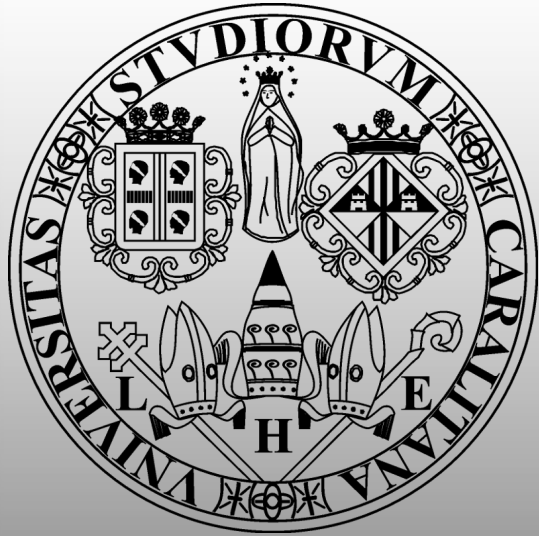




Roadwatch: Leveraging AI and Configurable Rules for Real-Time Traffic Anomaly Detection on Existing Camera Infrastructures

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Outline

- **Context**
- **System Architecture**
- **Validation Methodology**
- **Results**
- **Conclusion**

Context



The **growing density** of vehicles and pedestrians, together with the **increasing complexity** of modern road infrastructures limits the effectiveness of traditional human-centered monitoring approaches, which **hardly scale** to large urban areas



Context



Existing traffic monitoring systems face **open challenges**:

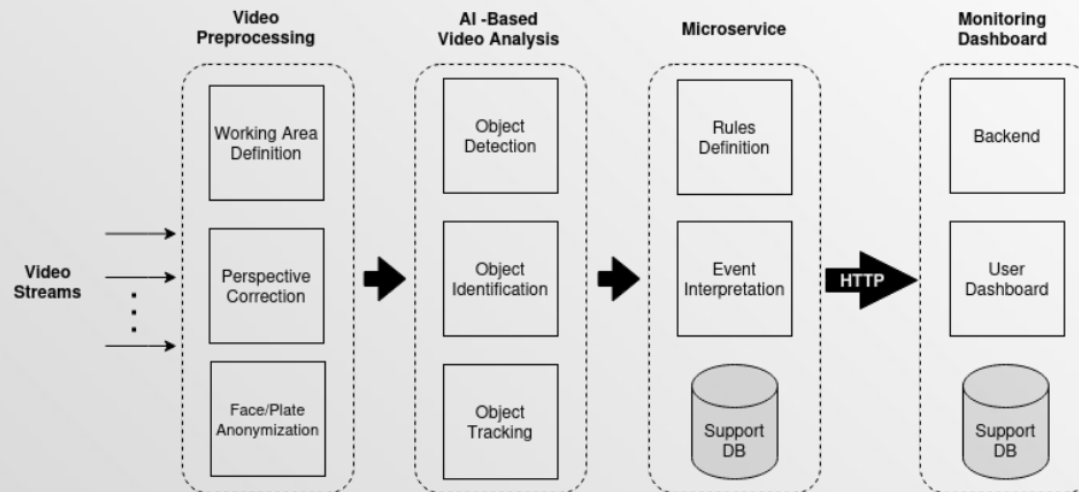
- Many **require dedicated hardware**, such as carefully positioned sensors or specific camera models
- Most rely on **low-level detections** rather than semantic traffic events

Roadwatch addresses both by combining **deep learning** with configurable, **rule-based** event interpretation

System Architecture

Roadwatch is built on **NVIDIA DeepStream** and **GStreamer**, organized as a real-time **modular pipeline** structured as follows:

- the **video preprocessing** stage: working-area definition, perspective correction, anonymization
- **AI** perception combines **detection (YOLOv4-CSP)** with **tracking (NvDCF)**
- a **microservice** layer applies **rule-based interpretation**



Validation Methodology



- Roadwatch adopts an **event-based validation** paradigm: **events**, not frames, are the unit of evaluation
- each event is **characterized**, then reviewed to confirm whether it is a true or **false positive**:

$$TP = \{e \in E \mid e \text{ is semantically and spatially correct}\}$$

$$FP = \{e \in E \mid e \text{ is semantically or spatially incorrect}\}$$

Validation Methodology



- False negatives are estimated via a **temporal sampling strategy** applied to a subset of the observation window
- The **sample recall** is used to **extrapolate** the **estimated false negatives** over the full **24h** window:

$$Recall_{sample} = \frac{TP_S}{TP_S + FN_S}$$

$$N_{real} \approx \frac{N_E}{Recall_{sample}}$$

$$FN_{est} = N_{real} - N_E$$

Results



- The experimental evaluation was carried out over a continuous 24-hour **observation window**, recorded by the Municipality of Cagliari:
- the system automatically detected **899 anomalous events**, fully logged by the system
- a **temporal sample of 82 real events** was reviewed: 74 correct, 8 missed
- Manual review confirmed **zero false positives**

Indicator	Value
Events detected by the system (TP)	899
Real events in the sample	82
Correctly detected / missed in sample	74 / 8
Estimated recall	0.902
Estimated total real events	≈997
Estimated total false negatives	≈98

Results



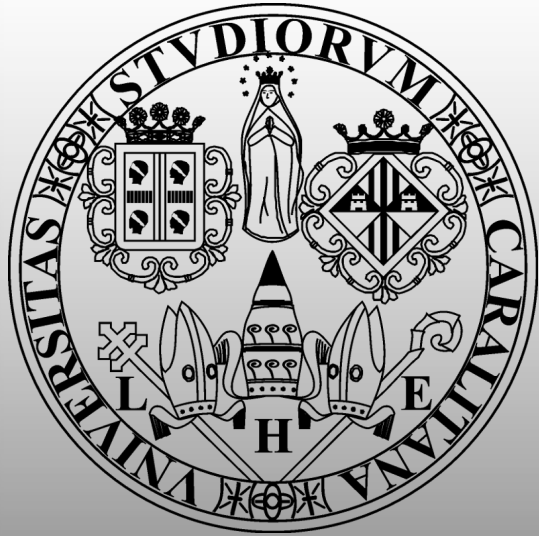
We analyzed the *distribution of detected events* by class, with false negatives **proportionally projected** across event types; manual review confirmed **zero false positives** across every category

Event	TP	FP	FN (est.)	TN *	Share (%)
ILLEGAL_WAY_CROSSING	616	0	67	n/a	68.52
ENTITY_ON_ROAD	273	0	30	n/a	30.37
AREA_INVASION	4	0	0.4	n/a	0.44
NO_PARK	5	0	0.5	n/a	0.56
RECKLESS_DRIVING	1	0	0.1	n/a	0.11
Total	899	0	98	n/a	100.00

*** Note:** True Negatives are not defined in event-based evaluation, as there is no finite set of "non-events" to count.

Conclusions

- Roadwatch combines **deep learning** perception with **rule-based** reasoning, **operating on existing camera** infrastructures without additional sensors
- An **event-based validation paradigm** with temporal sampling enables recall estimation on continuous real-world footage, where frame-level annotation is impractical
- Over 24h of real urban traffic, the system detected **899 events** with **zero false positives** and an estimated **recall of 0.902**



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THANK YOU FOR YOUR ATTENTION

