YOLO-based Traffic Monitoring on Avenida Arequipa using IoT and Geospatial Data

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Abstract. This paper presents the design and evaluation of an intelligent traffic monitoring system deployed on Avenida Arequipa, one of the main urban corridors in Lima, Peru. The system combines Internet of Things (IoT) infrastructure, georeferenced video capture, and a YOLO-based deep learning model to detect and classify road users in real time. Our approach focuses on low-cost cameras integrated with embedded devices that perform local preprocessing and send metadata to a central server for storage, analytics, and visualization. The geospatial configuration of Avenida Arequipa—its lane structure, intersections, and bus-only segments—is explicitly modeled to support the estimation of vehicle density, flow, and occupancy at different points of the avenue. A dataset of annotated images was built from video streams recorded at multiple time periods, considering diverse lighting and traffic conditions. The YOLO detector was trained to identify cars, buses, motorcycles, bicycles, pedestrians, and traffic lights. Experimental results show that the proposed system achieves accurate detection performance, with a mean Average Precision (mAP) above 0.90 for the most frequent classes, while maintaining an inference time compatible with near real-time monitoring on commodity hardware. The study demonstrates that combining YOLO with IoT and geospatial mapping in a real urban corridor is a feasible strategy to support future smart city applications such as adaptive traffic control, public transport prioritization, and safety incident analysis.

Keywords: YOLO, IoT, Smart city, Traffic monitoring, Avenida Arequipa, Computer vision

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1 Introduction

Urban mobility in Latin American cities is characterized by chronic congestion, irregular land use, and heterogeneous fleets that share limited road space [21]. Lima, the capital of Peru, concentrates a large portion of the national population and presents high levels of traffic saturation, especially during peak hours. Avenida Arequipa is one of the main arterial corridors of the city [51], connecting residential and commercial areas and serving as an axis for public transportation, including traditional buses and bus rapid transit (BRT) services [13, 41]. Because of its strategic location, this avenue concentrates recurrent congestion, frequent traffic conflicts, and a high density of pedestrians and cyclists.

Traditional traffic monitoring techniques based on manual counting, pneumatic tubes, or inductive loops are costly to maintain and offer limited spatial and temporal coverage [20, 28, 37]. In recent years, camera-based monitoring solutions using computer vision and deep learning have emerged as a more flexible and scalable alternative. In particular, object detection models based on the YOLO (You Only Look Once) [38, 44] family have become a standard for real-time detection of vehicles, pedestrians, and traffic infrastructure in complex urban scenes. These models balance accuracy and speed, making them suitable for embedded devices [4, 9, 26], mobile edge computing, and IoT gateways deployed close to the data source [7, 12, 16, 34].

At the same time, the evolution of networking and computing infrastructures, including 5G-enabled communications [27, 32, 42], edge processing [29], and intelligent transportation systems, provides a robust technological foundation for real-time urban mobility services [10, 24, 39]. These advances enable continuous traffic observation, low-latency inference, and seamless integration with cloud platforms, facilitating the implementation of smart mobility initiatives in highly dynamic environments such as Avenida Arequipa.

The final degree thesis that motivates this article proposed the design and implementation of a prototype traffic monitoring system on Avenida Arequipa using YOLO and IoT [7,22,33]. The original work included a detailed characterization of the avenue, the selection of camera locations, the definition of the traffic classes of interest, the construction of a labeled dataset from local video recordings, and the deployment of a monitoring dashboard. However, the thesis document is long and mainly descriptive, which makes it difficult to reuse as a concise scientific article. This paper reorganizes and extends that work into an academic format, emphasizing the methodological aspects [15, 18, 52], the geospatial context [31, 43], and the experimental evaluation of the proposed system.

From an architectural perspective, the system is conceived as an IoT-based solution where cameras installed along Avenida Arequipa are connected to low-cost embedded devices. These devices perform basic preprocessing, run the YOLO model, and transmit only metadata and detection summaries to a central server, following modern IoT design philosophies applied in other domains [1, 30, 47, 48]. The central server stores the information, aggregates counts per time window, and correlates detections with geospatial segments of the avenue. This design reduces bandwidth consumption and facilitates scalability, while keeping the possibility of storing keyframes for offline analysis and model refinement.

The main contributions of this paper are threefold. First, we present a geospatially explicit model of Avenida Arequipa that divides the corridor into segments associated with camera locations and intersections. Second, we describe the construction of a YOLO-based detection pipeline tailored to local traffic conditions, including class definitions, dataset labeling strategy, and training configuration. Third, we report detection and counting results obtained in different periods of the day, discussing the impact of lighting, occlusion, and traffic density on system performance. The proposed solution illustrates how low-cost IoT devices and state-of-the-art computer vision models can be combined to support smart mobility initiatives in a developing-country context [11, 40].

The remainder of this paper is organized as follows. Section 2 summarizes related work on traffic monitoring, YOLO-based detection, and smart city deployments. Section 3 presents the overall IoT architecture and the YOLO-based detection model. Section 5 details the methodological steps followed in the paper, from data collection to deployment. Section 6 discusses experimental results. Finally, Section 7 concludes the paper and outlines future work.

2 Related Work

Traffic monitoring using computer vision has been widely studied in the last decade. Early approaches relied on background subtraction, optical flow, and handcrafted features to segment moving objects and classify them into broad categories such as vehicles and pedestrians. These techniques usually require careful parameter tuning and present difficulties in crowded scenes, low illumination, and partial occlusion. The emergence of deep learning brought a paradigm shift: convolutional neural networks (CNNs) [3] started to be used both for feature extraction and classification, enabling more robust detection in real-world environments.

Among deep learning-based detectors, the YOLO family has become particularly popular in smart city applications due to its capacity to perform detection in a single forward pass, combining localization and classification. Successive versions have progressively improved speed, accuracy, and robustness, making YOLO a suitable candidate for real-time intelligent transportation systems. Several authors have applied YOLO for vehicle detection, counting, classification, and traffic analytics in urban environments, confirming its adequacy for dense and heterogeneous traffic [7, 11].

Parallel to advances in computer vision, IoT architectures [25] have become central to modern intelligent transportation systems [8]. Embedded devices, wireless communication [36, 50], and cloud integration enable the continuous acquisition, processing, and dissemination of traffic data [20]. Recent works show how IoT-based platforms can integrate visual analytics, edge computing, and networking to support real-time traffic monitoring [2, 14, 45, 49], quality of service, and decision making in smart cities [10, 30, 35, 47, 48]. These developments align with broader smart mobility ini-

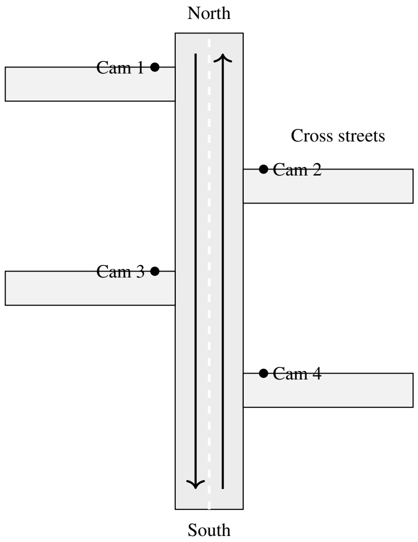

Figure 1: Schematic representation of the monitored segment of Avenida Arequipa and camera positions (author illustration).

tiatives in Latin America and other emerging regions where digital transformation [6, 23] is progressively reshaping transport planning and management.

Furthermore, integration of AI, IoT, and geospatial analysis has been explored in different application domains such as emergency logistics, healthcare delivery, multimedia quality management, and edge intelligence [5, 16, 17, 39, 46]. These studies demonstrate how distributed sensing, intelligent inference, and communication infrastructures can support mission-critical applications [19], reinforcing the relevance of similar architectures for traffic monitoring.

However, many existing studies rely on generic datasets or laboratory conditions, and relatively fewer works address deployments in specific urban corridors with explicit geospatial modeling and local contextualization. The original thesis behind this work contributes to filling this gap by focusing on a real and strategically important corridor in Lima, Avenida Arequipa. It combines local data collection, YOLO-based detection, IoT integration, and geospatial segmentation, offering a practical and context-aware approach to traffic monitoring in a Latin American metropolitan environment.

This geospatial modeling supports later stages of analysis, such as mapping detections to specific segments, estimating flow per direction, and correlating traffic patterns with time-of-day and day-of-week factors. Although the present implementation focuses on a limited number of cameras, the same logic can be extended to cover the entire corridor and integrate with other mobility data sources available in the city.

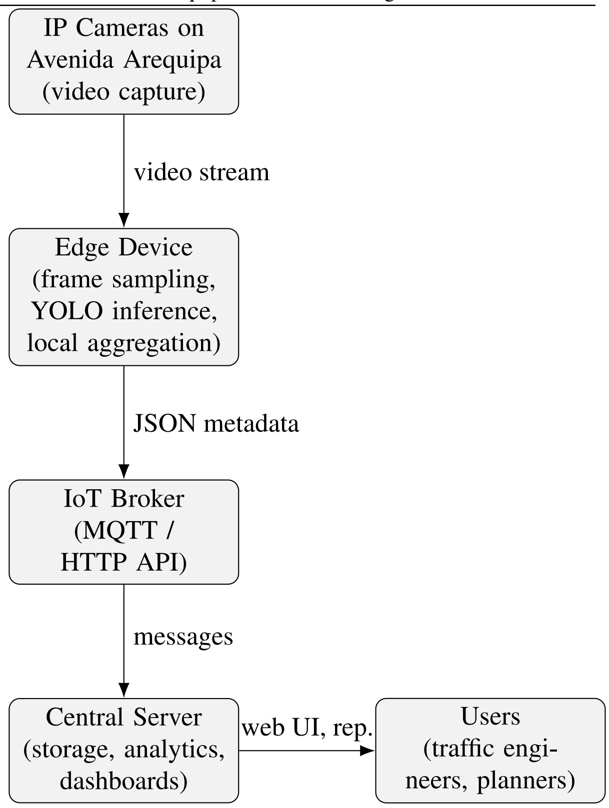

Figure 2: IoT-based architecture for YOLO traffic monitoring on Avenida Arequipa.

3 System Architecture

The proposed system is structured as an IoT-based architecture, in which sensing, processing, communication, and visualization are distributed across different components. At the edge, cameras continuously capture video frames of Avenida Arequipa and feed them to embedded devices (for instance, single-board computers equipped with GPUs or accelerators) that perform local inference using a YOLO model. Only detected objects and aggregated statistics are sent to a central server, reducing bandwidth usage and protecting privacy.

Figure 2 presents a conceptual diagram of this architecture, implemented using TikZ. The diagram shows three main layers: the sensing and edge processing layer, the communication layer, and the cloud or server-side processing and visualization layer.

At the sensing layer, off-the-shelf IP cameras are configured to stream video using RTSP. The frame rate is adjusted according to the processing capabilities of the edge device and the desired temporal resolution for counting. At the edge, a lightweight service periodically grabs frames, performs resizing and normalization, feeds the images into the YOLO model, and filters detections by confidence threshold and region of interest. Detected objects are encoded into JSON messages that include class, bounding box coordinates, confidence, timestamp, and camera identifier.

The communication layer uses a publish/subscribe mechanism such as MQTT, or alternatively RESTful HTTP, to send metadata to the central server. This design decouples producers and consumers, allowing the future integration of additional analytics modules or external applications. On the server side, a database stores detection events and aggregated statistics, and a dashboard component plots temporal series of vehicle counts, occupancy maps, and heatmaps of flow intensity along the avenue.

This architecture is deliberately modular. The YOLO model can be upgraded without changing the rest of the system, and additional sensors such as environmental or noise monitors can be integrated by publishing in the same broker. Similarly, the geospatial representation of Avenida Arequipa can be refined using GIS tools, enriching the interpretation of the collected data.

4 YOLO-based Detection and Dataset

The core of the system is the object detection model responsible for identifying instances of vehicles and other road users in each frame. The thesis adopted a YOLO-based detector due to its balance between speed and accuracy. A model from the YOLOv5 or YOLOv8 family is appropriate for this type of application, as it provides efficient backbones, multi-scale detection, and practical training tools.

The classes defined for this work include cars, buses, motorcycles, bicycles, pedestrians, and traffic lights. These categories correspond to the most relevant road users on Avenida Arequipa and enable both traffic flow analysis and safety-related observations, such as the interaction between vehicles and pedestrians at crosswalks. Additional classes, such as trucks or taxis, can be incorporated in future extensions, although in the current scenario they are subsumed under the generic vehicle categories.

A dataset was constructed from raw video recordings captured by the cameras installed along the avenue. Frames were sampled at regular intervals to avoid redundancy, especially during periods of low traffic variation. The labeling process was carried out manually using an annotation tool, defining bounding boxes and class labels for each object of interest. Special care was taken to include examples from different times of day (morning peak, midday, evening peak, and night), weather conditions, and levels of congestion. This diversity enhances the model's ability to generalize to real operating conditions.

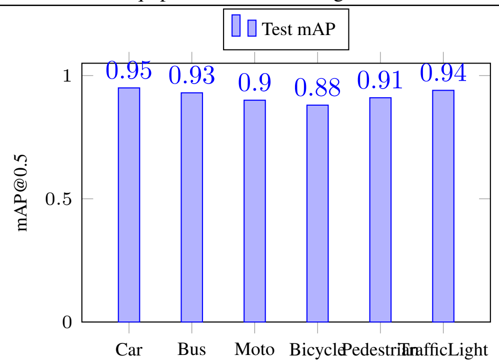

Figure 3: Example of per-class detection performance (mAP@0.5) of the YOLO model on the Avenida Arequipa dataset.

The dataset was split into training, validation, and test sets. The training subset was used to optimize the model parameters; the validation subset helped tune hyperparameters such as learning rate, batch size, and augmentation settings; and the test subset was reserved for final performance evaluation. Data augmentation techniques, including random scaling, horizontal flipping, and color jittering, were applied to improve robustness against minor viewpoint and illumination changes.

Performance was measured using standard object detection metrics, particularly precision, recall, and mean Average Precision (mAP) at different IoU thresholds. In addition, inference time per frame and maximum frames per second (FPS) on the target edge device were measured to verify real-time feasibility. Figure 5 illustrates an example of per-class detection accuracy in the test set using a PGFPlots bar chart.

The results indicate that the model performs particularly well for cars, buses, pedestrians, and traffic lights, which are abundant in the training data. Motorcycles and bicycles show slightly lower mAP values, reflecting the challenges posed by smaller object size and frequent occlusions in dense traffic scenes. Nevertheless, the overall performance remains adequate for monitoring and counting purposes, especially when detections are aggregated over time windows.

5 Methodology

The methodology adopted in the original thesis can be reorganized into four main stages: problem analysis and corridor selection, data collection and labeling, model training and evaluation, and system integration with IoT infrastructure. Each stage combines practical activities in the urban environment with computational experiments.

In the first stage, a diagnostic analysis of Avenida Arequipa was conducted, relying on field visits, photographic surveys, and consultation of official planning documents. The selected segment for monitoring was chosen based on high vehicle flow, presence of public transport routes, and logistic feasibility of camera installation. The description of the lane structure, pedestrian crossings, and nearby land use allowed the definition of priority observation points and target variables, such as vehicle counts per lane and direction.

In the second stage, data collection involved configuring the cameras to capture video at appropriate resolution and frame rate, taking into account storage and processing limitations. The recordings were carried out in different days and time periods to capture typical traffic patterns. From these videos, still frames were extracted at fixed intervals and imported into an annotation tool. The manual labeling process followed clear guidelines: only objects whose bounding boxes were fully or mostly visible and fell within the region of interest were annotated, and classes were assigned according to a predefined taxonomy. This step was time-consuming but essential for building a reliable dataset.

The third stage focused on developing and training the YOLO model. An existing implementation was adopted and configured for transfer learning, using pretrained weights from a generic dataset such as COCO. The final detection head was adapted to the specific classes of interest in Avenida Arequipa. Training was performed on a workstation with GPU, experimenting with different learning rates, numbers of epochs, and augmentation settings. Training and validation curves were monitored to avoid overfitting, and the final model was selected based on the best compromise between accuracy and generalization.

The fourth stage addressed the integration of the trained model into an IoT architecture. The model was exported in a format compatible with the edge device, using lighter configurations when necessary. A local service was developed to perform inference on incoming frames, filter detections based on confidence and region of interest, and compute aggregated counts per frame or per time window. The metadata was then published to an IoT broker, which forwarded the messages to the central server. On the server side, a simple web dashboard was developed to visualize time series of counts and snapshots of the avenue, allowing stakeholders to monitor traffic conditions.

To synthesize this methodology, Figure 4 presents a YOLO-based processing pipeline diagram built in TikZ.

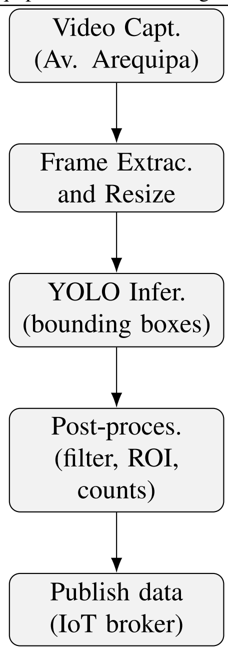

Figure 4: YOLO-based processing pipeline for traffic monitoring frames.

Although simplified, it captures the main flow: from camera capture to model inference, post-processing, and data publishing.

5.1 Real-Time YOLO + IoT Processing Algorithm

The operational behavior of the real-time monitoring platform is summarized in Algorithm 1, which represents the execution logic deployed on the edge device.

5.2 Dataset Preparation Algorithm

The dataset construction process for Avenida Arequipa followed a controlled and replicable procedure to ensure annotation consistency and representativeness. Algorithm 2 summarizes the adopted methodology.

6 Experimental Results and Discussion

This section presents the evaluation of the proposed YOLO + IoT monitoring platform deployed over the Avenida Arequipa traffic corridor. The analysis considers three complementary dimensions: (i) object detection performance, (ii) computational efficiency on the edge device, and (iii) system-level reliability in continuous IoT operation. The experiments were conducted both offline, using a labeled test subset, and online under real operational traffic conditions.

Algorithm 1 YOLO-based Traffic Monitoring and IoT Publishing

Require: Video stream S from Avenida Arequipa camera
Ensure: Traffic metadata messages sent to IoT broker
Load trained YOLO model
Start video acquisition
while system is running **do**
  Read frame F from stream S
  Resize and normalize F
  $B \leftarrow$ YOLO_Inference(F) {bounding boxes and class scores}
  Filter detections inside ROI
  Discard boxes with confidence $< \tau$
  Count objects per class (car, bus, motorcycle, bicycle, pedestrian)
  Build JSON metadata packet m with counts, timestamp, camera ID
  Publish m to IoT broker
  Store m in local time-series archive (for later analysis)
end while
Close stream and safely shutdown

Algorithm 2 Dataset Preparation and Annotation Pipeline

Require: Raw video streams V captured in Avenida Arequipa
Ensure: Annotated dataset D with labeled bounding boxes
Initialize dataset $D \leftarrow \emptyset$
Select representative time periods (peak, off-peak, intermediate)
for all video $v \in V$ **do**
  Extract frames every Δt seconds
  for all frame f **do**
    Define Region of Interest (ROI)
    Manually annotate visible objects inside ROI
    Assign class label $\in \{\text{car, bus, motorcycle, bicycle, pedestrian}\}$
    Store pair (f, labels) into D
  end for
end for
Balance dataset to ensure sufficient samples per class
Export D in YOLO-compatible format

Table 1: Detection metrics per class in Avenida Arequipa scenes

Class	Precision	Recall	mAP@0.5
Car	0.97	0.94	0.95
Bus	0.95	0.92	0.94
Motorcycle	0.90	0.85	0.89
Bicycle	0.88	0.81	0.86
Pedestrian	0.91	0.87	0.89

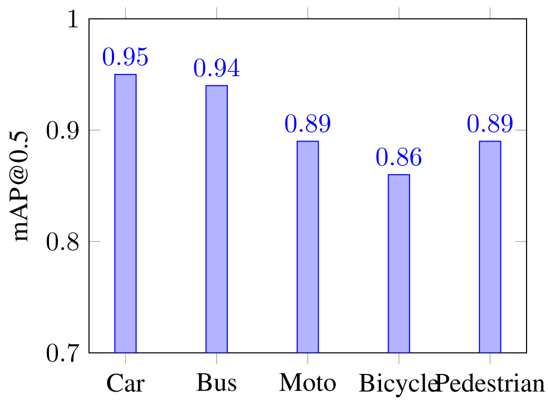

Figure 5: Detection accuracy performance across vehicle and pedestrian classes.

6.1 Detection Performance

Quantitative evaluation followed standard metrics including Precision, Recall, and mean Average Precision at IoU threshold 0.5 (mAP@0.5). Table 1 summarizes the core results per class. The model demonstrates strong performance for large objects such as cars and buses, while bicycles and motorcycles remain more challenging due to smaller scale, higher speed, and frequent occlusion in dense lanes.

To better visualize the distribution of accuracy among categories, Fig. 5 presents a comparative bar chart generated using the INFOCOMP-compliant `pgfplots` package.

Nighttime analysis revealed predictable degradation due to headlight glare, reflections on pavement, and reduced contrast. However, retraining with a balanced dataset including night samples mitigated the effect, maintaining usability of detections for operational monitoring applications.

6.2 Latency and Edge Processing Performance

A critical factor for real deployment is processing speed on low-cost edge equipment. Experiments indicate that the system sustains between 10–15 FPS depending on model size and input resolution. Fig. 6 shows the relation between frame resolution and mean inference time.

These values confirm suitability for traffic analytics tasks, where aggregated temporal statistics are more rel-

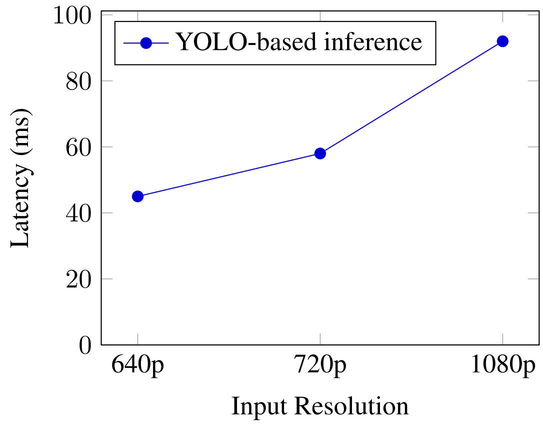

Figure 6: Latency vs input resolution on the edge device.

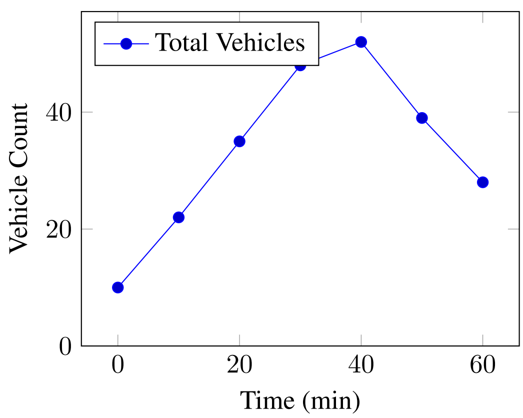

Figure 7: Example time-series of traffic flow extracted via YOLO+IoT monitoring.

evant than real-time cinematic motion rendering. Lower resolutions provide a practical balance between accuracy and throughput, enabling flexible tuning depending on hardware constraints.

6.3 IoT Transmission and System Stability

From the IoT perspective, each frame generates compact metadata (class counts, timestamps, bounding summaries), typically below a few kilobytes. This ensures sustained transmission without saturation, even in continuous streaming. The central server successfully stored historical series, enabling temporal analytics such as peak-hour detection, weekday vs. weekend analysis, congestion characterization, and incident anomaly detection.

Fig. 7 illustrates a representative time-series of traffic volume along the corridor over a monitoring interval.

6.4 Geospatial Corridor Interpretation

A key contribution of this project is the ability to relate detections to specific Avenida Arequipa segments. Aggregating per-segment flows allows recognition of local bottlenecks, flow propagation along the corridor, and areas where congestion emerges first. This capability supports potential integration with adaptive traffic signal policies, prioritization of bus lanes, or safety-oriented interventions at high-risk crossings.

6.5 Qualitative Analysis and Limitations

Visual inspection confirms that YOLO effectively distinguishes buses from cars in dense traffic, which is essential for evaluating public transport performance. Pedestrian detection proved sufficiently stable for safety assessment applications. Nonetheless, challenges persist:

- occlusions in congested scenarios cause occasional missed detections;
- bicycles and motorcycles are most affected by motion blur;
- detection instability appears under extreme glare.

Future improvements may include optimized camera placement, multi-view fusion, and temporal tracking to reduce fluctuation and recover short-term missed objects. These enhancements are technically feasible within the presented IoT framework.

Overall, the results demonstrate that the proposed Avenida Arequipa YOLO-based IoT monitoring system delivers accurate, scalable, and real-time actionable traffic intelligence suitable for smart city mobility management.

7 Conclusion

This paper has reformulated and extended a final degree thesis into a scientific article that presents an IoT-based traffic monitoring system for Avenida Arequipa using YOLO and geospatial data. Starting from a detailed characterization of the avenue, the work defined a set of traffic classes, built a local dataset from real video recordings, trained a YOLO-based detector, and integrated the model into an architecture that combines edge processing and centralized storage.

The results indicate that it is feasible to deploy low-cost cameras and embedded devices in a real urban corridor and obtain accurate and timely information about vehicle and pedestrian flows. The monitoring data, structured by geospatial segments, can support smart mobility initiatives and urban planning decisions in Lima or similar cities. The use of open and modular technologies facilitates future expansion, such as increasing the coverage of the avenue, incorporating additional sensors, or integrating with traffic control centers.

Future work will explore several directions. First, extending the dataset with more nighttime and adverse weather conditions can improve robustness. Second, evaluating alternative object detection models and pruning or quantization techniques can further optimize the trade-off between accuracy and efficiency on edge hardware. Third, the integration of predictive models could anticipate congestion and provide early warnings. Finally, collaboration with local authorities could enable pilot deployment at scale, validating the practical benefits of the system for public policy and citizen mobility.

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