PROJECT REPORT ON

GeoAI Amazon Basin Secret Runway Detection

YOLOv8-Based Detection of Clandestine Airstrips in the Amazon Basin: A Computer Vision Approach for Environmental Monitoring

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ACKNOWLEDGEMENT

We take this opportunity to express our profound gratitude to Nokia for granting us the opportunity to undertake this industrial project and for providing the required resources, infrastructure, and an enabling environment. The exposure to practical problem-solving and industry-standard practices has been invaluable in enhancing our technical knowledge and professional skills.

We would also like to extend our sincere thanks to PES University for its continued encouragement and support in facilitating this project as part of our academic curriculum.

Our heartfelt gratitude is due to our college mentor **Dr.Rajasekar M**,whose constant guidance, encouragement, and constructive feedback greatly assisted us in systematically approaching the problem and aligning our work with academic objectives.

We are equally indebted to our Nokia guide **Kodandaram Ranganath** sir whose technical expertise, insightful suggestions, and dedicated mentorship were instrumental in shaping the direction of this project and ensuring its successful completion.

This project would not have been possible without the combined support and cooperation of our mentors and the facilities provided by both PES University and Nokia.

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1.Abstract

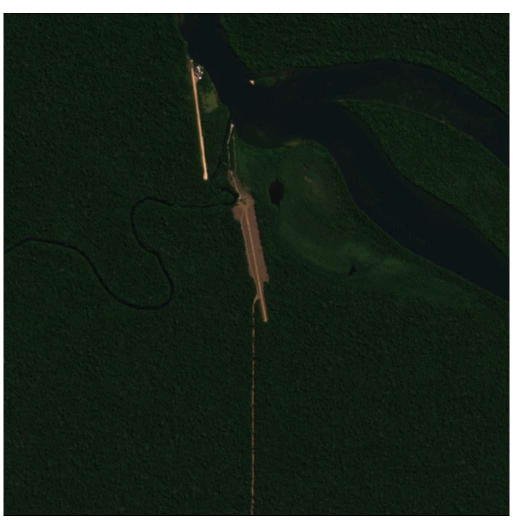
In the Amazon Rainforest Illegal activities like drug trafficking, illegal mining, and logging that use hidden airstrips hidden under thick vegetation are major threats . This study introduces an enhanced computer vision methodology for the automated identification of runways utilizing satellite imagery. To fix problems with localization accuracy and false positive rates seen in earlier methods, we switch from patch-based convolutional neural network (CNN) models to a YOLOv8 object detection framework. Our method uses data from the Sentinel-1 and Sentinel-2 satellites and changes binary mask annotations into bounding box labels that object detection frameworks can use. The YOLOv8 model shows better accuracy in finding runways while still being able to detect things. This makes it a better tool for monitoring and enforcing environmental rules in delicate ecosystems.

2.Introduction

The vast and remote geography of the Amazon Basin renders it an attractive setting for various illegal activities, among them clandestine airstrips, crucial for both drug-trafficking and the operations related to illegal mining and logging. Research recently gave some indication of the extent of the problem, with investigations reporting the presence of 128 illegal airstrips across six departments of the Peruvian Amazon alone, many hidden within forest concessions co-opted by drug traffickers.

These are either obscured by high canopy cover or located in areas inaccessible to survey teams, conditions that render manual detection of runways through satellite imagery labor-intensive and prone to errors. For this reason, the development of automated detection systems is an essential step toward timely interventions by enforcement and conservation agencies in these sensitive ecosystems.

Previous machine learning-based approaches have demonstrated that detection is feasible but often suffer from high false alarms and poor generalization across previously unseen geographical locations. This work investigates these limitations through the implementation of a YOLOv8-based object detection framework, which is known for its robust real-time detection with superior localization accuracy.



3. Literature Review and Background

3.1 Previous Approaches

The baseline methodology was developed by Team TerraPulse during the Zindi Amazon Basin Secret Runway Detection Challenge. This combined data preprocessing with deep learning and geospatial analysis. Their workflow used:

- **Data Sources**: The proposed methodology will rely on data from Sentinel-1 SAR imagery with VV and VH polarizations, together with Sentinel-2 MSI data with six spectral bands in the visible, near-infrared (NIR), and shortwave infrared (SWIR) spectral regions.
- **Processing Pipeline**: Merging into nine-band images, followed by cropping into 512 × 512 pixel tiles at a resolution of 10 m/px; normalization of spectral bands and augmentation techniques.
- **Model Architecture**: U-Net with ResNet50 encoder, pre-trained on ImageNet data, and hence supports bands beyond RGB with different learning rates.

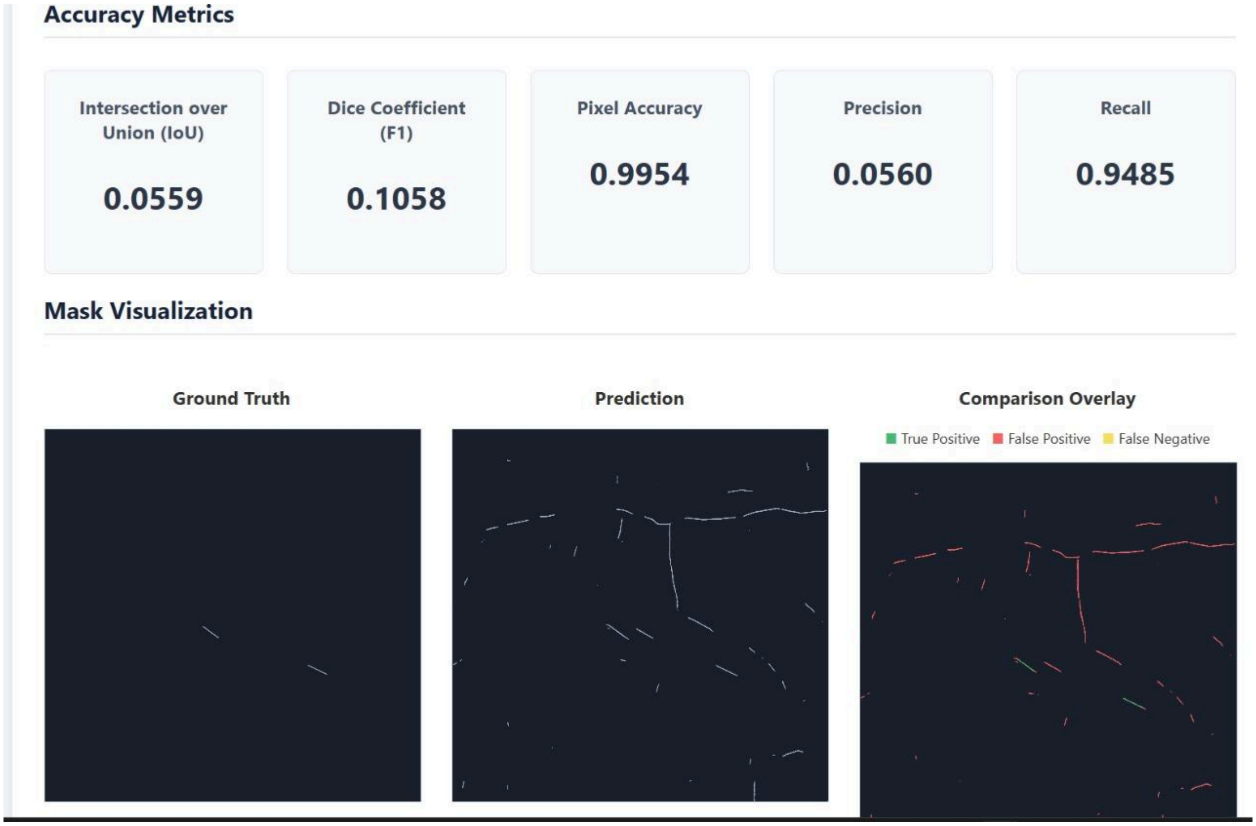
3.2 Characteristics of Satellite Data

The SENTINEL-1 satellites provide C-band SAR imagery that penetrates cloud, while SENTINEL-2 carries high-resolution optical multispectral images. SENTINEL-2A Level-1C data covers the wavelength range between 443 and 2190 nm; four bands at a resolution of 10 m and six at 20 m are captured. Free global coverage is provided by ESA's Copernicus mission for both satellites, rendering these sensors particularly suitable for large-scale monitoring applications.

3.3 Limitations of Existing Methods

The previous methods had several limitations:

- Issues of Accuracy: Many real runways, especially those partially obscured by vegetation, were missed.
- High False-Positive Rate: Most of the time, roads, riverbanks, and natural clearings were falsely classified as runways.
- Poor Localization: Patch-based classification methods provided incorrect boundaries and were cumbersome to check manually. Limited generalization can be seen through performance degradation when applied to new geographical areas outside its training distribution.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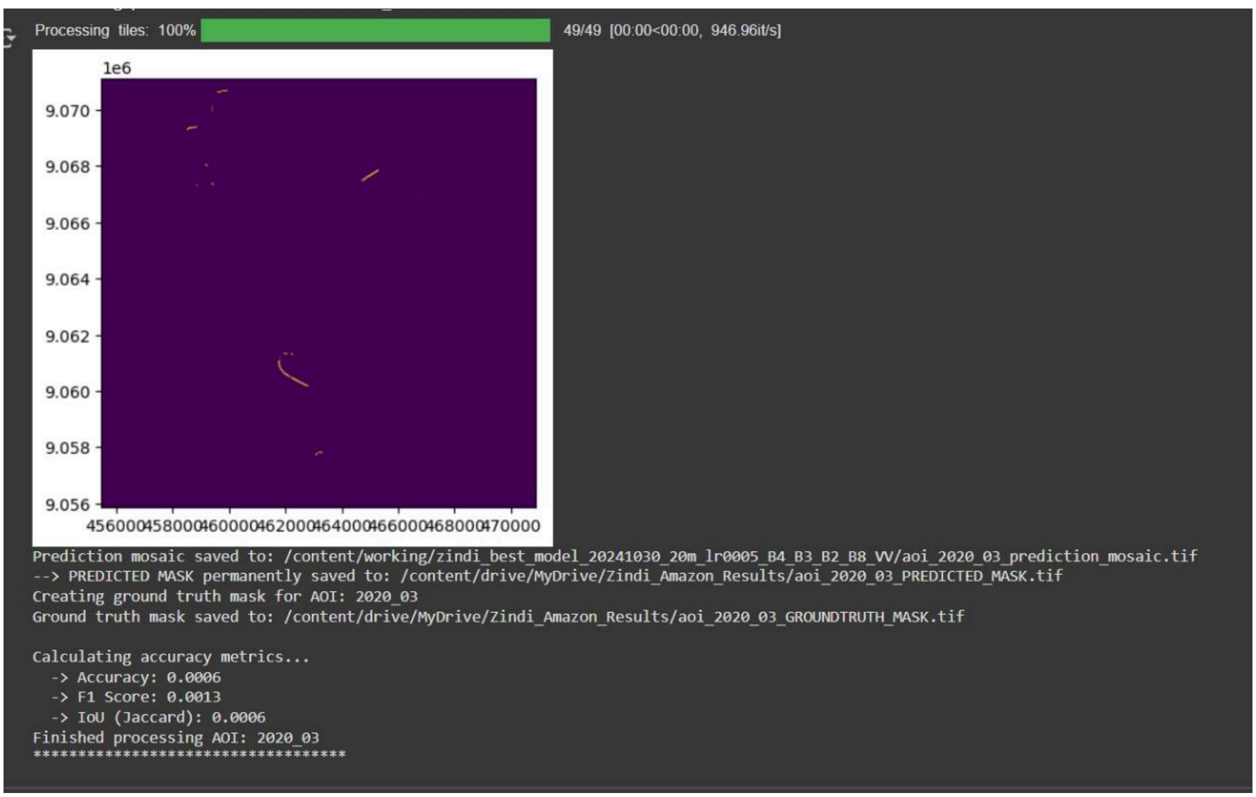
Intersection over Union (IoU)
0.0559
Dice Coefficient (F1)
0.1058
Pixel Accuracy
0.9954
Precision
0.0560
Recall
0.9485
Mask Visualization
Ground Truth
Prediction
Comparison Overlay
True Positive
False Positive
False Negative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49/49 [00:00<00:00, 946.96it/s]
1e6
9.070
9.068
9.066
9.064
9.062
9.060
9.058
9.056
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Prediction mosaic saved to: /content/working/zindi_best_model_20241030_20m_lr0005_B4_B3_B2_B8_VV/aoi_2020_03_prediction_mosaic.tif
--> PREDICTED MASK permanently saved to: /content/drive/MyDrive/Zindi_Amazon_Results/aoi_2020_03_PREDICTED_MASK.tif
Creating ground truth mask for AOI: 2020_03
Ground truth mask saved to: /content/drive/MyDrive/Zindi_Amazon_Results/aoi_2020_03_GROUNDTRUTH_MASK.tif
Calculating accuracy metrics...
-> Accuracy: 0.0006
-> F1 Score: 0.0013
-> IoU (Jaccard): 0.0006
Finished processing AOI: 2020_03
****

```
==================================================
           INFERENCE AND EVALUATION COMPLETE
==================================================

Accuracy Metrics Summary:
    accuracy  f1_score  iou_score aoi_name
0   0.000644  0.001288   0.000644  2020_03
1   0.000629  0.001256   0.000629  2022_01
2   0.003504  0.006983   0.003504  2022_02
3   0.003109  0.006199   0.003109  2020_02
4   0.004641  0.009238   0.004641  2024_01
5   0.000852  0.001703   0.000852  2020_01
6   0.003853  0.007676   0.003853  2023_01
7   0.000574  0.001147   0.000574  2021_04
8   0.003880  0.007731   0.003880  2021_01
9   0.001963  0.003918   0.001963  2021_02
10  0.003317  0.006612   0.003317  2021_03

Metrics summary saved to: /content/drive/MyDrive/Zindi_Amazon_Results/accuracy_summary.csv
```

4. Methodology

4.1 Data Collection and Preprocessing

We used satellite imagery from the Copernicus mission by ESA, leveraging both Sentinel-1 and Sentinel-2 products. Google Earth Engine was used for gathering cloud-free mosaics over the study areas. The 3-channel RGB PNG images from Sentinel-2 mosaics were extracted for use in training YOLOv8.

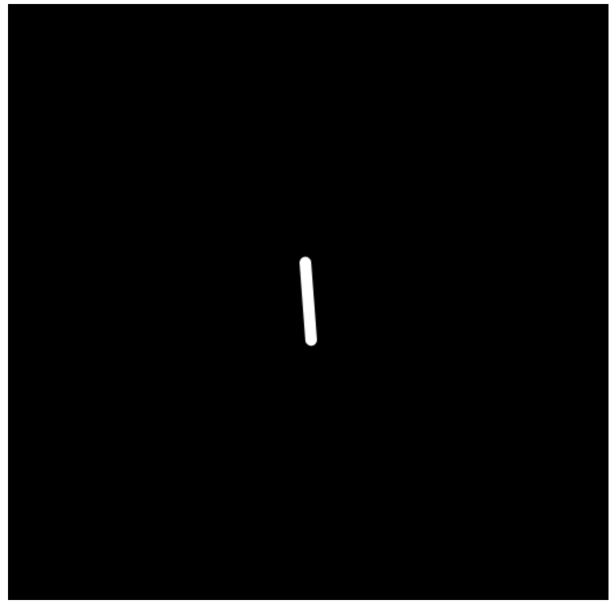
Dataset Composition:

1. Training: 708 labeled images
2. Validation: 177 images
3. Test (unseen): 307 images

4.2 Label Conversion Process

One of the main steps involved converting the binary mask annotations to YOLO-compatible bounding box labels using Create_yolo_bounds.ipynb. More specifically, it included the following:

- Matching each mask to its appropriate satellite chip
- Extracting bounding boxes from non-zero mask pixels
- Computing minimal enclosing boxes with pixel padding for context
- Normalizing the center coordinates and dimensions in YOLO format
- Generating empty label files for the negative samples

4.3 YOLOv8 Model Architecture and Training

For this work, we select YOLOv8 because it contains state-of-the-art one-stage detection that balances accuracy and speed. The key architectural highlights of YOLOv8 are:

- The anchor-free split-head design simplifies the learning process while enhancing localization.
- CSPDarknet-based backbone with PANet-like feature pyramids
- Abilities for multi-scale feature fusion, suitable for small and narrow object detection.

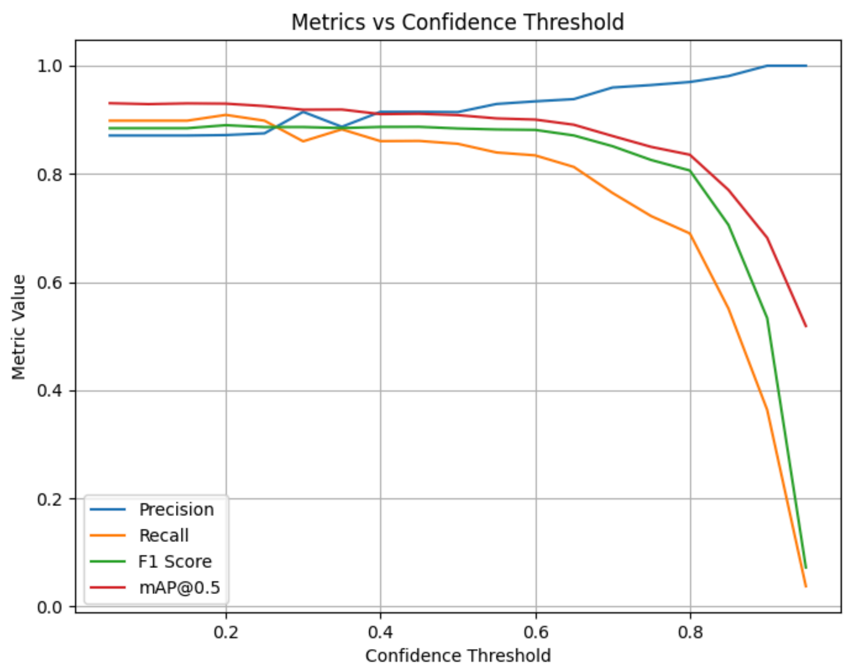
Training Configuration:

- Epochs: 100
- Dataset split: 80/20, training/validation
- Batch size: 16
- Input size: 640×640 pixels
- GPU acceleration used where available

4.4 Inference and Post-processing

Post-training inference included:

1. Running the trained model on 307 unseen test images
2. Confidence threshold tuning by systematic sweeping
3. Optimal threshold selection at ~30% based on maximizing F1-score
4. Visualization of predicted bounding boxes overlaid on RGB imagery



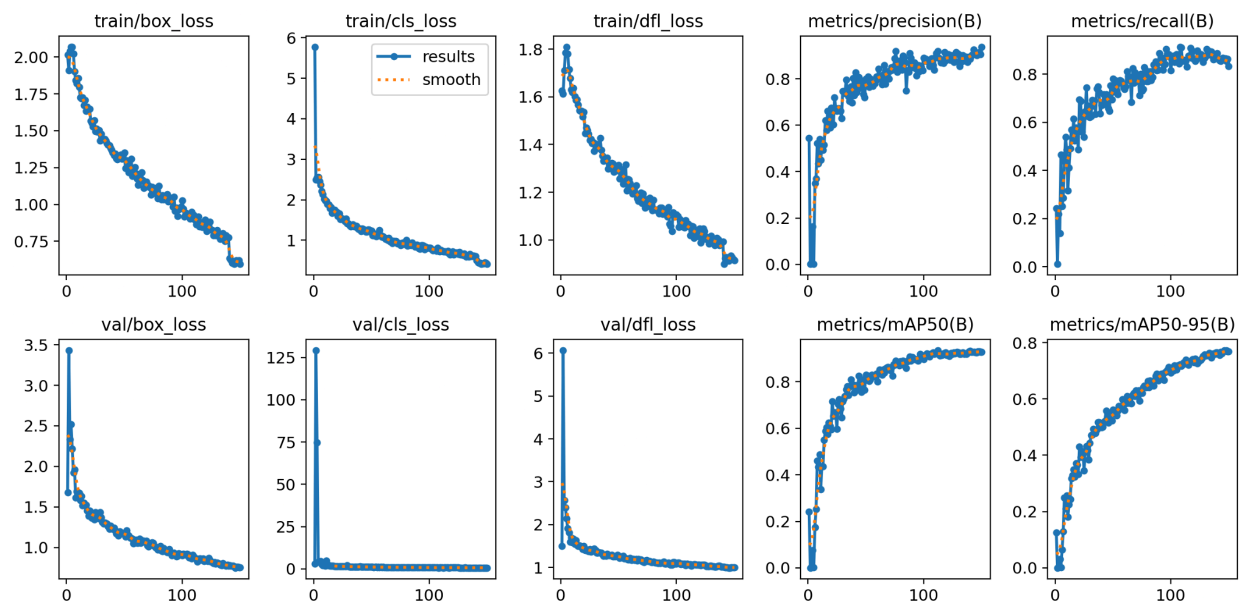
5. Results and Analysis

5.1 Training Performance

Training curves reflect stable learning at 100 epochs as the training and validation losses gradually decrease. Thus, this model converged without severe overfitting and learned to tell runway shapes apart with reasonable accuracy.

Final Validation Metrics:

- Precision: ~0.32
- Recall: ~0.45
- mAP@0.5: ~0.28
- mAP@0.5:0.95 : Lower values reflect localization challenges.



5.2 Comparative Analysis with Baseline Model

- Evaluation of our dataset through the original model of U-Net showed several limitations.

- Over-segmentation: Many non-runway clearings were mistakenly labeled.
- Poor Specificity: high rates of false positives over roadways, logging areas, and riverbanks.
- Fragmented Predictions: Overlapping patches produced inconsistent results.
- Limited localization: masks did not tightly align to runway edges.

YOLOv8 methodology showed clear improvements with respect to both localization accuracy and practical usability while sustaining the detection capabilities.


id_911.png
id_1364.png
id_1119.png
id_1467.png
id_1210.png
id_959.png
id_320.png
id_1174.png
id_306.png
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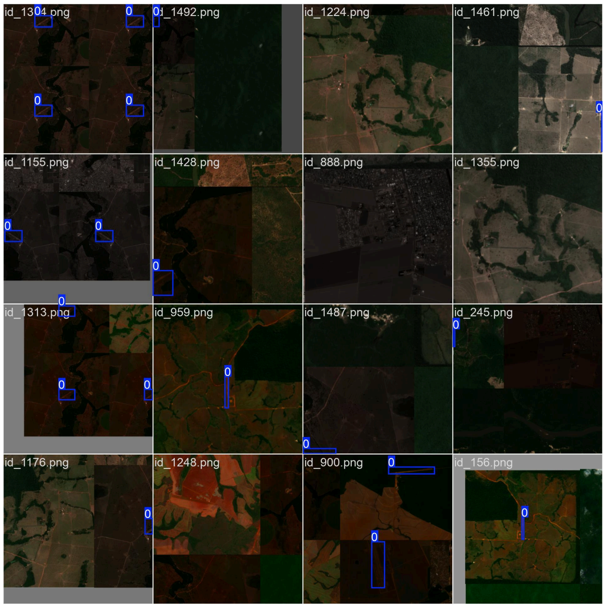
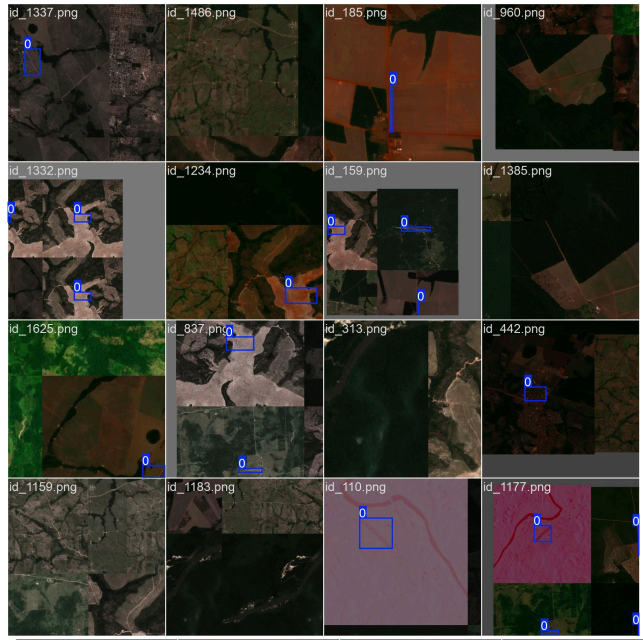
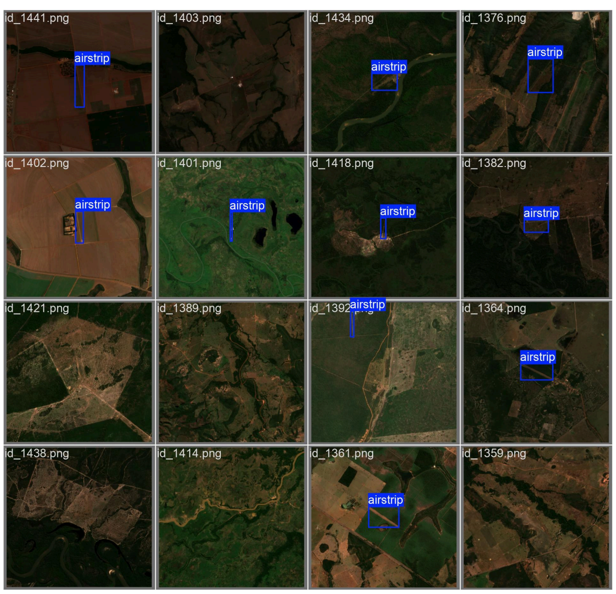
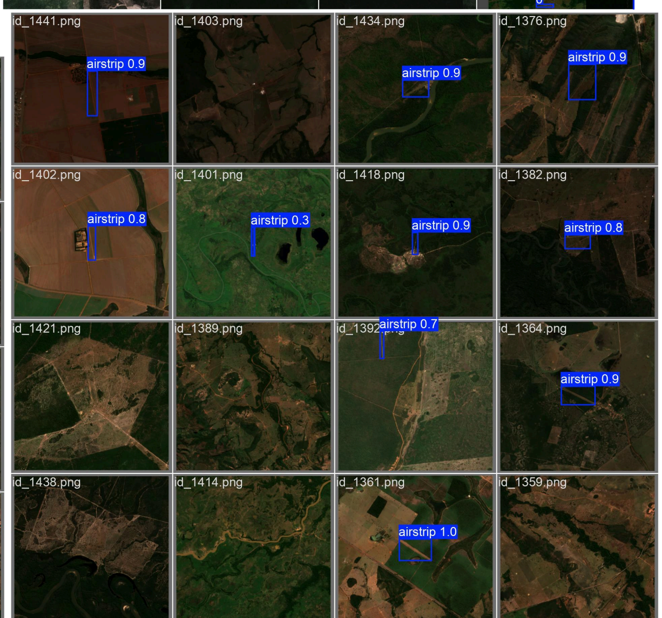








5.3 Error Analysis

False Positives:

- Linear, elongated features of runway-like geometry: roads, highways

- River edges and sandy bars of runway brightness
- Straight logging roads in cleared areas

False Negatives:

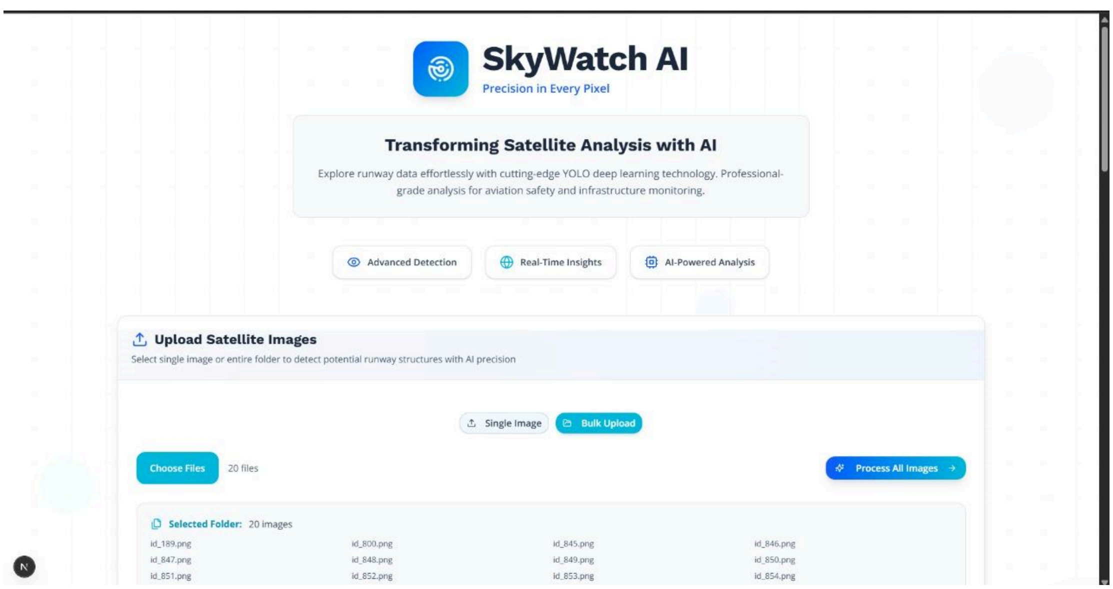
- Narrow strips, partly covered by vegetation
- Runways in heterogeneous terrain
- Cloud or shadow obscured areas in imagery

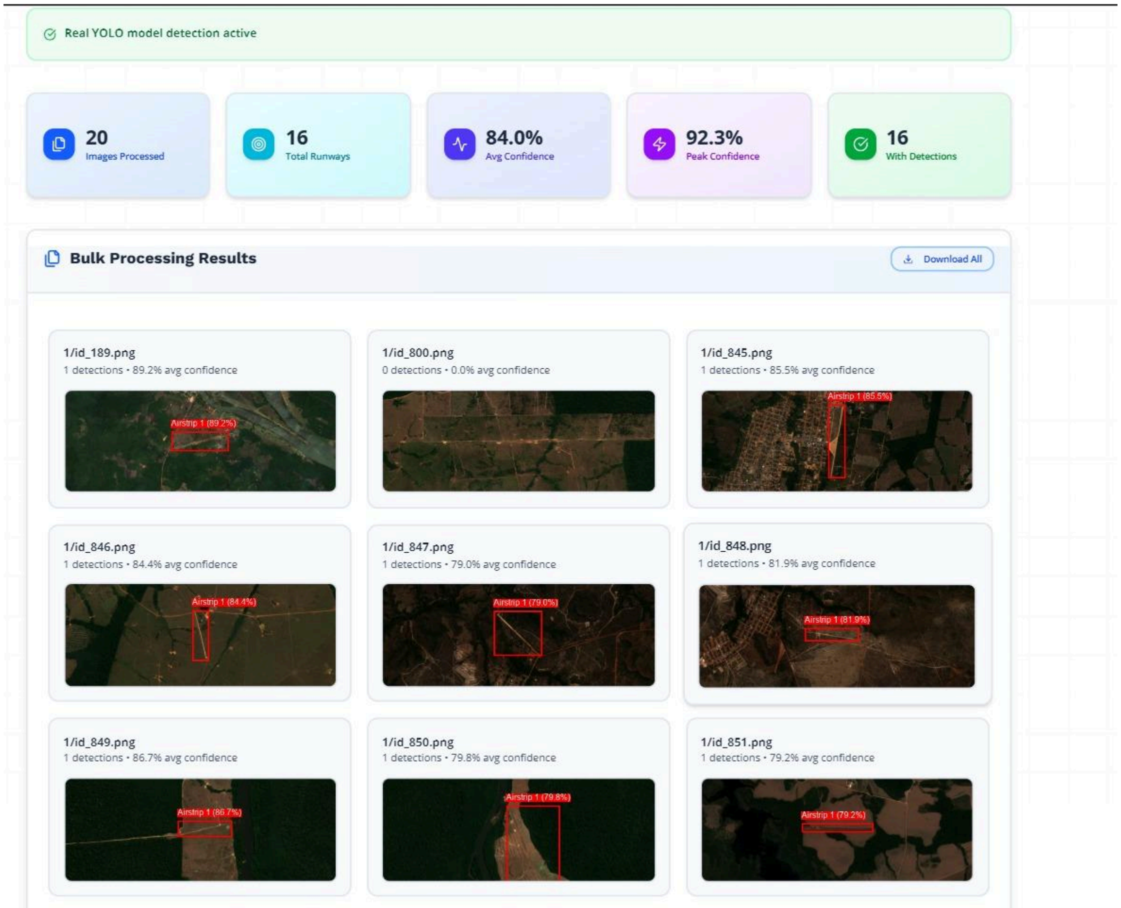
6. Evaluation of Results

6.1 Methodological Advantages

The key advantages of transitioning to YOLOv8 object detection:

- Precise Localization: Direct predictions of bounding box enable accurate runway positioning.
- Reduced Manual Verification: Clear box visualizations make human reviewing easier.
- Real-time Capabilities: Suitable for large-scale monitoring applications
- Improved Generalization: Better performance on different environmental conditions




Real YOLO model detection active
20
Images Processed
16
Total Runways
84.0%
Avg Confidence
92.3%
Peak Confidence
16
With Detections
Bulk Processing Results
Download All
1/id_189.png
1 detections • 89.2% avg confidence
1/id_800.png
0 detections • 0.0% avg confidence
1/id_845.png
1 detections • 85.5% avg confidence
1/id_846.png
1 detections • 84.4% avg confidence
1/id_847.png
1 detections • 79.0% avg confidence
1/id_848.png
1 detections • 81.9% avg confidence
1/id_849.png
1 detections • 86.7% avg confidence
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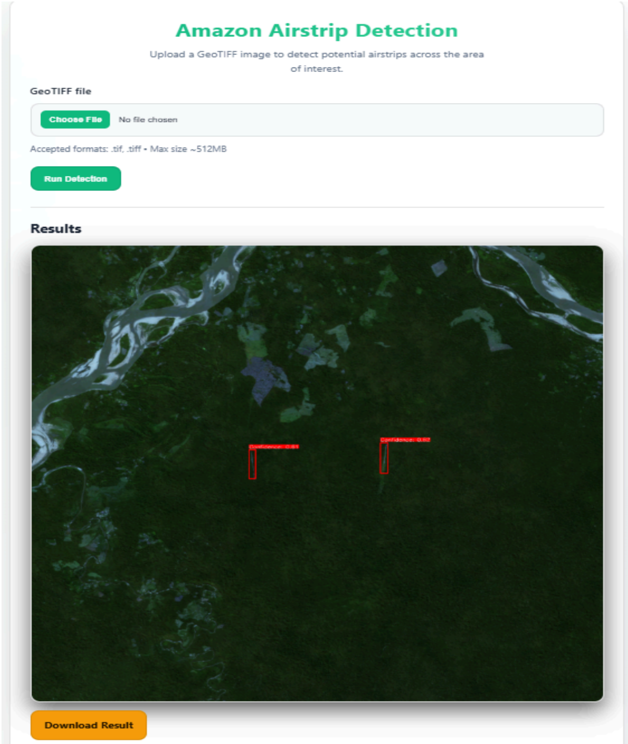
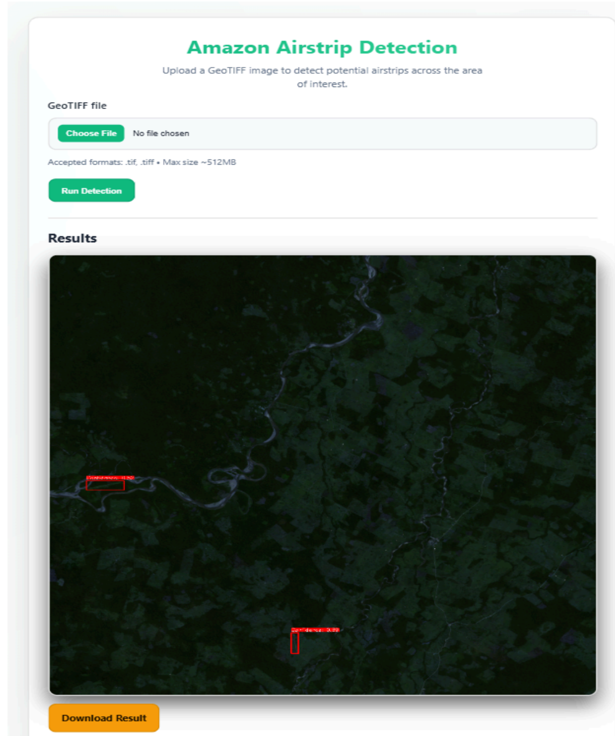
1 detections • 79.8% avg confidence
1/id_851.png
1 detections • 79.2% avg confidence





6.2 Limitations and Challenges

Despite improvements, many challenges remain:

- **Visual Similarity:** Runways share geometric features with roads and riverbanks
- **Spectral Limitations:** RGB-only input lacks discriminative power for subtle features
- **Environmental Factors:** Cloud cover and vegetation obscuration affect detection
- **Dataset Constraints:** Limited negative examples of confounding features

6.3 Implications for Environmental Monitoring

These increased detection capabilities have considerable impact on:

- Enforcement Operations: Rapid identification of criminal activities
- Conservation Efforts: Protection of sensitive ecosystems
- Intelligence Gathering: Further reach in non-accessible areas
- Policy Development: Data-driven approaches to environmental protection

7. Future Scope

7.1 Technical Enhancements

Multi-spectral Integration: Increase the number of Sentinel-2 bands by adding near-IR/SWIR and derived indices in order to improve discrimination among vegetation, soils, and cleared strips.

Fusion of SAR Data: Integrate Sentinel-1 radar channels, which supply information related to surface texture with increased cloud penetration.

Advanced Architectures: Explore the model ensembles including YOLOv8 with either oriented-box or segmentation models that constitute cross-validation.

7.2 Operational Improvements

Temporal Analysis: Apply multi-temporal imagery to identify new clearings and monitor runway activity over time.

Real-time monitoring by designing an automated dashboard system that will alert when new runways are detected.

Improved coverage: Extend the scale detection capability to other regions that also face comparable environmental and operational challenges.

7.3 Validation and Refinement

Field Validation: It involves the validation of detections through ground agencies and making iterative improvements in the model's accuracy.

Improved annotation: Increase the size of labeled datasets with examples, including negative samples, to enhance learning.

8. Conclusion

These results clearly indicate that switching to YOLOv8 object detection can bring significant improvements in clandestine airstrip detection over patch-based CNN approaches in the Amazon Basin. It reflects improved localization accuracy, reduction of false positive rates, and more practical output for both human verification and automated monitoring systems.

This YOLOv8-based approach, therefore, maintains a reasonable recall of actual runways while increasing precision; hence, this can be considered a meaningful advance for environmental monitoring and enforcement applications. Explicit bounding box outputs enable easier integration into operational workflows, thus allowing more efficient manual verification processes.

While there are still challenges with distinguishing the runway from similar-looking features and accounting for environmental variability, this work forms a promising basis for further development. Future enhancements will add multi-spectral data, SAR integration, and temporal analysis to yield higher accuracy levels and increased utility for operations.

Success of modern computer vision for such environmental monitoring challenges testifies to truly interdisciplinary approaches, merging remote sensing with machine learning and conservation science. Since illegal activities in the Amazon continue to threaten ecological integrity, automatic detection systems represent an essential tool for protection of this globally important ecosystem.