

A series of overlapping, thin black lines forming various geometric shapes and polygons, creating a complex, abstract pattern in the upper left and center of the page.

SEGMENTATION-BASED AVIATION VISUAL ANALYSIS USING SAM



Done By:

Chennakeshava Akhil Pillalamarri

MSDS-692 Data Science Practicum-1

Regis University

INTRODUCTION

- Aviation systems rely heavily on **visual monitoring across various operational stages**, including ground operations, taxiing, air traffic operations such as take-off and landing.
- Advanced **computer vision techniques enable automated scene understanding**
- Segmentation models provide pixel-level object understanding, improving analysis beyond traditional detection methods



PROBLEM STATEMENT

- Aviation environments generate **large volumes of visual data**
- Manual inspection of aircraft and operational scenes is **time-intensive**
- Object density varies across ground, taxiing, and takeoff contexts
- A structured **segmentation-based computer vision pipeline** is needed for systematic evaluation



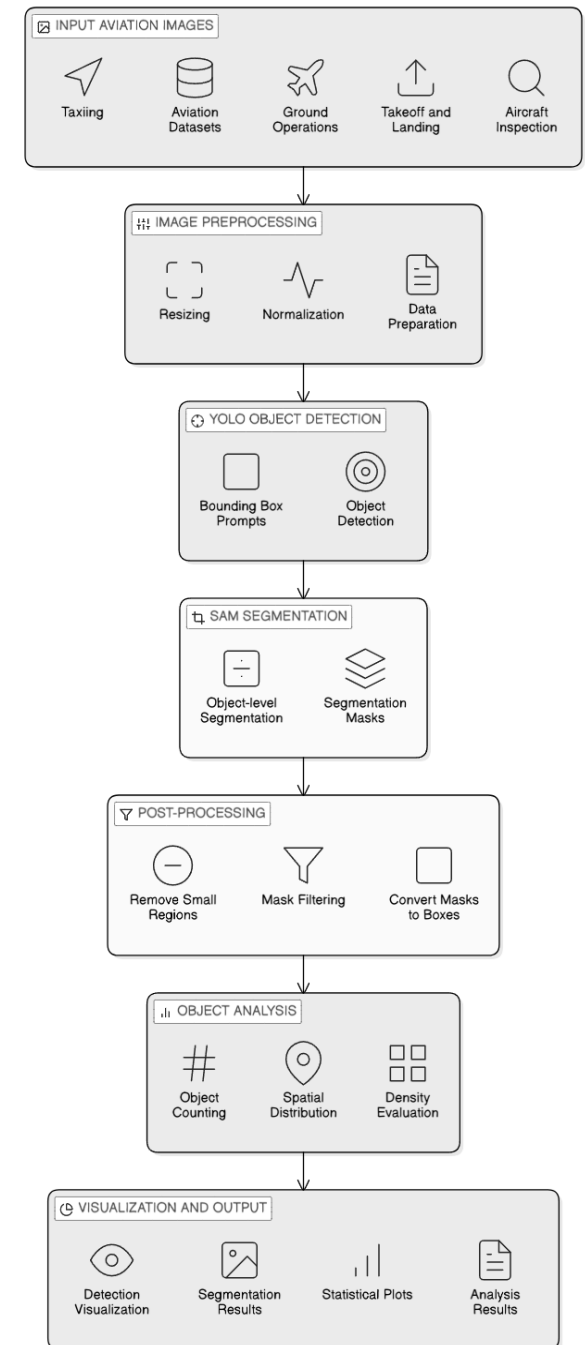
OBJECTIVES

- Develop a **segmentation-based computer vision pipeline** for aviation scenes
- Combine **Object Detection and segmentation models for better object localization**
- Apply the **Segment Anything Model (SAM)** for aircraft and object segmentation
- Analyze **object density and spatial distribution** across different operational contexts



METHODOLOGY OVERVIEW

- Aviation scene images collected across multiple operational contexts
- Images normalized and preprocessed for consistent model input
- **YOLO object detection used to generate bounding box prompts**
- **Segment Anything Model(SAM) applied for object-level segmentation of aviation scenes**
- Segmentation masks filtered and converted into bounding boxes
- Object counting and spatial analysis performed across multiple aviation scenes



WHY SEGMENT ANYTHING MODEL (SAM)

- **Foundation segmentation model trained on large-scale image datasets**
- **Demonstrates strong generalization across object categories and environments**
- Supports **prompt-based segmentation** using bounding boxes or points
- Effective for **complex scenes with varying object density**
- Reduces need for **extensive domain-specific model retraining**

Key Advantages:

- High-quality **pixel-level mask prediction**
- **Scalable segmentation** across operational scenarios
- Adaptable to **various complex scenes**



DATASET DESCRIPTION

- Aviation scene images collected from **publicly available aviation datasets**
- Includes multiple operational scenarios such as **ground operations, aircraft taxiing, takeoff/landing, aircraft damage inspection and aircraft detection datasets**
- Images show **variation in object density, scale, lighting, and background complexity**
- Images **preprocessed for resolution consistency and normalization**



Raw Dataset Samples

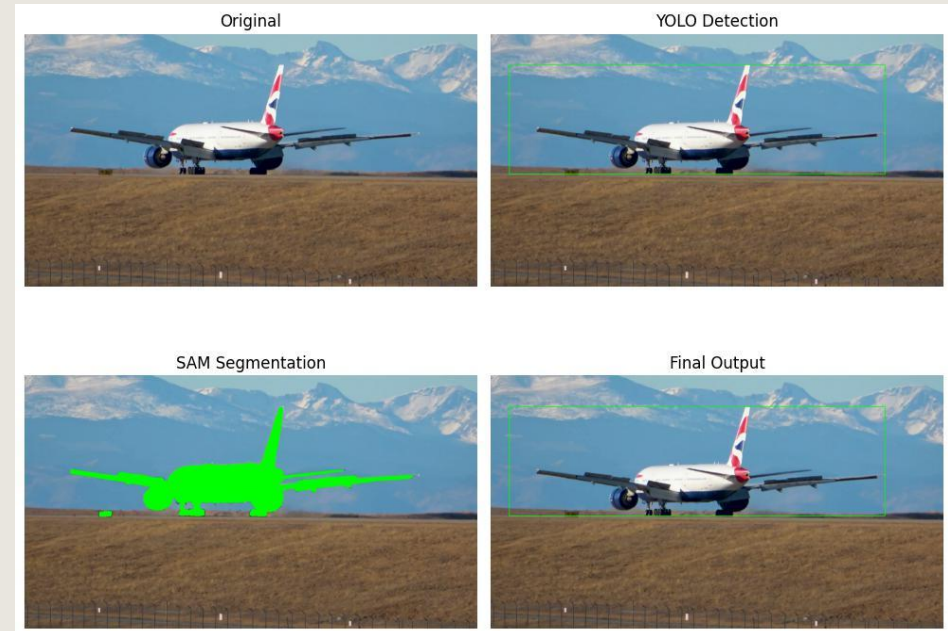
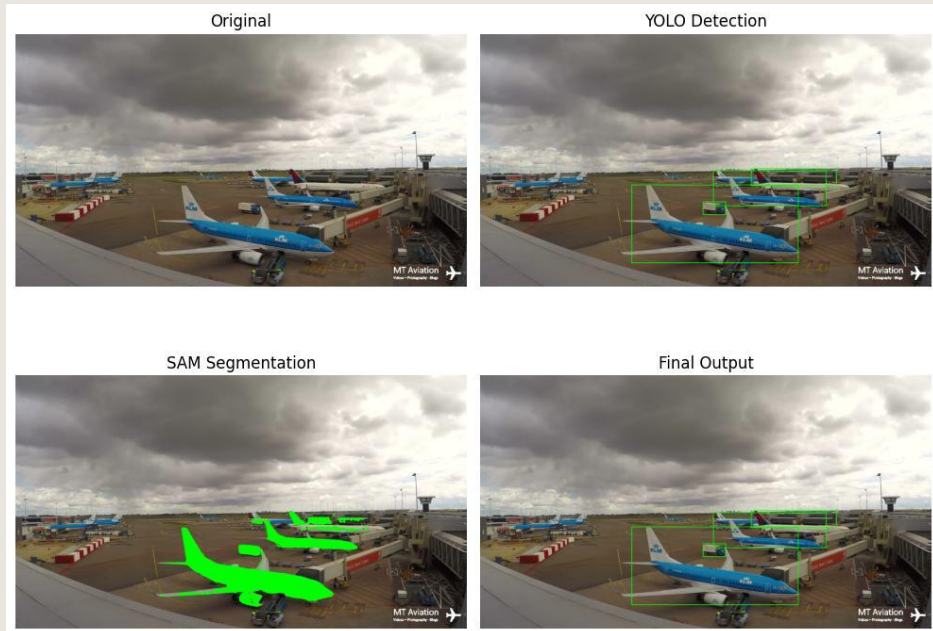
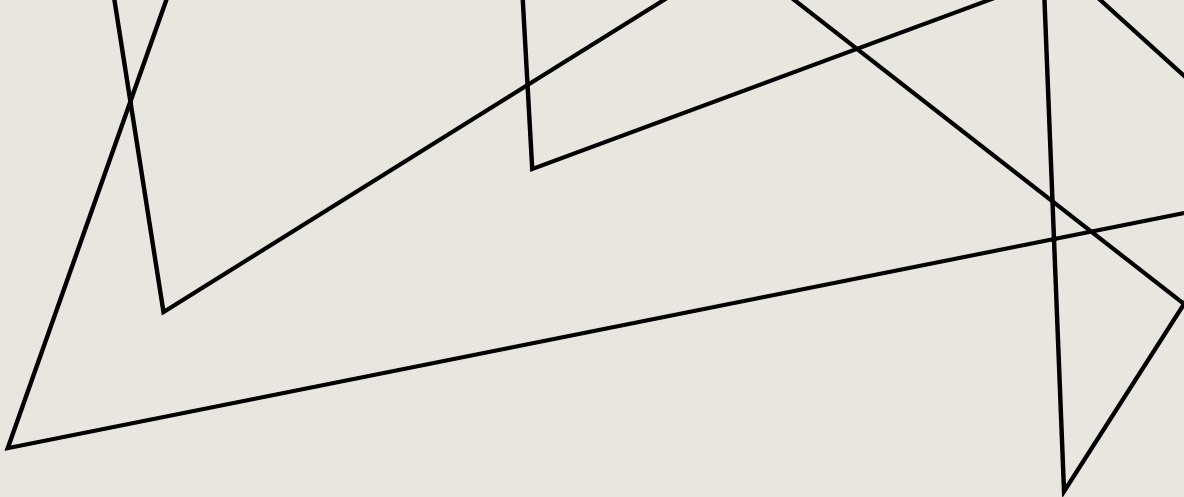


EXPERIMENTAL SETUP

- **YOLO object detection** used to generate bounding box prompts
- **Segment Anything Model (SAM)** applied in a **zero-shot segmentation setting**
- Segmentation masks generated and filtered using **area-based mask filtering**
- Bounding boxes extracted from segmentation masks for **object localization**
- Object counts computed for each image across aviation datasets



SEGMENTATION OUTPUT RESULTS

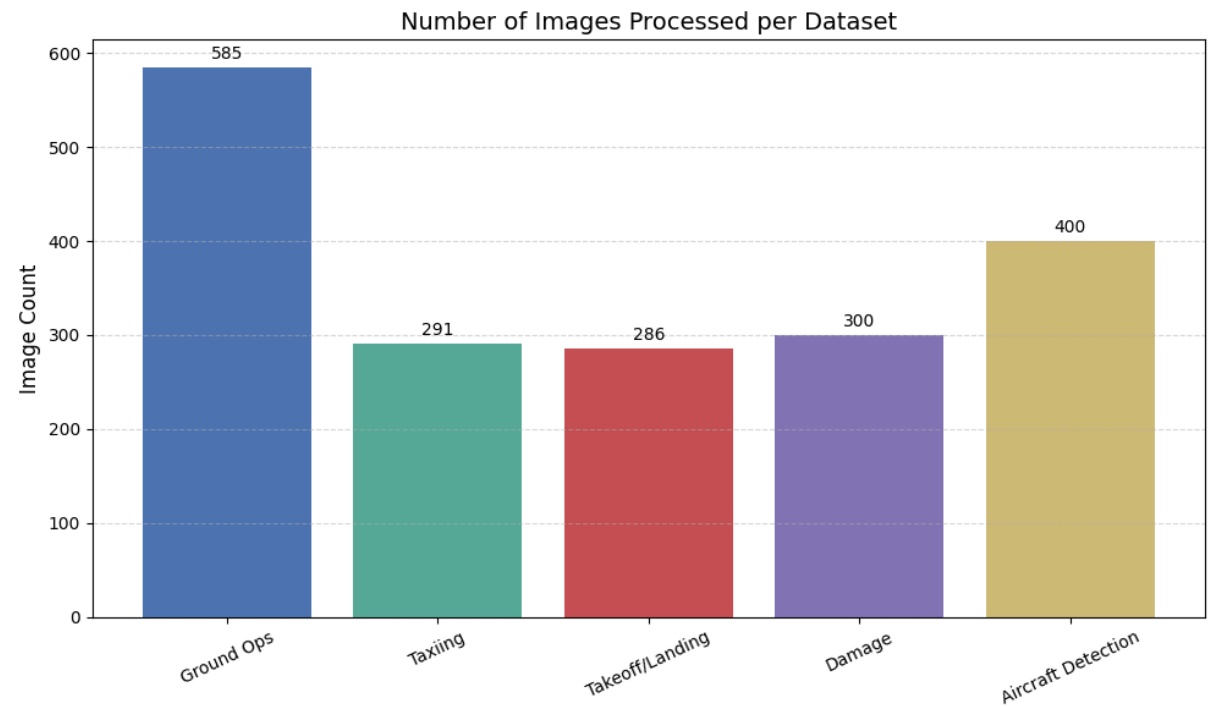


Examples of aviation scene processing showing the pipeline stages: Original Image, YOLO Detection, SAM Segmentation masks, and the final output



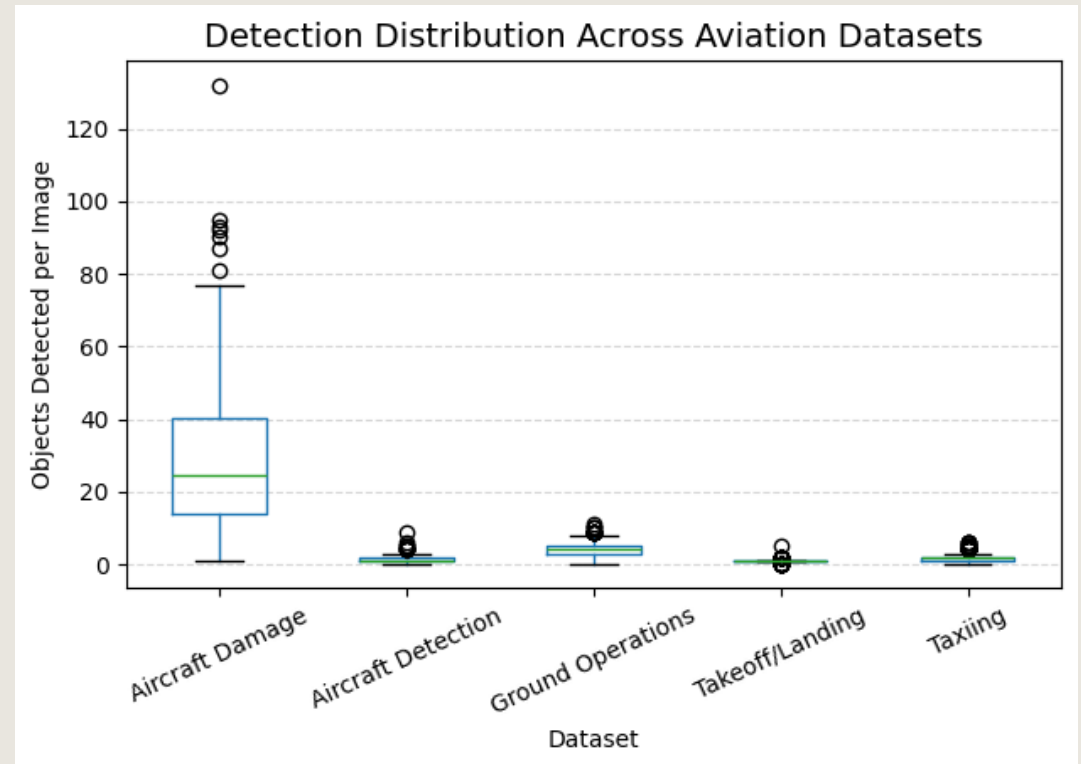
DATASET DISTRIBUTION ACROSS AVIATION SCENARIOS

- The aviation dataset includes images from multiple operational scenarios like ground operations, taxiing, takeoff/landing, aircraft damage detection, and aircraft detection tasks
- Ground operations contain the highest number of images, which shows the complexity and activity present in the airport ground environments

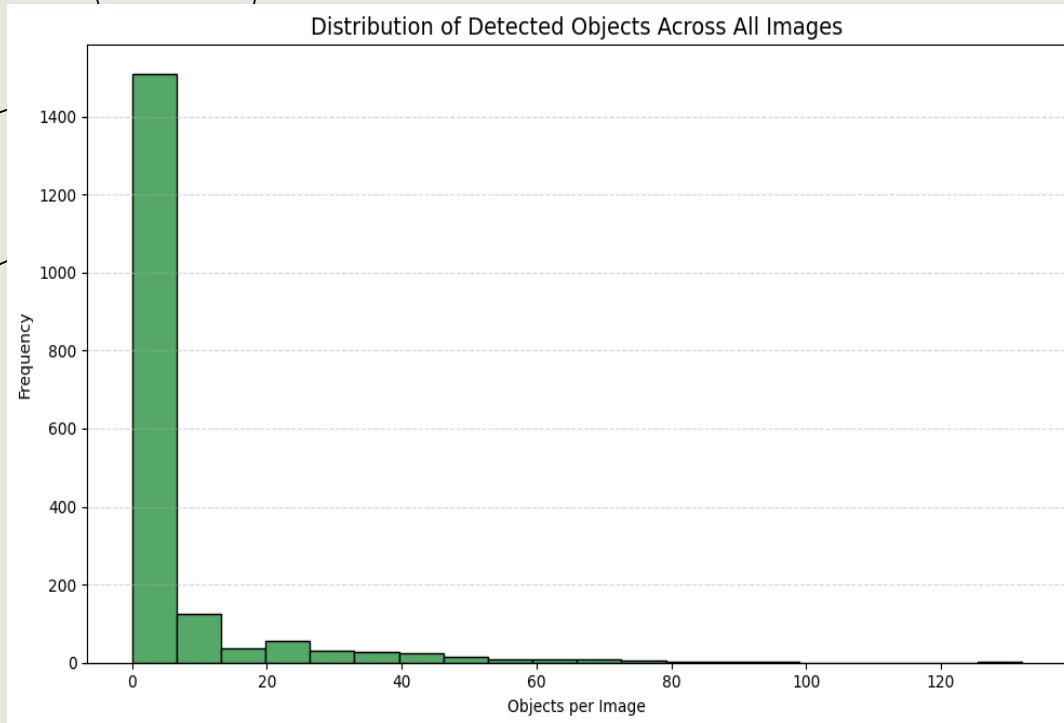


DETECTION DISTRIBUTION ACROSS AVIATION DATASETS

- The **box plot** shows the distribution of the detected objects per image across different aviation datasets
- **Aircraft damage images** show higher object counts due to the presence of multiple aircraft components and structural details
- Operational datasets like taxiing and takeoff scenes generally contain fewer detected objects, which indicates simple visual environments
- The variation across datasets highlights the differences in scene complexity and object density in aviation environments



DISTRIBUTION OF DETECTED OBJECTS ACROSS ALL IMAGES



- This histogram shows the overall distribution of detected objects per image across all aviation datasets
- Most images contain a **small number of detected objects**, indicating that many aviation scenes are visually simple
- A smaller number of images contain **higher object counts**, representing more complex scenes such as aircraft damage or crowded airport environments
- The distribution is **right-skewed**, meaning that while most images contain few objects, a few images contain significantly more detected elements



KEY OBSERVATIONS

- Aircraft damage datasets contain **the highest number of detected objects**, reflecting complex structural details
- Operational scenarios such as **taxiing and takeoff/landing contain fewer objects**, indicating simpler aviation scenes
- Most images contain **a small number of detectable objects**, while only a few complex scenes contain higher object counts
- The **YOLO+SAM pipeline improves object localization and segmentation**, allowing for a better analysis of aviation environments



FUTURE WORK

- Explore newer versions of the SAM to improve segmentation accuracy in complex aviation scenes
- Improve bounding box accuracy by integrating advanced object detection models like newer versions of YOLO, and deep learning architectures like **ResNet**, **VGG** or **Faster-CNN** for more precise localization
- Expand the dataset with additional aviation scenarios to improve model robustness and generalization across diverse environments
- Investigate the potential for **real-time deployment** of segmentation pipelines for airport monitoring and aviation-safety applications



CONCLUSION

- A computer vision pipeline combining **YOLO object detection and SAM segmentation** was developed to analyze aviation scene images
- The approach identified and segmented aircraft-related objects across multiple aviation scenarios including ground operations, taxiing, takeoff/landing, and aircraft damage inspection.
- Dataset analysis revealed variations in object density and scene complexity across different aviation environments
- The results demonstrate the potential of segmentation-based pipelines for **aviation image analysis and operational monitoring**





Thank You

Chennakeshava Akhil Pillalamarri | MSDS-692 | Regis University