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# Economical Traffic Analysis Methods

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**ABSTRACT**

*At present, there are various traffic analysis approaches and tools accessible in all areas; nevertheless, there are not enough, or by all-means, resources, and supplies for the application of these tools, as these tools differ in their competencies, input supplies, and productivity. This paper aims to provide a new way for a cost-effective traffic analysis implementation, which does not require a lot of resources, combining two machine learning algorithms to count the vehicles, estimate their speed, and segment lanes from a video recording., The video recording can be done using a conventional mobile phone camera and can be processed using a simple hardware toolkit. To bear out the cost-effectiveness of the proposed procedure, we provide a cost comparison analysis with a radar-based mobile traffic counting device.*

## Introduction

Traffic analysis has been playing a key role in transportation systems development and sustainability from the earliest time to the present day, as it affects the economic, social, and environmental aspects in a major way, and thus it has been studied for a long time. Traffic analysis has a crucial role in the development, creation, and management of the current transportation systems as it has helped in building reasonably priced systems and has improved defining the demand for transportation networks.

In the current time, technological innovations have offered the potential of improvement of complicated issues and concerns that face transportation systems and traffic analysis methodologies. Traffic simulation, machine learning, intelligent transportation systems and much more have helped to solve many challenges that face transportation systems in a valuable and cost-effective way. To focus on practical challenges in transportation systems in this paper, an overview of application schemes and new technologies for transportation systems is done, as also an overview, how they helped resolve many challenges that transportation systems face nowadays, especially because these systems deal with big data which gives unique prospects to solve transport complications that traditional approaches collapse when dealing with. On the other hand, some of these technologies are not very cost-effective, so, a new way of traffic analysis in this paper is proposed, which analyzes the traffic in an economical manner that does not require a lot of resources and tools. The goal is to provide an inexpensive alternative for a one-time temporary traffic-relevant data collection of an intersection, and to use this data for traffic simulation purposes.

## Traditional Ways of Traffic Analysis

During traffic surveys, we can basically distinguish two types of data collection methods. One method is called manual counting, the other is called machine (automatic) counting. Machine-based measurement has become more and more common, but manual counting still has some role in traffic analysis due to data validation. Manual counting can be performed in real-time or by manual processing of a video recording.

Traditional automatic traffic counting and classification (ATCC) methods are cost intensive because they need specialized devices and data collection and processing solutions developed especially for this purpose.

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Automatic traffic measurement stations are usually permamently installed and equipped with loop detectors, in some cases piezoelectric or axle load sensors. In general, it can be determined that cheapand older devices are not very precise, and they cannot detect extra parameters like vehicle speed or vehicle classification (passenger vehicle, truck, bus, motorcycle, etc). However, the installation and operation of these are costly as well. A review of some traditional traffic analyses for roads is in the following:

- Pneumatic Road Tube Counting: it uses a couple of sets of tubes (ducts) that can be stretched out within some lanes, where it can determine the vehicle path by recording which tubes set the vehicle first takes across, other than this way of vehicle counting is expensive and needs actual human workers to close the road and install the tubes, it also has the disadvantage that if more than one vehicle passes over it at the same time then their path can't be precisely known and recorded. Although it can count the vehicles precisely under the ideal condition, it has been shown that if these tubes can be optimized to estimate the speed and classification, the errors can be much greater than in counting the vehicles by humans [1].
- Magnetic Sensors: they detect vehicles by determining the difference in the earth's magnetic field when the vehicles pass over the sensor. This sensor can be submerged under the ground or covered in a container by the side of the road. One of its biggest disadvantages is that If vehicles are driving closely, the detector may have trouble distinguishing between them. If it can be fixed within a traffic light, based on the noise intensity, it can define the size of the vehicle and determine how fast it is traveling, this makes it available to recognize the type of vehicle also and thus improve assessments of how to monitor the traffic lights. [2]
- Inductive Loop Detectors: These involve a cable that produces a loop that can be fixed in or underneath the ground of the road. Those loops estimate the alteration when things (vehicles in this case) travel above them. So, when a vehicle drives above it, it lets the device sense the existence of the vehicle. Usually, it is used in combination with axle sensors to assemble information such as speed. They are usually more accurate when it is used under heterogeneous and fewer traffic conditions. [3]
- Doppler and Radar Microwave Sensors: communicate using a continuous signal of low-energy microwave radioactivity at the aimed zone, then evaluate the signal. Many research established that those sensors offer nearly precise vehicle detection only in typical weather environments, yet this precision might lessen significantly in unusual weather situations [4]

In most cases, vehicle classification machines use the axle number to identify vehicle classes. In the 2000s, a new possibility was the use of traffic counting devices built into traffic lights or benches, which were intended to support the measurement of road traffic passing through cities and the distribution of traffic. For instance, the Hungarian Public Roads Non-profit Ltd. in Hungary uses MINILOOP, MINIMAX, ADR-2000, Raktel-8000, CrossCount, MiniClass, QLTC, TDC (HI TRAC100, HI TRAC110, HI TRAC100+ HSWIM), WIMLOOP and XLOOP devices for traffic analysis. [5]

It is easy to see that if, for example, we want to perform an analysis based on automatic data collection in an intersection that is not equipped with modern devices, then acquiring and installing the appropriate target devices is an extremely expensive task, especially when taking into consideration the whole life cycle price data which can be crucial to the maintenance and keeping accurate fed data to the traffic analysis. Preliminary expense estimations should not only be the whole consideration. But the total expenses should also be considered, with a maintenance cost, energy, and most importantly time estimation.

The use of traditional mobile traffic counting devices (for instance, StatTrak) can be a reasonable alternative for one-time traffic analysis of an intersection, however, the cost of these devices is still extremely high, and their operation requires special knowledge.

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## Machine Learning (ML) Algorithms for Traffic Analysis

Machine learning models and algorithms have widely helped develop forecasting tools that produce precise and well-timed data on traffic. This data includes all parameters that can affect traffic, for instance, traffic signals, traffic jams, accidents, and maintenance on the roads as if prior data can be known, predicted, and analyzed it helps in the decision-making process. Lately, ML models have brought together many fields due to their capability to deal with categorization, knowledge of patterns, object recognition, and real-time flow modeling. The authors of [6] developed a real-time forecast and estimation methodology, based on univariate and multivariate state-space models to predict short-term passenger arrivals at transit stations. Additionally, the authors of [7] considered a daily-level profit maximization of a shared mobility-on-demand service with request-level control and solved this problem by designing a parametric policy and utilizing the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) to search for the optimal parameter, their study showed that the optimal pricing strategy produces significantly more revenue than basic policies myopic strategies but it increases the congestion level and reduces the capacity in the transportation system.

Simulation, optimization, and ML models have been studied to support and boost sustainability in transportation systems and showed that sustainable transportation systems, and hybrid techniques that use development techniques, such as ML algorithms, can solve sustainable transportation problems [8]. Another study that aims to research the ML outcome on transportation systems has shown that on transportation and data-focused techniques, such as autonomous vehicles, and traffic analysis and improvements, difficulties such as travel behavior predictions have been solved with an algorithm applying density-based 3-D gathering of applications with a sound algorithm for gathering travelers' preference locations [9].

In terms of efficiency, Rice et al. showed a good quality implementation of the linear regression model while giving only a small training dataset in their studies [10], [11]. Also, Kwon et al. merged linear regression with a step-by-step varying collection technique and tree-based method, while they made a prediction using flow, occupancy, and historical travel-time data [12].

Based on the literature, the value of combining two algorithms has also been distinguished and acknowledged, those algorithms are You Only Look Once (YOLO) and Simple Online and Realtime Tracking (SORT), and the combination has been designed using Python Language. This combination is being used to detect vehicles, lane segmentation, and estimate the speed of vehicles from video recording, while these videos can be recorded from unpretentious cameras, and those videos can be processed using simple processers and hardware, the usage of these algorithms showed that processing the videos recorded of the vehicle does not require a lot of time too, so their usage is not only time effective, but also an energy saver.

Joseph Redmon et al. proposed an integrated, fast, and simple architecture of YOLO for object detection, YOLO works basically by running a neural network on an image at test time to foresee detections, it runs at 45 frames/second, and it can process a video in real-time with less than 25 milliseconds. Additionally, YOLO accomplishes approximately more than twice the average accuracy of other real-time systems [13]. Later, Redmon et al. proposed a new and improved version of YOLO v2, which significantly improves the precision and speediness of object detection by eliminating the occupied assembly layers in the network, and group standardization [14]. And afterward, the third generation YOLO v3 has been introduced [15]. In the beginning, a homogenous image is used as input to the model, the next the image is distributed into S*S grids it then uses these grids to produce a probability map, bounding boxes, and confidence score. Lastly, the object candidate box with confidence and position is output on the image [16]. YOLO is being used in the Python library studied in this research for object detection, it detects the vehicles and the lanes on the road. Based on the literature review it was reached that YOLO is one of the most widely used algorithms for object

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detection, where it includes image classification, pathfinding, motion tracking, and more, in a fast and accurate way.

Regarding vehicles tracking, the SORT algorithm is used, SORT is one of the first algorithms which handles object tracking, it uses Faster Region CNN to classify and recognize the objects in specific frames, and after, the tracking of the objects is prophesied based on a Kalman filter, which estimates the new spot of the objects, after perceiving the new position, the Kalman filter renews it to a new spot. In simple words, this filter measures the overlap between predictions based on the preceding frame and actual recognitions. If the recognition and the Kalman prediction intersect, the detection is allocated to the track [17].

A number of ML models (for example, YOLO, SSD, RCNN, and SPPNet for object detection, and SORT, DeepSORT, and MdNet for object tracking) have been analyzed and evaluated, a summary of the most important aspects of why YOLO is chosen between these algorithms is listed in the following based on, [25], [26], and [27]:

- YOLO (You Only Look Once) is considered to be better than SSD (Single Shot MultiBox Detector), RCNN (Region-based CNN), and SPPNet (Spatial Pyramid Pooling Network) for object detection in some situations due to its unique architecture and design choices that make it faster and more efficient.
- YOLO uses a single CNN to predict object bounding boxes and class probabilities directly from full images in one evaluation, while SSD uses multiple feature maps of different scales to detect objects of various sizes and RCNN uses a region proposal method to generate potential regions of interest (ROIs) in an image, and then uses a CNN to classify and refine the bounding boxes of the objects in the ROIs, which increases the computational cost.
- YOLO is designed to be more robust to background clutter and partial occlusions.
- YOLO's architecture is simpler than that of SSD, RCNN, and SPPNet, it has fewer parameters and less computation which makes it faster and more efficient.

While SORT is considered to be better than DeepSORT (Deep Learning for Multi-Object Tracking) and MDNet (Multi-Domain Network) for object tracking in our study purpose due to its simplicity, robustness, and real-time performance, some of the major aspects that made SORT more suitable for this study are listed in the following based on [24]:

- SORT is robust to occlusions, camera motions, and variable object appearances.
- SORT is able to handle multiple object tracking with a low computational cost.
- SORT is able to handle multiple object tracking with a low memory cost.

It's important to note that YOLO uses a single convolutional neural network to predict multiple bounding boxes and class probabilities in one pass of the network, this approach is considered one of the main reasons behind its efficiency. Moreover, YOLO and SORT are typically trained on a large dataset of images that contain the objects of interest. The dataset must be labeled, meaning that for each image, the location and class of each object in the image must be specified using bounding boxes. The data that YOLO is trained on can vary depending on the task and the objects of interest. Common datasets used for training YOLO include the PASCAL VOC dataset, COCO dataset, and ImageNet dataset. These datasets contain a large number of annotated images and a wide variety of objects, which is useful for training a model that can detect a wide range of objects in different contexts. [23]

According to our analysis results, the combination of YOLO and SORT gives the fastest and most cost-effective video processing method to detect vehicles, track them, count them, detect lanes in the road, and estimate speed. The video recording of the road section is used as an input feed to the ML model, and after

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processing, the vehicle counting, speed estimation, and lane segmentations are characterized and prepared. The model gives a result output video that has the output data as in Figure 1.

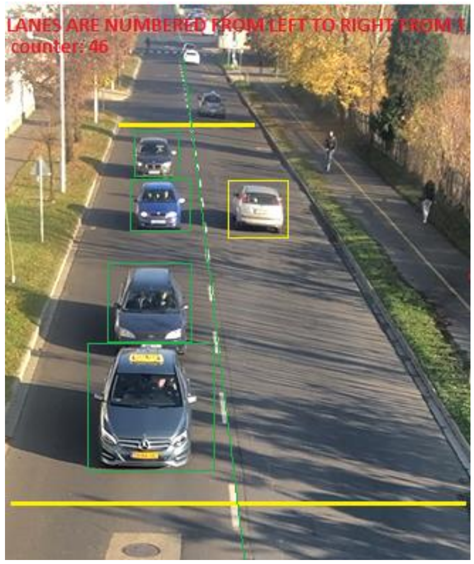


Figure 1: Output Video Example

Source: own construction

Estimating the speed is done in the model by drawing two perpendicular virtual lines (the yellow ones in Figure *1*), and as the actual distance between those two lines can be measured, it can be entered into the model, and since the time is known for each vehicle to pass between these two lines, the speed can be estimated using (1). It is alleged that this way of estimating the speed gives more accurate results, for example, if the camera shakes, it results in frame flaming, which means the traditional pixel distance traveled to km/h plotting, as if each frame flickers, the center of the bounding box also flickers subjectively. Additionally, A number of videos were recorded to examine and validate the detection outcomes of the proposed ML combination, the validation was done by comparing the manually counted vehicles, and the model that combines both YOLO and SORT algorithm-counted vehicles, also by comparing the detected speed with manually calculated speed, The speed was validated by measuring the exact distance between the drawn two virtual lines by the library (which are shown in Figure 1 as the two yellow perpendicular lines to the vehicles' moving lines), as the distance between these two lines is known, and the time each vehicle needs to pass between these two lines is also known, the speed was validated by calculating (1), there were only minor errors as listed in

Table 1 and Table 2.

$$Speed = d/t \quad (1)$$

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Table 1: Vehicles Counting Comparison Results for Three Hours

| Actual Number of Vehicles | Detected Number of Vehicles | Percentage Error |
| --- | --- | --- |
| **968** | 931 | 3.97% |

Table 2: Vehicles Average Speed Comparison for Three Hours

| Actual Average Speed of Vehicles (Km/h) | Estimated Average Speed of Vehicles (Km/h) | Percentage Error |
| --- | --- | --- |
| **29** | 28 | 3.44% |

The advantage of using a cell phone that it's not expensive, especially since it does not require a specialized camera. The authors of [25] have developed an automatic system for vehicle classification and counting, using AI technology on mobile phones, the camera in a mobile phone was used to take the video and run the needed assessment for detection, tracking, and counting in real time; the system reached a counting accuracy of 96%. According to our measurements, it is more accurate and adequate to process the recorded traffic videos later on a desktop computer because special programming knowledge and environment are needed for properly examining the code based on the road situation.

## Cost Comparison Between Traditional Traffic Analysis Tools and the Analyzed ML-based Video Processing

In the followings, a cost comparison between a number of traditional cost traffic analyses (which are listed in Table 3) and the analyzed traffic analysis tool in this paper (which is the two combined ML algorithms too) is provided. In Table 3 several traditional traffic analysis devices assessments are done, all the information listed in the table is based on Federal Highway Administration (FHWA) articles and reports.

Table 3: Traditional Traffic Analysis Tools Assessment, [19] [20]

| Tool Name | Advantages | Disadvantages | Applications | Cost |
|---|---|---|---|---|
| **Pneumatic Road Tube** | Quick installation, low power usage, simple maintenance | Inaccurate counting in large-volume vehicles, temperature sensitivity | Short-term traffic counting, vehicle classification by axle count, and spacing. | One lane: Approx. US $5,000, Four lanes: Approx. US $9,000. |
| **Inductive Loop** | Insensitive to severe weather conditions, good quality accuracy for counting compared to other tools | Installation needs pavement cut off, Installation and preservation demand lane shutting down, accuracy might decrease when it detects a large range of vehicle classes. | Traffic volume, vehicles speed, headway, and gap parameters. | Low Communication Bandwidth: Approx. 800$ |
| **Microwave Radar** | Insensitive to severe weather conditions, direct speed measurement, multiple lane processing | May not detect moving vehicles, and some types have a problem when used in big steel structures. | Traffic volume, vehicles speed | Low to moderate communication bandwidth: ($700-$2,000) |

The purchase and deployment of devices equipped with one of the above-listed technologies are relatively expensive, thus they are not suitable for a one-time traffic analysis of an intersection. We tried to find an easy-to-install and operate mobile traffic counting device and compare it with our proposed conventional camera-based ML video processing traffic analysis solution. We have chosen the StatTrak mobile traffic counting device and made a detailed comparative analysis with the studied video processing technology which captures the videos using a standard mobile phone camera, and then processes the videos using the combination of YOLO and SORT algorithms. StatTrak is an entirely combined multi-lane, bi-directional traffic data assembly device designed with a microwave sensor [21], the comparison is listed in the following Table 4, resources for Stattrak information are based on [21], [22],

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Table 4: Stattrak and Video Image Processing Comparison

| Attribute | StatTrak Traffic Data Collector | Mobile Phone Camera with Video Processing |
|---|---|---|
| Mounting height | 2-3.7 m | 2-5 m |
| Vehicle counting accuracy | max 96% in single-lane road<br>max 90% in multi lanes road | ~96% in single lane road<br>~94% in multi lanes road |
| Speed estimation error | Max 0.4% | ~3% |
| Detecting technology | 24.020-24.230 GHz (K Band) radar | Video image processing ML algorithm |
| Viewing angle (vertical x horizontal) | 20° x 60° | Camera lens dependent<br>40°-80° x 50°-120° |
| Advantages | No need for special technical knowledge to obtain the data;<br>easy installation and checking the accuracy (beeps when it's reading vehicles) | Sophisticated vehicle classification; more accurate results in vehicle counting |
| Disadvantages | Expensive, Approx 2700$;<br>it can only be used for specific traffic monitoring purposes;<br>only basic vehicle classification (small, medium, and large) | Special knowledge is needed for video image processing (the code is written in Python language, hence, programming knowledge is needed for examining the code based on the road situation) |

As a result, we can determine that our proposed conventional camera-based ML video processing traffic analysis method can be a much cheaper alternative for one-time mobile traffic analysis of an intersection.

As an application example, if we would like to study the traffic of a four legs cross-intersection with 2x2 lanes, and we could not install devices in the middle of the road, then we should use 8 PCs StatTrak traffic data collectors for simultaneous traffic data acquisition (Figure 2 on the left-hand side), and just the cost of the needed devices would be approximately $21 600 (8 x $2 700).

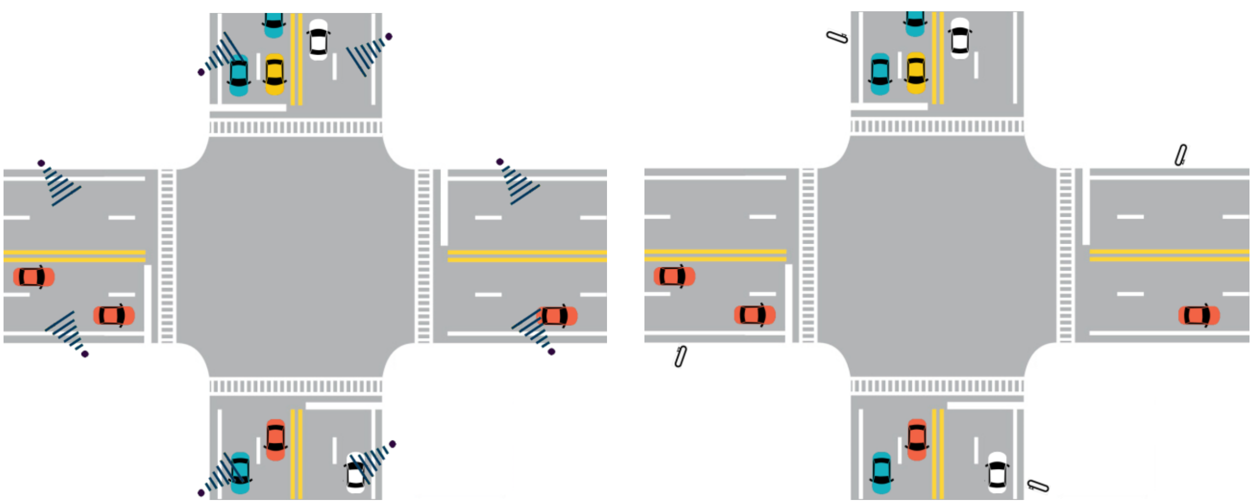

Figure 2: Intersection example for traffic analysis with StatTrak (left) and cell phone (right)

Source: own construction

Finding an appropriate high recording position or using a high stand (min 2-2.5m), four conventional cameras would be enough for capturing the videos from the 4 lines of the 4 crossing's legs (Figure 2 on the right-hand

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side). The use of these cameras, and processing the videos on commodity PC hardware does not mean any special cost, since the involved persons own such devices anyway

## Conclusions

Traffic analysis tools are essential in transportation engineering as these tools assess and estimate the influences of planned and anticipated decisions and take into consideration the efficiency and value of the improvements and decisions that should be made. In this paper, several traditional traffic analysis tools have been compared, and it has been found that using the proposed two ML algorithm combinations, traffic flow, vehicle speed, and lanes segmentation can be defined and known using only a mobile camera for recording a video and using the video as an input feed to the ML combined model. Traffic-relevant data can be obtained with a cost-effective procedure in terms of time, resources, and the needed tools, especially since this model can be processed using an unpretentious simple hardware toolkit, and it does not need any heavy-duty tools to process, which bounces an advantageous gain for its cost competence. It is believed that the proposed model can improve assessing the impact of traffic functioning of different transportation systems, as the output data can be essential in decision making. As a next research step, it is planned to use the output data as an input feed to a simulation model, using SUMO simulation software, which is an open-source cost-effective traffic simulation solution. With the findings of the simulation results, the transportation infrastructures can be improved, and make them more environmentally friendly by designing the roads or improving their current design in a way that produces less toxic emissions.

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