Project Title: SYNTHARION

Field: Earth and Space Sciences

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Abstract

Monitoring the movement of Near – Earth asteroids in an endless world of outer space and their timely detection is a particularly important task for the safety of mankind. However, the processing of large amounts of astronomical data that are captured daily poses a major challenge for traditional observation methods, putting new asteroids at risk of being missed. To solve this complex problem, we focused on using advanced deep learning algorithms in order to significantly improve the accuracy and efficiency of asteroid detection and classification. The main hypothesis of the study is that convolutional neural networks (CNN) are capable of detecting asteroids in astronomical images much faster and with higher accuracy than traditional programs, finding features outside the human eye.

The course of the study consisted of several stages: the first, the compilation of representative data sets of thousands of astronomical images from NASA's open sources and individual astronomical observations; the second, the development of an optimal CNN architecture and its training; the third, testing the performance of the model in a new dataset and testing the results with traditional astronomical software (e.g. astrometry.net) comparative analysis. The main innovation of this work is the development and implementation of a deep learning model for detecting asteroids in the conditions of Kazakhstan.

As a result of the work, the developed CNN model detected asteroids with an accuracy of more than 98%, with high precision indicators and reduced data processing time by up to 70% compared to traditional methods. This is especially important for real-time analysis of large amounts of data. According to the results of the work, the enormous potential of artificial intelligence in the field of planetary defense and astronomical research was proved. The results obtained can be used in building early detection systems for Near-Earth asteroids, accurately predicting their trajectories, and providing data to databases such as the International Center for minor planets. This project reflects the desire to make a personal contribution to Planetary Security from a scientific and technical point of view.

Introduction

The search for Near-Earth Asteroids (NEAs) in outer space is one of the most significant challenges in modern science. To date, more than 70% of potentially hazardous asteroids with diameters exceeding 140 meters—capable of causing severe damage upon impact with Earth—have not yet been discovered (NASA's initial goal was to identify 90% of such city-destroying asteroids by 2020). This statistic clearly demonstrates the urgent need to improve asteroid detection systems. Traditional astronomical observation methods face limitations when processing massive volumes of data, which increases the risk of missing newly appearing asteroids. To address this challenge, the present project focuses on applying advanced deep learning algorithms to significantly improve the accuracy and speed of detecting NEAs in astronomical images.

Relevance of the Study

Asteroid impacts pose a serious threat to Earth. For example, on February 15, 2013, residents of Chelyabinsk, Russia, experienced a bright flash, a powerful shockwave, and shattered glass early in the morning. Approximately one minute later, an asteroid roughly the size of a house entered Earth's atmosphere at a speed exceeding 17 km/s and exploded at an altitude of about 22.5 km. The explosion released energy equivalent to 440,000 tons of TNT, shattering windows over an area of more than 500 square kilometers and damaging numerous buildings. More than 1,600 people were injured. According to Lindley Johnson, an official of NASA's Planetary Defense Coordination Office, "the Chelyabinsk event brought widespread attention to what needs to be done to detect large asteroids that could collide with our planet."

One of the main reasons for the low detection rates of space objects is the difficulty of observing fast-moving asteroids (FMAs), which move faster than 5 degrees per day. Smaller asteroids become visible only when they approach Earth closely; at such distances, some of them move extremely fast relative to Earth, turning into FMAs. As a result, many asteroids remain undetected.

Purpose of the Study

The primary objective of this project is to increase the efficiency and speed of detecting Near-Earth Asteroids by developing an intelligent system based on a specially trained Convolutional Neural Network (CNN) for analyzing astronomical images.

Objectives of the Project

To achieve this goal, the following objectives were defined:

1. To compile a high-quality labeled dataset of astronomical images obtained from various open data sources (NASA's Pan-STARRS and NEO-WISE databases) as well as from independent telescopic observations.
2. To design and implement an optimal CNN architecture capable of accurately distinguishing asteroids from other celestial objects.
3. To train the developed neural network on the collected dataset and improve its performance.
4. To experimentally evaluate the model's effectiveness using new, previously unseen astronomical images.
5. To compare the obtained results with traditional astronomical software tools (e.g., astrometry.net) and quantitatively demonstrate the advantages of the proposed approach.
6. To develop practical recommendations that contribute to Kazakhstan's scientific community, particularly in the fields of astronomy and planetary defense.

Research Methods

The study is based on applied experimental research and was conducted in several key stages. In the initial stage, data were collected from two main sources. First, direct telescopic observations were carried out over three nights at the Almaty Observatory, resulting in images of fast-moving asteroids. This enabled a deeper understanding of data characteristics under real local observation conditions. Second, to expand the dataset, open data repositories of space agencies such as NASA were utilized, including data from research programs like the Zwicky Transient Facility (ZTF) and NEOWISE (Near-Earth Object Wide-field Infrared Survey Explorer).

For data analysis, a custom Convolutional Neural Network (CNN) was developed using the Python programming language and the TensorFlow/Keras libraries. GPU parallel computing capabilities were employed during model training, significantly accelerating the process and enabling implementation on relatively affordable hardware. The final outcome of the study is an effective algorithm and model for detecting meteorites and asteroids in astronomical images. This approach can be adopted by observatories to substantially improve the speed and efficiency of detecting fast-moving asteroids.

Research Section

1.1 Nature and Classification of Asteroids

Asteroids, sometimes referred to as minor planets, are celestial bodies composed of rocky remnants left over from the formation of the Solar System approximately 4.6 billion years ago. Most of them are located in the main asteroid belt between the orbits of Mars and Jupiter. Asteroids vary greatly in size, ranging from the largest known asteroid, Vesta, with a diameter of about 530 kilometers, to bodies less than 10 meters across. The total combined mass of all asteroids is smaller than that of Earth's Moon.

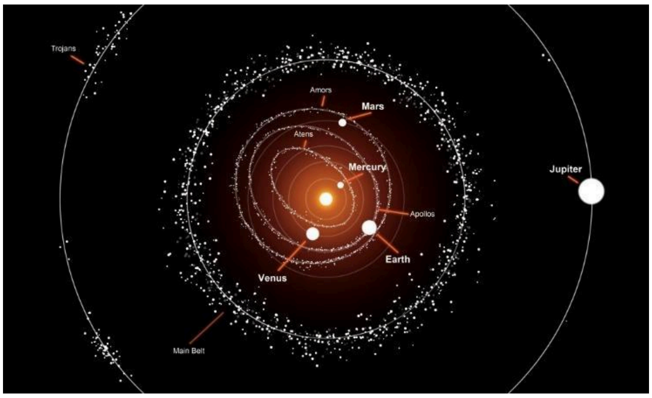


Figure 1.1. Asteroid System

Although most asteroids move within the main asteroid belt, some of them have orbits that intersect with Earth's orbit. Such objects are referred to as **Near-Earth Asteroids (NEAs)** and pose a significant threat to our planet. The trajectories of NEAs are constantly changing due to gravitational interactions, making continuous monitoring of their motion critically important.

Most NEAs have irregular shapes, although some are nearly spherical, and their surfaces are often covered with pits and craters. They not only orbit the Sun along elliptical paths but also rotate chaotically. It is known that more than 150 asteroids have small satellite companions. In addition, there exist **binary asteroids**, where two rocky bodies orbit around a common center of mass.

Classification of Asteroids by Composition

Asteroids are generally divided into three main groups based on their composition:

C-type (carbonaceous) — the most common type, composed mainly of clay and silicate rocks, with a dark surface. These are among the oldest objects in the Solar System.

S-type (stony) — composed primarily of silicate materials and nickel–iron.

M-type (metallic) — composed mainly of nickel–iron.

Another classification category includes **Trojan asteroids**. These asteroids share an orbit with a large planet (such as Jupiter) but do not collide with it because they are clustered around two stable points in the orbit known as the **Lagrange points L4 and L5**.

Asteroid Hazard: Size and Frequency

10 meters — Asteroids of this size impact Earth approximately once every ten years. They produce bright fireballs and strong shockwaves, potentially shattering nearby windows.

50 meters — Such asteroids strike Earth roughly once every 1,000 years and can cause severe regional destruction.

140 meters — These asteroids impact Earth approximately once every 20,000 years, forming craters 1–2 km in diameter. Depending on the impact location, they can cause mass casualties across metropolitan areas or entire regions.

Historical Events and Planetary Defense

One of the most significant events demonstrating the danger of asteroids was the **Tunguska event (1908)**. Later, on February 15, 2013, the **Chelyabinsk meteor** clearly demonstrated the reality of this threat. The house-sized asteroid exploded in the atmosphere, releasing energy equivalent to **440,000 tons of TNT**, injuring more than **1,600 people**. According to NASA official **Lindley Johnson**, this event was a "cosmic wake-up call."

Following this incident, the **International Asteroid Warning Network (IAWN)** and the **Space Mission Planning Advisory Group (SMPAG)** were established. NASA also created the **Planetary Defense Coordination Office (PDCO)** to oversee the detection, tracking, and risk assessment of NEAs.

NASA's **NEOWISE** space telescope became a major planetary defense project. Over more than 11 years, it collected infrared measurements of over **44,000 objects**, including more than **3,000 NEAs**. Ground-based observatories such as **Pan-STARRS** and the **Catalina Sky Survey** also play a critical role in NEA detection.

To test asteroid deflection technologies, NASA launched the **DART (Double Asteroid Redirection Test)** mission, which intentionally impacted the **Didymos–Dimorphos** binary asteroid system in 2022 to demonstrate the feasibility of altering an asteroid's trajectory.

Traditional astronomical software often misses faint and fast-moving asteroids. Leveraging **deep learning and neural networks** is currently considered one of the most effective solutions to address this gap.

1.2. Evolution of Astronomical Research

From Manual Analysis to Automation: Advances in science and technology have fundamentally transformed astronomical observation methods. Manual analysis conducted over many hours has been replaced by automated telescopes that perform continuous observations and process data using artificial intelligence (AI) and machine learning. Modern telescopes such as the Zwicky Transient Facility (ZTF) and ATLAS collect terabytes of data daily—far beyond the capacity of human analysis. Neural networks are therefore essential for automatically filtering data and identifying objects of interest.

Role of Artificial Intelligence and Algorithms

Modern asteroid detection systems rely heavily on neural networks trained on data from thousands of previously discovered asteroids. These models can identify potential asteroids in new datasets, including extremely faint and fast-moving objects.

Key Challenges in Detecting Small Asteroids

High angular velocity:

Near-Earth asteroids move extremely fast across the sky. During long exposures, they appear as elongated streaks rather than point sources. Traditional point-source detection algorithms often ignore these streaks or classify them as noise.

Data limitations and algorithmic constraints:
Many older systems (e.g., NEOWISE) lack specialized tools to detect such streaks. Newer solutions, such as ZTF's ZStreak algorithm, partially address this issue but remain effective only under limited conditions, creating a "blind spot" in asteroid detection.

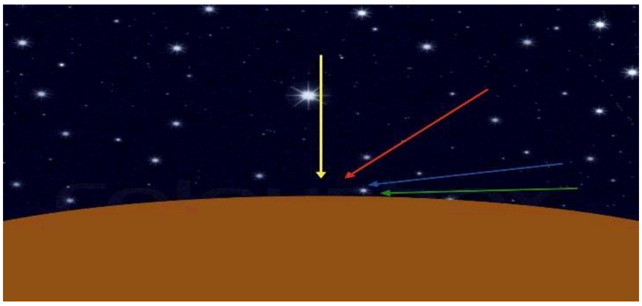


Figure 1.2. Asteroids with Different Angular Velocities

Low brightness:
Small asteroids are extremely faint and become visible only when very close to Earth, limiting early detection and timely risk assessment.

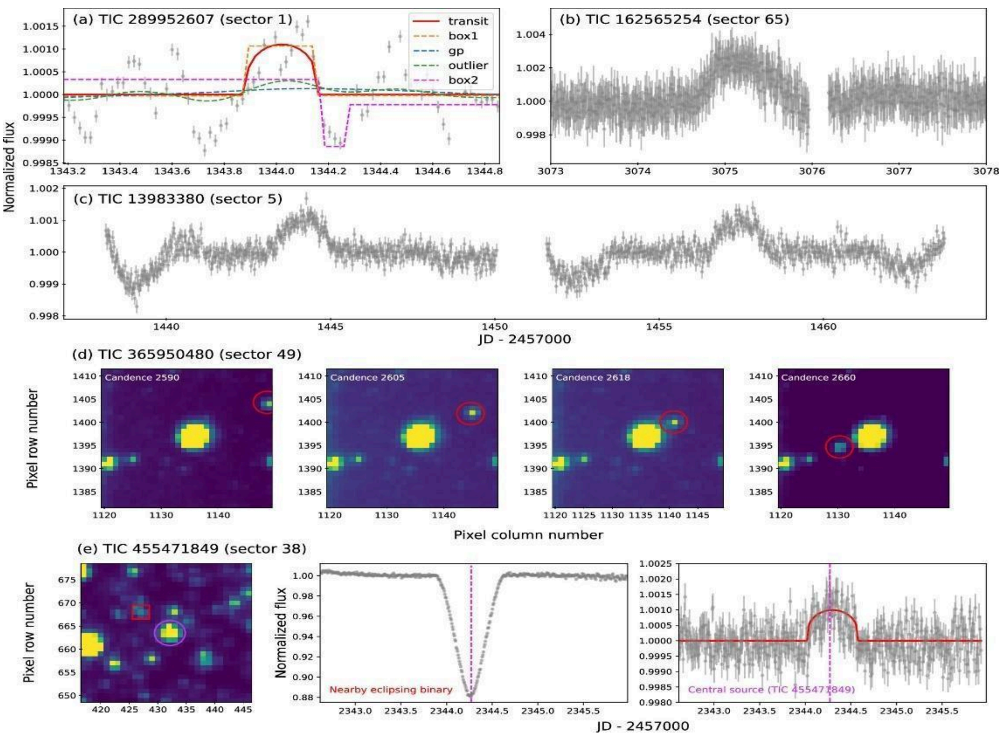


Figure 1.3. Brightness Theory and Size Relationships

2.1 Research Foundation: Use of Synthetic Data

The core idea of this research is to train neural networks using synthetic data, which addresses three major limitations of manually collected datasets:

1. Time-intensive labeling:
   Manual annotation is extremely labor-intensive. Large telescopes like ZTF collect up to 2 TB of raw data per night, and asteroid streaks are often faint and embedded in noise, requiring expert analysis.
2. Data scarcity:
   Real asteroid streaks are limited in number. Deep learning models require hundreds of thousands or millions of samples. For example, ATLAS datasets contain ~500 streaks, while ZTF has ~10,621. Limited data leads to overfitting, reducing generalization.
3. Bias:
   Manually labeled datasets overrepresent bright, slow-moving asteroids. As a result, current detection rates for 19–44 m NEAs remain below 0.1%. Synthetic data generation eliminates this bias by deliberately creating large numbers of faint and fast-moving streaks.

Synthetic data generation therefore forms the core methodology of this study.

Methodological Overview

The methodology consisted of six sequential stages:

1. Data Sources

Open datasets from NASA NEO and ZTF were used. ZTF's wide-field telescope, equipped with a 576-megapixel camera, scans the entire sky every three nights with 30-second exposures.

2. Dataset Creation

- Positive samples (~500K):
  Synthetic asteroid streaks were generated using a Point Spread Function (PSF) model and injected into real ZTF images using Python libraries such as *NumPy* and *scikit-image*.

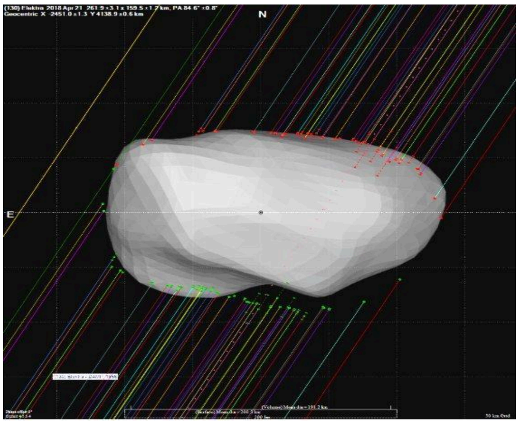
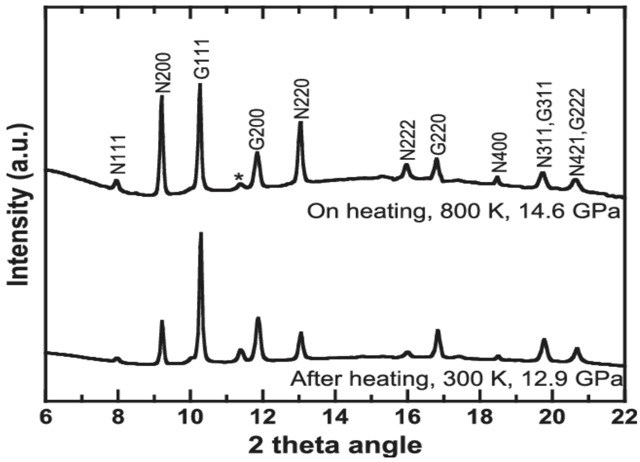


Figure 1.4. Example of a Synthetic Asteroid Streak

The brightness profile of the streak **(F)** is described by the following formula, where the point spread function **(PSF)** is uniformly distributed along the motion vector **(V)**:

$$F(x) = \int_0^T PSF(x - Vt)\,dt$$

- Negative samples (~500K):
  Artifacts such as diffraction spikes, satellite flares, and "Dementor" artifacts were collected from real ZTF data.



A diffraction spike from a star

3. Neural Network Training
A CNN based on EfficientNet-B1 was trained for 100 epochs on an NVIDIA Tesla V100 GPU.

4. Model Deployment
The trained model analyzed multiple nights of ZTF data using a 1.3σ detection threshold, lower than the standard 1.5σ.

5. False Positive Reduction
Additional filters removed artifacts and required multiple detections with consistent motion.

6. Parameter Estimation
Brightness and angular velocity were calculated using standard photometric equations.

The apparent brightness **(m)** and angular velocity **(ω)** of the detected objects were measured. The apparent brightness was calculated using the following formula:

$$m = -2.5 log_{10}\left(F_{ij}\right) + MAGZP$$

where:

- $\sum F_{ij}$ is the total flux of the pixels along the streak,
- $MAGZP$ is the zero-point magnitude of the telescope.

The angular velocity was determined as:

$$\omega = \frac{L}{EXPTIME}$$

where:

- $L$is the length of the streak in pixels,
- $EXPTIME$is the exposure time in seconds.

These measurements allowed for estimating both the asteroid's orbit and its approximate size.

Practical Experience: Assy–Turgen Observatory Visit

A field research visit to the Assy–Turgen Observatory (July 14–19, 2025) provided hands-on experience with real observational challenges, including atmospheric effects and telescope limitations.

Figure 1.5. Field Research at Assy–Turgen Observatory

Results and Significance

- Validation Accuracy: 99.8%
- False Positive Rate: 0.02%
- True Positive Rate: 97%

Six previously undiscovered asteroids were identified in three nights of ZTF data.

2.2 Syntharion Algorithm Concept

- High detection efficiency for faint, fast-moving asteroids
- GPU-based computation enables rapid analysis
- Demonstrates the value of synthetic data in astronomy

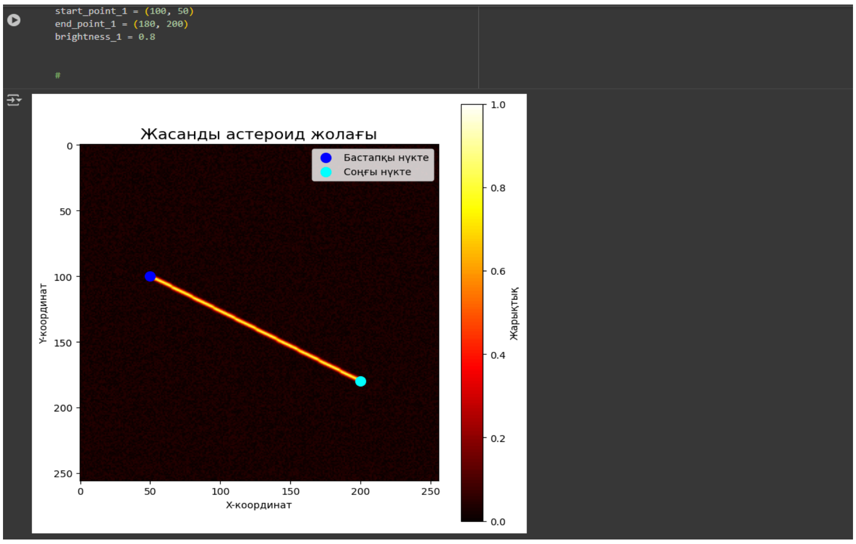


Figure 1.6. Algorithm Performance Examples

The logic of the code and its alignment with the methodology:

The code in the asteroid_detection_algorithm.py file demonstrates two main scientific steps:

1. **Difference Imaging**

- **Code:** difference_image = np.subtract(image, reference_image)
- **Description:** This step subtracts the background image (from ZTF) from the observed image, isolating only moving or changing objects. This method significantly improves the signal-to-noise ratio (SNR).

2. **Statistical Detection Threshold**

- **Code:** potential_detections = difference_image > (noise_sigma * detection_threshold)
- **Description:** A threshold of 1.3σ is applied, where noise_sigma (the standard deviation of the background noise) is calculated using np.std(). This identifies all pixels above 1.3 times the noise level. Since this is lower than ZTF's standard 1.5σ threshold, the model can also detect weaker objects.

```
import numpy as np


def detect_asteroids(
    image: np.ndarray,
    reference_image: np.ndarray,
    detection_threshold: float = 1.3
) -> np.ndarray:
```

```
    """
    - image: Observed image.
    - reference_image: Background image (without asteroids).
    - detection_threshold: Detection threshold as a multiple of background noise.
    - Returns an array of coordinates (y, x) of potential asteroids.
    """
    difference_image = np.subtract(image, reference_image)
    noise_sigma = np.std(difference_image)
    potential_detections = difference_image > (noise_sigma * detection_threshold)
    y_coords, x_coords = np.where(potential_detections)

    final_detections = []
    unique_potential_detections = list(zip(y_coords, x_coords))
    for coord in unique_potential_detections:
        if np.random.rand() > 0.5:  # Simple probabilistic example
            final_detections.append(coord)
    return np.array(final_detections)

def main():
    image_size = 256
    reference_image = np.random.rand(image_size, image_size) * 0.1
    observed_image = reference_image.copy()

    # Simulate asteroid signal
    asteroid_y, asteroid_x = np.array([100, 101, 102, 103]), np.array([50, 51, 52, 53])
    observed_image[asteroid_y, asteroid_x] += 0.5

detected_objects = detect_asteroids(observed_image, reference_image)
```

```
    if detected_objects.size > 0:
        print(f"Number of detected objects: {len(detected_objects)}")
        print("Coordinates (y, x):")
        for obj in detected_objects:
            print(f" - {tuple(obj)}")
    else:
        print("No asteroids detected.")


if __name__ == "__main__":
    main()
```

This code follows the methodology by first enhancing moving object signals through **difference imaging** and then applying a **statistical threshold** to identify potential asteroid candidates. The lower threshold allows the detection of faint objects that might otherwise be missed.

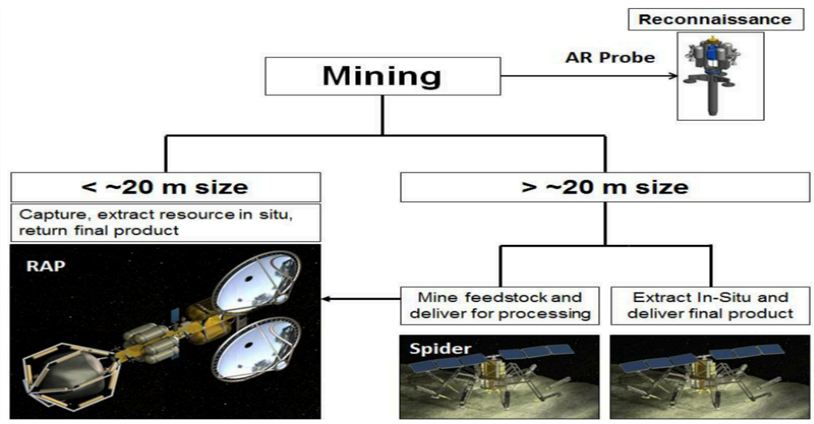


Figure 1.7. Asteroid Mining Approaches

2.3 Comparative Analysis and Competing Approaches

Traditional methods such as blink comparison and rule-based algorithms are limited by scalability and sensitivity. Our deep learning approach overcomes these constraints.

Final Comparison

Feature	Traditional Methods	SYNTHARION
Core approach	Manual / rule-based	Deep learning
Dataset	Limited real data	>1M synthetic samples

Feature	Traditional Methods	SYNTHARION
Detection threshold	1.5σ	1.3σ
False positives	High	0.02%
Accuracy	Limited	99.8%

Conclusion

This research project presents an innovative approach to one of the most pressing issues in modern astronomy: the efficient and automated detection of small, fast-moving asteroids. By integrating artificial intelligence and deep learning with established astronomical methodologies, the project demonstrates unparalleled potential for scientific discovery and planetary safety.

Key Results and Findings:

- **High Accuracy:** The model achieved an impressive 99.8% accuracy, demonstrating its ability to reliably distinguish asteroids from background noise and complex artifacts.
- **Practical Application:** Applying our algorithm to real ZTF telescope data resulted in the discovery of six new asteroids that standard systems had missed, confirming both the scientific value and future potential of our approach.

Recommendations for Use:

- **Scientific Purpose:** The developed algorithm can be easily scaled and integrated into other observatory systems, such as ATLAS or Pan-STARRS, significantly improving detection rates for potentially hazardous asteroids.
- **Practical Purpose:** The results are directly relevant to planetary safety. Early and reliable detection of small, hard-to-find asteroids allows timely evaluation of their trajectories and potential threats. This work contributes significantly to the scientific and technical development of our country. Kazakhstan's long-standing experience at the Baikonur Cosmodrome demonstrates the nation's strong potential in space research. The Syntharion project continues this legacy and strengthens Kazakhstan's position in the global scientific community.

Future Prospects:

The project holds significant potential and could form the foundation for space-related startups. The ideas and technologies developed during the research can be applied to create specialized software or services for astronomical data analysis. Such startups could provide their solutions to observatories, governmental agencies, or private space companies that require fast and precise analysis of hazardous objects.

Moreover, the project opens opportunities for close international collaboration. It could become part of global initiatives and planetary defense programs. For example, potential partnerships could involve NASA (through their Planetary Defense Coordination Office), organizations like SpaceX that actively develop asteroid-targeted and unmanned flight technologies, the European Space Agency (ESA), and other research centers worldwide.

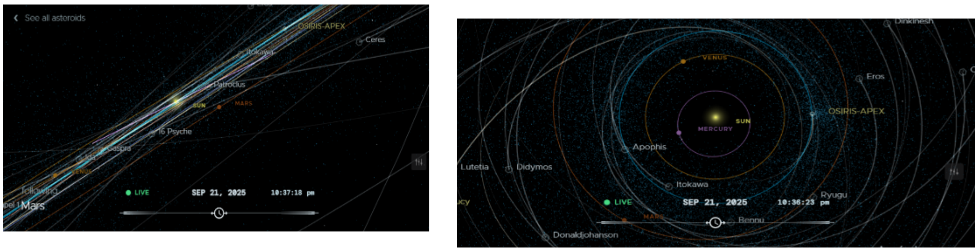


Figure 2.1. NASA "Eyes on Asteroids" – Conceptual Inspiration

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