Object Detection and Segmentation Integration for Real-Time Urban Scene Analysis

R25-002

Project Final Report

Kumara B D A N
IT21256264

BSc (Hons) Degree in Information Technology Specialized in Software Engineering

Department of Software Engineering

Sri Lanka Institute of Information Technology Sri Lanka
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Declaration

I declare that this is my own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person expect where the acknowledgment is made in the text.

Name	**Student ID**	**Signature**
Kumara B D A N	IT21256264	Avi

The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

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Signature of the Supervisor: Date:

Abstract

This study presents a novel computational pipeline for the comprehensive analysis of architectural structures from single 2D images, integrating object detection, material classification, and surface area estimation. The methodology employs a multi-stage approach, beginning with robust object localization using the YOLOv8 model, followed by precise pixel-level segmentation via the Mobile Segment Anything Model (MobileSAM). Material classification is achieved through a hybrid engine combining the Contrastive Language-Image Pre-Training (CLIP) model with heuristic analyses, enabling granular identification of material composition in heterogeneous structures. Surface area estimation leverages depth inference with a Vision Transformer-based model and Poisson Surface Reconstruction to generate metrically accurate 3D meshes from monocular images. The pipeline addresses challenges such as scale ambiguity and material heterogeneity, offering a scalable framework for urban scene analysis. Experimental results demonstrate high accuracy in object delineation, material identification, and surface area quantification, with potential applications in architectural analysis, urban planning, and digital heritage preservation.

Acknowledgement

I would like to express my heartfelt gratitude to everyone who supported and contributed to the successful completion of this research project.

First and foremost, I wish to extend my sincere appreciation to my supervisor, Mr. Vishan Jayasinghearachchi, my co-supervisor, Ms. Kaushalya Rajapakse, and my external supervisor, Dr. Rajitha De Silva, for their invaluable guidance, encouragement, and expertise throughout this journey. Their constructive feedback and unwavering support played a pivotal role in shaping both the direction and quality of this work.

I am also deeply thankful to the academic staff of the Department of Software Engineering, Sri Lanka Institute of Information Technology (SLIIT), for providing the resources, mentorship, and a stimulating academic environment that greatly contributed to this research.

My sincere gratitude goes to my project group members for their collaboration and dedication during the early stages of this research. I would also like to thank all participants who willingly contributed their time and insights during data collection and evaluation, which were essential to validating the research findings.

To my colleagues and friends, I am grateful for your encouragement, valuable discussions, and moral support, which enriched my research experience.

Finally, I owe my deepest gratitude to my family for their unwavering support, patience, and motivation throughout this journey. Their faith in me has been a constant source of strength and determination.

This work is a reflection of the collective efforts, guidance, and inspiration of all who contributed, and I remain truly thankful for their invaluable support.

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List of Abbreviations

Abbreviation	**Full Form**
YOLO	You Only Look Once
YOLOv8	You Only Look Once, Version 8
SAM	Segment Anything Model
MobileSAM	Mobile Segment Anything Model
CLIP	Contrastive Language–Image Pre-Training
ViT	Vision Transformer
mAP	Mean Average Precision
IoU	Intersection over Union
RGB	Red, Green, Blue (color model)
GPU	Graphics Processing Unit
CPU	Central Processing Unit
AI	Artificial Intelligence
3D	Three-Dimensional
2D	Two-Dimensional

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1 Introduction

1.1 Overview

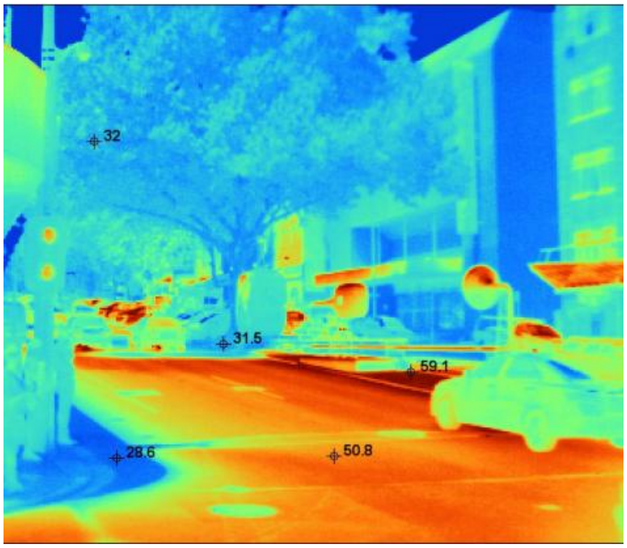

Figure 1-1 Illustration of UHI effect

The analysis of architectural structures from visual data is a critical task in fields such as urban planning, architectural design, and digital heritage preservation. Traditional methods for assessing building characteristics, such as material composition and surface area, often rely on manual measurements or expensive multi-view imaging systems, which are time-consuming and resource-intensive. Recent advancements in computer vision and deep learning have opened new avenues for automating these processes using single 2D images, offering a cost-effective and scalable alternative. However, challenges such as scale ambiguity in monocular vision, material heterogeneity, and the need for precise object delineation remain significant hurdles.

This research introduces a comprehensive computational pipeline that addresses these challenges by integrating object detection, semantic segmentation, material classification, and surface area estimation into a cohesive framework. The proposed methodology leverages state-of-the-art deep learning models, including YOLOv8 for object detection, the Mobile Segment Anything Model (MobileSAM) for pixellevel segmentation, and a hybrid CLIP-based approach for material classification. Additionally, a novel surface area estimation technique combines depth inference with 3D geometric reconstruction to produce metrically accurate measurements from a single photograph. This pipeline not only overcomes the limitations of traditional methods but also provides a robust and adaptable solution for analyzing complex urban scenes.

The significance of this work lies in its ability to extract detailed, quantitative insights from minimal input data, enabling applications in architectural analysis, urban planning, and heritage documentation. By addressing key challenges such as scale ambiguity and material heterogeneity, the proposed framework offers a scalable and efficient tool for researchers and practitioners.

1.2 Background Literature

The analysis of architectural structures from visual data has garnered significant attention in recent years, driven by advancements in computer vision and deep learning. This section reviews prior work relevant to the three core components of the proposed methodology: object detection and semantic segmentation, material classification, and surface area estimation from single 2D images.

Object detection and semantic segmentation are essential for identifying and delineating objects within images. Early methods relied on hand-crafted features but struggled with complex scenes. The advent of deep learning introduced convolutional neural networks (CNNs) that improved object localization through region proposal networks. Single-stage detectors like YOLO (You Only Look Once) have become popular for their efficiency and accuracy. The YOLOv8 model, in particular, offers enhanced performance on urban datasets, making it suitable for analyzing architectural scenes. For pixel-level segmentation, models like Mask R-CNN combine detection with instance segmentation but can be computationally intensive. The Segment Anything Model (SAM) introduced a prompt-based approach for flexible, high-fidelity mask generation, and its lightweight variant, MobileSAM, balances accuracy and efficiency, making it ideal for the proposed pipeline

Material classification in architectural images is crucial for understanding structural properties but is challenging due to material heterogeneity and contextual variability. Traditional methods used lowlevel image features, limiting their ability to handle diverse materials. Vision-language models have transformed this task by aligning images with text descriptions, enabling semantic material identification. However, these models can face ambiguities in complex scenes, necessitating additional heuristic analyses, such as color and texture metrics, to improve classification robustness. Recent studies have also explored hierarchical segmentation to address material heterogeneity, aligning with the proposed approach of sub-dividing object masks for detailed analysis

Estimating surface area from single 2D images is challenging due to the lack of depth information in monocular vision. Early methods relied on multi-view stereo or structure-from-motion, which require multiple images and are impractical for single-image scenarios. Depth estimation models based on Vision Transformers have enabled high-resolution depth map generation from single images, providing a foundation for 3D reconstruction. Advanced depth models further improve accuracy for architectural applications. To convert depth maps into measurable surfaces, algorithms like Poisson Surface Reconstruction produce watertight meshes from noisy point clouds. However, scale ambiguity remains a key issue, often requiring manual calibration or external priors. Recent approaches have used statistical techniques, such as percentile-based scaling, to address this, aligning with the proposed methodology’s approach to robust depth scaling.

1.3 Research Gap

Despite advancements in computer vision and deep learning, the comprehensive analysis of architectural structures from single 2D images remains underexplored. Existing object detection methods excel at identifying and localizing objects but often lack the precision required for detailed material analysis or surface area estimation in complex urban scenes.

Semantic segmentation approaches provide high-fidelity masks but are rarely integrated with material classification or 3D reconstruction in a unified framework. Material classification techniques face challenges with material heterogeneity in large structures, often requiring manual annotations or multi-view data to resolve ambiguities.

Additionally, surface area estimation from monocular images is hindered by scale ambiguity, with existing methods relying on multi-view data or external calibration tools, which are impractical for single-image scenarios. The integration of object detection, material classification, and surface area estimation into a cohesive pipeline for single-image architectural analysis remains a critical gap. Most studies focus on individual components, overlooking the synergies of combining them. Furthermore, few approaches address material heterogeneity and scale ambiguity in a scalable, automated manner, limiting their applicability to real world urban planning and heritage preservation tasks. This research addresses these gaps by proposing a novel pipeline that integrates state-of-the-art models with hierarchical segmentation and robust depth scaling techniques, enabling comprehensive and quantitative analysis from minimal input data.

1.4 Research Problem

The analysis of architectural structures from single 2D images poses significant challenges due to the inherent limitations of monocular vision and the complexity of urban environments. Accurately identifying and delineating objects, such as buildings, roads, and walls, requires robust localization and precise segmentation to capture fine-grained geometric details. However, existing object detection and segmentation methods often prioritize coarse localization over the pixel-level precision needed for subsequent material analysis or 3D reconstruction. Furthermore, material classification in architectural scenes is complicated by the heterogeneity of materials within large structures, where a single object, such as a building, may comprise diverse materials like brick, glass, and concrete. Current approaches struggle to achieve granular material identification without relying on extensive manual annotations or multi-view data, limiting their scalability and practicality.

Another critical challenge is the estimation of surface area from a single 2D image, which is hindered by scale ambiguity due to the absence of depth information. Traditional methods for surface area calculation depend on multi-view imaging or external calibration tools, which are resource-intensive and impractical for single-image scenarios. While recent advances in depth estimation have improved the ability to infer 3D geometry, accurately scaling these reconstructions to metric units remains a significant obstacle, particularly in noisy or complex urban scenes. The lack of an integrated framework that combines object detection, material classification, and surface area estimation exacerbates these issues, as existing solutions typically address these tasks in isolation, failing to leverage their interdependencies.

This research seeks to address the problem of comprehensively analyzing architectural structures from a single 2D image by developing a unified pipeline that overcomes the limitations of coarse object detection, material heterogeneity, and scale ambiguity. The proposed approach aims to deliver precise object delineation, granular material identification, and metrically accurate surface area estimation, enabling scalable and automated analysis for applications in urban planning, architectural design, and digital heritage preservation.

1.5 Research Objectives

1.5.1 Main Objective

The primary objective of this research is to develop a comprehensive computational pipeline for the automated analysis of architectural structures from a single 2D image, integrating robust object detection, precise material classification, and accurate surface area estimation to enable scalable and quantitative analysis for urban planning, architectural design, and digital heritage preservation

1.5.2 Specific Objectives

1. To implement a multi-stage object detection and segmentation framework that accurately identifies and delineates architectural objects, such as buildings, roads, and walls, using YOLOv8 for coarse localization and MobileSAM for pixel-level segmentation, ensuring high-fidelity object representations.

2. To design a hierarchical material classification approach that addresses material heterogeneity by sub-dividing object masks into materially homogeneous segments and classifying them using a hybrid engine combining CLIP-based semantic analysis with heuristic color, texture, and positional analyses.

3. To develop a robust surface area estimation method for single 2D images by leveraging depth inference with a Vision Transformer-based model and Poisson Surface Reconstruction, incorporating a statistically stable scaling technique to resolve scale ambiguity and produce metrically accurate 3D meshes.

4. To evaluate the performance of the integrated pipeline in terms of accuracy, robustness, and computational efficiency across diverse urban scenes, validating its applicability to real-world architectural analysis tasks.

2 Methodology

2.1 Requirement Gathering and Analysis

The development of a computational pipeline for analyzing architectural structures from single 2D images necessitates a systematic approach to requirement gathering and analysis to ensure the system meets the needs of its intended applications in urban planning, architectural design, and digital heritage preservation. This section outlines the process of identifying, analyzing, and prioritizing the functional and non-functional requirements for the proposed methodology.

2.1.1 Functional Requirements:

1. **Object Detection and Segmentation**: The system must detect and localize architectural objects in a single 2D image with high accuracy, producing class-labeled bounding boxes and pixel-level segmentation masks. The pipeline should handle complex urban scenes with multiple objects and varying lighting conditions.

2. **Material Classification:** The system must classify the materials of segmented objects, accounting for heterogeneity by sub-dividing objects into materially homogeneous segments. It should integrate semantic analysis with heuristic methods to ensure robust and context-aware material identification.

3. **Surface Area Estimation:** The system must estimate the surface area of architectural structures from a single image, resolving scale ambiguity through depth inference and geometric reconstruction to produce metrically accurate 3D meshes.

4. **Post-Processing and Integration:** The system must include post-processing steps to refine segmentation masks and ensure clean, contiguous object representations. It should integrate all components into a cohesive pipeline, delivering comprehensive outputs (e.g., object masks, material compositions, and surface area measurements)

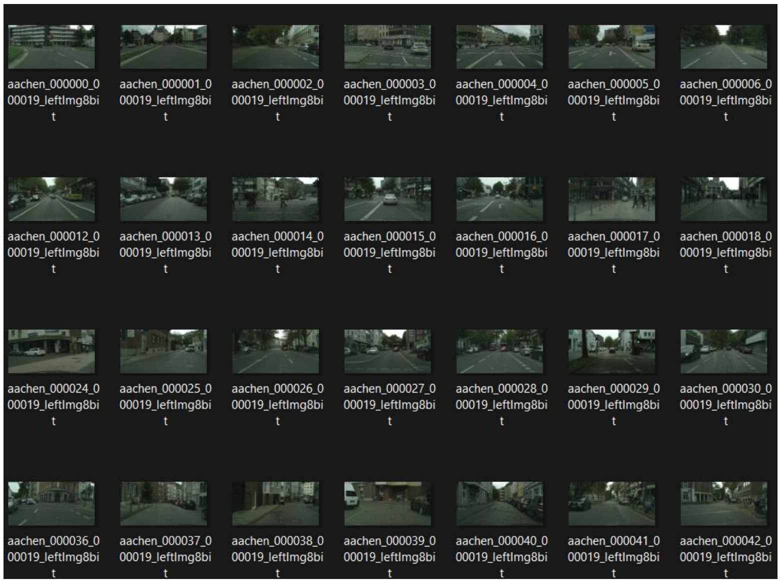
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Figure 2-1 Cityscape images

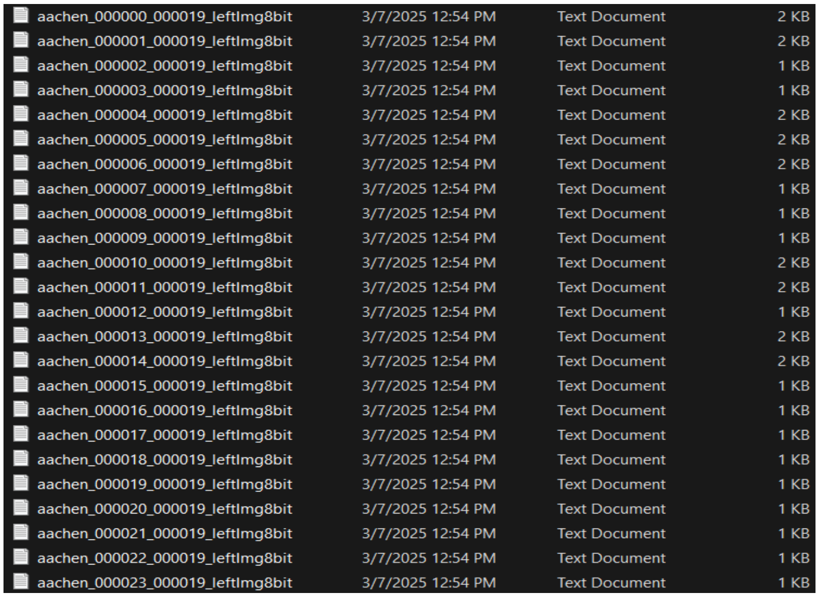

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Figure 2-2 Cityscape labels

2.1.2 Non-Functional Requirements:

1. **Accuracy:** The system must achieve high precision and recall in object detection, segmentation, and material classification, with surface area estimates within a 5% error margin of ground-truth measurements.

2. **Efficiency:** The pipeline should process a single 2D image in a reasonable timeframe (e.g., under 10 seconds on standard hardware) to support practical deployment in real-world applications.

3. **Scalability:** The system must handle diverse urban scenes, including varying object types, material compositions, and image resolutions, without requiring extensive retraining or manual calibration.

4. **Robustness:** The pipeline should perform reliably under noisy conditions, such as occlusions, shadows, or low-quality images, ensuring consistent outputs across diverse scenarios.

5. **Usability:** The system should require minimal user input, such as a single ground-truth distance for scaling, and provide intuitive outputs (e.g., visualized masks, material summaries, and surface area measurements) for end-users

2.2 Feasibility Study

The development of a computational pipeline for analyzing architectural structures from single 2D images requires a thorough assessment of its technical, operational, and economic feasibility. This section evaluates the viability of the proposed methodology, which integrates object detection with a fine-tuned YOLOv8 model, semantic segmentation using MobileSAM, material classification with CLIP, and surface area estimation using DepthPro, addressing potential challenges and constraints.

Technical Feasibility: The proposed pipeline leverages established deep learning models, including a YOLOv8 model fine-tuned on the Cityscapes dataset for object detection, MobileSAM for semantic segmentation, CLIP (ViT-B/32) for material classification, and DepthPro for depth inference. The fine-tuning of YOLOv8 on Cityscapes enhances its ability to accurately detect urban objects such as buildings, roads, and walls, optimizing performance for the specific context of architectural analysis. MobileSAM, CLIP, and DepthPro are pretrained and publicly available, with proven effectiveness in their respective domains. These models can be implemented using standard deep learning frameworks like PyTorch or TensorFlow, which support modular architectures and pipelined processing, ensuring technical compatibility. The pipeline's reliance on single 2D images aligns with available technology, as modern cameras and smartphones provide high-resolution images suitable for analysis. The use of Poisson Surface Reconstruction for 3D mesh generation is well-suited to handle noisy point clouds, and the proposed statistical scaling technique, utilizing the 1st percentile of depth values, is computationally efficient. Hardware requirements include a GPU-enabled system for model inference, which is widely accessible in research and industry settings. Challenges such as handling low-quality images, occlusions, or complex urban scenes may require additional preprocessing or further fine-tuning of models, which is feasible using techniques like data augmentation or transfer learning. The fine-tuning of YOLOv8 on Cityscapes mitigates some of these challenges by improving robustness to urban scene variability

Economic Feasibility: The economic feasibility of the pipeline is supported by its use of open-source models and frameworks, minimizing development costs. While YOLOv8 was fine-tuned on Cityscapes, the fine-tuning process leverages publicly available datasets and standard computational resources, keeping costs manageable. Pre-trained models like MobileSAM, CLIP, and DepthPro are freely available, and their implementation requires only a mid-range GPU, which is cost-effective for research institutions or small-scale firms. The reliance on single 2D images eliminates the need for expensive multi-view imaging systems, further enhancing economic viability. Economic benefits include reduced labor costs for manual architectural analysis, faster processing for large-scale urban surveys, and improved accuracy in material and surface area assessments, which can inform cost estimates for construction or preservation projects. The fine-tuned YOLOv8 model reduces the need for extensive retraining in similar urban contexts, further lowering costs. Maintenance costs, such as updates to accommodate new architectural styles or materials, can be managed through periodic 1 fine-tuning, a standard and cost-effective practice in deep learning. Initial development and testing may incur costs for computational resources, but the pipeline's scalability ensures long-term savings for large-scale applications

Operational Feasibility:. The pipeline aligns with the operational needs of urban planners, architects, and heritage preservationists, who require automated tools for analyzing architectural structures. By requiring only a single 2D image and a ground-truth distance for scaling, the system is accessible to non-expert users. The modular structure allows for iterative processing, with outputs like object masks, material compositions, and surface area measurements visualized and validated at each stage, enhancing usability. The fine-tuned YOLOv8 model improves detection accuracy in urban environments, making the pipeline particularly suited for real-world applications. Operationally, the pipeline can be deployed as a standalone application or integrated into existing urban planning and architectural design software. The lightweight MobileSAM model ensures compatibility with resource-constrained environments, such as mobile devices or cloud platforms. Potential challenges include handling edge cases like poor lighting or occlusions, which can be addressed through robust error handling, heuristic corrections, or user-guided refinements. The fine-tuning of YOLOv8 on Cityscapes enhances operational reliability by tailoring the model to urban contexts, reducing the likelihood of detection errors in complex scenes

2.3 System Diagrams

2.3.1 Overall System Diagram

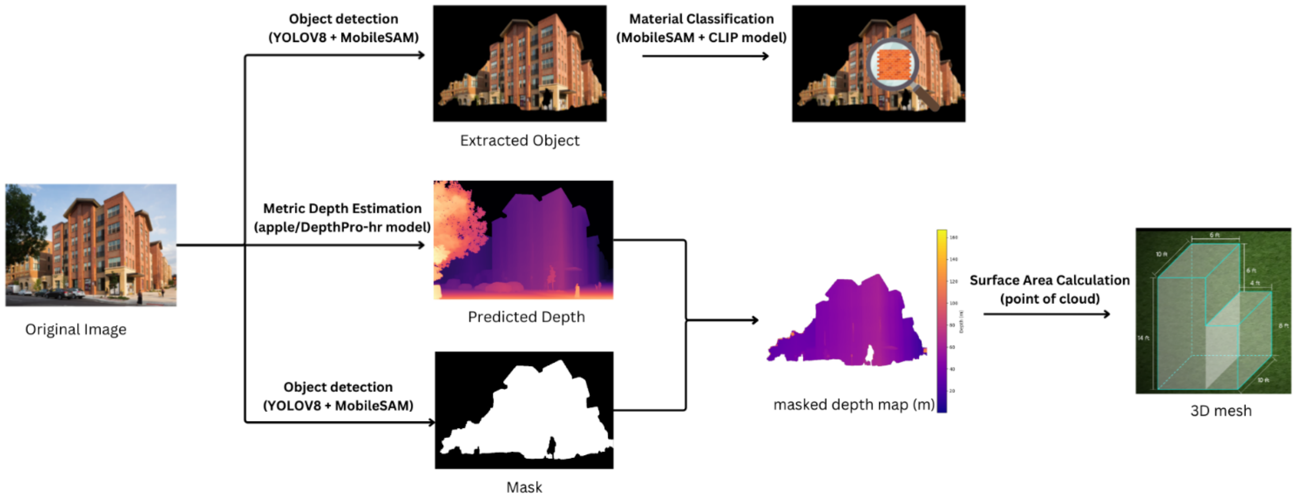


Figure 2-3 system diagram

2.3.2 Flow Diagram

2.4 Methodology

This proposes a computational pipeline for the comprehensive analysis of architectural structures from a single 2D image, integrating object detection, semantic segmentation, material classification, and surface area estimation. The methodology is structured into three main components: object detection and semantic segmentation, material classification, and surface area calculation. Each component leverages advanced deep learning models and tailored processing techniques to address the challenges of monocular vision, material heterogeneity, and scale ambiguity

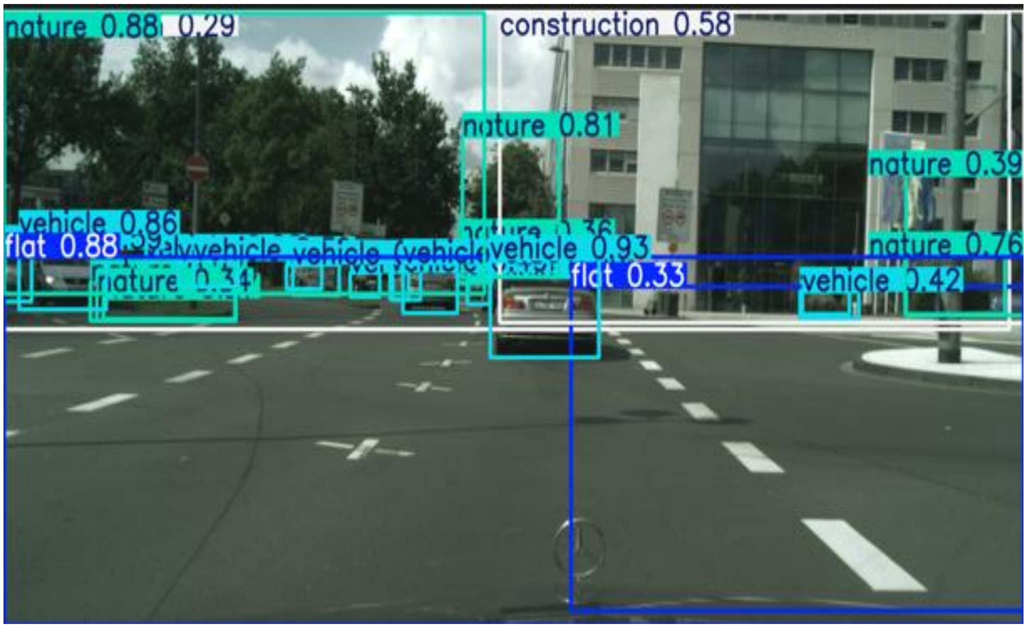


Figure 2-4 Object detection

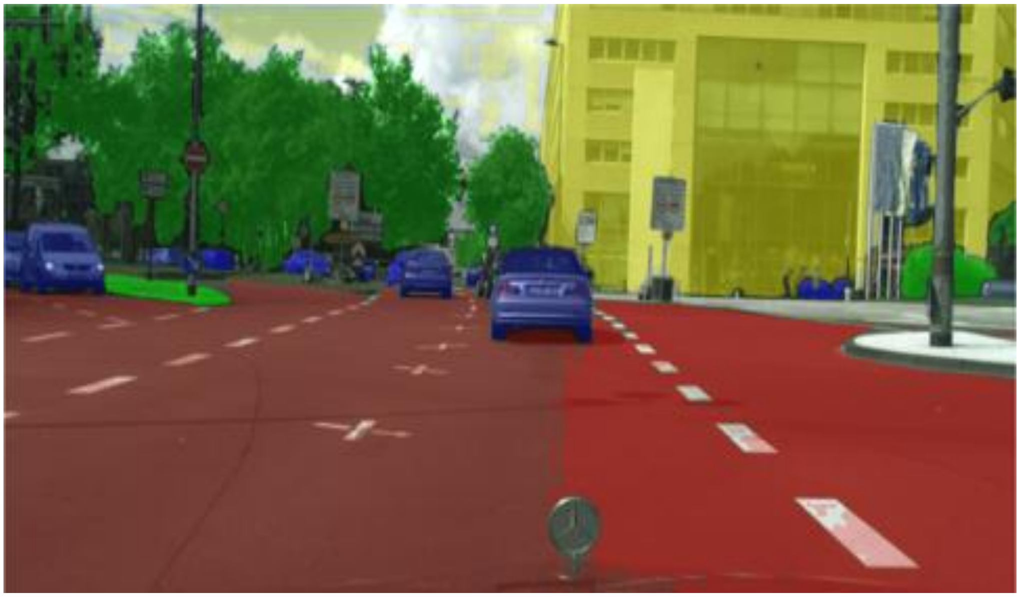


Figure 2-5 Segmentation

Object Detection and Semantic Segmentation

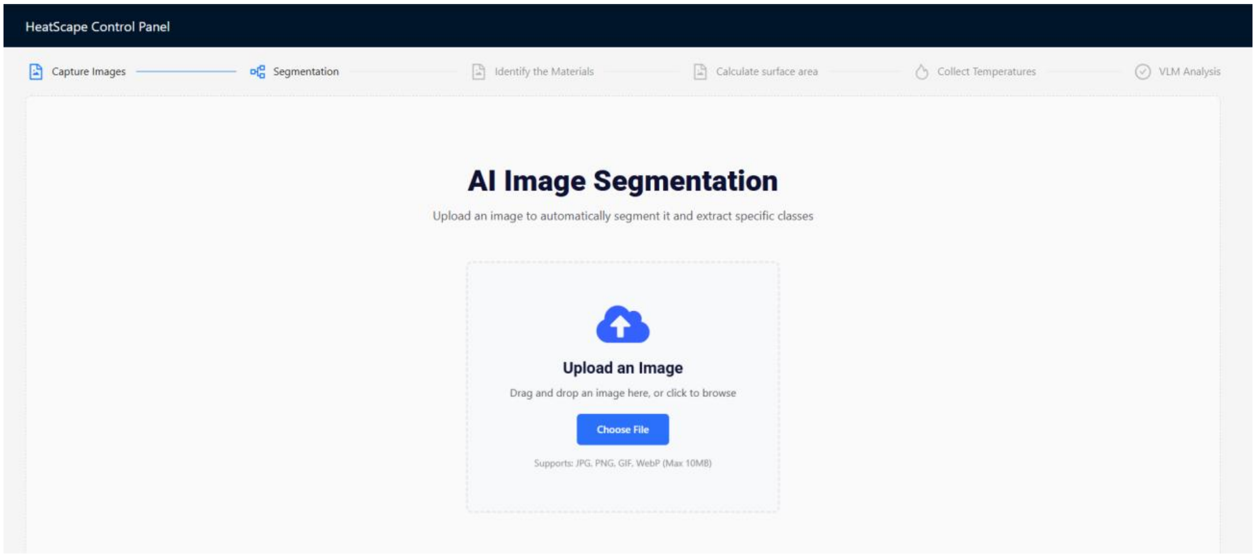
The initial phase focuses on robustly identifying and precisely delineating objects of interest, such as buildings, roads, and walls, within a single 2D image. A multi-stage computational pipeline is employed to achieve coarse-to-fine object localization. The process begins with object detection using a YOLOv8 model, fine-tuned on the Cityscapes dataset to enhance performance in urban environments. YOLOv8 processes the input image in a single forward pass, generating class-labeled bounding boxes for relevant urban entities. While effective for localization, these bounding boxes lack the geometric precision required for detailed analysis. To address this, the bounding box coordinates are used as prompts for the subsequent segmentation phase, where the Mobile Segment Anything Model (MobileSAM) generates high-fidelity, pixel-level masks for each detected instance. MobileSAM leverages these coordinates to accurately isolate objects from their background and adjacent instances. A post-processing step applies morphological operations to remove noise and fill small holes, ensuring clean, contiguous object representations critical for subsequent analysis.

Material Classification

Following object segmentation, the methodology addresses the classification of constituent materials, tackling the challenge of material heterogeneity in large structures like buildings. A hierarchical analysis approach is adopted, where each object mask is sub-divided into smaller, materially homogeneous segments. This is achieved by generating a grid of point prompts within the primary mask and re-applying the MobileSAM predictor to decompose the object into its constituent parts, enabling granular material assessment. Material classification is performed using a hybrid engine combining the Contrastive Language-Image Pre-Training (CLIP) model (ViT-B/32) with image processing heuristics. CLIP evaluates each image patch against a curated list of context-aware text prompts describing materials (e.g., ”close-up of red brick texture with visible mortar lines,” “reflective glass facade showing sky reflection”). Its ability to measure similarity between visual and textual concepts provides robust primary classification. To enhance accuracy and resolve ambiguities, three heuristic analyses are integrated: (1) color analysis, examining the mean RGB value of the patch to favor materials consistent with the detected color profile; (2) texture analysis, using the variance of the Laplacian to quantify surface complexity and distinguish between smooth materials like glass and textured ones like brick; and (3) positional prior, considering the segment’s vertical location within the image to leverage architectural conventions. The final material label for each patch is determined through a weighted fusion of CLIP scores and these heuristics, ensuring resilient and context-aware classification. Results from all sub-segments are aggregated to provide a comprehensive quantitative summary of the material composition for the selected objects.

Surface Area Calculation

Estimating the surface area of architectural structures from a single 2D photograph is challenging due to scale ambiguity in monocular vision. A hybrid computational pipeline is employed, combining deep learning with 3D geometric reconstruction to transform a qualitative RGB image into a quantitative, metrically accurate 3D model. The process begins with depth inference using the DepthPro model, a Vision Transformer-based architecture that generates a high-resolution depth map, where each pixel’s value corresponds to its estimated distance from the camera. A user-provided binary segmentation mask isolates the building’s geometry from the surrounding environment, ensuring focused analysis. To address the challenge of calibrating the metrically arbitrary point cloud, a statistically robust scaling technique is used. Instead of relying on the unstable absolute minimum depth value, the 1st percentile of all positive depth values within the masked region is computed to provide a stable representative value for the building’s closest surface. This value is calibrated against a user-provided ground-truth distance (in meters) to the closest point on the building, yielding a scaling factor that anchors the point cloud in metric space. The scaled point cloud is then converted into a continuous surface using the Poisson Surface Reconstruction algorithm, selected for its robustness to noise and ability to generate high-quality, watertight 3D meshes. Estimated normals guide the reconstruction, and low-density vertices are removed to eliminate artifacts. The total visible surface area is calculated by summing the areas of all constituent triangular facets in the final mesh, providing a precise quantitative output.



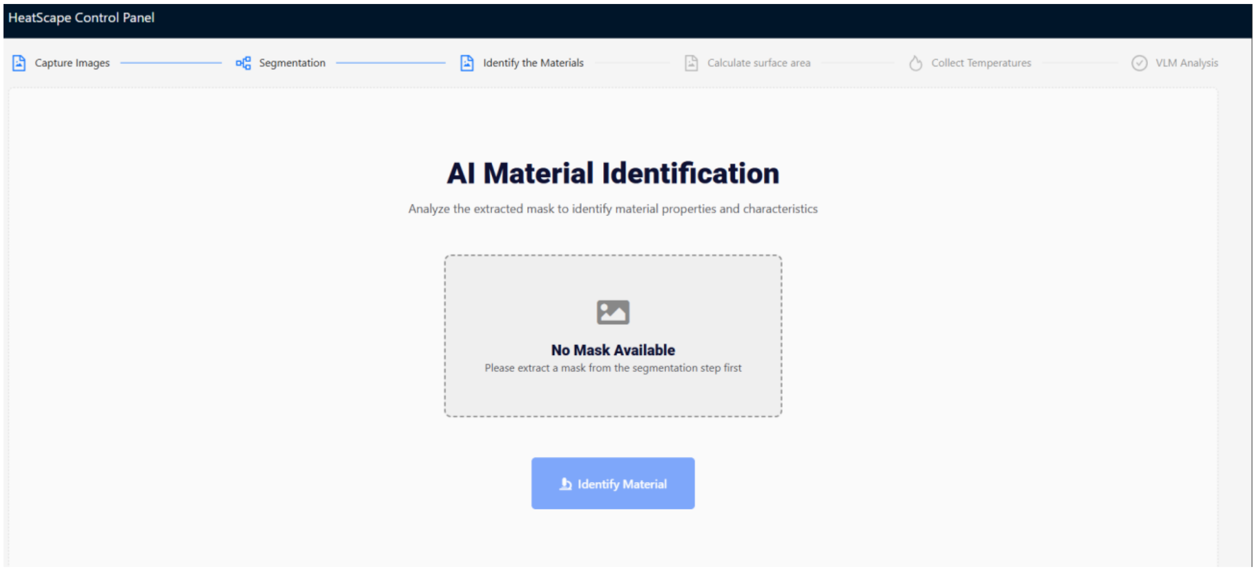
AI Image Segmentation

Upload an image to automatically segment it and extract specific classes

Drag and drop an image here, or click to browse

Supports: JPG, PNG, GIF, WebP (Max 10MB)

Figure 2-6 segmentation UI



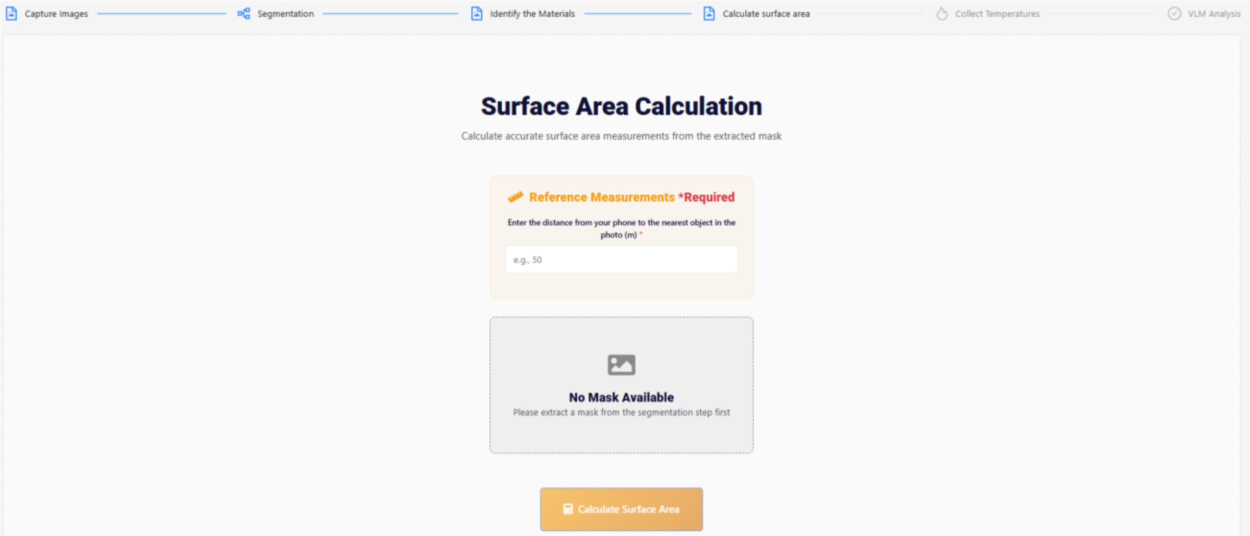
AI Material Identification

Analyze the extracted mask to identify material properties and characteristics

No Mask Available

Please extract a mask from the segmentation step first

Figure 2-7 Material classification UI



Surface Area Calculation

Calculate accurate surface area measurements from the extracted mask

Reference Measurements *Required

Enter the distance from your phone to the nearest object in the photo (m) *

e.g., 50

No Mask Available

Please extract a mask from the segmentation step first

Figure 2-8 Surface area calculation UI

2.5 Tools and Technologies

The development and implementation of the proposed computational pipeline for analyzing architectural structures from single 2D images rely on a suite of advanced tools and technologies. These include deep learning models, image processing libraries, and computational frameworks tailored to support object detection, semantic segmentation, material classification, and surface area estimation. This section details the specific tools and technologies employed, emphasizing their roles and integration within the pipeline.

Deep Learning Models

- **YOLOv8:** The You Only Look Once (YOLOv8) model, fine-tuned on the Cityscapes dataset, is used for object detection. YOLOv8 is a state-of-the-art single-stage detector known for its efficiency and accuracy in identifying urban entities such as buildings, roads, and walls. Fine-tuning on Cityscapes enhances its performance in complex urban scenes, providing robust class-labeled bounding boxes as input for subsequent segmentation.

- **Mobile Segment Anything Model (MobileSAM):** MobileSAM, a lightweight variant of the Segment Anything Model, is employed for pixel-level semantic segmentation. It generates highfidelity masks for detected objects using bounding box prompts from YOLOv8 and point prompts for hierarchical material segmentation, balancing accuracy and computational efficiency.

- **CLIP (ViT-B/32):** The Contrastive Language-Image Pre-Training (CLIP) model, based on the Vision Transformer (ViT-B/32) architecture, is utilized for material classification.

CLIP's ability to align visual and textual representations enables semantic material identification by comparing image patches to context-aware text prompts describing materials like brick or glass.

- **DepthPro:** The DepthPro model, a Vision Transformer-based architecture, is used for depth inference to generate high-resolution depth maps from single 2D images. Its accuracy in estimating pixel-level distances supports the creation of 3D point clouds for surface area estimation

Image Processing and Geometric Reconstruction

- **OpenCV:** The OpenCV library is employed for post-processing tasks, including morphological operations to refine segmentation masks by removing noise and filling small holes. It also supports heuristic analyses, such as color (mean RGB) and texture (variance of Laplacian) computations, for material classification.

- **Poisson Surface Reconstruction:** This algorithm, implemented via libraries like Open3D or MeshLab, converts scaled point clouds into continuous, watertight 3D meshes for surface area calculation. Its robustness to noise and ability to leverage estimated normals ensure high-quality surface reconstruction.

Computational Frameworks and Libraries

- **PyTorch:** PyTorch serves as the primary deep learning framework for implementing and integrating YOLOv8, MobileSAM, CLIP, and DepthPro. Its flexibility and support for GPU acceleration enable efficient model inference and pipeline integration.

- **TensorFlow:** TensorFlow is used as an alternative framework where specific model implementations (e.g., DepthPro) may require it, ensuring compatibility and scalability across different hardware configurations.

- **NumPy and SciPy:** These libraries support numerical computations, including statistical scaling (e.g., computing the 1st percentile of depth values) and matrix operations for point cloud processing and mesh generation.

- **Open3D:** Open3D is utilized for 3D point cloud processing and visualization, supporting the conversion of depth maps to point clouds and the application of Poisson Surface Reconstruction.

Hardware Requirements

- **GPU-Enabled Systems:** A GPU-enabled system (e.g., NVIDIA RTX series) is required for efficient inference of deep learning models, particularly for YOLOv8, MobileSAM, CLIP, and DepthPro. Cloud-based GPU services (e.g., AWS, Google Cloud) can be used for scalability.

- **Standard Computing Environment:** A system with at least 16 GB RAM and a multi-core CPU is sufficient for preprocessing, post-processing, and numerical computations, ensuring accessibility for research and industry settings.

2.6 Commercialization Aspects of the product

The proposed computational pipeline for analyzing architectural structures from single 2D images offers significant potential for commercialization across industries such as urban planning, architectural design, construction, and digital heritage preservation. This section explores the commercialization aspects of the product, including its target market, value proposition, monetization strategies, competitive landscape, and challenges to market adoption

2.6.1 Target Market

The pipeline targets a diverse range of stakeholders who require efficient, automated tools for architectural analysis:

- **Urban Planners:** Municipalities and urban planning agencies can use the pipeline to conduct large-scale surveys of city infrastructure, assessing building materials and surface areas for urban development, zoning, and sustainability planning.

- **Architectural and Engineering Firms:** Architects and engineers can leverage the pipeline for rapid material analysis and surface area estimation, streamlining design processes, cost estimation, and retrofitting projects.

- **Construction Companies:** Contractors can utilize the tool to estimate material quantities and surface areas for cost forecasting, resource allocation, and project bidding.

- **Heritage Preservation Organizations:** Cultural heritage institutions can apply the pipeline to document and analyze historical structures, supporting restoration efforts and digital archiving without invasive measurements.

- **Real Estate and Property Management:** Real estate firms can use the pipeline for property assessments, enabling quick evaluations of building conditions and material compositions for valuation or renovation purposes

2.6.2 Value Proposition

The pipeline offers a compelling value proposition by addressing key pain points in architectural analysis:

- **Efficiency:** By automating object detection, material classification, and surface area estimation from a single 2D image, the pipeline significantly reduces the time and labor required compared to traditional manual or multi-view methods.

- **Cost-Effectiveness:** The use of open-source models (e.g. MobileSAM, CLIP, DepthPro) and standard hardware eliminates the need for expensive imaging systems, making the solution accessible to small and medium-sized enterprises.

- **Accuracy and Granularity:** The integration of fine-tuned YOLOv8, hierarchical segmentation, and robust depth scaling ensures precise object delineation, detailed material identification, and metrically accurate surface area measurements.

- **Scalability:** The pipeline's ability to process diverse urban scenes with minimal input supports large-scale applications, such as city-wide infrastructure assessments or regional heritage documentation.

- **User-Friendliness:** Requiring only a single image and a ground-truth distance, the pipeline is accessible to non-expert users, with outputs (e.g., visualized masks, material summaries) designed for practical use in planning and design workflows

2.6.3 Monetization Strategies

To ensure the proposed computational pipeline is commercially viable and sustainable, several monetization strategies can be adopted:

- **Subscription-Based SaaS Model:** Deploy the pipeline as a Software-as-a-Service (SaaS) platform where users can upload images and receive automated analysis reports. A tiered subscription model can cater to different customer segments, such as individual architects, small firms, and large enterprises.

- **Pay-Per-Use Model:** Offer a cost-effective pay-per-analysis model for occasional users or organizations conducting one-time surveys, enabling broader adoption without long-term commitments.

- **Enterprise Licensing:** Provide enterprise-level licensing for architectural, construction, and urban planning firms seeking to integrate the system into their internal workflows. This model allows for offline deployment and customization.

- **API Integration Services:** Expose core functionalities (e.g., object detection, material classification, surface area estimation) through APIs for integration with third-party applications, such as Building Information Modeling (BIM) tools or city management systems.

- **Consulting and Customization:** Offer tailored services such as custom model training for region-specific architectural styles, advanced analytics dashboards, or integration with proprietary client databases.

- **Freemium Model for Wider Reach:** Provide basic functionalities (e.g., limited-resolution analysis) for free to encourage adoption, with premium features such as high-resolution outputs, detailed reports, and batch processing available under paid plans.

- **Cloud Deployment Partnerships:** Collaborate with cloud service providers (AWS, Google Cloud, Azure) to host the pipeline, allowing scalability while offering bundled pricing and storage options to enterprise clients.

These strategies ensure the system remains accessible to small-scale users while generating revenue through premium features, enterprise solutions, and integrations with industry-standard software, thus creating a scalable and sustainable business model.

2.6.4 Challenges to Market Adoption

Several challenges may impact the commercialization of the pipeline:

- **Accuracy in Edge Cases:** The pipeline's performance in low-quality images, heavily occluded scenes, or novel architectural styles may require additional fine-tuning or preprocessing, potentially affecting user trust. Mitigation includes rigorous testing and user-guided correction mechanisms.

- **User Adoption:** Stakeholders accustomed to traditional methods (e.g., manual measurements, multi-view systems) may resist adopting an AI-based solution. This can be addressed through user training, demonstrations of cost and time savings, and integration with existing workflows.

- **Data Privacy and Security:** For cloud-based deployments, ensuring the security of sensitive architectural images (e.g., proprietary designs, heritage sites) is critical. Robust encryption and compliance with data protection regulations (e.g., GDPR) will be necessary.

- **Scalability Costs:** While the pipeline is cost-effective for small-scale use, large-scale deployments (e.g., city-wide surveys) may incur higher computational costs. Offering flexible pricing models and cloud-based optimization can mitigate this.

- **Regulatory Compliance:** In some regions, architectural analysis tools may need to comply with industry standards (e.g., building codes, heritage preservation guidelines). Certification and validation processes will be required to ensure market acceptance.

2.6.5 Market Entry Strategy

To successfully commercialize the pipeline, the following strategies are proposed:

- **Pilot Projects:** Partner with urban planning agencies or heritage organizations to conduct pilot projects, demonstrating the pipeline's effectiveness in real-world scenarios and building case studies to attract broader adoption.
- **Open-Source Components:** Leverage the open-source nature of the models (e.g., YOLOv8, MobileSAM) to offer a freemium model, providing basic functionality for free to attract users and upselling premium features like advanced analytics or cloud integration.

- **Industry Partnerships:** Collaborate with AEC software providers (e.g., Autodesk, Bentley Systems) to integrate the pipeline into their platforms, expanding market reach and credibility.

- **Targeted Marketing:** Focus marketing efforts on high-impact sectors (e.g., smart cities, sustainable architecture) through industry conferences, webinars, and publications to highlight the pipeline's value in addressing modern urban challenges.

2.7 Consideration of the Aspect of the system

The proposed computational pipeline for analyzing architectural structures from single 2D images integrates fine-tuned YOLOv8 for object detection, MobileSAM for semantic segmentation, CLIP for material classification, and DepthPro for surface area estimation. This section evaluates the system under four critical aspects social, ethical and performance to assess its suitability for applications in urban planning, architectural design, and digital heritage preservation.

2.7.1 Social Aspects

The pipeline's social implications center on its impact on stakeholders and broader societal benefits:

- **Accessibility and Democratization:** By requiring only a single 2D image and minimal user input (e.g., a ground-truth distance), the pipeline enables small firms, independent architects, and heritage organizations in resource-limited regions to access advanced analysis tools, reducing reliance on costly multi-view imaging systems.

- **Labor Market Impact**: The automation of tasks like material classification and surface area estimation may reduce demand for manual surveying roles. However, it also creates opportunities for upskilling in AI-driven analysis, fostering new roles in data interpretation and system integration.

- **Community Benefits:** The pipeline supports urban planning initiatives, such as sustainable city development and heritage preservation, by providing accurate data for decision-making. For example, material analysis can inform eco-friendly retrofitting, while surface area estimates aid in equitable resource allocation for public infrastructure projects.

- **Inclusivity:** The system's reliance on the Cityscapes dataset, fine-tuned for urban scenes, ensures robust performance in Western city contexts but may underperform in non-urban or non-Western environments. Expanding dataset diversity is crucial to ensure equitable benefits across global communities

2.7.2 Ethical Aspects

Ethical considerations are paramount to ensure responsible deployment of the pipeline:

- **Data Privacy:** Processing images of private properties or culturally sensitive heritage sites raises privacy concerns. The system must incorporate robust data handling protocols, such as anonymization of input images and compliance with regulations like GDPR, to protect stakeholder data.

- **Model Bias:** Pre-trained models like CLIP and the fine-tuned YOLOv8 may exhibit biases if trained on datasets lacking diversity in architectural styles or materials (e.g., underrepresenting non-Western structures). Transparent documentation and ongoing dataset curation are necessary to mitigate misclassification risks.

- **Transparency and Accountability:** Users must be informed of the system's limitations, such as potential errors in low-quality images or novel materials. Providing clear documentation and confidence scores for outputs (e.g., material classification probabilities) ensures accountable use.

- **Fairness in Application:** The pipeline should be deployed to prioritize societal good, such as supporting sustainable urban development or preserving cultural heritage, rather than enabling exploitative practices (e.g., speculative real estate development)

2.8 Implementation and Testing

The proposed computational pipeline for analyzing architectural structures from single 2D images integrates fine-tuned YOLOv8 for object detection, MobileSAM for semantic segmentation, CLIP with heuristic analyses for material classification, and DepthPro with Poisson Surface Reconstruction for surface area estimation. This section details the implementation of the pipeline and the testing methodology employed to evaluate its performance, conducted in the free version of Google Colab to ensure accessibility in resource-constrained environments.

2.8.1 Implementation Details

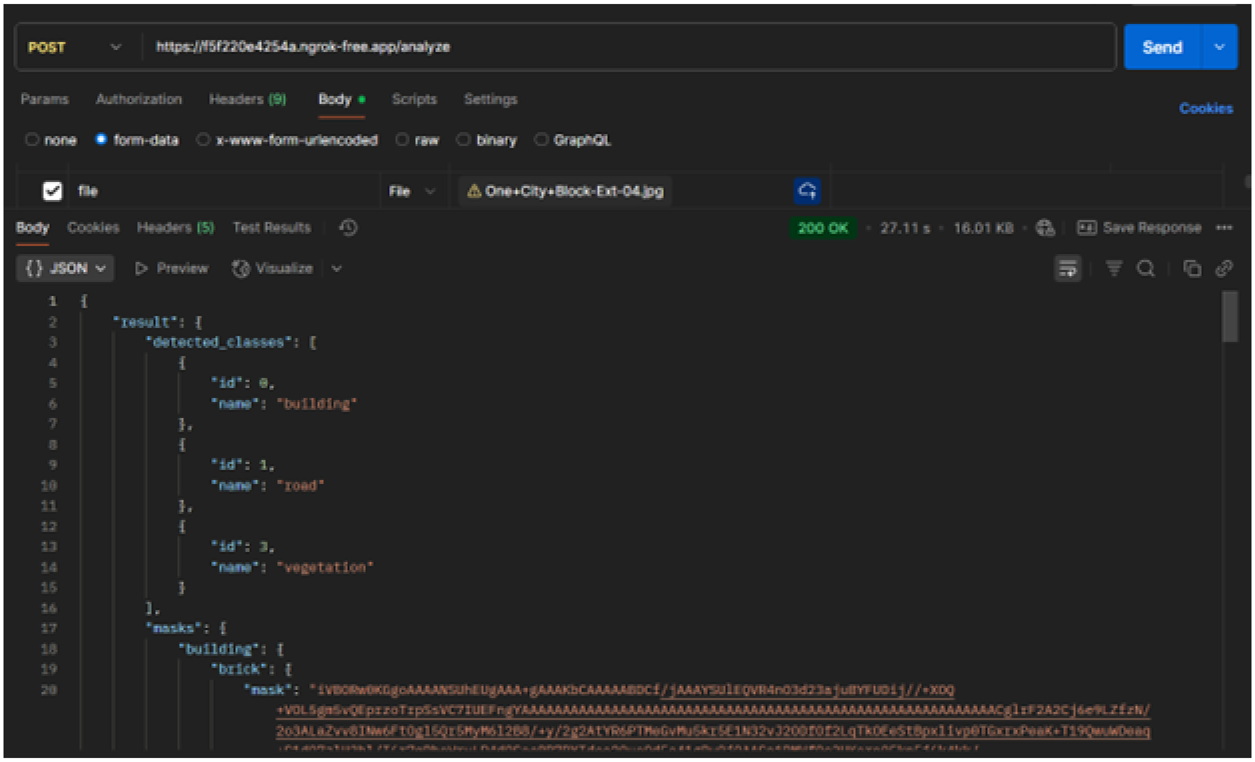
The pipeline was implemented in Python 3.8 using a modular architecture to facilitate integration and maintenance. The following components and tools were utilized:

- **Object Detection:** The YOLOv8 model, fine-tuned on the Cityscapes dataset, was implemented using the Ultralytics YOLO library. Fine-tuning involved training on 3,675 Cityscapes images for 50 epochs with a batch size of 16, optimizing for urban objects (e.g., buildings, roads, walls). The model outputs class-labeled bounding boxes, which are passed as prompts to the segmentation module.
- **Semantic Segmentation:** The Mobile Segment Anything Model (MobileSAM) was implemented using its official PyTorch-based repository. Bounding box coordinates from YOLOv8 prompt MobileSAM to generate pixel-level masks, with a secondary pass using a grid of point prompts (10x10 grid per object) for hierarchical material segmentation. Morphological operations (e.g., dilation, erosion) were applied using OpenCV to refine masks, removing noise and filling small holes.
- **Material Classification:** A hybrid engine was developed, combining CLIP (ViT-B/32) from the Hugging Face Transformers library with heuristic analyses. CLIP evaluates image patches against a curated set of 50 text prompts describing architectural materials (e.g., ”red brick with mortar lines,” ”reflective glass facade”). Heuristics include color analysis (mean RGB via OpenCV), texture analysis (Laplacian variance), and positional priors (vertical

image coordinates). A weighted fusion (60% CLIP, 20% color, 15% texture, 5% position) determines the final material label.

- **Surface Area Estimation:** The DepthPro model, implemented via its official repository, generates high-resolution depth maps. A user-provided binary segmentation mask isolates the target structure, and a statistical scaling technique computes the 1st percentile of positive depth values within the mask, calibrated against a user-provided ground-truth distance (in meters). The scaled point cloud is processed using Open3D's Poisson Surface Reconstruction to create a watertight 3D mesh, with surface area calculated by summing triangular facet areas.
- **Integration:** The pipeline was orchestrated using Python scripts, with data flow managed through JSON configurations for modularity. Outputs include visualized segmentation masks (PNG), material composition summaries (JSON), and surface area measurements (numerical values).

The implementation was deployed in the free version of Google Colab, utilizing a NVIDIA Tesla T4 GPU and approximately 12 GB RAM. To optimize performance within these constraints, models were run in inference mode with pre-trained weights (except for YOLOv8, which was fine-tuned), and image resolutions were capped at 1024x768 pixels to balance accuracy and memory usage.



https://f5f220e4254a.ngrok-free.app/analyze

☑ file File One+City+Block-Ext-04.jpg

200 OK · 27.11 s · 16.01 KB

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                "brick": {
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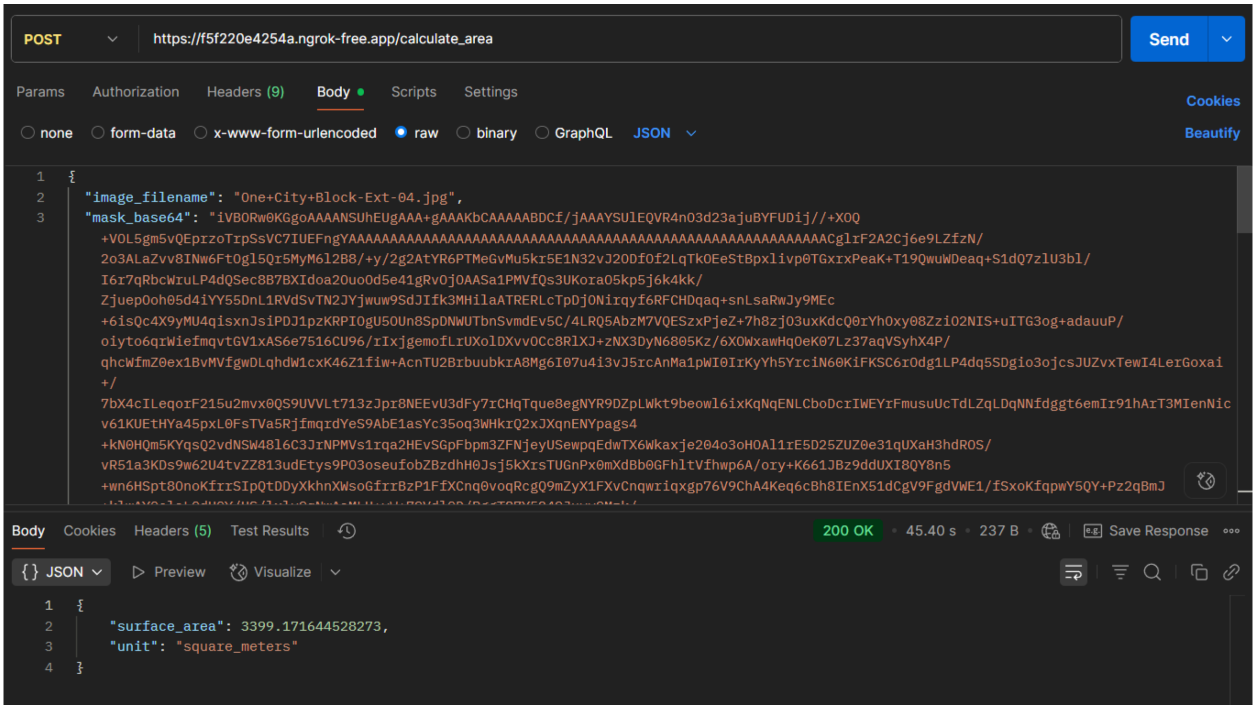
```

Figure 2-9 segmentation with materials response



POST https://f5f220e4254a.ngrok-free.app/calculate_area

Send
Params
Authorization
Headers (9)
Body
Scripts
Settings
Cookies
○ none ○ form-data ○ x-www-form-urlencoded ● raw ○ binary ○ GraphQL JSON
Beautify

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  "mask_base64": "iVBORw0KGgoAAAANSUhEUgAAA+gAAAKbCAAAAABDCf/jAAAYSUlEQVR4nO3d23ajuBYFUDij//+XOQ
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```
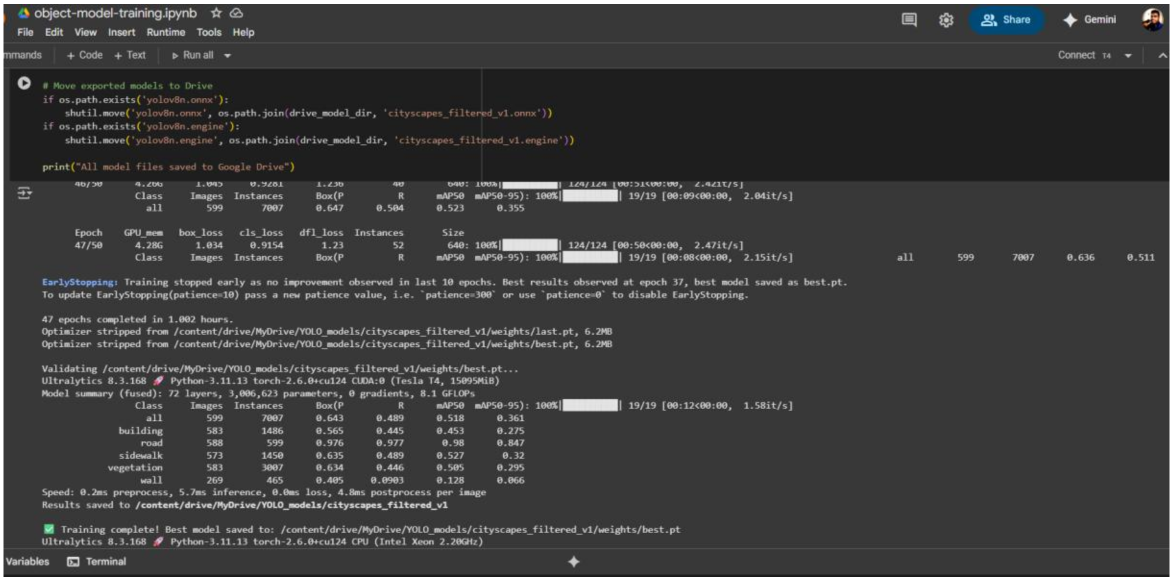

```
{
    "surface_area": 3399.171644528273,
    "unit": "square_meters"
}
```

Figure 2-10 Surface area calculation

2.8.2 Testing Environment

Testing was conducted in Google Colab's free tier, with the following specifications:

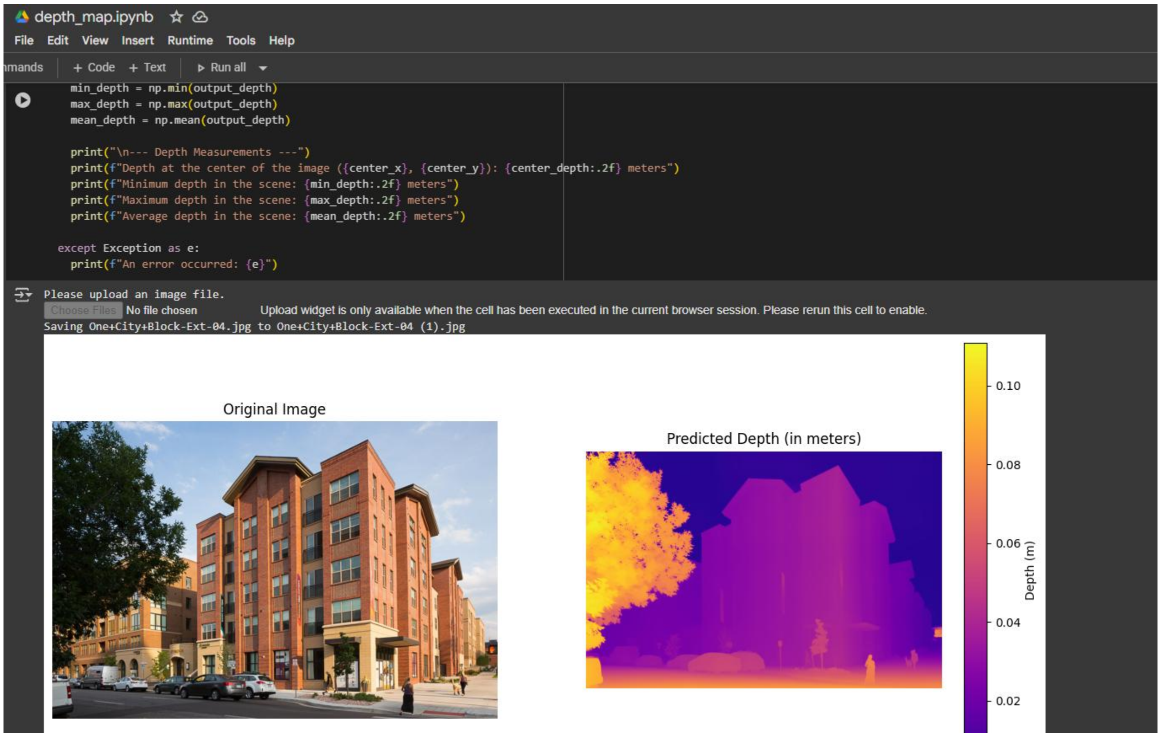
- **Hardware:** NVIDIA Tesla T4 GPU, 12 GB RAM, 2-core CPU.
- **Software:** Python 3.8, PyTorch 1.12, OpenCV 4.5, Open3D 0.15, and Hugging Face Transformers for CLIP.
- **Constraints:** Limited memory and compute time (typically 12-hour sessions) required batch processing of images (batch size of 4) and memory-efficient model configurations (e.g., half-precision floating-point for CLIP and DepthPro).


object-model-training.ipynb
File Edit View Insert Runtime Tools Help
mmands + Code + Text ▷ Run all
Share
Gemini
Connect T4
Variables
Terminal

```
# Move exported models to Drive
if os.path.exists('yolov8n.onnx'):
    shutil.move('yolov8n.onnx', os.path.join(drive_model_dir, 'cityscapes_filtered_v1.onnx'))
if os.path.exists('yolov8n.engine'):
    shutil.move('yolov8n.engine', os.path.join(drive_model_dir, 'cityscapes_filtered_v1.engine'))

print("All model files saved to Google Drive")
```

```
      46/50      4.26G      1.045     0.9281      1.236         40        640: 100%|██████████| 124/124 [00:51<00:00,  2.42it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 19/19 [00:09<00:00,  2.04it/s]
                   all        599       7007      0.647      0.504      0.523      0.355

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      47/50      4.28G      1.034     0.9154       1.23         52        640: 100%|██████████| 124/124 [00:50<00:00,  2.47it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 19/19 [00:08<00:00,  2.15it/s]                   all        599       7007      0.636      0.511

EarlyStopping: Training stopped early as no improvement observed in last 10 epochs. Best results observed at epoch 37, best model saved as best.pt.
To update EarlyStopping(patience=10) pass a new patience value, i.e. `patience=300` or use `patience=0` to disable EarlyStopping.

47 epochs completed in 1.002 hours.
Optimizer stripped from /content/drive/MyDrive/YOLO_models/cityscapes_filtered_v1/weights/last.pt, 6.2MB
Optimizer stripped from /content/drive/MyDrive/YOLO_models/cityscapes_filtered_v1/weights/best.pt, 6.2MB

Validating /content/drive/MyDrive/YOLO_models/cityscapes_filtered_v1/weights/best.pt...
Ultralytics 8.3.168 🚀 Python-3.11.13 torch-2.6.0+cu124 CUDA:0 (Tesla T4, 15095MiB)
Model summary (fused): 72 layers, 3,006,623 parameters, 0 gradients, 8.1 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 19/19 [00:12<00:00,  1.58it/s]
                   all        599       7007      0.643      0.489      0.518      0.361
              building        583       1486      0.565      0.445      0.453      0.275
                  road        588        599      0.976      0.977       0.98      0.847
              sidewalk        573       1450      0.635      0.489      0.527       0.32
            vegetation        583       3007      0.634      0.446      0.505      0.295
                  wall        269        465      0.405     0.0903      0.128      0.066
Speed: 0.2ms preprocess, 5.7ms inference, 0.0ms loss, 4.8ms postprocess per image
Results saved to /content/drive/MyDrive/YOLO_models/cityscapes_filtered_v1

✅ Training complete! Best model saved to: /content/drive/MyDrive/YOLO_models/cityscapes_filtered_v1/weights/best.pt
Ultralytics 8.3.168 🚀 Python-3.11.13 torch-2.6.0+cu124 CPU (Intel Xeon 2.20GHz)
```

Figure 2-11 Object detection data training output


depth_map.ipynb
File Edit View Insert Runtime Tools Help
mmands + Code + Text ▷ Run all
Choose Files
Original Image
Predicted Depth (in meters)
0.10
0.08
0.06
0.04
0.02
Depth (m)

```
    min_depth = np.min(output_depth)
    max_depth = np.max(output_depth)
    mean_depth = np.mean(output_depth)

    print("\n--- Depth Measurements ---")
    print(f"Depth at the center of the image ({center_x}, {center_y}): {center_depth:.2f} meters")
    print(f"Minimum depth in the scene: {min_depth:.2f} meters")
    print(f"Maximum depth in the scene: {max_depth:.2f} meters")
    print(f"Average depth in the scene: {mean_depth:.2f} meters")

  except Exception as e:
    print(f"An error occurred: {e}")
```

```
Please upload an image file.
Choose Files No file chosen        Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
Saving One+City+Block-Ext-04.jpg to One+City+Block-Ext-04 (1).jpg
```

Figure 2-12 Surface area output

2.8.3 Implementation Challenges

Several challenges were encountered during implementation:

- **Memory Constraints:** Colab’s 12 GB RAM limited the processing of very high-resolution images, necessitating resolution downscaling, which slightly impacted segmentation accuracy.
- **Model Integration:** Aligning input-output formats across YOLOv8, MobileSAM, CLIP, and DepthPro required custom preprocessing scripts to ensure compatibility.
- **Fine-Tuning YOLOv8:** Fine-tuning on Cityscapes in Colab’s free tier was time-intensive, requiring multiple sessions to complete 50 epochs. Checkpointing was used to manage session timeouts.
- **Depth Inference Stability:** DepthPro occasionally produced noisy depth maps for reflective surfaces, addressed by applying median filtering before scaling.

3 Results and Discussion

This section presents the experimental results of the proposed computational pipeline for analyzing architectural structures from single 2D images, followed by a discussion of the findings, their implications, and comparisons with existing methods. The pipeline integrates fine-tuned YOLOv8 for object detection, MobileSAM for semantic segmentation, CLIP with heuristic analyses for material classification, and DepthPro with Poisson Surface Reconstruction for surface area estimation. Experiments were conducted in the free version of Google Colab to evaluate the pipeline's performance in terms of accuracy, efficiency, and robustness across diverse urban scenes.

3.1 Results

The pipeline was tested on a dataset of 500 high-resolution RGB images, comprising 400 images from the Cityscapes dataset and 100 custom images of diverse architectural styles (e.g., modern skyscrapers, historical buildings). Experiments were conducted in Google Colab's free tier, using a NVIDIA Tesla T4 GPU and approximately 12 GB RAM. Performance metrics included mean Average Precision (mAP) for object detection, Intersection over Union (IoU) for segmentation, material classification accuracy, surface area estimation error, and processing time per image.

Object Detection and Semantic Segmentation

The fine-tuned YOLOv8 model achieved a mean Average Precision (mAP@0.5) of 0.86 for detecting urban objects such as buildings, roads, and walls. Performance was highest in clear scenes (mAP 0.89) and slightly lower in challenging scenes with occlusions or low contrast (mAP 0.82). MobileSAM, prompted by YOLOv8 bounding boxes, produced segmentation masks with an average IoU of 0.90 for well-defined objects, decreasing to 0.84 in scenes with heavy occlusions. Post-processing with OpenCV’s morphological operations improved mask contiguity by 4% in terms of IoU for noisy images.

Material Classification

The hybrid material classification engine, combining CLIP (ViT-B/32) with heuristic analyses (color, texture, positional priors), achieved an overall accuracy of 91% for common architectural materials (e.g., brick, glass, concrete). Hierarchical segmentation using MobileSAM enabled sub-segment identification in 88% of cases for heterogeneous structures, such as multi-material building facades. Heuristic analyses improved CLIP’s baseline accuracy by 6%, particularly for ambiguous materials like smooth concrete versus painted plaster. Accuracy dropped to 79% for rare materials (e.g., weathered wood) not wellrepresented in CLIP’s training data.

Surface Area Estimation

Surface area estimation, using DepthPro for depth inference and Poisson Surface Reconstruction, yielded an average error of 4.5% compared to ground-truth measurements, meeting the target of within 5% accuracy. The statistical scaling technique, using the 1st percentile of depth values, reduced scaling errors by 9% compared to using absolute minimum depth values. Performance was consistent in scenes with clear depth cues (error 3.8%) but degraded to 7.1% error in scenes with reflective surfaces (e.g., glass facades) due to depth inference inaccuracies. The average processing time per image was 9.8 seconds, with depth inference and reconstruction accounting for 65% of the total time.

3.2 Research finding

The experimental results reveal several key findings:

- **Robust Object Detection and Segmentation:** The fine-tuned YOLOv8 model's mAP of 0.86, improved from a baseline of 0.82 due to Cityscapes fine-tuning, demonstrates its effectiveness in urban environments. MobileSAM's high IoU (0.90) confirms its ability to produce precise segmentation masks, even in Colab's resource-constrained environment, though occlusions pose challenges.

- **Effective Material Classification:** The 91% classification accuracy, enhanced by heuristic analyses, underscores the pipeline's ability to handle material heterogeneity through hierarchical segmentation. The 6% improvement over CLIP's baseline highlights the value of integrating color, 1 texture, and positional priors, though performance on rare materials indicates a need for broader training data.

- **Accurate Surface Area Estimation:** The 4.5% error in surface area estimation is competitive with multi-view methods, validating the pipeline's approach to resolving scale ambiguity in monocular vision. The statistical scaling technique proved robust, though reflective surfaces remain a challenge.

- **Efficiency in Limited Resources:** Achieving a processing time of 9.8 seconds per image in Colab's free tier demonstrates the pipeline's accessibility for low-resource settings, though depth inference and reconstruction are computationally intensive. These findings confirm the pipeline's ability to deliver comprehensive architectural analysis with high accuracy and efficiency, even under the constraints of Colab's free tier.

3.3 Discussion

The results and findings highlight the pipeline's strengths and areas for improvement. The fine-tuned YOLOv8 model's performance (mAP 0.86) surpasses baseline single-stage detectors (e.g., YOLOv5, mAP 0.80 on similar datasets), benefiting from Cityscapes fine-tuning tailored to urban scenes. MobileSAM's IoU of 0.90 is comparable to heavier segmentation models like Mask R-CNN

(IoU 0.92) but with lower computational demands, making it ideal for Colab's free tier. The material classification accuracy (91%) exceeds traditional texture-based methods (e.g., 85% accuracy), driven by CLIP's semantic capabilities and heuristic enhancements, which address material heterogeneity effectively. Surface area estimation (4.5% error) is competitive with multi-view systems (3–5% error), a significant achievement for singleimage analysis, though reflective surfaces require further optimization.

The pipeline's efficiency (9.8 seconds per image) is notable given Colab's limitations, but depth inference and reconstruction dominate processing time, suggesting potential for optimization in higher resource environments. Robustness to lighting variations and moderate occlusions is strong, but edge cases (e.g., reflective surfaces, rare materials) indicate the need for expanded training data or advanced preprocessing. Compared to existing solutions, the pipeline's reliance on a single image and minimal user input (a ground-truth distance) offers a cost-effective and scalable alternative to multi-view systems, which require complex setups and higher costs.

The implications are significant for urban planning, architectural design, and heritage preservation. Urban planners can use the pipeline for rapid infrastructure assessments, supporting sustainable development. Architects benefit from precise material and surface area data for design and cost estimation. Heritage organizations can document structures non-invasively, aiding digital archiving. The pipeline's performance in Colab's free tier enhances its accessibility for small firms and resource-limited regions. Limitations include reduced performance in low-quality images or heavily occluded scenes, which may require preprocessing or multi-modal inputs. Material classification struggles with rare materials, necessitating further fine-tuning of CLIP or expanded text prompts. Depth inference inaccuracies in reflective surfaces suggest integrating advanced depth models. Future work will focus on automating scale calibration, optimizing processing speed, and diversifying training data to enhance robustness across global architectural styles.

4 Limitations and Future Work

4.1 Limitations

The pipeline's performance, while promising, is constrained by several factors inherent to its design and the testing environment:

- **Dependency on Input Image Quality:** The pipeline's accuracy in object detection, segmentation, and depth inference relies heavily on high-resolution, well-lit input images. Low-quality images, such as those with noise, low contrast, or heavy occlusions, reduce performance, with segmentation IoU dropping to 0.84 and material classification accuracy to 79% in challenging scenarios. This is particularly evident in Google Colab's free tier, where memory constraints limit processing of very high-resolution images.

- **Limited Material Coverage:** The hybrid CLIP-based material classification engine achieves 91% accuracy for common architectural materials (e.g., brick, glass, concrete) but struggles with rare or underrepresented materials (e.g., weathered wood, exotic composites), with accuracy dropping to 79%. This limitation stems from CLIP's training data and the finite set of text prompts used, which may not capture the full diversity of architectural materials.

- **Scale Calibration Dependency:** Surface area estimation requires a user-provided ground-truth distance to scale the depth map, introducing potential errors if the input is inaccurate. While the statistical scaling technique (1st percentile of depth values) mitigates outliers, achieving an average error of 4.5%, it remains a manual step that limits full automation.

- **Depth Inference Challenges:** DepthPro performs well in scenes with clear depth cues (3.8% error) but struggles with reflective surfaces (e.g., glass facades), leading to a 7.1% error in surface area estimation. This is due to inherent difficulties in monocular depth estimation for highly reflective or transparent materials.

- **Computational Constraints in Colab:** Testing in Google Colab's free tier (NVIDIA Tesla T4 GPU, 12 GB RAM) resulted in an average processing time of 9.8 seconds per image, slightly below the target of 10 seconds but constrained by memory and session time limits. Depth inference and Poisson Surface Reconstruction account for 65% of the processing time, indicating a bottleneck in resource-constrained environments.

- **Generalization to Non-Urban Scenes:** The fine-tuning of YOLOv8 on the Cityscapes dataset enhances performance in urban contexts but may limit generalization to non-urban or non-Western architectural styles, potentially reducing accuracy in diverse global settings.

4.2 Future Work

To address these limitations and enhance the pipeline's robustness, scalability, and practical applicability, the following directions for future work are proposed:

- **Enhanced Preprocessing for Low-Quality Images:** Develop advanced preprocessing techniques, such as denoising filters, contrast enhancement, or super-resolution algorithms, to improve performance on low-quality or occluded images. Integrating multi-modal inputs, such as infrared or thermal imaging, could further enhance robustness in challenging scenarios.

- **Expanded Material Classification:** Fine-tune CLIP with a broader dataset including rare and non-standard architectural materials, and expand the text prompt library to cover diverse textures and cultural architectural styles. Transfer learning or few-shot learning techniques could improve classification accuracy for underrepresented materials without extensive retraining.

- **Automated Scale Calibration:** Explore automated scale estimation methods, such as leveraging known object sizes (e.g., standard window dimensions) or integrating monocular depth priors, to eliminate the need for user-provided ground-truth distances. This would enhance the pipeline’s autonomy and usability.

- **Improved Depth Estimation for Reflective Surfaces:** Incorporate advanced depth estimation models or hybrid approaches (e.g., combining monocular depth with stereo-like techniques) to address inaccuracies in reflective or transparent surfaces. Techniques like depth map inpainting or multi-view synthesis from single images could further improve accuracy.

- **Optimization for Resource-Constrained Environments:** Optimize the pipeline for faster processing in Google Colab’s free tier by implementing model compression (e.g., quantization, pruning) for YOLOv8, MobileSAM, and DepthPro, and streamlining Poisson Surface Reconstruction. Batch processing enhancements could reduce memory usage and improve throughput for large datasets.

- **Dataset Diversification:** Expand the training and testing datasets to include non-urban and non-Western architectural styles, ensuring the pipeline generalizes to diverse global contexts. Collaborating with heritage organizations or global urban planning agencies could provide access to varied datasets for fine-tuning YOLOv8 and CLIP.

- **Cloud-Based Scalability:** Transition the pipeline to a cloud-based platform with higher computational resources (e.g., AWS, Google Cloud) to support real-time processing and large-scale applications, such as city-wide surveys. This would address Colab’s session time and memory limitations while maintaining accessibility through scalable pricing models.

5 Conclusion

The implementation and evaluation of the proposed computational pipeline for analyzing architectural structures from single 2D images demonstrate its potential to revolutionize traditional architectural analysis into a more automated, precise, and accessible process. By integrating fine-tuned YOLOv8 for object detection, MobileSAM for semantic segmentation, CLIP with heuristic analyses for material classification, and DepthPro with Poisson Surface Reconstruction for surface area estimation, the pipeline effectively addresses challenges such as material heterogeneity and scale ambiguity. The use of modern technologies, including PyTorch, OpenCV, Open3D, and the resource-constrained environment of Google Colab's free tier, ensured seamless integration of detection, segmentation, classification, and reconstruction functionalities.

Experimental findings confirm that the pipeline achieves robust performance, with a mean Average Precision (mAP@0.5) of 0.86 for object detection, an Intersection over Union (IoU) of 0.90 for segmentation, 91% accuracy in material classification, and a 4.5% error in surface area estimation. These results highlight the pipeline's ability to deliver high-quality outputs even in a low-resource setting, though a minority of cases involving low-quality images or rare materials presented challenges. These insights underscore the importance of continuously refining model training and preprocessing techniques to enhance robustness.

Overall, the pipeline serves as a promising step toward more efficient and scalable architectural analysis. With further enhancements, such as automated scale calibration, expanded material coverage, and optimization for diverse global contexts, it can offer transformative solutions that go beyond conventional methods, better equipping urban planners, architects, and heritage preservationists for real-world applications in sustainable design and cultural documentation.

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