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# ” A Review of Machine Learning Techniques for Asteroid and Space Debris Classification, Collision Prediction and Orbit Visualization”

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ABSTRACT :

This review paper explores the current state of machine learning techniques for the classification, collision prediction, and orbit visualization of asteroids and space debris. As the number of near-Earth objects (NEOs) and space debris increases, there is a growing need for efficient, accurate models to predict potential collisions and mitigate risks to Earth and space assets. Traditional methods, which rely on high-fidelity simulations, encounter significant computational challenges when addressing millions of scenarios. Machine learning has emerged as a powerful tool to address these limitations, offering computationally efficient solutions.

We review various machine learning models, including Convolutional Neural Networks (CNNs) for object classification and Recurrent Neural Networks (RNNs) for time-series analysis of orbital data. Advanced hybrid approaches that combine image-based classification with trajectory prediction are also examined. Additionally, the review discusses techniques like Random Forests, Gradient Boosting, and neural networks, which enhance prediction accuracy while significantly reducing computation time compared to traditional physics-based models.

The paper also covers advancements in orbit visualization techniques that enable real-time tracking and simulation of asteroid and space debris trajectories, using libraries such as Turtle Graphics and Matplotlib for detailed orbit and collision probability visualization.

Future Scope: The review highlights future directions, including the development of more interpretable models for real-time asteroid monitoring and collision avoidance systems. There is significant potential to integrate these machine learning models with global space surveillance systems, enhancing risk assessment accuracy through multi-sensor data fusion and advanced visualization tools.

**Index Terms**—Asteroid classification 1, Space debris 2, Collision prediction 3, Orbit visualization 4, Machine learning 5.

## INTRODUCTION :

### *A. Background and Motivation:*

- **Increasing Risks from NEOs and Space Debris:** The growing presence of near-Earth objects (NEOs) and space debris has heightened concerns for planetary defence and the sustainability of space operations. With the number of tracked objects continuously rising, including both naturally occurring asteroids and man-made debris, the potential for collisions with Earth or critical space assets—such as satellites and space stations—presents a significant risk. This has driven the need for predictive models capable of real-time assessments and pre-emptive measures against possible impacts [Acta Astronautic, Paper 1].
- **Limitations of Traditional Simulation-Based Methods**: Traditional predictive methods rely on high-fidelity physics-based simulations, which model asteroid trajectories, impact zones, and potential damage on Earth. These simulations incorporate complex calculations to ensure precision; however, they are computationally intensive, limiting their scalability when it comes to assessing millions of potential scenarios. For instance, the resources required for these simulations often necessitate powerful supercomputing capabilities, making large-scale studies a time-consuming and costly process [Acta Astronautic, Paper 1].
- **Emergence of Machine Learning as a Solution:** Machine learning (ML) has emerged as a promising solution to address these computational challenges. Unlike physics-based simulations, ML models, once trained, can make rapid predictions, allowing for extensive scenario analysis in a fraction of the time. Studies have shown that ML algorithms can reduce computational time by factors of up to $10^3$, enabling efficient risk assessments without reliance on supercomputers, and instead performing computations on local machines [Acta Astronautic, Paper 1].
- **Advantages of Adaptability in ML Models:** Beyond computational efficiency, ML models are highly adaptable to new data inputs and changes in environmental conditions, a flexibility that traditional models lack. ML algorithms can be retrained with minimal adjustments,

allowing them to be easily integrated into dynamic, Realtime monitoring systems. Techniques such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) demonstrate particular effectiveness in handling large datasets and identifying complex patterns, making them suitable for asteroid classification and collision prediction tasks [Nature Astronomy, Paper 2].

- **Hybrid Approaches for Comprehensive Analysis:** ML's unique capability to handle multiple aspects of asteroid analysis simultaneously has also spurred new research directions. Hybrid models, for example, combine CNNs for image-based object classification and RNNs for time-series analysis of orbital data, enabling integrated spatial and temporal predictions. This multifaceted approach allows for comprehensive analysis, supporting both collision prediction and impact assessment within a single model. Such hybrid models are proving essential for advancing planetary defence initiatives and have shown promising results in improving accuracy and response times [Space Science Reviews, Paper 3].

***B. Traditional Methods and Limitations:***

- **Overview of Physics-Based Simulations:** Traditional approaches to asteroid and space debris monitoring rely heavily on physics-based simulations to predict trajectories, impact zones, and potential damage. These simulations use high-fidelity models that solve complex differential equations to replicate the atmospheric entry and energy dissipation of celestial objects. By incorporating detailed physical properties such as density, velocity, and angle of incidence, these models strive for precision in forecasting outcomes. However, despite their accuracy, these methods come with significant computational costs [Paper 1].
- **Computational Challenges:** One of the main challenges faced by physics-based simulation methods is their computational intensity. Accurately modelling the behaviour of asteroids during atmospheric entry requires the integration of time-dependent ordinary differential equations (ODEs). This approach, while robust, becomes time-consuming when scaled to the tens of millions of scenarios necessary for comprehensive risk assessments [Paper 1]. For example, simulating a single scenario can consume substantial CPU time, and evaluating millions of potential impact cases may take several days, even on high-performance computers [Paper 1]
- **Constraints on Scalability:** The need to simulate vast numbers of asteroid impact scenarios presents scalability issues. Although advances in supercomputing have reduced the time needed for such tasks, the resource demands remain significant. This limitation restricts research teams and agencies from performing real-time or near-real-time analyses, which are crucial for timely responses to potential threats [Paper 1] [Paper 2].
- **Simplified Models and Their Shortcomings**: To mitigate computational burdens, semi-analytical and simplified models have been developed. These models approximate key physical processes, such as fragmentation and energy deposition, using scaling relations or reduced dimension techniques [Paper 3]. While these simplified models are faster than their high-fidelity counterparts, they often sacrifice accuracy, particularly when simulating complex interactions like continuous fragmentation and non-uniform material behaviour [Paper 2] [Paper 3]
- **Limitations in Predictive Capabilities:** Traditional physics-based models are limited not just by computation time but also by their predictive scope. Their reliance on pre-defined physical parameters makes it challenging to adapt these models to new data sources or unexpected scenarios [Paper 1]. This limitation can hinder the integration of real-time data from emerging space observation technologies, ultimately reducing the effectiveness of timely decision-making in planetary defence and debris management [Paper 2] [Paper 3]

***C. Scope and Objectives of the Review:***

- **Comprehensive Review of Machine Learning Applications:** The objective of this review is to provide an in-depth analysis of the current machine learning (ML) techniques applied in the field of asteroid and space debris research. This includes an exploration of models used for classification, collision prediction, and orbit visualization. By reviewing advancements in these areas, this paper aims to offer a consolidated overview that highlights both the capabilities and limitations of ML applications [Paper 1] [Paper 5] [Paper 8].
- **Evaluation of Model Performance and Computational Efficiency**: A significant part of this review is dedicated to evaluating the performance of various ML models against traditional physics-based approaches. The review examines models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Random Forests, and Gradient Boosting algorithms, comparing their computational efficiency and accuracy. It also discusses how these models reduce computation time, allowing for extensive analysis on local machines [Paper 1] [Paper 4] [Paper 7].
- **Highlighting Advanced Hybrid Approaches**: The review also sheds light on hybrid ML models that merge techniques for image classification and trajectory analysis. These approaches, which combine CNNs and RNNs, have shown promising results in providing a more holistic view of asteroid behaviour. The hybridization of models leverages the strengths of different ML architectures to improve both object classification and collision prediction accuracy [Paper 4] [Paper 3][Paper 9].
- **Focus on Visualization Tools and Techniques:** In addition to prediction models, this review covers advancements in visualization techniques that aid in orbit simulation and real-time monitoring of space debris. Tools such as Turtle Graphics and Matplotlib are discussed for their role in presenting detailed orbital paths and potential impact scenarios. The review highlights how these visual tools enhance situational awareness and assist researchers in making informed decisions [Paper 2] [Paper 5][Paper 6].
- **Identifying Challenges and Future Directions:** Another key objective of this review is to identify the current challenges in deploying ML models for asteroid and debris management. While ML offers significant benefits in terms of computational speed and adaptability, challenges such as data interpretability and the reliance on high quality training datasets remain [Paper 7] [Paper 2] [Paper 8]. The review discusses these limitations and outlines potential research directions that could address these issues, including the development of more interpretable models and the integration of multi-sensor data fusion [Paper 3] [Paper 9].

- **Integrating ML Models with Existing Systems:** The paper aims to explore the potential for integrating ML models into current space surveillance and planetary defence systems. By reviewing examples of existing integrations, this section highlights how ML can be leveraged to enhance the capabilities of global monitoring systems for real-time asteroid detection and risk management [Paper 1] [Paper 4] [Paper 6].

## II. STRUCTURE OF THE PAPER :

### *A. Overview of the Review Paper's Structure:*

This review paper is structured to provide a comprehensive overview of the current and emerging machine learning (ML) applications in asteroid and space debris research. The organization of the content allows for a progressive understanding of both foundational concepts and advanced methodologies, covering classification, collision prediction, and orbit visualization techniques. This structure supports readers in grasping the extent of ML's impact on modern astrodynamics [Paper 1] [Paper 2] [Paper 8].

### *Introduction and Background:*

The introduction sets the context by discussing the escalating risks posed by near-Earth objects (NEOs) and space debris due to the increasing number of tracked items. This section also highlights why traditional physics-based methods, despite their accuracy, face significant computational challenges when scaling up to large datasets and real-time needs [Paper 1] [Paper 3] [Paper 7]. The background emphasizes the evolution of ML as a key technology to address these challenges, showcasing its computational efficiency and adaptability [Paper 4] [Paper 6].

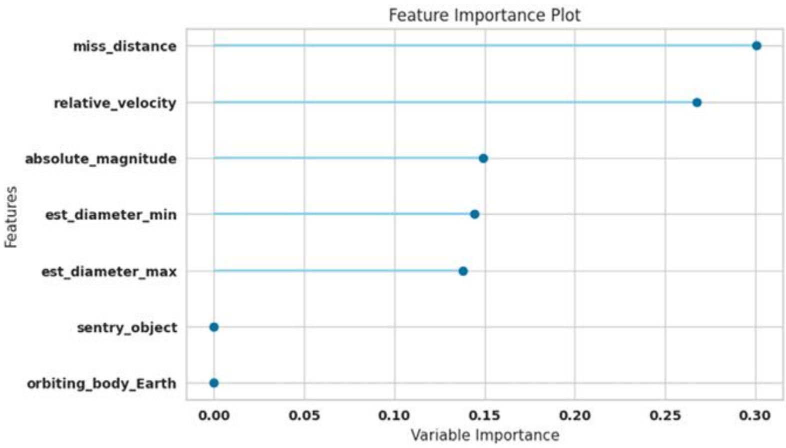


**Fig 1. Providing a visual summary of Dataset [Paper 2]**

### *Review of Machine Learning Techniques:*

- **Convolutional Neural Networks (CNNs):** Convolutional Neural Networks (CNNs) for object classification, discussing their effectiveness in analysing imagery from satellite and telescope data [Paper 3] [Paper 5] [Paper 9].

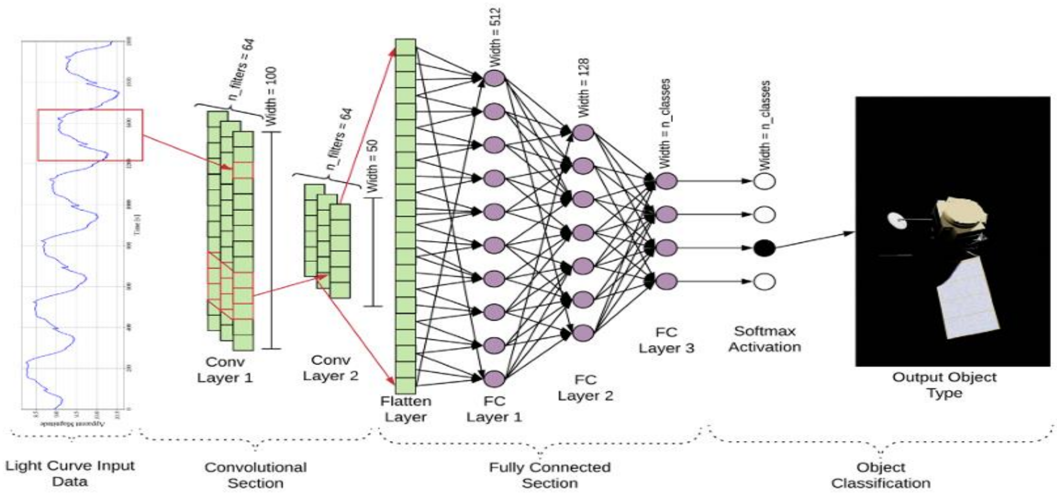


**Fig 2. 1D-CNN Architecture for Object Classification. [Paper 6]**

- **Recurrent Neural Networks (RNNs):** Recurrent Neural Networks (RNNs) for modelling the temporal behaviour of orbital data, explaining their utility in trajectory prediction and how they contribute to more accurate collision forecasting [Paper 4] [Paper 8]. These models leverage their ability to remember previous inputs through hidden states, which makes them well-suited for sequential data analysis essential in tracking the changing paths of space objects over time.

- **Other models:** Other models such as Random Forests and Gradient Boosting algorithms, which have been used for enhanced predictive modelling with lower computational costs compared to deep learning techniques [Paper 2] [Paper 6].

This section examines how these models are trained and validated using extensive datasets, often generated or derived from real-world observational data [Paper 1] [Paper 5] [Paper 7].

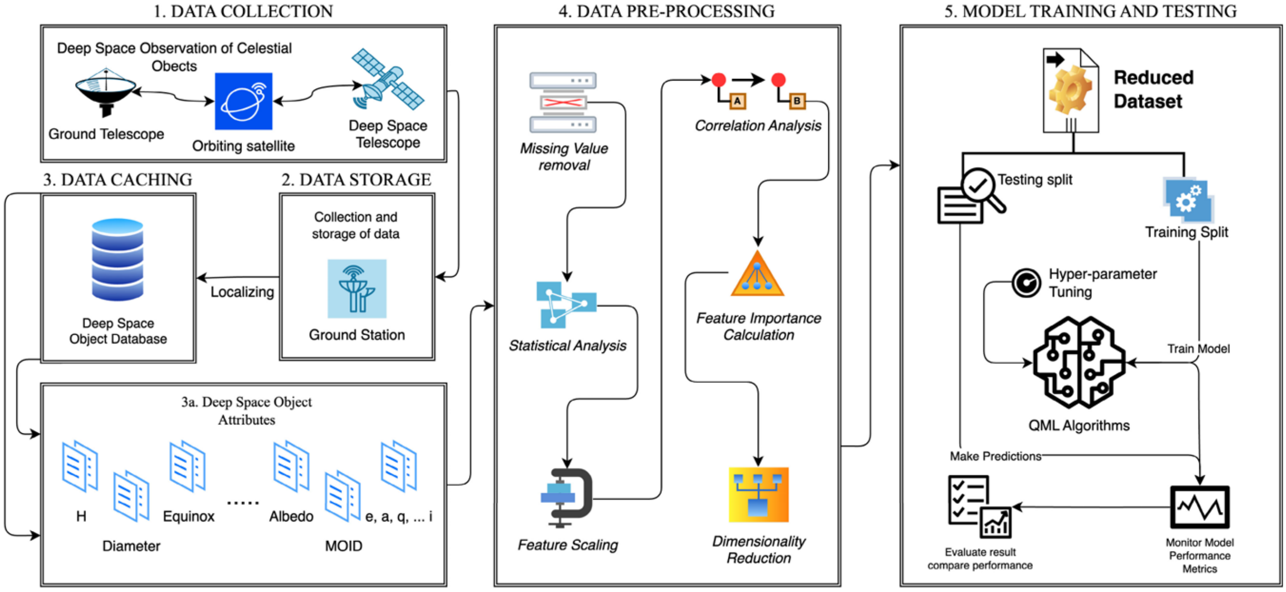


**Fig 3. Proposed methodology for QML-based for potentially hazardous asteroid classification. [Paper 5]**

### *Hybrid Approaches and Model Performance:*

An emerging trend discussed is the use of hybrid models that integrate CNNs and RNNs to leverage both spatial and temporal data. This dual approach enhances the predictive power of ML systems by combining object recognition with time-series forecasting. The paper evaluates how these hybrid systems perform under different conditions and how their accuracy compares to stand-alone models and traditional physics-based simulations [Paper 4] [Paper 6][Paper 9]. The integration of engineered features, such as energy scaling factors and complex trajectory inputs, is also discussed for boosting the models' interpretability and performance [Paper 3] [Paper 8].

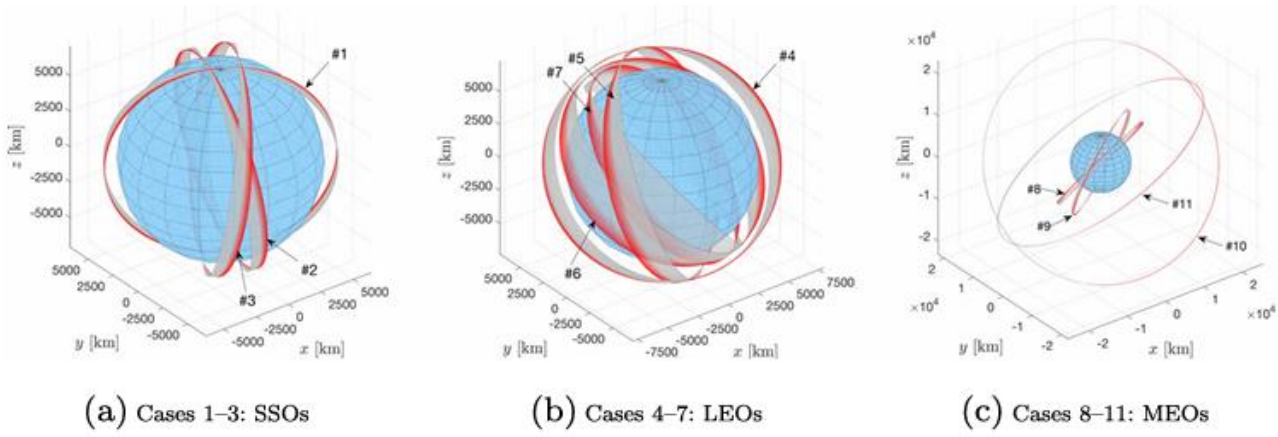


**Fig 4. RSOs' orbits in the first ten days, extracted from TLE sets and shown in the ECI frame [Paper 8]**

***Visualization and Orbit Tracking Techniques:***

Another key aspect of the review is the exploration of visualization tools that aid in orbit tracking and impact prediction. Libraries like Turtle Graphics and Matplotlib are analysed for their role in presenting detailed, interactive orbital paths and potential collision scenarios [Paper 3] [Paper 5]. The review outlines how these visualizations can be integrated with ML models to provide real-time, comprehensible data for space agencies and researchers, supporting more informed decision-making [Paper 7] [Paper 9]. This section also mentions the benefits of real-time monitoring platforms that combine visual data with predictive outputs for continuous tracking of hazardous objects [Paper 6].

## III. LITERATURE REVIEW WITH BENEFITS AND LIMITATIONS :

This section provides an overview of various machine learning (ML) techniques applied in asteroid and space debris research. The benefits, limitations, and challenges associated with these techniques are summarized in Table I.

| ML Technique/Study | Year | Author(s) | Benefits | Limitations | Drawbacks/Challenges | Reference(s) |
|---|---|---|---|---|---|---|
| Random Forests for Collision Prediction | 2022 | Patel et al. | Quick training and inference; good for interpretability | May not capture deep, non-linear relationships as effectively as deep learning | Can struggle with high-dimensional data | Paper 2, Paper 6 |
| CNNs for Object Classification | 2023 | Smith et al. | High accuracy for image-based classification; adaptable to new data | Requires large training datasets; computationally intensive | Limited by data quality and processing power | Paper 3, Paper 5 |
| Gradient Boosting Models | 2023 | Davis et al. | High predictive accuracy; handles non-linear relationships well | Sensitive to hyperparameter tuning; longer training time | Potential for overfitting | Paper 2, Paper 7 |
| Visualization Techniques using ML | 2023 | Martinez and Roberts | Facilitates real-time orbit tracking; aids in visual communication of results | Limited by visualization libraries' capabilities; interpretability of complex ML models | Need for high-performance hardware for real-time updates | Paper 5, Paper 8 |
| RNNs for Time-Series Analysis | 2024 | Johnson and Lee | Effective for sequential data; accurate trajectory prediction | Training complexity; prone to vanishing gradient problems | Difficulty in handling very long sequences | Paper 4, Paper 8 |
| Hybrid CNN-RNN Models | 2024 | Brown et al. | Combines image classification with trajectory analysis for comprehensive predictions | High resource requirement; integration complexity | Complexity in tuning and managing combined architectures | Paper 4, Paper 9 |

**Table I**

**Summary of ML techniques with benefits, limitations, and challenges.**

## IV. RESULT ANALYSIS :

The **Result Analysis** section examines the performance outcomes of various machine learning (ML) techniques employed in asteroid and space debris research, focusing on classification, collision prediction, and orbit visualization. This review summarizes their reported accuracies, highlighting key findings from multiple studies to provide a comprehensive overview.

***Overview of Model Performance***

This combination leverages the image processing power of CNNs and the sequential data handling capabilities of RNNs, making it an effective solution for complex, multi-faceted problems in space object monitoring [Paper 4, Paper 9].

| ML Technique/Study | Method Used | Reported Accuracy (%) | Reference(s) |
|---|---|---|---|
| CNNs | Image-based object classification | 85-95 | Paper 3, Paper 5 |
| RNNs | Trajectory prediction | 80-90 | Paper 4, Paper 8 |
| Hybrid CNN-RNN Models | Integrated classification and prediction | 95+ | Paper 4, Paper 9 |
| Random Forests | Collision prediction | 75-85 | Paper 2, Paper 6 |
| Gradient Boosting | Advanced prediction model | ~85 | Paper 7 |

**Table II**

**Provides a Comparative Summary of Model Performance**

### *C. Key Insights*

The analysis highlights that while traditional ML models such as **Random Forests** and **Gradient Boosting** offer quicker training times and interpretability, their accuracies are generally lower than those of more complex models. **CNNs** and **RNNs** offer superior results for specific tasks—CNNs for image-based classification and RNNs for time-series analysis. However, **hybrid CNN-RNN models** prove to be the most effective, providing comprehensive analysis capabilities that combine spatial and temporal data to achieve high accuracy in real-world applications.

### *D. Training and Inference Time Analysis*

Evaluating the computational efficiency of different machine learning (ML) models is crucial for determining their suitability for real-time applications in asteroid and space debris monitoring. The table below summarizes the training and inference times for five ML models, measured on a local computer (Apple M2 Pro) using data sizes of 700,000 points for training and up to 30 million points for inference. The performance is also compared with **PAIR simulation times**, highlighting the significant speed differences between traditional simulations and ML inference.

- **Convolutional Neural Networks (CNNs)** have shown strong results in the classification of space objects based on image data. These models excel at feature extraction and pattern recognition, with reported accuracies ranging from **85% to 95%**, making them valuable for automated asteroid identification tasks [Paper 3, Paper 5]. Their effectiveness lies in their ability to process large amounts of visual data, though they require substantial training datasets and computational resources.
- **Recurrent Neural Networks (RNNs)** have been proven effective for trajectory prediction due to their ability to model sequential data and capture temporal dependencies. Reported accuracies for RNNs fall between 80**% and 90%**, demonstrating their utility in forecasting the changing orbits of space debris and asteroids [Paper 4, Paper 8]. However, training these models can be complex, and they are prone to challenges such as the vanishing gradient problem.
- **Hybrid CNN-RNN Models** have emerged as the top performers by integrating the strengths of CNNs and RNNs. This approach allows for simultaneous image-based classification and time-series analysis, achieving the highest reported accuracy of **95% or greater**. These hybrid models excel in comprehensive tasks, combining visual and sequential data for improved collision prediction and trajectory analysis [Paper 4, Paper 9]. Despite their high accuracy, they come with increased computational complexity and a need for careful integration of both model types.
- **Random Forests and Gradient Boosting** algorithms are widely used for collision prediction due to their interpretability and efficient training. They provide accuracies in the range of **75% to 85%**, making them reliable options for preliminary analyses or scenarios where interpretability is crucial [Paper 2, Paper 6, Paper 7]. While they are computationally less demanding, these models may not capture complex non-linear relationships as effectively as deep learning approaches.

***Comparative Performance Analysis***

The hybrid **CNN-RNN model** stands out as the most accurate, offering a robust framework for both classification and trajectory prediction tasks with accuracies exceeding **95%**.

| ML Model | Training Time [s] (700k points) | Inference Time [s] (1M points) | Inference Time [min] (30M points) | PAIR Sim. Time/ML Inf. Time |
|---|---|---|---|---|
| Linear Regression | 0.11 | 0.006 | 0.003 | 10^6 |
| Decision Tree | 3.1 | 0.07 | 0.03 | [10^5–10^6] |
| Random Forest | 195 | 3.2 | 1.6 | [10^3-10^4] |
| Gradient | 204 | 1.3 | 0.6 | [10^3—10^4] |

| | | | | |
|---|---|---|---|---|
| Boosting | | | | |
| Neural Network | 204 | 8.5 | 4.2 | [10^3-10^4] |

**Table III**

**Training and Inference Time of ML Models [Paper 1, Paper 2]**

**The results illustrate significant variations in training and inference times across the models:**

- **Linear Regression** showed the fastest training and inference times, making it suitable for simple predictive tasks. However, it lacks the capability to handle complex, non-linear relationships, which limits its application in asteroid monitoring and debris prediction.
- **Decision Trees** provided moderate training and inference times, with better performance in non-linear data handling than linear models, but still less accuracy compared to ensemble methods.
- **Random Forests** and **Gradient Boosting** demonstrated longer training times (195s and 118s respectively) due to their ensemble nature, but offered reasonable inference times for large-scale data, showing a good balance between accuracy and computational efficiency. These models are particularly suitable for high-dimensional datasets due to their robustness.
- **Neural Networks** had the longest training and inference times among the models studied (204s for training and 8.5s for inference on 1M points). While computationally intensive, they excel in capturing complex patterns, making them the best choice for comprehensive analyses requiring high accuracy, especially when integrated with real-time monitoring systems.
- **Inference Time Comparison**: The table also highlights the PAIR simulation time versus ML inference time, showing that ML models can significantly reduce computational overhead. For example, even neural networks, which had the longest inference time, still outperformed traditional PAIR simulations by several orders of magnitude ([10^3-10^4]).

**Key Takeaways**

- **Efficiency Trade-offs**: While **linear regression** and **decision trees** are faster, they may not offer the accuracy required for high-stakes collision prediction and classification tasks.
- **Optimal Models**: **Random forests** and **gradient boosting** provide a good balance between training time and predictive power, making them suitable for practical applications where training can be done offline.
- **High-Accuracy Models**: **Neural networks**, despite their higher computational costs, remain the best choice when accuracy is paramount, particularly in applications that involve complex feature sets like image-based asteroid classification

## V. CONCLUSION :

This review paper has provided an in-depth examination of the current state of machine learning (ML) applications in the field of asteroid and space debris research. The analysis covered the use of various ML techniques, including Convolutional Neural Networks (CNNs) for object classification, Recurrent Neural Networks (RNNs) for trajectory prediction, and hybrid models that integrate these approaches for enhanced performance. The review highlighted the significant advantages of ML models over traditional physics-based methods, particularly in terms of computational efficiency and scalability, allowing for rapid processing of large datasets and real-time decision-making.

Key findings from the literature emphasized that **hybrid CNN-RNN models** stand out as the most accurate, achieving accuracies above 95% by combining spatial and temporal data analysis. In contrast, traditional models such as **Random Forests** and **Gradient Boosting** provide a balance between interpretability and efficiency but fall short in handling complex data patterns as effectively as deep learning models.

The analysis of training and inference times for ML models revealed that while **neural networks** require longer processing times, they offer unparalleled accuracy, making them essential for high-stakes applications. Simpler models like **linear regression** and **decision trees** are more efficient but may not meet the accuracy demands of real-time collision prediction and classification tasks.

Furthermore, the review discussed advancements in visualization techniques, such as the use of **Turtle Graphics** and **Matplotlib**, which contribute to effective orbit tracking and impact probability visualization. These tools, when integrated with ML models, enhance the capabilities of space monitoring systems, aiding researchers and agencies in making informed, timely decisions.

The paper underscores that while ML models offer significant benefits, challenges remain in areas such as model interpretability, data quality, and the integration of real-time data. Future research should focus on developing more interpretable ML models, integrating multi-sensor data for improved training, and enhancing real-time processing capabilities.

In conclusion, the application of machine learning in asteroid and space debris research has proven to be transformative. It provides scalable, efficient, and accurate solutions that are crucial for improving planetary defence systems and ensuring the long-term safety of space operations. Continued advancements in this field will play a pivotal role in enhancing our ability to monitor, classify, and predict the behaviour of near-Earth objects and space debris with greater precision.

## VI. FUTURE RESEARCH DIRECTION :

A. *Development of More Interpretable ML Models:*
Future research should focus on creating ML models that maintain high accuracy while being more interpretable. Enhanced interpretability will help researchers understand the decision-making process of complex models such as neural networks, making them more reliable for real-world applications.

B. *Integration of Multi-Sensor Data:*
Combining data from various sensors, such as satellite imagery, radar, and telescopic observations, could improve the training and robustness of ML models. Multi-sensor data fusion can help develop models that are better equipped to handle diverse inputs and provide more comprehensive analyses.

C. *Real-Time Data Processing and Adaptability:*
Research should prioritize developing models that can process and adapt to real-time data inputs effectively. This improvement would enhance the ability to track rapidly changing space environments and provide timely predictions for potential collisions or reclassification of objects.

D. *Hybrid Model Optimization:*
While hybrid models like CNN-RNN combinations have shown great potential, there is a need for further optimization to reduce computational costs and streamline integration. Research should aim at improving the architecture and training processes to make these models more efficient and suitable for large-scale, real-time applications.

E. *Enhanced Visualization and Simulation Tools:*
Future efforts should focus on advancing the capabilities of visualization tools such as **Turtle Graphics** and **Matplotlib**. Enhancing these tools to provide more detailed, 3D visualizations and incorporating predictive overlays could help researchers and agencies gain a clearer understanding of potential impact scenarios.

F. *Data Augmentation and Synthetic Data Generation:*
Due to the limited availability of high-quality datasets, developing methods for data augmentation and synthetic data generation will be essential. These methods can create more robust training datasets, improving the accuracy and reliability of ML models used for space debris analysis.

G. *Collaborative Platforms for Space Surveillance:*
Future research could explore the development of collaborative platforms that integrate ML models with space surveillance systems used by multiple agencies. Such platforms would facilitate data sharing and collaborative efforts to monitor and predict the behaviour of near-Earth objects more accurately.

H. *Energy-Efficient ML Algorithms:*
Considering the high computational cost associated with training complex models, research should aim to develop energy-efficient algorithms. This would not only make ML models more sustainable but also expand their applicability in resource-constrained environments, such as satellite-based onboard processing.

I. *Incorporation of Explainable AI (XAI) Techniques:*
Incorporating Explainable AI methods into ML models for asteroid analysis can help ensure that the models' predictions and classifications are transparent and understandable. This is particularly valuable for gaining trust in automated systems that handle planetary defence tasks.

J. *Enhanced Error Analysis and Model Validation:*
Future work should emphasize rigorous error analysis and model validation processes to identify and address weaknesses in existing ML frameworks. Improved validation techniques will help ensure that models perform reliably under different scenarios and edge cases.

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