Sat-Annotator

AI-Powered Tool for Annotating Satellite Images

Sponsored by the Egyptian Space Agency (EgSA)

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Outline

01. Egyption Space Agency

02. Introduction

03. Problem Statement

04. Related Work

05. Metrics Used For evaluation

06. Literature Review

07. Proposed Solution

08. Implementation

09. Comparison Bet. the Models

10. Approaches Explored

11. Evaluation & Results

12. Challenges & Solutions

13. Key Achievements

14. Conclusion

15. Future Enhancements

16. References

Egyption Space Agency (EgSA)

- The Egyptian Space Agency (EgSA) collaborated with us to define the tool's core requirements.
- Their input ensured the tool aligns with real-world needs in remote sensing.
- EgSA will use the tool to annotate satellite imagery for training machine learning models.
- This accelerates analysis of urban development, agriculture, and environmental changes.
- Monthly reports to the Prime Minister will include insights derived from the tool.
- The project enhances Egypt's sovereign AI capabilities in space technology.
- It directly supports national goals in data-driven policy and technological independence.

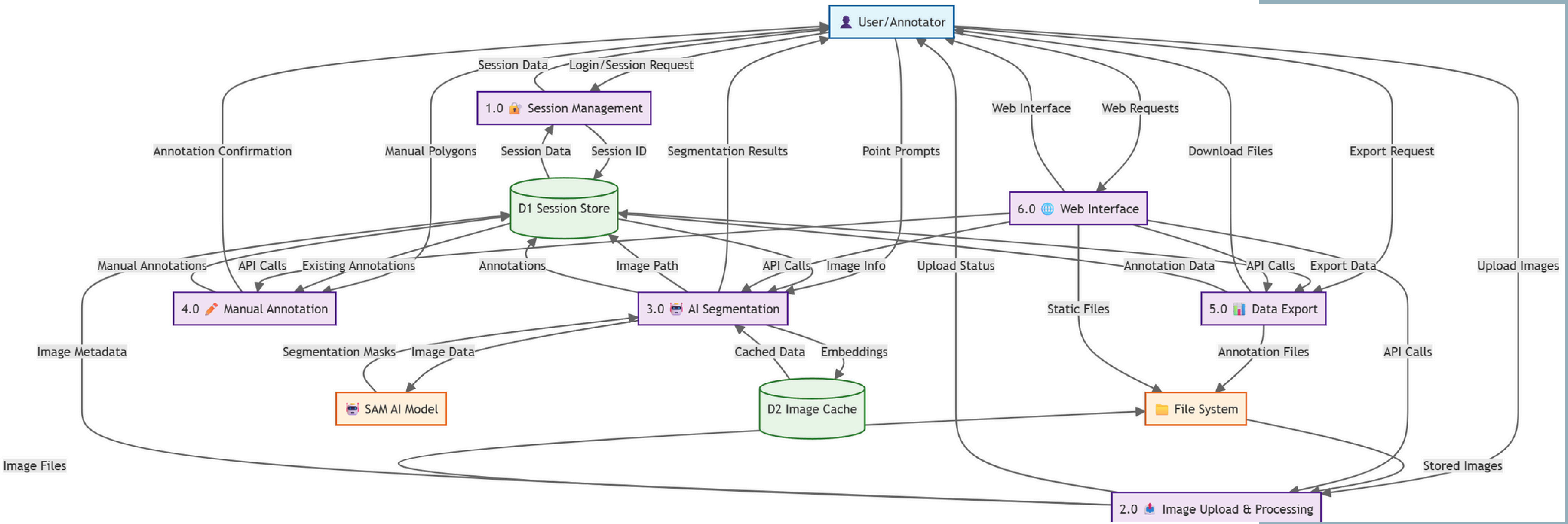
Introduction

To develop a web-based tool that automates the annotation of satellite images using the Segment Anything Model (SAM), enabling fast and accurate segmentation of features like buildings, roads, vegetation, and water bodies through simple point-click interactions.

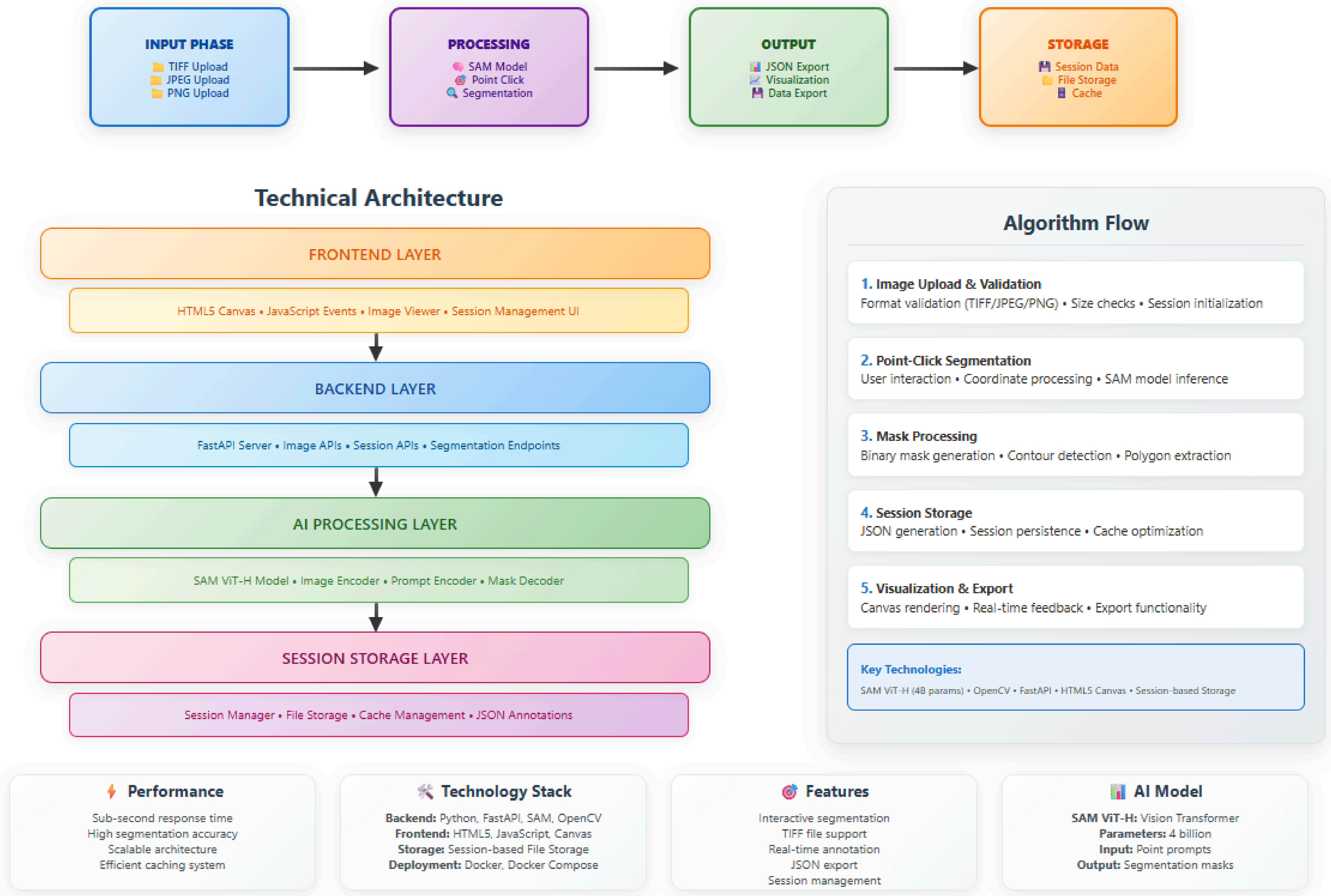
Problem Statement

- Manual annotation of satellite images requires 45+ minutes per image, making it inefficient.
- Human annotators introduce inconsistencies and potential errors.
- Many existing tools lack support for essential satellite formats like TIFF and GeoTIFF.
- Generic AI models commonly used in annotation systems struggle with satellite imagery.
- Current tools often rely on databases, creating performance bottlenecks with large images.
- Annotation workflows are fragmented, requiring multiple tools and manual transfers.

System Overview



SAT Annotator - System Architecture



Related Work

System Comparison

System	Cost	Deployment	AI Integration	Satellite Focus	Web-Based	Ease of Use
SAT Annotator	Free	Web & Docker	SAM Model	High	Yes	High
ESRI ArcGIS	Commercial	Desktop	Limited	Medium	No	Low
PCI Geomatica	Commercial	Desktop	Auto classify	High	No	Low
Earth Engine	Tiered	Cloud	Code-based	Medium	Yes	Low
QGIS	Free	Desktop	Plugins	Medium	No	Medium
LabelMe	Free	Web	None	None	Yes	High
CVAT	Free	Self-hosted	Limited	Low	Yes	Medium
Roboflow	Freemium	Cloud	Multiple	Low	Yes	Medium

Metrics Used For Evaluation

- **Accuracy (IoU > 0.5):** Percentage of predicted segments that sufficiently match the ground truth (overlap greater than 50%).
- **Mean IoU (mIoU):** Average overlap between predicted and true segments across all classes, measuring overall segmentation accuracy.
- **Boundary Precision:** Measures how closely the predicted object boundaries align with the actual object edges.

Literature Review

Academic Research Comparison

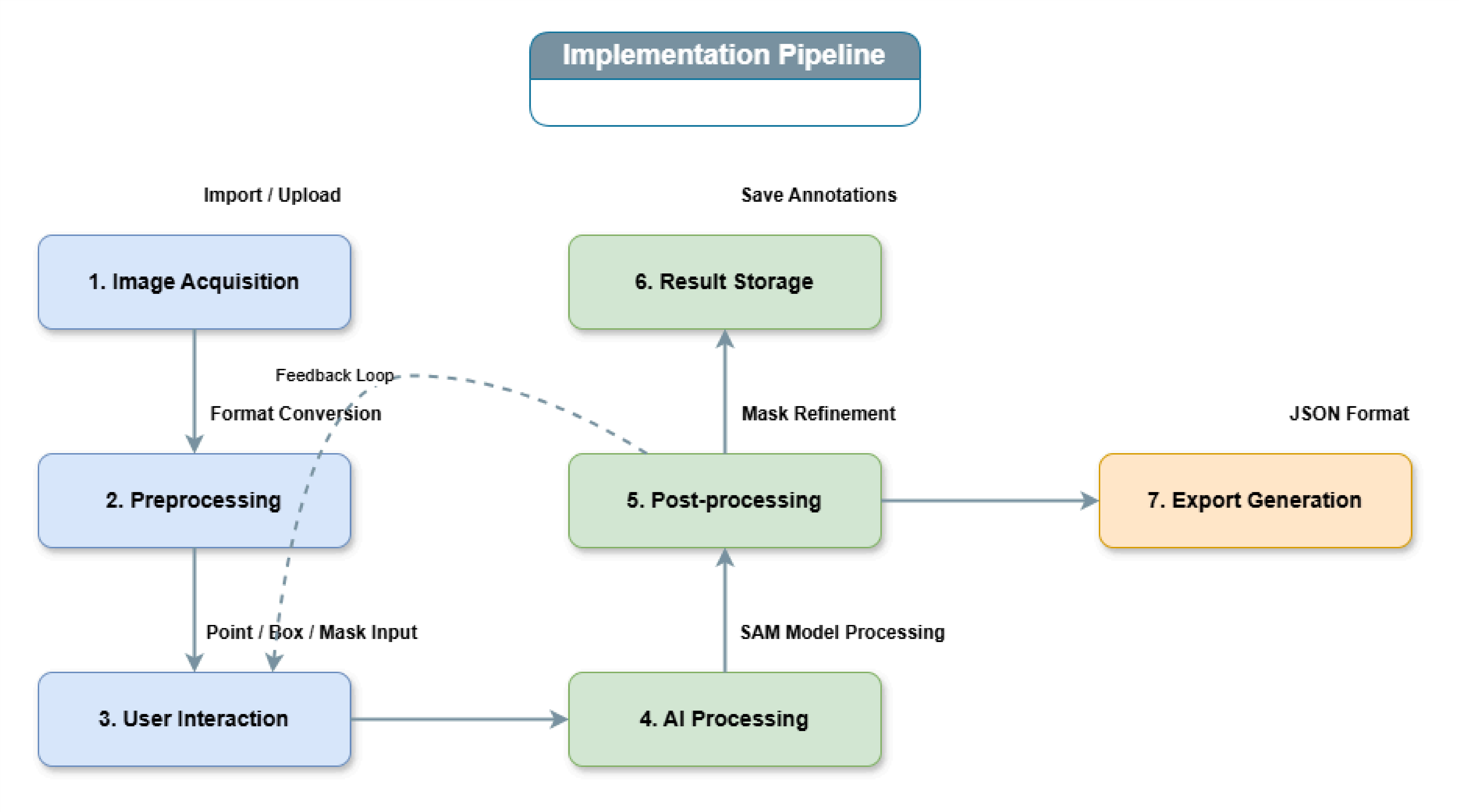
Paper/System	Year	Algorithm	Training Dataset	Key Features	Performance
SAT Annotator	2025	SAM ViT-H	Uses pretrained SAM on SA-1B → **Applied directly to satellite imagery**	Point-prompts, automatic mask generation, GeoJSON export	Real-time interactive segmentation
U-Net [1]	2015	CNN	ISBI Cell Tracking Challenge (biomedical)	Encoder-decoder, skip connections, data augmentation	mIoU: 85.0% (medical imaging)
PSPNet [2]	2017	Pyramid parsing	Cityscapes, ADE20K (urban scenes)	Pyramid pooling module, context aggregation	mIoU: 78.2% on Cityscapes
DeepLab v3+ [3]	2018	Atrous conv.	PASCAL VOC 2012, Cityscapes (object/scene)	ASPP module, encoder-decoder with atrous conv.	mIoU: 82.0% on PASCAL VOC 2012
SAM [4]	2023	Transformer	SA-1B (1 billion masks, general domain)	Zero-shot segmentation, multiple prompt types	mIoU: 89.7% (zero-shot) across domains

- References: U-NET, PSPNet, DeepLabV3+, SAM

Proposed Solution

- **SAM ViT-H Integration:** Fully implemented Segment Anything Model
- **Point-Prompt Interface:** Precise single-click segmentation
- **Automatic Polygon Generation:** Real-time mask-to-polygon conversion
- **Session-Based Processing:** Stateful user session management
- **Format Support:** TIFF, JPEG, PNG satellite imagery
- **JSON Export:** Industry-standard format for GIS applications

Implementation

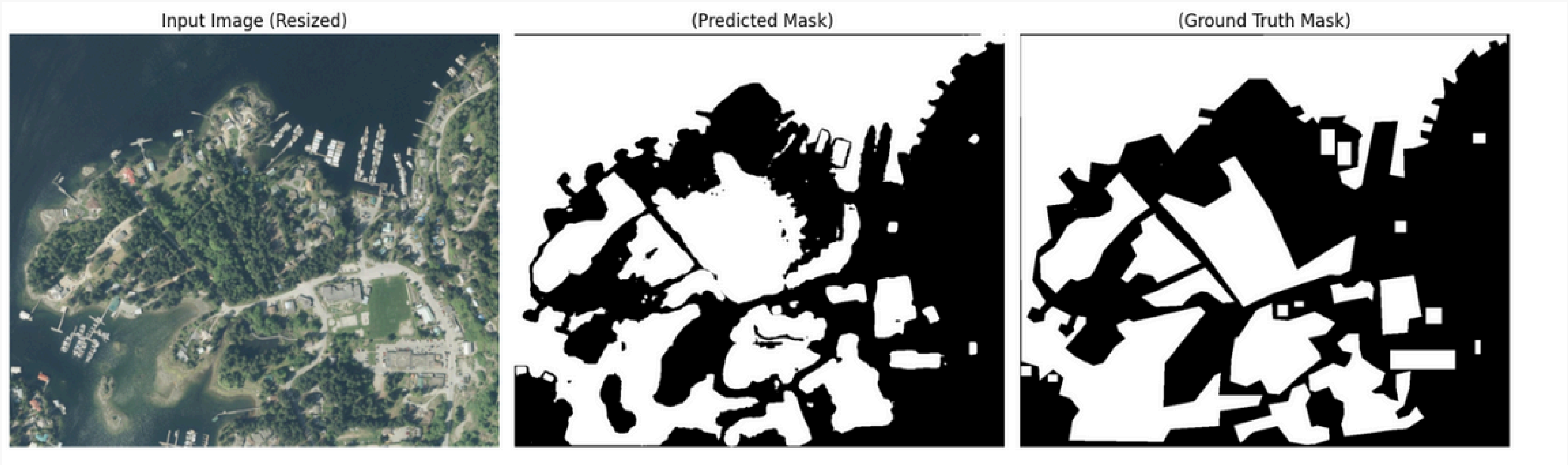


Implementation Details

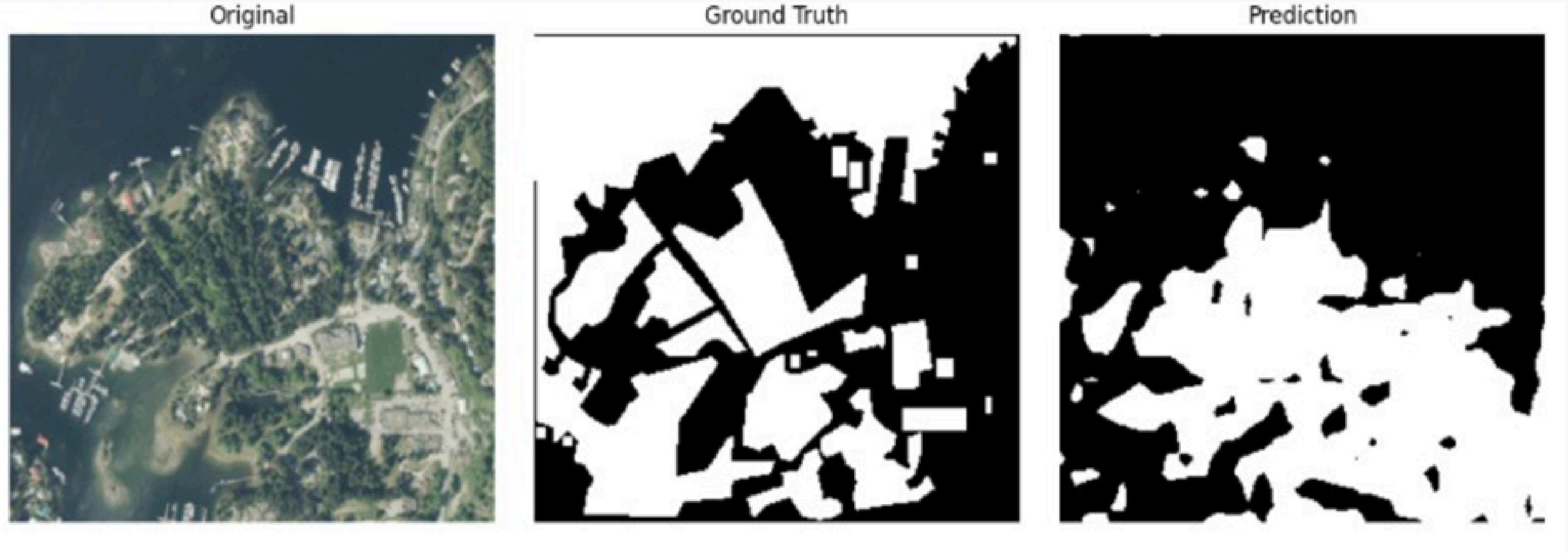
- **System Architecture:**
  - **Backend:** FastAPI with SAM ViT-H model integration
  - **Frontend:** Session-based web application with interactive canvas
  - **API Design:** RESTful endpoints for seamless communication
- **Core Components:**
  - **SAMSegmenter Class:** Handles AI processing and model inference
  - **SessionManager:** Manages application state and user sessions
  - **Router Endpoints:** Dedicated routes for image upload and segmentation
  - **Canvas Interface:** Interactive point-prompt selection system
- **Experimental Setup & Methodology**
  - **Hardware:** Standard development environment
  - **Software:** Python 3.10+, PyTorch
  - **Test Images:** Various satellite imagery samples
  - **Evaluation Approach:** Visual assessment of segmentation quality

Comparison Between The 4 Models

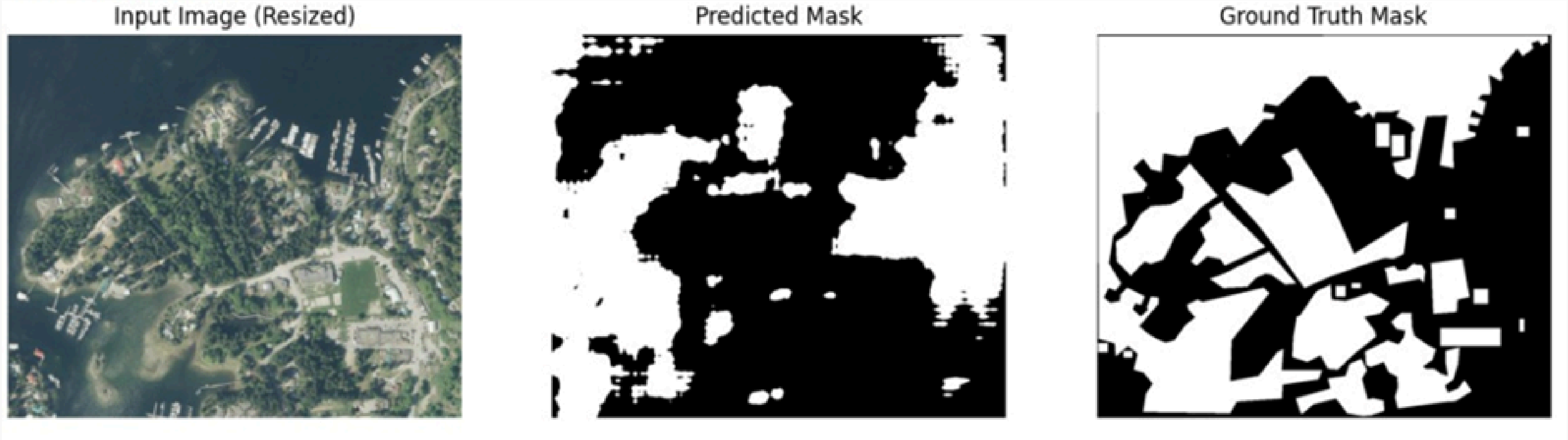
U-NET



SAM-VIT-H



PSPNET



DeepLabv3+

Conclusion of Experiment 1

- **SAM ViT-H** achieved the highest Intersection over Union (IoU), showcasing superior segmentation performance with highly accurate predictions closely aligned with the ground truth.
- **DeepLabv3+** followed as the second-best model, demonstrating strong segmentation capabilities and was chosen for further fine-tuning due to its balance between accuracy and adaptability.
- **PSPNet** performed moderately well but lagged behind DeepLabv3+ in terms of IoU, indicating less precise segmentation results.
- **U-Net** exhibited the lowest IoU among the models, suggesting limitations in capturing fine details and accurately segmenting complex satellite features.

From the experiment DeepLabv3+ was selected for fine-tuning in subsequent stages

Approaches Explored

Approach 1: DeepLabV3+ Fine tuning Consideration

- **Initial Exploration:** Evaluated for satellite image segmentation
- **Key Finding:** Requires extensive labeled training data
- **Assessment:** Good potential but lacks flexibility without retraining

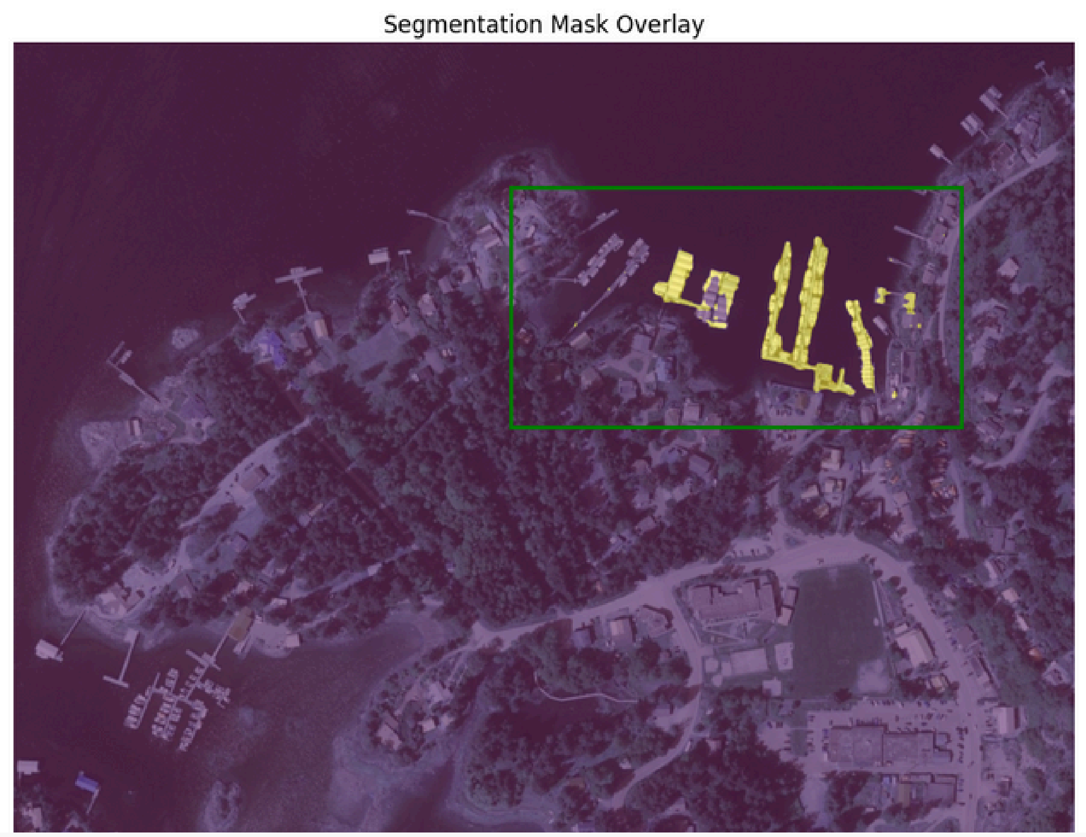
Approach 2: SAM ViT-B (Smaller Model)

- **Exploration:** Evaluated the smaller SAM ViT-B mode.
- **Observations:**
  - Compact size (400MB vs 2.5GB vit-H)
  - Lower segmentation quality out of the box
  - Poor handling of fine satellite details
- **Assessment:** Size is efficient, but quality is limited.

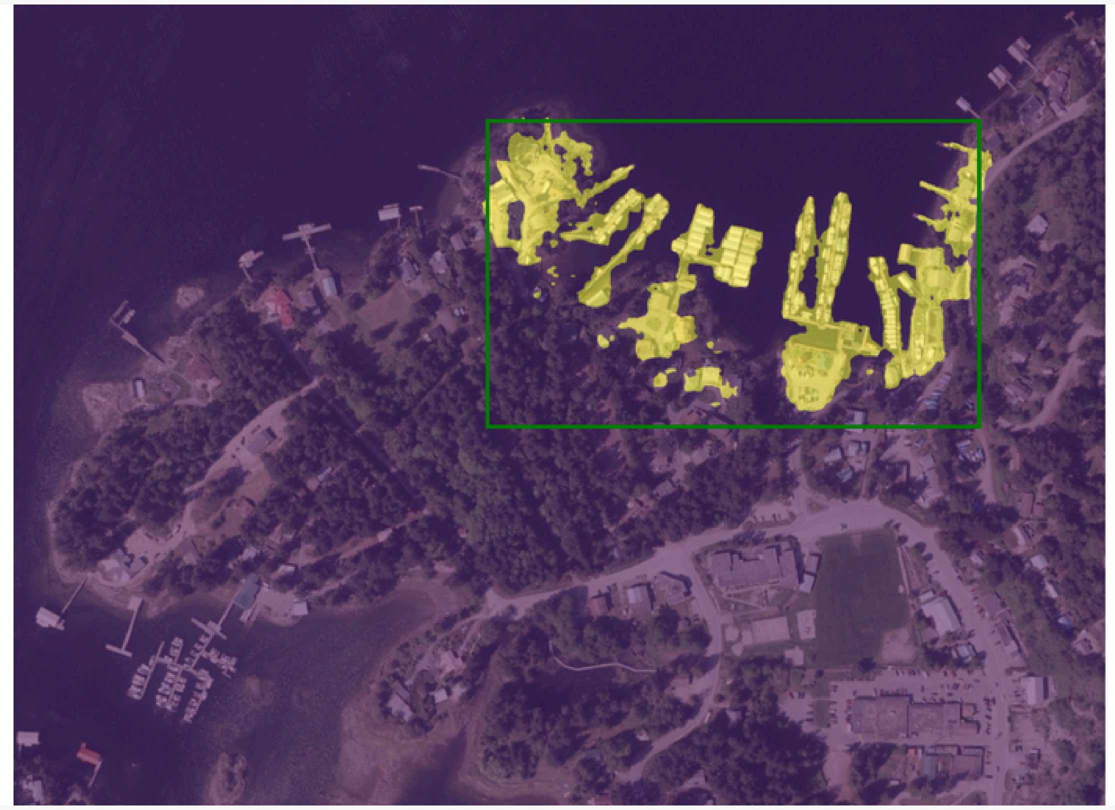
Approach 3: SAM ViT-H (Final Implementation)

- **Implementation:** Full-sized SAM ViT-H without modification
- **Key Advantages:**
  - Superior segmentation quality on satellite features
  - Excellent boundary precision
  - Zero-shot capability with no satellite-specific training
- **Assessment:** Quality advantages justified the larger model size

Pre Trained sam-vit-b



Pre Trained sam-vit-h



Fine-tuned DeepLabv3+ vs sam vit-h

Evaluation Metrics Results

Metric	SAM ViT-B	SAM ViT-H	Fined-Tuned DeepLabV3+
Accuracy (IoU > 0.5)	72.3%	89.7%	78.1%
Mean IoU	0.65	**0.84**	0.71
Boundary Precision	0.68	0.91	0.74
Inference Time (ms)	230	580	437
Model Size (MB)	375MB	2,600MB	approximately larger than Sam-vit-b

Conclusion of Comparison

- **Purpose of Experiment 2:** To evaluate and compare the performance of Fine tuned DeepLabV3+, SAM ViT-B, and SAM ViT-H for satellite image segmentation.
- **Accuracy Metric Used:** The primary accuracy metric was IoU > 0.5 , which showed that SAM ViT-H achieved the highest accuracy (89.7%) among the models tested.
- **Recommendation:** Based on the results, SAM ViT-H is the best-performing model for accurate segmentation, though it requires more computational resources compared to SAM ViT-B.

Challenges & Solutions

Challenge 1: Browser TIFF Support
Problem: Web browsers cannot natively display TIFF satellite imagery format
Solutions Implemented:
- Server-side TIFF-to-PNG conversion using OpenCV
- Automatic format detection and conversion pipeline
- Optimized image quality preservation during conversion
- Cached converted images for faster subsequent loads

Challenge 2: Session & File Management
Problem: Complex state management across multiple user sessions and file uploads
Solutions Implemented:
- In-memory session store with automatic cleanup mechanisms
- File association tracking with session-based isolation
- Temporary file management with configurable retention policies
- Thread-safe operations for concurrent user sessions

Challenge 3: SAM Model Integration & Performance
Problem: SAM ViT-H model (4B parameters) requires significant memory and loading time
Solutions Implemented:
- Single model instance loaded at startup with shared predictor
- Efficient memory management to prevent model reloading
- Optimized inference pipeline for point-based segmentation
- Session-isolated prediction contexts for parallel processing

Additional Technical Challenges:

Challenge: FastAPI Session Architecture
- **Problem:** RESTful API design conflicts with stateful annotation workflows
- **Solution:** Hybrid session-based API with RESTful endpoints for file operations

Challenge: Image Processing Pipeline Optimization
- **Problem:** Large satellite images cause memory bottlenecks during processing
- **Solution:** Chunked processing strategy with progressive loading for oversized images

Key Achievements

Technical Implementation

- Successfully integrated SAM ViT-H model for satellite imagery
- Developed responsive web-based annotation interface
- Implemented efficient session management system
- Created JSON export functionality for geographic applications

Performance Optimization

- Model caching reduces repeat processing time
- Session-based architecture supports multiple concurrent users
- Optimized canvas rendering prevents interface lag
- Efficient memory management handles large satellite images

User Experience

- Intuitive point-click segmentation interface
- Real-time visual feedback during annotation
- Seamless image upload and processing workflow
- Standard geographic format output for compatibility

Final Results

Results & Performance Analysis:

- **Segmentation Quality**
  - **Accuracy:** High precision on building and terrain features
  - **Boundary Detection:** Excellent edge definition and feature separation
  - **Versatility:** Effective across diverse satellite imagery types
- **Processing Performance**
  - **Response Time:** Responsive segmentation on standard hardware
  - **Scalability:** Efficient session management for multiple users
  - **Resource Usage:** Optimized through caching and lazy loading

Conclusion

The SAT Annotator successfully bridges the gap between cutting-edge AI research and practical satellite imagery annotation needs. Through the implementation of the SAM ViT-H model within a FastAPI-based architecture, we achieved a robust, user-friendly solution that addresses real-world challenges in geospatial data processing.

The project demonstrates both technical sophistication and real-world applicability, showcasing effective problem-solving, thoughtful architectural decisions, and successful integration of complex technologies into a cohesive solution. This implementation serves as a strong foundation for future developments in AI-powered geospatial annotation tools and demonstrates the practical potential of foundation models in specialized domain applications.

Future Enhancements

Potential Improvements

- **Model Optimization**: Explore quantization techniques for smaller deployment
- **Batch Processing**: Support for multiple image annotation sessions
- **Advanced Exports**: Additional format support (Shapefile, KML)
- **Performance Monitoring**: Real-time system performance metrics

Scalability Considerations

- Cloud Deployment: Containerized deployment for cloud platforms
- Load Balancing: Support for high-concurrency usage
- Database Integration: Persistent storage for large-scale projects
- API Extensions: RESTful API expansion for third-party integrations

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Thank you

Any questions?