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Hybrid Approach for Accurate Asteroid Path Prediction and Classification Using Ensemble Learning

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Abstract - This study presents a novel hybrid methodology that integrates classical physics-based orbital propagation with machine learning (ML) corrections to forecast the future trajectories of near-Earth asteroids while also assessing their hazard potential. The approach combines an analytical two-body orbit model with ML-based error correction—implemented using Long Short-Term Memory (LSTM) network—to significantly reduce prediction errors. Additionally, ensemble learning techniques using XGBoost and Random Forest are employed for asteroid hazard classification, achieving an accuracy of 99.08%. The results demonstrate that the hybrid approach not only improves long-term trajectory prediction accuracy but also enhances risk assessment, paving the way for more reliable planetary defense and space mission planning.

Key Words: Asteroid trajectory prediction, orbital mechanics, hybrid model, machine learning, neural networks, LSTM, XGBoost, Random Forest, ensemble classification, hazard assessment

1.INTRODUCTION

Near-Earth asteroids (NEAs) are of significant scientific interest and represent potential threats to our planet. Accurate prediction of their trajectories is critical for both planetary defense and the planning of space missions. Traditional methods based on two-body orbital mechanics provide a solid foundation but are prone to accumulating errors over extended propagation periods due to perturbations and measurement uncertainties. Furthermore, classifying asteroids based on their orbital and physical characteristics is essential for risk assessment.This paper introduces a comprehensive hybrid approach that combines physics-based orbit propagation with machine learning corrections to enhance trajectory predictions. In parallel, it employs ensemble classifiers to accurately categorize asteroids, thereby providing a robust framework for impact risk assessment and mission planning.

2. Data and Methodology

2.1 Dataset Details

Classification Dataset:

Approximately 5000 asteroids from NASA's NEO database and ESA's Risk Lists. This dataset includes key orbital elements (semi-major axis, eccentricity, inclination, perihelion distance, ascending node, argument of perihelion, mean motion), velocity/positional data (Earth and Jupiter MOIDs, orbit condition codes), and absolute magnitude (H). Data are split into 80% training, 20% testing, with a separate validation set.

Trajectory Prediction Dataset:

Historical orbital data from the NASA Horizons database, featuring long-term observations (e.g., Apophis, 2003 BR47) that capture dynamic variations in orbital paths. It includes astrometric and motion details (UTC timestamps, RA and Dec rate changes), essential orbital parameters (heliocentric coordinates, radial velocity, distance from Earth), brightness, phase angle, and precise sky coordinates.

2.2 Physics-Based Orbital Propagation

The initial stage involves estimating the asteroid's state by converting spherical coordinates (radial distance, ecliptic longitude, and latitude) into Cartesian coordinates. The initial velocity is computed using finite differences from early observations. A classical two-body orbit model is constructed using astrodynamics transformation formulas and is implemented via the Poliastro library. The orbit propagation is carried out with the Runge-Kutta 4th order (RK4) method. Although this model provides a robust baseline, it is sensitive to unmodeled perturbative effects over long durations.

2.3 Machine Learning Corrections

To address the limitations of the pure physics-based model, ML-based error correction strategies are employed:

LSTM-Based Trajectory Refinement:

Recognizing the sequential nature of orbital data, an LSTM network with three hidden layers (128, 64, and 32 neurons) is employed to learn temporal dependencies and refine trajectory predictions. Optimized using the Adam optimizer and trained over 200 epochs with early stopping, this model further reduces prediction errors—yielding an MSE of 0.000012 and an MAE of 0.001559—thus capturing complex error patterns that occur over longer time intervals.

2.4 Hybrid Prediction Process

The hybrid approach combines the strengths of both methods. Future asteroid positions are first forecasted using the physics-based orbit propagation, after which ML correction (LSTM) are applied to adjust these predictions. An optional post-processing step, such as phase alignment, ensures a smooth, continuous trajectory and effectively manages discontinuities during orbital wrap-around.

2.5 Asteroid Hazard Classification

In addition to trajectory prediction, the study employs ensemble learning for asteroid hazard classification. Both XGBoost and Random Forest classifiers are trained on engineered features derived from orbital and physical parameters (e.g., MOID, perihelion distance, eccentricity, and absolute magnitude). Hyperparameter tuning via grid search optimizes model performance. Both models achieved a classification accuracy of 99.08%, confirming the reliability of ensemble methods for hazard assessment.

3. Experimental Results and Discussion

3.1 Trajectory Prediction Performance

The hybrid trajectory prediction models were evaluated using standard error metrics on the training data:

•Physics Based Model:
MSE: 0.005144
MAE: 0.044949

•Hybrid Model:
MSE: 0.000012
MAE: 0.001559

These results highlight the dramatic improvement achieved by integrating ML corrections with the classical physics-based model, with reductions in error metrics exceeding 90% in certain configurations.

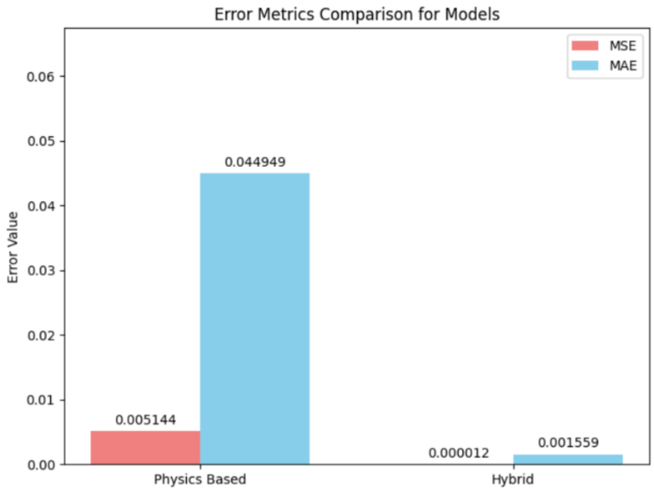

Fig -1: Error Metrics

3.2 Graphical Analysis

The effectiveness of the hybrid approach is further supported by various visual analyses:

Figure 2: Residuals Over Time: Line plots depict the evolution of residual errors, demonstrating that the majority of corrections remain minimal after ML adjustment.

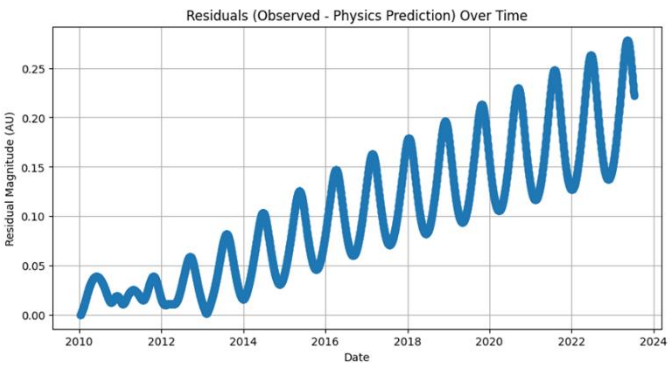

Fig -2: Residual Errors

Figure 3: Histogram of Residuals: Frequency distributions show that residuals are tightly concentrated near zero.

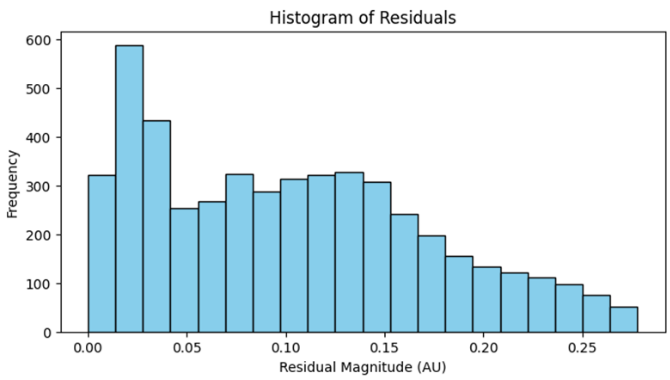

Fig -3: Histogram of Residuals

Figure 4: Scatter Plot Comparison: A scatter plot of observed versus hybrid predicted coordinates indicates a strong linear correlation.

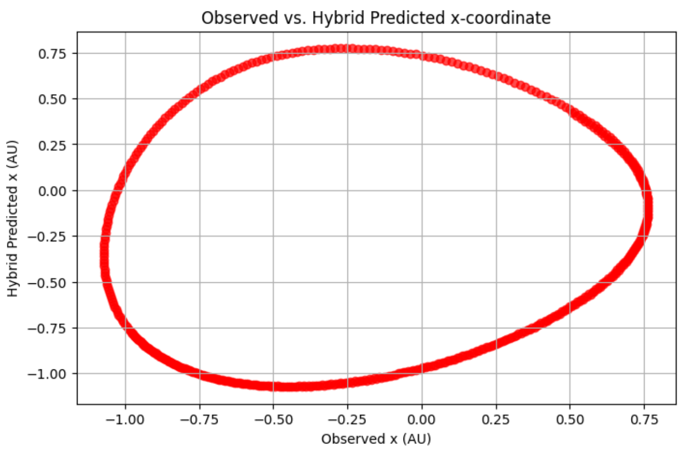

Fig -4: Scatter Plot

Figure 5: 3D Visualizations: Both static and animated 3D plots illustrate the close alignment between observed orbits and the hybrid predictions, with the Sun positioned at the center for reference.

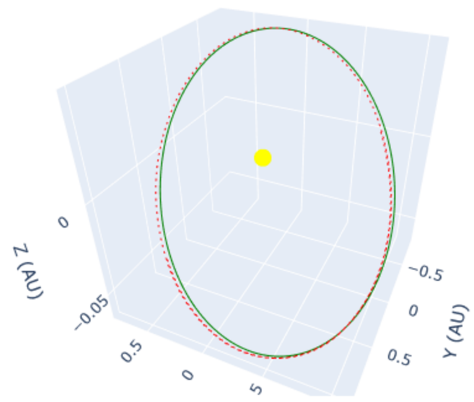

Fig -5: 3D Visualizations

Figure 6: Classification Accuracy:
A bar plot comparing the accuracy of the Random Forest and XGBoost classifiers.

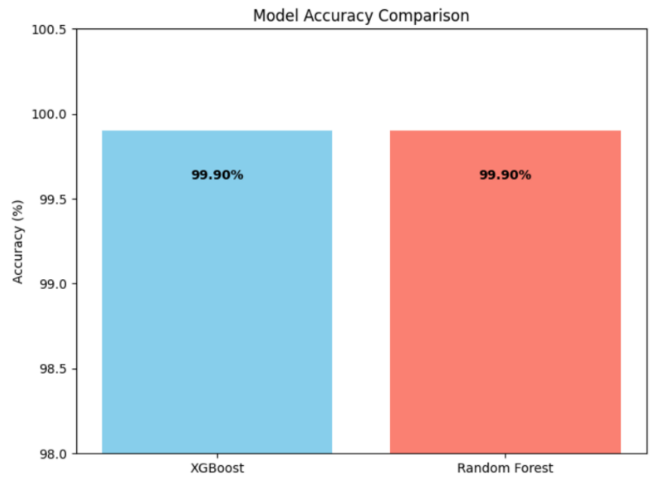

Fig -6: Bar Plot

Figure 7: Animated 3D Simulation:
An animated Plotly figure showcasing the dynamic evolution of the hybrid predicted orbit over time.

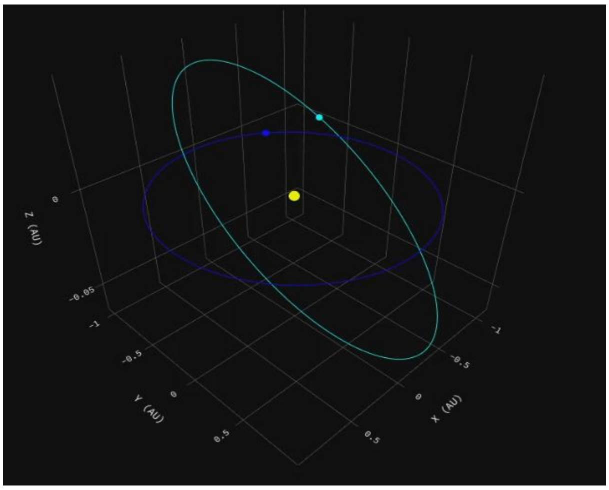

Fig -7: 3D simulation

3.3 Comparison with Traditional Methods

Traditional approaches used by organizations such as NASA and ESA rely on high-fidelity numerical integration and perturbation models. While these methods are highly accurate, they are computationally intensive and less adaptable to new data. The proposed hybrid approach not only reduces computational costs by leveraging ML corrections but also offers real-time adaptability and enhanced long-term accuracy.

3.4 Advantages and Future Applications

The integration of physics-based propagation with ML correction offers several advantages:

•Enhanced Accuracy: ML models significantly reduce errors by learning from historical residuals.

•Computational Efficiency: Rapid adjustments based on learned patterns minimize the need for exhaustive numerical simulations.

•Real-Time Adaptability: The framework is capable of integrating new observational data quickly, enhancing its responsiveness to dynamic conditions.

Looking ahead, integrating AI-assisted monitoring systems with real-time data could further refine trajectory predictions, thereby improving planetary defense strategies and supporting advanced space exploration initiatives.

4. Conclusion

This paper presents a comprehensive hybrid approach that effectively combines classical physics-based orbital propagation with machine learning corrections for both trajectory prediction and hazard classification of near-Earth asteroids. The integration of LSTM-based model results in significant reductions in prediction errors, while ensemble classifiers (XGBoost and Random Forest) achieve high hazard classification accuracy. Future work will aim to extend the dataset across multiple orbital cycles and further optimize the ML models to enhance long-term prediction reliability. This integrated methodology offers a promising tool for improving asteroid tracking, risk assessment, and space mission planning.

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