IDENTIFYING AND MITIGATING AVIATION INDUCED CONTRAILS USING MACHINE LEARNING AND BIG DATA ANALYTICS

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Abstract: The aviation sector is a cornerstone of global connectivity, yet it has a profound environmental impact, particularly through the formation of contrails. Contrails, or condensation trails, formed by aircraft exhaust in cold and humid atmospheric conditions, significantly contribute to radiative forcing, exacerbating global warming. Despite their transient nature, contrails have a more substantial short-term impact on climate than CO_2 emissions. This research presents a comprehensive framework for detecting, classifying, and mitigating contrails using satellite imagery and advanced machine learning techniques. By leveraging data from MODIS, Sentinel, and NOAA GOES-16 satellites, and deploying cutting-edge deep learning architectures like CNNs and UPerNet, this project achieves high-accuracy contrail identification. The study further investigates atmospheric conditions conducive to contrail formation and explores actionable strategies for their reduction through optimized flight routing. The outcomes of this research contribute to bridging significant gaps in sustainable aviation practices, offering tools for real-time monitoring and proactive environmental management. This work represents a pivotal step toward achieving a balance between aviation growth and environmental stewardship.

Key Words: Aviation, Contrails, Radiative Forcing, Global Warming, Climate Impact, Satellite Imagery, Machine Learning, Deep Learning, MODIS, Sentinel, NOAA GOES-16, Convolutional Neural Networks (CNNs), UPerNet, Contrail Detection, Sustainable Aviation, Flight Routing Optimization, Environmental Management, Real-Time Monitoring, Atmospheric Conditions, Climate Change Mitigation.

I. Introduction

The aviation industry plays a vital role in the modern global economy, enabling trade, tourism, and cultural exchange. However, it also poses significant challenges to environmental sustainability. While carbon dioxide emissions have long been a focus of climate mitigation strategies, non-CO_2 effects such as contrails have gained increasing attention due to their disproportionate impact on global warming. Contrails form when hot, moist exhaust gases from aircraft engines interact with the cold ambient air, creating streaks of ice crystals that trap heat in the Earth's atmosphere.

Mitigating contrail formation is critical for reducing the overall climate impact of aviation. However, monitoring and managing contrails present unique challenges due to their ephemeral nature and reliance on specific atmospheric conditions. The advent of advanced satellite imaging technologies and machine learning offers new opportunities to address these challenges. By integrating these tools, this study aims to enhance contrail detection accuracy, identify mitigation strategies, and support global efforts to combat climate change.

1.1. OBJECTIVE

This study's primary objective is to develop a robust system for contrail detection and mitigation using satellite data and advanced machine learning models. Specific goals include:

- Designing an efficient framework for real-time contrail monitoring.
- Investigating the relationship between contrail properties, atmospheric conditions, and flight paths.
- Proposing actionable strategies for the aviation industry to minimize contrail-induced climate effects.

1.2. SCOPE

- Leveraging large-scale satellite datasets for contrail detection and analysis.
- Utilizing state-of-the-art deep learning techniques to enhance detection accuracy.
- Providing insights and tools to support sustainable aviation practices. This interdisciplinary approach combines atmospheric science, computer vision, and aviation management to address a pressing environmental challenge

II. PROBLEM DEFINITION

Contrails contribute significantly to radiative forcing, a process where heat is trapped in the Earth's atmosphere, intensifying global warming. Their formation depends on specific atmospheric conditions, including temperature, humidity, and pressure. Despite their transient visibility, contrails can persist for hours and evolve into cirrus clouds, amplifying their climate impact. Existing systems for contrail monitoring are limited by inaccuracies, scalability issues, and the lack of real-time capabilities. Addressing these limitations is essential for mitigating the environmental impact of aviation and achieving global sustainability goals.

III. PROJECT DESCRIPTION

- This project utilizes a combination of satellite imagery, flight path data, and meteorological datasets to detect and mitigate contrails. Key components include:
- Data collection from MODIS, Sentinel, and NOAA GOES-16.
- Development of machine learning models like CNNs and UPerNet for contrail classification.
- Real-time integration with aviation routing systems to reduce contrail formation.

III. REQUIREMENTS

- Hardware Requirements:
- High-performance computing systems.
- Storage for large-scale satellite imagery.
- Software Requirements:
- Machine learning frameworks (TensorFlow, PyTorch).
- Satellite imagery processing tools.
- Data Requirements:
- Annotated satellite imagery datasets.
- Atmospheric and flight path data.

IV. METHODOLOGY

6.1 Data Collection: Sources: The dataset used is the Carvana Image Masking Challenge dataset from Kaggle, which includes high-resolution images of cars along with their corresponding segmentation masks. 6.2 Pre-Processing: Resizing: Images are resized to a consistent size to ensure uniform input dimensions for the model. Normalization: Pixel values are normalized to a range of [0, 1] to facilitate better convergence during training. Data Augmentation: Techniques such as random rotations, flips, and brightness adjustments are applied to increase the diversity of the training data and improve the model's generalization.Machine Learning Model:

- U-Net architecture, a convolutional neural network designed for semantic segmentation tasks. U-Net is known for its encoder-decoder structure, which captures context and enables precise localization. The implementation is based on the PyTorch framework, leveraging its dynamic computation graph and GPU acceleration capabilities.

6.3 Model Selection: The U-Net model is chosen due to its effectiveness in image segmentation tasks, particularly in medical imaging and other domains requiring precise localization. Its symmetric architecture with skip connections allows for efficient feature extraction and reconstruction, making it suitable for the Carvana Image Masking Challenge dataset.6.4 Training and Testing: Loss Function: The binary cross-entropy loss is used, which is appropriate for binary segmentation tasks. Optimizer: The Adam optimizer is employed for its adaptive learning rate properties, aiding in faster convergence. Batch Size: A batch size of 16 is used, balancing memory constraints and training stability. Epochs: The model is trained for 50 epochs, with early stopping implemented to prevent overfitting. Validation: A validation set is used to monitor the model's performance during training and adjust hyperparameters accordingly.

Evaluation Metrics:

- The primary evaluation metric used in the notebook is the Dice coefficient, a measure of overlap between the predicted segmentation mask and the ground truth mask. A higher Dice coefficient indicates better performance of the segmentation model.

V. LITERATURE REVIEW

Title	Authors	Year	Summary
Deep Semantic Contrails Segmentation of GOES-16 Satellite Images: A Hyperparameter Exploration	Gabriel Jarry, Philippe Very, Amine Heffar, Valentin Tordjman-Levavasseur	2024	Explores hyperparameter optimization for deep semantic segmentation models aimed at contrail detection in GOES-16 satellite imagery.
Contrail Altitude Estimation Using GOES-16 ABI Data and Deep Learning	Vincent R. Meijer, Sebastian D. Eastham, Ian A. Waitz, and Steven R. H. Barrett	2024	Develops a deep learning algorithm to estimate contrail altitudes based on GOES-16 ABI infrared imagery, crucial for understanding contrail formation and persistence in climate models.
Exploring Models and Band Selection for Improved Contrail Detection in Geostationary Satellite Imagery	Irfan Darmawan, Mochamad Al-Husaini	2024	Utilizes deep learning models and band selection techniques to enhance contrail detection in geostationary satellite imagery, focusing on Landsat-8 data.
Optimizing Contrail Detection: A Deep Learning Approach with EfficientNet-b4 Encoding	Qunwei Lin, Qian Leng, Zhicheng Ding, Chao Yan, Xiaonan Xu	2024	Presents a deep-learning approach utilizing EfficientNet-b4 for feature extraction, along with misalignment correction and soft labeling techniques to improve contrail detection.
The Application of a Convolutional Neural Network for the Detection of Contrails in Satellite Imagery	Jay P. Hoffman, Timothy F. Rahmes, Anthony J. Wimmers, Wayne F. Feltz	2023	Presents a CNN-based approach for contrail detection in satellite imagery, emphasizing the significance of monitoring contrails for climate change.
Combining UPerNet and ConvNeXt for Contrail Identification to Reduce Global Warming	Zhenkuan Wang	2023	Focuses on aircraft contrail detection in satellite images, developing a novel preprocessing technique for NOAA GOES-16 satellite images and integrating segmentation models for enhanced contrail identification.

- Performance Evaluation of Deep Segmentation Models for Contrail Detection (2022): This study benchmarks segmentation models for contrail detection, addressing the lack of labeled datasets and demonstrating the potential of state-of-the-art techniques.
- Exploring Models and Band Selection for Improved Contrail Detection in Geostationary Satellite Imagery (2022): Focuses on optimizing band selection for geostationary satellite data to enhance contrail detection.
- Deep Semantic Contrails Segmentation of GOES-16 Satellite Images: A Hyperparameter Exploration (2022): Examines hyperparameter optimization for semantic segmentation models in detecting contrails.
- Contrail Altitude Estimation Using GOES-16 ABI Data and Deep Learning (2022): Introduces a deep learning method to estimate contrail altitudes from satellite imagery.
- Optimizing Contrail Detection: A Deep Learning Approach with EfficientNet-b4 Encoding (2022): Presents an efficient deep learning model for accurate contrail detection using advanced feature extraction.
- Combining UPerNet and ConvNeXt for Contrail Identification (2022): Proposes a novel data preprocessing technique integrated with segmentation models to improve detection.

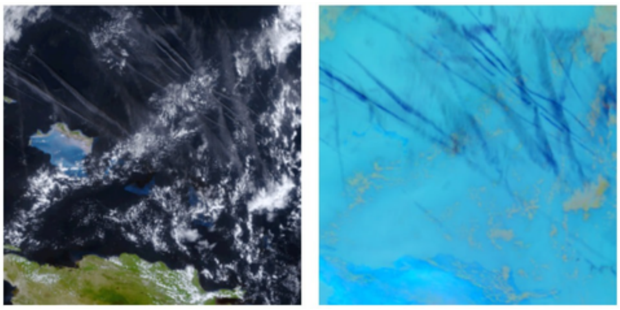

Fig.1 Satellite image onto the left with processed image onto the right to highlight contrails patterns

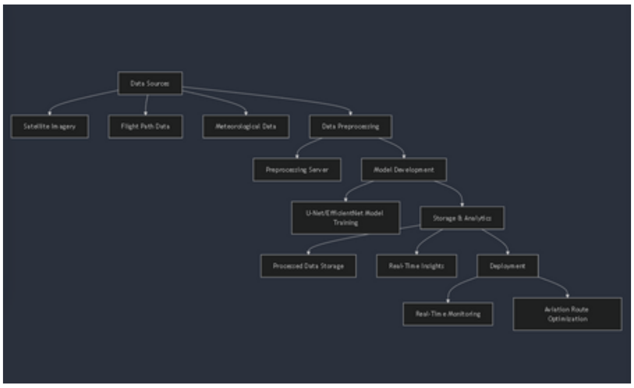

Fig.2 Workflow from data source to model training

VII. IMPLEMENTATION

Simple Unet Pytorch Baseline (Train)

Notebook Input Output Logs Comments (6)

```
In [24]:
NUM_EPOCHS = Config.num_epochs
model = UNet(Config).to(Config.device)

# run = wandb.init(project='Google Contrails',
#                  config={k:v for k, v in dict(vars(Config)).items() if '__' not in k},
#                  name=f"{Config.encoder}-{Config.num_epochs}epos-{Config.lr}-unet"
#                 )

total_steps = len(train_ds)
optimizer = get_optimizer(lr=Config.lr, params=model.parameters())
scheduler = get_scheduler(Config, optimizer, total_steps)

# wandb.watch(model, log_freq=100, log='all')

from timeit import default_timer as timer
start_time = timer()

model_results = train(model, train_dl, valid_dl, optimizer, NUM_EPOCHS, Config.device)

end_time = timer()
```

III. RESULTS

```
Train : 100% 642/642 [04:54<00:00, 2.34it/s]

Valid: 100% 58/58 [00:16<00:00, 5.18it/s]

 Train Loss: 0.0108 | Val Loss: 0.0124 | Val Dice: 0.6181
 Learning rate: 7.491063393793129e-06
 EPOCH: 29

Train : 100% 642/642 [04:54<00:00, 2.34it/s]

Valid: 100% 58/58 [00:14<00:00, 6.56it/s]

 Train Loss: 0.0108 | Val Loss: 0.0123 | Val Dice: 0.6196
 Learning rate: 1.8015407097782265e-08
 Total Training Time: 9333.491 seconds
```

Fig.3 Training model using pytorch U-Net

```
In [28]:
# Finding the Best Threshold
bdice = -1
bi = None
for i in tqdm(np.arange(0, 1.01, 0.01)):
    val_dice = dice_coef(ground_truths, predictions, i)
    if val_dice > bdice:
        bdice = val_dice
        bi = i

100% 101/101 [01:27<00:00, 1.16it/s]

In [29]:
print(f'Best Threshold: {bi}')
print(f'Best Validation Dice Score: {bdice}')

Best Threshold: 0.01
Best Validation Dice Score: 0.6216237299559233
```

Fig.4 62% accuracy of trained model

V. References

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