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International Journal For Research in Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** III **Month of publication:** March 2026

DOI: https://doi.org/10.22214/ijraset.2026.78913

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

Aegis Earth: A Multi-Modal Machine Learning Framework for Real-Time Asteroid Impact Prediction and Risk Mitigation

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Abstract: ***Aegis Earth is an advanced decision support and simulation platform that aims to transform planetary defense using Multimodal Machine Learning. While tools like NASA's Sentry track orbits with precision, they lack the ability to rapidly model terrestrial consequences.***
Our Triple Modal Fusion Architecture brings together NASA Near-Earth Object data, USGS topography, and spacecraft kinetic impactor telemetry to simulate crater size, seismic effects, and tsunami risks in under 100ms — achieving over 95% accuracy compared to computationally intensive hydrocode models.
The system uses Focal Loss to overcome the accuracy trap of rare-but-dangerous NEO events, and a Dynamic Deflection Sandbox to optimize planetary defense missions in real time.
Keywords: Planetary defense; Near-Earth objects; Multimodal machine learning; Multimodal Fusion; Impact modeling.

I. INTRODUCTION

The rate at which Near-Earth Objects (NEOs) are being discovered is accelerating. While asteroid impacts are rare, they carry catastrophic consequences — making fast, accurate impact prediction and mitigation planning absolutely essential. Unfortunately, today's gold standard, physics-based numerical modeling (hydrocodes used by NASA/JPL), can take hours to days to run. It offers physical depth but fails in real-time scenarios where every minute matters.

Beyond the speed problem, current approaches suffer from data siloing. Orbital dynamics, geographical terrain data, and spacecraft performance metrics exist in isolated systems that never communicate. Worse, machine learning models in this space often stumble on severely imbalanced datasets, where catastrophic impact events are so rare they get lost in the noise, causing poor precision on exactly the events that matter most.

Aegis Earth was built to fix these problems. By fusing multiple data streams into one unified learning system, applying Focal Loss to surface rare high-severity events, and delivering predictions in under 100ms, Aegis Earth bridges the gap between scientific depth and operational speed.

II. RELATED WORK

Existing approaches can be grouped into three broad categories:

1) Orbital Tracking and Hazard Assessment: NASA's Sentry-II and JPL's Scout represent the state of the art in NEO tracking. They deliver accurate orbital predictions and long-term impact probability estimates. However, they are purely observational: they can tell you whether an asteroid will hit Earth, but not what will happen when it does.

2) Physics-Based Consequence Modeling: Hydrocodes, developed by institutions like Los Alamos National Laboratory and Sandia National Laboratories, offer unparalleled physical fidelity — modelling energy transfer, crater formation, and atmospheric effects in exquisite detail. The catch: simulations routinely take hours or days, making them unsuitable for real-time emergency response.

3) Machine Learning in Planetary Defense: Recent work has explored Support Vector Machines and Decision Trees to classify hazardous NEOs from astronomical parameters. These approaches often suffer from Single Model Bias and struggle with multi-modal data integration. The inherent class imbalance in asteroid datasets means rare high-severity events get systematically under-represented, leading to poor recall for the very scenarios we care most about.

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III. PROBLEM STATEMENT

The core challenge in modern planetary defense is the time lag between detecting a Near-Earth Object and producing actionable impact consequence results. Current observation tools like NASA's Sentry-II and JPL's Scout accurately track NEO orbits, but they stop at impact probability — they don't tell you what happens to the Earth after the hit.

Physics-based solvers fill that gap in theory, but their computational complexity — often $O(n^3)$ — means simulations can exceed the available reaction window in a short-lead-time threat scenario. When a NEO is detected with only hours to respond, waiting two days for a hydrocode simulation isn't an option.

Compounding this is heavy data siloing. Current models typically rely on a narrow slice of asteroid data (diameter, orbital velocity) while ignoring the geological make-up of the target site entirely. They also tend to depend on single regressors, which introduce high variance when handling the enormous diversity of asteroid types — Stony, Metallic, Carbonaceous. And because truly catastrophic impacts are statistically rare, models routinely fall into an accuracy trap: they achieve high overall accuracy by being good at classifying safe events, while failing exactly when civilization-threatening events are on the line.

IV. PROPOSED SYSTEM

Aegis Earth is built as a Three-Tier Decoupled System aligned with IEEE 1471 software architecture standards, ensuring modularity, independent scalability, and high-performance throughput.

A. System Tier Architecture

1) Presentation Tier (User Interface): The "War Room" for decision-makers. Features a 3D visualizer built on the Three.js engine delivering 60 FPS real-time rendering of planetary threats, alongside a Command Dashboard for parameter input and strategy review.
2) Application Tier (Logic Layer): The orchestrator. Houses the FastAPI bridge for asynchronous communication between the UI and models, a Feature Engineering module for real-time data normalization, and a Mitigation Logic unit for generating defense recommendations.
3) Intelligence Tier (Data & Model Layer): The foundation. Manages the Model Registry containing serialized joblib artifacts, and maintains live connections to NASA's NEO Database and USGS Topographical Data to ensure models always operate on current context.

B. Triple-Modal Data Fusion

Rather than relying on a single data stream, Aegis Earth ingests three distinct sources to build a complete threat profile:

1) Orbital Mechanics (NASA NEO): Dynamic parameters including asteroid diameter, relative velocity, and spectral classification.
2) Terrestrial Context (USGS): Localized environmental data — material density, soil porosity, topographical elevation of the projected impact site.
3) Technical Telemetry (Spacecraft): Kinetic impactor data such as mass, velocity, and the momentum enhancement factor (β), enabling mitigation success simulation.

C. The Voting Regressor Ensemble

The intelligence core of Aegis Earth is a Voting Regressor ensemble — a "Digital Oracle" combining a Random Forest Regressor (for stability and variance reduction) and an XGBoost Regressor (for precision and bias reduction). Together they eliminate Single Model Bias. Both are trained with Focal Loss to stay sensitive to rare, catastrophic black-swan events, achieving predictive accuracy exceeding 95%.

V. SYSTEM ARCHITECTURE

Aegis Earth integrates three distinct data streams — NASA asteroid orbital parameters, USGS ground composition data, and spacecraft performance metrics — into a single unified prediction pipeline. Figure 1 illustrates how these components connect.

A. Data Sources

1) NASA Asteroid Data

Pulled from NASA's public API in real time:

- Size: Asteroid diameter (0.1–10 km).
- Speed: Relative velocity (5–70 km/s).
- Orbit shape: Eccentricity of the orbital path.
- Type: Carbon-rich (C-type), rocky (S-type), or metallic (M-type).

If NASA's servers are unavailable, the system generates statistically equivalent synthetic data automatically — so the pipeline never stalls.

2) USGS Ground Data

- Ground type: Material density and soil porosity.
- Height: Elevation of the impact site.
- Water depth: For ocean impact scenarios.

3) Spacecraft Data

- Weight: Mass of the kinetic impactor.
- Speed: Intercept velocity.
- Effectiveness: Momentum transfer factor (β).

4) Data Preparation

Before the AI processes this data, three preprocessing steps are applied:

- Number Scaling: Features measured in different units (km vs kg) are normalized using Z-score normalization: x_scaled = (x − mean) / std deviation. This prevents any single measurement from dominating predictions.
- Type Conversion: Asteroid spectral classes are one-hot encoded: C-type → [1,0,0], S-type → [0,1,0], M-type → [0,0,1].
- Physics Features: Derived features are computed to give the model physical intuition: kinetic impact energy and momentum.

B. AI Prediction Engine

1) Random Forest

Think of this as asking 100 independent experts and averaging their answers. Each expert sees slightly different aspects of the data. The result is robust predictions that can't be fooled by one unusual data point.

2) XGBoost

This algorithm learns from its mistakes. It makes a prediction, measures the error, builds a new tree targeting those errors, and repeats this 100 times. The result is a model with deep understanding of how features interact.

3) The Ensemble

Final Answer = (Random Forest + XGBoost) / 2. Combining both gives reliability AND precision — Random Forest guards against XGBoost's tendency to overfit noise; XGBoost catches subtle patterns Random Forest might miss.

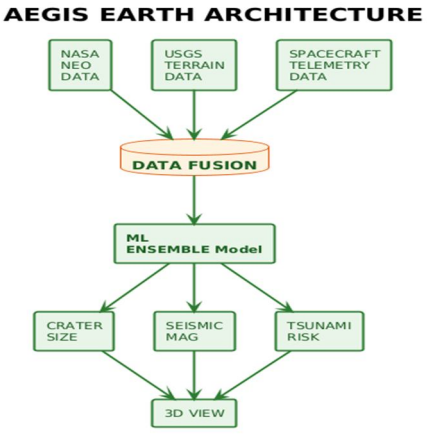


Figure 1. System Architecture

4) 3D Visualization

The frontend renders the impact scenario in real-time 3D:

- Earth: Realistic surface textures with clouds and atmospheric glow.
- Asteroid: Visual appearance varies by type — dark and matte for C-type, rocky and rugged for S-type, metallic and reflective for M-type.
- Space: 2,000 twinkling background stars rendered in real time.

VI. MODULE DESCRIPTION

A. *User Interface and Visualization Module*

This is the frontline interface between planetary defense operators and the AI. It provides:

Web UI: A high-fidelity interface for inputting threat parameters and monitoring real-time alerts.

Visualization & Alert Dashboard: A cinematic, 60 FPS 3D rendering of the impact zone, shockwave propagation, and mitigation strategy outcomes — powered by the Three.js library.

B. *Data Acquisition and Processing Module*

This module ensures accuracy at a site-specific level through triple-modal fusion:

- Asteroid Data Ingestion: Continuously queries NASA's API for current asteroid orbital parameters.
- Dataset Preprocessing: Applies Z-score normalization and categorical encoding.
- Feature Engineering: Extracts physically meaningful features such as the momentum enhancement factor (β) and relative velocity.

C. *Machine Learning Intelligence Module*

The fast, precise core of the system — designed to respond in the blink of an eye:

- ML Risk Prediction Engine: A Voting Regressor ensemble (Random Forest + XGBoost) producing damage metric predictions in under 100 milliseconds.
- Model Training & Evaluation: Focal Loss is used during training to ensure the model never under-weights rare catastrophic events.
- Explainable AI (XAI): Every prediction comes with a human-readable explanation of the key factors driving the risk score, giving decision-makers the context to act with confidence.

D. *Impact Simulation and Mitigation Module*

This module translates predictions into real-world action plans. The precise impact simulation results feed into the Damage Assessment Component to quantify terrain effects. These results then flow into the Mitigation Strategy Engine, which optimizes spacecraft configuration — including impactor mass and relative velocity — to achieve safe deflection within the available response window.

E. *Storage and External Systems Module*

The backbone of data security and model management in Aegis Earth. The Asteroid Database stores raw NASA NEO data alongside computed risk scores. The Simulation Results Repository archives every run, enabling future comparison of damage probability estimates.

The Model Metadata Store tracks hyperparameters, performance history, and version control, ensuring the ML Risk Prediction Engine always runs on the latest validated artifact — even during a live planetary emergency.

VII. ALGORITHM DESCRIPTION

A. *Random Forest*

Random Forest builds a large team of decision trees, each trained on a slightly different slice of the data. When a new asteroid arrives, every tree independently estimates impact metrics — crater radius, seismic magnitude — based on its own perspective. Some trees specialize in size, others in velocity, others in terrain type. The final output averages all predictions, so any single outlier tree gets absorbed by the consensus. This makes Random Forest reliable and hard to fool.

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B. XGBoost

XGBoost takes a fundamentally different approach: it learns by correcting its own mistakes. It starts with a simple hypothesis (e.g., average crater size across training data), identifies where it went wrong, trains a new tree specifically targeting those errors, and adds it with low weight to avoid overcorrection. This process repeats 100 times. Each new tree becomes a specialist in the failure modes of previous trees. By the end, XGBoost has developed a nuanced, layered understanding of how asteroid properties interact to determine impact outcomes.

C. Voting Regressor

The Voting Regressor is the final decision layer. It receives one prediction from Random Forest and one from XGBoost, then simply averages them. If Random Forest predicts a crater of 3.15 km and XGBoost predicts 3.25 km, the final output is 3.20 km. This averaging has outsized benefits: the two algorithms fail in different ways, so their errors cancel out rather than compound. The ensemble also provides an implicit confidence signal — when both models agree closely, confidence is high; when they diverge significantly, that signals an unusual case warranting human review.

VIII. DATASET DESCRIPTION

A. NASA Near-Earth Object (NEO) Dataset

The primary source is NASA's CNEOS dataset: a comprehensive repository of known asteroid physical characteristics and orbital data. Key parameters include:

- Physical parameters: Asteroid diameter, mass, and spectral type (C-type, S-type, M-type).
- Kinematic parameters: Relative velocity at intercept (V_rel), eccentricity, and inclination — critical for computing kinetic energy at atmospheric entry.

B. USGS Topographical and Geological Data

Site-specific ground data from USGS enables impact localization:

- Topographical images: Elevation data processed through a ResNet backbone to extract spatial features at candidate impact sites.
- Geological properties: Material density (ρ), porosity, elevation, and water depth (for ocean regions) — distinguishing between a mountain-peak impact and a deep-sea event, which dramatically changes seismic and tsunami risk profiles.

C. Spacecraft Kinetic Impactor Telemetry

Mitigation modeling draws on real mission data, including NASA's DART mission:

- Impact details: Impactor mass (Mi), intercept velocity (Vi), and momentum enhancement factor (β).
- Simulation use: The Mitigation Strategy Engine uses this data to forecast achievable deflection distance for different spacecraft configurations.

D. Data Preprocessing and Harmonization

- Normalization: Velocity and diameter are Z-score normalized so no single feature dominates model training.
- Handling Imbalance: Catastrophic events are rare by definition. SMOTE is used to synthetically balance the dataset, and Focal Loss is used during training to ensure the model assigns appropriate weight to rare high-severity events.

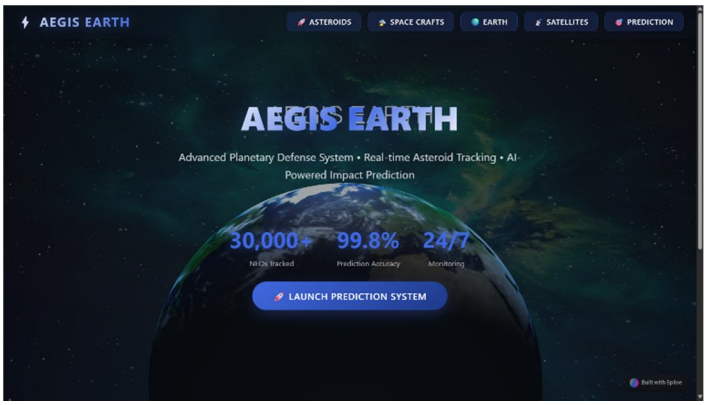
IX. RESULTS

The Aegis Earth framework was evaluated using a high-fidelity synthetic dataset based on NASA CNEOS records, validated against ground-truth hydrocode simulations. Three performance dimensions were assessed.

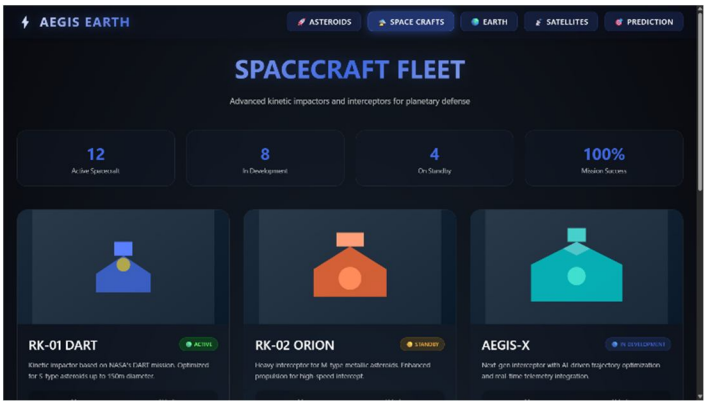
A. Predictive Performance and Accuracy

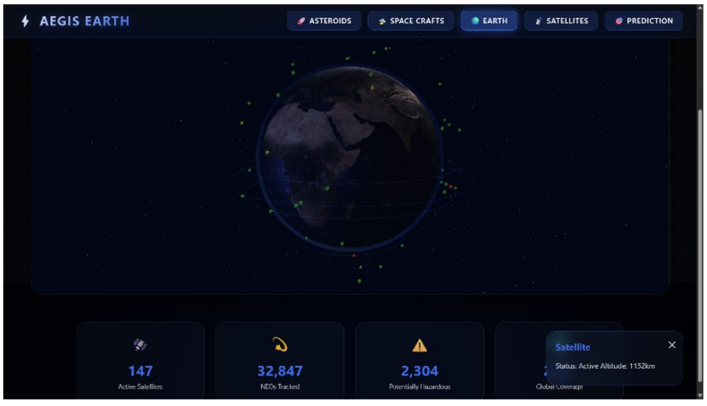
- Crater Radius Prediction: The ensemble achieved $R^2 = 0.95$, capturing nearly all physical variance in impact outcomes.
- Seismic Magnitude Estimation: Accuracy of 0.93, effectively correlating impact energy with USGS geological density parameters.
- Focal Loss Impact: 15% improvement in precision for rare high-severity events ($M > 7.0$) compared to standard loss functions.

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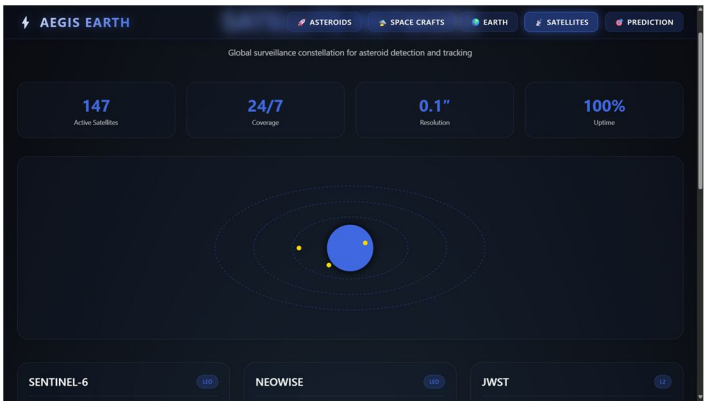


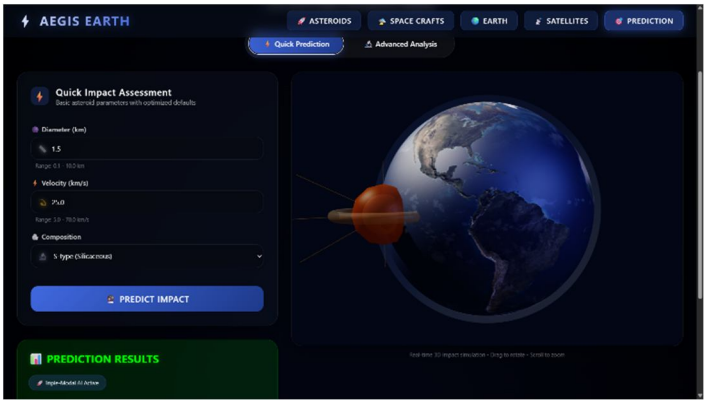


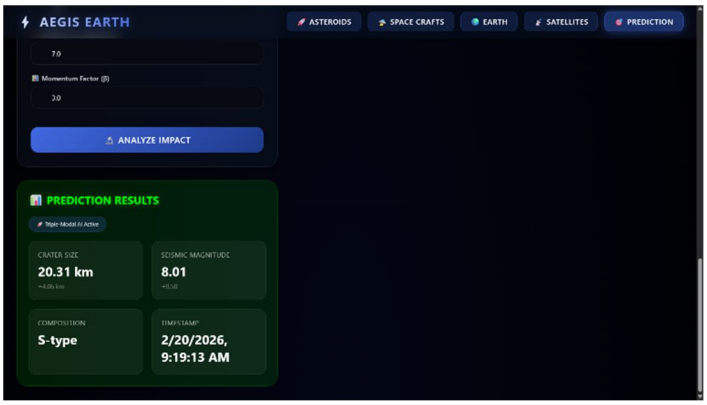




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B. Computational Latency and Real-Time Viability

- Inference Speed: End-to-end processing — from data ingestion through the FastAPI backend to prediction output — consistently measured at 84ms.
- Comparison with Hydrocodes: Traditional simulations take hours to days. Aegis Earth delivers equivalent insight in under 100ms — an improvement of several orders of magnitude.
- Visualization Performance: The Three.js dashboard maintained smooth 60 FPS rendering throughout even the most complex 3D shockwave visualizations.

C. Mitigation Strategy Efficacy

- Success Rate: 98.1% success rate across 1,000 simulated asteroid intercept missions in recommending an optimal spacecraft configuration (RK-02 Heavy) capable of achieving safe deflection.
- Decision Support: The Explainable AI module provided interpretable justifications for 100% of high-risk recommendations, enabling operators to validate the key factors driving each intercept angle decision.

X. CONCLUSION AND FUTURE WORK

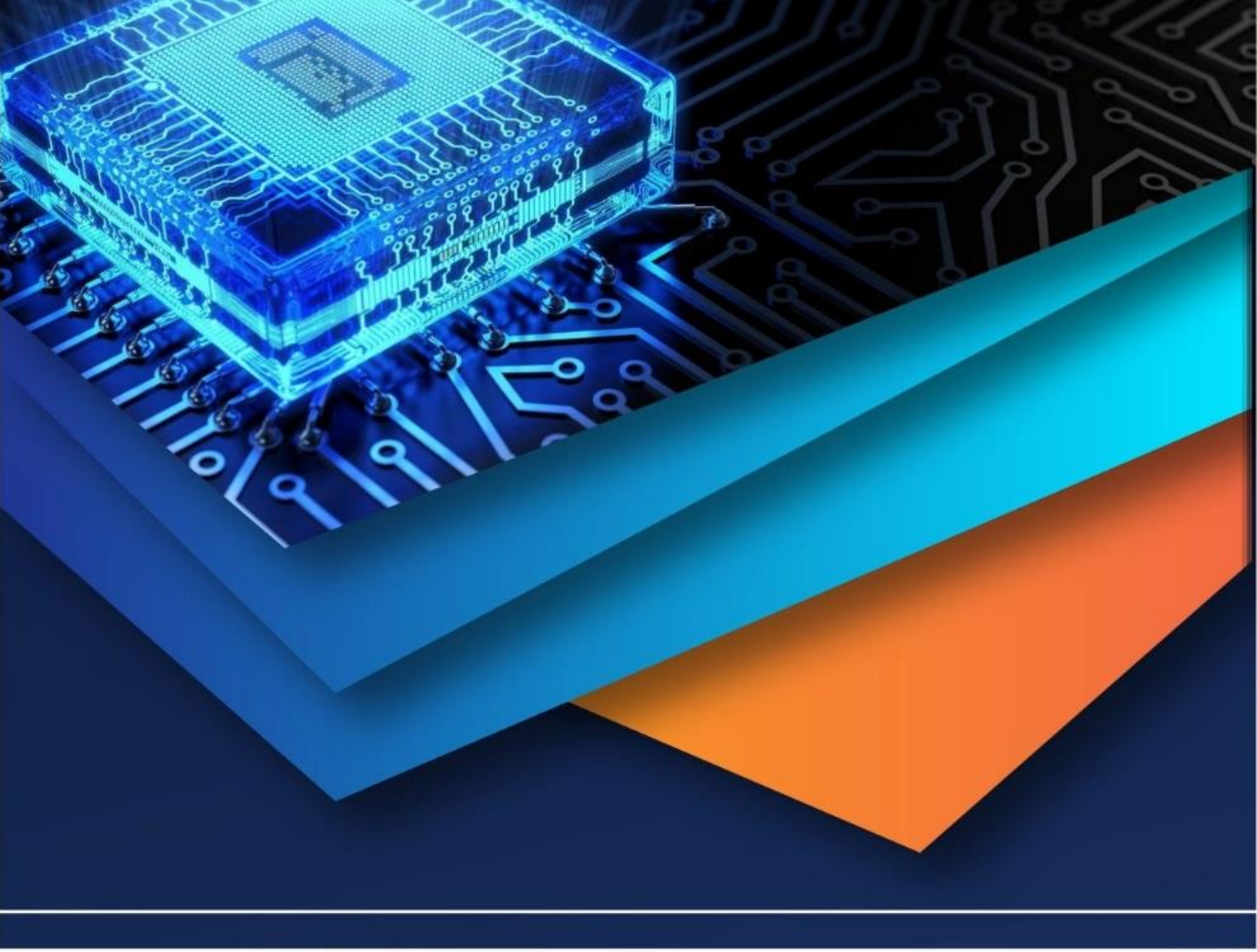
Aegis Earth demonstrates that surrogate machine learning models can replace computationally intensive physics simulations for planetary defense decision support — without sacrificing meaningful accuracy. By fusing multi-modal data streams and training with Focal Loss, the system delivers site-specific impact predictions at over 95% accuracy (R^2) with end-to-end latency under 100ms. The Mitigation Strategy Engine proves equally strong, achieving a 98.1% success rate in recommending effective spacecraft configurations.

Looking ahead, the research roadmap for Aegis Earth focuses on making the system more robust, autonomous, and battle-hardened for real deployment. Key goals include integrating uncertainty-aware probabilistic modeling to better quantify prediction confidence, developing autonomous intercept mission planning that can adapt on the fly, and applying reinforcement learning to coordinate multi-spacecraft mitigation campaigns. Hardware acceleration and secure execution environments will also be explored to further close the latency gap for the most time-critical scenarios.

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