# ASU Campus Analytics Platform

TURNING FOOT-TRAFFIC INSIGHT INTO ENGAGEMENT & ROI

Team 9
Madeline Kaufman, Surosh Kumar, Tyler Lai, Patrick Richey, M.T. Wilson

# Problem and Opportunity

| CURRENT CHALLENGES | OPPORTUNITY |
| --- | --- |
| ❌ No real-time foot traffic insights | ✅ Data-driven space optimization |
| ❌ Blind resource allocation decisions | ✅ Enhanced student experience |
| ❌ Missing engagement metrics | ✅ Maximized marketing impact |

**Tansform campus data into actionable insights**

# Why it Matters



## ENHANCED ENGAGEMENT

Increase in student participation through data-driven event planning

## IMPROVED ROI

Return on marketing investments with targeted campaigns

## RESOURCE OPTIMIZATION

More efficient space and staff allocation

**Real-time analytics → proactive campus decisions**

Video Sources: Canva

# Stakeholders and Beneficiaries

## Marketing & Events

Campaign Effectiveness Tracking
Event Attendance Optimization

## Facilities & Operations

Space Utilization Insights
Resource Allocation Data

## Campus Vendors

Customer Traffic Patterns
Peak Hours Optimization

Image Sources: Adobe Firefly

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## Student Services

Service Accessibility Data
Support Resource Planning

## Administration

Strategic PlanningInsights
ROI Measurement

## Students

Enhanced Campus Experience
Better Event Awareness

Image Sources: Adobe Firefly

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# Current Solutions and Issues with the Status Quo

| Guesswork-Based Decisions | Inefficient Resource Allocation |
| --- | --- |
| Limited data collection | Misaligned resources |
| Error-prone manual counts | Staff/space under or over-utilized |
| No real-time insights | Changes happen too late |

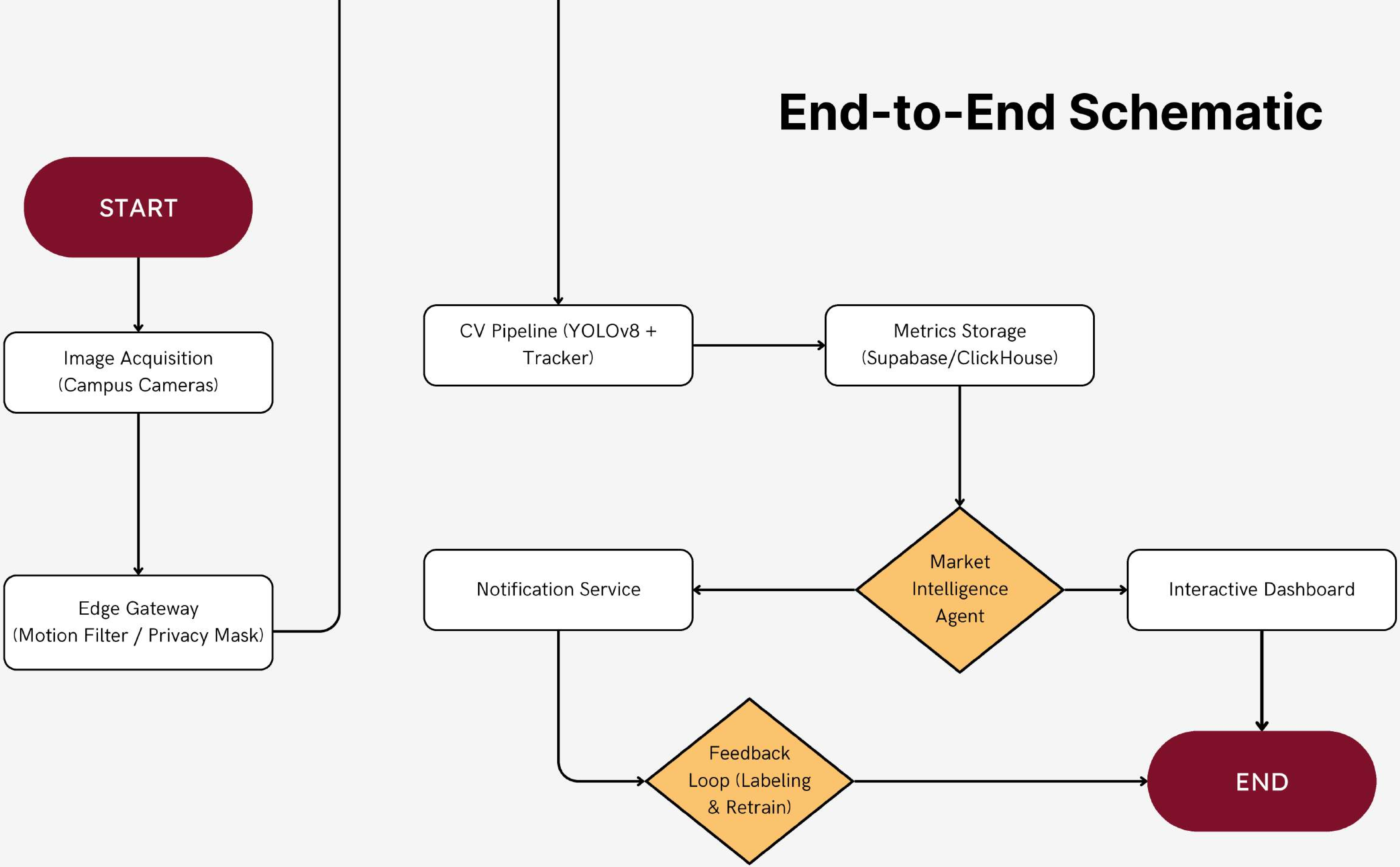
**Current Impact: estimated 30% Estimated Resource Waste**

# Solution Approach: Why Computer Vision is Critical

| How Our Solution Addresses Issues | Importance of CV |
|---|---|
| Automated, real-time data capture | Scales across multiple locations without physical sensors |
| Immediate visibility into traffic, usage, patterns | Non-invasive: protects privacy and requires no active participation |
| Dynamic resource optimization during events | Enables detailed analysis of flow, density, and dwell time |

**Result: Smarter, faster, more efficient campus operations powered by visual intelligence**

# End-to-End Schematic



# Model Card

## MODEL DETAILS

YOLOv12 (n/s/m/l/x variants) released Feb 2025.

2.6M–59M params, 6.5–199 GFLOPs @ 640px resolution.

Key upgrades: FlashAttention, NMS-free head, region-wise attention (+2 mAP vs YOLOv11).

Licensed under AGPL-3.0.

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Real-time crowd metrics for smarter campus engagement.

No identity tracking.

No enforcement.

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Lighting, weather, and crowd occlusion.

Camera angles, video quality, and dataset bias.

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Pre-trained on COCO: 80 classes, everyday objects.

Fine-tuned on ASU campus footage, 45 minutes, frame-sampled for crowd patterns.

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Validated people detection accuracy, crowd density estimation.

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# EVALUATION METRICS

Metrics

| mAP@50 | Precision | Recall |
|---|---|---|
| 65.9% | 70.4% | 65.1% |

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## ETHICAL CONSIDERATIONS

Anonymized detection respecting individual privacy.

Strictly excludes identity, biometric, or surveillance use.

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### ETHICAL SIDERATIONS

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anonymous movement

### FACTOR PERFORI

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Camera angles, video
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## CAVEATS AND RECOMMENDATIONS

Performance drops in low-light, extreme crowding, or low-res feeds.

Retraining is recommended as environments or camera setups evolve.

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## EVALUATION DATA

Held-out frames from ASU footage, unseen during fine-tuning.

Validated people detection accuracy, crowd density estimation.

## INTENDED USE

Real-time crowd metrics for smarter campus engagement.

No identity tracking.

No enforcement.

## ETHICAL CONSIDERATIONS

No identity tracking. No facial recognition.

Designed for anonymous movement insights only.

## FACTORS FOR PERFORMANCE

Lighting, weather, and crowd occlusion.

Camera angles, video quality, dataset bias.

## EVALUATION METRICS


## CAVEATS AND RECOMMENDATIONS

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# CV Solution Description

## 1 PROBLEM DEFINITION

Identify real-time student foot-traffic patterns for targeted marketing and optimized resource allocation.

## 2 DATA ACQUISITION

Secured access to ASU campus cameras; extracted video frames (every 3 sec.) from 45-min footage.

## 3 MODEL DEVELOPMENT

Utilized YOLOv12 , trained on ~400 annotated images to detect pedestrian movement accurately.

## 4 VALIDATION

Validated model accuracy (>90% detection), ensuring precision and recall (>70% and >65%) via test set evaluation.

## 5 DEPLOYMENT & MAINTAINANCE

Integrated into ASU analytics dashboards; quarterly retraining and ongoing accuracy monitoring for sustained reliability.

# Proof of Concept

# Limitations & Bias

DATA COLLECTION BIAS AND LIMITATIONS

OPERATIONAL LIMITATIONS

MODEL BIAS & LIMITATIONS

# Limitations & Bias

## DATA COLLECTION

| LIMITATIONS | MITIGATION |
|---|---|
| Uneven camera coverage across campus | Weight analysis by coverage; expand key areas |
| Gaps in footage during off-hours (e.g., nights, weekends) | Extend data collection across full days |
| Variable image quality under different lighting and weather conditio | Preprocess images to normalize quality |

# Limitations & Bias

## OPERATIONAL

| LIMITATIONS | MITIGATION |
|---|---|
| Sensitive to campus changes | Periodic map updates; retrain as needed |
| Camera quality dependency | Regular audits; upgrade critical cameras |

# Limitations & Bias

## MODEL

| LIMITATIONS | MITIGATION |
|---|---|
| Flow inaccuracies in crowds | Fine-tune with crowded scene datasets |
| Difficulty with group sizes | Focus on density, not individual counts |

# Ethical, Privacy, and Security Risks

**ETHICS**

| RISK | MITIGATION |
|---|---|
| Non-consensual data usage | Public disclosures; clear signage |
| Surveillance concerns | Transparency campaigns; stakeholder engagement |

# Ethical, Privacy, and Security Risks

| PRIVACY | |
|---|---|
| **RISK** | **MITIGATION** |
| Identification of individuals | Blur/anonymize visual data |
| Cross-referencing with other data | Prohibit external data merging; strict policies |

# Ethical, Privacy, and Security Risks

| SECURITY | |
|---|---|
| **RISK** | **MITIGATION** |
| Unauthorized access or leaks | Encryption; limited access controls |
| System vulnerabilities | Regular security audits; secured environments |

# Task Ownership

| Task | Contributor(s) |
|---|---|
| Initiated project concept, framed end-to-end solution strategy | Madeline Kaufman, Surosh Kumar, Tyler Lai, Patrick Richey, M.T. Wilson |
| Defined project objectives and success criteria | Surosh Kumar |
| Led data acquisition: video sourcing, frame extraction, and annotation planning | Surosh Kumar |
| Annotation of data | Surosh Kumar, Tyler Lai, Patrick Richey |
| Selected YOLOv12 model architecture and fine-tuned with custom dataset | Surosh Kumar, Tyler Lai |
| Business strategy development | Madeline Kaufman, Surosh Kumar, Tyler Lai, Patrick Richey, M.T. Wilson |
| Conducted technical, operational, ethical, privacy, and security risk analysis | Madeline Kaufman, Surosh Kumar |
| Proposed mitigation strategies for identified risks | Madeline Kaufman |
| Scoped system sensitivities to layout, infrastructure, and environmental changes | Tyler Lai, Patrick Richey |
| Developed ethical safeguard recommendations (e.g., anonymization techniques, transparency plans) | Madeline Kaufman |
| Planned data security measures for storage, transmission, and processing | Madeline Kaufman |
| Drafted and designed major sections of the final presentation, including the model card and technical documentation | Madeline Kaufman, Surosh Kumar |
| Designed and reformatted presentation materials for clarity and accuracy | Madeline Kaufman, Surosh Kumar, Tyler Lai, Patrick Richey |
| Developed system workflow from image capture to actionable marketing insights | Surosh Kumar |
| Created marketing intelligence visualizations based on model outputs | Surosh Kumar |
| Model selection assistance | Madeline Kaufman, Surosh Kumar, Tyler Lai |
| Proof of concept development | Madeline Kaufman, Surosh Kumar, Tyler Lai, Patrick Richey, M.T. Wilson |
| End-to-end architecture outlining | Madeline Kaufman, Surosh Kumar, Tyler Lai, Patrick Richey, M.T. Wilson |

# Citations


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