



## Article

# Quality of Automatic Traffic Volume Counting by Cameras and Impact on the Qualitative Indicators of Traffic

Gëzim Hoxha <sup>1</sup>, Arjanit Fandaj <sup>2</sup> and Xhevahir Bajrami <sup>2,\*</sup>

<sup>1</sup> Department of Traffic and Transport, Faculty of Mechanical Engineering, University of Prishtina “Hasan Prishtina”, 10000 Prishtina, Kosovo

<sup>2</sup> Department of Mechatronics, Faculty of Mechanical Engineering, University of Prishtina “Hasan Prishtina”, 10000 Prishtina, Kosovo

\* Correspondence: xhevahir.bajrami@uni-pr.edu

**Abstract:** This paper presents research on the collection, analysis, and evaluation of the fundamental data needed for road traffic systems. The basis for the research, analysis, planning and projections for traffic systems are traffic counts and data collection related to traffic volume and type. The quality and accuracy of this data are very important for traffic planning or optimization. Therefore, the purpose of this research is to apply advanced methods of automatic counting of motorized traffic and to evaluate the impact of this data on the measurement of important traffic indicators. The accuracy of measurements arising from the traditional method of data collection through manual counting will be compared with the most advanced methods of automatic counting through cameras. For this purpose, an analytical algorithm for the recognition and processing of data related to road users as a function of the time of day was applied. The program was written in the programming language Python, and the accuracy of the data and its effect on the results of qualitative traffic indicators were analyzed using the Synchro software model. The developed program is capable of recognizing and classifying different types of vehicles in traffic, such as motorbikes, motorcycles, cars, pick-ups, trucks, vans and buses, as well as counting the traffic volume over time. The results obtained from these two models show the advantages of applying advanced methods of data collection and processing related to dynamic traffic processes, as well as the quality in terms of the impact on the measurement of qualitative traffic indicators. A comparison of the quality of results for the different time intervals and varying levels of visibility in traffic is presented using tables and graphs. At nighttime, when visibility was poor, the discrepancy between the manual and automatic counting methods was around 9.5%. However, when visibility was good, the difference between manual counting and the automated program was 4.87% for the period 19:00–19:15 and 3.64% for the period 05:00–05:15. This discrepancy was especially noticeable when distinguishing between vehicle categories, due to the limitations in the accuracy in recognizing and measuring the dimensions of these vehicles. The difference between the two calculation models has a minor effect on qualitative traffic indicators such as: approach LOS, progression factor,  $v/s$ ,  $v/c$ , clearance time, lane group flow, adj. flow, satd, and flow approach delay.

**Keywords:** automatic counting; motorized traffic; data collection; traffic indicators; traffic processes; data accuracy; software model



**Citation:** Hoxha, G.; Fandaj, A.; Bajrami, X. Quality of Automatic Traffic Volume Counting by Cameras and Impact on the Qualitative Indicators of Traffic. *Infrastructures* **2023**, *8*, 44. <https://doi.org/10.3390/infrastructures8030044>

Academic Editors: Ján Dižo, Rafał Melnik, Stasys Steišūnas and Miroslav Blatnický

Received: 30 January 2023

Revised: 20 February 2023

Accepted: 24 February 2023

Published: 28 February 2023



**Copyright:** © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

Planning a traffic road network, designing traffic systems, or modelling these systems in order to manage traffic problems starts with collecting data about the traffic volume or basic data related to the road users. The demand for motorized traffic has increased enormously in urban centers and this is accompanied by major problems in traffic operation being manifested in a decrease in the quality of motorized and unmotorized movement, traffic delays and other safety problems [1]. The main indicators that are related to traffic demand and are important for modelling, optimization, and the analysis of proposed

solutions are based on these traffic measurements. In this regard, the quality and accuracy of these basic data are very important for the other processes of traffic planning or optimization to show acceptable results. In relation to the increased demand for motorized movement and the need for temporal and spatial non-linearity analysis, there is a need to find a new approach or a new, more favorable measurement model such as the automatic numbering model, which would save time compared to manual counting and the results would be qualitative. Due to the impact on the measurement of qualitative indicators of traffic, especially of heavy vehicles in traffic, the accuracy of the categorization of the vehicles that are part of motorized traffic is very important. The objective of the study is to enhance the accuracy of qualitative traffic indicators by exploring the effect of the techniques employed for qualitative baseline measurements.

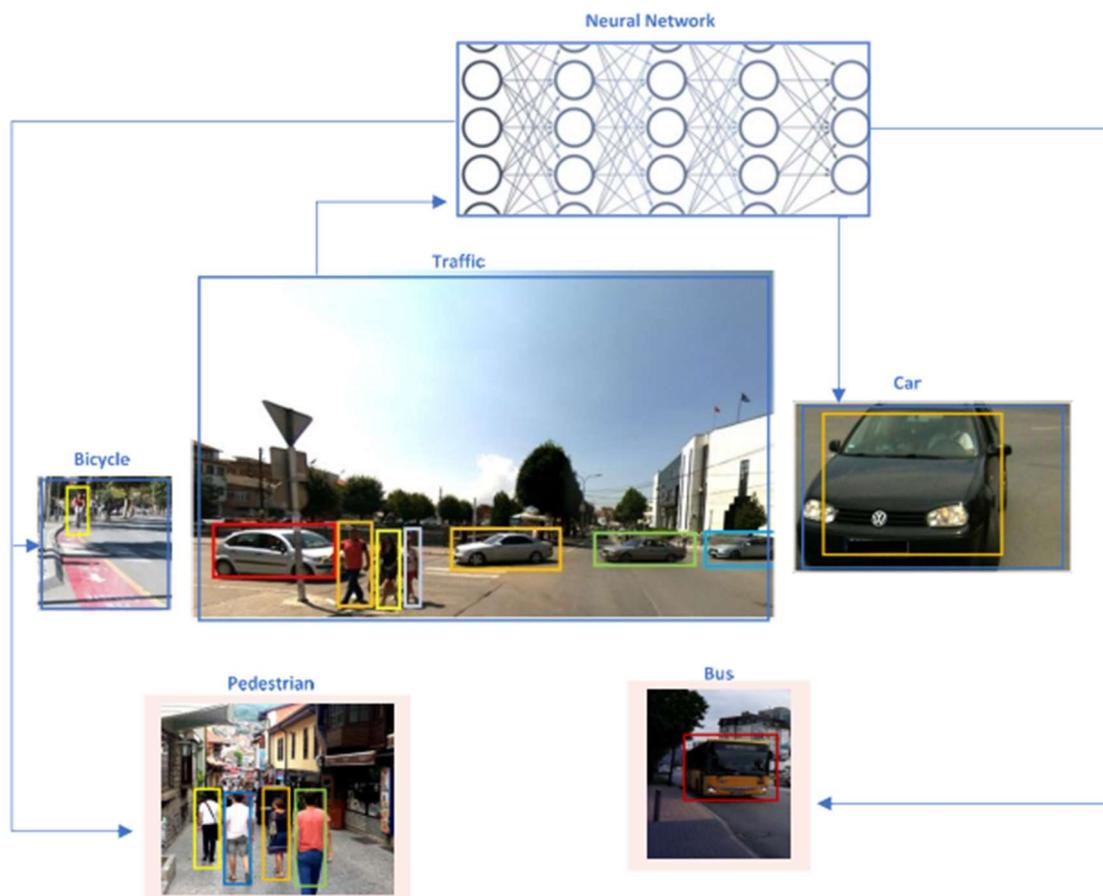
Consequently, we will answer three questions:

1. What is the difference in data accuracy between the manual and automatic numbering models?
2. What is the impact of the basic data obtained from two models in the determination of qualitative traffic indicators?
3. How accurate is the data obtained by automatic counting in conditions of poor visibility at night?

We address these questions below, with the concrete results obtained by also applying the data comparison model. Traffic processes are complex and dynamic; therefore, there is a need for frequent traffic counts in relation to time and space, especially in urban areas, because there is a need to adapt the forms of traffic control, traffic optimization or supply, in accordance with the traffic's demand [2]. Until recently, traffic volume counts were usually realized through a manual method. Now, with the beginning of the use of advanced automatic techniques, special devices are being applied through which the realization of traffic counts is enabled automatically. Therefore, the analysis and evaluation of the quality of the basic information (traffic counts) obtained through cameras and the processing of this information in comparison to the methods of manual traffic counting have been the target of this research. Opportunities to bring engineering support specialties together through technology may be found by utilizing the performance technology and database capabilities of technology information management systems [3]. YOLO has developed a similar system which consists of dividing an image into  $N$  equally sized grids of  $M \times M$ . Each grid is responsible for detecting and localizing any objects that are present in its region [4]. These grids can also predict the bounding box coordinates of an object, relative to the coordinates of the cell, as well as the object marker and the probability of the object being present in the cell. This process reduces the computational burden since both the detection and recognition of objects are handled by the cells of the image; however, it can lead to a lot of repetitive predictions due to numerous cells detecting the same object with distinct bounding box predictions [4]. Some authors [5] have proposed a scheme as part of a research project that concluded shortly before the public release of YOLO version 4, which includes new methods that likely improve classification, detection, and counting rates [5]. Abdelwahab [6] evaluated the proposed method; three experiments were employed using five videos representing different circumstances. In all experiments, the GMM was used for creating the background model for only the ROI [6]. Other authors (Ref. Lin Zheng, Junjiao) provided a new method for the rapid detection and classification of traffic anomalies and improved the accuracy of detection and classification [7]. Although manual methods for traffic counting have been shown to be successful in terms of the quality of the data obtained, they require time and commitment, a large number of staff, and also the data processing requires time equivalent to the counting time. Therefore, the application of automatic counting methods, enabling efficiency in terms of the time required to obtain the information and the data processing as well as the quality of this information, is an enormous contribution to the planning, projection and efficiency of traffic management. Automated traffic data collection has been sought in transportation applications to reduce cost and improve efficiency compared to manual data collection [8].

*Approach and Methodology*

For research purposes, an algorithmic model was applied to recognize the different categories of vehicles in traffic, enabling data processing. The program was built using the programming language “Python” and the accuracy of the data was analyzed through the built-in software model “Synchro” to assess the impact on the results of qualitative traffic indicators. Object detection is the process of predicting the class of one or more objects within an image and drawing a bounding box around them (Figure 1). This is commonly used to identify specific objects, such as vehicles, in a given frame [9]. Deep learning is a form of artificial intelligence where the system tries to learn from data without the need for labels or pre-defined features. In particular, convolutional neural networks (CNNs) are used to perform unsupervised object detection [10].



**Figure 1.** Object detection process of predicting the class of one or more objects within an image.

Object detection models generally have two corridors:

1. An encoder takes a frame (image) as input and applies a series of layers and blocks to it in order to generate statistical data that can be used to identify and label the objects within the frame, such as vehicles;
2. The encoder will send the data to a decoder, which will then use the information to generate bounding boxes and labels for every object present [11–13].

The tracker of objects utilizes the Euclidean distance concept to monitor an object [4].

The authors of [14] formulated a speedy algorithm that can be used to count vehicles in traffic videos without requiring vehicle tracking. A reference model was generated for a small area in the video frame to enable this and the proposed algorithm increased the speed of video processing by utilizing every third frame instead of every frame [14].

The authors of [15] implemented a virtual detection line in each of the traffic lanes to count the number of cars. The points at which the vehicles entirely crossed these lines



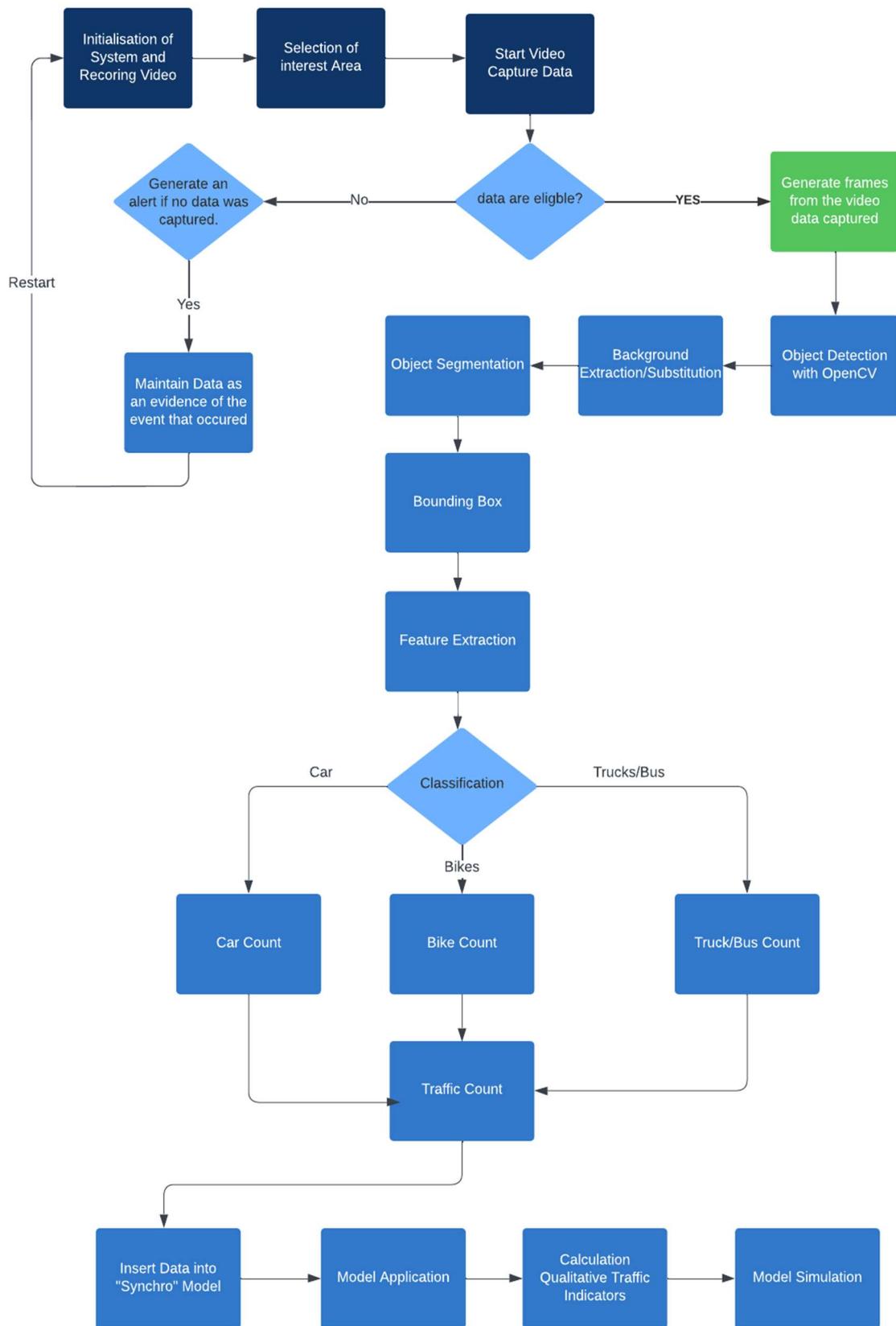


Figure 3. Process and methodology used for the traffic count.

Parts of the analytical pseudo Algorithms 1 and 2 are shown below.

**Algorithm 1:** Finding the left of the frame (image).

```

Input: Parameters  $x, y, h$  and  $w$ 
Output: Banderas of the different vehicles,  $N_1 \rightarrow N_N$ 
     $int \in (x, y, h \text{ and } w)$ 
    for 1 to  $N$  do
         $self_{(x,y)} \rightarrow w, h$ 
             $selfc_x \rightarrow x + self_{(x,y)}$ 
             $selfc_y \rightarrow y + self_{(x,y)}$ 
    return  $\rightarrow self_{(x,y)}$ 
    def  $\rightarrow$  different vehicles,  $N_1 \rightarrow N_N * self_{(x,y)} [N * M]$ 
         $(x, y, h \text{ and } w) \cong I_d \exists I_{d \rightarrow box}$ 

    Center  $\forall self_{(x, y, h \text{ and } w)}$ 
    for  $x_i, y_j$  to Center do
    # Finding the position of the vehicle
    if  $y_j \rightarrow Po_{line}$  and  $y_j \rightarrow Po_{midel\_line}$ 
        if  $\nexists U_{list}$  and  $U_p \exists U_{plist}$ 
            elif  $y_j \exists D_{ow_{po_{line}}}$  and  $y_j \exists D_{ow_{midel\_line}}$ 
        end
        if  $\nexists D_{ow_{po\_line}} \rightarrow I_d \exists I_{d \rightarrow box}$ 
            elif  $y_j > D_{ow_{po\_line}}$ 
                if  $\nexists U_{plist} \rightarrow I_d \exists I_{d \rightarrow box}$ 
            elif  $y_j > D_{ow_{po\_line}}$ 
        end
         $U_{list} \cong I_d \exists I_{d \rightarrow box}$ 
    Center  $\forall self_{(x, y, h \text{ and } w)} \rightarrow 2RGB, \pm 1$ 
    end end
    
```

Measurement data from recordings through cameras and the application, for several 15 min intervals, for different visibility conditions, for one intersection, are presented in Figures 4–6 as well as Tables 1–3.



**Figure 4.** Traffic count from camera and data processing in program (05:00–05:15).

---

**Algorithm 2:** Part of the algorithm for counting and categorizing vehicles during automatic counting through cameras.

---

```

import cv2
class RealTime(Processing):
    def __init__(self):
        super().__init__()
        def realTime(self):
            # Set the frame rate of the video capture device
            cap = cv2.VideoCapture(0)
            cap.set(cv2.CAP_PROP_FPS, 800)
            while True:
                # Read the video frame and resize it
                ret, frame = cap.read()
                frame = cv2.resize(frame, (self.width, self.height))
                # Create a blob from the image
                blob = cv2.dnn.blobFromImage(frame, self.scale, (self.width, self.height),
                (self.mean, self.mean, self.mean), swapRB=True, crop=False)
                # Set the input of the neural network
                self.net.setInput(blob)
                # Get the output layers of the network
                layers = self.net.getUnconnectedOutLayersNames()
                # Feed the data to the network and get the output
                outs = self.net.forward(layers)
                # Call the postProcess() function from the Processing class
                objects = self.postProcess(frame, outs)
                # Draw the counting texts in the frame
                for obj in objects:
                    label = obj [0]
                    confidence = obj
                    xmin = obj [2]
                    ymin = obj [3]
                    xmax = obj [4]
                    ymax = obj [5]
                    cv2.rectangle(frame, (xmin, ymin), (xmax, ymax), (0, 255, 0), 2)
                    cv2.putText("Kamionete, Autobus, Kamion, Veture, Biciklete, kem-besore ", frame,
                    label + " " + str(round(confidence, 2)), (xmin, ymin-5), cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0,
                    255, 0), 2)
                    # Write the counting data into a csv file
                    self.writeData(objects)
                # Show the frame
                cv2.imshow("Real Time", frame)
                # Press 'q' to quit
                if cv2.waitKey(1) & 0xFF == ord('q'):
                    break
                # Release the video capture device and destroy all windows
            cap.release()
            cv2.destroyAllWindows()

```

---

The results of automatic measurements from the video recording for the period 05:00–05:15, for different categories of vehicles in traffic are presented in Table 1.

The results of automatic measurements from the video recording for the period 19:00–19:15 (Figure 5), for different categories of vehicles in traffic are presented in Table 2.

The results of automatic measurements from video recording (Figure 7) for the period 21:00–21:25, for different categories of vehicles in traffic are presented in Table 3.

The summary results, as shown in Tables 4 and 5 and Figures 8–10, prove the quality of the data obtained from the automatic count in terms of accuracy of measurements and adequate categorization of vehicles participating in the traffic.

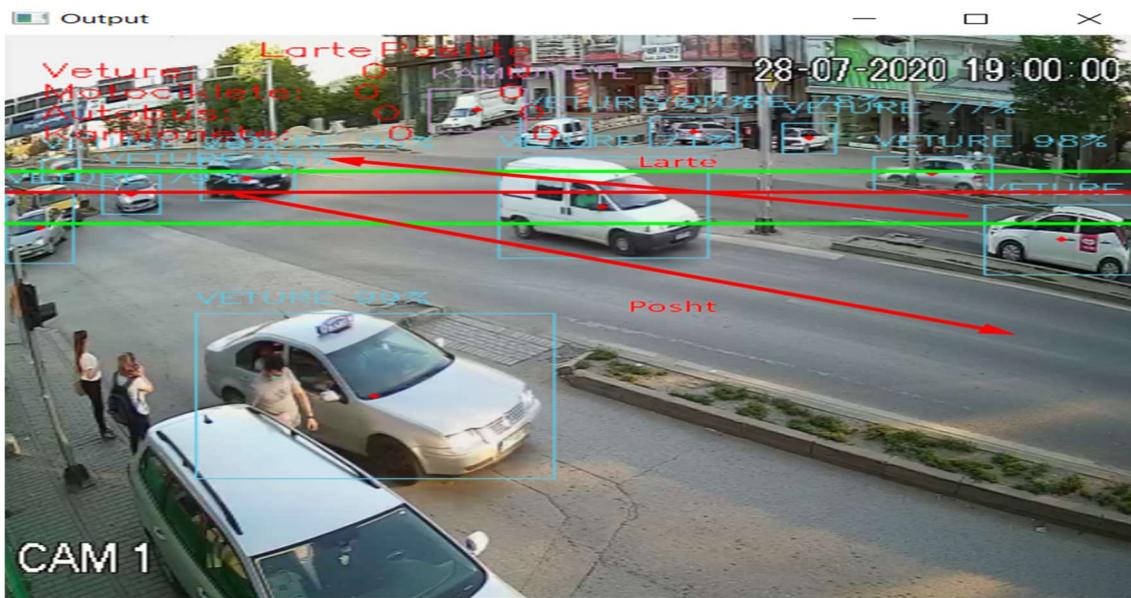


Figure 5. Traffic count from camera and data processing in program (time: 19:00–19:15).

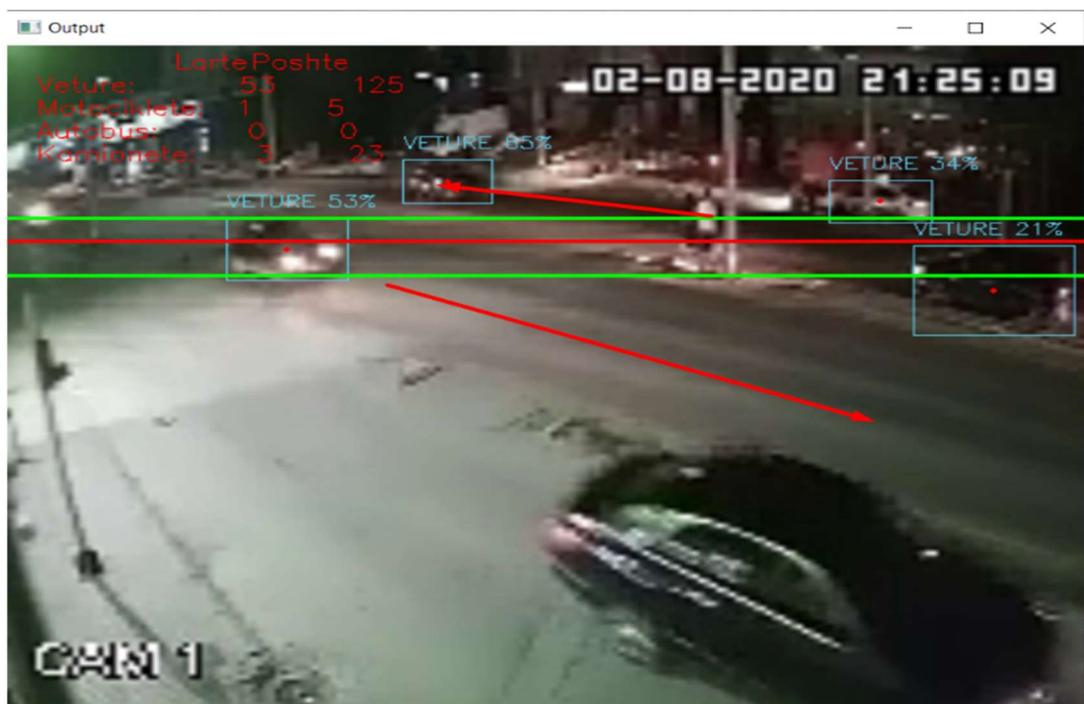


Figure 6. Traffic count from camera and data processing in program (time: 21:00–21:15).

Table 1. Results obtained from camera count in the morning.

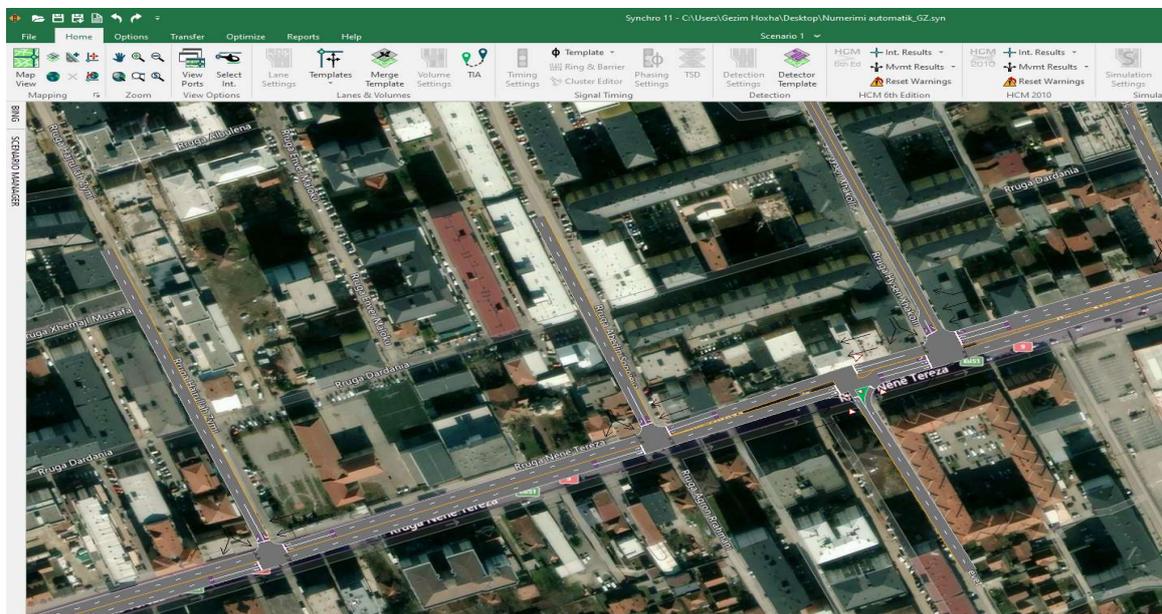
Direction	Car	Motorcycle	Bus	Trucks	Total
Time period: 05:00–05:15					
Up	19	0	0	2	21
Down	14	0	2	3	19
Total	33	0	2	5	40

**Table 2.** Results obtained from camera count during the day.

Direction	Car	Motorcycle	Bus	Trucks	Total
Time period: 19:00–19:15					
Up	149	0	0	9	158
Down	224	1	7	22	254
Total	373	1	7	31	412

**Table 3.** Results obtained from camera count in the evening.

Direction	Car	Motorcycle	Bus	Trucks	Total
Time Period: 21:00–21:15					
Up	53	1	0	3	57
Down	125	5	2	23	212
Total	178	6	2	26	212



**Figure 7.** Road traffic network in “Synchro” model.

**Table 4.** Results obtained from camera count in the different time periods.

Direction	Car	Motorcycle	Bus	Trucks	Average Difference in Counting	Processing Time of the Data
Time Period: 21:10–21:25						
Manual	195	7	0	30	9.43%	15 min
Automatic	178	6	2	26		
Time Period: 19:00–19:15						
Manual	427	1	9	36	4.87%	15 min
Automatic	412	1	7	31		
Time Period: 05:00–05:15						
Manual	40	0	3	3	4.54%	15 min
Automatic	38	0	2	4		

Table 5. Result obtained by “Synchro” model.

Movement	 EBL	 EBT	 WBT	 WBR	 SBL	 SBR
Lane configurations						
Traffic volume (vph)	20	178	195	110	98	100
Future volume (vph)	20	178	195	110	98	100
Ideal flow (vphpl)	1900	1900	1900	1900	1900	1900
Total lost time (s)	4.5	4.5	4.5	4.5	4.5	
Lane util, factor	1.00	0.95	0.95	1.00	1.00	
Frbp, ped/bikes	1.00	1.00	1.00	0.45	0.83	
Flpb, ped/bikes	1.00	1.00	1.00	1.00	1.00	
Frt	1.00	1.00	1.00	0.85	0.93	
Flt protected	0.95	1.00	1.00	1.00	0.98	
Satd, flow (prot)	1770	3539	3539	714	1406	
Flt permitted	0.95	1.00	1.00	1.00	0.98	
Satd, flow (perm)	1770	3539	3539	714	1406	
Peak-hour factor, PHF	0.92	0.92	0.92	0.92	0.92	0.92
Adj. flow (vph)	22	193	212	120	107	109
RTOR reduction (vph)	0	0	0	48	29	0
Lane group flow (vph)	22	193	212	72	187	0
Confl. peds. (#/hr)	220			200	200	200
Turn type	Prot	NA	NA	Perm	Prot	
Protected phases	7	4	8		1	
Permitted phases				8		
Actuated green, G (s)	20.5	100.5	75.5	75.5	16.5	
Effective green, g(s)	20.5	100.5	75.5	75.5	16.5	
Actuated g/C ratio	0.16	0.80	0.60	0.60	0.13	
Clearance time (s)	4.50	4.50	4.50	4.50	4.50	
Lane grp cap (vph)	287	2822	2120	427	184	
v/s ratio prot	c0.01	0.05	0.06		c0.13	
v/s ratio perm				c0.10		
v/c ratio	0.08	0.07	0.1	0.17	1.02	
Uniform delay, d1	44.7	2.7	10.8	11.3	54.8	
Progression factor	1.00	1.00	0.87	0.58	1.00	
Incremental delay, d2	0.5	0	0.1	0.80	71.1	
Approach delay (s)		7.1	8.7		125.9	
Approach LOS		A	A		F	
Intersection Summary						
HCM 2000 control delay	41.4	HCM 2000 level of service				D
HCM 2000 volume to capacity ratio	0.28					
Actuated cycle length (s)	126	Sum of lost time (s)				13.5
Intersection capacity utilization	39.60%	ICU level of service				A
Analysis period (min)	15					
Critical lane group						

With colored numbers are selected as the main indicators of traffic.

Referring to the results obtained from the automatic method and manual counts performed by personnel employed to count vehicles, the largest changes in data quality are observed in the period of limited overnight visibility (time 21:10–21:25).

In this period, the counting data had a deviation of about 9.5%, while in other measurement periods, when visibility was good, the differences between the manual counting method and the automatic method through the applied program followed a deviation of about 4.87% for the period 19:00–19:15 and 4.54% for the period of measurements 05:00–05:15. In the quality of automatic measurements and accurate categorization of vehicles, the position of the cameras is also important; in this case, they were put at a certain angle to the direction of movement of the vehicles; therefore, the accuracy loss was likely to be greater. These deviations are more pronounced especially in the process of categorizing

vehicles, due to the reduction in opportunities for accurate recognition and measurement of the dimensions of these vehicles.

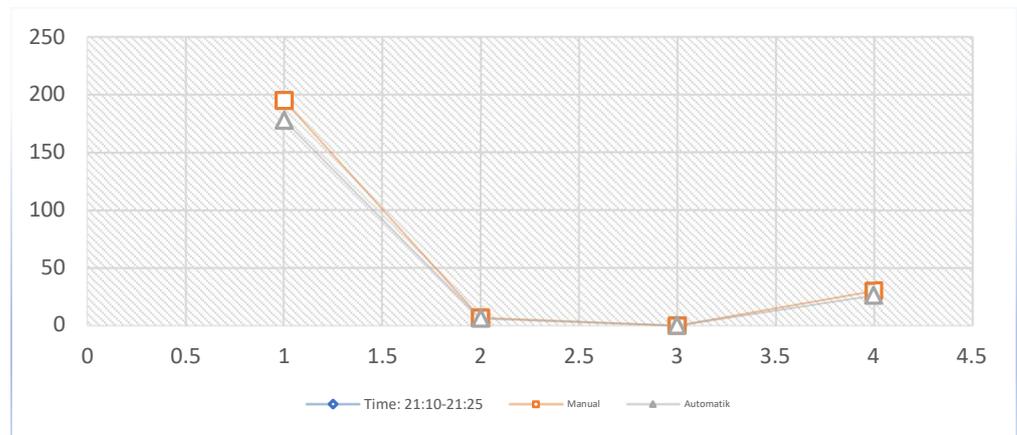


Figure 8. Difference between automatic and manual vehicle counts (time 21:10–21:25).

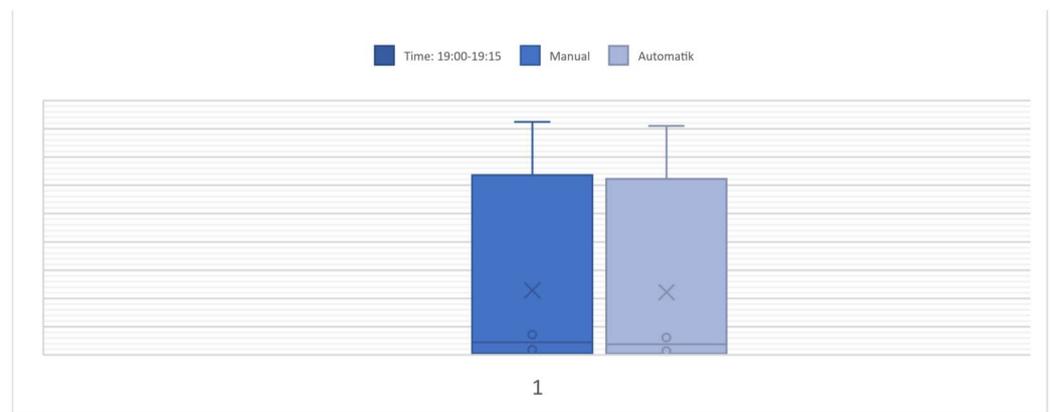


Figure 9. Difference between automatic and manual vehicle counts (time 19:00–19:15).

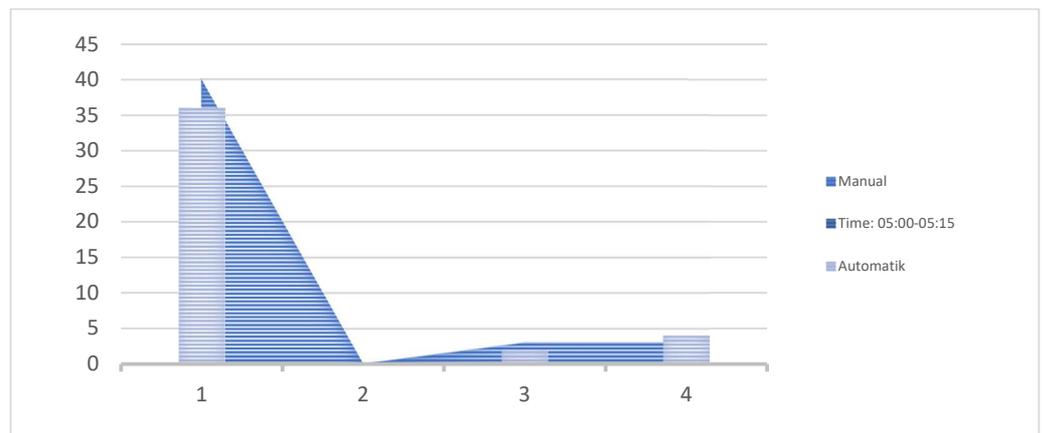
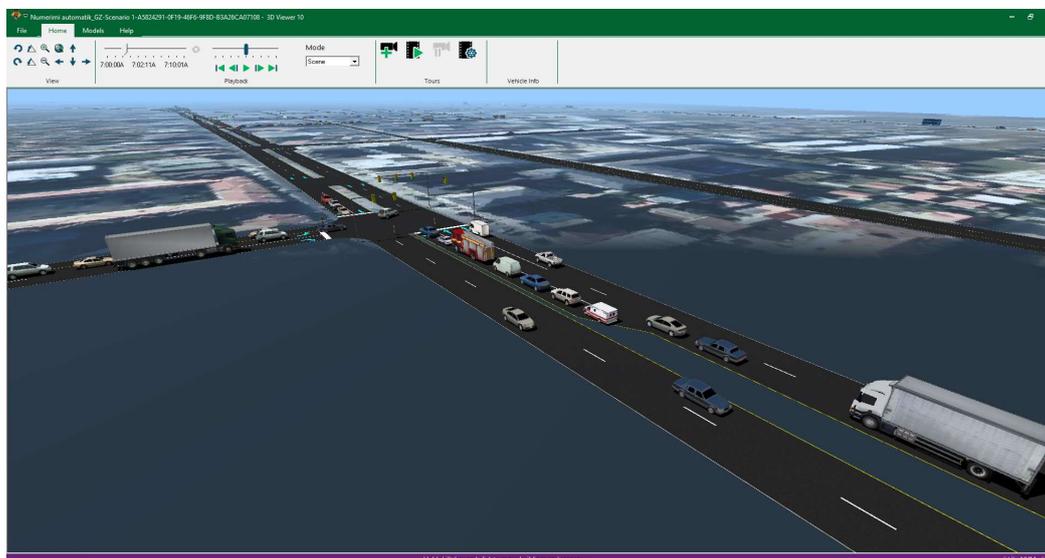


Figure 10. Difference between automatic and manual counts of vehicles (time 05:00–05:15).

### 3. Impact on Qualitative Traffic Indicators

The analysis and evaluation of the qualitative indicators of traffic operation are based on the basic data obtained in the research, traffic surveys or recordings; therefore, it is very important that this data be of the highest quality. In the concrete case of this research, based on the maximum difference of 9.5% between the sets of data obtained from manual and automatic counts, for the period with limited visibility at night (21:10–21:25), we used the “Synchro” model to analyze the impact of this on the results of important indicators of traffic

operation such as: lane utilization factor, standard flow, adjusted flow, lane group flow,  $v/s$  ratio,  $v/c$  ratio, progression factor, approach delay and approach LOS. The construction of a road network in the model "Synchro", including traffic modes and certain traffic demands by means of manual and automatic methods of measurements as well as the simulation of traffic operation, is presented in Figures 7 and 11.



**Figure 11.** Road traffic simulation in "Sim" model.

The results of the qualitative traffic indicators obtained from the "Synchro" model are shown in Figure 8. Referring to the results obtained, no significant changes were observed in the results of traffic indicators which were analyzed through the "Synchro" model (Figure 8); therefore, we can conclude that both the quality, and the accuracy of the data obtained from the use of the automatic method through the cameras and the application of the analytical algorithm formulated in the programming language "Python" are high. As such, we recommend this model for use for the purpose of traffic counts and categorization of vehicles circulating in traffic, because even in the most extreme conditions with the possibility of greater accuracy loss in results at night (conditions of limited visibility), the impact of these losses on the analysis of important traffic indicators is negligible.

#### 4. Conclusions

The analysis and evaluation of the qualitative indicators of traffic operation are based on the basic data obtained in the research, traffic surveys or recordings; therefore, it is very important that this data be of the highest quality. Referring to the results obtained from the automatic method (Python algorithm application) and manual counts performed by personnel employed to count vehicles, the largest changes in data quality were observed in the period of limited overnight visibility (time 21:10–21:25). In this period, the counting data had a deviation of about 9.5%, while in other measurement periods, when visibility was good, the differences between the manual counting method and the automatic method through the applied program followed a deviation of about 4.87% for the period 19:00–19:15, 4.54% for the time period of measurements 05:00–05:15. These deviations are more pronounced especially in the process of categorizing vehicles, due to the reduction in opportunities for the accurate recognition and measurement of the dimensions of these vehicles. Referring to the results obtained, no significant changes were observed in the results of the traffic indicators which were analyzed through the "Synchro" model; therefore, we can conclude that both the quality, and the accuracy of the data obtained from the use of the automatic method through the cameras and the application of the analytical algorithm formulated in the programming language "Python" is high. This model provides accurate

results even during traffic counts in conditions with poor visibility at night. As such, we recommend this model for use for the purpose of traffic counts and the categorization of vehicles circulating in traffic because, even the most extreme conditions giving the possibility of a greater accuracy loss in results at night (conditions of limited visibility), the impact on the analysis of important traffic indicators of these losses is negligible. The authors' next study will focus on developing a methodology for measuring the accuracy of traffic counts and traffic quality indicators in adverse weather conditions such as snow, rain, and fog using edge computing and IoT.

**Author Contributions:** Conceptualization, G.H.; methodology, G.H.; software, A.F.; validation, G.H. and X.B.; formal analysis, X.B.; investigation, G.H.; resources, G.H.; data curation, G.H.; writing—original draft preparation, X.B.; writing—review and editing, X.B. and G.H.; visualization, X.B. and G.H. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** Not applicable.

**Conflicts of Interest:** The authors declare no conflict of interest.

### Abbreviations

LOS	level of service
N9	national road of Kosovo
CNN	convolutional neural networks
Blob	binary large object
v/s	the highest flow ratio for a given signal phase
v/c	volume capacity ratio

### References

- Gëzim, H.; Ahmet, S.; Ramë, L.; Xhevahir, B. Mathematical Model for Velocity Calculation of Three Types of Vehicles in the Case of Pedestrian Crash. *Stroj. Časopis-J. Mech. Eng.* **2018**, *68*, 95–110. [CrossRef]
- Hoxha, G. *Urban Mobility; Dispensë për Përdorim të Brendshëm*: Prishtinë, Kosovo, 2022.
- Dinh, H.; Tang, H. Simple method for camera calibration of roundabout traffic scenes using a single circle. *IET Intell. Transp. Syst.* **2014**, *8*, 175–182. [CrossRef]
- Vehicle Counting, Classification & Detection using OpenCV & Python. Available online: <https://techvidvan.com/tutorials/opencv-vehicle-detection-classification-counting> (accessed on 5 January 2023).
- Sonnleitner, E.; Barth, O.; Palmanshofer, A.; Kurz, M. Traffic, Measurement and Congestion Detection Based on Real-Time Highway Video Data. *Appl. Sci.* **2020**, *10*, 6270. [CrossRef]
- Abdelwahab, M.A. Fast approach for efficient vehicle counting. *Electron. Lett.* **2019**, *55*, 20–22. [CrossRef]
- Zheng, L.; Li, J. Application of Fast P2P Traffic Recognition Technology Based on Decision Tree in the Detection of Network Traffic Data. *J. Electr. Comput. Eng.* **2022**, *2022*, 8320049. [CrossRef]
- Subedi, S.; Tang, H. Development of a multiple-camera 3D vehicle tracking system for traffic data collection at intersections. *IET Intell. Transp. Syst.* **2018**, *13*, 614–621. [CrossRef]
- Gidaris, S.; Komodakis, N. Object detection via a multi-region & semantic segmentation-aware CNN model. In Proceedings of the IEEE International Conference on Computer Vision, Las Condes, Chile, 11–18 December 2015.
- Du, J. Understanding of object detection based on CNN family and YOLO. *J. Phys. Conf. Ser.* **2018**, *1004*, 012029. [CrossRef]
- Chandra, A.M.; Rawat, A. A Review on YOLO (You Look Only One)-An Algorithm for Real Time Object Detection. *J. Eng. Sci.* **2020**, *11*, 554–557.
- Hoxha, G.; Shala, A.; Likaj, R. Vehicle Speed Determination in Case of Road Accident by Software Method and Comparing of Results with the Mathematical Model. *Stroj. Časopis-J. Mech. Eng.* **2017**, *67*, 51–60. [CrossRef]
- Chen, Y.; Lu, J. Multi-Loop Vehicle-Counting Method under Gray Mode and RGB Mode. *Appl. Sci.* **2021**, *11*, 6831. [CrossRef]
- Harikrishnan, P.M.; Thomas, A.; Nisha, J.S.; Gopi, V.P.; Palanisamy, P. Pixel matching search algorithm for counting moving vehicle in highway traffic videos. *Multimed. Tools Appl.* **2020**, *80*, 3153–3172.
- Rosas-Arias, L.; Portillo-Portillo, J.; Hernandez-Suarez, A.; Olivares-Mercado, J.; Sanchez-Perez, G.; Toscano-Medina, K.; Perez-Meana, H.; Orozco, A.L.S.; Villalba, L.J.G. Vehicle counting in video sequences: An incremental subspace learning approach. *Sensors* **2019**, *19*, 2848. [CrossRef] [PubMed]
- YOLOv4 vs YOLOv4-Tiny. Available online: <https://medium.com/analytics-vidhya/yolov4-vs-yolov4-tiny-97932b6ec8ec> (accessed on 5 January 2023).

17. Ojagh, S.; Cauteruccio, F.; Terracina, G.; Liang, S.H. Enhanced air quality prediction by edge-based spatiotemporal data preprocessing. *Comput. Electr. Eng.* **2021**, *96*, 107572. [[CrossRef](#)]
18. Yao, J.; Cai, D.; Fan, X.; Li, B. Improving YOLOv4-Tiny's Construction Machinery and Material Identification Method by Incorporating Attention Mechanism. *Mathematics* **2022**, *10*, 1453. [[CrossRef](#)]
19. Fredianelli, L.; Carpita, S.; Bernardini, M.; Del Pizzo, L.G.; Brocchi, F.; Bianco, F.; Licitra, G. Traffic flow detection using camera images and machine learning methods in ITS for noise map and action plan optimization. *Sensors* **2022**, *22*, 1929. [[CrossRef](#)] [[PubMed](#)]

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.