Hypervelocity Impact Detection and Classification for Satellite Structural Integrity

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***Abstract*—Satellites in the orbit are frequently exposed hypervelocity strikes by micrometeoroids and space debris (man-made items in space), which travel at rates averaging 10 km/s (22,000 mph). This "space junk" collides with spacecraft and satellites, potentially causing significant damage or catastrophic failure. These collisions pose a life-threatening risk to astronauts engaged in extra-vehicular activities in space. Understanding the current orbital debris environment is critical for minimizing the degree of an impact's damage. Craters, dents, cracks, punctures, and broken panels are some of the damage that these things can produce. These damages can cause structural degeneration, communication or sensor faults, and breakdowns in essential onboard systems. Traditional damage assessment relies on **ground-based radar tracking or manual image analysis, which are slow, expensive, and frequently overlook small but critical damages. While some monitoring systems rely on sensor data, sensor-based detection has drawbacks. Sensors may not identify minor surface damage. Not all satellites have inbuilt sensors for impact detection. A non-invasive, cost-effective, and scalable solution to monitor and classify damage without relying on sensors can be provided by creating infrared detection algorithms to identify damage caused by hypervelocity collisions, which are crucial for spacecraft.**

***Index Terms*—Hypervelocity Impact, Satellite damage detection, Infrared imaging, Space debris, Micrometeoroids**

I. Introduction

Satellites are very important assets with applications ranging from communication, monitoring of weather, navigation, observation of earth, scientific research, and national defence. Nevertheless, these spacecraft are also in a permanent danger of hypervelocity impacts due to presence of micrometeoroids and orbital debris (MMOD). These objects move at such high velocities – frequently above 10 km/s (22 000 mph), and even relatively small particles may cause severe or devastating damage if they hit satellite surfaces.

This is a rising issue because of the rapid increase in satellites being put into space, especially in the times of mega-constellations and low Earth orbit (LEO) proliferation. The greater the number of space assets that are launched, the more the space debris and this increases exponentially the risk of impact events. These collisions may lead to surface craters and punctures, cracking, delamination, and even vaporization of component parts of satellites. The consequences are far-reaching: from deteriorated performance and loss of communication, to full satellite failure. In manned missions, such damage presents an imminent danger to the lives of the astronauts while undertaking spacewalks.

Conventionally, damage due to these high-velocity impacts have been evaluated using ground-based radar systems or onboard sensors, or by a manual examination of satellite images. Although these methods provide some level of detection, they are too expensive, unable to capture fine-grained surface damage, or cannot scale to a large satellite constellation. Ground-based tracking systems regularly fail to detect small yet essential damage, onboard sensors are not a universal solution and increase the complexity of payload, and manual image analysis is tedious and error-prone.

To work around these limitations, this study offers a unique, completely image-based artificial intelligence system that is capable of detecting and classifying the MMOD-induced damage on satellite surfaces. Unlike traditional approaches, the proposed system does not need physical sensors and uses approaches based on computer vision and deep learning to process satellite imagery. The pipeline starts from detecting satellite segments by Detectron2 which is a state of the art object detection model. The segmented areas are then processed through a super-resolution network (EDSR), which allows to see fine textures and micro-damage that may be lost in low-resolution pictures. These improved patches are initially sent to a binary classifier so as to identify damaged from undamaged areas. For segments recognized as damaged, another classification stage is more in-depth and uses a multimodal approach to merging RGB images with simulated infrared, depth, and topographic data, and the spatial coordinates of the impact region to determine the type of damage accurately.

The system can identify five major types of damage that are normally associated with HVI: cratering, penetration, spallation, cracking and melting or vaporization. These damage modes are based on the actual testing data obtained from hypervelocity impact archives of such agencies as NASA and ESA. The adoption of the multimodal image fusion in this work presents a distinct aspect to it, the model is enabled to leverage thermal and geometric clues other than the usual visual characteristics.

What sets this study apart is its scalability, cost-efficiency, and adaptability to various spaceborne platforms. By eliminating the dependency on hardware sensors and enabling autonomous, image-driven diagnostics, this approach offers a significant advancement in satellite health monitoring. It not only aids in preventing mission failures but also contributes to the broader goals of maintaining long-term orbital sustainability and ensuring the safety of human operations in space. This work lays a foundation for future systems capable of performing onboard self-assessment, enabling satellites to independently monitor their structural integrity and respond proactively to environmental threats in the harsh environment of space.

II. Literature Survey

In this literature survey, we systematically analyze and categorize 18 research papers relevant to spacecraft damage detection, hypervelocity impact analysis, and intelligent aerospace perception. To present a clearer understanding of existing research directions and technological advancements, the papers have been grouped into six distinct thematic clusters based on their core methodologies and application domains: 1) Infrared/Thermal Imaging-Based Damage Detection 2) Deep Learning and Machine Learning-Based Detection & Prediction 3) Experimental and Numerical Studies on Hypervelocity Impacts 4) Fragmentation and Satellite Breakup Modeling 5) Structural Integrity and Protection Mechanisms 6) Computer Vision for Aerospace and Remote Sensing Applications The following sections explore each group in detail, summarizing key contributions, methodologies, and research gaps to guide future investigations in the domain of space impact dynamics and autonomous damage assessment.

The new development of non-destructive testing (NDT) via the thermal imagery has proved to be effective in detecting and segmenting the damage of the spacecraft. A multi-target segmentation method based on improved mean-shift clustering and thermal image reconstruction for extracting features of hypervelocity damage was proposed by Lei et al. [1]. Leveraging similar foundations, Tan et al. [2] combined thermal images with guided filtering and transient thermal responses (TTRs) to extract damaged areas with improved visibility. Yang et al. [3] proposed a more advanced segmentation approach which involved the use of a double layer, multi-target framework coupled with evolutionary optimization in detecting spacecraft surface defects. Moreover, Zhang et al. [4] developed a Naïve Bayesian classifier, trained using transient temperature features, for real-time infrared-based impact assessment, demonstrating an improvement over the previous approaches including the FCM and ICA.

Such techniques as data-driven are also gaining popularity. Angeletti et al. [5] presented a Bi-LSTM-based deep learning model trained on simulation data for identifying multiple damage sites in spacecraft composites, which showed its superiority over traditional sensors. Larsen, etc. [6] developed a hybrid deep neural network (DNN) with Analytic Continuation to predict hypervelocity debris trajectories from satellite explosions to address another issue of space threat management. In another complementary dissertation, Larsen [7] also studied machine learning model such as KNN and GMM for flyout characterization, which had greatly enhanced debris prediction capabilities.

In terms of experiment, Ryan [8] studied momentum transfer mechanisms in solar arrays based on SPH-based simulations and he evaluated the Momentum Enhancement Factor for projectile materials and geometries. Carriere and Cherniaev [9] carried out a detailed review of the HVIs subjected to sandwich structures, which involved examining the effects of projectile type, core design, and impact angle on the shield's behavior. In earlier fundamental studies, Tennyson and Lamontagne [10] used a combination of experimental and finite element studies to understand damage in composites, confirming models using real impact data. For real-time monitoring, Li et al. [11] integrated fiber Bragg grating (FBG) sensors to determine the location of impacts on aluminum plates with high spatial precision. Similar to Yu et al. [12], a probabilistic hyperbola localization method for stiffened spacecraft structures was presented, based on TDoA and SPH modeling for precise damage follow-up. Chhabildas and Orphal [13] provided a wider historical context through their survey about decades' worth of progress in hypervelocity impact technologies, from test facilities to material models to shielding strategies.

In the context of satellite fragmentation and the modeling of debris, Ren et al. [14] performed a survey of satellite breakup models induced by HVIs and explosions, with experimental benchmarks and issues in the state-of-the-art predictive schemes (SPH and FEM-SPH).

Djojodihardjo [15] reviewed spacecraft protection strategies, focusing on structural design trade-offs under the thermal, vibrational, and environmental challenges. Wen et al. [16] further expanded on this with an extensive review of the Whipple shield innovations, classifying phases of the shield and suggesting lightweight, high-resilience configurations for future space missions.

Last but not least, deep learning has proven beneficial to intelligent aerospace perception in its own right. Chen et al. [17] conducted an exhaustive review of computer vision tasks related to space perception, including pose estimation and 3D reconstruction, identifying transformer models and multimodal combination as future directions. In the area of surveillance, Azam et al. [18] presented a comparative study of object detectors for aircraft recognition in satellite imagery, in which YOLO and Faster R-CNN architectures were discussed for their accuracy-speed trade-offs.

Combined, these studies offer a versatile array of approaches, ranging from thermal imaging and real-time sensing, to deep learning and shielding design, which will set the stage for more resilient, intelligent, and responsive spacecraft systems in the era of orbital threats.

III. Dataset Description

In this study, two distinct types of datasets were collected to support the classification of spacecraft surface damage caused

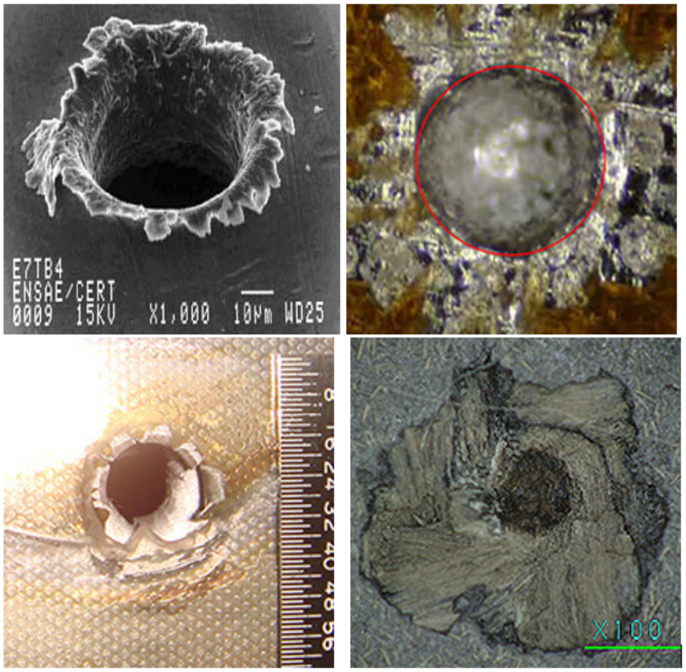

Fig. 1. Sample MMOD damage images

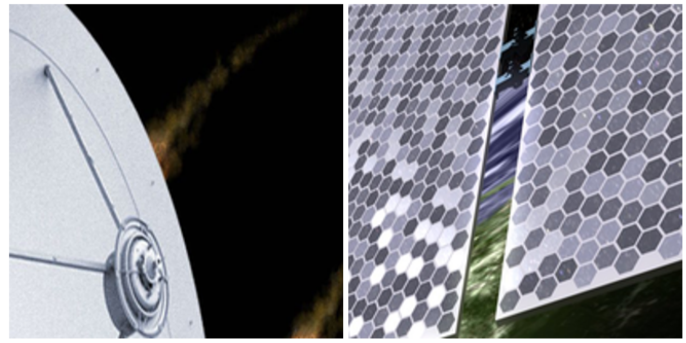

Fig. 2. Sample Non-damage Satellite Images

by Micrometeoroids and Orbital Debris (MMOD). The first dataset consists of MMOD damage images and, in contrast to for classification and ensure the robustness of the detection model, a second dataset of non-damage satellite imagery was collected

A. MMOD Damage Dataset

This consists of MMOD damage images, sourced from specialized hypervelocity impact testing archives love NASA Hypervelocity Impact Testing (HVIT) image site and ESA's Meteoroids and Debris Website (MADWEB) databases. These images typically capture microscopic or zoomed-in views of damage inflicted on various spacecraft materials, including aluminum panels, shielding tiles, and layered composites. The images are of high resolution, often 1024x1024 pixels or greater, and come in formats such as JPEG, PNG, or TIFF. They depict various types of damage including penetration holes, craters, delamination, and surface spallation. Alongside the images, detailed metadata is often available, specifying the material type, impact velocity, angle of collision, and characteristics of the projectile used during testing. These attributes provide critical context for training models to detect and differentiate between various damage patterns. However, most of these images are not pre-labeled and may require manual or semi-automated annotation to distinguish between different damage severities or types.

The images in Fig.1 is a sample from the dataset comprises real-world images. These images capture the aftermath of simulated micrometeoroid and orbital debris collisions on spacecraft materials, typically conducted under controlled hypervelocity impact testing environments.

The dataset includes diverse impact scenarios, such as crater formation, delamination, and surface rupture as shown int TableI, and serves as a valuable resource for training and evaluating models in automated space damage detection and analysis.

B. Non-Damage Satellite Images Dataset

This dataset includes clean, undamaged images of satellites and Earth's surface captured from space. These images vary in resolution—ranging from small 64x64 pixel tiles to high-definition 512x512 pixel frames—and are primarily in RGB format, though some multispectral images are included depending on the source. They are categorized into scenes such as forests, urban environments, water bodies, and agricultural regions, but importantly, contain no MMOD-related artifacts or damage. The non-damage images play a vital role as negative samples during training, allowing the classification model to effectively differentiate between normal satellite imagery and those impacted by orbital debris. Together, these two datasets form a comprehensive training base for developing a reliable MMOD damage detection system.

The images in Fig.2 are some Non damage dataset samples of the satellites. It includes a wide range of satellite images like this in the dataset.

IV. Methodology

The methodology for this project comprises a sequential deep learning pipeline designed to identify, isolate, and classify structural damage on satellite surfaces caused by hypervelocity impacts from micrometeoroids and orbital debris (MMOD). This process involves multiple stages including image segmentation, resolution enhancement, damage detection, and multimodal classification. The proposed system is purely image-based, requiring no onboard sensors, making it scalable and deployable across various satellite missions. A comprehensive view of the complete workflow is shown in the figure below.

Fig. 3 outlines the end-to-end pipeline that will be elaborated on in the following sections, including references to individual blocks as they appear in the diagram.

A. Satellite Detection and Segmentation using Detectron2

The next step in the pipeline of the dataset collection is isolation of the satellite structure from a larger image of space or orbital imagery. This is done with the help of Detectron2, a deep learning based object detection and segmentation framework based on the Mask R-CNN architecture. The process of detection starts with the process of feature extraction where

TABLE I
TYPES OF DAMAGE SHOWCASED IN THE MMOD DATASET

Damage Type	**Description**	**Visual Appearance**	**Typical Causes**
Crater	Small to large bowl-shaped depressions on the material surface.	Round concave dent, often with sharp edges.	High-velocity impact of small debris particles.
Penetration Hole	Complete perforation through the material due to high energy impact.	Clean or ragged holes, may be circular or irregular.	Impact by sharp, fast debris at high angle or energy.
Spallation	Fragments ejected from the back side of the impact location.	Surface appears chipped or flaked around the rear of the hit.	Shockwave traveling through and bursting from back.
Melting & Charring	Surface melted or burnt due to heat from kinetic energy conversion.	Discolored, blackened, or glassy textures.	Extremely high-velocity impacts or plasma generation.
Cracks	Cracks extending outward from the impact point, resembling a spiderweb.	Starburst or radial crack patterns.	Brittle failure due to sharp impacts.

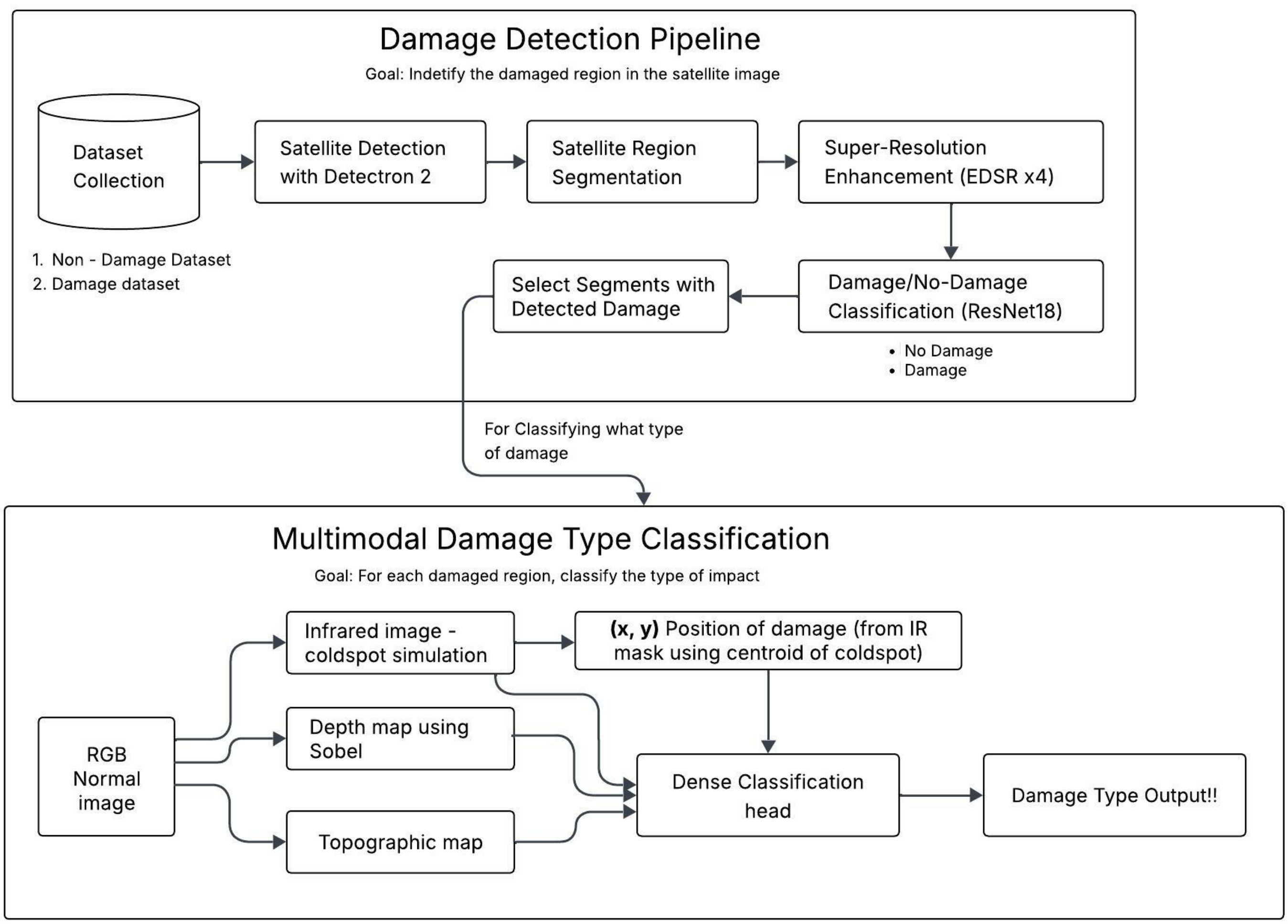

Fig. 3. Complete damage detection and classification workflow: From image-based satellite detection and super-resolution to multimodal classification of hypervelocity impact damage

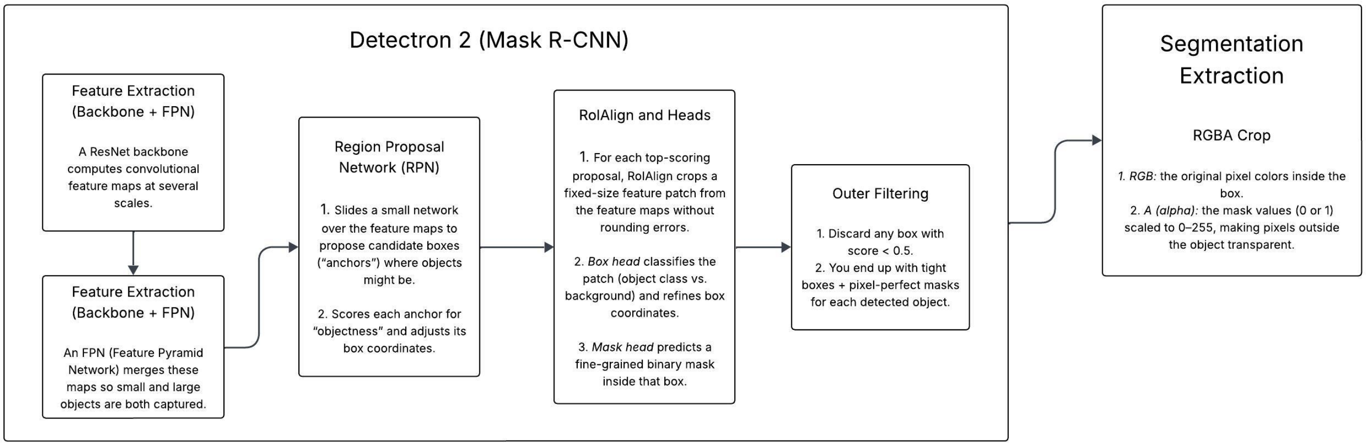

Fig. 4. Detectron2-based satellite detection and segmentation

a Resnet based backbone produces multi-scale convolutional feature maps from the input image. These maps go through the Feature Pyramid Network (FPN) that improves object detection capability for objects of different sizes.

When the features are extracted, the Region Proposal Network (RPN) appears over the maps and proposes possible locations of objects, i.e. anchors, and scores them for their likelihood to contain an object. High scoring proposals are given to the RoIAlign module where fixed size feature patches with pixel accurate alignment are extracted. These patches are then labeled into object vs background by the head of the network, and a mask is predicted to denote the specific region covered by the satellite.

After the satellite is separated from the background, the desired area is taken out as an RGBA crop. The RGB channels will show the original image colours, whilst the alpha channel will be the form of the binary mask predicted by Detectron2. This mask guarantees that only the satellite pixels are kept and the background is to be made transparent. These chopped pieces then continue downstream for further processing. This enhances computational efficiency and limits the damage classification to only those areas that need to be classified.

Fig 4 Detectron2-based satellite segmentation: A Mask R-CNN pipeline extracts pixel-perfect satellite regions using a combination of convolutional backbones, proposal networks, and segmentation masks.

B. Super-Resolution Enhancement (EDSR x4

The satellite segments extracted from the Detectron2 model often lack the necessary detail for microscopic damage detection. To overcome this, the cropped RGBA patches are passed through a Super-Resolution model—specifically, an Enhanced Deep Super-Resolution (EDSR) network. This network is designed to upscale the image by a factor of two or more, while enhancing edge sharpness and fine surface texture.

The EDSR network uses a series of convolutional and residual blocks to hallucinate and reconstruct higher frequency details. Pixel shuffle layers are used for efficient and artifact-free upsampling. By applying super-resolution, surface anomalies such as cracks, tiny punctures, or texture inconsistencies that are otherwise invisible at lower resolutions become much more distinguishable.

C. Binary Damage Classification usinf ResNet18

Once the super-resolved satellite patches are generated, each patch is passed through a binary classifier to determine whether it contains any form of damage. For this task, a lightweight ResNet18 architecture is employed, capable of distinguishing damaged from undamaged surfaces with relatively high accuracy. The classifier is trained on two distinct datasets: one containing MMOD (Micrometeoroid and Orbital Debris) impact images and the other consisting of undamaged satellite segments.

Only the patches classified as containing damage are forwarded to the next stage, which involves detailed categorization of damage type. This two-step approach improves computational efficiency and ensures that unnecessary classification efforts are avoided on clean images.

D. Multimodal Damage Type Classification

For patches that are proven to have damage a more sophisticated multimodal model is used in order to type the exact type of impact. The RGB image is enhanced by obtaining other visual modalities such as IR simulation and depth maps, topographic maps. The IR images are performed by coldspot simulation, whereby they simulate the way thermal sensors may identify impact zones. Depth maps are computed from Sobel edge gradients to encode geometric variations in elevation while topographic maps are coloured variations of the depth values.

Also, the (x, y) coordinates of the damage location are extracted in the form of thresholding and centroid detection from the IR image. These positional features are normalized and they are used in numerical form.

Each modality (RGB, IR, depth, and position data) goes through its own branches of a neural network. Convolutional neural networks (CNNs) perform the processing of the inputs, which are image based, while a multi-layer perceptron (MLP) takes care of the (x, y) coordinate data. The output of the extracted features from all branches are concatenated into a single embedding vector, which is then fed to dense layers and a final classification head. The output is a softmax vector of damage type prediction. cratering, penetration, spallation, cracking, melting/vaporization.

V. RESULTS AND DISCUSSION

The proposed multimodal pipeline for hypervelocity impact detection and damage classification was trained and evaluated on a curated dataset consisting of annotated MMOD-damaged satellite images and undamaged control samples. The goal was to classify impacted regions not only as damaged or undamaged but also to further identify the specific type of physical damage. The evaluation of the system is presented in terms of binary classification performance, multiclass damage classification accuracy, and qualitative visual outputs.

A. Binary Damage Classification Results

The binary classification model was to decide whether a satellite segment had been damaged by MMOD or not. This model operated on RGB image patches and gave out a binary label. As it can be seen in the validation set report, the model provided an overall accuracy of 89.47%, which is quite a good improvement compared to previous versions of the model.

In other words, the model achieved a precision of 0.8571, recall of 0.8571, and F1-score of 0.8571 for the MMOD_Damage class. For the No_MMOD_Damage class, the model did even better with all metrics being 0.9167. The macro-averaged F1 score (also known as Macro Dice) was 0.8869 and micro-averaged F1 score was 0.8947. Also, the ROC AUC score of 0.9762 (both macro and micro) shows that the classifier has good discriminative power that successfully distinguishes between damaged and non-damaged class.

TABLE II
BINARY CLASSIFICATION REPORT FOR MMOD DAMAGE DETECTION (VALIDATION SET)

Class	**Precision**	**Recall**	**F1-Score**	**Support**
MMOD_Damage	0.8571	0.8571	0.8571	7
No_MMOD_Damage	0.9167	0.9167	0.9167	12
Accuracy			**0.8947**	**19**
Macro Avg	0.8869	0.8869	0.8869	19
Weighted Avg	0.8947	0.8947	0.8947	19

Additional Metrics:

- Macro-Dice (sklearn F1): **0.8869**
- Micro-Dice (sklearn F1): **0.8947**
- Macro ROC AUC: **0.9762**
- Micro ROC AUC: **0.9762**

Table II displays the Validation set results for binary classification: The model shows high accuracy, strong recall, and excellent ROC AUC, indicating robust separation of damaged and undamaged satellite segments."

These results confirm that the binary classification stage in the pipeline performs reliably and can be effectively used to filter satellite segments before applying more complex damage classification techniques.

B. Multiclass Damage Type Classification Results

Even though the performance of the damage-type classifier was functionally complete, it had some limitations. Out of the five categories of damages, only the Cratering was successfully detected while the Penetration, Spallation, Cracking and Melting were not detected. This led to an overall classification of 42.86% with F1-score of 0.2571.

TABLE III
MULTICLASS DAMAGE TYPE CLASSIFICATION REPORT (TEST SET)

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Cratering	0.43	1.00	0.60	6
Penetration	0.00	0.00	0.00	2
Spallation	0.00	0.00	0.00	2
Cracking	0.00	0.00	0.00	3
Melting	0.00	0.00	0.00	1

Overall Results:

- Accuracy: **42.86%**
- F1-Score: **0.2571**
- Precision: **0.1837**
- Recall: **0.4286**

The model was able to detect cratering damage, which was the most common class in the test set. However, it did not manage to make any proper predictions for the minority classes. penetration, spallation, cracking, and melting. This led to a precision, recall, and F1-scores of 0.00 for these classes.

Such performance is a clear indication of a dire class imbalance problem with the dataset which skewed the model towards over-represented labels. The absence of predictions for rare types of damage indicates that the model has failed to learn enough distinguishing features for them, which is probably because there are not enough pieces of training data per class. Future work should aim to overcome this imbalance by augmentation, resampling strategies, or loss weighting methods.

C. Qualitative Results and Visual Explanation

To provide a visual understanding of how the model worked, outputs were visualized on every stage of the pipeline. These were satellite detection masks from Detectron2, super-resolved patches and annotated predictions from the damage classifier.

In the detection stage, the model was able to segment satellite components from background space scenes. The RGBA cropping kept the structural integrity of the detected object while masking out the irrelevant regions. The super resolution stage obviously improved fine texture by bringing out surface-level abnormalities that could otherwise not be effectively demonstrated.

In the classification visualization, damaged patches were labelled with predicted class labels and bounding boxes around the suspected impact sites. For the properly predicted Cratering class, the visible depressions on the surface were found as was expected in high activations in the IR and depth maps.

This output in Fig. 5 shows how Detectron2 accurately segments the satellite body from the background, producing a binary mask that isolates only the relevant structure for further processing.

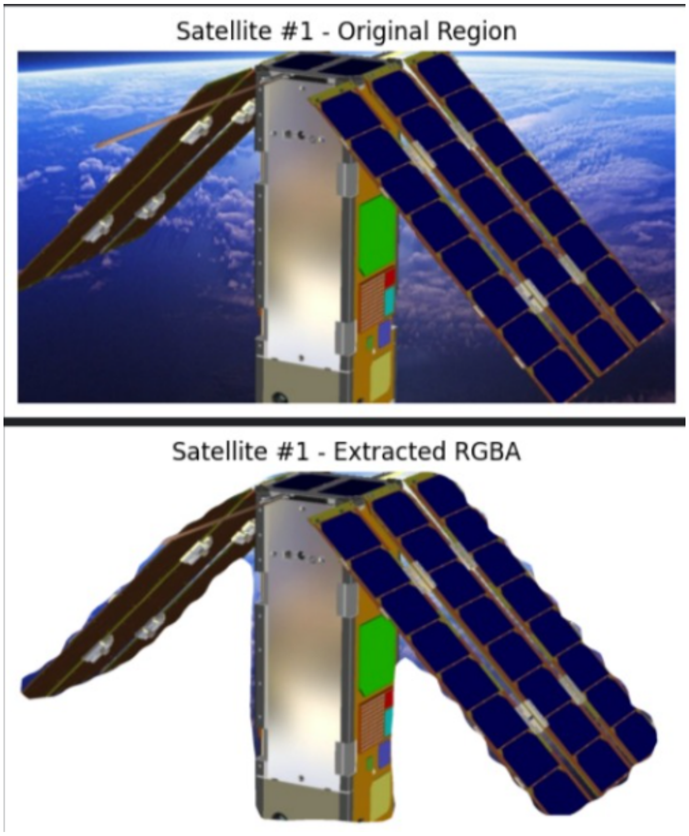

Fig. 5. Satellite segmentation using Detectron2 with overlaid pixel-accurate mask.

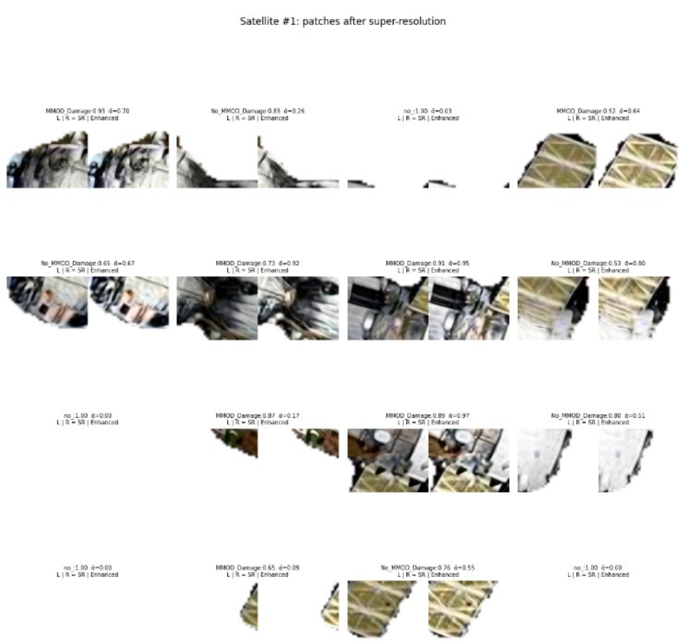

Fig. 6. Super-resolved satellite patch with enhanced surface details

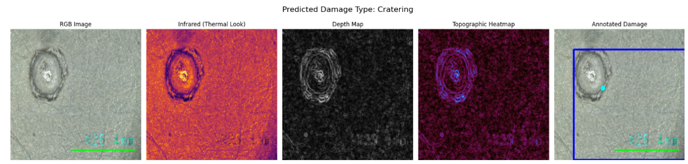

Fig. 7. Final damage classification result with predicted label and location

Using EDSR, this image patch Fig. 6 is upscaled to reveal fine structural textures, enabling better visibility of micro-cracks and subtle MMOD impact traces.

In the Fig. 7, the model identifies the damage type Crater and locates it on the RGB image with the aid of a bounding box and centroid overlay for interpretation and validation in visual form.

The binary classifier has achieved a mature level of performance, with robustness in terms of major evaluation metrics. Nevertheless, the multiclass model is still limited because of the skewness of data distribution. The use of such techniques as class rebalancing, data augmentation, or synthetic sample generation for under-represented damage types can be quite fruitful and lead to a considerable improvement.

The use of multimodal inputs (visual, thermal, depth, and positional) is still a new and efficient technique, as is demonstrated by the Cratering predictions success. With better training data, the model can be extended to a strong onboard system that can monitor the health of satellites in real-time.

In this work, the viability of a sensorless, image-based system for detecting and classifying the damage on satellite surfaces due to hypervelocity impacts is established. The achieved results — especially high accuracy in damage detection — prove that computer vision can be an essential element of ensuring the resilience of satellite and reliability of mission and sustainability in orbit.

VI. Conclusion and Future Scope

This study introduces an image-based AI system capable of detecting and classifying hypervelocity impact damage on satellites from the use of RGB, IR and depth and positional data. The pipeline combines Detectron2 for the task of segmentation, EDSR for super-resolution, and multimodal deep learning for classification. The binary classifier had good results (89.47%) but the multiclass model was restricted by class imbalance. Notwithstanding, the system shows a scalable sensor free mechanism for monitoring satellites health, with ability to detect structural damage, without manual inspection or onboard sensors. It is a basis for autonomous, image based diagnostics in future satellite missions.

Future work will involve the balancing of class by obtaining additional data for rare damage types. Improvements include real-time onboard deployment with light-weight model optimization and addition of uncertainty estimation on more interpretable results. The extension of the pipeline to manage temporal data on satellite video feeds can allow for damage tracking over time. The incorporation of this system in operational satellites would facilitate autonomous health monitoring in the orbit with less ground-dependency. Such an approach can be vital in developing self-assessing and early fault detecting resilient spacecraft in progressively crowded and dangerous space environments with additional improvements.

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