

SatStreaks: Towards Supervised Learning for Delineating Satellite Streaks from Astronomical Images

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Abstract—Delineation of satellite streaks in astronomical images is an important aspect of ground based space studies. While deep learning algorithms show promise, training and validation of deep learning models for satellite streak segmentation is challenging due to the limited availability of large-scale, annotated datasets. We introduce *SatStreaks*, a dataset comprising of 3,130 densely annotated, real images of satellite streaks captured through ongoing citizen science projects. We utilize *SatStreaks* to develop a U-Net based model for the streak segmentation and conduct an experimental evaluation of data-driven image segmentation algorithms. The satellite streak segmentation codebase consisting of various deep learning models, and the SatStreak dataset has been made publicly available (<https://github.com/jijup/SatStreaks>) to facilitate the advancement of computer vision algorithms for space studies.

Keywords—Satellite streak segmentation; Astronomical image dataset; Supervised learning

I. INTRODUCTION

In the modern era, artificial satellites play an indispensable role in global communication, navigation systems, and scientific explorations. Monitoring satellite streaks has been essential to mitigate their impact on astronomical objects or events in the Earth's orbit and optimize satellite-based communication and navigation systems. Satellite streak segmentation is a process of identifying and isolating the trails of artificial satellites in the night sky imagery. Satellite streaks are usually visible during dawn, dusk, and nighttime when other astronomical objects including stars, planets, comets, etc. are also visible. These additional objects in the night sky images introduce complexity in the accurate detection of satellite streaks in night sky images. Moreover, the rapid growth in the commercial space sector has introduced the presence of several clusters of satellites such as Starlink or Eutelsat OneWeb, among other mega-constellations in the sky images [1]. This growth indicates the infeasibility of manual image masking for large datasets due to its labor-intensive nature and necessitates automatic image segmentation techniques with better efficiency, adaptability, scalability, and accuracy.

In recent years, deep learning techniques have demonstrated remarkable advancements in the field of

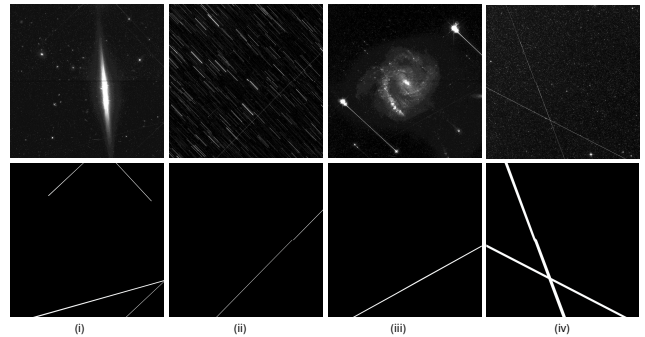


Figure 1. Representative images from our dataset (top row) with their masks (bottom row) showing the dataset's accurate masking in a variety of cases such as less visible satellite events, multiple and intersecting occurrences of satellite streaks, noisy background, and other streak-like instances.

image segmentation. These networks can generate highly accurate and robust segmentation outcomes with proper training. A recent review article on sky image datasets [2] provides a detailed overview of publicly available datasets for the classification and segmentation of clouds for solar power forecasting. This survey presents the need for publicly available and properly annotated datasets for the segmentation of different sky objects. However, these datasets in [2] along with other night sky image datasets (e.g., [3], [4]) lack annotations for satellite streaks and thus, cannot be used as training data for satellite detection and segmentation. A recent study [1] on the effect of satellite streaks on Imaging Atmospheric Cherenkov Telescopes (IACTs) uses data generated from the High Energy Stereoscopic System (HESS) array consisting of overall 1658 satellite streaks which is insufficient for deep learning models. Therefore, to address this lack of sufficiently large and publicly available datasets for training models for satellite streak segmentation, we introduce a new hand-annotated dataset consisting of night sky images featuring satellite trails with pixel-level annotations. Raw imagery for this dataset is sourced from the NASA Satellite Streak Watcher citizen science project [5] and the Asteroid

Hunters dataset [4]. We have used a user-friendly image annotation tool *labelme* [6] to manually annotate satellite trails in every sourced image by collaborating with citizen scientists through a dedicated website [7]. Our dataset consists of 3073 Hubble Space Telescope (HST) images containing satellite streaks with ground truth pixel-level annotations. This annotated dataset can be used to train deep-learning models for satellite streak segmentation. Figure 1 shows a few representative images from our dataset with their masks. Our dataset contains accurate masking for a variety of cases in astronomical images such as faint occurrences of satellite streaks (Figure 1 (i) and (iii)), multiple satellite streaks (Figure 1 (i) and (iv)), and intersecting satellite streaks (1 (iv)). Our dataset also consists of images for various astronomical events, such as streak-like occurrences caused by meteors, asteroids, space debris, etc., and provides precise masking for satellite streaks (Figure 1 (ii) and (iii)).

Satellite streak segmentation involves the identification of image pixels which represent the streaks formed by satellites orbiting the earth. Convolutional neural networks such as U-Net have shown promising results for image segmentation in various domains, from transportation [8] to environmental analysis [9] and medical imaging [10], including cloud segmentation [11]. These models consider the inherent relationships and dependencies between different parts of the object and hence capture the sequential nature of linear structures, their geometric properties, and contextual information within the scene. However, distinguishing between artificial satellite trails and celestial bodies amidst a field of stars requires robust algorithms capable of proper handling of variations in appearance, occlusions, and dynamic scenarios. Therefore, we propose an enhanced U-Net model for satellite streak segmentation and present an experimental analysis on our SatStreaks dataset. Further, we provide a detailed comparative study of the performance of the proposed model against various deep-learning segmentation models.

II. RELATED WORK

A. Satellite Streaks Datasets

A mock observation data of wide-field small aperture telescopes (WFSATs) is generated using Monte Carlo simulation with the help of the Skymaker application [12] in [13]. After data augmentation, the final dataset consists of 2000 training images and 500 testing images of 800x800 pixels. The authors also collected 600 real night-sky images (75%-25% train-test split) from WFSATs to evaluate the performance on real-world data. The images consist of point-like objects (stars, supernova, and tidal disruption flares) and streak-like objects (comets, asteroids, meteors, and space debris). This synthetic dataset of 2500 images was further augmented to a total of 8000 images in [14]. Similarly, [15] uses 6000

greyscale night-sky images containing satellite and airplane streaks captured at Zwicky Transient Facility (ZTF) with a 576MP camera installed on 1.2m Schmidt Telescope. Data labeling is done using a web-based tool Zwickyverse¹. Another streak detection model [16] uses 85 images to detect 196 streaks captured through Takahashi telescope with a 10MP ST-8300 Monochrome camera. Another recent deep learning framework [17] uses 8000 training and 2000 validation samples of 256×256 pixel synthetic night-sky images generated using Pyradon simulation tool [18]. In most of these works, the number of synthetically generated images was increased by applying multiple data augmentations on the initial dataset. However, the enhancement of model performance on real data requires a large dataset of real-world night-sky images with properly annotated satellite streaks.

B. Streak Segmentation: Traditional Approaches

Edge-based [19], [20] and threshold-based [21] image segmentation methods are useful in applications where accurate delineation of regions of interest is essential. These methods are based on the intensity level variations in the image. One of the thresholding-based methods, otsu [21] calculates the threshold value that maximizes the variance between different-class pixels, thus minimizes the intra-class variance. Therefore, such methods can be used for satellite streak detection [20].

In astronomical image analysis, identifying linear features, commonly referred to as streaks, is crucial in various applications. The work by Guy Nir et al.[18] is important in many ways: in detecting fast-moving near-Earth asteroids, discerning or flagging faint satellite streaks, and eliminating undesired artifacts like diffraction spikes, pixel bleeding, and line-like cosmic rays. Cross-correlating astronomical images with a template of a line broadened by the point-spread function of the imaging system is essential for streak detection, and it can be optimized by using the Radon transform, which can be applied to both simulated and real astronomical images, demonstrating its efficacy in recovering theoretical signal-to-noise ratios. Traditional detection methods rely on high-resolution images to reduce errors, but they come with substantial computational demands, potentially jeopardizing the efficient delivery of satellite coordinates. Seunghyeok Shin et al.[22] addressed this challenge by proposing a method that strategically narrows the streak search area through the application of line fitting. In this context, Automatic Saliency Thresholding (AST) [20], an automatic thresholding technique, generated binary masks to facilitate the identification and elimination of satellite streaks from such imagery. The AST leverages a multi-step approach combining Gaussian filtering, saliency-based thresholding, morphological filtering and line detection using Probabilistic

¹<https://github.com/dmitryduev/zwickyverse>

Hough Transformation, to accurately identify satellite trails while ensuring efficient processing and robust performance across diverse night sky image datasets. Comparative analysis against existing methods demonstrates the superior accuracy and speed of AST. Another method ASTRiDE [23] offers a sophisticated approach to identify streaks amidst varying backgrounds, aiding in the precise localization and characterization of satellite streak artifacts in satellite imagery datasets.

C. Deep Learning for Streak Segmentation

Traditional methods for detecting and classifying astronomical targets in observed images, particularly in the context of optical transient observations, relied on manual or semi-automated approaches, which are typically time-consuming and inefficient when dealing with large volumes of data. In response to these challenges, there has been a growing interest in leveraging deep learning techniques, particularly deep neural networks, to automate the process of detecting and classifying astronomical targets. The work presented by Peng Jia et al. [13] introduces a novel framework that builds upon the foundations of deep learning, utilizing concepts from the Faster R-CNN architecture [24]. It incorporates a modified Resnet-50 as its backbone network, augmented by a feature pyramid network to extract relevant features from images capturing different astronomical targets. Training on both simulated and real images enhances the generalization capability of the model, and its detection performance evaluated in rigorous testing was found to be comparable to traditional methods for bright and isolated sources while exhibiting a notable improvement.

In recent years, the advent of wide-field surveys has revolutionized the field of astronomy, enabling the detection of transient and fast-moving celestial objects with unprecedented efficiency. One such initiative, the ZTF [15], harnesses Samuel Oschin 48-inch Telescope at the Palomar Observatory in California, USA. Further, the DeepStreaks framework is introduced as a robust and automated system to identify fast-moving near-Earth objects (NEOs) detected by ZTF. This CNN-based model is tailored specifically to efficiently analyze ZTF data and identify fast-moving objects. Notably, DeepStreaks achieves an impressive true positive rate ranging between 96%-98%, depending on the night, while effectively maintaining a false positive rate below 1%.

In [16], a prototype for automatic satellite streak detection is proposed for identification and initial orbit determination from optical observations. It aims to streamline the process of extracting valuable information from astronomical images for SSA purposes. Leveraging Hough transform-based feature detection, the pipeline accurately identifies light streaks and extracts equatorial positions based on header information in FITS format image.

A recent study in [17] proposes a machine-learning ap-

proach, based on the U-Net platform, specifically designed to detect and mask out pixels affected by satellite streaks, offering a promising alternative to traditional filtering methods. The contributions extend beyond the development of the model itself; the authors introduce a novel metric, the Star Occlusion Factor (SOF), to quantitatively evaluate data loss caused by masking pixels containing scientifically useful information. Through performance evaluations, the authors demonstrate the superior accuracy and efficiency of the proposed model compared to existing techniques. This paper thus represents a significant advancement in addressing the challenges posed by satellite streak artifacts in astronomical observations, with implications for enhancing the reliability and efficiency of scientific data analysis in the field.

Streak detection is a critical aspect of space situational awareness and space asset protection, particularly in the identification of moving targets such as satellites, space debris, or meteorites within images of the sky. A comparative analysis of two astronomical frameworks for streak detection, both leveraging deep CNNs has been presented in [14]. The first framework utilizes the extended feature pyramid network (EFPN) in conjunction with faster region-based CNNs (Faster R-CNN), while the second framework employs the feature pyramid network (FPN) with Faster R-CNN. Given the scarcity of publicly available astronomical datasets, the study resorts to utilizing simulated data to train the models. The experimental findings reveal a notable superiority of the EFPN-based framework over the Faster R-CNN framework based on the FPN model in streak detection.

III. SATSTREAKS: THE DATASET CURATION AND ANNOTATION

In this section, we present the satellite streaks image dataset, referred to as *SatStreaks*, for training and evaluation of satellite segmentation algorithms. SatStreaks features over 3,100 images containing pixel-level annotations of satellite streaks. We believe that the SatStreaks dataset has the potential to serve as the main reference for evaluating the performance of traditional as well as deep-learning satellite streak segmentation algorithms. The ground truth data of SatStreaks provides a reliable basis for assessing the accuracy and effectiveness of various segmentation algorithms in detecting and segmenting satellite streaks. In the subsequent sections, we describe the source data (Section III-A), dataset characteristics (Section III-B), and the hand annotation procedure (Section III-C).

A. The Source Datasets

NASA Satellite Streak Watcher (NSSW) [5]: SatStreak leverages publicly available images from two projects: Satellite Streak Watcher citizen science project by NASA [5] and Asteroid Hunters [4]. NASA Satellite Streak Watcher citizen science project consists of 233 ground-based images of the

night sky containing satellite streaks. The dataset consists of a collection of images taken by participants, showcasing satellite streaks across various locations and timeframes. The project focuses on photographically tracking satellite streaks across the night sky, providing valuable insights into the extent of sky pollution caused by satellites. This dataset is part of a long-term project aimed at monitoring the population growth of satellites and studying their impact on ground-based astronomy. The images were captured under different lighting conditions, with varying exposures, cameras, and settings. Amateur skywatchers captured the images, so not all images were usable for this study. The images were selected based on several factors, including the signal’s complexity, the satellite trail’s size, and its visibility in the image. As a result of these constraints, 57 images were selected and used to generate hand annotated ground-truth masks to test the performance of our algorithm.

Asteroid Hunters Dataset (AHD) [4]: The Asteroid Hunters dataset [4] contains the largest collection of publicly available images of satellite streaks to date. The dataset contains 114,607 images taken by the Hubble Space Telescope (HST) over 19 years and was classified using online crowd-sourcing to provide labels that describe the image contents. These images of size 4096X4096 pixels have been processed to combine individual exposures, resulting in composite images without geometric corrections or filling the gap between detectors. The dataset provides classifications for 3,073 images containing satellite streaks, carefully reviewed and validated by the authors. It includes observation IDs, instrument information, exposure details, celestial coordinates, and image URLs. The satellite classifications were conducted through a combination of citizen science contributions and machine learning. However, many applications require more than the classification of images into satellite and non-satellite streaks, i.e., accurate delineation of satellite streaks. To support such applications through facilitating the development of deep learning algorithms, we curate a ground truth dataset with pixel level annotation by collaborating with citizen scientists through a dedicated website [7]. This annotated dataset serves as a reliable reference for assessing the performance of various segmentation models in our experimental evaluation (Section V).

B. The Citizen Science Data Annotation Project

A citizen science data annotation project [7] was created to help reduce the burden of labeling the Asteroid Hunters dataset. Participants were asked to download polygon labeling software and a dataset segment and are provided instructions. Their task is to carefully examine each image and annotate the satellite streaks they encounter. Once the annotation task is completed, participants upload their results, creating a comprehensive annotated image dataset. Engaging citizen scientists in this collaborative effort expanded our study to include a quantitative analysis of segmentation

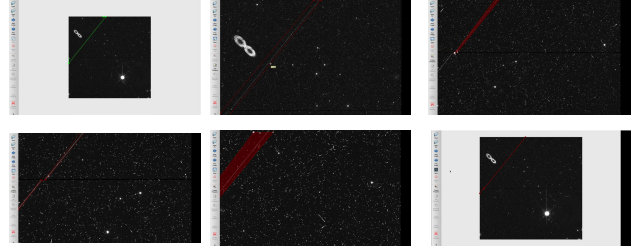


Figure 2. Illustration of Image Annotation Procedure. A short video showcasing the procedure is available on [7].

algorithms on astronomical images.

The AHD dataset was visually sorted into two groups. The first group (1276 images) contained detection masks containing isolated satellite trails with little to no star/noise residue. The second group (1797) contained the remaining images comprised of noisy/partial/missed detection. The satellite trails in the datasets were hand-annotated to establish a ground truth for evaluating and comparing the performance of various deep learning and traditional segmentation algorithms. This process involved manually identifying and marking the satellite trails within each image. An annotation tool, such as a polygon tool, was utilized to outline the paths of the satellite trails accurately. This allowed for precise delineation of the regions corresponding to the trails in the images.

The Annotation Principle: During the hand annotation process, several factors were taken into consideration. One important aspect was the identification of the satellite streak itself. Each image was carefully examined to locate the distinct streak or path created by the satellite’s movement across the night sky. This involved differentiating the streak from other image features, such as stars, noise, or asteroids. Additionally, the presence of diffuse lighting from some satellite trails posed a challenge during the annotation process. In these cases, it was not always clear where the satellite streak’s edge was. It was crucial to capture the entire satellite streak, so masks were made larger to accommodate both the edge and the residual glow. By carefully examining the characteristics of the satellite streak and considering the overall lighting conditions, annotators produced a reliable ground truth dataset that accurately captured the presence and location of the satellite trails. Increasing the width of the annotated area to include the diffused light caused by the streak will also help future machine-learning models learn the features necessary for successful detection.

C. Image Annotation Process

The data annotation process (Figure 2) for our citizen science project involved three main steps.

1. Prepare the Data Packs. Volunteers started by downloading the datapackDownloader script, which provided access to one of the 43 Hubble Space Telescope image

data packs. Each data pack contained a unique set of images that required annotations. After obtaining the script, volunteers extracted the contents of the downloaded zip file to a folder of their choice on their computer. To ensure efficient collaboration and avoid duplicate efforts, volunteers were encouraged to check the comments section below the download link to see if the data pack they intended to work on had already been annotated by other participants. Once the data pack was successfully extracted, volunteers extracted the files to a location on their computer.

2. Annotation using Labelme [6]. To facilitate the data annotation process, volunteers were recommended to download the latest release of “labelme” [6], a user-friendly image annotation tool. Once installed, volunteers launched the application and navigated to a directory namely “HSTData” which was located within the script directory. This folder contained the Hubble Space Telescope images that needed annotations. Using “labelme”, volunteers could easily mark regions of interest directly on the HST images to annotate satellite trails. Upon completing the annotation for a given image, volunteers were encouraged to save their annotations to the “annotations” folder inside the “HSTData” directory.

3. Collaborative Discussion and Submission. To foster collaboration and coordination among volunteers, a comments section was available on the website. Volunteers were encouraged to leave comments indicating which data pack they were working on and sharing progress updates. By doing so, participants could easily identify data packs already annotated by others and avoid duplication. Once the data annotation task for a specific data pack was completed, volunteers were requested to zip the “annotations” folder containing the annotated images and submit it through the designated submission process. Through these three steps, the citizen science website enabled volunteers to contribute to the data annotation process effectively, ensuring the successful implementation of the satellite trail detection pipeline.

IV. SATELLITE STREAK SEGMENTATION

Satellite streak segmentation is difficult due to severe noise effects in the astronomical images usually introduced by atmospheric disturbances such as air glow, cosmic rays, etc., or instrument misalignments such as shot noise, dark noise, and read-out noise. Preprocessing astronomical images is quite often warranted to remove background variations (e.g., clouds or light pollution from other objects) and time consuming. The small and faint streaks within an image along with the overlapping objects pose additional challenges to efficient segmentation. In this section, we first analyze the specific geometric and photometric characteristics of satellite streaks, briefly verify the suitability of general segmentation models for streak delineation, and then propose a modification to U-net for efficient segmentation of satellite streaks.

A. The Curvilinear Geometry of Satellite Streaks

In general, curvilinear geometry includes lines, curves, contours, or their combinations representing real-world objects such as roads, rivers, railway tracks, satellite streaks, powerlines, blood vessels, and fingerprints, among others. Such regions of pixels within an image can be referred to as *curvilinear structures*. Being a curvilinear structure, satellite streaks possess certain geometric characteristics [25]. Pixels of satellite streaks are mostly connected and cover a thin region across long paths with smoothly varied widths. The local curvature profile of satellite streaks is mostly straight and the overall segmentation of satellite streaks can be seen as a sequence of disconnected segments. Photometrically, the intensities of satellite streaks are found to be different from their background with smooth variations and the intensity values across the streaks normally follow a specific distribution (e.g., Gaussian).

Utilizing strategies adopted for linear geometry, curvilinear structure segmentation can be accomplished using the following methods. The first method captures the local and global information of each pixel in a vector of features, a per-pixel feature vector can be used to perform per-point classification with the help of image transformations. However, the method fails in cases with severe occlusion and therefore lacks fidelity under such conditions. Another method estimates the border of the curvilinear structure at first and then the internal area is linked to this boundary assuming it to belong to the same segment. The third category of methods uses predefined templates to compare the similarities between the image and the templates. It commonly employs the eigenvalues of the Hessian matrix to discern flat, blob-like, and curvilinear structures. Methods falling into these two categories can not leverage the global structure of the object. Region-based methods post-process on the initially extracted area by applying constraints which are designed to differentiate the curvilinear structure area from the rest of the region. This requires careful designing of constraints and selection of optimal threshold values. User-assisted methods select a few seed points through user interactions which is further extended to provide feedback on the segmentation generated using algorithms. In contrast to these methods, learning-based methods infer predictions on new image samples using machine learning models previously trained on expert data.

Deep learning-based models for curvilinear structures perform differently for multiple-width objects. This can be handled through the aggregation of convolution of the image with the derivative of multiple Gaussian shapes [26]. Similarly, linear filters [27] can also be enlarged or shrunk based on the size of the structure. Another possible solution is to detect the centerline of these objects to capture concavities or to use clustering algorithms. Another challenge is densely packed curvilinear objects which is hard to handle

by multiple-scale filters or gaussian functions. Therefore, dual-gaussian or bi-gaussian function kernels [28], [29] can aid in such structures.

B. Adaptability of Segmentation Models for Satellite Streaks

Feature learning on images for satellite streak segmentation can be performed using several methods such as Random Forest, fully convolutional networks (FCNs), encoder-decoder architectures, dilated convolutions, recurrent neural networks (RNN), and attention-based Models. Random Forest effectively discerns linear features within geometric data, aiding in precise and robust segmentation [30] by leveraging ensemble learning and random feature selection. Similarly, in FCN, fully connected layers are replaced with convolutional layers to preserve spatial information that enables end-to-end pixel-wise predictions to facilitate precise segmentation [31]. Moreover, inspired by the success of U-Net architecture, deep learning models such as DeepLabv3 and PSPNet integrate encoder-decoder structures [32] with their respective specialized modules *atrous convolutions* and *pyramid pooling*, to capture multi-scale contextual information and refine segmentation accuracy [33]. In such models, the encoder extracts hierarchical features from linear structures, while the decoder reconstructs segmented outputs with enhanced spatial resolution that results in precise delineation of linear geometry objects for tasks such as road detection, building footprint extraction, and infrastructure monitoring.

Such multi-scale and pyramid networks incorporate parallel pathways or hierarchical structures and efficiently capture both local and global context which facilitate accurate delineation of intricate linear details while maintaining computational efficiency [34]. In dilated convolutions or atrous convolutions, gaps are introduced between filter elements to effectively expand the receptive field without sacrificing spatial resolution and capture contextual information at multiple scales [35] which is beneficial in tasks where fine-grained details and global context are essential for accurate detection. Further, RNN excel in identifying patterns and structures within linear datasets, facilitating precise segmentation of linear features such as roads, rivers, and boundaries to capture contextual information along linear features [36]. Hence it finds application in diverse domains such as satellite imagery analysis, urban planning, and environmental monitoring, underscoring their significance in addressing the complexities of linear structure perception [37]. Attention mechanisms [38] in RNNs enhance the model's ability to focus on relevant features, further improving segmentation accuracy. Moreover, self-attention and spatial attention allow the model to selectively focus on relevant features by dynamically weighting the importance of different spatial locations and thus identify linear features with enhanced precision and accuracy. These models demonstrate their versatility and effectiveness in various fields and provide a versatile and efficient solution for linear geometry segmentation.

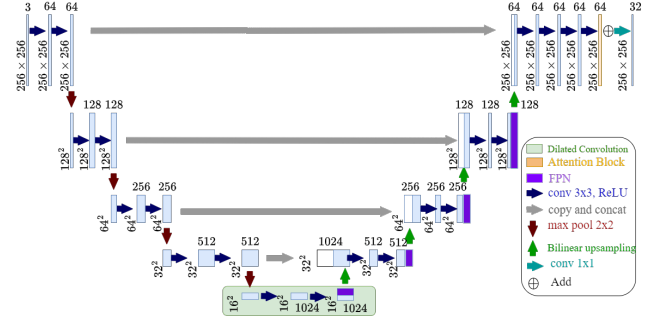


Figure 3. Architecture of the enhanced U-Net model.

C. Enhanced U-Net

For satellite streak segmentation, we propose an enhanced U-Net network comprising an expansive path, a feature pyramid network (FPN), a dilated convolution layer, and an attention layer. The expansive path consists of multiple convolutional layers followed by max-pooling operations to progressively upsample the input image and refine and enhance the detailed features present in the input image. Then, the high-resolution feature information extracted from the input is fed to the FPN module that captures multi-scale representations of the input images and masks. As satellite streaks can vary in length, width, and orientation, FPN helps capture these variations by providing a hierarchical representation of features at different scales. Satellite streaks often extend over large regions in astronomical images, therefore we use a dilated convolution layer to increase the receptive field without losing spatial resolution and hence capture the contextual information necessary for streak detection. We incorporate an attention layer, to selectively emphasize informative regions for streak detection while suppressing irrelevant background features. This helps in enhancing the accuracy and robustness of the segmentation process in case of noise or other image artifacts. To capture linear patterns in the satellite streaks, A 1D convolutional layer tailored to capture these distinctive features is added after the attention layer. Figure 3 shows the overall network architecture of the proposed model. Placing components in a sequential manner allows them to interact and complement each other effectively and facilitate hierarchical feature extraction, where low-level features are progressively refined and combined with higher-level contextual information.

V. EVALUATION ON SATSTREAK DATASET

In this section, we evaluate our model along with a few other representative streak segmentation techniques on the *SatStreaks* dataset. The ultimate objective is to quantify the performance of various image segmentation models on real-world night-sky images for satellite streak segmentation. The deep learning segmentation models chosen for our

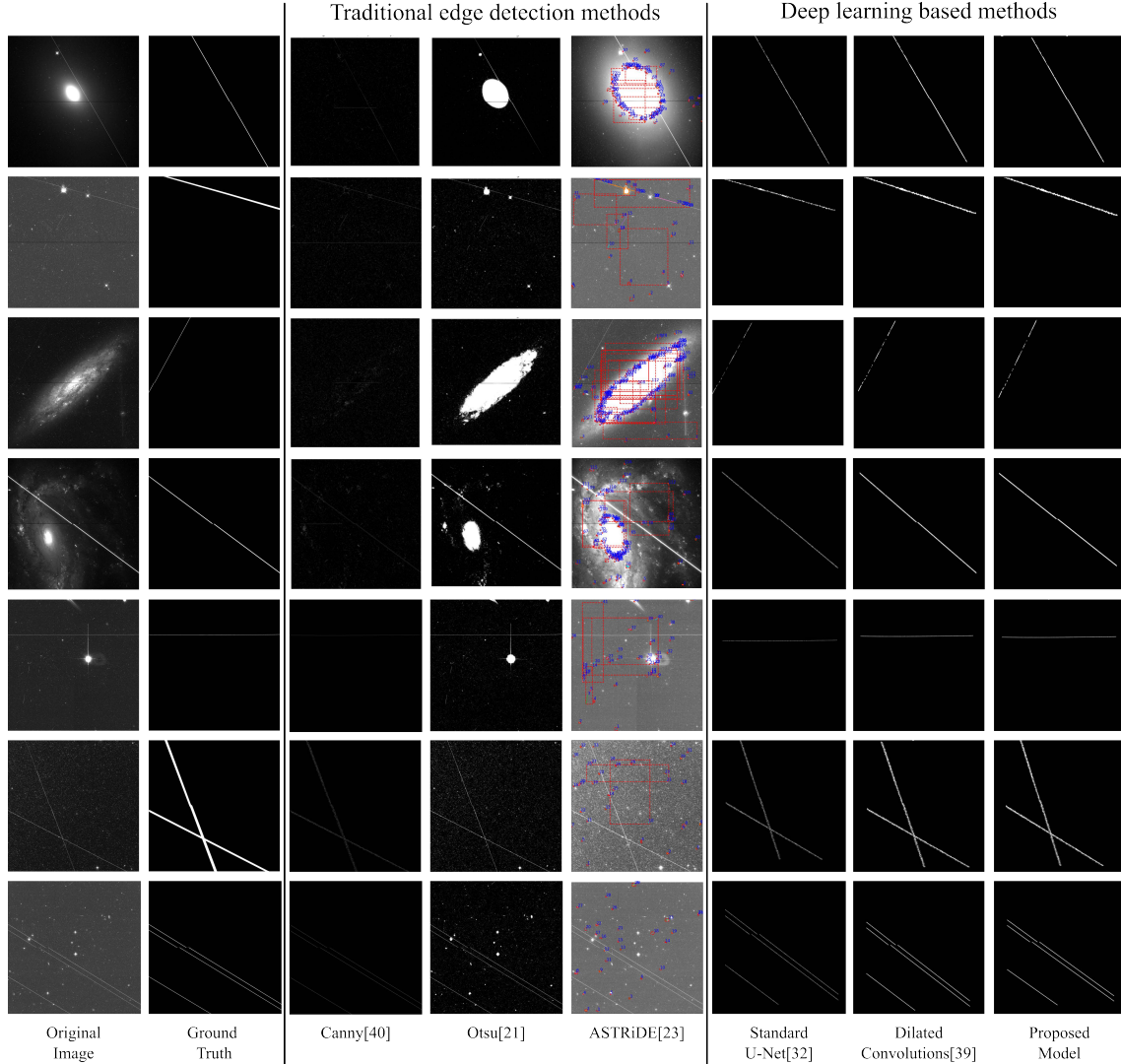


Figure 4. Qualitative results of different satellite streak segmentation techniques on our dataset (*SatStreaks*).

evaluation include standard U-Net [32], smoothed dilated convolution-based network (SDC) [39], and Deepstreaks [15] for quantitative-based comparative analysis. Additionally, traditional methods such as canny [40], Otsu [21] and ASTRiDE [23] are included in qualitative analysis.

A. The Setting

The Satstreak dataset comprises a total of 3130 astronomical images with annotations of satellite streaks and background pixels. Further, we split our dataset into 2504 training images and 626 testing images. During preprocessing, images are resized to standard resolution and converted to binary form. To enhance the generalization capacity of the deep learning networks, we augment the dataset with random rotations between -20 degrees to 20 degrees, horizontal and vertical translation of 10%, random scaling and shear by 20% along with random horizontal and vertical

flipping. In all our experiments we train networks for 50 epochs with ADAM optimizer with a default learning rate of 0.001 and a dropout rate of 0.5. As we are segmenting foreground and background pixels, we employ binary cross-entropy loss [41]. The model layers were implemented using TensorFlow and Keras while leveraging a CPU machine with a GPU-accelerated system for computational efficiency and demonstrate reproducibility within a Jupyter Notebook environment.

B. Performance Metrics

For quantitative analysis of the performance of different methods, we use four standard evaluation metrics: accuracy, precision, recall, and F1 score that is defined using True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). Accuracy measures the correct classification in the test image against the ground truth

Table I
SATELLITE STREAK SEGMENTATION RESULTS ON *SatStreak* DATASET.

Method	Accuracy	Precision	Recall	F1 Score
SDC [39]	85.4	77.4	77.6	77.4
Deepstreaks [15]	90.5	88.5	86.4	87.27
U-Net [32]	45.34	38.89	36.89	37.89
U-Net + Attention	85.3	70.60	71.45	71.09
U-Net + dilated Conv.	89.5	77.6	77.4	77.5
U-Net + FPN	91.5	81.5	83.4	82.4
Enhanced U-Net	94.41	86.42	91.67	88.87

image and hence, $\text{accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$. Precision assesses the model performance for positive instances, i.e. $\text{precision} = \text{TP} / (\text{TP} + \text{FP})$. Recall measures the sensitivity of the model for positive instances, hence $\text{recall} = \text{TP} / (\text{TP} + \text{FN})$. Finally, the F1 score is the accuracy of the method considering both precision and recall. Therefore, $\text{F1 score} = 2 \times \text{precision} \times \text{recall} / (\text{precision} + \text{recall})$. For better precision and recall, a higher value of F1 score is required.

C. Quantitative Comparison

Table I reports the performance of different satellite streak detection models on our dataset. Deepstreaks [15] and the proposed model performs better in comparison to other methods. The proposed model shows better results with 3.91% higher accuracy, 5.27% higher recall, and 1.6% higher F1 score than that of Deepstreaks. Further, we performed an ablation study by taking standard U-Net as the baseline and adding each of our features modules, i.e. dilated convolution block, FPN, and attention block respectively. The study shows a gradual increase in accuracy with the inclusion of dilated convolution, FPN, and attention module to U-Net. While only the attention and dilated convolution module with U-net provide 85.3% and 89.5% accuracy respectively, the FPN module with U-Net provides a relatively higher accuracy of 91.5%.

We believe that the poor performance of the standard U-Net [32] model is due to its limited receptive field, which may restrict its ability to capture long-range dependencies and contextual information across large satellite images. Besides, in U-Net architecture, there is no scope for feature hierarchy. The proposed model compensates this limitation with FPN in the decoder, dilated convolutions in between contracting and expansive path, and attention layer at the last stage. While FPN incorporates features from different levels of the hierarchy which allows the model to capture both local and global contextual information, dilated convolutions increase the receptive field of convolutional layers and make it useful for capturing long-range dependencies and global context in the input image. The attention mechanism helps prioritize the detection of linear features, such as streaks, while filtering out distractions from the surrounding environment. Finally, the 1D convolutional layer is used after the attention mechanism that acts as a feature aggregator,

aggregating information across channels (or features) within each spatial location.

D. Qualitative Analysis

Figure 4 shows a qualitative comparison among different streak detection techniques on our dataset. It is evident that most of the traditional detection methods detect other objects along with desired streaks and hence fail to perform satellite streak segmentation efficiently. On the other hand, deep learning models avoid the identification of other celestial objects in the image and hence provide better segmentation results for satellite streaks. Our proposed model accurately delineates streak pixels even in the presence of other celestial objects in close vicinity to the satellite streak (Row 1, 2, and 4). Also, unlike other methods, in case of a less visible streak in the original image (Row 2, 3, and 5), our model detects and segments streak pixels efficiently. Our model identifies multiple instances of satellite streaks in an image (Row 6 and 7) and accurately segments two intersecting streaks (Row 6). Additionally, our method is capable of distinguishing the satellite streak from the occurrence of other streak-like objects (Row 5). Therefore, these results demonstrate that our model offers an efficient solution for satellite streak segmentation, considering the challenges posed by real-world images, such as the presence of other celestial objects and noise that obscure the clarity of streaks and introduce unwanted artifacts.

VI. CONCLUDING REMARKS

Existing learning-based methods utilize synthetic images with satellite streaks which are labeled and annotated using web-based tools. To evaluate the performance of existing deep learning models for satellite streak segmentation, we built a new real-world night-sky image dataset with annotations for satellite streaks. In our dataset, satellite streaks are accurately masked even in the presence of other point-like and streak-like objects. Compared with the existing datasets, our dataset offers more practical data with reliable annotations for linear geometry segmentation of satellite streaks. We benchmark traditional streak detection techniques along with deep learning-based streak segmentation models on our dataset, to verify their applicability to real-world images with noise, occlusion, and overlapping celestial objects. We also propose a U-net-based satellite streak segmentation model and compare its performance with state-of-the-art on our dataset. Experimental results and analysis show that our model performs better than the existing models on real-world astronomical images.

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