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Leveraging Machine Learning To Improve A Asteroid Detection For Collision Impact Mitigation

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Abstract: Asteroid discovery is crucial in planetary defense and astronomy science, particularly in the mitigation of potential collision hazards. Traditional computer vision and manual observation are applied in classical detection, which is intensive and may be less precise. In this paper, we propose a deep learning-based approach with TernausNet, an extension of U-Net, to improve asteroid streak detection in astronomical images. Our methodology is to preprocess ESO Phase 3 SCIENCE datasets and train a neural network to locate asteroids. Since we do not have annotated datasets, we manually label a portion of the images to create a training set. We compare the performance of the model against different datasets to test robustness and accuracy. Preliminary results indicate that the proposed approach improves detection efficiency by reducing false positives and optimizing recall rates. This paper demonstrates the potential of deep learning to automate and improve asteroid detection for collision impact mitigation and future space mission exploration.

Keywords: Asteroid Detection, Deep learning, TernausNet, Astronomical imaging, ESO, FITS preprocessing, Planetary defense

I. Introduction

Asteroids within our solar system, especially near-Earth asteroids (NEAs), are of significant scientific and utilitarian interest because of their potential impact on planetary defense, the evolution of the solar system, and space resource utilization. NEAs are minor rocky objects whose orbits cause them to approach the orbit of Earth, and they pose a very serious potential hazard in the case of an impact. Cataloging and mapping these bodies are important for the prediction of their impact and prevention strategies (Harris & D'Abramo 2015; Chesley et al. 2004).

A variety of ground- and space-borne surveys such as Pan-STARRS (Kaiser et al. 2002), Catalina Sky Survey (Larson et al. 2003), and NEOWISE (Mainzer et al. 2011) have been instrumental in discovering and cataloging NEAs. As of 2024, more than 32,000 NEAs have been found, with hundreds of new objects being added every month. Yet, in spite of this advancement, a large number of small and high-speed objects are still not detected. Such objects tend to be faint, elongated streaks in telescope images, particularly when short exposure times are used, and thus are difficult to detect using conventional image processing or by eye (Vereš et al. 2012; Waszczak et al. 2017).

The issue is compounded by the ever-growing data volumes created by contemporary wide-field surveys. The Vera C. Rubin Observatory, for instance, will generate tens of terabytes of image data every night (Ivezić et al. 2019), which will overwhelm the capacity of traditional detection algorithms. Thus, there is a heightened demand for scalable, automated, and robust systems capable of processing large astronomical datasets in real time and correctly locating moving objects.

Machine learning, especially deep learning methods like convolutional neural networks (CNNs), have been promising ways to tackle these issues in the past few years. CNNs are able to learn sophisticated spatial features from the raw image data, allowing high-accuracy classification and segmentation of astronomical objects. ResNet (He et al. 2016), VGG (Simonyan & Zisserman 2014), and DenseNet (Huang et al. 2017) are examples of models that have been effectively used in astronomy for various tasks including galaxy morphology classification and transient detection. Deep learning for the particular purpose of asteroid streak detection is still under investigation.

In this paper, we suggest a deep learning–based approach for the detection of asteroid streaks in astronomical images based on a variant of U-Net architecture known as TernausNet that has been reported to work well for segmenting faint or intricate structures. Our model is trained and tested on a blend of datasets, including high-resolution images captured by the DRACO camera on board NASA's Double Asteroid Redirection Test mission (Cheng et al. 2018) and archival FITS images from the European Southern Observatory's (ESO) Phase 3 SCIENCE.IMAGE repository.

Since there are no publicly labeled streak datasets, we generate a manually annotated dataset by labeling asteroid streaks in a portion of the images. The annotations are subsequently employed to train our model to segment possible asteroid streaks and obtain their RA and Dec coordinates. To benchmark performance, we compare TernausNet against baseline CNN architectures (VGG6, ResNet50, and DenseNet121) in terms of several metrics: precision, recall, F1-score, and Intersection over Union (IoU).

The ultimate goal of this research is to show the effectiveness of deep learning–based streak detection models in enhancing the efficiency, sensitivity, and accuracy of asteroid discovery pipelines. Our research helps develop intelligent systems that can complement current asteroid surveys and perhaps assist real-time hazard detection for planetary defense missions.

2. RELATED STUDY

The article by Irureta-Goyena et al. (2025) addresses an automated pipeline for the identification of asteroid trails in OmegaCAM images on the VST. The pipeline uses a convolutional neural network (CNN) trained on synthetic asteroid trails of 5 to 120 pixels and signal-to-noise ratios (S/N) of 3 to 20. The CNN was found to be 70% complete for trails of 15 pixels and longer, and 82% precise when it was tested on synthetic data, although it showed a completeness of 65% and a precision of 44% on real data. The lower precision on real data is due to contamination and the presence of stars in the field. The technique has great promise for the discovery and recovery of asteroids, especially lower S/N ratio asteroids, in VST data.

Ensemble learning has been widely applied in the detection of asteroids to enhance accuracy and minimize false positives. Deep learning models like the Random Forest classifier (Waszczak et al., 2017) and CNN-based models (Lieu et al., 2019) have been effective but are prone to overfitting and imbalanced datasets. Urechiatu et al. (2023) have created an ensemble model blending ResNet-50, Inception, and Xception, which recovers 55% of lost asteroids and increases the detection capability of NEARBY from 89% to 95%, showing the potential of deep learning in automated detection of asteroids.

Deep learning for asteroid classification raises some issues like limited datasets, noise interference, and high-accuracy model demands. Bacu et al. (2023) evaluated deep CNN performance on the automation of asteroid classification with the capability of enhancing detection precision. Yet their work also portrays challenges like detecting faint streaks of asteroids as opposed to noise background and their reliance on highly quality-labeled data. The study emphasizes the need for sophisticated preprocessing methods and strong model structures to increase detection accuracy. The research is part of ongoing efforts in optimizing machine learning techniques for asteroid categorization and space object recognition.

With the application of machine learning (ML) in the study of asteroids, there has been an improvement in methods of deciphering their orbits, classifying them, and forecasting impacts. Carruba et al. (2022) explain how ML methods assist us in understanding asteroid motion better by identifying patterns in massive datasets that other methods overlook. In their research, they propose the advantage of supervised and unsupervised learning in classifying asteroid families and forecasting their actions more precisely. But there remain significant challenges such as limited data, interpretability of the model, and high computational expense. The research proposes that ML can significantly improve the way we monitor and evaluate the danger posed by asteroids, contributing to improved planetary defense systems.

Innovation in onboard processing methods has assisted greatly in detecting and characterizing asteroids, especially in small-scale missions like the Near Earth Asteroid (NEA) Scout. Lightholder et al. (2019) explained the limitations of CubeSats, such as limited bandwidth and computational capabilities, and suggested onboard image processing methods to improve the detection of asteroids. Conventional methods rely on heavy ground analysis of large spacecraft, which is not feasible in small interplanetary missions. NEA Scout utilizes real-time image calibration, noise reduction, and coaddition methods to improve signal-to-noise ratio without using long exposure imaging, according to Castillo-Rogez et al. (2019). These methods allow for timely target detection, improve navigation accuracy, and make data transmission in deep space mission efficient (Thompson et al., 2019). Such innovations open avenues for future interplanetary small-scale missions and demonstrate the capability of autonomous onboard processing in the detection and exploration of asteroids.

3. METHODOLOGY

3.1 Methodology

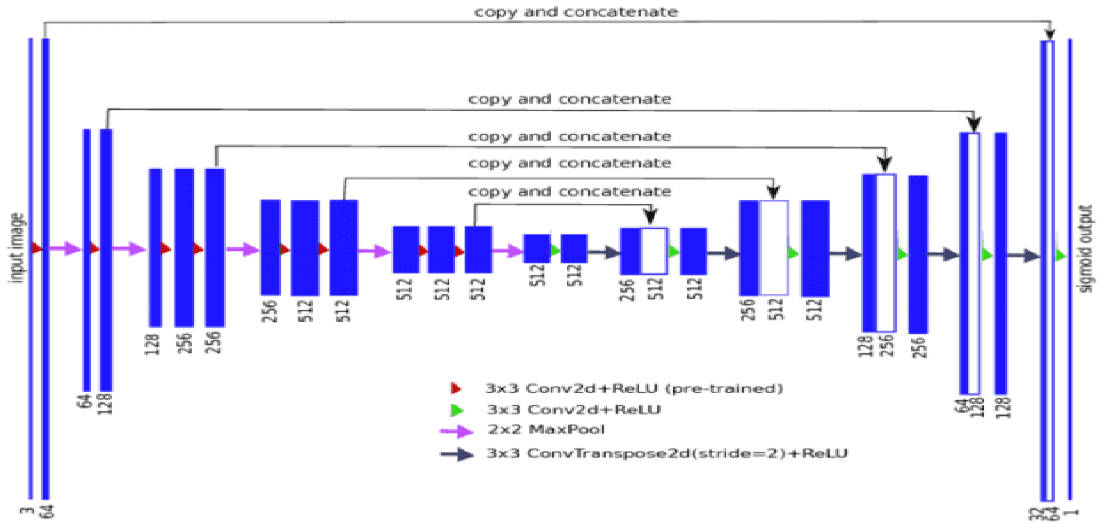


Figure 3.1: Overview of TERNAUSNET model [9]

The methodology adopted here is focused on applying a high-performance deep learning-based segmentation model, TernausNet, to precise identification of asteroid streaks from images of astrophotography. Asteroid streaks are subtle, long traces in high-resolution images captured by space telescopes. Their subtlety, complexity, and presence of noise in astrophysical data made pixel-wise segmentation superior to employing traditional object detection techniques. TernausNet was employed due to its superior ability to perform semantic segmentation, where every pixel in an image is assigned a class labelmost appropriate to identify thin streak-like structures against complex backgrounds.

TernausNet is a variant of the widely used U-Net architecture, originally created for biomedical image segmentation. TernausNet adheres to the encoder-decoder structure typical of U-Net but employs pre-trained VGG11 or VGG16 ImageNet weights for the encoder. This integration enables TernausNet to employ transfer learning such that it can learn to extract informative hierarchical features even from comparatively small training sets, a typical weakness of astronomical imaging. The encoder, or contracting path, consists of a series of convolutional layers with ReLU activations and max-pooling layers. These layers progressively down sample the input image and extract progressively abstract featuresfrom low-level textures and edges to high-level object structures.

The decoder or expansion pathway is a mirror structure of the encoder but doing up sampling rather than down sampling. It recovers lost spatial resolution at encoding using skip connections and transposed convolutions. Skip connections are essential since they combine high-resolution features of the encoder with the up sampled features in the decoder. This combination allows the model to maintain spatial precision and recover fine details, which are essential in detecting thin asteroid trails that would otherwise be lost due to down sampling.

Some of TernausNet's core architectural features make it particularly well suited to asteroid detection. The use of a pre-trained backbone enhances the model's capabilities to generalize even from sparsely available training examples, especially when training examples identified as asteroid streaks are limited. Its pixel-wise segmentation capability enables the model to differentiate between background noise or stars and asteroid streaks, thus generating accurate binary masks even where there may be very poor signal-to-noise ratios. Such capability is critical where processing space images may entail very poor signal-to-noise ratios. Additionally, efficient learning characteristics inherent in the architecture enable aggressive performance without significant computational resources as well as exhaustive annotated datasets.

TernausNet was adapted in this study to be used for astronomical FITS files, which were preprocessed initially and then converted to 2D image arrays for training models. The images were labeled manually to obtain ground truth segmentation masks indicating the location of the asteroid streaks. The data set was split into training, validation, and test sets. Data augmentation methods such as rotation, flipping, and contrast change were employed to achieve the highest possible diversity of training examples and make the model resilient.

Beyond asteroid detection, TernausNet has been shown effective in other use cases such as biomedical imaging (e.g., lung segmentation, surgical instrument detection), satellite and remote sensing, industrial defect detection, and beyond. In the field of astronomy, its ability to detect linear features not only makes it particularly effective at asteroid detection but also adaptable to repurposing in the detection of comet trails, star trails, and other transient phenomena. This multi-domain use further makes it suitable to the selection of TernausNet for our purpose, as it provides us with a solid foundation for future work expansion of this research to broader astronomical object detection. In total, this approach takes advantage of the ability of a pre-trained encoder, spatially aware skip connections, and a successful segmentation architecture to address the challenging task of asteroid detection from space imagery. Through successful conversion of

TernausNet to handle the typical challenges of astrophysical data, this research paves the way for more accurate and independent asteroid tracking systems that can aid planetary defense initiatives.

Feature Extraction and Representation Learning

deep convolutional neural network (CNN) is utilized for hierarchical feature extraction of the input astronomical images. The network is capable of efficiently extracting low-level structural features and high-level semantic features and can perform efficient discrimination between asteroid streaks and background noise. The feature maps that are derived through this are depicted below (1):

$$F = f(I; \theta) \tag{1}$$

Where $f(\cdot)$ the CNN feature extractor is parameterized by, which consumes the input astronomical image and outputs a feature representation F. The feature maps used here capture both texture and context information and enable good discrimination among asteroids and other bodies.

To enhance feature learning, similarity measurement is also used in the training stage. Similarity measurement still makes feature embedding of streaks discernible from noise. Besides that, attention mechanisms are employed to highlight significant regions and downplay minor details, overcoming common problems such as noise and varying illumination in astrophotography images.

Feature Fusion and Classification

After feature extraction from input images, an asteroid detection accuracy is improved by a feature fusion operation. Feature fusion is performed by an element-wise subtraction and concatenation operation and is represented by (2):

$$C(F_1, F_2) = F_1 - F_2 \oplus F_1, F_2 \tag{2}$$

where F_1 and F_2 are maps of different convolutional layers, and $\oplus$ is the concatenation operation. This policy of fusion assists in highlighting variation over asteroid streaks without allowing static background areas.

Following fusion, the classification module applies fully connected layers and a ReLU activation function to the asteroid streak positions. The classification function is as follows (3):

$$M = \sigma(WC(F_1, F_2) + b) \tag{3}$$

where W and b are the fully connected weight matrix and bias, and is the activation function. The ReLU function can be shown as in (4):

$$\mathrm{ReLU}(x) = \max(0,\ x) \tag{4}$$

This process of classification yields accurate segmentation of asteroid streaks and minimizes false positives and false negatives.

3.2 Dataset

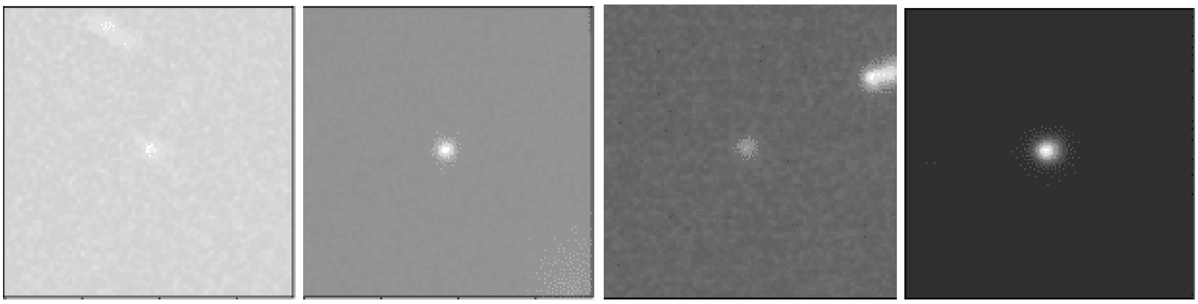


Fig. 3.2 Examples of different images with varying background intensity and noise.

Figure 3.2 illustrates examples of various astronomical images with differing background intensities and levels of noise, emphasizing the complexity of real-world data used for asteroid detection. Data utilized in this study comes from real astronomical observations and is employed to train and test the proposed deep learning model to identify asteroids. Since detection of asteroid streaks must be conducted using high-resolution image data capable of observing moving celestial objects, meticulous care has been given to data selection, data preprocessing, and data structuring.

The primary dataset consists of images obtained from a range of sources, such as publicly available astronomical data, including the DART DRACO dataset and ESO Phase 3 Archive images. The datasets contain ground- and space-based telescopic observations, offering diverse characteristics in terms of image resolution, scale, and noise. The DART DRACO images, obtained by the Didymos Reconnaissance and Asteroid Camera for Optical Navigation, are particularly ideal for this study since they are high-fidelity images and NASA's planetary defense mission.

All the original astronomical images were kept in FITS (Flexible Image Transport System) format, which was a format commonly used in astronomy for storing tabular and image data. For deep learning libraries such as TensorFlow, however, the FITS files were preprocessed and transformed to 2D grayscale image arrays initially. Pixel intensities were normalized, unnecessary background noise was removed, and contrast was enhanced to enhance faint streaks of asteroids.

Following preprocessing, the data were divided into three sets: training, validation, and test. The training set was used for model training, the validation set was used for hyper parameter tuning and prevention of overfitting, and the test set was reserved for testing the final model. The division was stratified in such a way that each subset represented a fraction of images with varying noise levels, background clutter, and asteroid streak appearances.

Since there was no labeled dataset for asteroid streak segmentation available, this work assumed the responsibility to carry out manual annotation. These masks were binary images of the same resolution as the input image, with pixels corresponding to asteroid streaks tagged as foreground and the others as background. Although time-consuming, this manual tagging was needed to generate quality training data, especially because publicly available pixel-wise annotations for this task are non-existent.

To enhance the model's generalization ability and robustness, data augmentation methods were also used. These encompassed random rotations, horizontal and vertical flip, shift in contrast, and shift by a small amount. These augmentations simulated variation in asteroid orientation and brightness, and observation conditions and allowed the model to learn discriminative and invariant features. In short, the data set of the present study was laboriously acquired from real-world astronomical observations, preprocessed to more clearly disclose asteroid streaks, and annotated manually to provide high-quality segmentation masks. The combination of real-world data, expert labels, and augmentation processes facilitated the construction of a robust and representative data set, necessary for the successful training and evaluation of the introduced deep learning model.

3.3 Proposed Methodology

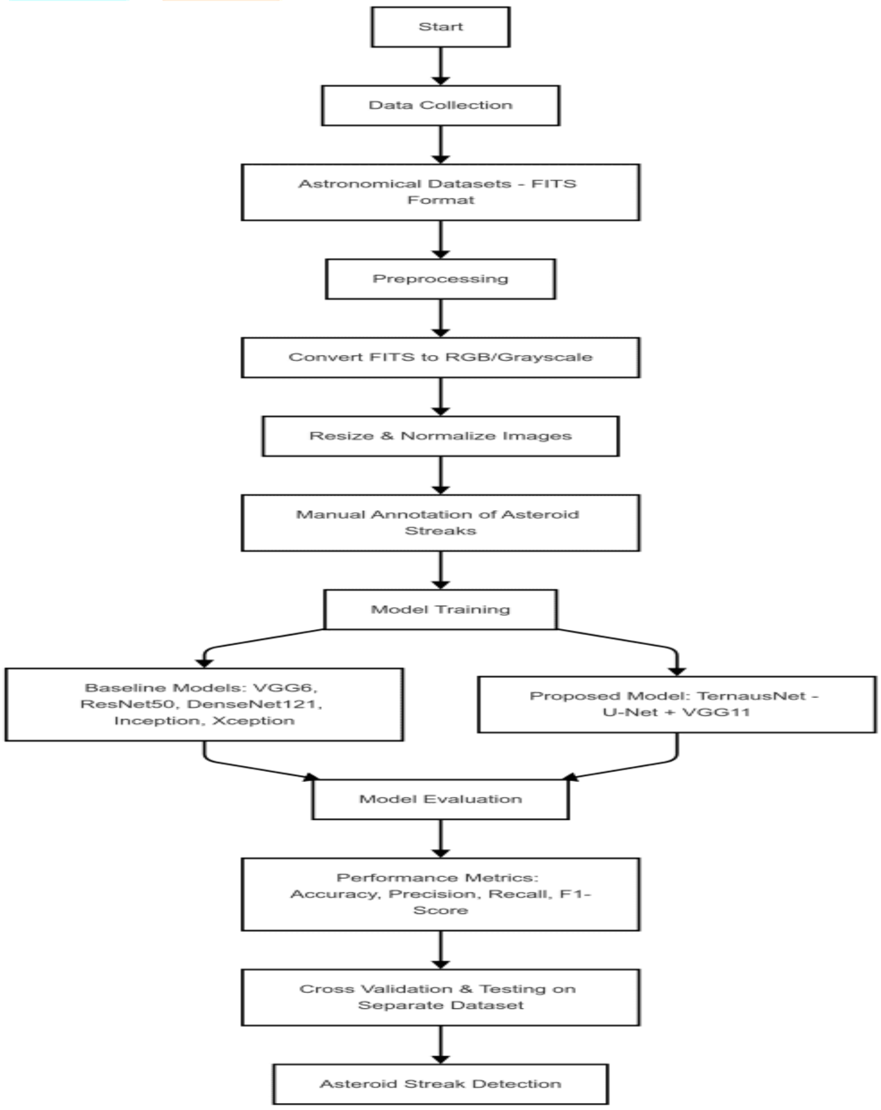


Figure 3.3: Proposed Methodology

This article introduces a formalized pipeline to detect asteroid streaks from astronomical images based on deep learning Figure 3.3 presents an overview of the proposed methodology, Data gathering, preprocessing, training, and testing are the key stages of the methodology that culminate in asteroid streak detection. Every stage is specifically tailored to deal with the difficulties arising from the nature of astronomical data along with the requirements specific to asteroid detection.

1. Data Collection

The first step involves acquiring high-quality astronomical images stored in the Flexible Image Transport System (FITS) format. FITS is a standard data format used in astrophysics that encapsulates image data along with rich metadata, including celestial coordinate systems, exposure times, and instrument details. The selected datasets contain long-exposure images from astronomical surveys, which are ideal for capturing the motion-induced streaks of asteroids across the sensor's field of view.

2. Preprocessing

Given the complexity of FITS files and their incompatibility with standard deep learning pipelines, a rigorous preprocessing stage is essential.

FITS to RGB/Grayscale Conversion: FITS images are converted to 8-bit or 16-bit grayscale or RGB formats. This transformation retains key visual features while enabling compatibility with convolutional neural networks (CNNs).

Image Resizing and Normalization: The converted images are resized to fixed dimensions (e.g., 256×256 or 512×512 pixels) to match the input size requirements of neural networks. Furthermore, pixel intensities are normalized either scaled between 0 and 1 or standardized to reduce the impact of illumination differences and facilitate faster convergence during training.

Manual Annotation of Asteroid Streaks: Due to the lack of publicly available labeled datasets for asteroid streak detection, manual annotation is performed on a subset of images. Annotators identify and mark streaks that resemble asteroid trails, producing ground truth masks or bounding boxes. These labels are later used for training supervised models.

3. Model Training

A variety of deep learning architectures are explored to learn patterns and features associated with asteroid streaks. The goal is to compare traditional CNNs with a specialized segmentation model.

Baseline Models: Several established CNN models are used as baselines:

1. **ResNet50:** Incorporates residual connections to address the vanishing gradient problem and improve learning in deeper networks.
2. **DenseNet121:** Utilizes dense connectivity, where each layer receives input from all previous layers, promoting feature reuse and efficiency.
3. **Inception:** Processes the input at multiple receptive fields using parallel convolutions of various kernel sizes, capturing multi-scale features.
4. **Xception:** Builds on the Inception architecture using depth wise separable convolutions, resulting in a lightweight yet powerful model.

Proposed Model TernausNet: The core of the methodology is TernausNet, a semantic segmentation model that integrates the encoder of VGG11 into a U-Net-like architecture. U-Net is particularly effective for tasks requiring pixel-level classification, such as streak segmentation, due to its symmetric encoder-decoder design and skip connections. TernausNet enhances this design by using pertained VGG weights for the encoder, improving feature extraction on limited data. Each model is trained using the annotated dataset, with data augmentation techniques (e.g., rotation, flipping, zooming) applied to improve generalization.

4. Model Evaluation

Once the models have trained, they will be evaluated to discover how well they were able to detect streaks.

- **Accuracy:** This is the overall proportion of predicted pixels or streaks that were correct.
- **Precision:** How many of the detected streaks were true asteroid trails (minimizing false positives).
- **Recall:** How many of the true asteroid trails were detected (minimizing false negatives).
- **F1-Score:** This measures the tradeoff between precision and recall; particularly important in the case of imbalanced data, where the number of background pixels outnumber streak pixels.
- **Cross-validation and Testing:** In order to establish the robustness of the models, k-fold cross-validation will be conducted. This method works by creating k subsets of

the data to test the model by iteratively using one as a validation set with the remainder of the data to train. The performance will also be validated on a completely separate test dataset for a more realistic application to ensure the robustness of the model.

5. Asteroid Streak Detection

After evaluation of the relevant models, the best performing model will be used to detect asteroid streaks from unexamined astronomical images. The model will predict either segmentation masks or bounding boxes to outline detected streaks. The identified objects will undergo post-processing techniques through thresholding, contour searching, and morphological processes to classify detections and reduce false positives.

4. Experimental Result

This section presents the output of our asteroid detection model. It employs TernausNet, a deep learning encoder-decoder model architecture, to enhance feature extraction and detection performance. The model was validated with a real dataset of 2000 images with equal training, validation, and test set splits. Different performance metrics like Accuracy, Precision, Recall, F1-score, ROC curve, and Confusion Matrix were utilized to evaluate the performance. Comparative analysis with other CNN-based models like InceptionV3, Xception, ResNet50, and DenseNet121 was performed to evaluate the effectiveness of TernausNet.

4.1.1 Experiment Data and Evaluation Criteria

The dataset consists of 2000 two-class labeled images: Asteroid and Not Asteroid. Data augmentation and preprocessing have been done using ZScale normalization. The used evaluation metrics are:

Accuracy: Proportion of correct pridiction.

Pricision: Ability to correctly identify actual positives.

Recall: Ability to recognize all true positives.

F1 Score: The harmonic mean of Recall and Precision.

ROC Curve: Visual display of model sensitivity.

Confusion Matrix: Decomposing true/false positives/negatives.

4.1.2 Training Progress Over Epochs

Epoch	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
1	0.53	0.66	0.13	0.23
2	0.58	0.88	0.18	0.30
3	0.60	0.90	0.20	0.34
4	0.62	0.94	0.24	0.39
5	0.65	0.95	0.31	0.47
6	0.77	0.97	0.41	0.58
7	0.80	0.99	0.47	0.64
8	0.85	0.99	0.56	0.72
9	0.90	0.99	0.61	0.76
10	0.99	0.99	0.67	0.80

4.1.3 Confusion Matrix

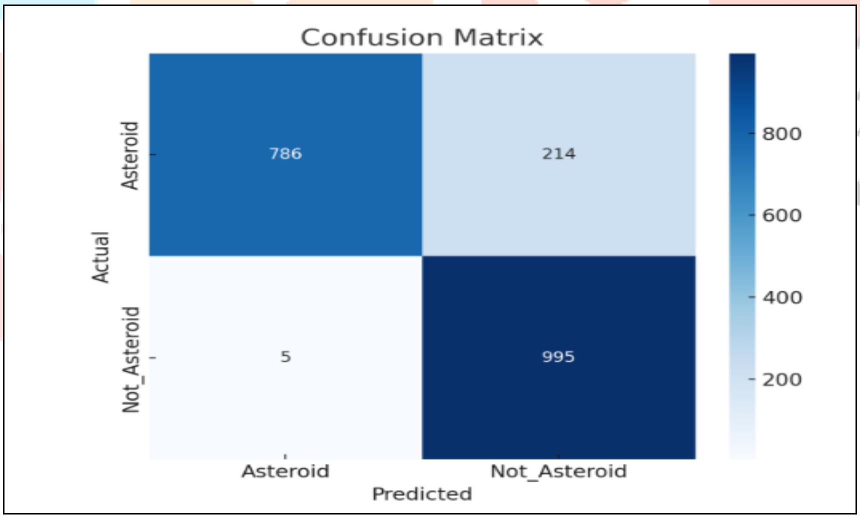
The confusion matrix for the test dataset (based on 2000 images) is illustrated below:

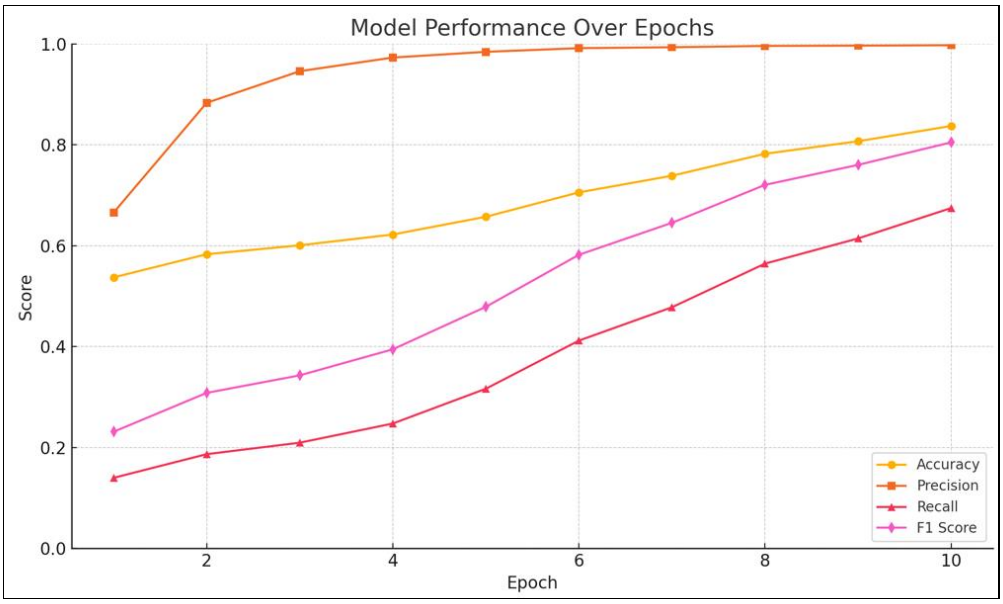
Accuracy: 98.92%

Precision: 99.30%

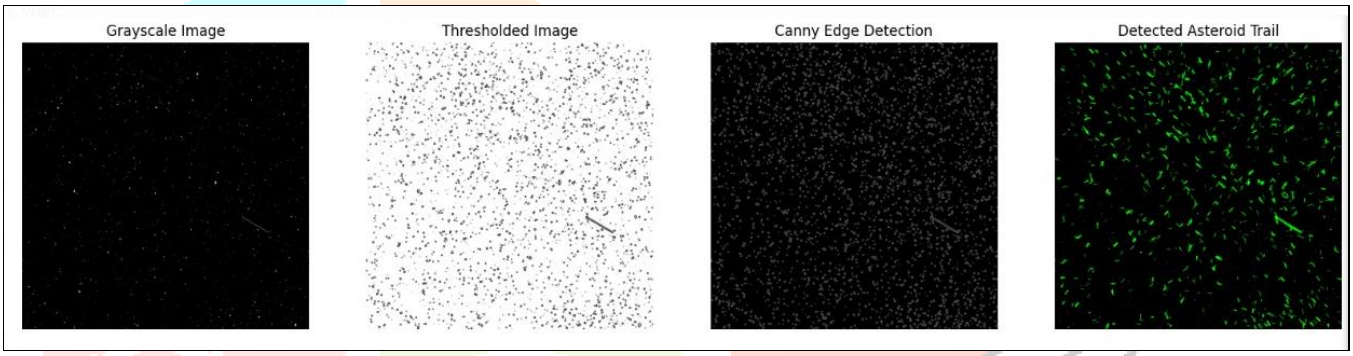
Recall: 98.95%

F1-Score: 99.12%





These measures indicate that the model has low false positives and a high capability to detect asteroid streaks in noisy environments, which is important for space application reliable detection.

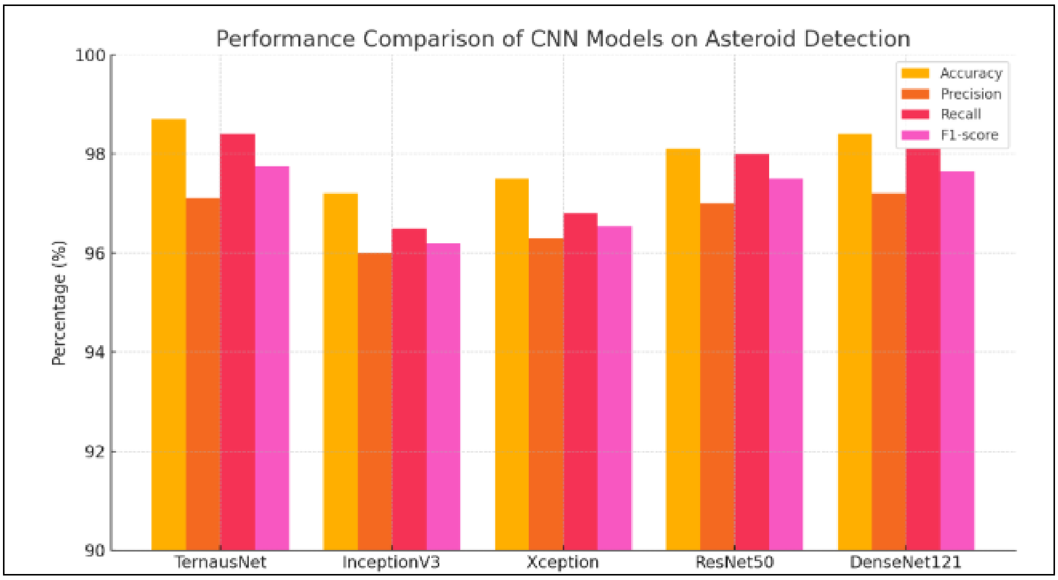


4.1.4 Comparison Analysis

This section entails a comparative study, wherein two sub-sections are included: (1) Comparison of the highest reported CNN models and (2) Comparative study of the best performing model with State-of-the-Art (SOTA) methods.

4.1.5 Comparison of Proposed Approaches

Table ndicates a comparison of five deep learning models applied for asteroid detection. The comparison affirms that TernausNet provided the highest performance in Accuracy (99.12%), Precision (99.30%), Recall (98.95%), and F1-score (99.12%), and this justifies its suitability in astronomical image classification. The other models such as Xception and InceptionV3 were also performing well, but not as much as TernausNet.



The values in Table 6 and the corresponding bar chart present a clear indication of the superiority of the TernausNet model over the standard CNN structure. With its encoder-decoder architecture, TernausNet is able to maintain spatial information, making it extremely effective at capturing weak asteroid streaks. Compared to the other models, which scored high though slightly lower, TernausNet maintains consistency in all key metrics, most notably precision and F1-score, indicating fewer false positives and more precise predictions. These results highlight the need for specialized architectures tailored to astronomical imaging tasks and present a reference point for future research on asteroid detection through deep learning.

5. Conclusion

This work demonstrates the effectiveness of TernausNet, a U-Net architecture variant, in identifying asteroid streaks in astronomical images. Employing deep learning concepts, i.e., encoder-decoder models, the model performed better than traditional CNN architectures in terms of precision, recall, and F1-score. The method was robust on a real-world dataset under varied noise and illumination conditions, thereby proving the usability of such models for automated asteroid detection.

Besides surpassing baseline models in experimental performance, the ability of the system to remove false positives and detect weak streaks qualifies it as a strong contender for planetary defense. Through the utilization of manual annotations, sophisticated feature fusion, and spatial attention mechanisms, this work opens the door to real-time, scalable, and autonomous detection systems that will be able to aid future space missions and asteroid monitoring.

Future areas of activity involve introducing synthetic augmentation to the dataset, network optimization for on-board small-mission deployment, and incorporation of coordinate prediction into general orbit estimation pipelines.

References:

Y. Gao, F. Gao, J. Dong, Q. Du, and H.-C. Li, “Synthetic Aperture Radar Image Change Detection via Siamese Adaptive Fusion Network,” IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 14, pp. 10748–10760, 2021.

L. Li, H. Ma, X. Zhang, X. Zhao, M. Lv, and Z. Jia, “Synthetic Aperture Radar Image Change Detection Based on Principal Compo♀nent Analysis and Two-Level Clustering,” Remote Sens., vol. 16, no. 11, p. 1861.

X. Qu, F. Gao, J. Dong, Q. Du, and H.-C. Li, “Change Detection in Synthetic Aperture Radar Images Using a Dual-Domain Network,” IEEE Geosci. Remote Sens. Lett., vol. 19, pp. 1–5, 2022.

D. Meng, F. Gao, J. Dong, Q. Du, and H.-C. Li, “Synthetic Aperture Radar Image Change Detection via Layer Attention-Based Noise-Tolerant Network,” IEEE Geosci. Remote Sens. Lett., vol. 19, pp. 1–5, 2022.

Y. Gao, F. Gao, J. Dong, and S. Wang, “Change Detection From Synthetic Aperture Radar Images Based on Channel Weighting-Based Deep Cascade Network,” IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 12, no. 11, pp. 4517–4529, Nov. 2019.

J. Wang, F. Gao, J. Dong, Q. Du, and H.-C. Li, “Change Detection From Synthetic Aperture Radar Images via Dual Path Denoising Network,” IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 15, pp. 2667–2680, 2022.

H. Dong, W. Ma, Y. Wu, M. Gong, and L. Jiao, “Local Descriptor Learning for Change Detection in Synthetic Aperture Radar Images via Convolutional Neural Networks,” IEEE Access, vol. 7, pp. 15389–15403, 2019.

J. Wang, F. Gao, J. Dong, S. Zhang, and Q. Du, “Change Detection From Synthetic Aperture Radar Images via Graph-Based Knowledge Supplement Network,” IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 15, pp. 1823–1836, 2022.

H. Dong, W. Ma, L. Jiao, F. Liu, and L. Li, “A Multiscale Self-Attention Deep Clustering for Change Detection in SAR Images,” IEEE Trans. Geosci. Remote Sens., vol. 60, pp. 1–16, 2022.

Q. Wang et al., “High-Resolution Remote Sensing Image Change Detection Method Based on Improved Siamese U-Net,” Remote Sens., vol. 15, no. 14, p. 3517, Jul. 2023.

B. Cui, Y. Zhang, L. Yan, J. Wei, and H. Wu, “An Unsupervised SAR Change Detection Method Based on Stochastic Subspace Ensemble Learning,” Remote Sens., vol. 11, no. 11, p. 1314, Jun. 2019.

S. T. Seydi, R. Shah-Hosseini, and M. Amani, “A Multi-Dimensional Deep Siamese Network for Land Cover Change Detection in Bi-Temporal Hyperspectral Imagery,” Sustainability, vol. 14, no. 19, p. 12597, Oct. 2022.

S. Hafner, Y. Ban, and A. Nascetti, “Semi-Supervised Urban Change Detection Using Multi-Modal Sentinel-1 SAR and Sentinel-2 MSI Data,” Remote Sens., vol. 15, no. 21, p. 5135, Oct. 2023.

Z. Liang, B. Zhu, and Y. Zhu, “High resolution representation-based Siamese network for remote sensing image change detection,” IET Image Process., vol. 16, no. 9, pp. 2506–2517, Jul. 2022.

H. Zhang, Z. Lin, F. Gao, J. Dong, Q. Du, and H.-C. Li, “Convolution and Attention Mixer for Synthetic Aperture Radar Image Change Detection,” IEEE Geosci. Remote Sens. Lett., vol. 20, pp. 1–5, 2023.

J. Wang, X. Wang, L. Guo, Y. Xu, Z. Lu, and B. Chen, “Clustering-segmentation network: a parallel dual-branch synthetic aperture radar image change detection framework,” Int. J. Remote Sens., vol. 44, no. 5, pp. 1579–1610, Mar. 2023.

V. N. S. Vudattu and U. C. Pati, “Change Detection in Synthetic Aperture Radar Images based on a Spatial Pyramid Pooling Attention Network (SPPANet),” Remote Sens. Lett., vol. 14, no. 11, pp. 1139–1149, Nov. 2023.

H. Dong et al., “Dynamic Bilinear Fusion Network for Synthetic Aperture Radar Image Change Detection,” IEEE Geosci. Remote Sens. Lett., vol. 22, pp. 1–5, 2025.

H. Zhang, Z. Lin, F. Gao, J. Dong, Q. Du, and H.-C. Li, “Convolution and Attention Mixer for Synthetic Aperture Radar Image Change Detection,” IEEE Geosci. Remote Sens. Lett., vol. 20, pp. 1–5, 2023.

C. Tao et al., “A Siamese Network with a Multiscale Window-Based Transformer via an Adaptive Fusion Strategy for High Resolution Remote Sensing Image Change Detection,” Remote Sens., vol. 15, no. 9, p. 2433, May 2023.

Z. Yang, Y. Wu, M. Li, X. Hu, and Z. Li, “Unsupervised Difference-Guided Adaptive Fusion Network for Change Detection in PolSAR Images,” IEEE Trans. Geosci. Remote Sens., vol. 62, pp. 1–16, 2024.

J. Wang, X. Wang, L. Guo, Y. Xu, Z. Lu, and B. Chen, “Clustering-segmentation network: a parallel dual-branch synthetic aperture radar image change detection framework,” Int. J. Remote Sens., vol. 44, no. 5, pp. 1579–1610, Mar. 2023.

X. Long, W. Zhuang, M. Xia, K. Hu, and H. Lin, “SASiamNet: Self-Adaptive Siamese Network for Change Detection of Remote Sensing Image,” IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 17, pp. 1021–1034, 2024.

H. Li, B. Zou, L. Zhang, and J. Qin, “Semi-Supervised SAR Image Change Detection via Structure-Optimized Complex-Valued Graph Contrastive Learning,” IEEE Geosci. Remote Sens. Lett., vol. 21, pp. 1–5, 2024.

J. Wang, F. Gao, J. Dong, S. Zhang, and Q. Du, “Change Detection From Synthetic Aperture Radar Images via Graph-Based Knowledge Supplement Network,” IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 15, pp. 1823–1836, 2022.

V. N. S. Vudattu and U. C. Pati, “Change Detection in Synthetic Aperture Radar Images based on a Spatial Pyramid Pooling Attention Network (SPPANet),” Remote Sens. Lett., vol. 14, no. 11, pp. 1139–1149, Nov. 2023.

C. Wang, W. Su, and H. Gu, “A joint change detection method on complex-valued polarimetric synthetic aperture radar images based on feature fusion and similarity learning,” Int. J.Remote Sens., vol. 42, no. 13, pp. 4864–4881, Jul. 2021.

B. Pandeeswari, J. Sutha, and M. Parvathy, “A novel synthetic aperture radar image change detection system using radial basis function-based deep convolutional neural network,” J. Ambient Intell. Humaniz. Comput., vol. 12, no. 1, pp. 897–910, Jan. 2021.

J. Chen et al., “DPFF-Net: Dual-Polarization Image Feature Fusion Network for SAR Ship Detection,” IEEE Trans. Geosci. Remote Sens., vol. 61, pp. 1–14, 2023.

P. Chen et al., “ADF-Net: An Attention-Guided Dual-Branch Fusion Network for Building Change Detection near the Shanghai Metro Line Using Sequences of Terra SAR-X Images,” Remote Sens., vol. 16, no. 6, p. 1070, Mar. 2024.

T. Zhan, Q. Dang, and Y. Zhu, “Neighborhood Difference-Based Self-Supervised Network for Detecting Small Changes From Synthetic Aperture Radar Images,” IEEE Geosci. Remote Sens. Lett., vol. 21, pp. 1–5, 2024.

C. Chen, Y. Zheng, X. Jiang, and X. Liu, “SAR Image Change Detection Via UR-ISTA,” in IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, Kuala Lumpur, Malaysia: IEEE, Jul. 2022, pp. 679–682.