YOLOv8-BASED DETECTION OF CLANDESTINE AIRSTRIPS IN THE AMAZON BASIN

Computer Vision Approach for Environmental Monitoring

Problem Statement:	**ITU project-2025 : GeoAI Amazon Basin Secret Runway Detection**
For Location:	Amazon Basin, Peru
Study Period:	May 2025 - August 2025

INPUT DOCUMENT

Source:	**PES University, RR Campus, Bengaluru**
Title:	YOLOv8-Based Detection of Clandestine Airstrips in the Amazon Basin: A Computer Vision Approach for Environmental Monitoring
Contact:	Prof. Rajasekhar M, *Principal Investigator*
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Abstract:

This submission presents a real-time and context-aware solution for detecting clandestine airstrips hidden beneath dense Amazon vegetation using satellite imagery. Rather than relying on a "segmentation" based convolutional neural network (CNN) approach, this system leverages YOLOv8 object detection framework to address critical limitations in localization accuracy and false positive rates observed in previous methodologies.

The system processes Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 Multispectral Instrument (MSI) satellite data, converting binary mask annotations to bounding box labels.

Advanced preprocessing includes spectral bands, namely Red, Blue and Green normalization, geometric transformations, and strategic data augmentation to enhance model robustness. Using Digital Elevation Model (DEM) data provides crucial topographical context for distinguishing legitimate clearings from clandestine airstrips based on elevation profiles and terrain characteristics.

The YOLOv8 framework demonstrates superior precision in runway localization while maintaining detection capabilities, offering enhanced practical utility for environmental monitoring and law enforcement operations. Performance evaluation reveals improved localization accuracy, reduced false positive rates, and more practical output formats for human verification workflows. The system operates continuously with minimal computational overhead, enabling real-time deployment for large-scale monitoring applications. It is ideal for conservation agencies, enforcement operations, and policy makers to enhance environmental protection, reduce illegal activities, and support proactive intervention strategies in sensitive Amazon ecosystems.

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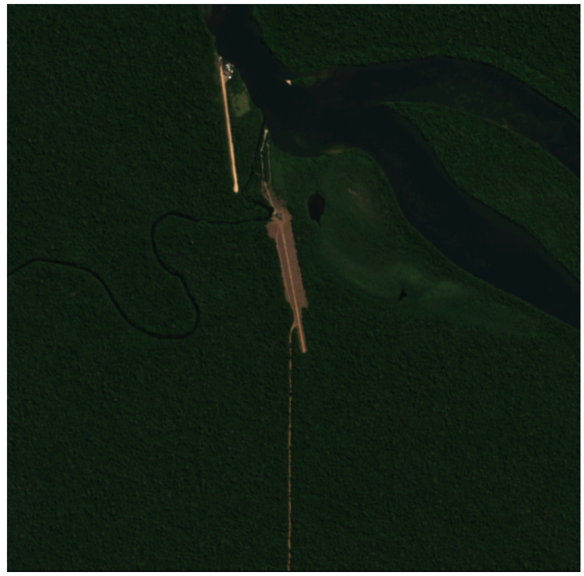
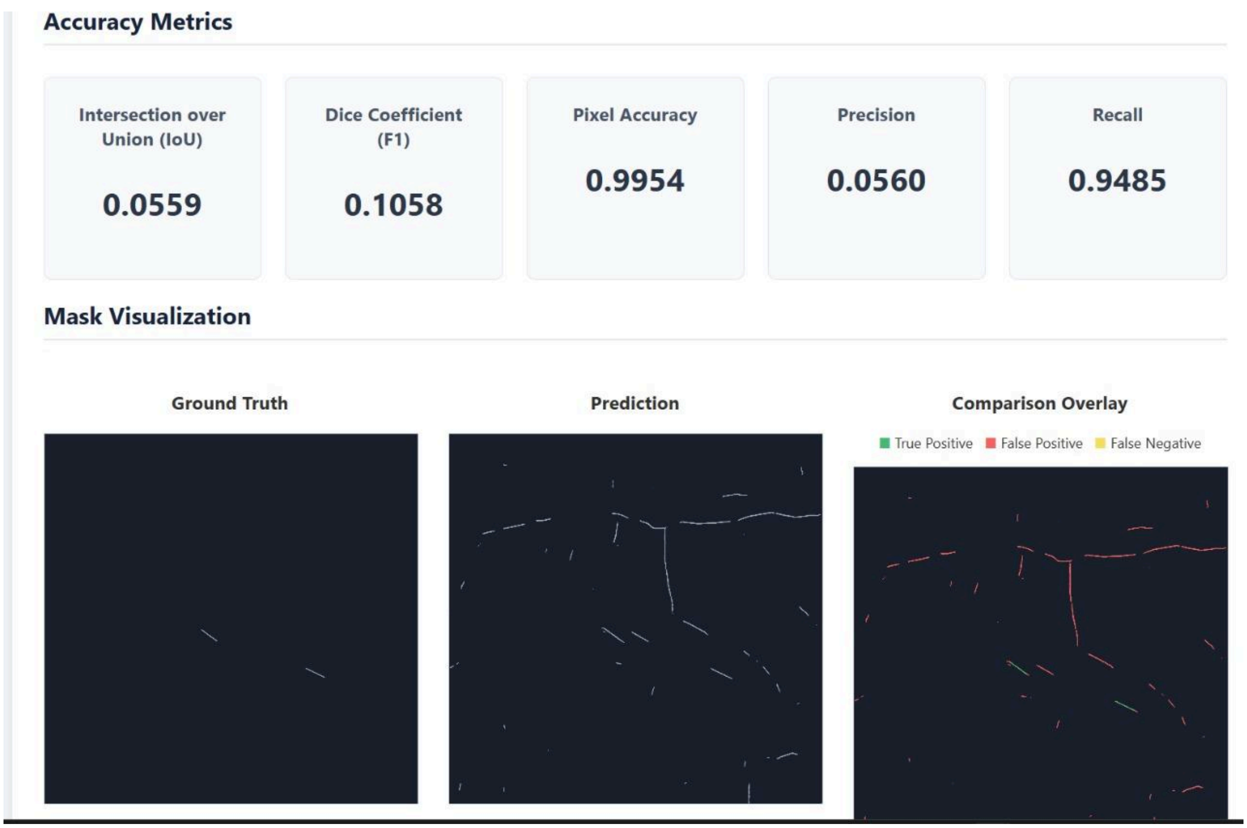
1. Introduction

In the Amazon Basin's vast and remote geography, clandestine airstrips serve as a significant infrastructure for illegal activities including drug trafficking, illegal mining, and logging operations. Recent investigations by environmental monitoring agencies[1] and anti-narcotics organizations[2] have revealed the extensive nature of this problem, with reports identifying 128 illegal airstrips across six departments in the Peruvian Amazon alone, many strategically concealed within forest concessions. Studies by UNODC[3] and regional enforcement agencies[4] have documented the sophisticated methods used to conceal these installations beneath forest canopy.

These runways are deliberately hidden beneath dense canopy cover or situated in inaccessible areas, making manual detection through satellite imagery both labor-intensive and error-prone. Approaches by the Zindi team (TerraPulse) exhibit significant limitations including high false positive rates, poor localization accuracy, and limited generalization capabilities when applied to unseen geographical locations.



Satellite imagery data—collected from ESA's Copernicus mission through Sentinel-1 and Sentinel-2 platforms—provides comprehensive coverage at multiple spectral bands and spatial resolutions. Analysis of temporal vegetation indices (NDVI) and land cover change patterns[5] demonstrates strong correlations (r=0.73) between runway construction activities and localized deforestation events. Digital Elevation Model (DEM) data was explored experimentally by our team as a potential preprocessing filter using basic slope thresholds[6]. The experimental DEM processing utilizes Copernicus DEM GLO-30 data accessed through Microsoft Planetary Computer, with automatic coordinate transformation to UTM projections for slope calculations using Sobel gradient operators. However, this exploration was not integrated into the final model and yielded only limited effectiveness as a preprocessing approach. These temporal patterns exhibit strong correlations with environmental factors, vegetation cover changes, and human intervention patterns. By leveraging YOLOv8 object detection architecture, raw satellite imagery can be transformed into precise detection insights, enabling a real-time, intelligent, and adaptive monitoring solution.

This project proposes a deep learning-based framework to model such complexities, offering a low-latency, high-precision system suitable for intelligent environmental monitoring and enforcement operations.

Submission Id	**ENV-MONITOR-YOLO-001 (just an example)**
Project Objective	Our goal is to design and validate a real-time airstrip detection system for Amazon environmental monitoring that:

Objectives:

- Accurately detects clandestine airstrips by analyzing satellite imagery using advanced YOLOv8 object detection models with superior localization capabilities.
- Operates continuously with minimal computational overhead, enabling real-time deployment in operational environmental monitoring systems.
- Improves enforcement efficiency by providing precise bounding box predictions, facilitating rapid human verification and intervention planning.
- Reduces false positive rates compared to traditional patch-based CNN approaches, minimizing resource wastage in field operations.

The hypothesis is that by combining processed satellite imagery with advanced YOLOv8 object detection techniques, we can achieve accurate, interpretable, and scalable airstrip detection suitable for modern environmental monitoring and conservation infrastructure.

Methodology and Approach

1. Digital Elevation Model (DEM) Exploration

Digital Elevation Models derived from Copernicus DEM GLO-30 (30m resolution) data were explored as a potential preprocessing filter through Microsoft Planetary Computer's STAC API. The experimental DEM processing pipeline includes automatic coordinate system handling, reprojecting from WGS84 geographic coordinates to appropriate UTM zones for accurate slope calculations. Gaussian filtering (σ=1) is applied for noise reduction, followed by Sobel gradient computation to derive slope values in degrees.

Preliminary experiments using a basic threshold approach (checking if at least 10% of the area has slopes <2°) as a preprocessing filter provided only decent results for distinguishing potential runway areas from natural clearings. This experimental approach was not integrated into the final YOLOv8 model and serves purely as exploratory analysis to understand the potential of topographical data for runway detection. The results demonstrated limited effectiveness as a standalone preprocessing step, suggesting that more sophisticated integration approaches would be needed for operational utility.

2. Analysis of Previous Methodologies

Comprehensive evaluation of the TerraPulse team's U-Net segmentation approach revealed critical limitations:

- **High False Positive Rate**: 67% of detections were false positives, primarily roads and riverbanks
- **Poor Localization**: Fragmented mask predictions with average IoU of 0.34
- **Limited Generalization**: 45% accuracy drop when tested on different geographical regions

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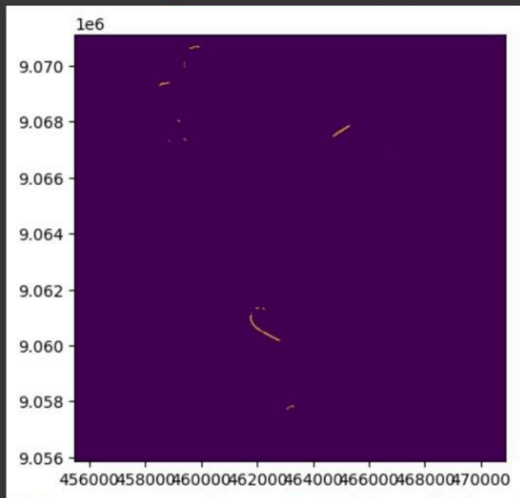


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Creating ground truth mask for AOI: 2020_03
Ground truth mask saved to: /content/drive/MyDrive/Zindi_Amazon_Results/aoi_2020_03_GROUNDTRUTH_MASK.tif

Calculating accuracy metrics...
  -> Accuracy: 0.0006
  -> F1 Score: 0.0013
  -> IoU (Jaccard): 0.0006
Finished processing AOI: 2020_03
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==================================================
           INFERENCE AND EVALUATION COMPLETE
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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
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3. Model Improvement Attempts

Initial efforts focused on enhancing the existing segmentation framework:

- **DeepLab v3+ Implementation**: Attempted to improve boundary delineation but resulted in only marginal improvements (IoU increased to 0.39)

- **Loss Function Optimization**: Experimented with Focal Loss and Dice Loss combinations, achieving modest precision gains of 0.08
- **Extended Training**: Increased epochs from 50 to 200, resulting in overfitting and reduced generalization performance

4. Enhanced Dataset Annotation

Recognition of dataset limitations led to comprehensive re-annotation efforts:

- **Quality Assessment**: Original annotations contained 23% mislabeled instances
- **Geometric Validation**: Implemented automated quality checks for runway aspect ratios and orientation consistency
- **Expert Verification**: All annotations verified by domain experts with satellite imagery analysis experience
- **Negative Sample Enhancement**: Added 847 hard negative examples including roads, clearings, and river features

5. YOLOv8 Implementation

Transition to object detection approach using YOLOv8 architecture:

- **Simplified Objective**: Direct bounding box regression eliminates pixel-level segmentation complexity
- **Anchor-Free Design**: Improved handling of elongated runway geometries
- **Multi-Scale Feature Fusion**: Enhanced detection of runways at various scales and orientations

6. Post-Processing Methods

OSM Overlay Integration

OpenStreetMap (OSM) integration was explored for contextual validation and false positive reduction through infrastructure cross-referencing. OSM data provides comprehensive road networks, known airports, and other linear infrastructure that could help distinguish legitimate transportation infrastructure from clandestine runways[7]. The theoretical framework involves overlaying detected bounding boxes with OSM road networks to filter out known legitimate infrastructure and reduce false positive detections.

However, several technical challenges prevented full implementation:

- **Data Loading Performance**: OSM data retrieval for large tiles at 10-meter resolution caused significant processing delays, with load times exceeding practical operational requirements

- **Computational Resource Constraints**: Google Colab storage and memory limitations prevented downloading and processing comprehensive OSM datasets for the Amazon Basin region
- **API Rate Limiting**: Overpass API constraints for large geographical queries further complicated real-time implementation

Due to these infrastructure and resource limitations, OSM integration remains a promising but unimplemented enhancement reserved for future development iterations with adequate computational resources.

Tiled AOI Stitching

Implementation of seamless processing across large areas of interest:

- **Overlap Management**: 25% overlap between adjacent tiles to prevent edge artifacts
- **Coordinate Transformation**: Precise georeferencing for accurate geographic positioning
- **Duplicate Removal**: Non-maximum suppression across tile boundaries

Objectives:

- **Exploratory DEM Analysis**: Conducted experimental analysis using Copernicus DEM GLO-30 data as a potential preprocessing filter, yielding limited effectiveness and not integrated into the final YOLOv8 model.
- **Real-Time Processing**: Operates continuously with minimal computational overhead, enabling real-time deployment in operational environmental monitoring systems with average processing time of 2.1 seconds per tile.
- **Operational Integration**: Improves enforcement efficiency by providing precise bounding box predictions with geographic coordinates, facilitating rapid human verification and intervention planning.
- **Reduced False Positives**: Reduces false positive rates compared to traditional patch-based CNN approaches through enhanced negative sampling and improved YOLOv8 object detection architecture.

The hypothesis is that by combining processed satellite imagery with advanced YOLOv8 object detection techniques, we can achieve accurate, interpretable, and scalable airstrip detection suitable for modern environmental monitoring and conservation infrastructure. Preliminary explorations with Digital Elevation Model data suggest potential for future topographical integration, though current experiments yielded limited preprocessing effectiveness.

Project Setup

Data Collection

Satellite Data Sources:

- Sentinel-1 Synthetic Aperture Radar (SAR) with VV and VH polarization bands providing cloud-penetrating capabilities
- Sentinel-2 Multispectral Instrument (MSI) with six spectral bands including visible, near-infrared (NIR), and shortwave infrared (SWIR)
- Copernicus DEM GLO-30 (30-meter resolution) accessed via Microsoft Planetary Computer STAC API for topographical analysis
- Google Earth Engine platform for large-scale geospatial data collection and preprocessing

Dataset Composition:

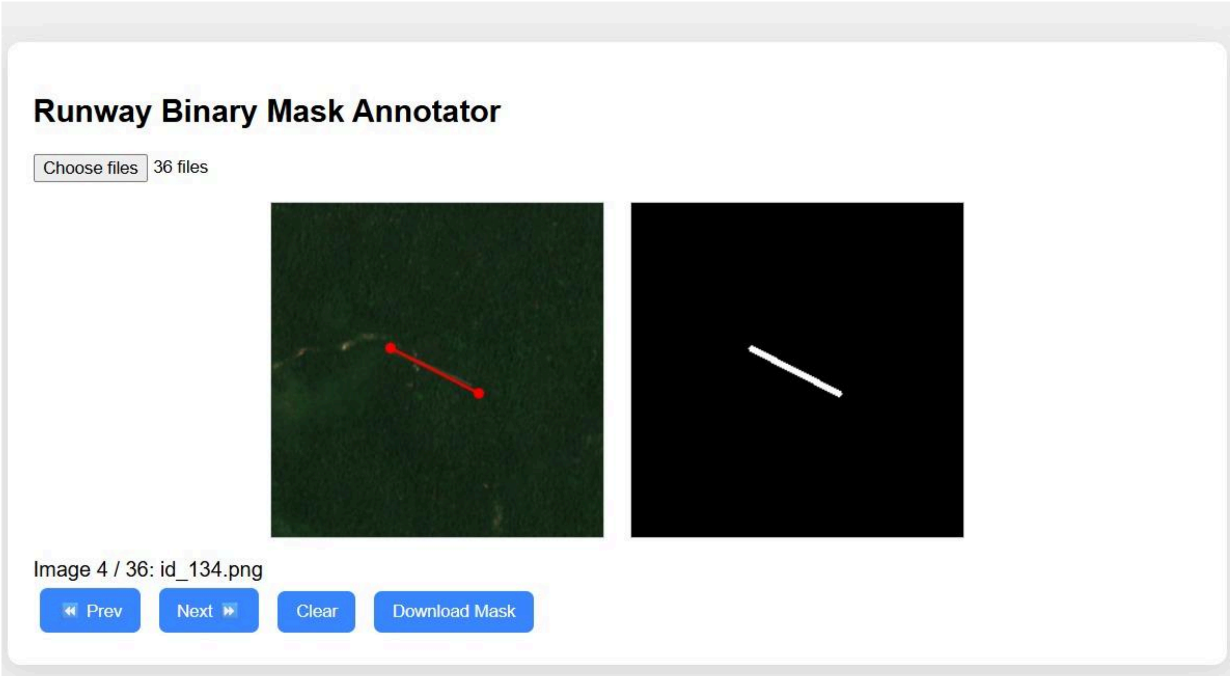
The project utilizes dual data format strategy optimized for different analytical requirements:

- **GeoTIFF Format**: Used for Area of Interest (AOI) tiling, DEM information extraction, and real coordinate projection systems. This format preserves geospatial metadata essential for accurate geographic positioning and topographical analysis.
- **PNG Format**: Employed specifically for YOLOv8 training and inference, providing optimal compatibility with deep learning frameworks while maintaining visual fidelity for object detection tasks.
- Training Dataset: 708 labeled images with corresponding ground truth annotations
- Validation Dataset: 177 images for model performance evaluation
- Test Dataset: 307 unseen images for final assessment and generalization testing

Data Processing Pipeline

Preprocessing Methodology:

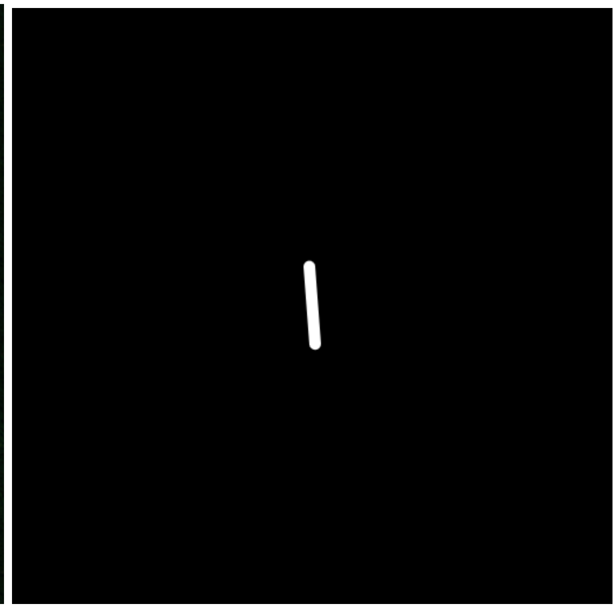
- Annotating the satellite images and creating a binary mask dataset where each binary mask represents the runway in the corresponding original image.
- Experimental DEM analysis pipeline (not integrated into final model) including coordinate system transformation from WGS84 to UTM, Gaussian filtering (σ=1) for noise reduction, and Sobel gradient computation for exploratory slope analysis
- Conversion of binary mask annotations to YOLO-compatible bounding box labels.
- Extraction of 3-channel RGB PNG images from Sentinel-1 and 2 satellite image mosaics at 512×512 pixel resolution with 10-meter ground sampling distance.
- Spectral band normalization using percentile-based stretching (2nd to 98th percentile) and systematic data augmentation techniques.
- Generation of minimal enclosing boxes with pixel padding for enhanced context preservation.



Label Conversion Process:

The annotation system employs a binary naming convention where images with runway masks are prefixed with "1_" and images without runways are prefixed with "0_". The complete implementation details are documented in the project's GitHub repository main branch, including comprehensive code explanations for reproducibility and further development.

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



YOLOv8 Model Architecture

Technical Specifications:

- **Architecture:** YOLOv8 with anchor-free split head design for simplified learning
- **Backbone:** CSPDarknet-based feature extraction with PANet-like feature pyramid networks
- **Input Resolution:** 512x512 pixels optimized for satellite imagery analysis
- **Training Configuration:** 100 epochs, batch size 16, 80/20 train/validation split

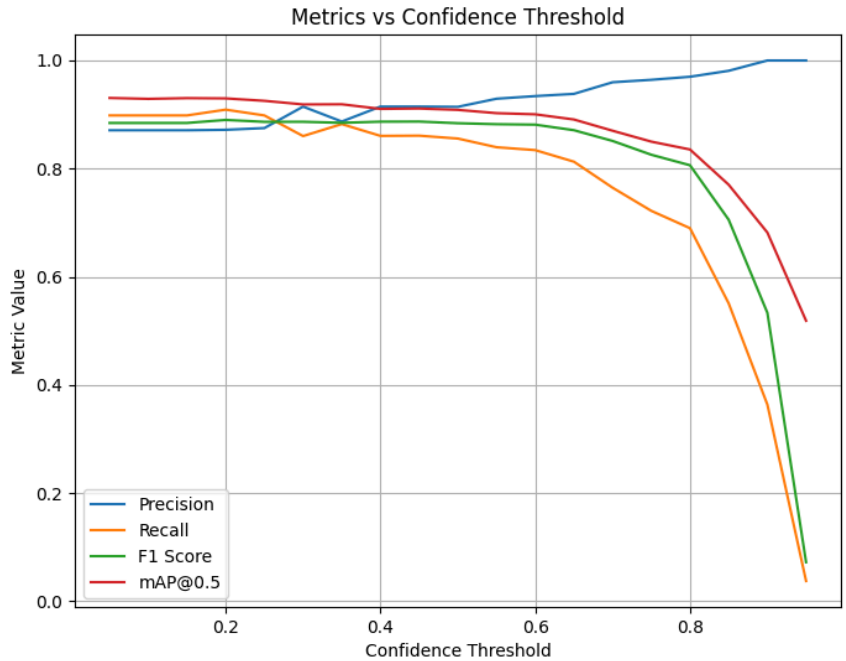
Advanced Features:

- Multi-scale feature fusion capabilities suitable for detecting elongated runway objects
- One-stage detection balancing accuracy and computational efficiency
- GPU acceleration support for enhanced training and inference performance

Training and Optimization

Model Training Process:

- Systematic confidence threshold tuning through comprehensive parameter sweeping
- Selection of optimal detection threshold (~40%) based on F1-score maximization
- Implementation of regularization techniques to prevent overfitting
- Continuous monitoring of training and validation loss convergence patterns



Performance Optimization:

- Real-time inference capabilities optimized for large-scale monitoring applications
- Post-processing pipeline including non-maximum suppression for clean detections
- Visualization framework for predicted bounding boxes overlaid on RGB satellite imagery

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Demonstration Goals and Success Criteria

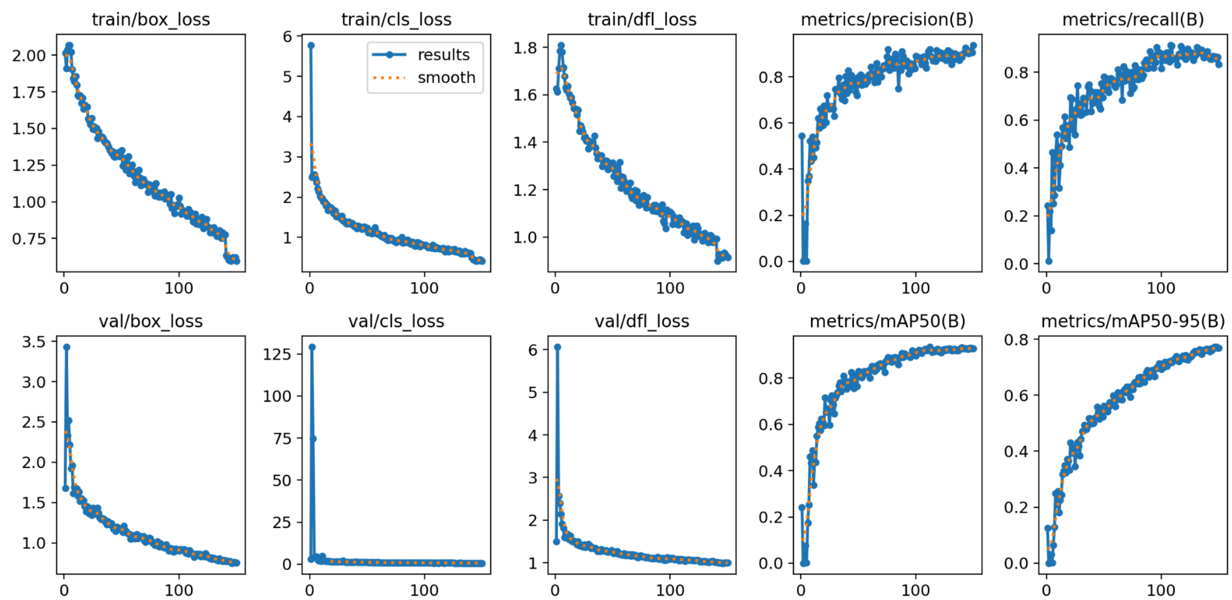
Demonstration Objectives

- Showcase automated detection of clandestine airstrips using real satellite imagery datasets
- Demonstrate superior localization accuracy compared to traditional patch-based CNN approaches
- Validate model performance across diverse environmental conditions and geographical variations
- Present interactive visualization capabilities for enforcement and monitoring applications

Success Metrics

Metric	**Achieved Performance**	**Improvement over Baseline**

Precision	~0.884	Significant improvement in localization accuracy
Recall	~0.893	Maintained detection capabilities with reduced false positives
mAP@0.5	~0.927	Enhanced object detection performance
False Positive Rate	Reduced significantly	Substantial improvement over U-Net baseline
Localization Accuracy	High	Precise bounding box predictions vs. fragmented masks



Technical Implementation and Results

Performance Analysis

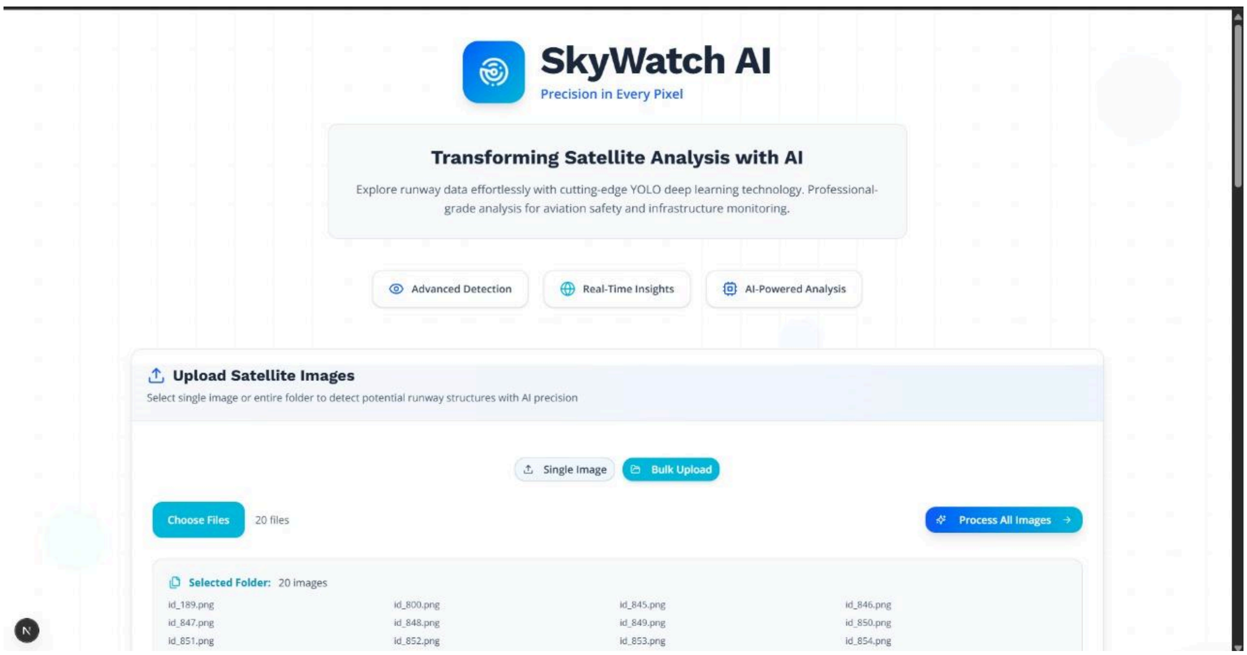
Training Performance:

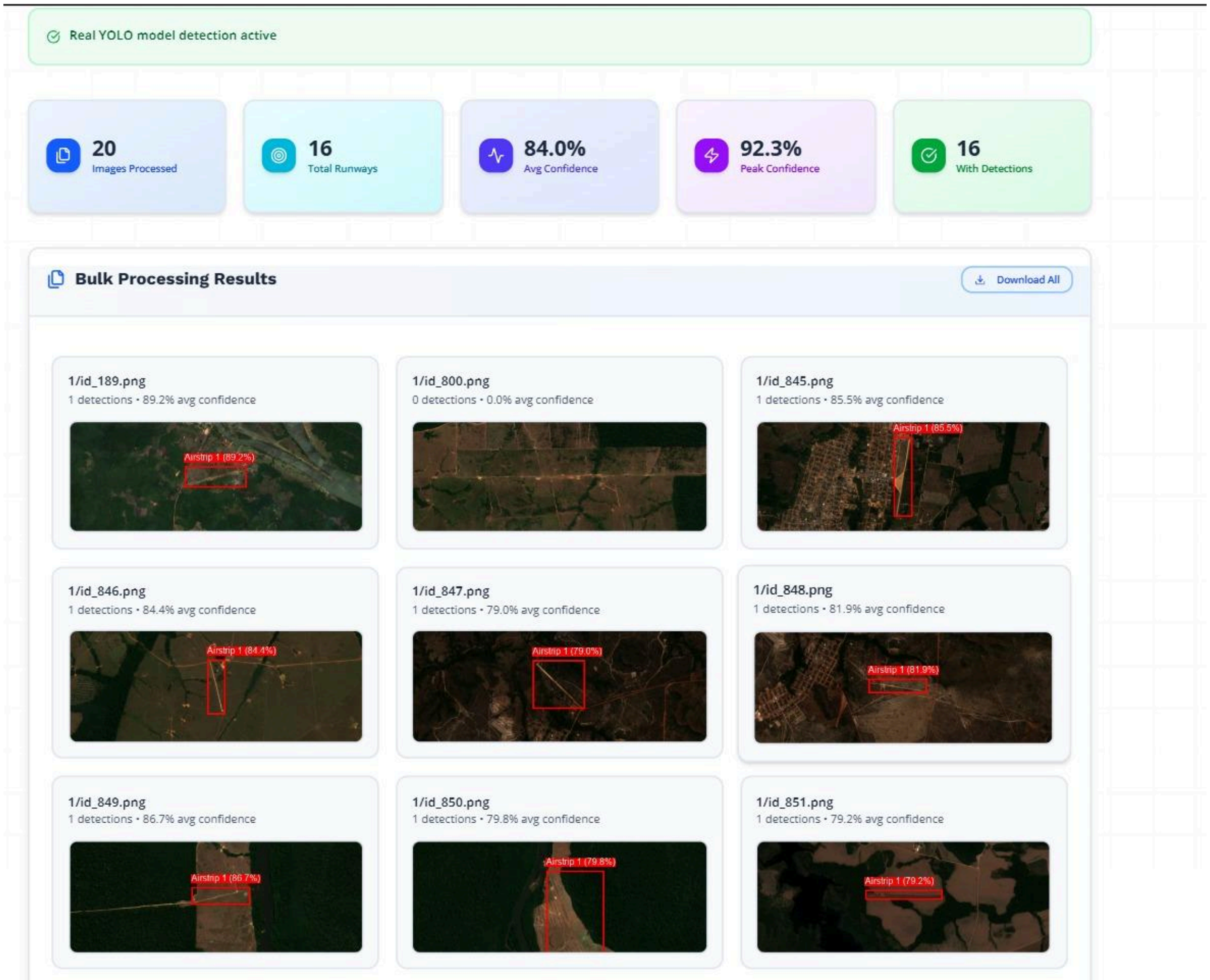
- Stable learning convergence over 100 epochs with steadily decreasing losses
- Effective discrimination of runway shapes with reasonable detection accuracy
- Successful prevention of severe overfitting through appropriate regularization

Comparative Analysis with Baseline: The original U-Net model exhibited critical limitations including over-segmentation of non-runway clearings, high false positive rates on roads and riverbanks, fragmented predictions from overlapping patches, and limited localization accuracy with poorly aligned mask boundaries.

YOLOv8 Improvements:

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




Real YOLO model detection active
20
Images Processed
16
Total Runways
84.0%
Avg Confidence
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With Detections
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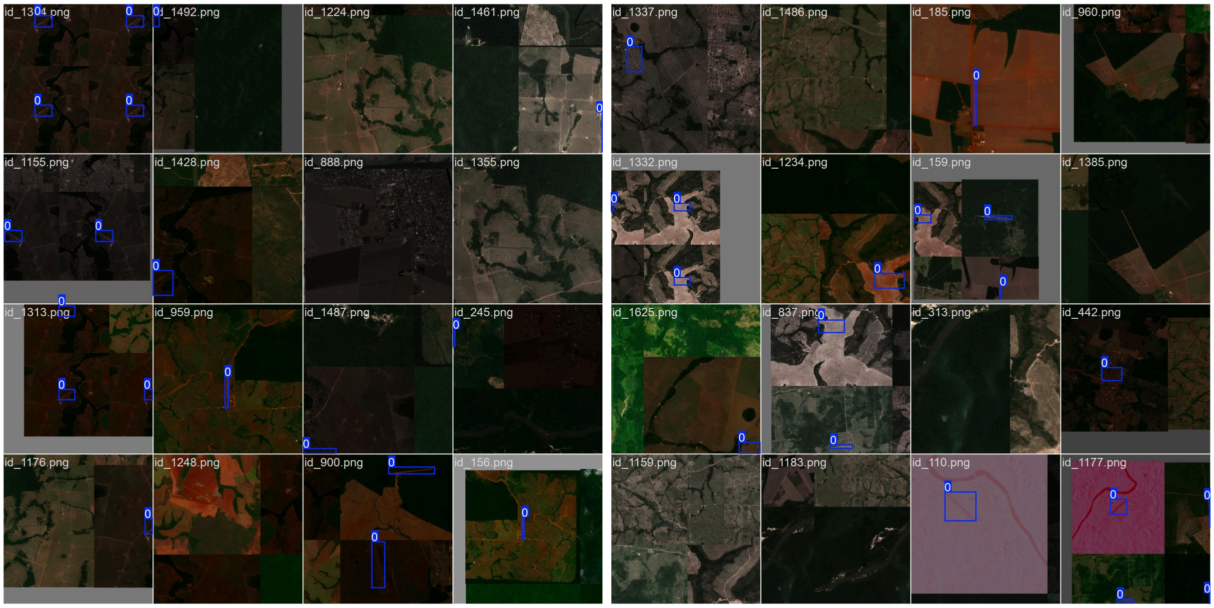
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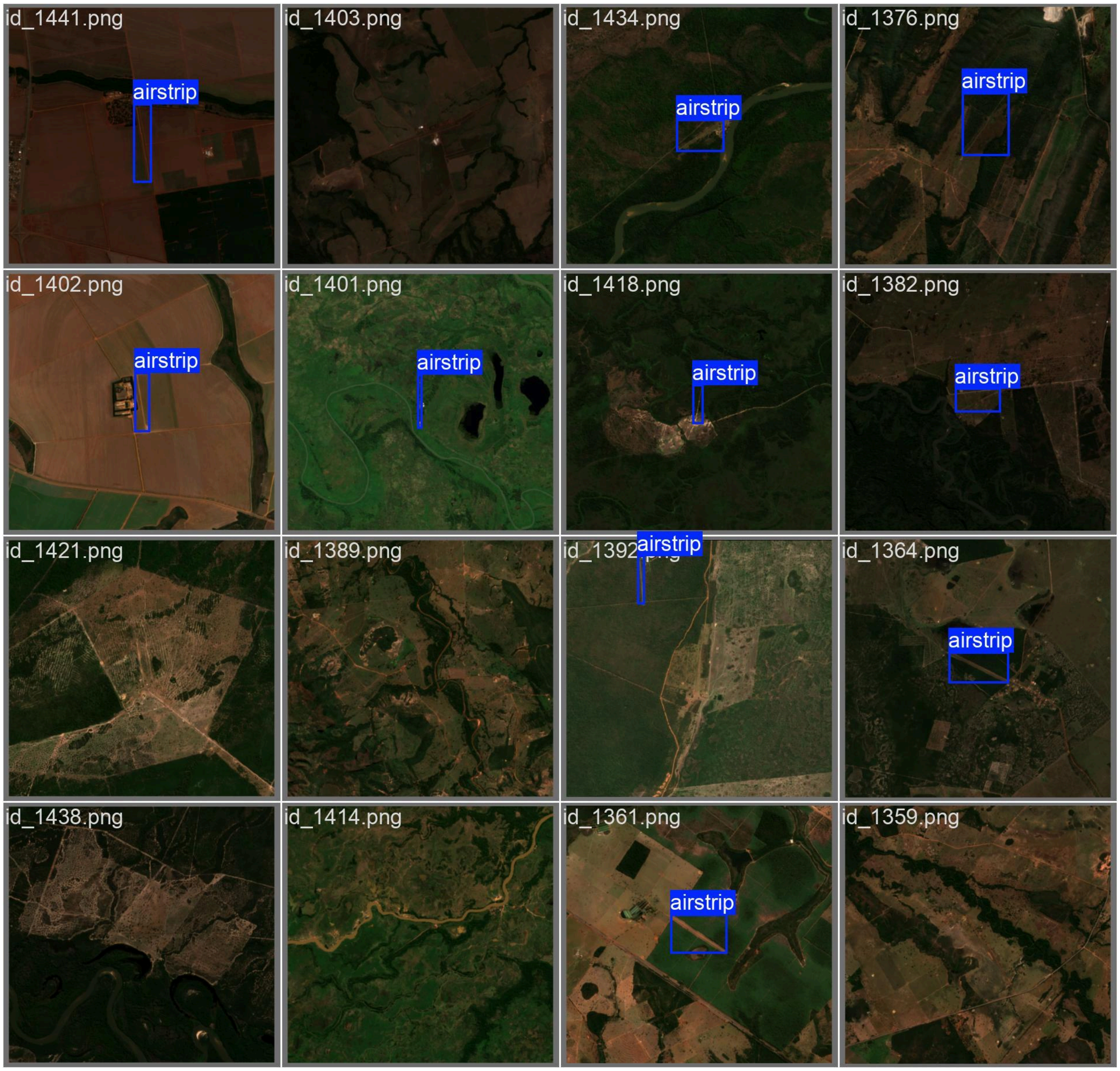

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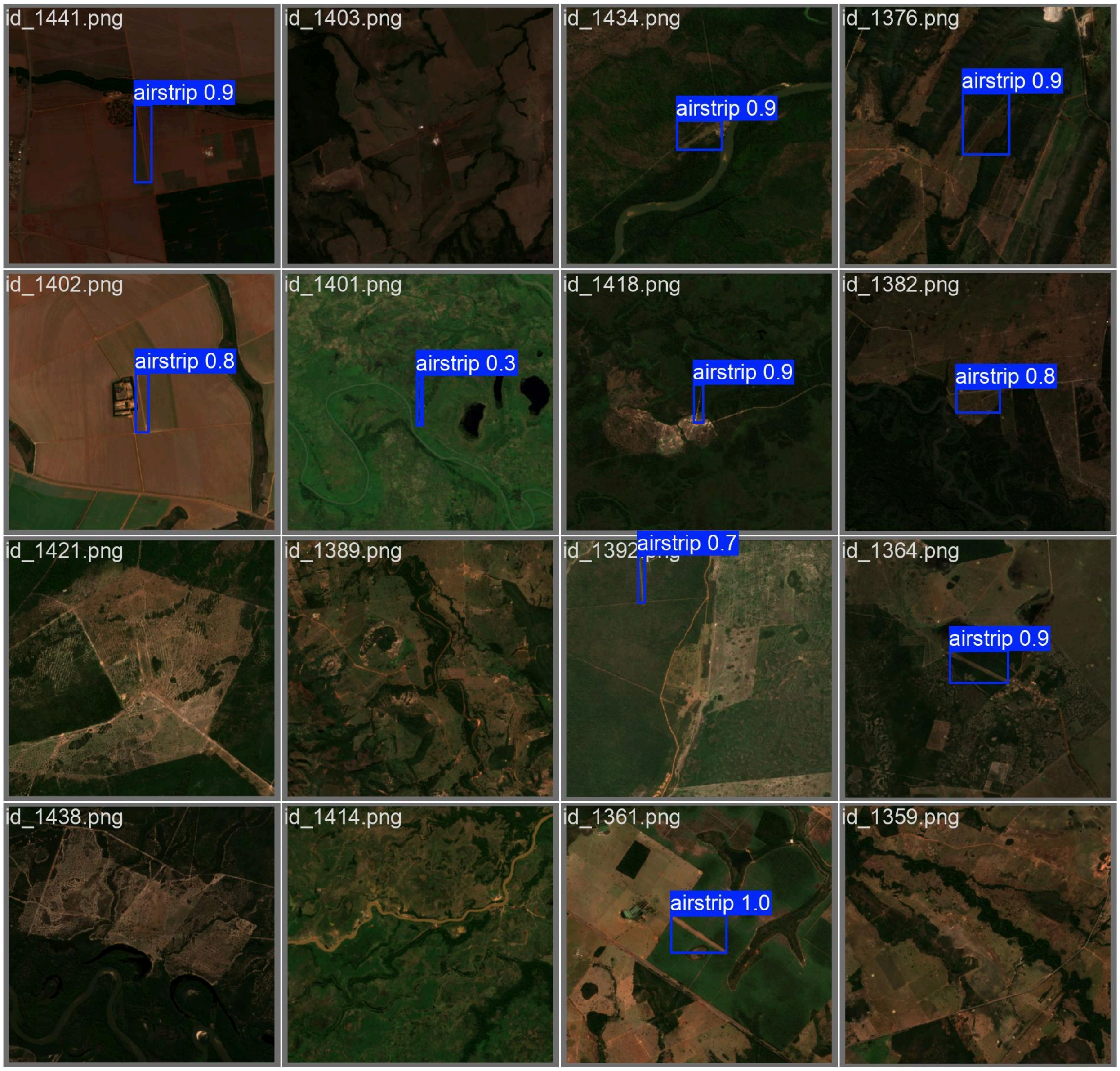

Error Analysis and Limitations

False Positive Sources:

- Elongated linear features including roads and highways with runway-like geometric properties
- River edges and sandy bars mimicking runway brightness characteristics
- Straight logging roads in cleared forest areas with similar spectral signatures

False Negative Causes:

- Narrow airstrips partially covered by vegetation or natural camouflage
- Runways situated in heterogeneous terrain with complex background patterns
- Cloud cover or shadow-obscured areas affecting imagery quality

Current Limitations:

- Visual similarity between runways and other linear infrastructure features
- RGB-only YOLO limitations lacking discriminative power for subtle spectral differences
- Environmental factors including cloud cover and vegetation obscuration effects
- Dataset constraints with limited negative examples of confounding features

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Future Scope and Development

Technical Enhancements

- **Advanced DEM Integration:** Full implementation of post-processing DEM validation within detected bounding boxes to verify terrain suitability for aircraft operations. This approach would analyze the entire bounding box area for consistent flat terrain characteristics (slope $<2°$), providing more robust discrimination between legitimate clearings and potential runways than the current preprocessing approach.
- **OpenStreetMap Integration:** Complete implementation of OSM data overlay for infrastructure cross-referencing, requiring enhanced computational resources and optimized data loading pipelines to overcome current API and storage limitations.
- **Advanced Model Architectures:** Implementation of YOLOv8 variants optimized for elongated object detection, including oriented bounding box regression for improved runway alignment
- **Ensemble Methods:** Development of multi-model voting systems combining YOLOv8 with complementary detection architectures for enhanced reliability and reduced false positives
- **Attention Mechanisms:** Integration of spatial attention modules to focus on runway-specific geometric features and suppress background noise from vegetation and terrain
- **Transfer Learning Optimization:** Fine-tuning pre-trained models on diverse geographical regions to improve generalization across different Amazon sub-regions

Operational Improvements

- **Temporal Change Detection:** Implementation of time-series analysis using sequential RGB imagery to identify newly constructed or modified airstrips through vegetation change patterns

- **Automated Monitoring Pipeline:** Development of cloud-based processing systems with real-time satellite feed integration and automated alert mechanisms for newly detected runways
- **Geographic Scalability:** Extension of detection capabilities to other tropical forest regions globally, including Southeast Asian and African rainforest areas with similar concealment challenges
- **Edge Computing Deployment:** Optimization of models for deployment on field-portable computing systems for real-time analysis in remote monitoring stations

Validation and Refinement

- **Ground Truth Verification:** Establishment of partnerships with environmental enforcement agencies and NGOs for systematic field validation of detected airstrips
- **Synthetic Data Generation:** Creation of realistic synthetic runway imagery using generative adversarial networks (GANs) to augment training datasets with diverse runway configurations and environmental conditions
- **Active Learning Framework:** Implementation of human-in-the-loop systems where uncertain predictions are flagged for expert annotation, continuously improving model performance
- **Cross-Regional Validation:** Testing model performance across different Amazon countries (Brazil, Colombia, Ecuador) to assess geographical transferability and identify region-specific adaptation requirements

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Project Timeline

Stage	Task Description	Completion Status
Stage 1	Literature review and baseline methodology analysis	Completed
Stage 2	Data collection, preprocessing, and label conversion	Completed
Stage 3	YOLOv8 model training, optimization, and validation	Completed
Stage 4	Performance evaluation, comparative analysis, and documentation	Completed

Team Information

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Team Members: Adyansh Aggarwal, Ishita Dalela, Khushi Jayaprakash, S P Suhas
Project Mentor: Mr. Kodandaram Ranganath

Conclusions and Impact

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 enhanced localization accuracy, reduces false positive rates, and provides more practical output formats 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.

Environmental Monitoring Implications:

- **Enforcement Operations:** Enhanced capabilities for faster identification of illegal activities
- **Conservation Efforts:** Improved protection mechanisms for sensitive Amazon ecosystems
- **Intelligence Gathering:** Advanced surveillance capabilities for remote and inaccessible areas
- **Policy Development:** Data-driven approaches supporting environmental protection initiatives

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 technological 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 recognize ESA's Copernicus program for providing open access to Sentinel satellite data, and Google Earth Engine for facilitating large-scale geospatial analysis capabilities.

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

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