et al., 2024). Machine learning-based data reconstruction approaches have been applied to wave analysis, vibrational systems, and nonlinear signal modeling in modern physics research (Pagliaro et al., 2025). This demonstrates that the integration of machine learning with experimental data can serve as a modern alternative to numerical methods for the analysis of physical systems.

Table 2. Initial Signal Reconstruction Data

No	Time (s)	Observed X	Observed Y	Physics X	Physics Y	KNN X	KNN Y
0	0.000000	0.149014	-0.424611	0.000000	0.000000	0.149014	-0.424611
1	0.030303	0.348089	0.333572	0.387352	0.753679	0.348089	0.333572
2	0.060606	0.973443	0.807708	0.774704	1.498349	0.973443	0.807708
3	0.090909	1.625614	1.111588	1.162057	2.234011	1.625614	1.111588
4	0.121212	1.488027	1.736626	1.549409	2.960665	1.488027	1.736626
5	0.151515	1.877600	2.329959	1.936761	3.678311	1.877600	2.329959
6	0.181818	2.811173	3.189323	2.324113	4.386948	2.811173	3.189323
7	0.212121	2.957208	3.081556	2.711465	5.086577	2.957208	3.081556
8	0.242424	2.975704	3.503156	3.098817	5.777198	2.975704	3.503156
9	0.272727	3.668882	3.791256	3.486170	6.458811	3.668882	3.791256
...	...	...	...	...	...	...	...
90	2.727273	35.090266	5.166817	34.861697	31.752986	35.090266	5.166817
91	2.757576	35.741304	5.206712	35.249049	31.695921	35.741304	5.206712
92	2.787879	35.629663	4.654034	35.636401	31.629847	35.629663	4.654034
93	2.818182	36.131548	3.847089	36.023753	31.554766	36.131548	3.847089
94	2.848485	36.501783	3.894762	36.411105	31.470676	36.501783	3.894762
95	2.878788	36.569929	3.571391	36.798457	31.377578	36.569929	3.571391
96	2.909091	37.487388	2.794619	37.185810	31.275471	37.487388	2.794619
97	2.939394	37.866437	2.700865	37.573162	31.164357	37.866437	2.700865
98	2.969697	38.179222	2.258174	37.960514	31.044234	38.179222	2.258174
99	3.000000	38.496880	1.474775	38.347866	30.915102	38.496880	1.474775

Table 2 shows the relationship between experimental data, theoretical physics models, and reconstruction results using the KNN method for projectile motion. The Time (s) column represents the observation time during the motion, while Observed X and Observed Y are the object's positions obtained from video analysis using Tracker. These data illustrate a parabolic trajectory influenced by initial velocity and gravitational acceleration. In the horizontal direction (X-axis), the object's position increases almost linearly with time because there is no significant horizontal acceleration. In the vertical direction (Y-axis), the object's position rises until it reaches a maximum point and then decreases again due to the effect of Earth's gravitational acceleration. The Physics X and Physics Y columns show the results of calculations based on the theoretical equations of parabolic motion. The horizontal position follows a linear relationship with time, while the vertical position follows a quadratic equation due to the presence of gravitational acceleration. Projectile motion is a combination of two types of motion: uniform linear motion along the X-axis and uniformly accelerated linear motion along the Y-axis. The KNN X and KNN Y columns show the results of trajectory reconstruction using machine learning based on experimental data. The KNN prediction results, which closely match the observed data, indicate that the algorithm is capable of effectively learning the physical patterns of motion from real-world data.

Another important finding is that the theoretical physics model consistently predicts a trajectory that is higher than the experimental observations. This discrepancy arises because the analytical equations of projectile motion assume ideal conditions, including negligible air resistance, perfect initial velocity measurements, and the absence of experimental uncertainties. In reality, the projectile experiences aerodynamic drag, which continuously dissipates kinetic energy during flight. As a result, the object reaches a lower maximum height and a shorter horizontal range than predicted by ideal theory. Furthermore, uncertainties associated with video tracking, camera calibration, frame resolution, and manual point selection can introduce additional deviations between measured and theoretical positions. Therefore, the higher trajectory generated by the theoretical model reflects the limitations of idealized assumptions rather than inaccuracies in the experimental data. Similar differences between theoretical and experimental trajectories have been reported in studies involving physics-based modeling under real environmental conditions (Schmitz, 2024; Vargas et al., 2024). The integration of the laws of physics has been shown to improve the stability of predictions and the generalization ability of models compared to conventional machine learning approaches (Muzelak et al., 2024). The use of the KNN method is important because the algorithm can learn local patterns from experimental data directly without having to rely entirely on theoretical equations.

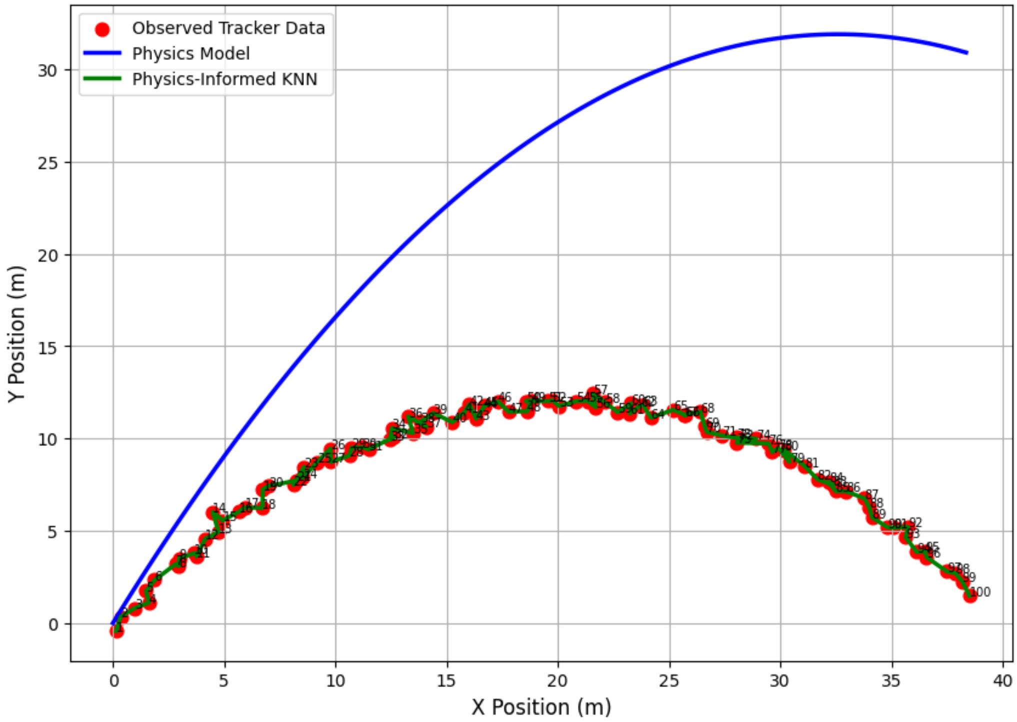

Figure 3. Projectile Motion Reconstruction using Physics-Informed KNN

Figure 3 shows a comparison between the experimental data from the Tracker, the theoretical parabolic motion model, and the reconstruction results using the Physics-Informed KNN method. The theoretical model produces a parabolic trajectory that is higher than both the experimental data and the KNN results. This difference indicates that the ideal physics model does not fully represent real experimental conditions, likely due to external factors such as air resistance, measurement uncertainties in the Tracker video, and experimental data noise. The Physics-Informed KNN method is able to adapt to real data patterns, thereby producing a trajectory reconstruction that is closer to the observed results.

Physics-informed neural networks demonstrate that integrating physical differential equations into machine learning models can significantly improve the accuracy of reconstructing vibration responses, resonant systems, and nonlinear dynamics (Yokota et al., 2024; W. Zhang, 2024). Even with sparse and noisy data, physics-based approaches are still able to capture the system's dynamic behavior effectively (Hassan et al., 2025). This reinforces the fact that the physics-informed KNN approach holds great potential for application in experimental reconstruction and the modeling of dynamic systems in modern computational physics. It demonstrates that data-driven approaches can serve as alternative solutions in modern computational physics for the analysis of dynamic systems. This research demonstrates that the combination of physics models and machine learning not only improves prediction accuracy but also supports the development of intelligent physics experiments based on video analysis and numerical modeling.

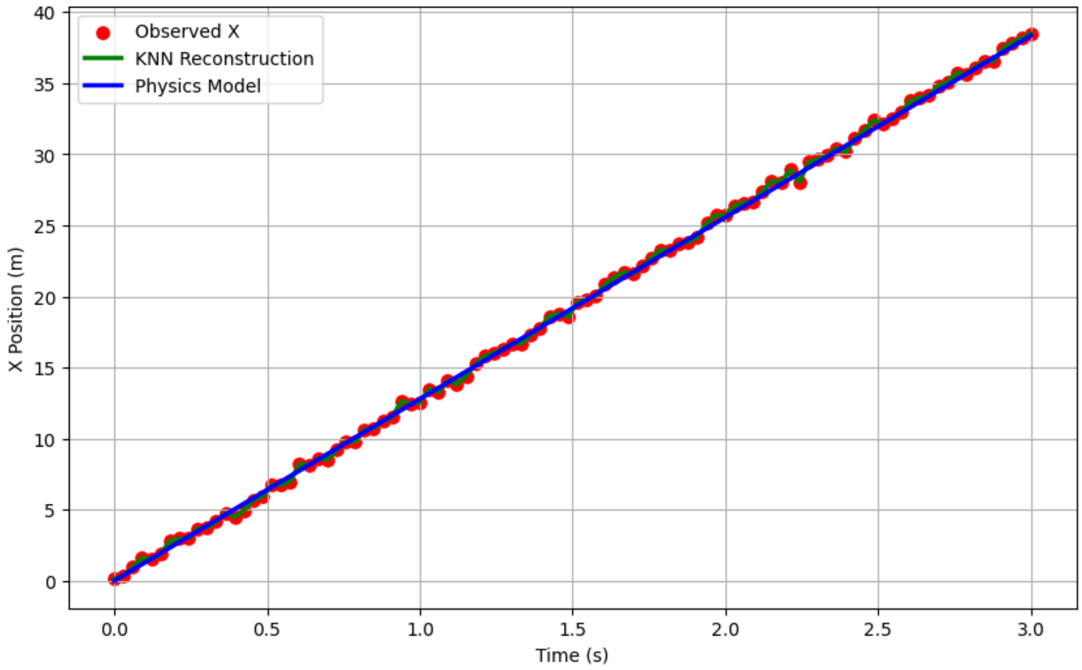

Figure 4. Horizontal Projectile Motion

Figure 4 shows the relationship between the horizontal position of an object and time in projectile motion. The red dots represent observational data from the Tracker video analysis, the green line shows the reconstruction results using the K-Nearest Neighbors method, while the blue line represents the results of the theoretical physics model.

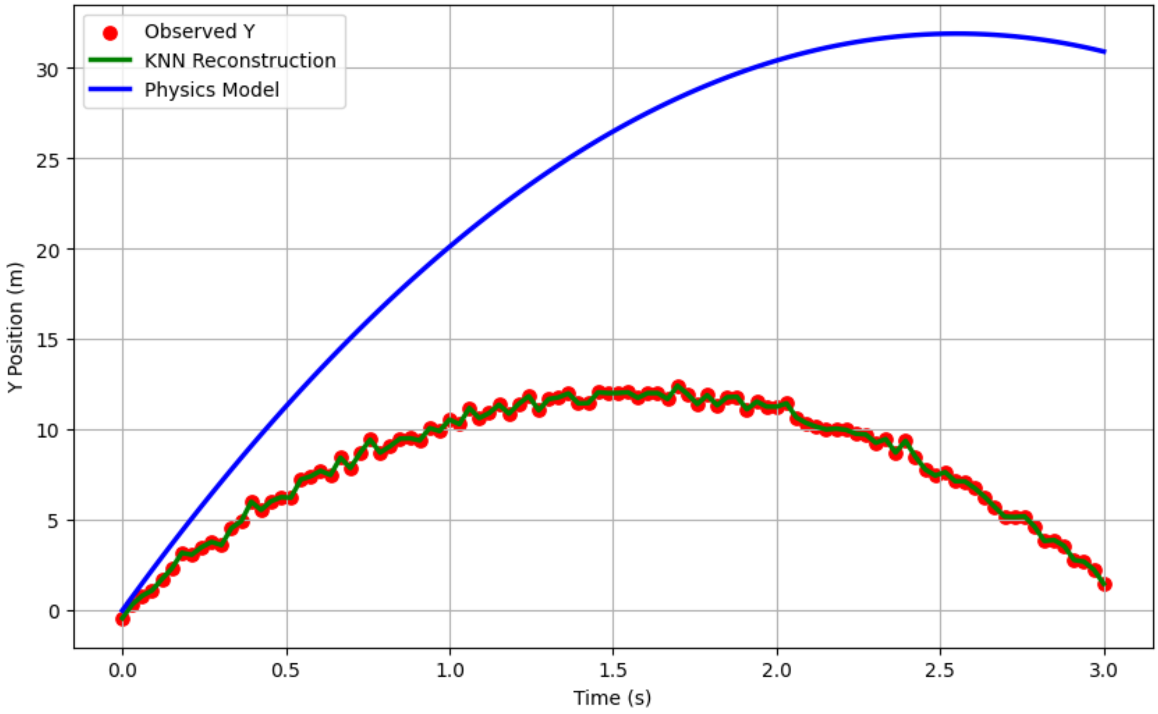

Figure 5. Vertical Projectile Motion

Figure 5 shows that the red dots represent the observational data from the Tracker video analysis, the green line shows the reconstruction results using the K-Nearest Neighbors method, while the blue line represents the results of the theoretical physics model. This pattern forms a parabolic trajectory, which is a key characteristic of bullet motion in classical mechanics. The KNN reconstruction results appear very close to and almost coincide with the observed data, demonstrating the machine learning model's ability to accurately represent vertical motion patterns; thus, the higher the model's fit to the observed physical phenomena (Knights et al., 2024). A physics-informed machine learning approach can improve prediction accuracy and reduce errors in nonlinear systems and experimental data containing noise (W. Zhang, 2024).

In the graph, the theoretical model (blue line) produces a higher maximum altitude than the experimental data. This discrepancy indicates that the idealized physical model does not account for real-world factors such as air resistance, tracker measurement errors, and experimental noise. A physics-informed machine learning approach can improve prediction accuracy and maintain model stability in dynamic systems that involve noise and experimental data uncertainty (Parfenyev et al., 2024; Pilar & Om, 2024; Zou et al., 2024a, 2024b). The integration of the laws of physics into learning models can result in more realistic system reconstructions than conventional machine learning approaches (Dermul & Dierckx, 2024; Lee et al., 2024). The connection between physics concepts and the KNN method is evident in the algorithm's ability to learn movement patterns directly from experimental data.

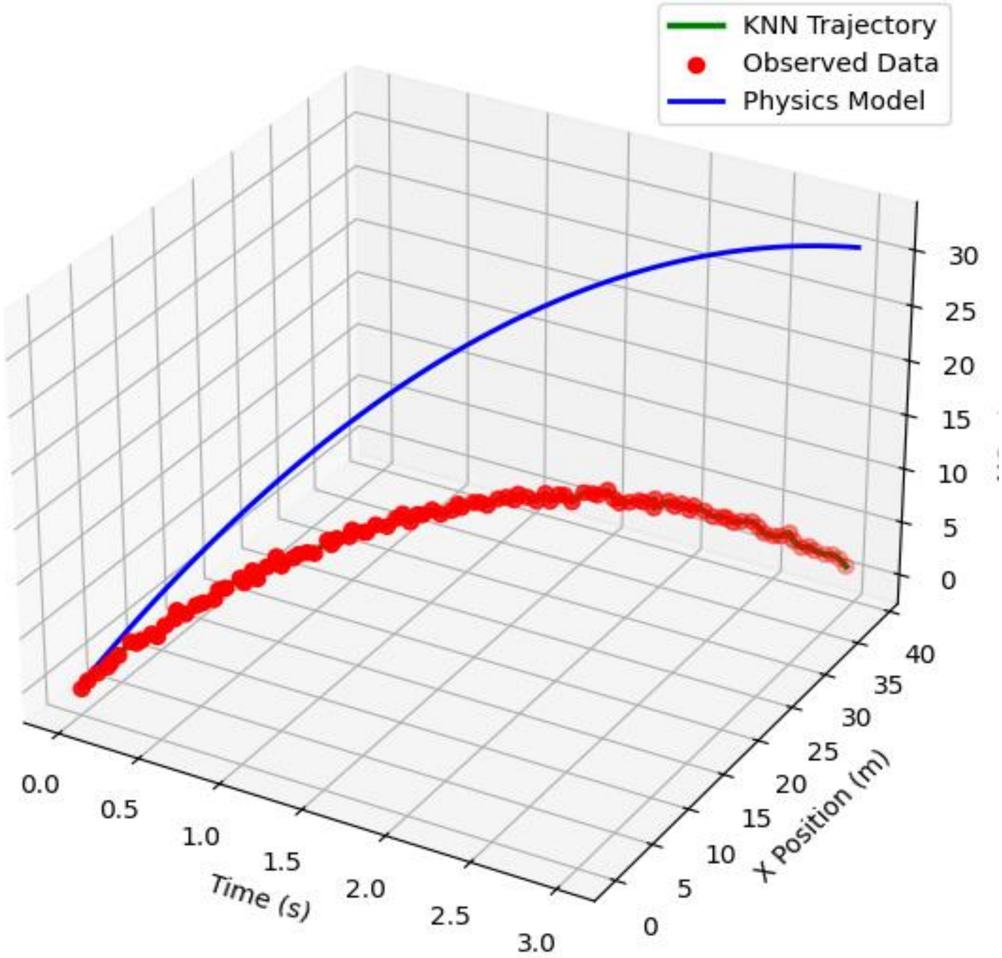

Figure 6. 3D Projectile Motion Reconstruction

Figure 6 reconstructs the trajectory of parabolic motion in three-dimensional (3D) space by comparing three approaches: actual observational data (red dots), data-driven estimates using the K-Nearest Neighbors (KNN) algorithm (green line), and theoretical predictions based on an idealized physical model (blue line). The reconstructed trajectory generated by KNN appears much closer to the experimental data than the theoretical model because the algorithm learns directly from the measured observations. Unlike the physics-based model, which relies on predefined equations and ideal assumptions, KNN implicitly incorporates all factors present in the experimental environment, including air resistance effects, measurement uncertainties, and other unmodeled disturbances. Consequently, the reconstructed trajectory reflects the actual behavior of the projectile rather than an idealized representation. This ability to adapt to real-world conditions explains why the KNN predictions almost coincide with the Tracker data in both two-dimensional and three-dimensional visualizations. The result highlights a fundamental advantage of data-driven approaches: they can capture physical phenomena that are difficult to model explicitly through analytical equations alone. Similar advantages of physics-informed machine learning have been reported in dynamic system reconstruction, vibration analysis, and nonlinear physical modeling, where integrating observational data with physical knowledge produces more realistic predictions than purely theoretical approaches (Dermul & Dierckx, 2024; Lee et al., 2024; Zou et al., 2024b, 2024a). The data-driven approach can be used to identify hidden physical parameters, such as the air resistance coefficient, through a learning process based on real experimental data (Parfenyev et al., 2024; Pilar & Om, 2024). This visualization underscores the importance of integrating computational modeling to bridge the gap between theoretical predictions and experimental reality, with this real-world data serving as feedback to refine the physical equations by incorporating air resistance coefficients.

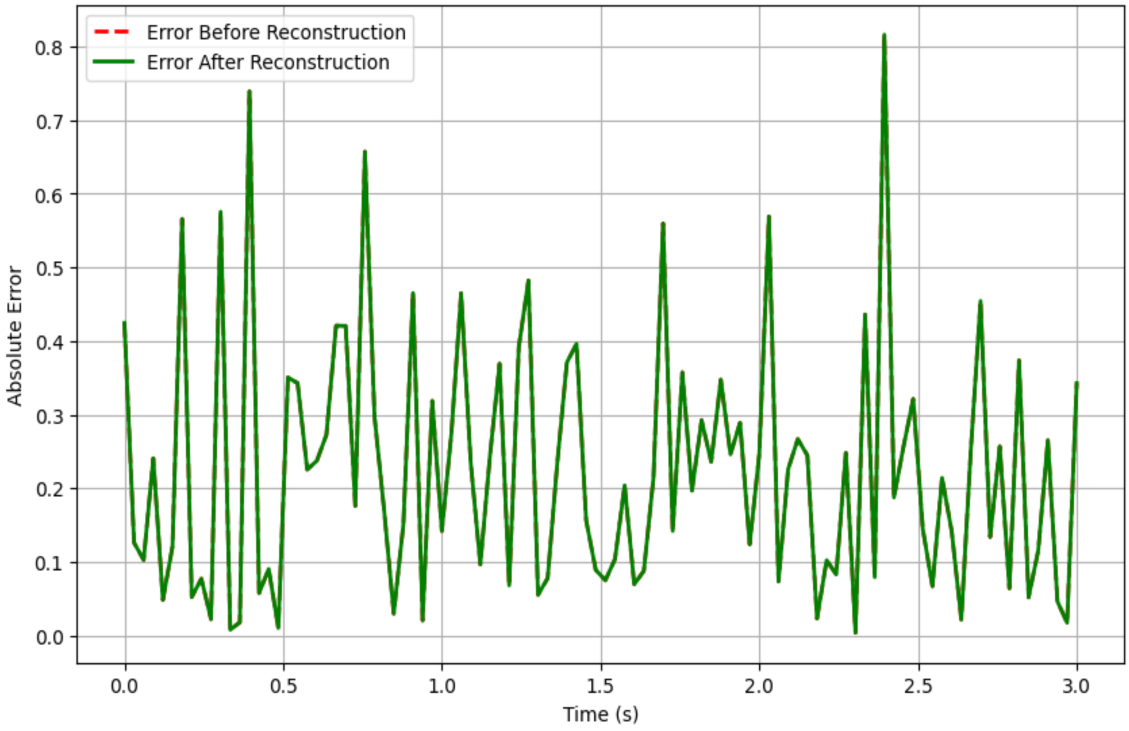

Figure 7. Error Reduction using Physics-Informed KNN

Figure 7 shows a graph of the absolute error values on the vertical axis versus time on the horizontal axis, ranging from 0.0 to 3.0 seconds. There are two reference lines in the legend: a red dashed line (Error Before Reconstruction) and a solid green line (Error After Reconstruction). However, upon closer inspection, the two lines overlap with great precision throughout the time domain. This visually indicates that the error values before and after reconstruction using the Physics-Informed KNN method do not undergo significant changes; in other words, the KNN algorithm directly adopts the characteristics of the original raw data without performing noise reduction or shifting values away from the initial observed data.

The absence of improvement between the "before" and "after" reconstruction metrics, indicated by an improvement value of 0.00%, also requires careful interpretation. Rather than suggesting a failure of the reconstruction process, this result indicates that the KNN model has already reproduced the experimental trajectory with very high fidelity. Since the reconstruction process uses the observed data as the primary reference, the resulting trajectory remains nearly identical to the original measurements. Consequently, there is little room for additional numerical improvement. In this context, the role of the Physics-Informed KNN model is not to alter the data substantially but to preserve the observed physical structure while providing a stable computational representation of the trajectory. The overlapping error curves shown in Figure 7 support this interpretation, demonstrating that the algorithm retains the essential characteristics of the original motion rather than introducing artificial smoothing that could distort physically meaningful features.

The concept of physics-informed here ideally integrates the laws of conservation or the equations of motion in physics as constraints for machine learning algorithms. When the green line remains aligned with the noisy raw data, this physically indicates that the physics-informed KNN model treats data fluctuations as valid representations of motion, or acts as a filter that preserves local data structure to avoid losing important physical details that might be considered errors by a purely statistical model.

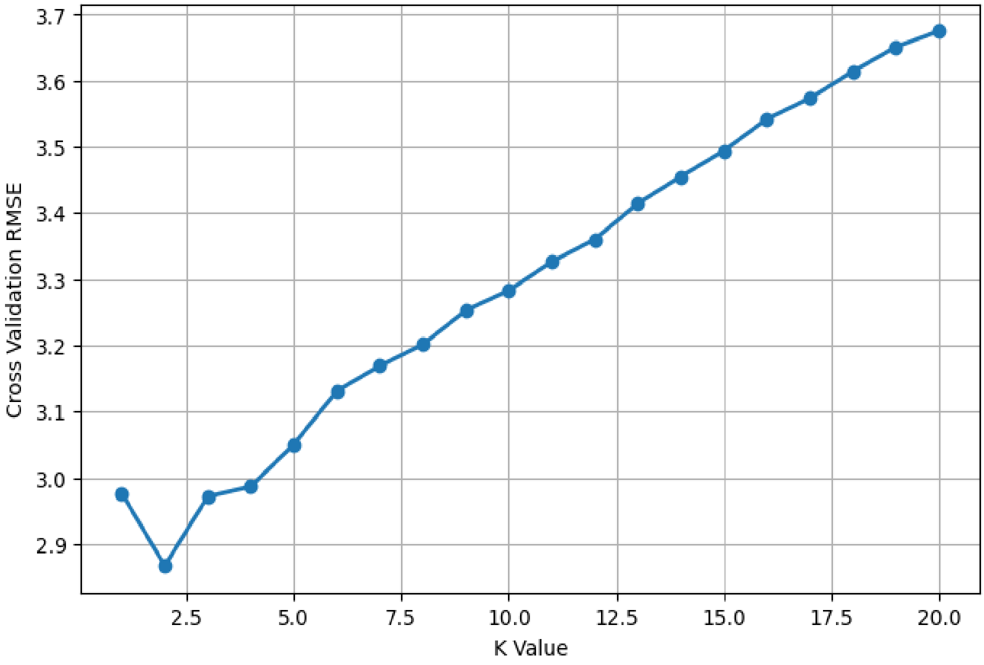

Figure 8. Optimization of K Value

Figure 8 plots the value of the K parameter in the KNN algorithm on the horizontal axis (range from 1 to 20) against the Root Mean Squared Error (RMSE) from cross-validation on the vertical axis (range from approximately 2.85 to 3.70). The optimization results show that the lowest cross-validation error was obtained at K = 2. This finding suggests that the trajectory data possess strong local characteristics, meaning that the most relevant information for predicting a point is contained within its closest neighboring observations. When K is increased beyond 2, the prediction process incorporates more distant neighbors whose physical states may correspond to different phases of motion. Consequently, the averaging process begins to smooth the trajectory excessively, reducing the model's ability to capture local curvature in the projectile path. In projectile motion, particularly near the peak and descending phases, the trajectory changes continuously with time. Therefore, using only two nearest neighbors allows the model to maintain sensitivity to these local variations while still avoiding excessive susceptibility to measurement noise. This explains why K = 2 provides the optimal balance between variance and bias for the present dataset (Xie et al., 2024).

Overall, these findings demonstrate that the superior performance of the Physics-Informed KNN approach originates from its ability to combine local data learning with physical insights. The low RMSE values, the optimal performance at K = 2, the close agreement with experimental observations, and the stability of reconstruction errors collectively indicate that the model successfully captures the underlying dynamics of projectile motion under real experimental conditions. Rather than replacing physical theory, the machine learning model complements it by accounting for environmental effects and measurement uncertainties that are not represented in ideal analytical formulations. This integration offers a promising framework for future computational physics applications involving experimental data reconstruction and dynamic system modeling.

CONCLUSION

This study investigated whether a Physics-Informed KNN approach could effectively reconstruct projectile motion trajectories from experimental video data while maintaining consistency with the underlying laws of motion. The findings indicate that integrating physical knowledge with a simple machine learning algorithm enables trajectory reconstruction that more closely represents experimental observations than the idealized projectile motion model alone. These results suggest that incorporating physical constraints into data-driven models can improve their ability to adapt to real-world experimental conditions, where measurement noise, environmental influences, and model simplifications often limit the accuracy of purely theoretical approaches.

Beyond the specific case of projectile motion, this study demonstrates the potential of combining interpretable machine learning methods with established physical principles to bridge the gap between theoretical models and experimental observations. The proposed Physics-Informed KNN framework provides a lightweight and computationally efficient alternative to more complex physics-informed learning approaches while preserving physical plausibility in the reconstructed trajectories. This highlights its potential applicability in educational laboratories, intelligent physics experiments, video-based motion analysis, and other dynamic system reconstruction problems.

Nevertheless, several limitations should be acknowledged. The study was conducted using a single projectile-motion experiment and a limited dataset, which restricts the generalizability of the findings to other physical systems and experimental conditions. In addition, the analysis considered only a specific set of experimental parameters and did not explicitly model factors such as varying aerodynamic effects or different measurement configurations. Future research should evaluate the proposed approach using larger and more diverse datasets, multiple experimental scenarios, and comparisons with other machine learning and physics-informed methods to further assess its robustness and broader applicability.

Overall, the results indicate that the Physics-Informed KNN approach shows promise as a practical framework for data-driven trajectory reconstruction and may serve as a foundation for developing more adaptive and interpretable computational tools in experimental physics.

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