SSRG International Journal of Civil Engineering
ISSN: 2348-8352/ https://doi.org/10.14445/23488352/IJCE-V13I7P111

Volume 13 Issue 7, 176-194, July 2026

Original Article

Automatic Vehicle Counting in Complex Traffic Zones Using Computer Vision: A Case Study in the City of Huancayo

Rosali Ramos Rojas[1], Giancarlo Fernando Meza Terbullino[1*]

[1]*School of Civil Engineering, Universidad Continental, Huancayo, Perú.*

[*]*Corresponding Author : gmezat@continental.edu.pe*

Received: 20 April 2026 Revised: 10 June 2026 Accepted: 22 June 2026 Published: 29 July 2026

Abstract *- The analysis of road traffic is fundamental for obtaining reliable information about itself. This paper presents Automatic Smart Vehicle Counting System – Intelligent System (CONTEV-SYS), a framework of a vehicle counting system developed in Python, employing YOLO v8n and the OpenCV library. A mixed method approach was adopted. Initially, a survey in the Likert scale was applied to 40 specialist identified the most extensive processing methods, errors in the data, and the impact in the weather as critical barriers of the traditional manual traffic counting system. Later on, a quantitative validation was carried out in nine vial scenarios, where different circulation patterns are presented in the city of Huancayo, comparing the system with a careful and accurate manual counting system. The results show that the CONTEX-SYS system has an average estimation efficiency of 89.40%, a Mean Absolute Percentage Error (MAPE) of 10.60%, reaching a maximum of 96% in scenario number 5, with a conservative behavior, that is, reducing the false positives in the severe occlusion case ($R^2 = 0.921$). The system attain a high precision in the vehicle classification, standing out the identification of heavy vehicles. In terms of operation, it saved 49.49% processing time, ensuring that the analysis was carried out in strict real-time. Finally, its implementation results to be highly promising in the field of civil engineering, particularly in the specialties of transportation and traffic.*

Keywords *- Vehicle detection, Vehicle counting, Road, Deep learning, Graphical user interface.*

1. Introduction

A counting and classification process of vehicles that are precise is indispensable for getting reliable information about road traffic [1]. This information is employed, lately, in the management of efficient traffic, as well as in urban planning. Besides, robust traffic studies are a previous requisite for building new roads [2] because they permit to propose designs of infrastructures that are more efficient and sustainable [3]. On the other side, smart counting of vehicles is important for the traffic control in real time on the highways [4]. The traditional method for vehicle counting is the manual one; nonetheless, this approach requires too much labor, and it is prone to significant errors [5].

To address these deficiencies, the automated systems are now modern research centers. There are two methods that employ deep learning, like YOLOv8, for identifying vehicles from photographic material or video material in real time [6]. Additionally, other advance techniques were employed, like vehicle segmentation, with the purpose to generate high-precision counting [7, 8]. In spite of these advances, two critical gaps persist. In the first place, many of these technologies re redeveloped and validated mainly in the north hemisphere, with very few studies that can confirm their efficiency in Latin-American environmental or infrastructural contexts because they are unique [9]. In second place, the performance of any system-based vision system depends on the scenario of implementation in a critical manner. These situations makes necessary the identification of the optimal geometric and environmental conditions for an efficient performance [10].

Although computer-vision methods have improved the speed and precision of vehicle counting, their practical application in complex urban traffic zones remains a challenge. Recent studies have demonstrated the effectiveness of YOLO-based systems for vehicle detection, tracking, counting and traffic-flow management under urban conditions, achieving high levels of accuracy and real-time performance [11-13]. The majority of existing systems have been validated in ideal or highly specific road test scenarios with stationary cameras and distinct lane separation and vehicle movement. These conditions are distinct from those in Huancayo, where the mixed traffic, road geometry, frequent occlusion, lighting conditions and non-uniform traffic may impact detection, tracking and counting accuracy. Thus, the gap in the literature is not only in the implementation of YOLO based vehicle-counting models in the context of the Andes in Latin America, but also in the determination of the geometric, environmental and operational conditions where the system can perform reliable operation. To enable traffic studies with automated tools that are faster, more consistent, and applicable to local road infrastructure, it is necessary to address this gap.

In this paper, the following shortcomings are examined, and the Automatic Smart Vehicle Counting System – Intelligent System (CONTEV-SYS) is presented, which is a framework that is being developed using the tools Python, YOLOv8 and OpenCV [14]. The approach is based on three general principles: Vehicle detection, Movement tracking, and Trajectory processing, which was shown to be feasible to achieve a high efficiency in the traffic studies [15]. The framework is designed for offering flexibility, being able to process both pre-recorded videos and live streaming coming from fixed cameras or Unmanned Aerial Vehicle (UAV) [16]. It leverages the capacities of YOLOv8n and OpenCV for recognizing vehicles in movement, confirm the detection, and register the counting when these cross the predefined limit [17, 18].

The main purpose of this research is to identify and characterize the necessary conditions that are needed in order to apply the CONTEV-SYS system with maximum efficiency and minimum time of execution. Thus, the CONTEV-SYS system is subjected to mathematical trials in nine road scenarios of Huancayo city, Peru, with the objective of this system. This research contributes to the fields of transportation and traffic engineering, as well as the geometric design on roads [19], because of extending the practical knowledge based on programming for analyzing the traffic [20]. The results no only validate the CONTEV-SYS system, but also provide tangible guidelines for its implementation, offering valuable data for future research about vehicle capacity, road deterioration, and regional infrastructure planning.

The novelty of this study is not just using a YOLOv8n and OpenCV-based vehicle counting system, but also testing the conditions under which this system functions effectively in complex urban traffic regions. In contrast to previous works which had focused their work primarily on improving accuracy and robustness of the vehicle detection under the specific technological configuration and environmental conditions [21, 22], this study deals with nine real road scenarios in Huancayo, Peru, taking into account geometric, environmental and operational factors which are directly affecting the system performance.

So the relevance of this work is twofold: firstly, it is the validation of the CONTEV-SYS framework in a Latin American Andean urban environment, and secondly, it is the practical contribution of the criteria for the selection of appropriate implementation conditions for AVC in traffic engineering studies.

For better conceptual clarity, the following standardizations are made on the technical terms used throughout this study. Average Daily Index (ADI) is the estimated number of visits to the site per day, which is calculated during the counting session. Average Daily Weekly Index (ADWI) and Annual Average Daily Index (AADI) are wider traffic indicators needed for more accurate projections over the longer term. Peak Hour (PH) refers to the time of the day when most traffic demands occur, and Hourly Peak Factor (HPF) refers to the fluctuation in traffic during that peak time. For the computer-vision part, the Region of Interest (ROI) is the region of the image on which the vehicle detection and counting is carried out. The statistical indicators used for validation include Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), coefficient of determination (R^2), estimation efficiency and reliability percentage.

1.1. Related Work

The counting methods of vehicles based on video are gaining more relevance in all of Latin America, and the researchers are developing diverse approaches adapted to local traffic conditions. In Mexico, for instance, León et al. [23] employed a system of devices that were installed in the traffic lights with the purpose to detect and classify vehicles, managing extracted data in a PostgreSQL database in order to design strategies for the reduction of traffic [24]. In Chile, the research made by Farias et al. [1] has leveraged from the Deep learning models, a solution that is distinguished by the use of video transmission to remote serves for their processing.

In Peru, the efforts focused on improving the traffic management in urban centers like Lima (Peru’s Capital city). The investigation of Chavez [25] introduced an automatic counting system that classified parked vehicles utilizing adaptive Gaussian mixed models. This research determined that the counting efficiency can also be improved by employing computational techniques in clusters [26]. In the same way, to address severe traffic congestion in Bogota, Colombia [27], a counting and classifying system for vehicles were developed based on convolutional neural networks with the aim to propose solutions for the optimization of traffic flow.

Although these investigations exhibit a clear trend towards the adoption of advanced computational techniques in the region, the most common shortage is the lack of attention paid to the systematic evaluation of how specific conditions of implementation (like the camera’s placement, road’s geometry, and environmental factors) influence in the performance of the systems. This research addresses these deficits, presenting a common counting framework that is efficient, based on YOLOv8n and OpenCV, and characterizing the ideal scenarios for their application.

The methodological underpinnings of the present study include some key breakthroughs in the field of deep learning and object detection. The foundation of extracting hierarchical visual features from images was laid by convolutional neural networks, and the ability of real-time localization and classification of objects in complex scenes was provided by modern object-detection architectures like Faster R-CNN, SSD and YOLO. These developments enabled the transition from traditional image-processing and background-subtraction methods to real-time vehicle detection, tracking and counting in traffic monitoring. Despite the strong performance demonstrated by recent systems based on YOLO, however, there has been little documentation of the system's transferability to urban settings in Latin America. So the role of CONTEV-SYS is not only to implement a detection model, but also to validate the geometric, lighting and traffic-flow operational performance in real conditions in Huancayo.

2. Materials and Methods

This investigation will focus on the analysis of video data obtained from static cameras. These cameras were placed in strategic locations with a constant plan orientation of 45° in respect to the roadway plane with the purpose to guarantee a clear and standardized perspective of the traffic flow [28]. The video transmission was recorded for their later analysis and processing.

The process of developing the CONTEV-SYS system was done by an iterative approach followed the Scrum methodology that allowed the construction of an initial functional prototype and its evolution and improvement in successive improvement sprints, addressing specific challenges that created different scenarios of the road. For handling dynamic traffic scenarios, the vehicle detection algorithm was designed, using the vision of the YOLO8vn and OPENCV that allowed the detection of vehicles in motion and the assurance of reliable detection in various recording conditions [29].

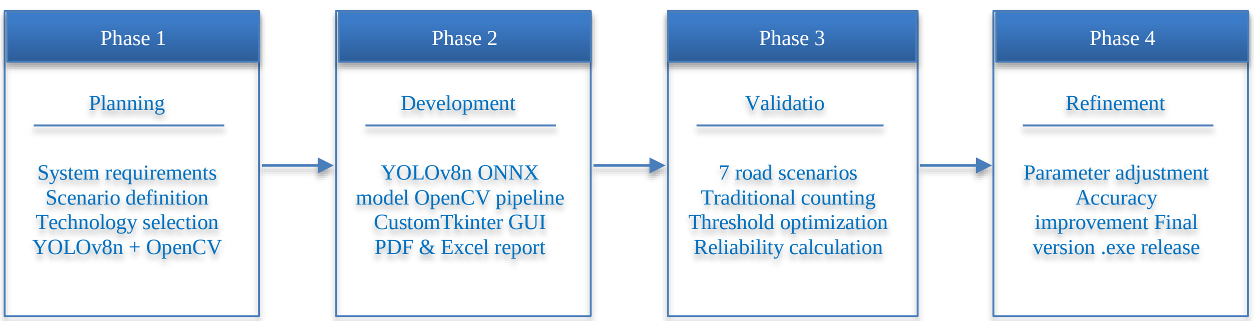

Fig. 1 CONTEV-SYS system development methodology based on Scrum

Table 1. Hardware and software specifications

Component	Specifications
Camera	Smartphone iPhone; 48 MP main sensor (f/1.79), 8 MP wide-angle (f/2.2), stabilized on a 1.40 m metallic tripod.
Programming Language	Python 3.12
Core Library	OpenCV (latest version); used for real-time computer vision tasks.
Detection Model	YOLOv8n in ONNX format; used for vehicle detection through OpenCV DNN.
Graphical Interface	CustomTkinter; used for the development of the desktop graphical user interface.
Ground Truth Tool	Manual tally counter; used for manual vehicle counting to validate the system's accuracy.

2.1. System Components and Setup

The components of the hardware and software that were employed are detailed in Table 1. The camera of a Smartphone was chosen because of its high resolution and the ease of its use, while a tripod guaranteed a stable recording of the scenarios. For the detection of the vehicles, the YOLOv8n model was integrated into the ONNX format, processed through the OpenCV DNN, altogether with a graphic interface of a desktop user developed in CustomTkinter. With the aim to validate it, a manual counting device was employed in order to stablish the reference in the process of counting vehicles.

2.2. CONTEV-SYS System Architecture

The scheme of the system CONTEV-SYS is illustrated in Figure 2. The system processes video photograms for obtaining a final counting of vehicles. The scheme can be divided in four stages:

- Video input: fixed camera provides recorded videos in situ or live transmission, which are processed with the aim to guarantee the conditions of uniform tests.

- Image processing module: employing YOLO v8n and OpenCV for each flow photogram of the video, two key operations were performed: vehicle detection, the ONNX model of the YOLO8vn identifies the vehicles in movement, generating a limiting box for each detection. Vehicle tracking: the system processes the identified objects, assigning a unique ID for each one, and follows a trajectory through consecutive photograms.
- Control and counting module: The trajectory data (ID and position) of each vehicle is transmitted to this module. The user predefines a virtual counting line within the photogram through the graphic interface of the desktop user.
- Results: The final counting stages are shown in real time through the user's graphic interface and are later exported as a PDF report at the end of the session.

2.3. Development Methodology

An Initial Functional Prototype of the CONTEV-SYS was built, and it was later progressively enhanced though continues modifications based on performance evaluations in real contexts. This flexible methodology based on Scrum is common in the development of modern software [18], and allowed a quick adaptation of specific challenges that posed different traffic scenarios. The physical materials numbered in Table 1 were employed for the acquisition of data in the nine established scenarios, while the programming components were employed for the system implementation.

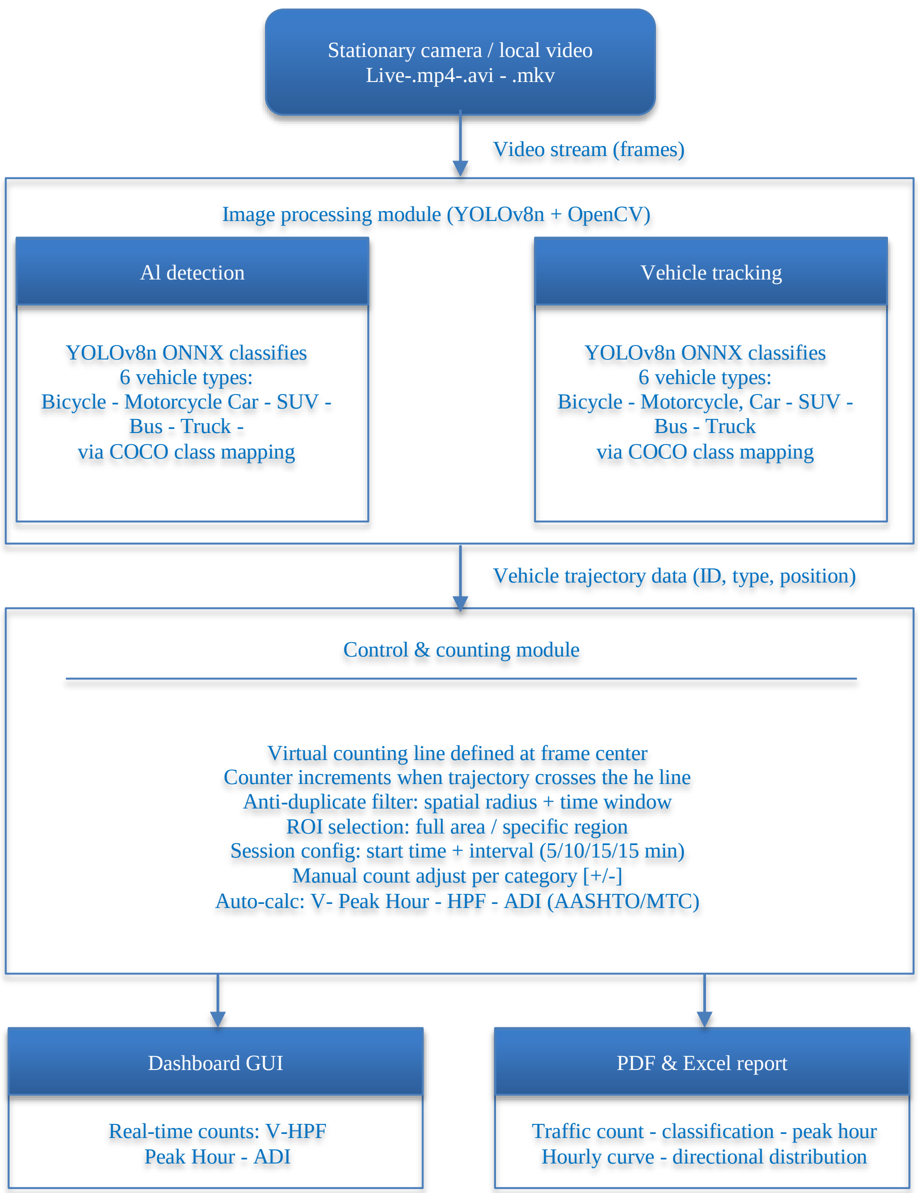

Fig. 2 System architecture of the proposed CONTEV-SYS framework

2.4. Experimental Scenarios

With the objective to validate the performance of the CONTEV-SYS system and identify their optimal operative conditions, data were extracted from a group of nine real situations in the main roads in Huancayo (Peru). All the videos were recorded by employing an iPhone mounted on a tripod of 1,4 m. The specific characteristics of each scenario are detailed in Table 2. The nine scenarios represent the typical traffic conditions in Huancayo. Figure 3 exhibits a visual representation of these nine scenarios.

Table 2. Description of video recording scenarios

Scenario	Height (m)	Location / Description	Figure
Scenario 1	9.5	View from the Tambo Norte pedestrian bridge	Figure 3a
Scenario 2	2.4	View from the UNCP pedestrian bridge (north view)	Figure 3b
Scenario 3	10.1	View from the UNCP pedestrian bridge (south view)	Figure 3c
Scenario 4	7.05	Two-lane road segment (Quebrada Honda)	Figure 3d
Scenario 5	8.1	Downhill road segment (Quebrada Honda south)	Figure 3e
Scenario 6	-	Lateral road segment (Lateral Giraldez)	Figure 3f
Scenario 7	-	Downhill road segment (Quebrada Honda north)	Figure 3g
Scenario 8	-	East road segment (Lateral Giraldez East)	Figure 3h
Scenario 9	-	West road segment (Lateral Giraldez West)	Figure 3i

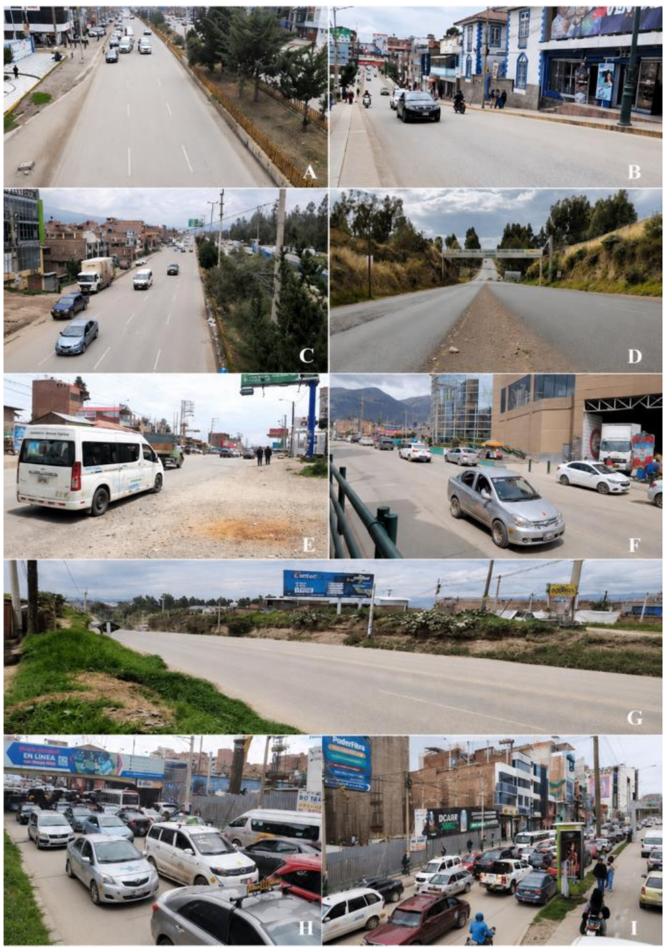

Fig. 3 Graphical representation of the nine test scenarios evaluated in the city of Huancayo. The details of each scenario are described in Table 2

2.4.1. Analysis of Scenario Conditions

The analysis of the system performance in these nine different contexts revealed that the scenarios offered an elevated and unobstructed view of the roads, which provided more precise vehicle counting. Specifically, it was determined that the conditions presented in Figures 3a, 3b, and 3c, as well as the views from the pedestrian bridge, were adequate for attaining a high efficiency.

These optimal scenarios share key characteristics:

- Clear line of sight: the camera was placed at a sufficient height for avoiding the obstruction among vehicles.
- Ordered traffic flow: the vehicles tend to circulate in well-defined lanes without frequent or erratic movements.
- Uninterrupted segments: the supervised zone is a long section of the road without intersections, traffic lights, or other elements that can make the vehicles to stop or accumulate.

The results herein support that the recording context of the geometry configuration is a significant aspect of successful counting systems for vehicles using vision.

2.5. Vehicle Detection

Figure 4 depicts the welcome interface of the system CONTEV-SYS developed through CustomTkinter. CustomTkinter is broadly used in vision computer projects because of its capacity to build modern graphic interfaces on Python. The landing page permits the users to select the source of the video: live camera (streaming) or a local file (.mp4), which allows the system to invoke OpenCV for the capture and processing of photograms for vehicle counting. Figure 5 exhibits the counting and detection process of vehicles in real time. OpenCV processes each photogram of the video flow and passes it to the YOLOv8n ONNX model, which labels and determines a unique ID, simultaneously classifying six vehicle categories: bicycles. motorcycles, automobiles, pickup trucks, busses and trucks. The right panel represents the total counting for each category, with controls [+] and [−] that permit the user to adjust the counting process manually in the case of a correction in the field. The PDF and EXCEL buttons in the superior bar for exporting the results.

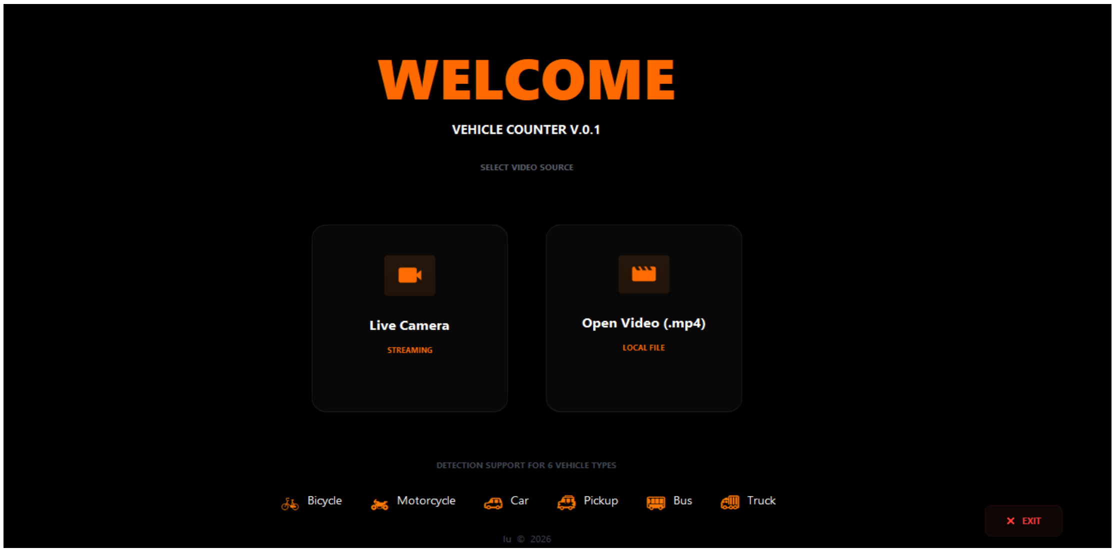

Fig. 4 CONTEV-SYS system welcome interface

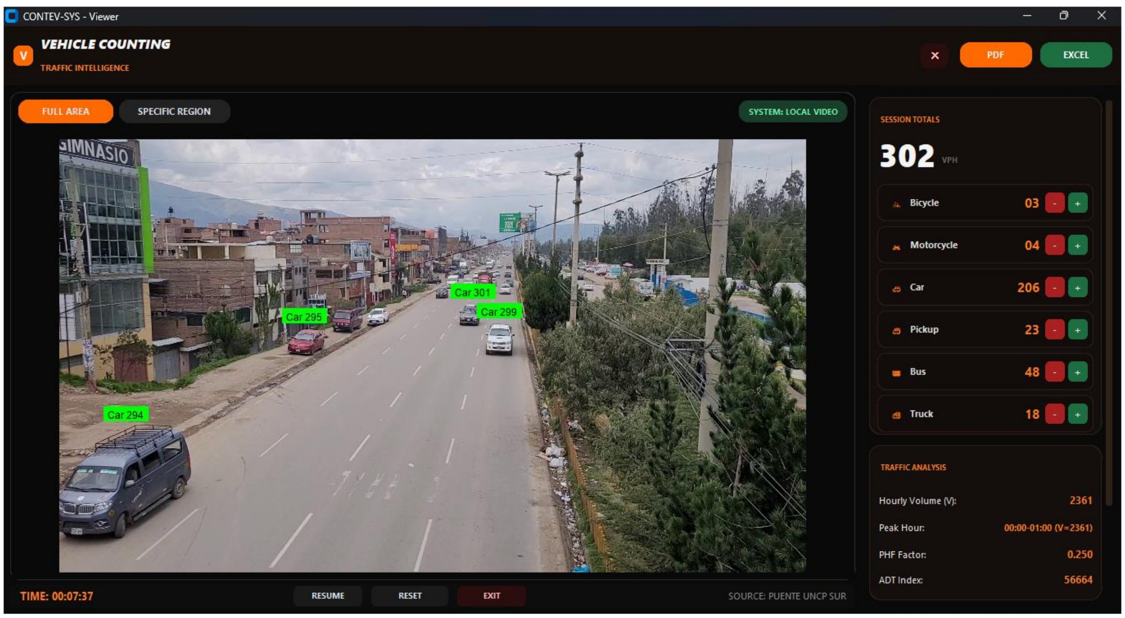

Fig. 5 Real-time vehicle detection and classification using YOLOv8n and OpenCV

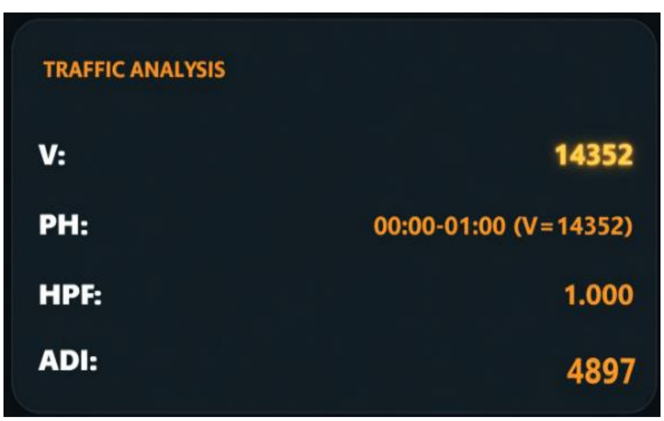

Fig. 6 Traffic Analysis Panel: Hourly Volume, Peak Hour, HPF and ADI

Figure 6 depicts the traffic analysis panel, which presents the four fundamental indicators for the road design in real time: Hourly Volume (V), Peak Hour (PH), Hourly Peak Factor (HPF), and Average Daily Index (ADI), calculated automatically according to the AASHTO/MTC based on the accumulated counting in the session.

Figure 7 exhibits the Session Configuration module, which allows the user to define the start time and the counting interval, which is configurable in 5, 10, 15 minutes or a specific one before starting to count the traffic. These parameters determine the granularity of the temporary record and are the base for calculating the Hourly Peak Factor (HPF) and the Average Daily Index (ADI) according to the approach determined by the MTC.

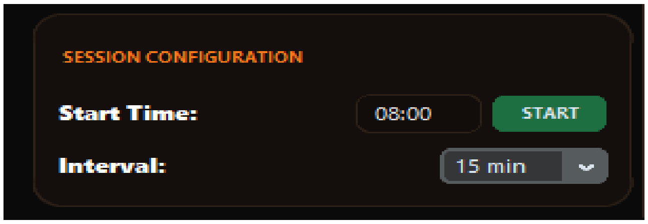

Fig. 7 Session configuration module: Start time and count interval

Figure 8 exhibits the Interactive selection of the Region of Interest (ROI) that is activated through the Specific Region button, where the user draws a polygon with the mouse over the lane in which the vehicle counting will be made. OpenCV employs this region as a mask over the photogram, restricting the processing only in the delimited lane, which permits to reach the independent capacity limits by lane in roads with multiple lanes and with different direction flows.

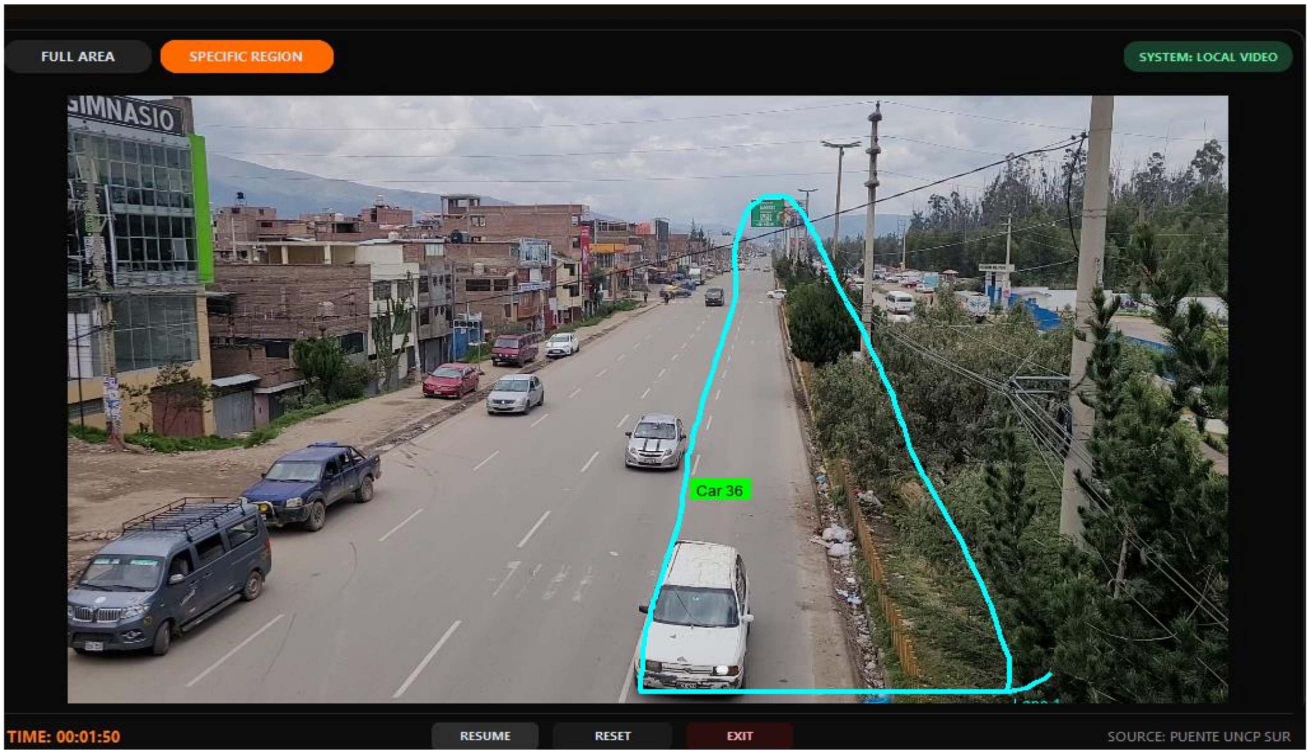

Fig. 8 Interactive selection of ROI per lane

Lastly, it automatically creates technical reports of vehicle counting as per the AASHTO/MTC approach for report generation when clicking on the PDF and Excel buttons, which include the Maximum Hourly Volume (V), Hourly Peak Factor (HPF), Average Daily Index (ADI), and Peak Hour (PH) disaggregated by intervals. Similarly, Vehicle Volume graphics as well as the directional distribution are provided, complementing the analysis and being ready for integration with technical files and microsimulation models.

2.6. Ground-Truth Annotation and Statistical Validation

The ground truth vehicle counts were manually collected using a traditional method that involved counting all vehicles counted in each recorded video, which is widely used to get reference traffic data and validate vehicle volume estimation methods [30]. Vehicles crossing the countable predefined virtual counting line were counted and categorized in the same manner as done with CONTEV-SYS (bicycles, motorcycles, automobiles, pickup trucks, buses and trucks). A manual count was used as the benchmark since it enabled the direct comparison of automatic output to an observed traffic condition in each of the videos. Manual counting was checked using recorded material to minimize the biases in the annotation process, and the questionable cases due to occlusion or overlapping trajectories were examined on a frame-by-frame basis.

To validate the statistical data, a comparison was made between the manual count and the CONTEV-SYS count in the 9 road scenarios according to the procedure widely used to validate automated counting systems against the manually collected reference data [31]. Absolute difference, relative Error, Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), estimation efficiency and reliability percentage were the main indicators. Besides, linear correlation analysis and coefficient of determination (R^2) were used to investigate the relationship between automatic and manually collected counts. To aid in the interpretation of the average Error and reliability values, confidence intervals were included. It was possible to assess not only the overall system accuracy, but also its stability for other geometric and operational traffic conditions during the procedure.

2.7. Ethical Considerations and Privacy Protection

This study adhered to ethical and professional practices for traffic video data collection and use. In line with recent AI-based traffic monitoring methods emphasizing vehicle detection and classification while maintaining data privacy [32, 33], he recorded videos were only employed for vehicle counting and classification purposes. The system did not use facial recognition, personal identification, or license-plate recognition, nor attempt to identify drivers, passengers, or pedestrians. Only vehicle types and traffic features needed for engineering purposes were covered. This is also consistent with the existing intelligent traffic surveillance systems based on privacy-preserving data processing and analysis of urban mobility using aggregated traffic information [33, 34]. Moreover, only academic and technical processing of the videos was done for the validation of the CONTEV-SYS framework.

As for the specialist survey, the survey was voluntary, and all respondents were addressed with regards to the academic objective of the study. No sensitive personal data was collected by the survey, nor was it analysed on a personal level. For this reason, the research minimised any risk to privacy and kept the participants' and road users' confidentiality.

3. Results

3.1. Qualitative Evaluation of Traditional Counting Limitations

With the purpose of contextualizing the necessity of methodological optimization, the perception of the simple of the analysts with experience in traffic engineering (N = 40) was evaluated through the employment of the Likert scale questionnaire. The outcomes corroborated critical operative deficiencies in the traditional manual vehicle counting process.

AS it is detailed in Figure 9, the “processing time”, “Time-consuming”, and the “frequent data errors” accumulated most of the mentioned frequencies. These findings validate that the temporary factors and the human reliability constitute the main operative barriers of the traditional method. Additionally, the “weather impact” was identified as a factor that promotes data loss and the cancellation of studies. Simultaneously, a discrepancy was identified between the manual limit capacities and the demands of modern engineering. As observed in Figure 10, the 86% of the specialists indicated that their microsimulation and planning models require analytical precision equal to or superior to 90%. Nonetheless, the inherent errors to manual vehicle counting compromise the standard constantly, which stabilized the need to transition towards solutions based on deep learning.

3.2. Quantitative Validation of the CONTEV-SYS System in Complex Traffic Scenarios

After recognizing the necessity of automation, the CONTEV-SYS was subjected to empirical evaluation in nine road scenarios. The performance of the algorithm was contrasted numerically with the control database that was obtained through exhaustive manual counting. The analytical results are consolidated on Table 3.

The system reached an efficiency of global estimation of 89.40% and a Mean Absolute Percentual Error (MAPE) of 10.60%, values that represent a competitive performance for complex traffic zones. The descriptive analysis reveals that the system tends to undercount instead of generating false positives, which reduces the introduction of erroneous data in the empirical base. This deviation was corroborated by the RMSE of 26.57 vehicles per scenario, which is attributable to mainly the severe occlusion phenomenon in rush hours.

The consistency of the models are exhibited in Figure 11. The linear regression analysis between the predictions of the system and the real traffic volume depicts a coefficient of determination $R^2 = 0.921$, which demonstrates that the system maintains its predictive capacity in a stable way, independently of the volume and the geometric complexity of the scenario.

Table 3. Evaluation of the accuracy of vehicle counting and overall error metrics of the CONTEV-SYS system in nine complex scenarios

Escenario	Manual counting	CONTEV-SYS	Absolute difference	Relative Error (%)
scenario 1	276	224	52	18.84
scenario 2	191	171	20	10.47
scenario 3	182	151	31	17.03
scenario 4	163	139	24	14.72
scenario 5	192	184	8	4.17
scenario 6	281	250	31	11.03
scenario 7	201	183	18	8.96
scenario 8	257	244	13	5.06
scenario 9	275	261	14	5.09

Note. MAPE = 10.60%, RMSE = 26.57 Vehicles, Efficiency= 89.40%

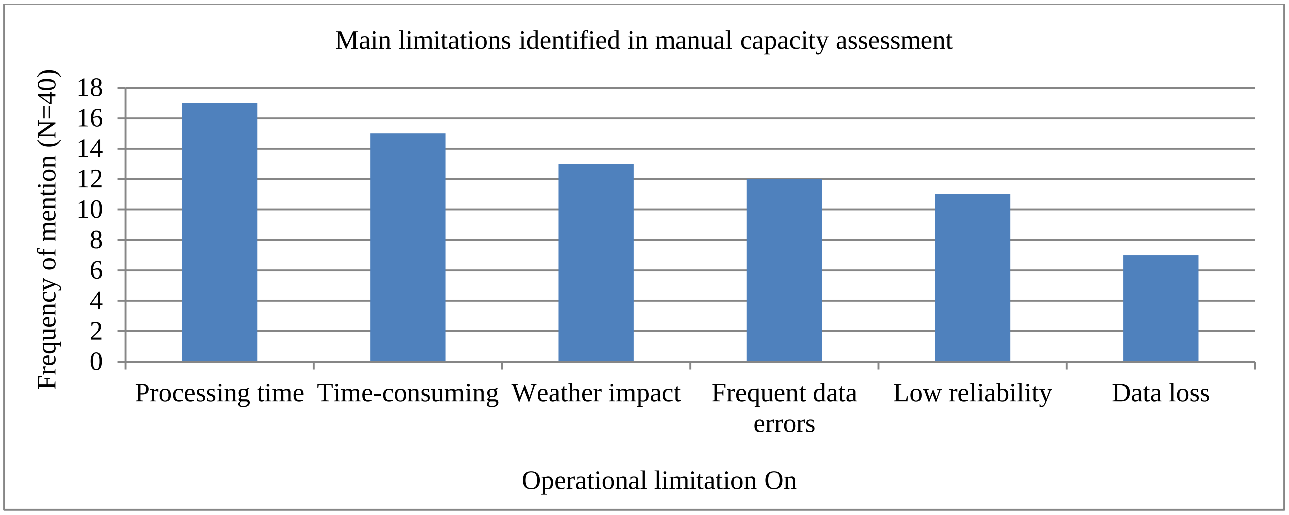

Fig. 9 Main operational limitations perceived in manual traffic counting

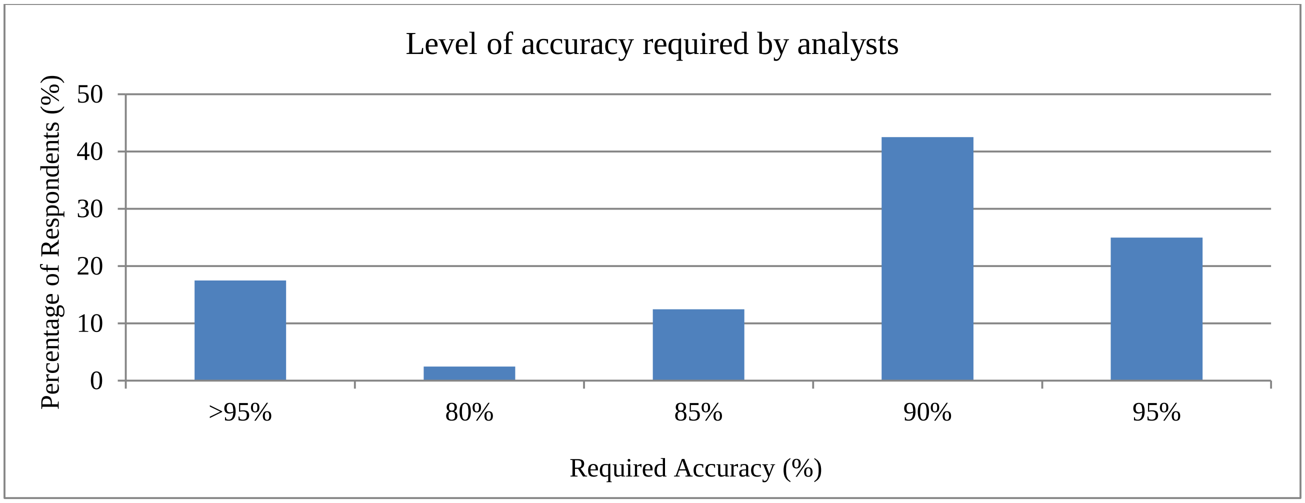

Fig. 10 Level of analytical accuracy required by traffic engineering specialists

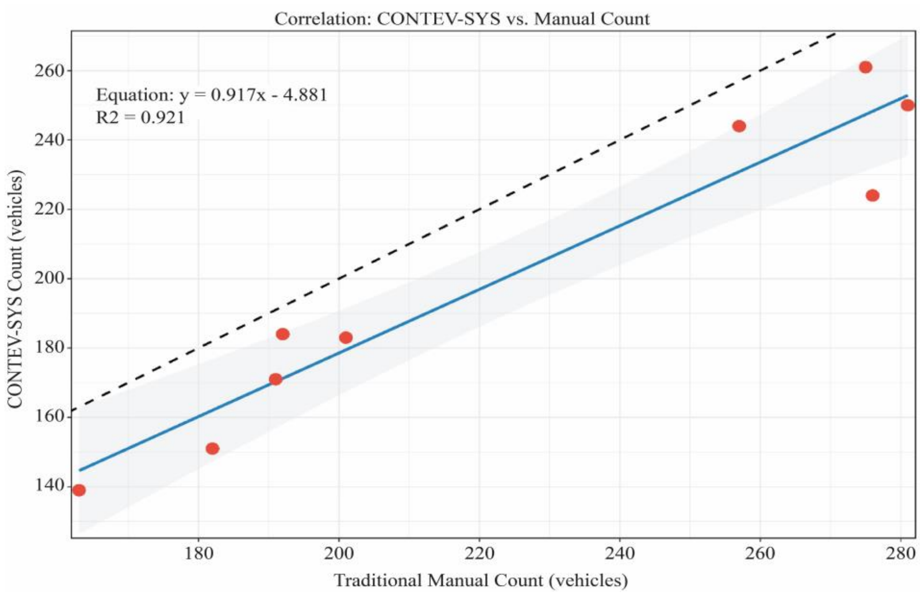

Fig. 11 Correlation analysis and metric validation: Predictions of the CONTEV-SYS model versus traditional manual counting (Ground Truth)

3.3. Vehicle Classification by Type

Besides to the total counting presented in Table 3, the CONTEV-SYs system classifies the detected vehicles in six categories: bicycles, motorcycles, automobiles, pickup trucks, buses, and trucks. Table 4 presents the breakdown of types of vehicles of scenario 9 (West Giraldez), selected because of concentrating the higher vehicle diversity of the dataset, where the manual counting registered 275 vehicles and the CONTEV-SYS 261 system.

Table 4. Count breakdown by vehicle type - Scenario 9 (West Giraldez)

Vehicle Type	Traditional Counting	CONTEV-SYS
Bicycle	3	2
Motorcycle	12	11
Automobile	185	177
Pickup truck	32	30
Bus	26	25
Truck	17	16
Total	**275**	**261**

The classification results in Scenario 9 provide additional evidence about the behaviour of CONTEV-SYS by vehicle type. The highest absolute difference was observed for automobiles, with eight missed detections out of 185 manually counted units, which is expected because this category represented the largest share of the traffic flow.

However, the category of bicycles had the largest percentage difference due to a small sample size and a smaller visual area in the frame. The differences in classification for heavy vehicles were, however, less marked, with a single misclassification for 26 buses and a single misclassification for 17 trucks.

The outcome is applicable in civil engineering applications as heavy vehicles affect the pavement deterioration more than light vehicles, have increased structural demands and affect on road design parameters.

Therefore, although the system showed a general undercounting tendency, its performance was more stable for vehicle categories that are most relevant for infrastructure assessment.

3.4. Reliability Estimation by Scenario

The analyzed videos were examined through the traditional counting approach and later compared with the CONTEV-SYS counting system.

The percentage of reliability was determined by using the traditional counting system as a reference for the nine analyzed videos. The reliability calculation formula is shown in Equation (1). Table 5 exhibits the results of the reliability calculation.

$$\%Reliability = \frac{CONTEV-SYS}{Traditional} \quad (1)$$

Table 5. Reliability in different scenarios

Tests	% de Reliability
Scenario 1	81%
Scenario 2	89%
Scenario 3	83%
Scenario 4	85%
Scenario 5	96%
Scenario 6	89%
Scenario 7	91%
Scenario 8	95%
Scenario 9	95%

The first scenario depicted a low reliability, while the higher reliability rate of 96% corresponds to the road videos of Huancayo city, in scenario 5, because it presents the most adequate characteristics, like a continuous flow of vehicles.

3.5. Operating Time Results

Table 6 compares the processing time of both approaches. While the manual method required up to 18 minutes per video, the CONTEV-SYS system kept a constant time of 7 minutes, which is equivalent to the real duration of the event (1:1 ratio), representing an average saving of 49.49%.

Table 6. Comparison of processing times and operational efficiency gains by scenario

Tests	Traditional Counting Time (minutes)	Time Count by CONTEV-SYS (minutes)	Ahorro (%)
scenario 1	**17**	7	58.82
scenario 2	**14**	7	50.00
scenario 3	**13**	7	46.15
scenario 4	**10**	7	30.00
scenario 5	**11**	7	36.36
scenario 6	**18**	7	61.11
scenario 7	**15**	7	53.33
Scenario 8	**16**	7	56.25
Scenario 9	**15**	7	53.33

Note. 49.49% of the global average time saving

The execution time, in relation with the counting time of the proposed system, is obtained through equation 2. The traditional counting approach is employed as a reference for determining the real rate of time with the automatic system approach.

$$\%\ Real\ Time\ Rate = \frac{Count\ time\ CONTEV-SYS}{Time\ Traditional\ Counting} \quad (2)$$

The outcomes of the real-time rate are exhibited in Table 7. From these findings, it could be observed that the traditional time rate increases in a direct proportional way to the complexity of the scenario because it is also affected by the number of vehicles [6]. When the scenario is more complex, it takes longer to do the counting process. One plausible explanation is the high density of the traffic on the roads: the road intersections generate a source of continuous disorder in the flow and the illumination problems due to weather changes and the geography [35]; therefore, this makes the manual counting approach to be difficult.

Table 7. Real-time rate

Tests	Traditional Real Time Rate	Real Time Rate CONTEV-SYS
scenario 1	41%	100%
scenario 2	50%	100%
scenario 3	54%	100%
scenario 4	70%	100%
scenario 5	64%	100%
scenario 6	39%	100%
scenario 7	47%	100%
scenario 8	44%	100%
scenario 9	47%	100%

Table 8. Cost breakdown of the integrated CONTEV-SYS system implementation

Component	Cost USD
Smartphone Iphone	3500
Trípode metálico 1.40 m	28
Computadora (i5, 8GB RAM)	400
Software (Python, YOLOv8n)	0
PyInstaller (.exe)	0
Costo total	3928.00

3.6. Implementation Cost

The economic viability of the CONTEV-SYS system represents a significant advantage for its application in traffic studies in cities with limited technological resources. The implementation of the system requires a conventional computer, a camera of a mid-range Smartphone, and a tripod, while the employed software is a totally an open source one.

The system was packed as a portable executable (.exe) using PyInstaller, which eliminates the necessity to install Python and other dependencies on the computer of the end user. Table 8 depicts the details of the implementation costs of the system.

3.7. Application in Civil Engineering

In the Civil Engineering application, the obtained data helped to get a starting point in the DG-2018-MTC [36]. This standard is indispensable for road design in Peru because it brings the types of roads and road infrastructures regarding the number of vehicles that are found through the software. When starting the tests, the software unveiled a superior computational efficiency, finding matrixes about the vehicle quantity of 40%, this reflects that the software provides a time reduction compared to the manual conventional methods, as it can be observed in Figure 6, providing data instantly. This precision ensures that the simulation models reflect the behaviour of the vehicle flow in an exact manner. Therefore, the tool is represented as a robust resource that maximizes the technical productivity of the study and minimizes the uncertainty in mobility diagnosis. This data was later compared to the conventional counting process, seen in Figure 11, having an approximation of 90% due to the fact that the conventional counting approach and the software did not contemplate the adequate standard because of either a wrong configuration or either because of an absence of personal training, according to Abdali et al. [37] The outcomes give optimum values in the critical parameters in the rush hours (higher vehicle traffic). In the rush hour, according to what was observed in the field, is where the high risk of accidents over pedestrians is generated, being the 90% of light vehicles that ones that generated chaos and adding 10% of the accident rates, according to Kennedy et al., [38] El programa fue diseñado con el objetivo de automatizar el cálculo de la capacidad vial y niveles de servicio, con la finalidad de acortar el tiempo de dicho proceso. Esto podemos reflejar en la Tabla 9. Tan solo al tener el (ADI), podríamos estar calculando de manera preliminar un ancho de carril o el tipo de calzada a construir respecto a su demanda vehicular.

Table 9. Description of video recording scenarios

Description	Annual Average Daily Traffic (AADT/IMDA)	Divided Roadway by Median	# of Lanes	Min Lane Width
First Class Freeway	> 6000 veh/day	6.00 meters	>2	3.60 meters
Second Class Freeway	6000 < IMDA < 4001 veh/ day	6.00 meters < S < 1 .00 meters	>2	3.60 meters
First Class Freeway	4000 < IMDA < 2001 veh/ day	------	2	3.60 meters
Second Class Freeway	2000 < IMDA < 400 veh/ day	------	2	3.30 meters
First Class Freeway	< 400 veh/ day	------	2	3.00 meters
Second Class Freeway	< 200 veh/ day	-------	-------	4.00 meters

The software permits to identify or verify rush hours through configurations according to the time. This is very adequate data because, in the conventional methods, it would be necessary to perform the back-office process and verify the vehicle quantity found in specific hours, according to Mohana et al., [39]. All the authorization software is in constant update; thus, the CONTEV-SYS software could be complemented with data related to vehicle pollution, and then obtain a more robust research that not only studies the infrastructure, nut also the environmental impact.

In Table 9, the estimated vehicle demand is depicted, which constitutes the base for the design and execution of the proposed road infrastructure. According to the obtained results, the lane is classified as a Second-class Freeway because the software determined an (IMDA) = 4897 vehicles/day.

$$IMD = \frac{\sum V}{n}$$

Where:
ADI: Average Daily Index.
V: Vehicles circulating in a determined time.
n: Time period.

Based on this value, the corresponding normative analysis was performed, which establishes the necessity to implement a divided roadway, incorporating a central separator of 6.00m, with the purpose to improve the safety road and to optimize the traffic. Likewise, the standards demand the minimum number of two lanes per direction, and considering the report vehicle volume reported by the software, a transversal section is needed with lanes with a width of 3.60 m, permitting to an adequate handling of the vehicle flow without affecting the capacity nor the service level of the lane. With the obtained data, the next step is to acquire the Average Daily Weekly Index (ADWI) and the Average Daily Annual Index (ADAI)

$$IMDs = \frac{V_L + V_M + V_M + V_J + V_V + V_S + V_D}{7}$$

$$IMDA = IMDs * FC$$

Where:
ADWI: Average Daily Weekly Index
ADAI: Average Daily Annual Index
FC: Seasonal Adjustment.

Subsequently, the Weekly Average Daily Index (ADI) was calculating, acquiring an average value of 4179 vehicles/day, data that, along with the maximum volume registered, constitutes an essential parameter for the determination of the Hourly Peak Factor (HPF). These conditions are reflected in the existing infrastructure because the Mariscal Castilla Avenue currently has two lanes that meet the minimum needed dimensions for handling the calculated demand. Finally, the applied methodology and the obtained results are supported by the Hourly Peak Factor (HPF), a parameter defined in the Highway Capacity Manual (HCM), the one that permits to evaluate the variation of the vehicle flow during maximum demand.

$$FHP = \frac{V}{4 * V_{15}}$$

Where:
V: Hourly Volume.
V15: 15-minute interval with the most traffic.

HPF > 1: Indicates that traffic volume during peak hour is greater than the daily average.

HPF ≈ 1: Means traffic volume during peak hour is similar to the daily average volume.

HPF < 1: Indicates that volume during peak hour is less than the daily average (less common).

The traffic analysis permitted to determine that the rush hour occurs between 7:00 a.m. and 8:00 a.m., a period in which a higher vehicle flow is observed mainly due to the related displacements triggered by the start of the school activities (preschool, primary, secondary), as well as the entry to higher education centers and the labor sectors of the public or private spheres. During this Schedule, a total of 326 vehicles was registered, being this volume being the highest in all the evaluated days. That value represents the most critical condition for the road capacity analysis.

Finally, when applying the corresponding formula, an HPF = 3.02 was obtained, which indicates that the vehicle flow during the maximum demand hour is considerably superior to the registered daily average.

In Figure 12, can be seen the incidence over the number of registered vehicles in 24 hours; the HPF value is based on the studied rush hours. This theory is demonstrated in Figure 12, where the peak hours are from 06:00 am – 08:00 am. This is also the time in which the traffic increases the most, with more intensity if the flow of light vehicles (public transportation). Another higher point is in the interval between 11:30 am to 14:00 pm. This is manifested with the same light vehicle flow or public transportation. The last peak house is from 05:00 pm to 07:00 pm, and then the traffic reduction occurs, and traffic decreases due to the work schedule.

What can be observed is that the biggest data collection occurred on the lateral sides of each lane, while the collection in the middle lane is lower. The premise of these characteristics is due to the presence of a higher education that is nearby that zone, as well as the surrounding houses; hence, they had a bigger participation.

Figure 13 exhibits how the vehicle flow in three lanes is distributed along the entire day. It can be observed that none of the lanes dominate in a constant way, but the participation of each of them changes as time passes, which is normal in lanes that have demand variations, overtaking maneuvers or lane changes.

During most of the day, the three lanes maintain relatively close values, moving in ranges of approximately 0.25 to 0.40. This exhibits that the traffic is distributed in a relatively equitably manner and does not solely concentrate in one lane.

Lane 1 presents moderate variations during almost all of the period, but its participation increases in the evening-night, especially from 19:00 to 20:00, where it surpasses 0.40 and even depicts a peak near to 0.60. This might happen because the demand increases in that Schedule and the drivers tend to use this lane because it is faster and more direct.

Lane 2 is the most stable, having a range of values of 0.30 to 0.40. However, in the middle of the day, a higher concentration of vehicles is noted at the intermediate hours (around mid-morning and the first few hours of the afternoon), and therefore, this lane attracts the maximum vehicle flow, possibly due to the merging of the traffic stream or due to the even distribution of the traffic.

The lane 3 depicts a more irregular behavior in the morning, with values relatively high when it's close to 07:00 am, but then it tends to stabilize at around 0.30. At night, its participation decreases slightly, which suggests that during high congestion hours, the vehicles prefer to move forward more utilized lanes with the purpose to keep their speed.

In Figure 14, the curve of the schedule variation for the total volume permits to clearly visualize how the traffic changes along the day. It can be observed how the vehicle flow does not remain constant, but it presents marked increases in specific schedules, which reflects the typical behavior of an urban lane with a high daily activity.

This study identified a strong increase in the morning, approximately from 7:00 a.m. to 8:00 a.m., where the volume reaches its maximum values. This increment is associated mainly with the start of the work and school day because it is in these schedules where the displacements towards the educational centers, institutions and job zones are concentrated. The first peak is followed by a significant reduction in volume from 8 am until 11:30 am, and then a period of relatively low and stable volumes, suggesting a lower level of vehicle demand. Subsequently, at around noon and the first hours of the afternoon (approximately from 12:30 p.m. to 1:30 p.m.), the highest peak of the day is registered, reaching the highest registered value of all the curve. This behavior can be explained by the traffic combination generated by the partial exists from the job activities, displacements for having lunch or commercial movement in the evaluated zone.

Finally, a third important increase is observed in the afternoon hours, approximately from 5:30 p.m. to 6:30 p.m., which corresponds to the return of the population towards their houses. After this period, the volume decreases progressively again as time reaches the night, reaching minimum values at the end of the evaluated Schedule.

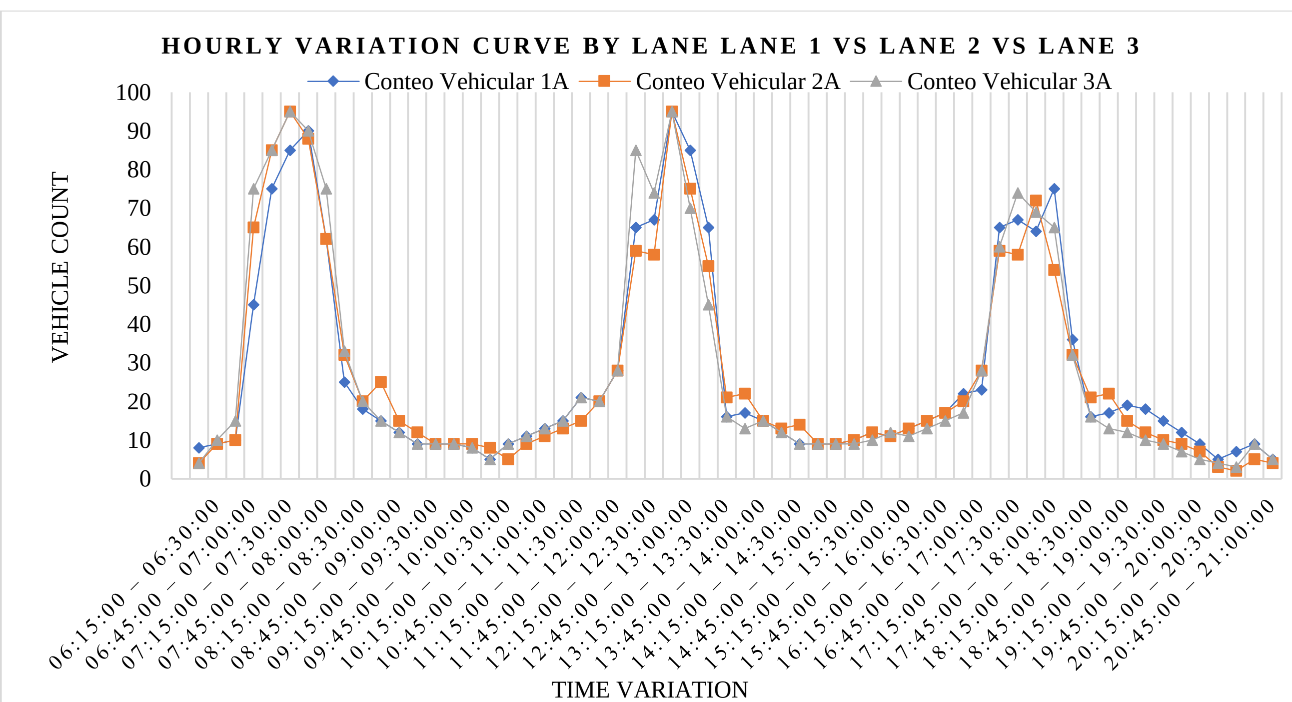

Fig. 12 HvsC variation curve "C-1, C-2, C-3"

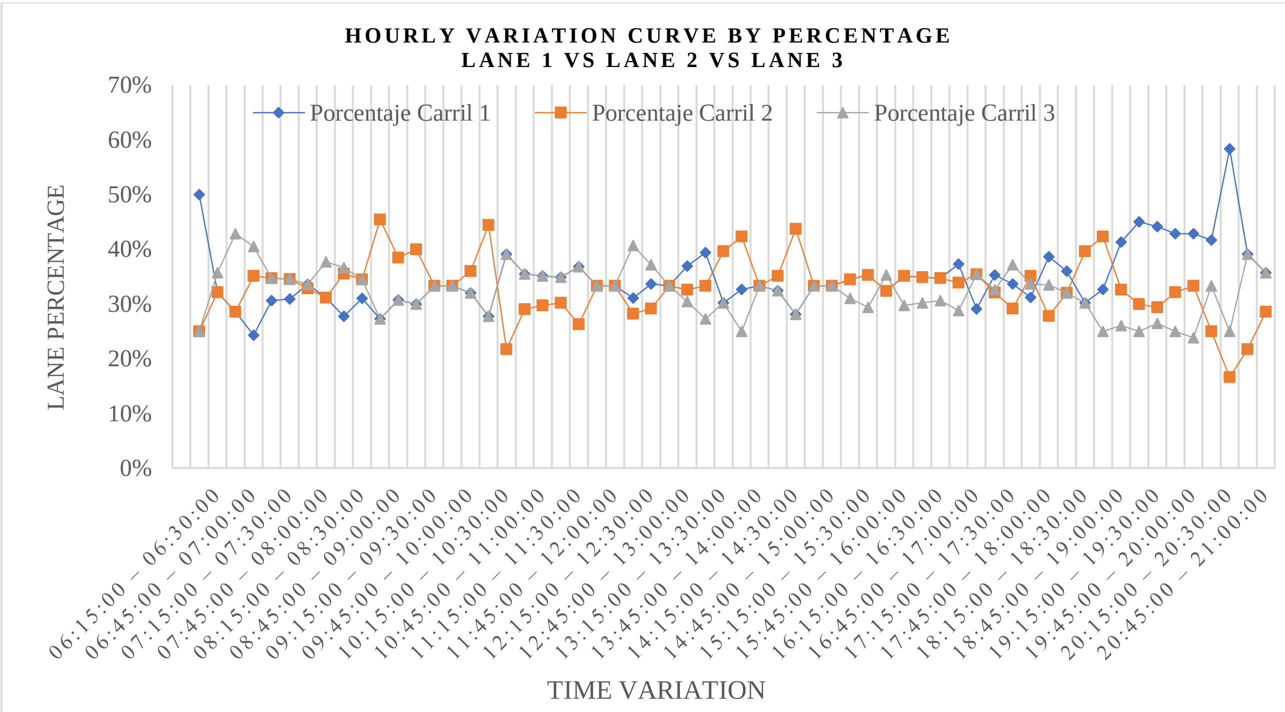

Fig. 13 HvsP variation curve "C-1, C-2, C-3"

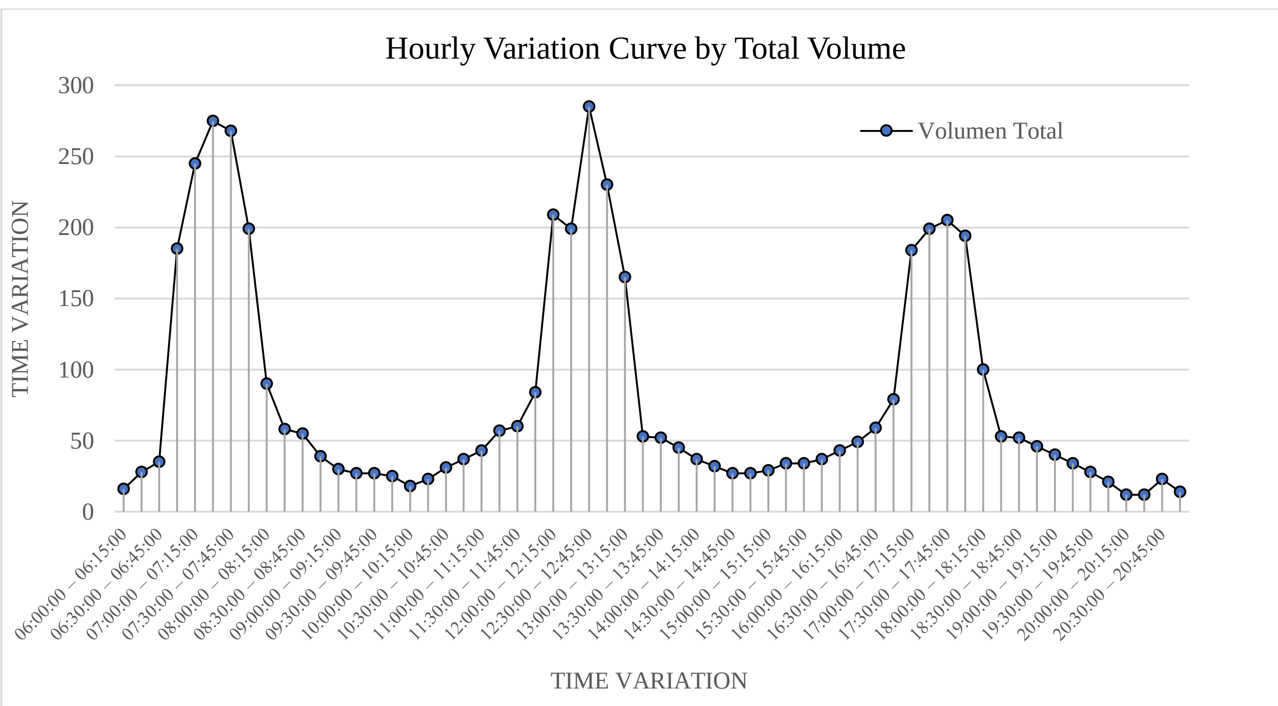

Fig. 14 Total volume variation curve "C-1, C-2, C-3"

4. Discussion

These results indicate that CONTEV-SYS is able to estimate the efficiency of the road, with an average of 89.40% in Huancayo, and a maximum of 96% under favourable conditions. This performance is comparable with other studies [6, 35] that have used a single CCTV camera for the task, reporting accuracy ranging from 80% to 98%, and a reliability of near 90%, respectively. As a result, the results it yielded are seen to be a reliable measurement for preliminary traffic analysis and road infrastructure planning at an acceptable level.

The competitive performance of CONTEV-SYS relative to systems reported in the past can be attributed to algorithmic and field-implementation issues. It is used as YOLOv8n ONNX through OpenCV-DNN, which provides the balance between detection accuracy and speed, and the detection can be done in real time without relying on specific GPU hardware. Second, a fixed camera position, a stable tripod and a predefined counting line was adopted in the experimental setup, thus the random variation during vehicle tracking was reduced. Thirdly, the selection of ROI proved useful in narrowing the scope of the analysis to the appropriate traffic area, minimizing background noise, and consistency in the counting procedure. Ultimately, the most successful scenario was a geometry that was favourable, and the environment was conducive to continuous flow, proper lighting and less occlusion. This is why, while the overall average efficiency was reduced in more complex scenarios with intersections, multilane and vehicle occlusion, CONTEV-SYS was able to reach up to 96% reliability in optimal cases.

The level of counting accuracy was highest when the road conditions were best, i.e. there was uninterrupted traffic flow, sufficient light, good visibility and little vehicle interference. The system was, however, less effective when the geometric complexity of the roads increased (e.g. when roads had more than two lanes and intersections). These conditions are the factors of vehicle occlusion and decreased count accuracy, consistent with Song et al., [4] that found the factors of congestion and complex traffic flow reduce count accuracy.

In terms of processing speed, CONTEV-SYS achieved real-time operation for all cases evaluated. This is important since when the processing time rate is equal or below 100%, the video can be analysed in real time and instant traffic information can be provided [7]. So the system has an important advantage over manual counting, which saves processing time and enables the traffic information to be available.

One of the main advantages of CONTEV-SYS is its implementation with the OpenCV library, the model YOLOv8n and the ONNX format. The combination makes vehicle detection and counting possible within proper computational efficiency and does not need special hardware like GPUs. The result is in line with Datondji et al., [40], who noted that computer vision-based approaches are known for their high processing speed and minimal hardware requirements. Likewise, this kind of approach has been shown to be feasible in previous research, e.g., Gupte et al. [41]. For cities with developing technological infrastructure, CONTEV-SYS can be seen as a pragmatic and accessible option.

In spite of these benefits, the performance of the system will be greatly affected by its implementation conditions. One of the key factors impacting reliability was vehicle occlusion in dense traffic situations, where the system can miss a vehicle. This deficiency has been addressed in recent years using tracking methods like Deep SORT [42] that incorporate appearance measures for tracking vehicle identity when occlusion occurs. Perspective distortion, which can be attributed to the camera angle and the variation of vehicle pixel size, can also cause the vehicle centroid to shift and create errors in counting. This one has been seen as a challenge of scale invariance in vehicle detection studies [43]. Therefore, future versions of CONTEV-SYS should integrate more robust tracking and perspective-normalisation algorithms.

Another relevant limitation is the system's dependence on adequate illumination. Low-light conditions reduce detection accuracy and limit night-time operation. This agrees with Premaratne et al. [44], who indicated that poor illumination considerably affects the performance of most vision-based traffic monitoring systems. Considering these limitations, the CONTEV-SYS reached an average efficiency of 89.40% and a maximum reliability of 96% in ideal conditions, incorporating YOLOv8n through OpenCV, an evolution of the Bochkovskiy et al.[45] principles, this permits to reach a higher precision in a wider range of scenarios. Therefore, CONTEV-SYS offers a sufficient reliability for practical applications in daily planning and an implementation cost that is radically lower than that is a decisive factor in the context of cities with limited resources, like in Huancayo.

Practicality, CONTEV-SYS can be helpful in getting the Average Daily Index (ADI) for initial traffic studies. This kind of information gives an initial estimation of traffic volume and helps make initial decisions on road design, according to Khan and Rishe et al. [46]. However, the software's range of application is still somewhat constrained as it only calculates the Average Daily Index (ADI), and not other indexes, yet like the Weekly Average Daily Index (ADWI) or the Annual Average Daily Index (AADI). As noted by Muñoz et al. [47], these are required for more comprehensive and representative traffic studies.

CONTEV-SYS is also applicable in the area of public investment and management of road infrastructure. Vehicle counting tools can play a significant role in helping to manage traffic in municipalities and regional governments, as noted by Battal et al., [48]. Similarly, when reviewing projects, the use of reliable traffic data can help minimize the project review processes required by the Multi-year Investment Programming framework and OPMI guidelines [49]. Thus, CONTEV-SYS shall be able to help prepare and validate technical files for road projects.

But the quality of the video that is captured is an important factor. As mentioned by Hayauchi et al. [50], it is necessary to use a stable energy source, to have a good camera resolution, and to properly fix the camera. The lack of these conditions can lead to a loss of vehicles or incorrect vehicle count as reported by Wilczewski et al. [51]. This problem can arise when cameras are mounted on poles, bridges or structures that are subject to wind or vibration. Thus, proper camera positioning and stable image acquisition are critical for reproducible outcomes.

Having the vehicle increase at a national and district level as a premise, and considering, specifically, the Mariscal Castilla avenue in Huancayo-Tambo as a strategic point related to the vehicle increment in Huancayo; through the raw data collection performed by personnel, it will be subjected to Error and chaos, according to Othman et al. [52].

The use of CONTEV-SYS along Mariscal Castilla Avenue resulted in a significant increase of vehicle circulation compared to the previous years. Previous studies reported ADI values of 806 vehicles/day [53], 971 vehicles/day [54], and 1837 vehicles/day [55], while the present study obtained an ADI of 4897 vehicles/day. This increase indicates that the road currently has a greater traffic demand than was taken into account for previous pavement evaluations. This has meant that the enhanced traffic volumes could be a factor for early deterioration of the pavement, particularly since the road work done in 2021 was intended to last for 20 years.

In general, CONTEV-SYS is a low-cost, efficient and practical solution for initial vehicle count in urban road applications. The principle benefits of this are that it is processed in real time, doesn't require manual counting, is less susceptible to human Error, and has a reliability that is acceptable in favorable conditions. However, there is scope for future developments to include night-time detection, occlusion handling, camera stabilisation, perspective correction, and the addition of further traffic indicators (ADWI, AADI, ESAL) to further enhance the use of this in road design, pavement assessment and infrastructure planning.

The relative Error was on average 10.60%, with a rough 95% confidence interval of (6.46%, 14.73%). The results are compared to the recent vision-based traffic monitoring frameworks, which focus on counting reliability and robustness in real traffic, with an average reliability of 89.40% and an approximate 95% confidence interval of [85.27%, 93.54%] [46], which is similar to the results reported here. The paired comparison analysis between manual and automatic counts revealed a systematic undercounting tendency, and this was attributed not to an overcounting of traffic but rather to a conservative behavior of the system in occlusion conditions.

5. Conclusion

This investigation has proven through success the implementation and effectiveness of the CONTEV-SYS system in the vehicular counting process in the city of Huancayo. By leveraging YOLOv8n and the OpenCV library, the system offers an efficient solution for traffic supervision in critical routes, validated through a survey with a Likert scaled applied to 40 experts that confirmed the long processing times, human errors and the impact of the weather as a critical barrier of the traditional manual vehicle counting process. The results exhibit that the system reached an average estimated efficacy of 89.40% and a maximum precision of 96% in favorable conditions, as observed in Scenario 5, characterized by visibility without obstacles, continuous flow, and good illumination. Besides, the analysis showed that the image capturing process at a 45-degree angle enhances the counting precision. Despite the fact that CONTEV-SYS offers significant advantages regarding processing speed and reduces the vehicle counting time by 49.49% compared to the traditional manual approach, it still has limitations that are closely related to the night conditions. Future development should have to aim to overcome these limitations by the integration of headlight matching techniques, allowing the traffic track throughout the 24 hours of the day. día.CONTEV-SYS offers an indispensable tool for road infrastructure project planning. It can be at the beginning of the Project by the data collection process as part of the evaluation itself because the evaluators and inspectors of local governments or municipalities can employ this tool with the objective to validate collected data by the plant personnel that in in charged of the vehicle counting process.CONTEV-SYS is an adequate tool for road projects and the preparation of technical files because it fulfills the main requisite stablished by INVIERTE.PE, which manifests the close of gaps related to the state resources. With its operation-counting vehicle system, unbeatable results compared to the conventional approach can be obtained. In future updates, this software could estimate real-time damage, it could provide traffic study for road projects, such as ESAL, and it can also help with the road design and rigid or flexible pavement design. The software, CONTEV-SYS, validated a general estimation efficacy of 89.40%. This performance is consistent with what was reported by Bui et al [35], who stablish precision ranges between 82% and 98% for systems based on just one camera, and it is aligned with a reliability of 90%, which is mentioned by Dai et al [35]. In the Mariscal Castilla Avenue, the system identified that the vehicle flow is distributed evenly among the three lanes during most of the day (ranges from 0.25 to 0.40). Nonetheless, a trend is observed among the drivers to choose a certain lane from 06:00 pm. For higher speed maneuvers, a certain lane is chosen from 07:00 pm onwards. This increment implies to place speed controllers or speed bumps that help to mitigate future accidents because this is a busy area and traffic accidents are latent. Through the implementation of the CONTEV-SYs software, this will be a determinant factor for the success of the preliminary analysis because this system helps to identify the characteristic parameters of the Highways Geometric Design. The software helps, in a great manner, because it has a broader and more realistic field of each zone of study through the interaction of each vehicle (light or heavy). Regarding the roadway, the interaction among these indicators will adjust the design of the road infrastructure, including lanes, rigid or flexible pavement, traffic signs, drainage, shoulders, and medians. This is something relevant because real-time data will be obtained, so the experts can design an adequate lane to what CONTEV-SYs presents; this is the importance of the placement of this device.

CONTEV-SYS needs to be first deployed in pilot studies of selected road corridors, varying traffic volumes and different lane configurations and lighting conditions and then extended to the wider network. The pilots would enable cities and governments to test the system by operating it routinely in the field before expanding its application to other traffic monitoring programs. Multi-camera integration and vehicle tracking in intersections, roundabouts and multilane corridors should also be considered for future versions to eliminate blind spots and enhance vehicle tracking. Moreover, a wider test would allow for assessing the system's robustness to various road configurations, vehicle mix, weather conditions and urban mobility patterns in other cities in Peru and Latin America.

References

[1] Humberto Farias, Mauricio Solar, and Daniel Ortiz, "A Deep Learning Tool to Classify Vehicles in Real Time," *2021 Eighth International Conference on eDemocracy & eGovernment (ICEDEG)*, Quito, Ecuador, pp. 215-218, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[2] Hana Rabbouch, Foued Saâdaoui, and Rafaa Mraihi, "Unsupervised Video Summarization using Cluster Analysis for Automatic Vehicles Counting and Recognizing," *Neurocomputing*, vol. 260, pp. 157-173, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[3] Yingfeng Li, and Yong Bai, "Comparison of Characteristics between Fatal and Injury Accidents in the Highway Construction Zones," *Safety Science*, vol. 46, no. 4, pp. 646-660, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[4] Huansheng Song et al., "Vision-based Vehicle Detection and Counting System using Deep Learning in Highway Scenes," *European Transport Research Review*, vol. 11, no. 1, pp. 1-16, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[5] Ishank Mishra et al., "Methods for Vehicle Detection Using Roadside Sensors in Complex Environment," *Sustainable Infrastructure Development*, pp. 117-124, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[6] Kaijie Zhang et al., "Research on Mine Vehicle Tracking and Detection Technology based on YOLOv5," *Systems Science & Control Engineering*, vol. 10, no. 1, pp. 347-366, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[7] William Wai Leung Lam, Clement Chun-Cheong Pang, and Nelson Hon Ching Yung, "Highly Accurate Texture-Based Vehicle Segmentation Method," *Optical Engineering*, vol. 43, no. 3, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[8] Dilshad Islam, Tanjim Mahmud, and Tanjia Chowdhury, "An Efficient Automated Vehicle License Plate Recognition System Under Image Processing," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 29, no. 2, pp. 1055-1062, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Debojit Biswas et al., "An Automatic Car Counting System Using OverFeat Framework," *Sensors*, vol. 17, no. 7, pp. 1-13, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[10] Rui Zhao, and Xiaogang Wang, "Counting Vehicles from Semantic Regions," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 2, pp. 1016-1022, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[11] Youssef Aitrais et al., "AI-Driven Traffic Flow Management System: Real-Time Blockage Detection, Emergency Prioritization, and Road Hazard Monitoring," *Proceedings of the International Conference on Advanced Communications with Modern Circuits and Systems Technologies*, pp. 428-435, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[12] Ahsen Battal, Yunus Emre Avcı, and Adem Tuncer, "Real-Time Detection of Vehicle Queue States in Urban Traffic Using Deep Learning," *El-Cezeri*, vol. 12, no. 3, pp. 356-364, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[13] Bl Shilpa, M. Mayank, and S Md Fakruddin, "Adaptive Urban Traffic Control Using Camera Vision and Emergency Vehicle Mobile Interface," *2025 Second International Conference on Computing, Semiconductor, Mechatronics, Intelligent Systems and Communications (COSMIC)*, Mangalore, Karnataka, India, pp. 48-53, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[14] C.R Rashmi, and C.P Shantala, "Vehicle Density Analysis and Classification using YOLOv3 for Smart Cities," *2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, Coimbatore, India, pp. 980-986, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[15] Zhe Dai et al., "Video-Based Vehicle Counting Framework," *IEEE Access*, vol. 7, pp. 64460-64470, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[16] Huy Van Pham, and Byung-Ryong Lee, "Front-View Car Detection and Counting with Occlusion in Dense Traffic Flow," *International Journal of Control, Automation and Systems*, vol. 13, no. 5, pp. 1150-1160, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[17] Gary Bradski, The OpenCV Library, United States Patent and Trademark Office, 2000. [Online]. Available: https://ptacts.uspto.gov/ptacts/public-informations/petitions/1558289/download-documents?artifactId=8E9mKCVRLTzAIHYKaMMeW0Y7vRNLW2jO3IgIxCIvFTojVG2bGeGwSDI

[18] Laurie Williams, *Agile Software Development Methodologies and Practices*, Advances in Computers, vol. 80, pp. 1-44, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[19] Qizi Huangpeng et al., "Automatic Vehicle Detection and Counting Approach using Low-Rank Representation and Locality-Constrained Linear Coding," *Engineering Computations*, vol. 35, no. 8, pp. 2825-2843, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[20] Rui Wang et al., "AAC: Automatic Augmentation for Crowd Counting," *Neurocomputing*, vol. 500, pp. 90-98, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] Zhaojian Liu et al., "YOLO-DC for Vehicle Detection Using Deformable Convolutional Networks and Cross-Channel Coordinate Attention," *Scientific Reports*, vol. 16, no. 1, pp. 1-16, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[22] Miao He et al., "Real-Time Vehicle Detection Methods based on an Improved YOLO-Lite Approach in Edge Computing Scenarios," *Discover Artificial Intelligence*, vol. 6, no. 1, pp. 1-20, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[23] M. A. León-Tejeda et al., "Vehicle Traffic Analysis System Using Traffic Light Infrastructure," *International Journal of Research and Technological Innovation*, vol. 9, no. 51, pp. 1-15, 2021. [Google Scholar] [Publisher Link]

[24] Miguel Angel Mendoza-Lugoa, and Oswaldo Morales-Nápoles, "Vehicular Loads Hazard Mapping through a Bayesian Network in the State of Mexico," *Proceedings of the 31st European Safety and Reliability Conference*, pp. 2510-2517, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[25] Eliseo Chávez-Alarcón, and Avid Roman-Gonzalez, "Analysis of Vehicle Flow Using Auto Vehicle Counting," *2018 IEEE Third Ecuador Technical Chapters Meeting (ETCM)*, Cuenca, Ecuador, pp. 1-5, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[26] Juan C. Perafan-Villota, Oscar H. Mondragon, and Walter M. Mayor-Toro, "Fast and Precise: Parallel Processing of Vehicle Traffic Videos Using Big Data Analytics," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 8, pp. 12064-12073, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[27] Camilo Camacho, César Pedraza, and Carolina Higuera, "An Artificial Vision Based Method for Vehicle Detection and Classification in Urban Traffic," *Pattern Recognition and Image Analysis*, pp. 394-403, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[28] Xiuliang Jin et al., "Estimates of Plant Density of Wheat Crops at Emergence from Very Low Altitude UAV Imagery," *Remote Sensing of Environment*, vol. 198, pp. 105-114, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[29] Zhipeng Dong et al., "Object Detection Method for High Resolution Remote Sensing Imagery Based on Convolutional Neural Networks with Optimal Object Anchor Scales," *International Journal of Remote Sensing*, vol. 43, no. 7, pp. 2698-2719, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[30] Mofeng Yang et al., "Big-Data Driven Framework to Estimate Vehicle Volume Based on Mobile Device Location Data," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2678, no. 2, pp. 352-365, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[31] Ryan W. Klein, Christopher L. Dutton, and Andrew K. Koeser, "Development of a Low-Cost Traffic Counter for Assessing Likelihood of Impact for Tree Risk Assessment," *Arboricultural Journal*, vol. 45, no. 1, pp. 49-71, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[32] Konda Hari Krishna et al., "Vision-Driven Dynamic Traffic Light System for Smart Cities using Edge AI," *2026 6th International Conference on Image Processing and Capsule Networks (ICIPCN)*, Dhulikhel, Nepal, pp. 1193-1199, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[33] Shubham Sahu et al., "Edge-Enabled Smart Traffic Surveillance System with Federated Learning Approaches," *2025 International Conference on Sensors and Related Networks (SENNET) Special Focus on Digital Healthcare(64220)*, Vellore, India, pp. 1-6, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[34] R. Venkatesh, *Harnessing Artificial Intelligence for Road Traffic Surveillance: A Comprehensive Overview of AIbased Statistical Models for Traffic Monitoring and Flow Prediction*, AI-Based Statistical Modeling for Road Traffic Surveillance and Monitoring, pp. 233-253, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[35] Khac-Hoai Nam Bui, Hongsuk Yi, and Jiho Cho, "A Multi-Class Multi-Movement Vehicle Counting Framework for Traffic Analysis in Complex Areas Using CCTV Systems," *Energies*, vol. 13, no. 8, pp. 1-17, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[36] Geometric Design of Highways DG-2018, Ministry of Transport and Communications (MTC), 2018. [Online]. Available: https://portal.mtc.gob.pe/transportes/caminos/normas_carreteras/documentos/manuales/Manual.de.Carreteras.DG-2018.pdf

[37] Mohanad Jabbar Abdali et al., "Employment of videogrammetric Techniques to Obtain Real-Time Traffic Survey Data," *AIP Conference Proceedings*, vol. 3379, no. 1, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[38] Kennedy Eloy Apolinario Tadeo, "*Evaluation of Service Levels and their Effect on Traffic Flow at the Access Points to the Huallaga Bridge in the City of Huánuco, 2023*," Daniel Alcides Carrión National University, pp. 1-38, 2023. [Google Scholar] [Publisher Link]

[39] Mohana et al., "Artificial Intelligence (AI) Enabled Vehicle Detection and Counting Using Deep Learning," *2022 International Conference on Computer Communication and Informatics (ICCCI)*, Coimbatore, India, pp. 1-5, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[40] Sokèmi René Emmanuel Datondji et al., "A Survey of Vision-Based Traffic Monitoring of Road Intersections," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 10, pp. 2681-2698, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[41] S. Gupte, O. Masoud, and P. Papanikolopoulos, "Vision-based Vehicle Classification," *IEEE Intelligent Transportation Systems, Proceedings (Cat. No.00TH8493)*, Dearborn, MI, pp. 46-51, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[42] Nicolai Wojke, Alex Bewley, and Dietrich Paulus, "Simple Online and Realtime Tracking with a Deep Association Metric," *2017 IEEE International Conference on Image Processing (ICIP)*, Beijing, China, pp. 3645-3649, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[43] O. Sidla et al., "Vehicle Recognition for Highway Lane Survey," *Proceedings. The 7th International IEEE Conference on Intelligent Transportation Systems (IEEE Cat. No.04TH8749)*, Washington, WA, USA, pp. 531-536, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[44] Prashan Premaratne et al., "Comprehensive Review on Vehicle Detection, Classification and Counting On Highways," *Neurocomputing*, vol. 556, pp. 1-13, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[45] Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection," *arXiv preprint*, pp. 1-17, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[46] Md Rezaul Karim Khan, and Naphtali Rishe, "A Unified Framework for Vehicle Detection, Tracking, and Counting across Ground and Aerial Views Using Knowledge Distillation with YOLOv10-S," *Remote Sensing*, vol. 18, no. 5, pp. 1-27, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[47] Solange Munoz et al., "Best Practices for the Application of Automated Traffic Counting Using Computer Vision in Chile," *21st Chilean Congress on Transport Engineering*, Valparaíso, pp. 1-18, 2023. [Publisher Link]

[48] Ahsen Battal, Yunus Emre Avcı , and Adem Tuncer, "Real-Time Detection of Vehicle Queue States in Urban Traffic Using Deep Learning," *El-Cezeri Journal of Science and Engineering*, vol. 12, no. 3, pp. 356-364, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[49] OPMI, UF and UEI, Ministry Of Economy and Finance, 2026. [Online]. Available: https://www.mef.gob.pe/es/?option=com_wrapper&language=es-ES&Itemid=100898&lang=es-ES&view=wrapper

[50] Gen Hayauchi et al., "From Sensing to Impact: LiDAR-Based Parking Guidance for Narrow Streets in a Coastal Tourist Village," *International Journal of Intelligent Transportation Systems Research*, vol. 24, no. 1, pp. 64-73, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[51] Grzegorz Wilczewski, Tomasz Czarnecki, and Krzysztof Perlicki, "Optoelectronic Systems for Automatic Vehicle Counting and Classification in Rest Areas," *Proceeding SPIE 10445, Photonics Applications in Astronomy, Communications, Industry, and High Energy Physics Experiments*, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[52] Nashwan Adnan Othman, Zahraa Zakariya Saleh, and Bishar Rasheed Ibrahim, "A Low-Cost Embedded Car Counter System by using Jetson Nano Based on Computer Vision and Internet of Things," *2022 International Conference on Decision Aid Sciences and Applications (DASA)*, Chiangrai, Thailand, pp. 698-701, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[53] Isaías Irigoín Barboza, "*Evaluation of the Premature Deterioration of the Rigid Pavement of Av. Micaela Bastidas, Chota, 2019*," National Autonomous University of Chota, pp. 1-226, 2020. [Google Scholar] [Publisher Link]

[54] Fabian Montes, and Clever Wilbert, "*Improvement of the Vehicular and Pedestrian Transit Service on Av. Salaverry, Section: Av. Mariscal Castilla – Jr. Callao in the AA.HH. La Victoria of the District of El Tambo - Huancayo – Junin*," Degree Tesis, Peruvian University of the Andes, 2021. [Google Scholar] [Publisher Link]

[55] Torres Cortez et al., "*Diagnosis and Proposal to Reduce Queue Lengths in Public Transport at the Intersection of Av. Mariscal Castilla and Av. Evitamiento in the City of Huancayo, Using Traffic Microsimulation*," Tesis, Peruvian University of Applied Sciences, pp. 1-88, 2020. [Google Scholar] [Publisher Link]