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

Authors: Prof. Rajasekhar M,
S P Suhas, Ishita Dalela, Adyansh Aggarwal, Khushi Jayaprakash
Mentor: Mr. Kodandaram Ranganath

Abstract

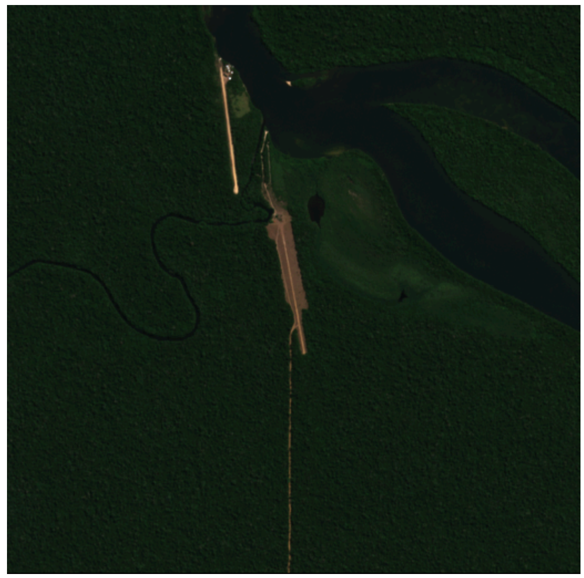
The Amazon rainforest faces significant threats from illegal activities including drug trafficking, illegal mining, and logging operations that rely on clandestine airstrips concealed beneath dense vegetation. This study presents an improved computer vision approach for automated detection of such runways using satellite imagery. We transition from patch-based convolutional neural network (CNN) models to a YOLOv8 object detection framework to address limitations in localization accuracy and false positive rates observed in previous approaches. Our methodology leverages Sentinel-1 and Sentinel-2 satellite data, converting binary mask annotations to bounding box labels compatible with object detection frameworks. The YOLOv8 model demonstrates improved precision in runway localization while maintaining detection capabilities, offering a more practical tool for environmental monitoring and enforcement in sensitive ecosystems.

1. Introduction

The Amazon Basin's vast and remote geography makes it an attractive location for illegal activities, with clandestine airstrips serving as critical infrastructure for drug trafficking, illegal mining, and logging operations. Recent investigations have revealed the extensive nature of this problem, with reports identifying 128 illegal airstrips across six departments in the Peruvian Amazon alone, many hidden within forest concessions co-opted by drug traffickers.

These runways are strategically concealed beneath dense canopy cover or situated in inaccessible areas, making manual detection through satellite imagery both labor-intensive and error-prone. The development of automated detection systems represents a crucial advancement for enforcement and conservation agencies, enabling timely interventions in these sensitive ecosystems.

While previous machine learning approaches have demonstrated the feasibility of detecting clandestine runways, they have suffered from high false positive rates and poor generalization when applied to unseen geographical locations. This research addresses these limitations by implementing a YOLOv8-based object detection framework, known for its robust real-time detection capabilities and superior localization accuracy.



2. Literature Review and Background

2.1 Previous Approaches

The baseline methodology, developed during the Zindi Amazon Basin Secret Runway Detection Challenge by Team TerraPulse, employed a combination of data preprocessing, deep learning, and geospatial analysis. Their workflow utilized:

- **Data Sources:** Sentinel-1 Synthetic Aperture Radar (SAR) with VV and VH polarization bands, and Sentinel-2 Multispectral Instrument (MSI) with six spectral bands including visible, near-infrared (NIR), and shortwave infrared (SWIR)
- **Processing Pipeline:** Merging datasets to produce nine-band images, cropping into 512×512 pixel tiles at 10 m/px resolution, spectral band normalization, and augmentation techniques
- **Model Architecture:** U-Net with ResNet50 encoder pre-trained on ImageNet, supporting additional bands beyond RGB with separate learning rates

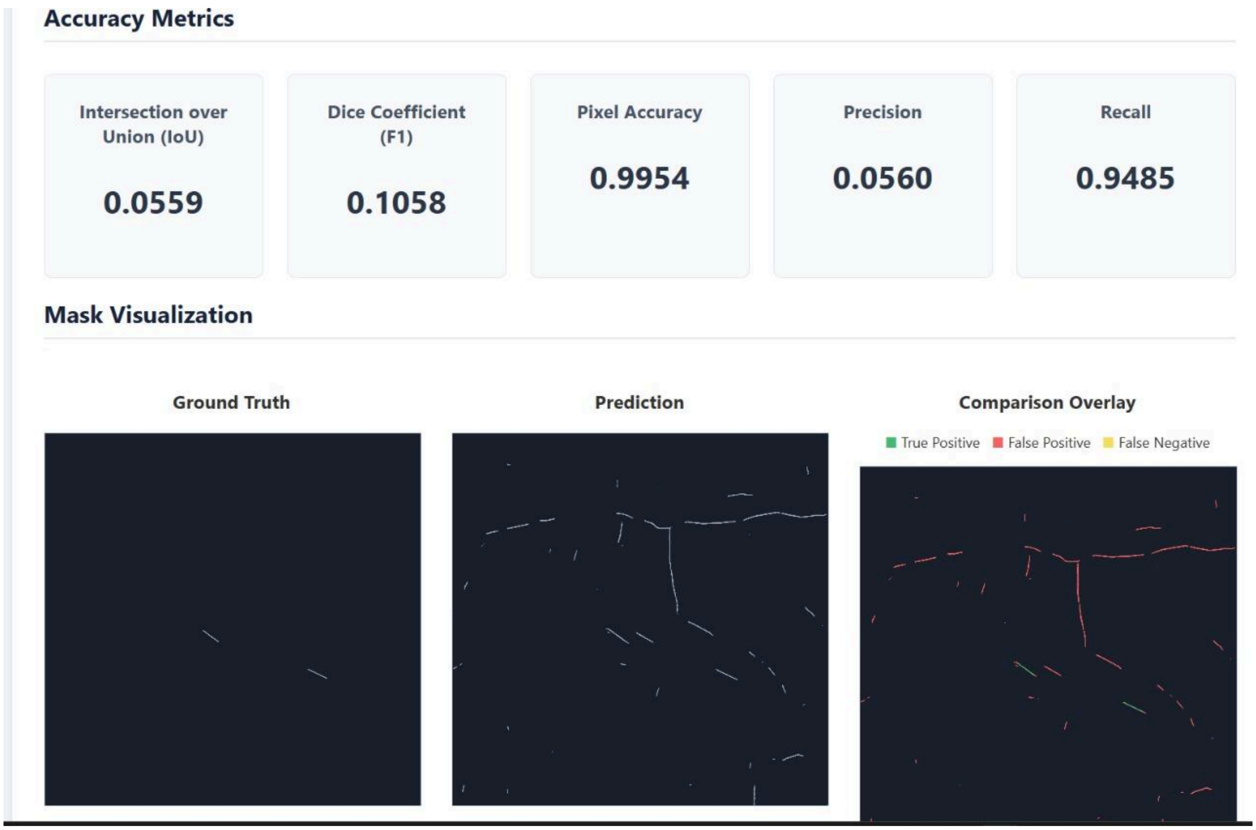
2.2 Satellite Data Characteristics

Sentinel-1 provides C-band SAR imagery that is cloud-penetrating, while Sentinel-2 offers high-resolution optical multispectral images. Sentinel-2A Level-1C data covers 443–2190 nm wavelengths, with four bands at 10 m resolution and six at 20 m resolution. Both satellite systems provide free, global coverage through ESA's Copernicus mission, making them ideal for large-scale monitoring applications.

2.3 Limitations of Existing Methods

Previous approaches exhibited several critical limitations:

- **Accuracy Issues:** Many genuine runways, particularly those partially obscured by vegetation, were missed
- **High False Positive Rates:** Roads, riverbanks, and natural clearings were frequently misclassified as runways
- **Poor Localization:** Patch-based classification approaches did not provide precise boundaries, complicating manual verification
- **Limited Generalization:** Performance degraded significantly when applied to new geographic areas outside the training distribution



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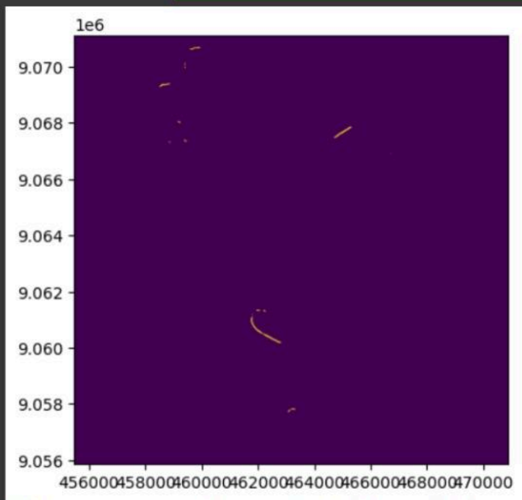


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  -> F1 Score: 0.0013
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2   0.003504  0.006983   0.003504  2022_02
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3. Methodology

3.1 Data Collection and Preprocessing

Our dataset consisted of satellite imagery from ESA's Copernicus mission, utilizing both Sentinel-1 and Sentinel-2 products. Google Earth Engine was employed to collect nearly cloud-free mosaics over study areas. For YOLOv8 training, we used 3-channel RGB PNG images extracted from Sentinel-2 mosaics.

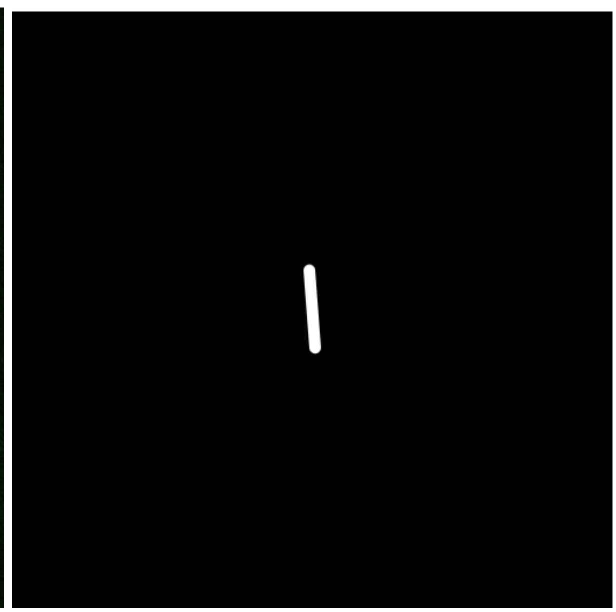
Dataset Composition:

- Training: 708 labeled images
- Validation: 177 images
- Test (unseen): 307 images

3.2 Label Conversion Process

A critical component of our methodology involved converting binary mask annotations to YOLO-compatible bounding box labels using the Create_yolo_bounds.ipynb script. This process involved:

1. Matching each mask with its corresponding satellite chip
2. Extracting bounding boxes from non-zero mask pixels
3. Computing minimal enclosing boxes with pixel padding for context
4. Normalizing center coordinates and dimensions for YOLO format
5. Generating empty label files for negative samples

3.3 YOLOv8 Model Architecture and Training

We selected YOLOv8 for its state-of-the-art one-stage detection capabilities that balance accuracy and speed. Key architectural features include:

- **Anchor-free split head design** for simplified learning and improved localization
- **CSPDarknet-based backbone** with PANet-like feature pyramids
- **Multi-scale feature fusion** capabilities suitable for detecting small, elongated objects

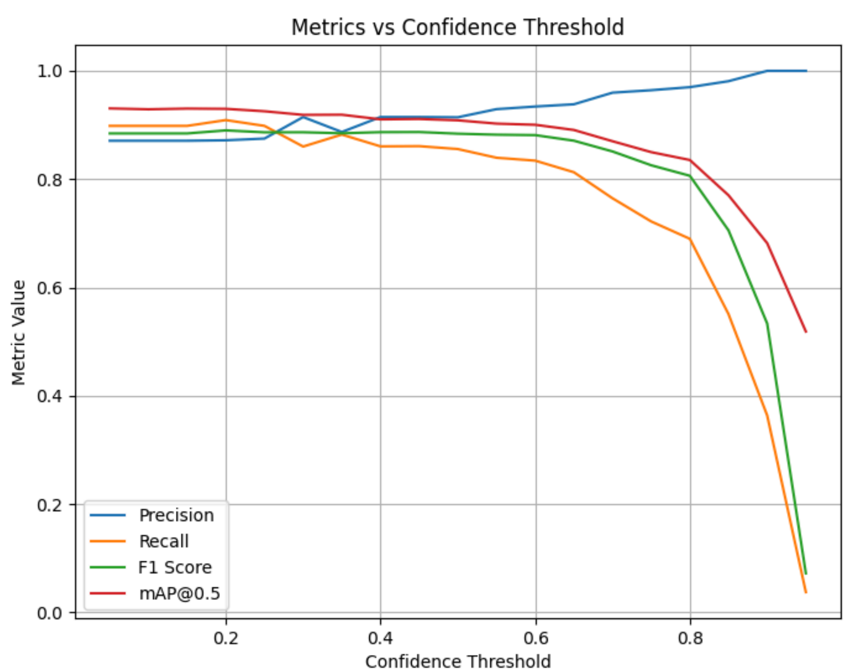
Training Configuration:

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

3.4 Inference and Post-processing

Post-training inference involved:

1. Running the trained model on 307 unseen test images
2. Confidence threshold tuning through systematic sweeping
3. Selection of optimal threshold (~30%) based on F1-score maximization
4. Visualization of predicted bounding boxes overlaid on RGB imagery



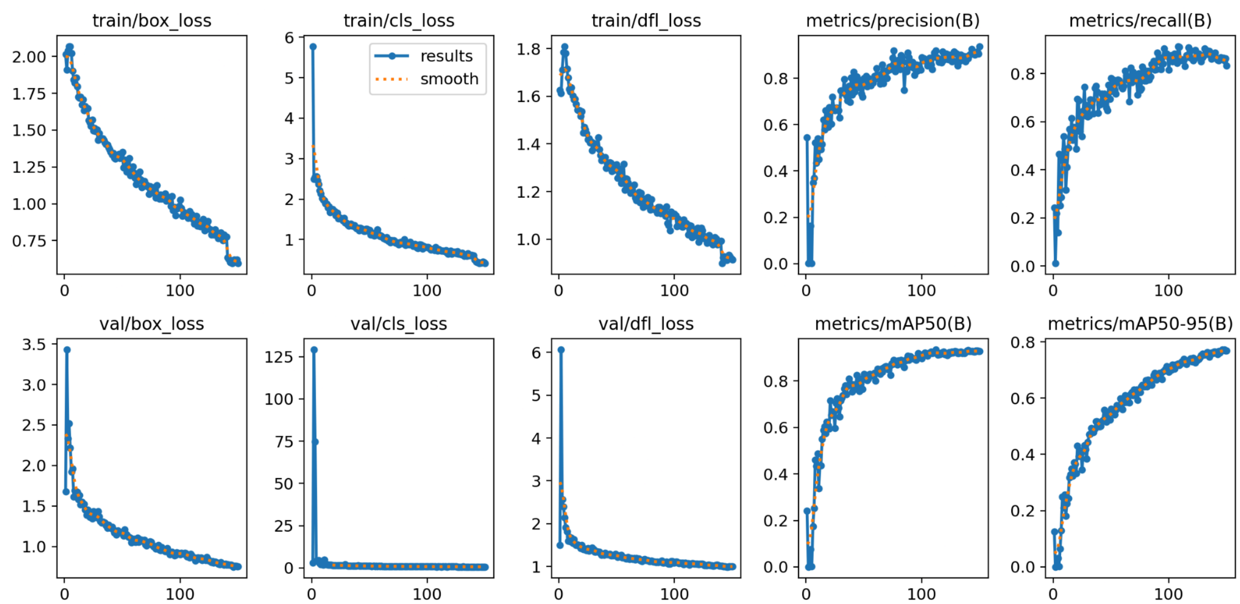
4. Results and Analysis

4.1 Training Performance

Training curves demonstrated stable learning over 100 epochs with steadily decreasing losses for both training and validation sets. The model achieved convergence without severe overfitting, learning to discriminate runway shapes with reasonable accuracy.

Final Validation Metrics:

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



4.2 Comparative Analysis with Baseline Model

Assessment of the original U-Net model on our dataset revealed significant limitations:

- **Over-segmentation:** Many non-runway clearings were erroneously labeled
- **Poor Specificity:** High false positive rates on roads, logging sites, and riverbanks
- **Fragmented Predictions:** Overlapping patches led to inconsistent outputs
- **Limited Localization:** Masks did not tightly align with runway edges

The YOLOv8 approach demonstrated clear improvements in localization accuracy and practical usability while maintaining detection capabilities.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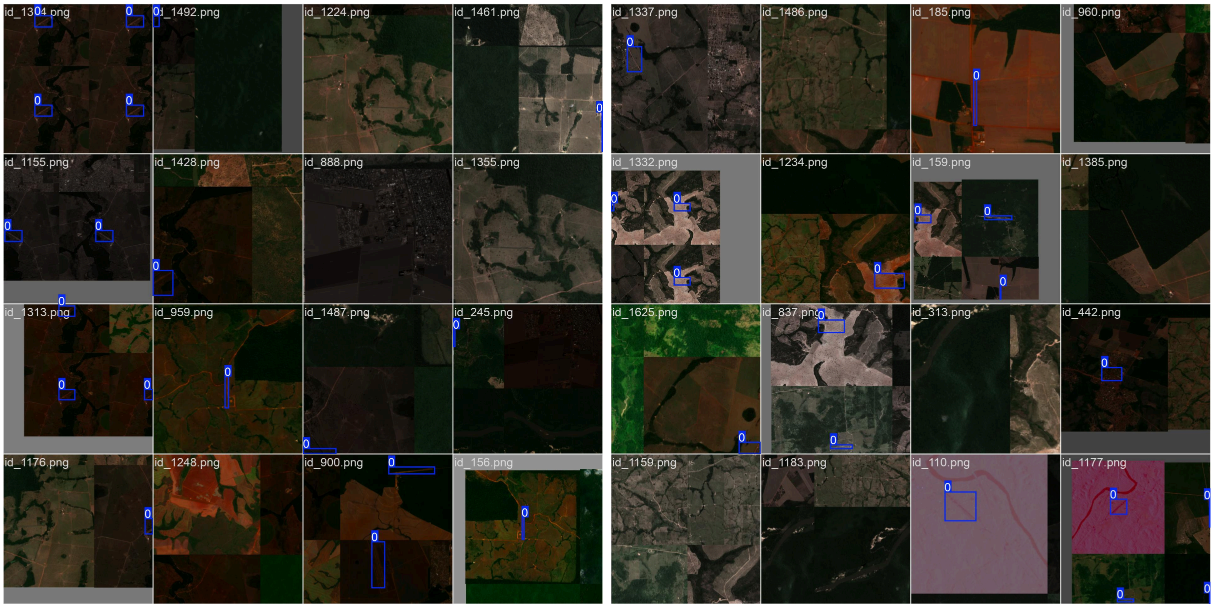
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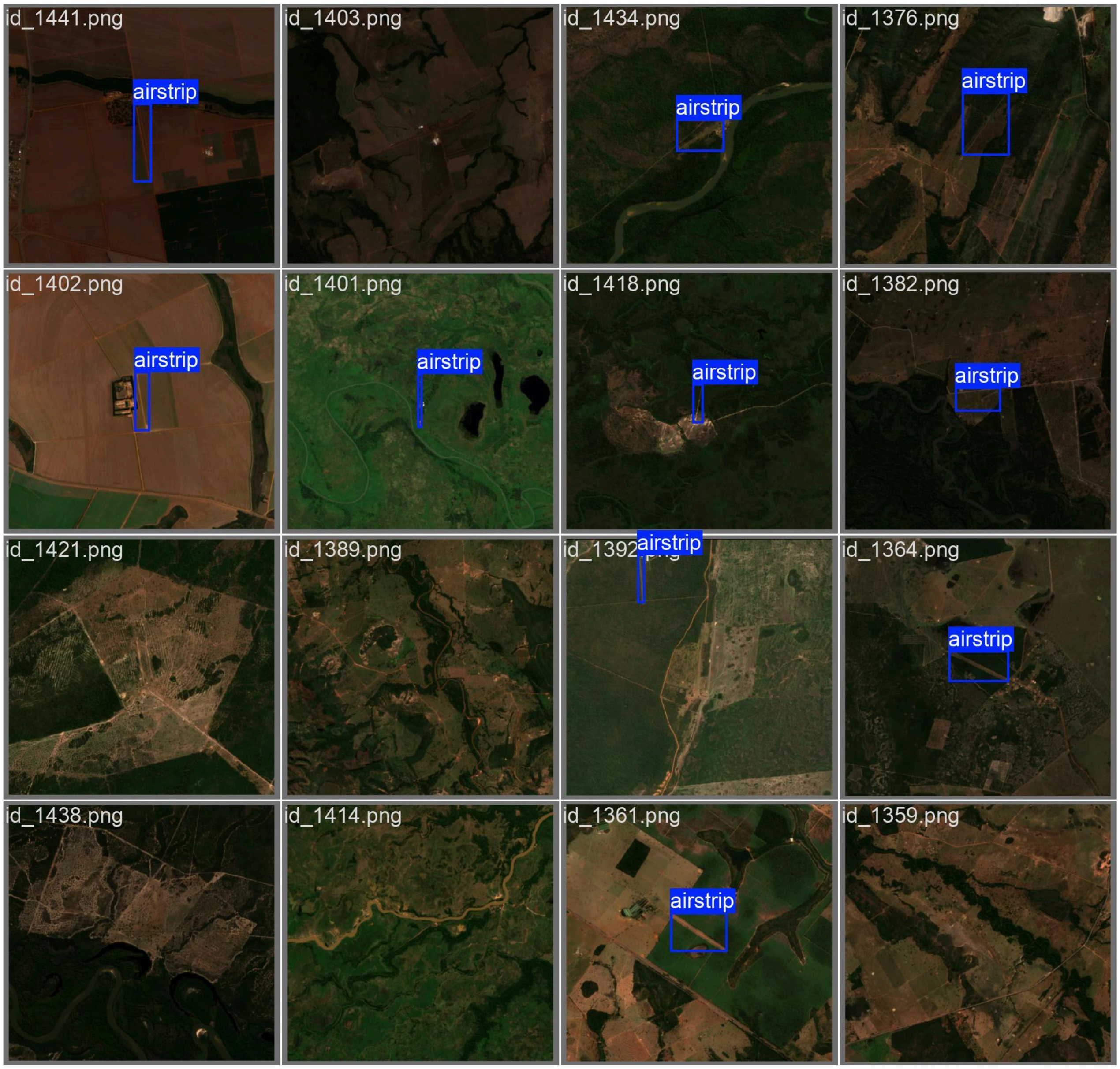
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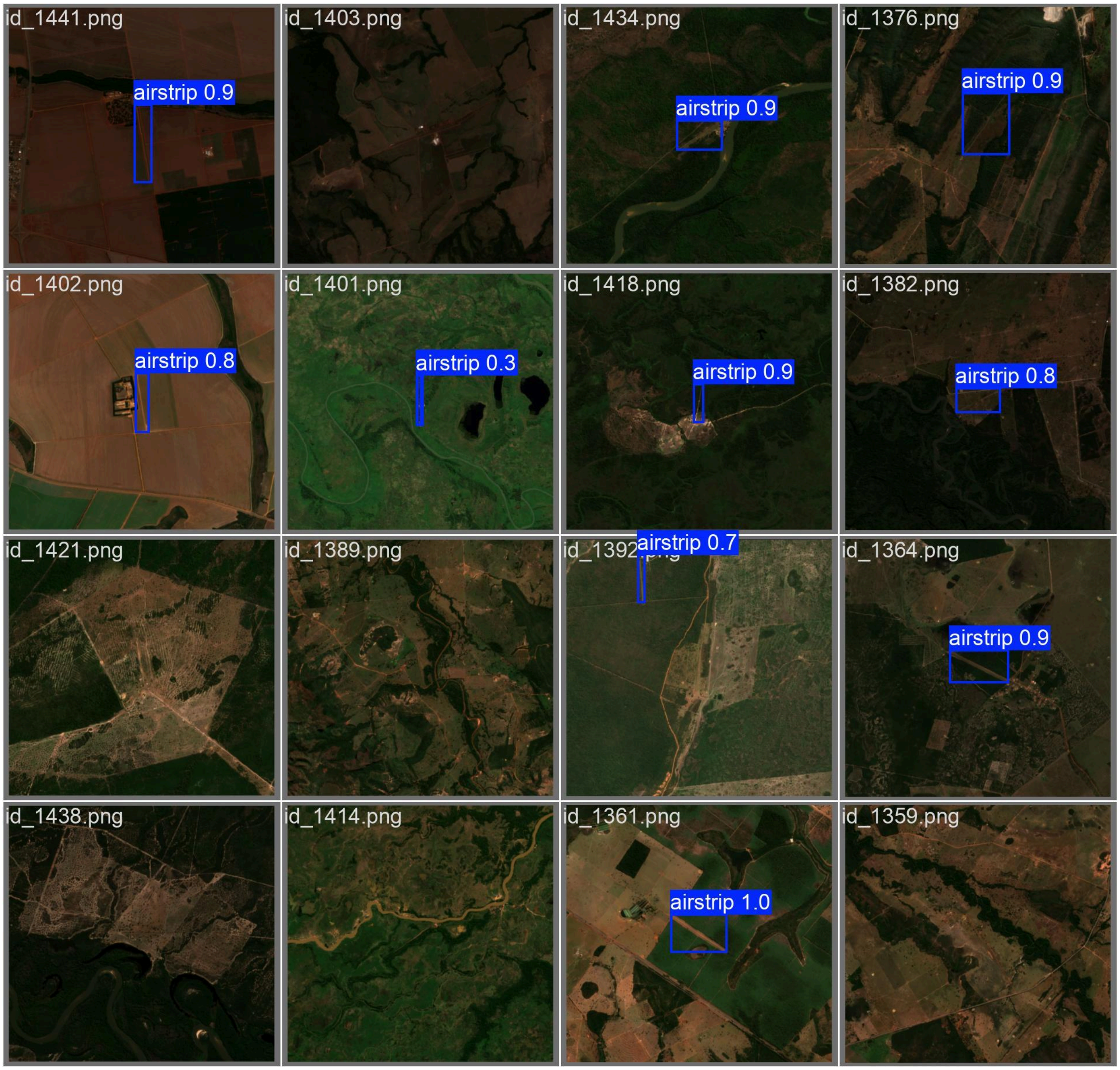


4.3 Error Analysis

False Positives:

- Elongated linear features (roads, highways) with runway-like geometry
- River edges and sandy bars mimicking runway brightness
- Straight logging roads in cleared areas

False Negatives:

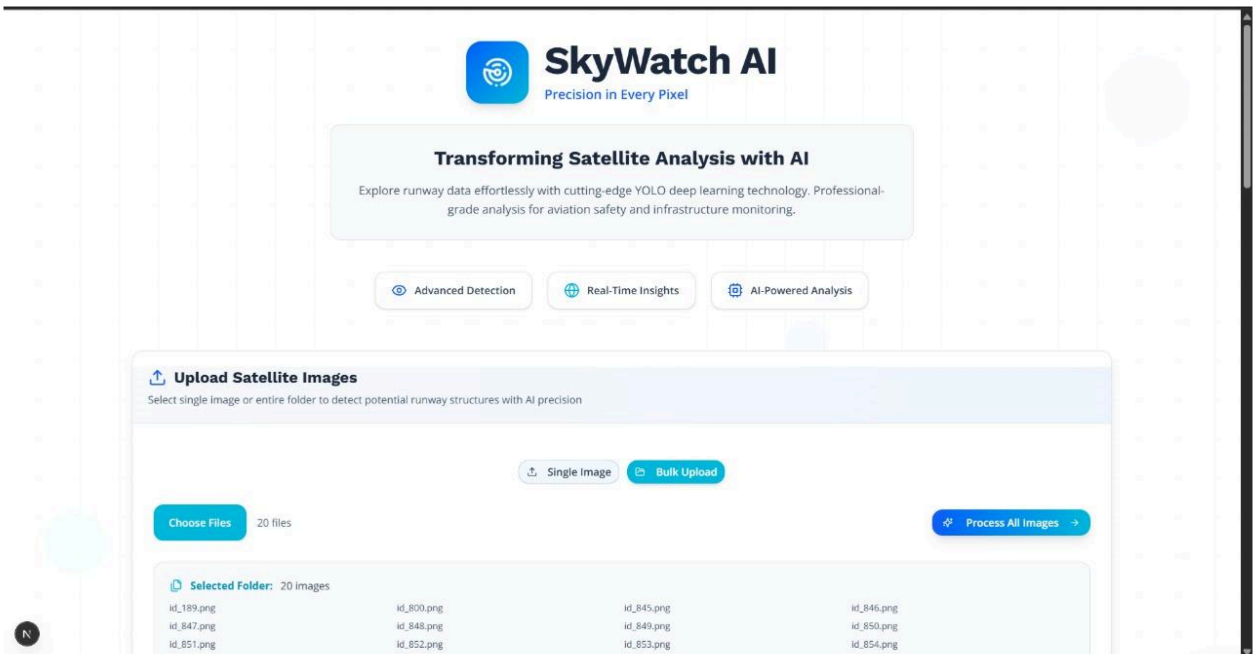
- Narrow strips partially covered by vegetation
- Runways in heterogeneous terrain
- Cloud or shadow-obscured areas in imagery

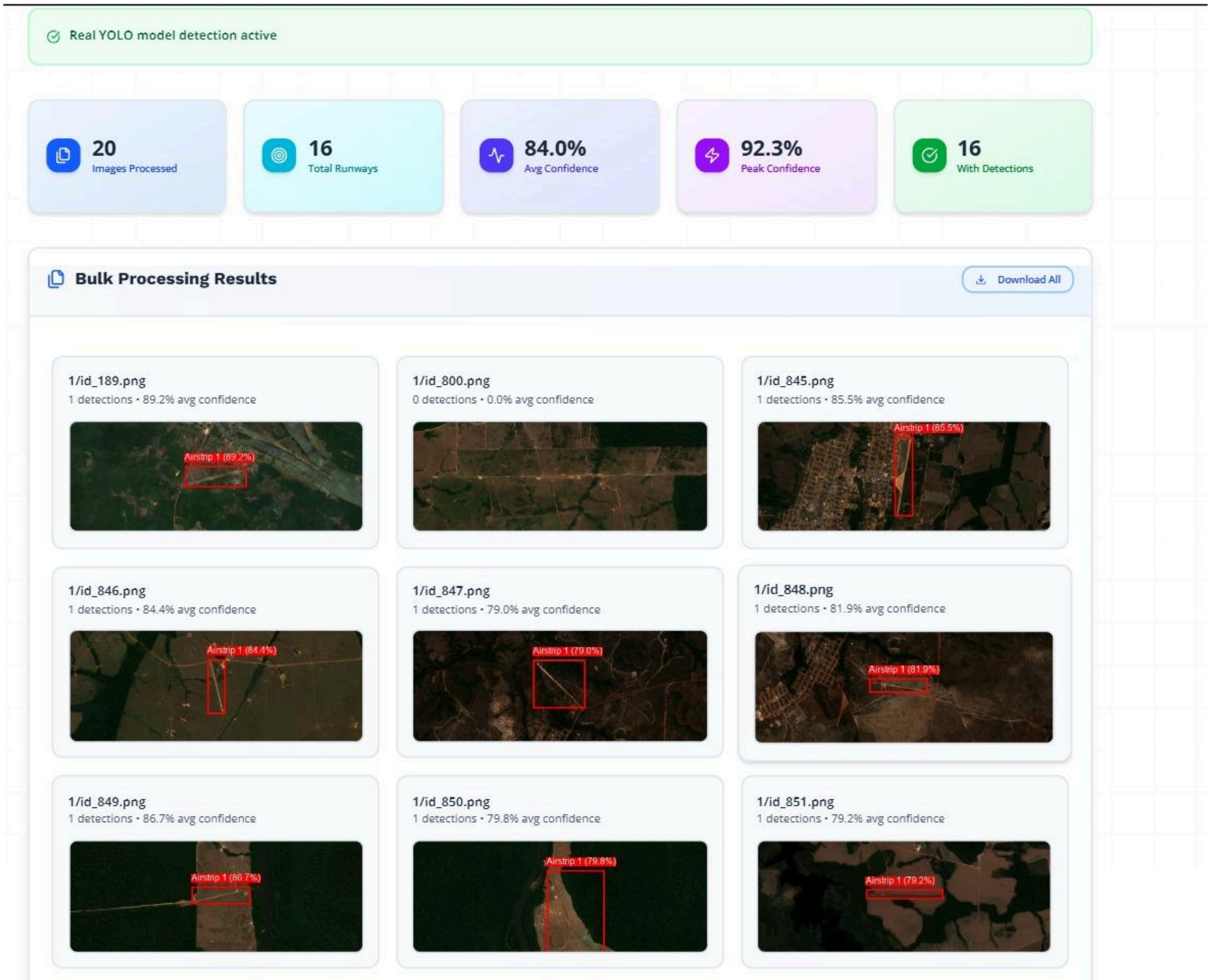
5. Discussion

5.1 Methodological Advantages

The transition to YOLOv8 object detection offers several key advantages:

- **Precise Localization:** Direct bounding box predictions enable accurate runway positioning
- **Reduced Manual Verification:** Clear box visualizations facilitate human review
- **Real-time Capabilities:** Suitable for large-scale monitoring applications
- **Improved Generalization:** Better performance on varying environmental conditions





5.2 Limitations and Challenges

Despite improvements, several 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

5.3 Implications for Environmental Monitoring

The improved detection capabilities have significant implications for:

- **Enforcement Operations:** Faster identification of illegal activities
- **Conservation Efforts:** Protection of sensitive ecosystems
- **Intelligence Gathering:** Enhanced surveillance capabilities for remote areas
- **Policy Development:** Data-driven approaches to environmental protection

6. Future Scope

6.1 Technical Enhancements

Multi-spectral Integration: Incorporate additional Sentinel-2 bands (near-IR/SWIR) and derived indices to improve discrimination between vegetation, soils, and cleared strips.

SAR Data Fusion: Include Sentinel-1 radar channels to provide texture information and cloud-penetrating capabilities.

Advanced Architectures: Explore model ensembles combining YOLOv8 with oriented-box or segmentation models for cross-validation.

6.2 Operational Improvements

Temporal Analysis: Exploit multi-temporal imagery to detect new clearings and monitor runway activity patterns.

Real-time Monitoring: Develop automated dashboard systems with alert mechanisms for newly detected runways.

Expanded Coverage: Scale detection capabilities to other regions with similar environmental and operational challenges.

6.3 Validation and Refinement

Field Validation: Coordinate with ground agencies to confirm detections and iteratively improve model accuracy.

Enhanced Annotations: Expand labeled datasets with more examples and negative samples to improve learning.

Semi-supervised Learning: Leverage unlabeled data to augment training datasets.

7. Conclusion

This research demonstrates that transitioning from patch-based CNN approaches to YOLOv8 object detection significantly improves the detection of clandestine airstrips in the Amazon Basin. The methodology achieves better localization accuracy, reduces false positive rates, and provides more practical output for human verification and automated monitoring systems.

The YOLOv8-based approach maintains reasonable recall of actual runways while improving precision, representing a meaningful advancement for environmental monitoring and enforcement applications. The explicit bounding box outputs facilitate easier integration into operational workflows and enable more efficient manual verification processes.

While challenges remain in distinguishing runways from visually similar features and handling environmental variations, the foundation established by this work provides a promising platform for continued development. Future enhancements incorporating multi-spectral data, SAR integration, and temporal analysis have the potential to further improve detection accuracy and operational utility.

The successful application of modern computer vision techniques to environmental monitoring challenges demonstrates the value of interdisciplinary approaches combining remote sensing, machine learning, and conservation science. As illegal activities continue to threaten the Amazon's ecological integrity, automated detection systems represent crucial tools for protecting this globally significant ecosystem.

Acknowledgments

The authors acknowledge the contributions of Team TerraPulse from the Zindi Amazon Basin Secret Runway Detection Challenge for establishing the baseline methodology. We also recognize ESA's Copernicus program for providing open access to Sentinel satellite data, and Google Earth Engine for facilitating large-scale geospatial analysis.

Data Availability

Satellite imagery utilized in this study is available through ESA's Copernicus program and Google Earth Engine. Code implementations and processing workflows are documented in the provided Jupyter notebooks of our GitHub profile. (Create_yolo_bounds.ipynb and Yolo2.ipynb).