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Evaluating AI-Based Video Analytics for Traffic Engineering: Accuracy, Calibration, and Practical Use

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Abstract

This paper examines the potential and reliability of AI-based video analytics for solving key traffic engineering problems. The objectives were to compare several commercially available tools for collecting traffic data and, through practical examples, to show that AI-processed data can be used for the development, calibration, and validation of traffic models. Four AI-based video analytics (StreetLogic Pro, DataFromSky, CVEDIA RT Studio, and Camlytics Single) were tested using field video recordings at a signalized intersection on an urban arterial in Split, Croatia. Detection accuracy, usability, and sensitivity to camera placement and recording conditions are analyzed, and selected microscopic parameters (saturation flow rate and control delay) were obtained and compared with values derived from HCM procedures. DataFromSky and CVEDIA RT Studio achieved 97–99% vehicle detection accuracy and provided detailed trajectory data suitable for scientific applications, while StreetLogic Pro achieved 100% accuracy for operational vehicle counting. AI-based estimates of saturation flow rate and control delay differed by less than 1% and 5%, respectively, from traditional field measurements. The main novelty of this research lies in its practical comparison of AI-based video analytics tools combined with a worked example of using AI-derived data to calibrate analytical models, providing practical guidance for researchers and practitioners in traffic engineering.

Keywords: AI Vehicle Detection; Traffic Engineering; Driver Behavior; Vehicle Trajectory.

1. Introduction

Traffic engineering is based on the collection and analysis of traffic data, especially traffic volume and its distribution. In the early stages of traffic engineering, the main focus was on manual vehicle counts at selected sites on key road segments. This practice emerged in the late 19th and early 20th centuries [1, 2], coinciding with mass automobile production and the construction of higher-quality roads. Because the reliability and precision of traffic data directly affect the accuracy and reliability of traffic analyses and models, methods for collecting such data are continuously evolving and improving. The evolution of traffic data collection methods, from manual counting to automatic monitoring and the latest AI-based approaches, is presented in the following sections.

1.1. Evolution of Traffic Data Collection

With the continuous growth in motorization, traffic data collection has become increasingly complex, especially at intersections where it is necessary to record vehicle size, category, turning movements, and pedestrian flows. Early practice relied on manual counting, often using mechanical or electronic tally counters with separate buttons for each movement.

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In the 1970s, inductive loops embedded in roadways were introduced for continuous automated traffic counts. For example, Croatia implemented loop-based systems in 1975 [3]. From the mid‑20th century, more advanced technologies such as microwave radar, infrared sensors, and video recording systems were increasingly used for real‑ time data collection. Radar devices were first tested in the 1950s, with documented deployment in Chicago in 1954 [4], while infrared sensors for vehicle detection began to see wider adoption in the 1990s [5].

Closed‑ circuit television (CCTV) systems for urban traffic monitoring appeared in the 1950s [6–8], initially in London and later in other European cities. Early video‑ based vehicle detection relied on relatively simple computer vision methods, detecting changes between subsequent frames and distinguishing vehicles from a static background.

These technological developments enabled not only vehicle counting but also the collection of detailed traffic data, including vehicle class, speed, travel, and crossing times as well as microscopic parameters of driver and vehicle behavior (e.g., headway, saturation headway, reaction time, acceleration, and start‑ up lost time). Such comprehensive traffic data became essential for the development, calibration, and validation of analytical and simulation traffic engineering models and remains a key requirement in contemporary traffic engineering research and practice.

Following the evolution of traffic data collection technologies described above, researchers in previous studies used the collected detailed traffic data to calibrate various parameters of analytical and simulation traffic models. Some of them used videography technique combined with manual observations and counting [9, 10], while others utilized extensive LiDAR datasets [11, 12]. Whitley et al. [13] applied a data-driven approach to calibrate microscopic traffic simulation models using high-resolution trajectory data from hundreds of connected vehicles, along with traffic volume data obtained by remote traffic microwave sensors.

However, most of these researchers still based their studies on conventional data collection and processing methods, whereas in recent years they have increasingly used AI technologies for these purposes. For example, Lopukhova et al. [14] used a machine learning-based approach to calibrate traffic models using real-time traffic video stream data. With the increasing application of AI-based video analytics for automated and high-resolution traffic monitoring, the following section explores its role and potential in traffic engineering.

1.2. AI-Based Video Analytics in Traffic Engineering

AI-based video traffic analytics tools have become a standard approach for extracting relevant information from video recordings and live streams. Over the past decade, a wide range of deep‑ learning‑ based systems have been developed for automated vehicle detection in urban environments. Based on deep neural networks trained on large sets of real or synthetic images, these systems can detect and track vehicles, reconstruct trajectories, and record vehicle type, speed, lane position, and other attributes. Most of these systems are based on You Look Only Once (YOLO) and DeepSORT techniques [15–17]. YOLO detects objects in real time, while DeepSORT tracks their movement through video frames. Technically, YOLO uses regression models and convolutional neural networks (CNNs) to predict bounding boxes around vehicles (x, y, width, height), object confidence scores, and class probabilities by dividing the input image into an S×S grid of cells. DeepSORT integrates the Kalman filter and Hungarian algorithm to predict object states (bounding box [x, y, a, h] and velocities [vx, vy, va, vh]), enabling real-time processing (tracking) in traffic video analytics.

As detection and tracking techniques continue to evolve, newer versions of YOLO and alternative tracking algorithms, such as StrongSORT, have been developed to improve tracking accuracy and robustness [18]. Through continuous and rapid development, these tools are becoming increasingly accurate and reliable, enabling the expansion of their application in traffic engineering practice.

For example, Lin et al. [15] proposed a vehicle counting method based on the fusion of virtual detection areas and vehicle tracking, achieving up to 99% counting accuracy in real time with various light and traffic conditions, camera angles, and resolutions. Berwo et al. [16] presented various deep learning techniques for vehicle detection and traffic density estimation, with reported accuracy of up to 98%. Vu et al. [17] used YOLOv9s and DeepSORT for vehicle detection, tracking, and counting from real-time urban street traffic videos. When compared to manual field measurements, the average error rate was below 4%.

The reviewed literature clearly shows that traffic engineers have widely used integrated traffic monitoring approaches in recent years. By combining video systems, roadside sensors, and AI‑ based data analytics, traffic engineers can continuously monitor both macroscopic and microscopic traffic flow parameters. These data support traffic planning, real‑ time management, safety analysis, signal control optimization, and the design of sustainable solutions within intelligent transport systems (ITS).

1.3. Research Objectives

Civil engineering researchers, educators, and students engaged in traffic engineering frequently employ analytical and simulation traffic models to plan and analyze street network operations, selecting optimal alternatives based on predefined performance and other criteria. To ensure reliable results, these models must be calibrated, tested, and validated against local conditions for each type of network element. Therefore, the reliability of traffic data directly affects the quality of traffic engineering analyses, particularly the calibration and validation of analytical and simulation models that estimate roadway capacity and level of service. Such models, based on car‑following theory, queuing theory, and gap‑acceptance concepts, require detailed knowledge of microscopic driving behavior and vehicle dynamics.

Microscopic insights into driver behavior at signalized intersections are especially important in urban street networks because these locations often determine corridor and network capacity. In this context, AI-based video analytics offers significant advantages over conventional data collection approaches. Specifically, AI-derived trajectories enable more efficient extraction of calibration parameters, such as start-up lost time, saturation headway, end gain, and queue discharge patterns, at larger scales than traditional survey methods.

Numerous commercial solutions are currently applied in cities for traffic monitoring and management, including systems that Rekor, Miovision, Hikvision, and other companies developed. However, these platforms are rarely used for practical applications or research in traffic engineering problems because they are primarily designed for real-time traffic management rather than high-resolution model calibration. For instance, determining key calibration and validation parameters for traffic models, such as saturation headway and control delay, requires precise information on the time each vehicle joins a queue and the duration it remains in the queue until it departs from the stop line. In particular, estimation of saturation headway requires a queue of at least eight vehicles. In these complex traffic management and monitoring systems, cameras are typically installed on signal poles and focused primarily on the stop line and conflict zone. As a result, their field of view often does not extend far enough upstream to cover the full length of queues during peak periods. Consequently, vehicle arrivals at the end of long queues may not be recorded, thereby compromising the estimation of saturation flow rate.

There has been a noticeable increase in the use of AI-based video analytics in traffic engineering. The previously reviewed studies primarily focus on the application of techniques such as YOLO and DeepSORT for vehicle detection and counting within integrated traffic management and monitoring in ITS systems. However, relatively few researchers have investigated the suitability and practical applicability (in traffic engineering problems) of commercially available, cost-effective solutions from an engineering and scientific perspective.

A review of the literature indexed in Scopus and Web of Science identified only one study by Yan et al. [19] used AI-derived microscopic traffic data to compare results with traditional traffic model procedures. Yan et al. [19], based on research by Ke et al. [20], used image recognition and tracking algorithms to extract vehicle trajectories from video recordings to obtain saturation headway (i.e., saturation flow rate) at intersections with interweaving movements. The results were compared with the Highway Capacity Manual (HCM) method, showing higher accuracy.

Therefore, despite the increasing adoption and broad application potential of commercially available AI-based video analytics tools, a clear gap remains in the literature regarding their use for traffic engineering model calibration. Most previous studies have focused on vehicle detection and counting within operational ITS frameworks, while little attention has been paid to their capability to extract microscopic calibration parameters required for analytical and simulation traffic models. Furthermore, systematic comparison of commercially available AI-based applications from the perspective of engineering practice and scientific research remains limited. Accordingly, the primary objective of this research is to evaluate and compare the suitability, reliability, and user-friendliness of several available AI-based solutions for gathering traffic data on urban road networks to facilitate practitioners, researchers, educators, and students in the process of choosing the appropriate solution for their problem. The second objective is to show in an example how these solutions can significantly contribute to the calibration and validation of analytical and other types of traffic engineering models. It is crucial to emphasize that the focus of this research is not solely on detection accuracy but on assessing the practical feasibility of applying specific types of tools, with the aim of bridging the gap between academic research and engineering practice.

2. Research Methodology

The research methodology consists of several key steps, presented in the workflow diagram in Figure 1. At first, four commercially available AI-based video analytics tools (StreetLogic Pro, DataFromSky, CVEDIA RT Studio, and Camlytics Single) were selected and tested on the same field video recording. The tools selection procedure is described in Section 2.1, while an overview of the main characteristics of the selected tools is provided in Section 3. The recording was obtained using low-cost equipment under controlled geometry and stable image conditions at an urban signalized intersection on a major arterial in Split, Croatia. Each selected tool processed the same recording, and performance was evaluated in terms of vehicle detection accuracy, usability, and sensitivity to camera placement. Manual vehicle counts were used as reference values. This process, including field data acquisition, performance evaluation, and result comparison, is presented in Section 4. Furthermore, the potential application of data processed using AI-based video analytics for the calibration and validation of traffic models is demonstrated. This analysis is illustrated through the estimation of saturation flow rate and control delay, whose values obtained using DataFromSky were compared with field-measured values based on traditional HCM methods [21]. The practical implications are described in detail in Section 5. Finally, the results of the conducted analysis, with an emphasis on the applicability of each tool for academic research and engineering practice, are given in Section 6.

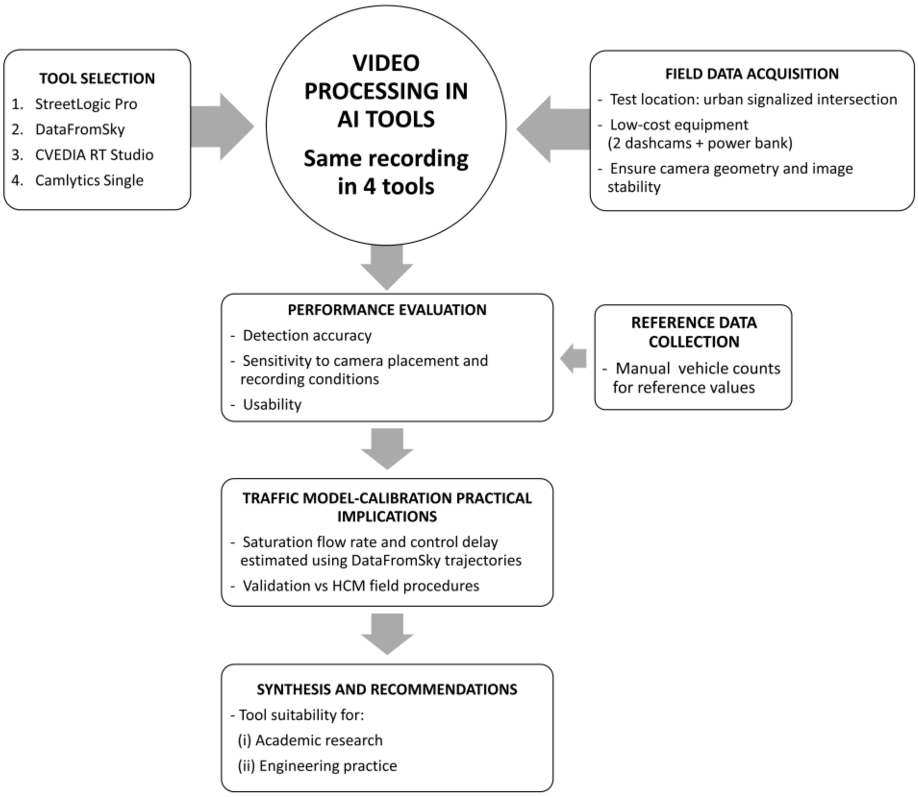

Figure 1. Workflow of the research methodology

2.1. Selection of AI-Based Video Analytics in Traffic Engineering

Selection of AI-based video analytics tools began by investigating the primary purposes of existing solutions, followed by identifying options accessible and affordable for traffic engineering research and practice.

There are two different categories of AI-based video analytics tools based on their intended purpose. The first is designed for collecting data essential to traffic engineering practices and research, while the second supports complex integrated traffic and safety management. The first category involves deploying cameras at predefined locations to gather and process data for calibrating and developing street network traffic models. This enables analysis and selection of optimal network solutions based on existing and planned traffic volumes (e.g., intersection number and types, distances between them and so on). The second category forms an integral part of comprehensive ITS. It receives real-time data from numerous cameras positioned at intersections and road segments across the network, forwarding it to a traffic control center for centralized management of traffic.

This study analyses two representative tools from each category. Selection for the first group was based on prior experience and web searches for low-cost, time-efficient solutions, while for the second group, web searches were conducted targeting affordable and accessible options.

Therefore, this study evaluates the following four solutions:

- StreetLogic Pro [22];
- DataFromSky [23];
- CVEDIA RT Studio [24];
- Camlytics Single [25].

StreetLogic Pro is simple, popular application for traffic engineering problems that more than 3,300 engineers and planners in 78 countries used to collect accurate transportation data [22]. It is developed in the US and has users in all states [22]. DataFromSky, developed in the Czech Republic over 13 years ago, is popular in Europe among researchers and students. It has been used in more than 700 large traffic studies [23] and has 34 partners and cooperates with 20 universities [23].

CVEDIA is primarily designed as a tool for hardware integration, rather than end-user application. While it does not report a large number of single users, it can be used as a flexible tool for custom traffic applications. In contrast, Camlytics Single has recorded approximately 4,000 downloads [26].

3. Overview of Selected Solutions

StreetLogic Pro and DataFromSky are commercial services designed for processing videos in all standard formats and extracting traffic data, making them specialized for traffic engineering purposes. In contrast, CVEDIA RT Studio and Camlytics Single are components of broader software suites (on servers) that process streams from numerous video cameras installed on urban network facilities, providing real-time data on various object movements.

The full server packages of these systems are commercial products, while CVEDIA RT Studio is entirely free, and Camlytics Single can be purchased for a nominal price (about $100), allowing users to try out the application's features. Both tools can handle a single stream or video file in standard formats.

The primary difference between them is in their intended use. CVEDIA RT Studio is a modular system designed for various purposes (crowd estimation, intelligent traffic system, models playground, person-vehicle-animal detection, SecuRT, and unmanned aerial vehicle - UAV detection module). It also offers integration with custom systems and supports application development via Application Programming Interface (API). Camlytics Single, in contrast, is primarily intended for traffic video analytics on street networks.

The fundamental differences in technology and neural network approaches of the AI-based video analytics tools are summarized in Table 1.

Table 1. The fundamental characteristics of AI-based video analytics tools

Tool	Technology & Neural Network Approach	Training Method & User Interaction	Notable Features
StreetLogic Pro	Pretrained deep learning models for vehicle detection	Closed models, no user training or model adjustment; cloud processing	Easy-to-use cloud service delivering aggregated traffic data
DataFromSky	Deep convolutional neural networks combined with multi-hypothesis tracking; optimized especially for drone video recording	Models trained on mixed real and synthetic datasets; no user retraining	Detailed microscopic trajectory tracking and classification
CVEDIA RT Studio	Modular system with multiple models trained extensively on synthetic and real datasets	Advanced users can customize, retrain, and integrate own models; parameters tuning available	Heavy use of synthetic data for robustness; API integration
Camlytics Single	Traditional computer vision with optional custom deep learning models (YOLO, SSD, Faster R-CNN)	Default "black-box" models for detection; option for user-trained custom models	User-friendly with adjustable detection settings

More detailed description of the selected tools is presented in the next subchapters.

3.1. StreetLogic Pro

StreetLogic Pro is a commercial platform tailored to traffic engineers and offers the following:

- Support for multiple video formats
- A free countCAM4 utility to compress and merge videos and annotate screenshots (e.g., street names, intersection approach, compass orientation)
- A cloud-based CountCLOUD service that processes uploaded video and returns detailed Excel reports (usually within one day, up to three days).

Reports include traffic volumes and vehicle classifications (ranging from 2 to 13 classes according to Federal Highway Administration standards), bicycle and pedestrian counts per approach, and time series data in 15-minute intervals. The declared accuracy ranges from 95% to 98%. StreetLogic Pro also provides proprietary cameras with integrated radar sensors for data verification. The solution is primarily intended for operational data collection in engineering practice, but it is not typically used for scientific or model calibration purposes. It also provides an appropriate graphical and tabular representation of the traffic distribution at the intersection (Figure 2).

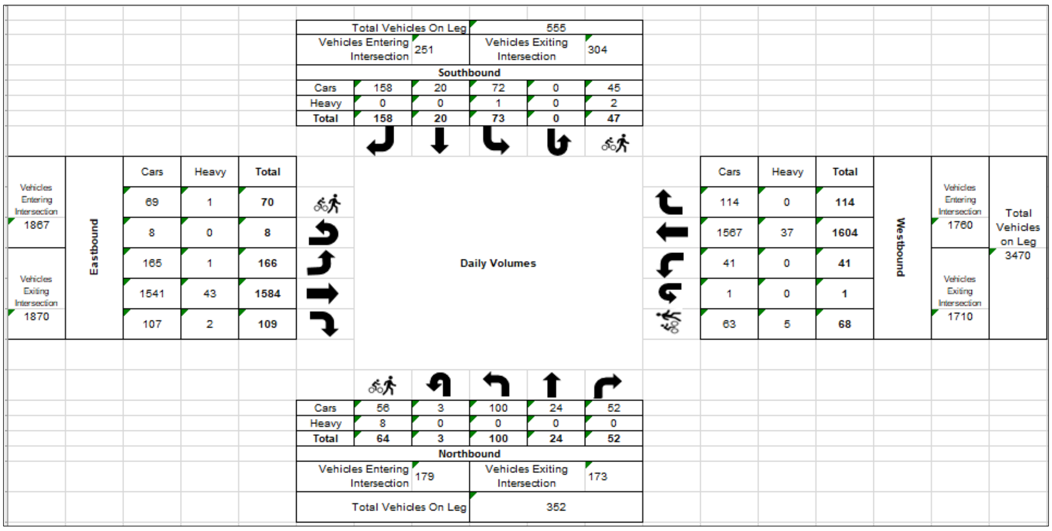

Figure 2. Tabular view of vehicle count distribution (StreetLogic Pro)

3.2. DataFromSky

DataFromSky provides advanced, microscopic AI analysis for both drone and fixed camera videos. Its key features include the following:

- 13–20 vehicle categories;
- Full vehicle trajectory reconstruction (position, speed, and acceleration at every moment);
- Speed and density measurement;
- Origin-destination (OD) matrices;
- Data relevant for safety analyses and simulation/model calibration;
- User-friendliness: simple registration, upload, and fast results accessible in a free desktop viewer.

DataFromSky is practically an end-to-end solution, that is, users upload a video of an intersection or road section on a website and obtain tracking log data after a few hours. Using the free desktop application DataFromSky Viewer, users can define count lines (gates) and observation zones (Figure 3) to extract all parameters needed for traffic model development, calibration, and validation (e.g., start-up lost time, headway, acceleration, speed, stop delay, control delay, end gain time, density).

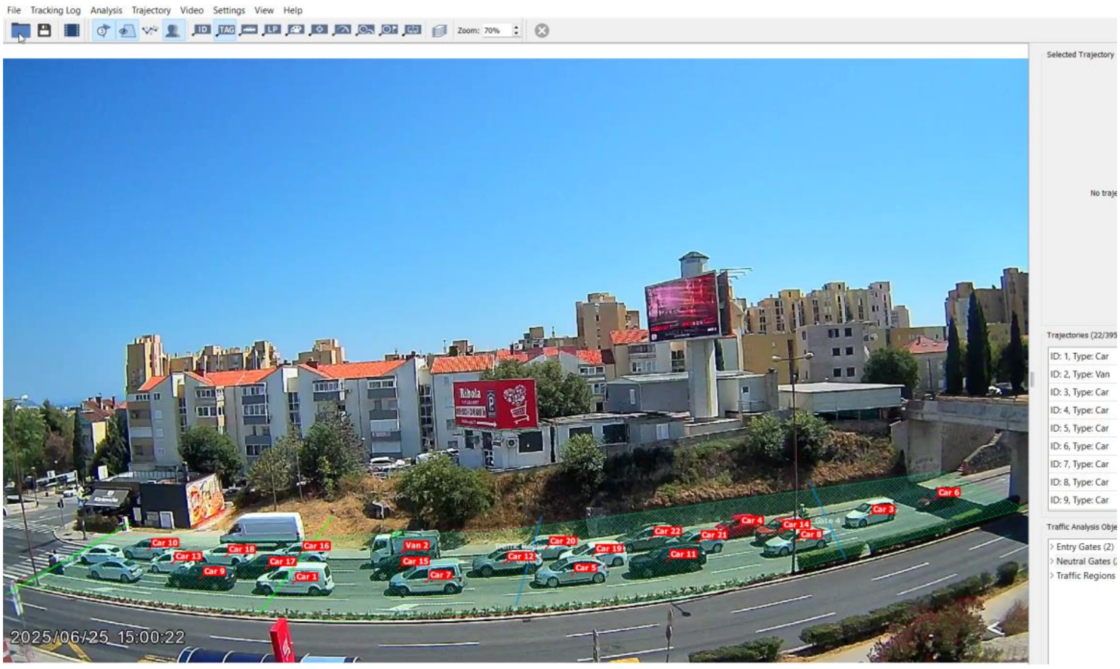

Figure 3. Definition of gates and area (DataFromSky Viewer)

DataFromSky is widely referenced in scientific research for its advanced microscopic approach [27–30]. For example, Ali et al. [30] used two methods to collect traffic data at urban arterials at various locations in the national capital region of India over a 30-minute period. They first used a drone flying at 25 m and 50 m altitudes with a 60° downward tilt. They then used a camera mounted on a footbridge at 5.5 m height with a ~30° field of view from horizontal. The percentage error of vehicle counting was about 1% when the researchers used the drone's bird's eye view, and about 2 % when they used the mounted camera.

In summary, when the conditions of high video resolution and a tight recording angle are met, DataFromSky emerges as a robust, reliable application capable of delivering near complete (98%) detection accuracy. These attributes make it highly suitable for extracting both microscopic and macroscopic traffic data from video recordings, highly valued in traffic engineering and ITS applications.

The system supports comprehensive data export and visualization formats, including Comma-Separated Values (CSV), Drawing Exchange Format (DXF), and Microsoft Excel spreadsheet files, and maintains reliable detection when vehicles occupy 2%–8% of the image width.

3.3. CVEDIA RT Studio

CVEDIA RT Studio is modular AI-based platform supporting multiple traffic and security applications:

- Crowd estimation
- Intelligent traffic systems
- Detection of people, vehicles, and animals
- UAV detection
- Security applications (SecurRT)

The system uses synthetic and real data to train robust object detection models using several plug-ins to minimize system demands. REST API integration supports remote control and interaction with traffic analytics or security systems. The SecuRT module, especially suited for traffic analysis, permits the definition of count lines and observation zones similar to DataFromSky. Detection is reliable if objects occupy at least 2% of the image frame [24]. While powerful and highly configurable, the system is primarily suitable for advanced users due to its complex calibration requirements.

As shown in Figure 4, the CVEDIA RT SecureRT module allows users to define crossing, counting, and tailgating within specified gates, as well as crowding, occupancy, and intrusion movement within zones. At the bottom of Figure 4, the settings for the advanced tripwire are illustrated (which includes crossing and tailgating). Users can define the counting direction; cross and cool down bandwidth (the minimum distance an object must travel to be recognized and avoid false positives); and the specific object reference point used for detection (bottom center, top left, center, bottom left, etc.).

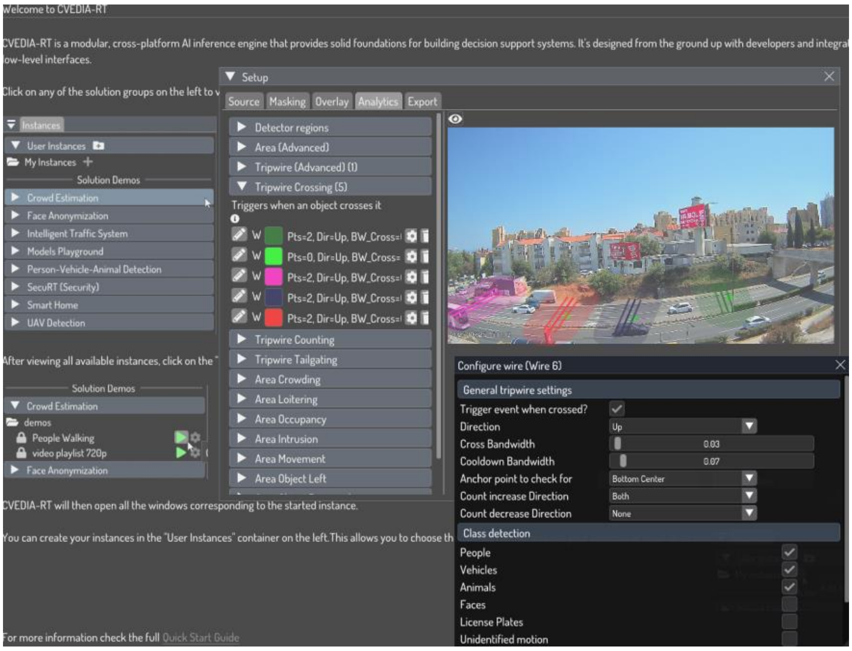

Figure 4. Definition of gates and area (CVEDIA RT Studio)

When the selected module is started, numerous additional parameters can be set, such as whether to classify vehicles by type, the sensitivity of object and motion detection, recognition probability, and many others for advanced users.

3.4. Camlytics Single

Camlytics Single is a cost-effective, intuitive video analytics tool enabling the following:

- Vehicle and pedestrian counting
- Entry/exit and dwell statistics
- Zone congestion mapping
- Export of CSV reports, heat maps, and movement statistics

Setup involves the following:

- Defining count lines and monitoring zones
- Calibrating by specifying minimum detectable vehicle size (using an onscreen ruler)
- Adjusting sensitivity settings to fit traffic, weather, and video quality conditions

Camlytics recommends a minimum object size of 4% (frontal/rear viewing) or 10% (side viewing) of video frame width [25]. High sensitivity settings accommodate low-light or distant views, while low sensitivity helps minimize false detections in busy or cluttered scenes.

Figure 5 shows the vehicle detection interface, while Figure 6 presents the corresponding output window.

Figure 5. Vehicle detection (Camlytics Single)

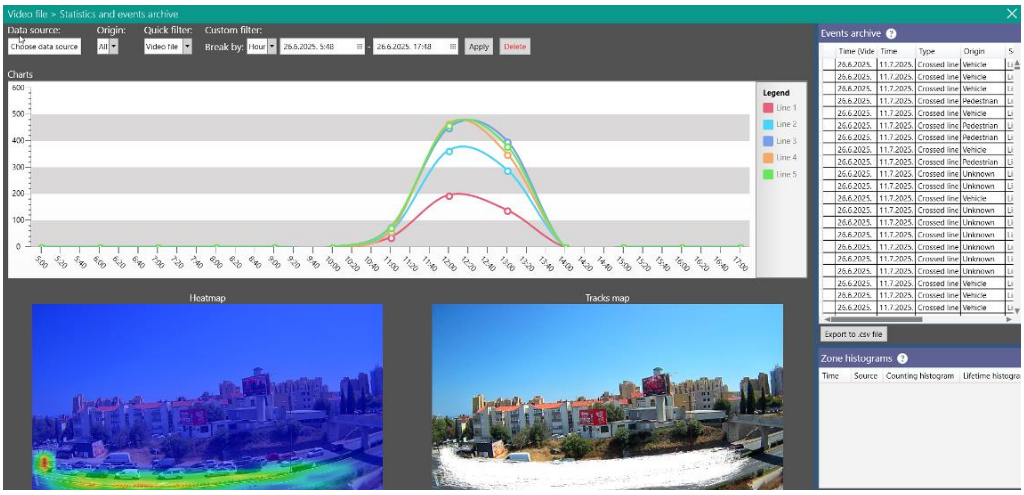

Figure 6. Output window (Camlytics Single)

4. Field Study: Methods and Findings

To evaluate the performance and reliability of AI-based video analytics tools for traffic data collection, a field experiment was conducted at an urban signalized intersection in Split, Republic of Croatia. Split is a midsize city that the Roman Emperor Diocletian founded in the third century. Today, it is a premier tourist destination with around 200,000 inhabitants and serves as the capital of Split-Dalmatia County. It is the Adriatic's largest passenger port and the Mediterranean's third-largest, with more than 4 million passengers annually [31]. The city features two main arterial entrances leading to its center: Poljička Street and Domovinskog rata Street. Figure 7 shows the southern entrance, that is Poljička Street (marked with a red line) and the location of the intersection selected for the field survey (marked with a yellow circle).

Figure 7. Field survey location

In the following sections, the test location and data collection setup are described in detail, followed by an overview and performance results for each of the applied solutions.

4.1. Test Location and Setup

The effectiveness of AI-powered video analytics depends on numerous factors:

- Camera mounting position (overhead vs. side)
- Recording distance and height
- Camera specifications
- Recording method (drone vs. stationary camera)

Drones provide the most reliable overhead view by minimizing the risk of vehicles being obscured behind longer or taller vehicles. However, their deployment has drawbacks, including higher operational cost, limited battery life (often requiring tethered power stations for extended sessions), and vulnerability to weather (wind can cause image instability).

The ideal camera tilt angle for vehicle recognition is below 22 [32]. Cameras should be positioned from 10 to 40 m away for license plate recognition and up to 60 m for vehicle class detection [33–35], ideally equipped with zoom and angle adjustment features. For detection without plate recognition, it is generally sufficient for vehicles to occupy at least from 2% to 5% of the image width [22–24, 36], though reliability improves with larger relative object size. The minimum required object size can also depend on the camera viewpoint (frontal, rear, or side) [25].

A representative test was conducted on the western approach of a three-lane urban arterial at a four-leg signalized intersection in Split, Croatia. Due to the environment, side mounted (tilt) cameras were used because the use of drones for extended periods was not feasible and was further complicated by interference from gulls. Early attempts with loosely mounted cameras in high winds resulted in inaccurate data due to image instability.

Final recordings were made during peak weekday hours in ideal weather conditions using side-mounted (tilt) budget cameras with a resolution of 2.5K (1440P), a 160° wide angle (about 2.8 focal length), a maximum aperture of F1.8, and a frame rate of 30 frames per second. The cameras were positioned 20 m from the edge of the roadway, at a height of about 7 m (second-floor level, marked with a red dot on Figure 8), resulting in a tilt angle of less than 20°. Two cameras were used: one covered the approach area (marked with red lines in Figure 8), while the other recorded the intersection zone to determine the OD matrix and verify traffic counts.

Figure 8. The camera position (red dot), the recorded approach area (green) and defined gates (yellow lines)

In the video of the intersection approach, count lines (gates) were consistently placed at the stop line and at multiple points toward the overpass, as illustrated in yellow in Figure 8. Two independent observers conducted manual reviews of the video recordings and identified a total of 871 vehicles (including 65 motorcycles) crossing the stop line during the 30-minute observation period (15:00–15:30). The counts were compared to ensure consistency and served as the reference (ground-truth) dataset.

4.2. StreetLogic Pro Performance Evaluation

The CountCloud application from the StreetLogic Pro service resulted in a total count of 871 vehicles, with the same number detected in both processed video clips (the approach and the entire intersection). Although this application is capable of tracking 13 vehicle categories, only two were used in this case: passenger vehicles and longer vehicles. The application provides data solely on vehicle counts and directions of movement (through, left, and right), that is, the OD matrix. It demonstrated excellent recognition performance (100%) and fulfilled its intended purpose. In this application, the user does not set vehicle sizes or define the camera position; the service handles these tasks.

4.3. DataFromSky Performance Evaluation

The DataFromSky application successfully detected 842 vehicles at the stop line, including 44 motorcycles, which corresponds to a recognition accuracy of 97%. The system continuously tracks the trajectory of each vehicle from its first appearance to final recognition, recording speed, acceleration, category, color, and time of detection. All recorded parameters are easily accessible for every visible vehicle (refer to Figure 9), enabling quick visual identification of any unrecognized vehicle. Most undetected vehicles were motorcycles (21) whose trajectories disappeared just before reaching the counting point (first gate at the stop line) probably due to small vehicle size in respect to image width. Figure 9 shows the detected vehicles and the trajectory of one motorcycle successfully recorded at the gates located near the center of the frame but not at the gates located at the edges of the frame (at the stop line and near the overpass). Therefore, it can be assumed that as smaller vehicles move away from the camera's focus, both their resolution and size on the image decrease relative to the frame width, causing their recognition to cease. In contrast, at gates closer to the camera's focus, the system successfully recorded trajectories of all motorcycles.

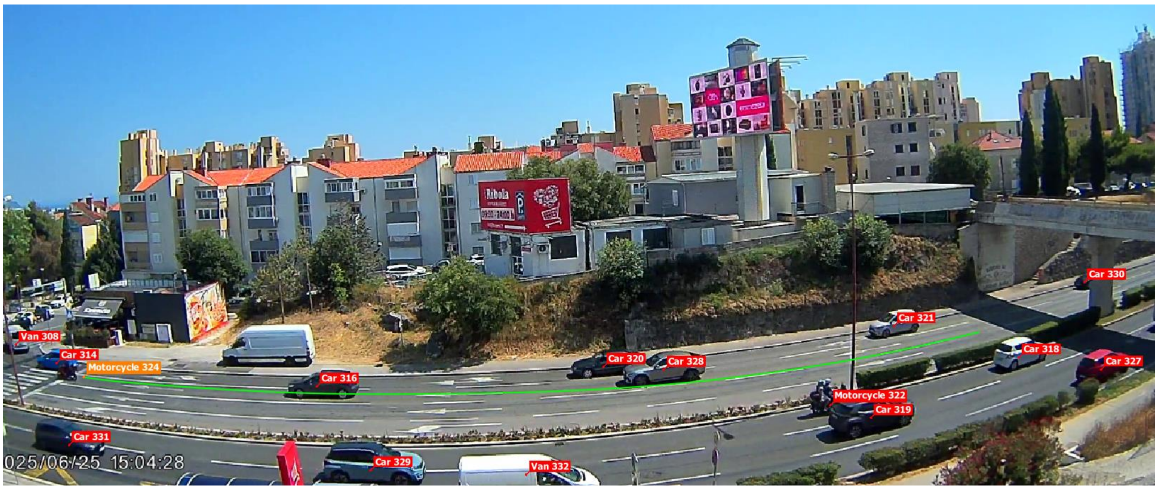

Figure 9. Vehicles detected (DataFromSky)

A few other vehicles were not recorded because they were obscured by larger vehicles in adjacent lanes. When motorcycles are excluded from consideration, the application's reliability increases to 99%, similar to the other gates (2, 3, and 4 on Figure 10), where no motorcycle trajectories disappeared.

Figure 10. Definition of counting gates and detected vehicle trajectories (DataFromSky)

Therefore, consistent results were achieved across multiple gates along the approach, further confirming the reliability of the application.

4.4. CVEDIA RT Studio Performance Evaluation

CVEDIA RT Studio is an application with multiple modules designed primarily for advanced users. It offers customizable models for various problems, including vehicle detection through module SecuRT.

This module has numerous configurable parameters such as the following:

- Object detection sensitivity;
- Motion detection sensitivity;
- Observation time in the frame;
- Recognition probability factor.

Selecting the optimal calibration parameters presents a challenging task for the average traffic engineer. In this study, basic parameters were initially set according to the manufacturer’s guidelines, resulting in the detection of 811 vehicles, corresponding to a reliability of 93%. Given the average user, default settings, selected camera angle, and distance using a wide angle camera lens, this level of reliability is more than satisfactory. According to CVEDIA [24], it is likely that an advanced user could achieve even better results with this free tool, which offers extensive options for calibration, integration, and further development. Thus, in this study, an additional effort was made with the aim of optimizing parameters for a specific problem. The original resolution was used instead of software downscaling, and “Accurate” performance mode was tested. This mode uses higher neural network resolutions, improving detection and classification accuracy while reducing false positives and negatives. Detection sensitivity was set to “High” to compensate for vehicles appearing smaller at greater distances. It was found that the key factors affecting reliability are high recording resolution, the choice of “Accurate” mode, and increased object detection and movement sensitivity parameters. These adjustments summarized in Table 2 increased detection reliability to 99%.

Table 2. Default and optimal calibration parameters in CVEDIA RT Studio

Parameter	Default values	Used values
Preset max. size	1050p (software)	Original value
Object detection sensitivity	Medium	High
Movement detection sensitivity	Medium	High
Performance mode	Balanced	Accurate

4.5. Camlytics Single Performance Evaluation

In Camlytics Single, four counting lines (gates) were defined (see Figure 4), stretching from the stop line toward the overpass. The system observed significant differences of detected vehicles on different gates. It detected the lowest number of vehicles at the stop line, while it detected the highest at the last gate beneath the overpass. Review of video showed that when vehicles slow down or stop, the bounding box used to outline recognized vehicles frequently disappeared, resulting in the system not recording those vehicles. At counting lines located further upstream, where vehicle slowdowns and stops were less frequent, the system detected significantly more vehicles. Various settings were tested, including the appropriate object size and detection sensitivity. Regardless of the parameter set, the same trend persisted: fewer vehicles were detected near the stop line. The best results were achieved with defined high motion sensitivity at the last gate (approximately 70% detection). The lowest detection rates were observed at the stop line.

Overall, this straightforward program demonstrated reasonably good detection performance on road segments farther from the intersection, especially where stops were rare, but it was less successful within the intersection area. The use of a wide-angle camera from a considerable distance combined with bright sunlight and glare likely reduced the detection model's sensitivity. Camlytics defines a 10% minimum object size in relation to width of video record for the camera's lateral detection position. Tested video often featured objects smaller than this (less than 6%), leading to missed detections. The software functions much better when video is captured from a closer range, minimizing wide angle distortion. In a comparative test, Camlytics Single was evaluated using close up video of vehicles. Recognition performance in this scenario aligned with stated specifications, achieving more than 90% detection accuracy (see Figure 11). Even better detection results would likely be achieved by directing cameras toward the vehicles because Camlytics Single is a part of the Camlytics service primarily designed to receive streams from multiple cameras mounted on traffic signal poles and to notify users of specific events (such as vehicle passage or zone entry/exit).

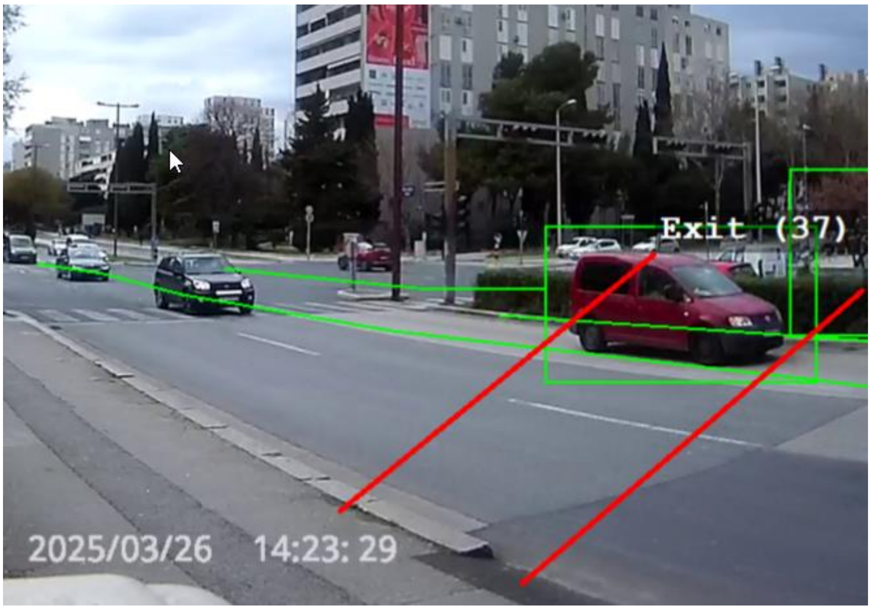

Figure 11. Close up video (Camlytics Single)

4.6. Comparison of Results

Table 3 provides a brief summary of the recognition accuracy of all four tested traffic analysis services, along with key observations regarding their performance. StreetLogic Pro demonstrated the highest detection accuracy. However, its primary limitation for research purposes is that it provides only basic traffic data, that is, traffic volume and directional distribution. Among the evaluated applications, DataFromSky also demonstrated a high level of precision, especially when motorcycles were excluded from the dataset. CVEDIA RT Studio also demonstrated high precision, especially after parameter optimization. A major advantage of both DataFromSky and CVEDIA RT Studio is that, beyond traffic volume estimation, they provide detailed microscopic traffic parameters from vehicle trajectory data, making them well suited for research applications as well as practitioners for the calibration and validation of analytical and simulation traffic models. Camlytics Single showed the weakest performance under the tested conditions, detecting approximately 70% of vehicles. The primary factor contributing to this reduced accuracy was the camera position (facing sideways instead of toward vehicles) causing small relative size of vehicles in respect to the video frame width.

Table 3. Comparison of AI-based traffic analysis applications tested

Service	Recognition Accuracy	Notes
StreetLogic Pro	100%	The user only defines cardinal directions in the footage; the service handles everything else. It provides basic data on traffic volume and distribution for traffic engineering problems.
DataFrom Sky	97% to 99%	Excluding motorcycles, reliability increases to 99%, detecting almost all vehicles not obscured by others. It records detailed temporal and spatial trajectory data (microscopic parameters).
Camlytics Single	Approximately 70% (up to 90%)	The vehicle size relative to frame width does not meet manufacturer recommendations, likely causing lower accuracy. Reliability increased up to 90% when video mostly met the guidelines. It records temporal vehicle data (gate crossing, area intrusion).
CVEDIA RT Studio	93% to 99%	Performant for beginners; highly customizable for advanced users, enabling even greater accuracy after detailed calibration. It records detailed temporal and spatial trajectory data (microscopic parameters).

5. Practical Implications of AI-Based Model Calibration

This section demonstrates how trajectory data obtained from AI-based video analytics (using DataFromSky as an example) can be used to calibrate and validate analytical models commonly applied in traffic engineering, with a focus on the crucial parameter and validation values, that is, saturation flow rate and control delay on an urban arterial intersection.

5.1. Saturation flow rate estimation using DataFromSky

Saturation flow rate is defined as the number of vehicles that would pass through an intersection approach in one hour (3600 s) if a continuous green signal were provided for a given movement. It is calculated as:

$$s = \frac{3600}{h} \tag{1}$$

where, s is saturation flow rate (veh/h/lane), and h is saturation headway (s). The saturation headway (h) is commonly defined as the average headway from the fourth to the last passenger car in the queue at the onset of green because the first few vehicles at the beginning of the queue take longer to cross the stop line due to the driver's reaction time in starting and accelerating the vehicle.

Every analytical methodology for calculating intersection performance begins with the input of the ideal saturation flow value. The ideal saturation flow is the flow that occurs on a road lane with ideal characteristics under ideal traffic conditions: grade 0%, lane width 3.6 m, only passenger cars, no parking or bus stopping manoeuvres, no pedestrian or bicycle traffic, no left or right turns, no specific roadside activities that attract additional traffic, no physical constraints downstream of the intersection (uninterrupted outflow), and no queue spillback caused by congestion at the next (downstream) signalized intersection. The ideal saturation flow does not have a universal value, and various recommendations exist based on studies of driver behavior, which differs across societies with different driving habits [37]. The most commonly used value of about 1 900 veh/h is applied under almost ideal conditions, such as favorable geometry, large distances to neighboring intersections, good visibility, a low number of pedestrians, and minimal impacts from bus stops and parking maneuvers. Under average to poor conditions, including a moderate to high number of pedestrians and significant impacts of bus stops and parking manoeuvres, this value decreases to 1 750 veh/h. Saturation flow rate is a crucial parameter for calibration in analytical traffic capacity methodologies, such as HCM [21]. In practice, the methodology uses various adjustment factors to convert the ideal saturation flow to the actual one, taking into account prevailing traffic and roadway conditions (bus and parking maneuvers, lane width, grade, and so on). The HCM methodology proposes to use an ideal saturation flow that is calibrated for local conditions. Calibration is performed using the prevailing saturation flow rate observed in the field under saturated traffic conditions at the intersection taking into account real intersection traffic and geometry conditions through adjustment factors according to the following Equation:

$$s_o = \frac{s_i}{N \cdot F} \tag{2}$$

where, s_i is saturation flow rate of lane group i under prevailing conditions (veh/h), s_o is ideal saturation flow per lane (veh/h of green/lane), N is number of lanes in the lane group, and F is product of 13 adjustment factors (lane width, grade, parking maneuvers, etc.).

In this study, the prevailing saturation flow rate was determined using DataFromSky and compared with the widely applied HCM Control Delay Field Study method [21]. The reported values were obtained for the two middle through lanes on the western approach of the selected intersection because these lanes are dedicated to through movements while only marginally affected by turning maneuvers in adjacent lanes.

Thirty cycles of 100 s were observed. For each cycle, the time differences between successive passenger vehicles that were queued at the start of green were extracted from the trajectory data. This procedure is operationally straightforward in DataFromSky because a separate virtual gate can be defined for each lane. The resulting mean saturation headway for the through movement was 2.152 s, corresponding to a mean saturation flow rate of 1 673 veh/h/ln. The ideal saturation flow rate can then be estimated by substituting the actual traffic and roadway characteristics (such as grade, lane width, and the number of bus and parking maneuvers) into Equation 2.

For comparison, the prevailing saturation flow rate was also estimated using the technique recommended by the HCM [21], which is based on manually determining the average saturation headway from detailed field observations. The average saturation headway is calculated by dividing the duration of the saturation flow period by the number of saturation headways after the fourth vehicle. The saturation flow period begins when the front axle of the fourth vehicle in the queue crosses the stop line and ends when the front axle of the last surveyed vehicle in the stopped queue crosses the stop line. If n denotes the ordinal number of the last surveyed vehicle, the average saturation headway is given by

$$h = \frac{t_n - t_4}{n-4} \tag{3}$$

where, t_4 and t_n (s) are passage times of the fourth and the last surveyed vehicle, respectively. The saturation flow rate is then calculated according to Equation 1.

The resulting mean saturation flow rate for the same through movement was 1 663 veh/h/ln. The difference between the two estimates is negligible (0.6%), indicating that AI-based video analytics can reproduce saturation flow values obtained from established survey methods, while considerably reducing field and in-office effort and time.

5.2. Control Delay Estimation using DataFromSky

Control delay is one of the most commonly used performance measures in the testing and validation of analytical and simulation models for all types of intersections. At signalized intersections, control delay is defined as the difference between the actual travel time through the intersection and the travel time that would occur without signal control. It includes stopped delay as well as time lost due to deceleration and subsequent acceleration. Control delay therefore represents the average delay experienced by all vehicles during the analysis period.

In this study, control delay was estimated at the same intersection approach used for saturation flow rate analysis. The estimation was performed using DataFromSky and subsequently compared with the widely used HCM Control Delay Field Study method (queue-count technique) [21]. Based on the trajectory data, the following time stamps were extracted for each vehicle that was queued before the start of the green phase:

- The time when the vehicle was first detected on the approach, and
- The time when the vehicle crossed the stop line (virtual gate).

From these data, the total time spent on the approach was determined for all vehicles and averaged. The average free-flow travel time (time required to traverse the approach at free-flow speed without stopping) was then subtracted to obtain the average control delay per vehicle. Using DataFromSky AI-based procedure, the calculated control delay was 20.7 s/veh.

The HCM queue-count technique [21] for control delay measurement is based on direct observation of the numbers of vehicles in queue for a subject lane group at fixed time intervals during the survey period. Delay during deceleration and a portion of acceleration is not measured directly. Instead, appropriate adjustment factors are applied for sampling errors and unmeasured acceleration–deceleration delay. First, the average time spent in queue per vehicle (d_{vq}) is calculated from the observed vehicle-in-queue counts and then adjusted using acceleration–deceleration correction factor (CF). The average time in queue per vehicle is computed as

$$d_{vq} = 0.9 \cdot \left(I_s \cdot \frac{\sum V_{iq}}{V_{tot}} \right) \tag{4}$$

where, d_{vq} is average time spent in queue per vehicle (s/veh), I_s is interval between vehicle-in-queue counts (s), $\sum V_{iq}$ is sum of vehicle-in-queue counts (veh), and V_{tot} is total number of vehicles arriving during the survey period (veh). The factor 0.9 in Equation 4 accounts for sampling errors. The total control delay is then calculated as:

$$d = d_{vq} + d_{ad} \tag{5}$$

where the acceleration–deceleration component is:

$$d_{ad} = FVS \cdot CF \tag{6}$$

and FVS is fraction of vehicles stopping, while CF is acceleration-deceleration correction factor (s/veh). The fraction of vehicles stopping is calculated as:

$$FVS = \frac{V_{stop}}{V_{tot}} \tag{7}$$

where, V_{stop} is the number of stopped vehicles. The correction factor (*CF*) is selected from the tabulated values in the HCM [21] as a function of approach speed and the average number of vehicles stopping.

Applying the described HCM Control Delay Field Study procedure to manual field observations on the same approach as that used for the DataFromSky analysis yielded an average delay of 19.7 s/veh. The difference of less than 5% lies well within the range considered acceptable in validation studies of delay estimation methods for signalized intersections, where differences of 10%–15% are generally regarded as tolerable for well-calibrated models [38]. This indicates that AI-based delay estimation can effectively complement or replace traditional field observation methods, with significantly higher time efficiency.

5.3. Summary of Practical Benefits

The presented example demonstrates how AI-based video analytics can provide high-quality microscopic data that support the calibration and validation of analytical applications such as HCM. The key advantages include

- Accurate estimation of critical parameters such as saturation flow, start-up lost time, and control delay, and
- Substantial reduction in field effort and processing time (by more than ten times less compared with traditional survey methods).

These features make AI-based video analytics a powerful practical tool for traffic engineers engaged in the development, calibration, validation, and application of analytical and simulation traffic models.

5.4. Discussion

In this study, a comparison between four AI-based traffic video analytics applications (StreetLogic Pro, DataFromSky, Camlytics Single, and CVEDIA RT Studio) has been performed. The evaluation was based on a video recording obtained using budget equipment consisting of two dashcams and an external power bank at a signalized intersection approach on a main urban arterial. The analysis focused on the applications' detection reliability, usability, sensitivity to camera placement and weather conditions, and their suitability for use by researchers, educators, and practitioners in traffic models calibration and validation. The comparison shows differences in accuracy and applicability of the analyzed applications, which makes it possible to distinguish those more appropriate for academic purposes from those more suitable for engineering and monitoring tasks.

Using budget equipment, all analyzed tools demonstrated vehicle detection effectiveness ranging from 90% to nearly 100%, which is consistent with previously cited scientific research on the efficacy of AI-based video analytics [15–17]. Similar empirical studies typically report overall detection accuracies in the range of 96%–99% under favorable camera geometry and lighting conditions, which is consistent with the performance observed in this field experiment.

DataFromSky offers advanced analytics, including tracking of trajectory, speed, acceleration, entry and exit times, and occupancy. It achieves recognition accuracy of 97%–99%, making it highly recommended for scientific researchers, particularly those focused on car-following theory, modeling microscopic and macroscopic traffic flow parameters, as well as for practitioners for the calibration and validation of analytical and simulation traffic models. In addition, the ability to export complete trajectory data in standard formats (CSV, DXF, Excel) facilitates direct integration with microscopic simulation tools and supports advanced analyses such as headway distributions, queue discharge patterns, and safety surrogate measures, which are difficult to obtain using traditional survey techniques.

StreetLogic Pro is specialized for efficient and precise vehicle counting at road sections and intersection approaches. It also provides cameras with cloud-based video processing, ensuring reliability for OD matrix generation. This makes it an excellent solution for traffic engineers requiring input data for further operational analyses. In the present example, an accuracy of 100% was achieved, and the software offers an intuitive tabular and graphical display of traffic volume distribution per movement direction in the analyzed period.

Camlytics Single provides a practical and cost-effective solution for vehicle counting using fixed cameras. Its reliability depends on recording quality, camera position (side, head-on, or overhead), and vehicle size (in pixels or as a percentage of image width). Side recording from a distance yielded good detection where there were no stationary vehicles, while accuracy dropped below 50% in areas with slow-moving or stopped vehicles despite calibration efforts. When the camera distance and position adhered to the manufacturer's guide, reliability exceeded 90%. As part of the Camlytics server suite for real-time analysis of numerous networked cameras, Camlytics Single serves as an accessible solution for familiarization with complete suite possibility. Therefore, it is best suited for less demanding traffic engineering projects.

CVEDIA RT Studio is a flexible, modular application for real-time video analytics in integrated systems. Developed for advanced users, it supports model customization to diverse needs, requiring advanced technical knowledge yet offering high adaptability and reliability dependent on the configuration effort. It can extract detailed microscopic flow parameters, making it highly relevant for research in car-following theory and for the development and calibration of analytical and simulation models. In practice, with basic parameters it achieved reliability above 93%, with the potential for even greater accuracy up to 99% through advanced parameter tuning by skilled users.

Based on the results, DataFromSky and CVEDIA RT Studio emerge as the most suitable for research, development, testing, and calibration of analytical and simulation models used in traffic engineering. DataFromSky distinguishes itself through user-friendly operation and detailed graphical and tabular presentations of all microscopic and macroscopic flow parameters. It functions as an end-to-end solution, that is, users upload a video of the intersection or road segment on a website and receive processed tracking log data after a few hours. Users do not adjust model parameters but instead define intersections and zones within the DataFromSky Viewer application to extract required data.

CVEDIA RT Studio similarly delivers comprehensive traffic data, though its setup and data export processes are more complex, making it ideal for advanced users. Because it is not an end-to-end solution, significantly higher precision can be achieved by adjusting parameters based on camera characteristics and position, object size, lighting, and resolution, compared to the initial results obtained using default parameter values. In this study, parameter tuning increased detection accuracy for all vehicles from 93% to 99%, with the greatest improvement in recognizing shorter vehicles, that is, motorcycles. A major advantage of CVEDIA RT Studio is that it is entirely free for single use, making it an ideal tool for educators and students. A disadvantage compared to DataFromSky is that data can only be exported after processing the recording, which occurs mostly in real time (or slower, depending on the computer's available memory), while DataFromSky provides fully processed data, that is, tracking logs for uploaded videos.

Finally, chapter 5 shows how data obtained from DataFromSky could be used to calibrate and validate analytical traffic models commonly applied in traffic engineering problems.

In addition to performance comparison, this study examined the practical application of AI-based traffic video analytics using two key parameters for the calibration and validation of analytical traffic models: saturation flow rate and control delay. The values obtained using the DataFromSky system were compared with those derived from traditional manual field observation techniques and only minor differences were observed. These findings confirm that AI-based video analytics represent a suitable and efficient alternative to conventional, labor-intensive traffic survey methods, offering substantial advantages in terms of time efficiency and data richness.

Overall, the combination of high detection accuracy and detailed microscopic output data confirms that AI-based video analytics can provide more precise data quality in comparison with established field methods, while substantially reducing the effort required for data collection and processing, especially when tools are applied within their recommended operating conditions.

6. Conclusion

This study evaluated four commercially available AI-based video analytics tools for traffic engineering applications and examined their potential to support the calibration and validation of analytical models. Field video recordings from a signalized urban intersection in Split, Croatia, were processed using StreetLogic Pro, DataFromSky, CVEDIA RT Studio, and Camlytics Single. The tools were assessed in terms of detection accuracy, usability, sensitivity to camera placement and recording conditions, and suitability for use by researchers, educators, and practitioners.

StreetLogic Pro achieved the highest detection accuracy (100% in the test case) and provides user-friendly tabular and graphical summaries of turning movements, making it highly suitable for operational traffic counting and OD matrix development in engineering practice. DataFromSky and CVEDIA RT Studio reached 97%–99% detection accuracy and offer detailed microscopic information, including vehicle trajectories, speeds, and accelerations. These features make it particularly appropriate for scientific research and practitioners in processing the calibration and validation of analytical and simulation traffic models. Camlytics Single demonstrated acceptable performance only when camera placement and object size followed the manufacturer's recommendations, indicating that it is best suited for less demanding applications and closer-range monitoring scenarios.

A worked example based on DataFromSky showed that AI-derived estimates of saturation flow rate and control delay can closely match values obtained using HCM field procedures. The differences were less than 1% for saturation flow rate and below 5% for control delay, which lies within the range considered acceptable in previous validation studies. These findings confirm that AI-based video analytics can effectively complement or replace conventional manual surveys, providing substantial gains in efficiency and data richness. The main limitations of this study are the use of a single urban site, side-mounted cameras, and one set of equipment. Future research should extend the analysis to different intersection types, camera viewpoints, traffic compositions, and longer observation periods. Nevertheless, the results provide practical guidance for selecting AI-based video analytics tools in various traffic engineering challenges and demonstrate a clear pathway for integrating AI-derived trajectory data into established analytical modeling frameworks.

7. Declarations

7.1. Author Contributions

Conceptualization, D.C. and B.M.; methodology, D.C. and S.V; software, D.C. and S.V.; validation, S.V.; formal analysis, D.C. and S.V.; investigation, D.C.; resources, B.M. and S.V.; data curation, B.M. and S.V.; writing—original draft preparation, D.C.; writing—review and editing, B.M. and S.V.; visualization, B.M. and S.V.; supervision, D.C.; project administration, B.M.; funding acquisition, B.M. All authors have read and agreed to the published version of the manuscript

7.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.4. Conflicts of Interest

The authors declare no conflict of interest.

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