Detection of Contrails Using Deep Learning

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***Abstract*—Contrails are the line-shaped ice clouds formed behind the aircrafts that traps the emissions produced from aircrafts and forms the supersaturated regions in the humid areas. These are characterized by the ice particle properties, such as size, concentration, extinction, ice water content, optical depth, geometrical depth, and cloud coverage etc., As per the studies it is known that the radiative effect of contrails is on par with or even greater than the CO2 emissions from airplanes. It is estimated that by 2050, the radiative forcing from global contrail cirrus may treble to around 160 m W m2. In the current study we are planning to detect the contrails based on the satellite image data and climatic data with respect to each image using deep learning techniques. We have decided on using the satellite image data from GOES-16 Advanced Baseline Imager (ABI) and successfully collected the data. By leveraging the deep learning techniques such as Upernet, Convnext model, image segmentation we seek to develop a model that can advance our understanding of the con- trail properties and their detection.**

***Index Terms*—Contrails, Convnext, UperNet, ABI**

I. Introduction

The rising need for addressing the aviation emissions, mainly with contrails as focus. Contrail detection using machine learning is known to be the most cost effective and environmentally friendly method of reducing the aviation emissions [3]. Though there is a lot of study going on this topic currently still there exists few gaps that needs to be handled. With contrails being the major concerns due to their contribution in increasing the radiative forcing on earth atmosphere. Its important to understand their properties and mechanism by which we can detect them. So, we believed deep learning models such as Upernet along with advanced image segmentation can be an innovation approach in understanding these contrails. This project not only handles the contemporary issues, but also aligns correctly with my study goals. This work exposes me to a complete data science project lifecycle. I get the chance to work with cutting edge deep learning models, image segmentation tasks etc. By deeling into advanced convnext models and handling the misbalancing issues in data and models along with optimizing the methods, this research helps us in applying all the knowledge we have gained all through our study.

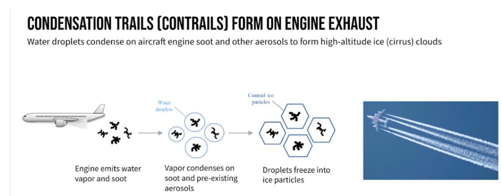


Fig. 1. Contrails from an Engine Exhaust

Contrails were first found by the military when they are formed due to aircrafts approximately 75 years ago. Then studies were first started by scientists in Europe on contrail detection. There are models developed for contrail detection such as automatic contrail detection system(ACTA), [6] Advanced Very-High-Resolution Radiometer (AVHRR), Spinning Enhanced Visible Infra-Red Imager (SEVIRI) etc., Aviation's contributions to climate changes has extended beyond co2 emissions and also leading to non co2 emissions such as contrails that players a major role in global warming. These are the line shaped structures formed on the back of planes at higher altitudes in humid areas. Their temporal behavior such as forming as lines and developing into cirrus of clouds and their inconsistent lifetime that varies in between seconds to a maximum of 18 hours[4, 2]. Various methods have been developed in this area of study however there still exists inconsistencies, due to the need for integration of data from different sources, and limitation of the proper techniques for measuring and validating the performances. Many techniques involved integration of computer vision, image segmentation and deep learning however still there exists issues such as difficulty in separating contrails from terrestrial objects and improving the image quality etc.

Among the models developed recently the popular method used in many researches is the MIT model [5] which involved image segmentation using applied on images formed by in-

Fig. 2. Contrails in the sky

frared channels which included 3 channels, red, green and blue. These three channels helps in easily identifying contrails on using the Unet model. Validation is highly important when identifying the contrails on satellite images, as they cannot capture the newly born contrails that vary in range and might die in little while. Its also studied that knowing which flight has produced a contrail would give more information regarding its condition suitable for their formation. The current is following the same method, however we are trying to integrate the climatic data, such as the humidity.

II. Related Work

Contrail detection related research is getting advanced in the recent years, mainly focusing on the leveraging the image segmentation methods for identifying and analyzing in a accurate way. This research work has integrated advanced image segmentation techniques for contrail detection. The research implemented the SegX-net architecture, combined with Deeplab3+ and ResNet-101 for higher accuracies[3] They incorporated the data preprocessing methods, and the transfer learning is enhancing the resilience and adaptability of model to multiple environmental conditions. All these advancements are very crucial in image segmentation techniques in addressing the key issues related to contrail detection, paves the way for improvising the understanding and the mitigation of the impact for environment of aircraft emissions. This model has demonstrated higher performance rates.

That field that utilises the images from satellites, data related to air traffic and weather modelling is contrail detection, which is finally identify and even track the atmospheric phenomena. The techniques related to Deep learning that may be Mask-RCNN are the one mostly used for the purpose of delineate the contrails from the background imagery very accurately [1]. The paper focuses on the synthetic datasets which are generated for training the detection models. All the future related directions includes the global coverage refinement and the integration of ground-truth dataset. In the remote regions the enhancement of the contrail detection accuracy can be achieved using the Satellite-based ADS-B. The combination of contrail detection techniques and the radiative forcing estimation is the most crucial one for the validation of climate impact models. This approach towards creating the dataset helps in validating several contrail models.

All the advancements in the contrail detection have been demonstrating the effectiveness of the CNN, all for analyzing the satellite imagery for the purpose of identifying the aviation-induced cirrus clouds. The authors by using the U-Net architecture for valid detection of the contrails in the data of satellite, which achieves a very significant probabilities of the detection and even the rates of low false alarm [2]. All these techniques leverage the thermal infrared bands on the GOES for the purpose of providing a very comprehensive coverage. The author's focus is on using the brightness temperature difference imagery, coming to future research it works on exploring the multi-channel approaches and the incorporation of the atmospheric conditions for the purpose of enhancing the detection accuracy in the future. ML techniques advancements and integrating them with the flight path data can offer us a wide range of opportunities to refine the whole contrail detection algorithms.

The research uses semantic segmentation to improve contrail detection in global satellite images. It entirely conducts a new approach for data pre- processing and generating false-colour images to enhance the model perception with the use of brightness temperature data. To handle the class imbalances. With the help of the UPerNet architecture, ConvNeXt settings, cross-entropy loss, and AdamW optimizer fine-tuning, the approach performs exceptionally well, ranking in the top five of contrail detection competitions[7]. In addition to that, integrating the pretraining strategies, like demonstrated with the networks ConNeXt, has showed a very valid efficacy in improvising the generalization and the performance of the model. All these developments portrays the potential of the sophisticated neural network architectures for finally achieving the most ribust contrail detection and the for the segmentation, leads into a way for the more effective and valuable analysis of the data related to remote sensing for the research on the atmosphere and aviation applications.

III. Objectives

Using deep learning, the study aims to achieve the following objectives:

1) Developing and selecting a model that can accurately identify contrails from grayscale images.
2) Establishing efficient training techniques, such as the AdamW optimizer with appropriate learning rates and cross-entropy loss with positive class weights, to prioritize precise contrail identification and optimize model parameters.
3) Improving contrail detection by selecting an appropriate model through the integration of two ConvNeXt configurations with the UPerNet architecture.
4) Discovering inference methods for creating binary prediction masks, including a multi-model prediction fusion strategy and a contrail determination threshold.

IV. Data Set

The dataset for contrail detection was created using geostationary satellite imagery from the GOES-16 ABI instrument.

While the raw imagery doesn't show early contrails due to low resolution, they are visible later in their life- cycle due to their warming effect. A "grey" false colour scheme was used to enhance the visibility of contrails in the imagery. Image patches of 500x500km were extracted from full-disk images and down sampled to 281x281 pixels for annotators. Polygons were drawn around the dark pixels representing contrails. Finally, both images and contrail masks were cropped to 256x256 pixels and sequences of images captured at 10-minute intervals were provided for temporal context.

TABLE I
DATA FOLDERS AND FILES

Data Folders and Files	No. of Files
Contrails	22,385
Train_df	20529
Valid_df	1856

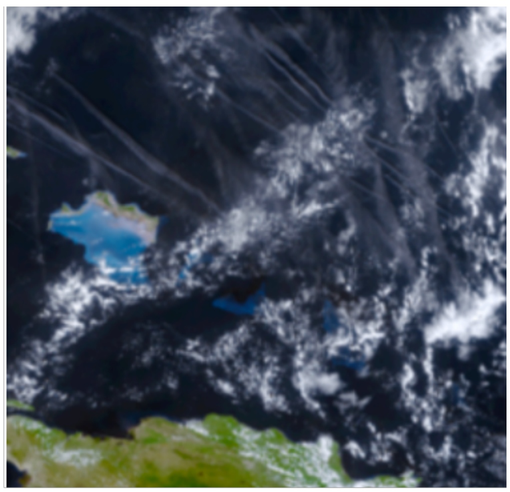


Fig. 3. Original Image

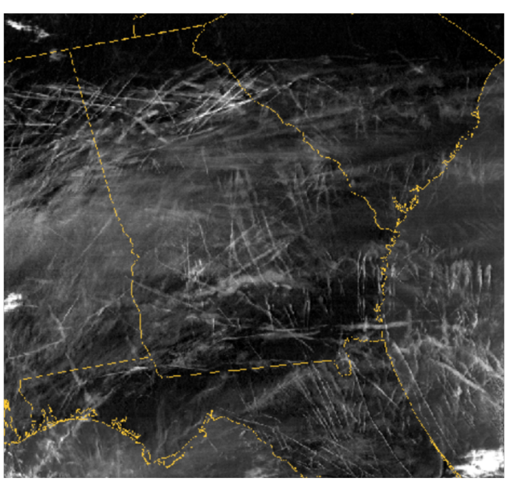


Fig. 4. Grey Scale Image

There are studies that used convolutional neural networks for determining the contrails however most of them didn't reach the acceptable performance quality. This is because humans were able to label and detect the images as they consider the contrail formation with respect to previous pixels as well, as we know that contrails change in size over time. Models lack this which results in reduced performance. Hence to avoid this we are trying to implement a new model.

In the dataset we have three files in total one is the folder that has the images and their labels in .npy format which is basically a numpy array this is because of the easy access of the images in numerical form. So the other two files are .csv files which basically contains the name or ID's of the npy files from the Contrails folder discussed above.

Actually the raw dataset that's driven from the google repository we have the data at around 450 GB. Since its hard to use the entire dataset we have sampled the data to around 7 GB that has in total 22,385 items. To avoid the class imbalence, this sampled dataset has human labeled contrails, And we have also made other changes such as including only 20% of the contrails has lesser then ten flight tracks and five percent of the images without advected flight tracks. We have also considered climatic data in terms of sampling this data as mentioned in the abstract, that is we have included five percent of the images with relative humidity less then 90% as contrails tend to form at humid regions at higher altitudes[8].

V. Research Methodology and Hypothesis

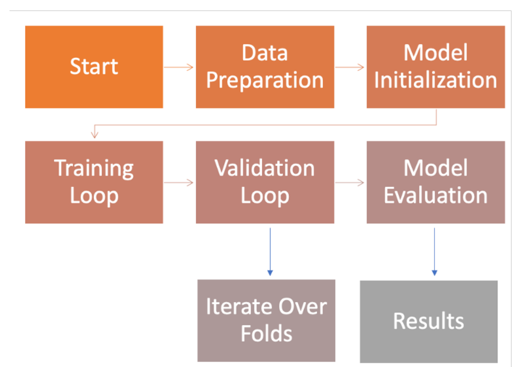


Fig. 5. Research Design

For this project, we used the same dataset and architecture as the paper referenced. For data extraction, the satellite images are open-source satellite images which are open to public on Google Cloud. For data analysis, we used image segmentation algorithm called UPerNet which is tasked to assign a label to each pixel in an image according to the object it belongs to. As a backbone network to the UPerNet, we are using ConvNeXt Method. Steps followed are, UNet Establishes a baseline UNet model trained only on images with corresponding labels. Different encoder to U-Net Uses pretrained ResNet models for initialization to potentially improve training speed and performance. Unified Perceptual Parsing Network Leverages a multi-task framework and training strategy to learn from diverse image annotations for comprehensive scene understanding. ConvNeXt Network Experiments with a recent convolutional neural network model (ConvNeXt) known for its exceptional performance in image classification and recognition tasks.

The hypothesis of the study we are trying to execute is to leverage the advanced image segmentation techniques out there which is Upernet algorithm alonhg with ConvNext as its backbone architecture in this case. By implementing the Sequence analysis, multi tasking at learning time and considering the temporal data we are trying to achieve the maximum performnce in contrail detection. We believe these advanced modifications in the model use would overcome the issues persisted in the models used in the previous studies.

VI. Data Analysis

Here the model we are employing is UNet architecture which is effective in image segmentation tasks. We have customized the model by creating encoder and decoders where in the encoder captures the input image features and the decoder processes these features and provides pixel wise predictions. The encoder is provided with the pre trained model weights from the imagenet dataset for better understanding of hierarchical representation.

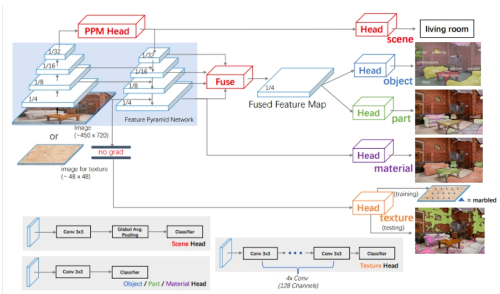
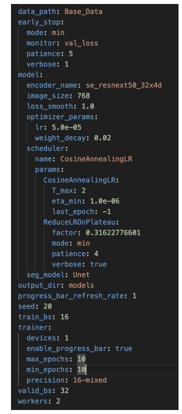


Fig. 6. UNet Model Architecture

To enhance the feature localization and discrimination we employed attention mechanism, Spatial and Channel-wise Squeeze and Excitation (SCSE).The loss functions incorporated in the project are Dice-loss and we have used the optimizers AdamW optimizer with a cosine annealing learning rate scheduler for stable training. Through out their training process we have logged the performance parameters such as F1 score, Dice loss, Accuracy and precession in each epoch.

Above image shows the details from the model configuration and parameters were have used. We have CosineannealingLR as shedular with adam optimiser and the pre-trained model 'se_resnext50_32*4d', that has showed higher performance over reputed datasets like 'ImageNet'. Coming to the training and other parameters we have used around 5 folds for batching the dataset with batch size of 32 and the number of epochs used have kept varying through out the research. This is because of the lack of computing power, The data files we are trying to use here are are taking more time as they are heavy and we are not able to run the tests on GPU. Hence we started the epoch count with 30 and then kept reducing until 15 finally.So we have used Dice coefficients that are calculated to



```
data_path: Base_Data
early_stop:
  mode: min
  monitor: val_loss
  patience: 5
  verbose: 1
model:
  encoder_name: se_resnext50_32x4d
  image_size: 768
  loss_smooth: 1.0
  optimizer_params:
    lr: 5.0e-05
    weight_decay: 0.02
  scheduler:
    name: CosineAnnealingLR
    params:
      CosineAnnealingLR:
        T_max: 2
        eta_min: 1.0e-06
        last_epoch: -1
      ReduceLROnPlateau:
        factor: 0.31622776601
        mode: min
        patience: 4
        verbose: true
  seg_model: Unet
output_dir: models
progress_bar_refresh_rate: 1
seed: 20
train_bs: 16
trainer:
  devices: 1
  enable_progress_bar: true
  max_epochs: 10
  min_epochs: 10
  precision: 16-mixed
valid_bs: 32
workers: 2
```

Fig. 7. Configurations Used

evaluate the differences between predicted and actual values. Validation loss is also logged for each epoch.

VII. Data Visualisations and Results

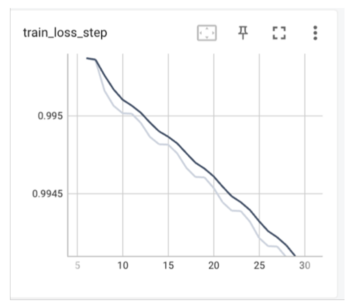


Fig. 8. Train_loss_step

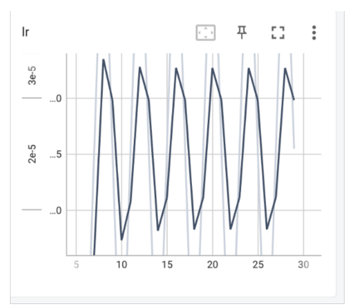


Fig. 9. Learning Rate

We have connected the results to TensorBoard for better understanding of the training rates and other performance metrics distribution with each epoch, which are provided below. Here we are visualizing the train and valid loss values for each training epoch. Initially, we loaded the training model parameters to fine-tune the data and then separately assessed the performance on test data files. Since we are using Dice coefficient as the evaluation metric here, we are logging these values for every epoch. Combining all these effects, we obtained a Dice coefficient of 0.65495, which represents good

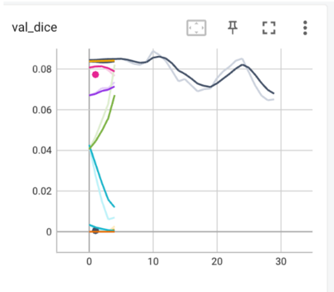


Fig. 10. Val Dice

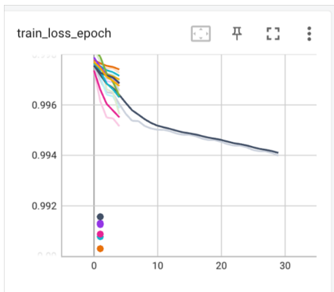


Fig. 11. Train_Loss_epoch

performance of the model in contrail detection. The obtained results are presented below.

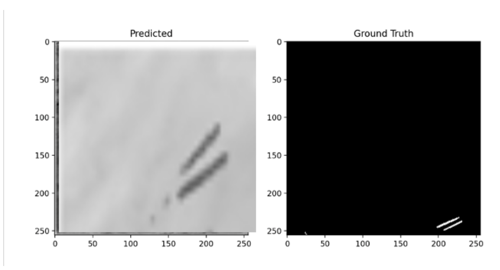


Fig. 12. Predicted lables

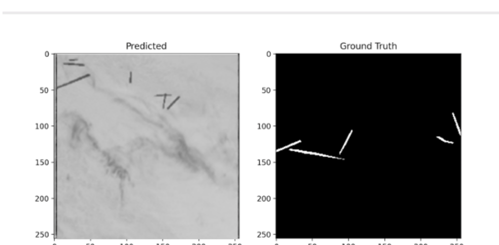


Fig. 13. Predicted Lables

VIII. Conclusion

This model architecture has been adapted from the results of a competition on contrail detection. In this work, we converted the images to grey false color for better detection of the contrails. Moreover, we used positive cases (already labeled images) for training and fine-tuning to avoid class imbalances in the dataset. This project primarily focuses on identifying contrails and mitigating their impact on the environment. We processed NOAA GOES-16 dataset using UPerNet (for architecture) and ConvNeXt (for configuration). For model optimization, we used the Adam optimizer. The primary goal of this project is to detect contrails effectively and reduce their environmental impact. The results demonstrate that the model performed well in detecting contrails.

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