INTEGRATION OF DEEP LEARNING MODELS FOR VEHICLE COUNTING: TOWARDS OPTIMIZED PLANNING OF URBAN CHARGING INFRASTRUCTURES

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ABSTRACT:

Amidst the rising prevalence of electric vehicles (EV) and the corresponding need for adequate charging infrastructures, this study presents an innovative application of deep learning models to analyze urban traffic. Utilizing the YOLO v3 model, our research focuses on developing a prototype for counting vehicles at an urban roundabout connecting three main roads, providing essential data for planning EV charging infrastructures. This work involves adapting and optimizing the YOLO v3 model to accurately identify and count vehicles passing through the roundabout. The aim is to measure traffic volume and identify circulation trends, which are crucial for understanding the spatial and temporal distribution of vehicles. The collected data not only estimate the number of EVs likely to traverse this area but also predict the needs for charging infrastructure in and around this specific roundabout. Our prototype demonstrated high accuracy in vehicle counting, allowing detailed analysis of traffic patterns at different times of the day. This analysis reveals significant variations in traffic flows, providing valuable insights into the most suitable times and locations for installing EV charging stations. While this study focuses on a single roundabout, it establishes a precedent for using advanced deep learning techniques in assessing EV charging infrastructure needs in broader urban contexts. The results suggest that such methods can be extended to other urban areas for more comprehensive and effective planning of EV charging infrastructures, thus contributing to more sustainable and intelligent urban mobility management.

1. INTRODUCTION

The global transition to electric vehicles (EV) is a crucial step in the fight against climate change and the reduction of greenhouse gas emissions (Lutsey, 2015). It aligns with sustainable development goals and promotes cleaner, more environmentally-friendly mobility in urban areas (Riesz et al., 2016). However, this transition, while beneficial, also brings its share of challenges, particularly in terms of logistics and infrastructure (Juan et al., 2016). One of the main challenges is the provision of a suitable and accessible recharging infrastructure to meet the growing demand for EVs (Yazdekhasti et al., 2021). The availability and strategic location of charging stations are essential to encourage the adoption of EVs and ensure their harmonious integration into the urban fabric (Hatton et al., 2009). Effective planning and deployment of these charging infrastructures cannot be achieved without a detailed, up-to-date understanding of vehicle traffic patterns in the city (Kim and Mahmassani, 2015). It is imperative to know not only the overall volume of traffic, but also the specific travel habits of users, traffic peaks, and the most frequented routes (Çolak et al., 2016). This knowledge makes it possible to determine where the demand for recharging will be highest, and thus to optimize the location of charging stations to maximize their usefulness and accessibility (Shahraki et al., 2015).
The application of cutting-edge technologies, such as deep learning, is a major asset in this process. Deep learning, a branch of artificial intelligence, makes it possible to analyze large quantities of data with unrivalled precision and speed ("Sandro Skansi - Google Livres," n.d.). In particular, the use of deep learning models such as YOLO v3 (You Only Look Once, version 3) for vehicle counting opens up new perspectives in urban traffic analysis (generator, 2020). YOLO v3 is an advanced image recognition model that can detect and classify objects (in this case, vehicles) in real time with great precision (Oltean et al., 2019). Its integration into urban traffic studies enables detailed information on vehicle flow to be obtained quickly and reliably, which was previously difficult to achieve with traditional methods.
Our study focuses on the development of an innovative prototype using the YOLO v3 model to assess traffic flow in a key urban roundabout. This roundabout, serving as a junction for three main lanes, is a strategic crossroads in urban traffic and an ideal site for analyzing vehicle flows. The goal of this prototype is to collect accurate data on traffic volume, including variations throughout the day, to identify areas of high traffic density (Kadim et al., 2020). This information is essential for determining the most strategic locations for installing EV charging stations.
The choice of YOLO v3, an advanced real-time object detection system, is justified by its ability to rapidly process and analyze large quantities of images (Lin et al., 2021). This capability is particularly relevant in complex urban environments, where vehicle density and the diversity of visual elements can hamper traditional counting methods (Chen et al., 2023). Through its application, we aim to achieve not only a vehicle count, but also an understanding of traffic patterns, such as peak hours, seasonal variations, and predominant vehicle types.
In addition, this study explores the feasibility and effectiveness of extending this technology to other intersections and urban areas. Although focused on a single traffic circle, the approach adopted here could serve as a reference for similar studies in other urban contexts, enabling more comprehensive and effective planning of EV charging infrastructures. In this way, our research makes a significant contribution to the literature on electric mobility and urban planning, demonstrating how deep learning tools can be harnessed to address some of the most pressing challenges in managing 21st century urban mobility.

2. MATERIALS

2.1 Study Area

The study area of this research focuses on a specific traffic circle located in Bouskoura, a peripheral area of the city of Casablanca, Morocco (Figure 1). Casablanca, the country's economic capital, is a dynamic metropolis located in west-central Morocco on the Atlantic coast, some 80 km south of Rabat, the administrative capital. With a population that makes it the largest city in the Maghreb, Casablanca is a nerve center for the Moroccan economy and culture (Puschmann, 2011).

Covering a total area of 1,140.54 km² and divided into 16 prefectures, the city of Casablanca features a diversity of urban and suburban areas (“Region Population Projections.pdf,” n.d.). The traffic circle studied, located in Bouskoura, is an important convergence point in the transport network, linking several major routes and handling a substantial flow of vehicles on a daily basis. This site was specifically chosen because of its strategic role in traffic flow and its potential for the installation of charging infrastructures for electric vehicles.

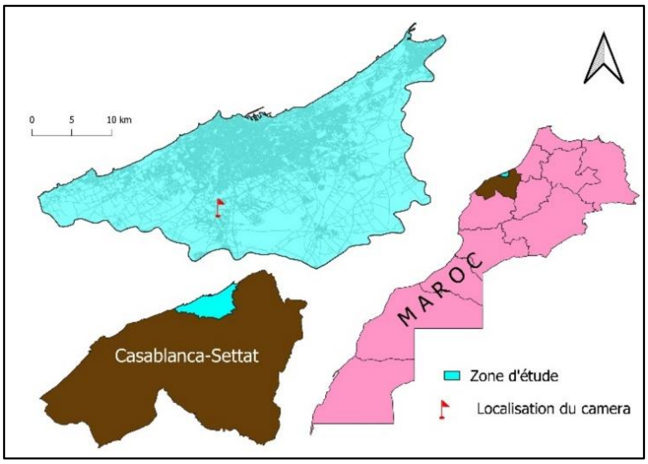

Figure 1: Location of the study area

The video analyzed in this study was extracted from a surveillance camera strategically positioned above this traffic circle. This camera provides clear, continuous images of traffic, enabling precise, detailed analysis of traffic patterns. The camera's position provides an ideal overview for counting vehicles and analyzing traffic patterns at this crucial location.

Figure 2: The location of the surveillance camera in Bouskoura

Casablanca geographical location, combined with its role as an economic center, makes it an ideal location for a study into urban traffic patterns and the need for charging infrastructure for electric vehicles. The dense population and high concentration of vehicles in the city make it a relevant study site for understanding and improving urban electric mobility. Furthermore, as an economic center, Casablanca is likely to experience a rapid increase in the number of electric vehicles, reinforcing the importance of proactive planning of charging infrastructures.

The geographical location of Casablanca, combined with its status as an economic hub, makes it an ideal place to study urban traffic patterns and EV charging infrastructure needs. The population density and high concentration of vehicles make this city particularly relevant for a study aimed at understanding and improving urban electric mobility. Additionally, as an economic center, Casablanca is likely to be one of the first Moroccan cities to see a significant increase in EVs, highlighting the importance of proactive planning for charging infrastructure.

2.2 Related Work

In this section, we explore the various methodologies employed in vehicle detection, an essential aspect of traffic management. Vehicle detection techniques have evolved significantly, ranging from traditional computer vision methods to the more advanced deep learning approaches (Wei et al., 2020). Initially, vehicle detection relied heavily on traditional computer vision, which used the movement of vehicles against a static background to identify them (V. et al., 2019). This approach often utilized features like the Histogram of Oriented Gradients (HOG) (Zhang and Wang, 2013) and Haar-like features (Momin and Mujawar, 2015). HOG method involves analyzing the directions of gradient orientations in small sections of an image to detect shapes, while Haar-like features focus on the contrast between adjacent rectangular areas within the image, visualized in black and white patterns. However, these traditional methods were not without limitations, often resulting in a high number of false positives due to their inability to adapt to varying conditions and complexities in real-world scenarios. The introduction of convolutional neural networks (CNNs) marked a paradigm shift in vehicle detection (Girshick et al., 2014). CNNs, a subset of deep learning algorithms, process input images by assigning importance to various features and effectively distinguishing between them. Unlike traditional methods, CNNs require less pre-processing and can autonomously learn to identify diverse filters and features. This learning ability sets them apart from traditional methods, which are static in their feature identification. The structure of CNNs is inspired by the human brain's neuronal connections, optimizing computational efficiency and data processing speed. The advancement in CNNs led to the development of a two-stage approach (Hu et al., 2019), which first involves using algorithms to create candidate boxes around objects and then classifying these objects using the CNN. This method enhanced the accuracy of object detection by refining the process through which objects are identified and classified. In contrast to this, the YOLO framework represents a more streamlined, one-step approach. It simplifies the object detection process by converting the task of bounding box positioning into a regression problem, eliminating the need for generating candidate boxes. This approach decomposes the image into a predefined number of grids, with each grid tasked with predicting the objects present within it, based on the location of their center points. The YOLO method is notable for its speed and efficiency, making it a preferred choice in scenarios where real-time detection is crucial.

3. DATA AND METHODS

3.1 Data collection

As part of this study, we collected data from a surveillance video captured at the Bouskoura traffic circle in Casablanca. This video is essential for our analysis, as it provides a direct and continuous visualization of traffic in this specific area. Recorded on August 04, 2022 at 1:56 pm, the video lasts approximately one minute and 30 seconds and offers a resolution of 720x480, which is adequate for clear identification of vehicles and accurate analysis of their movements. The video's frame rate is 24 frames per second, offering a balance between image fluidity and the amount of data generated. This frequency is sufficient to capture traffic dynamics without overloading the analysis process. This time slot was chosen to represent a typical moment of urban activity, as it aims to provide a concentrated overview of traffic during a representative period, while remaining manageable for processing by our deep learning model. Notably, the video was used without pre-processing to preserve the authenticity of the data, facilitating direct and reliable traffic analysis via the YOLO v3 model, for an accurate assessment of vehicle flows in this key area.

3.2 Data sets

For vehicle detection and counting in our study, the YOLO v3 model was applied using the COCO (Common Objects in Context) dataset. COCO is a

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large and diverse dataset, developed and maintained by a community of researchers and engineers. It comprises 80 different object classes, ranging from cars and people to airplanes and bicycles (Radovic et al., 2017). This wealth of classes enables the model to recognize and differentiate a wide variety of elements in complex environments, which is essential for accurate analysis of urban traffic. The dataset consists of 80,000 images for training and 40,000 images for verification, providing a considerable amount of data to train the YOLO v3 model with high accuracy. In our study, we specifically selected vehicle classes such as cars, motorcycles and trucks for data processing. This targeted selection allows us to focus the analysis on vehicles relevant to our traffic study at the Bouskoura traffic circle, excluding other object classes not directly related to our vehicle counting objective (Figure 3).

Figure 3: Examples of vehicle class images in the dataset

3.3 Image segmentation

Image segmentation is a key process in image processing, aimed at detecting and grouping pixels according to certain criteria, such as intensity or spatial location (Mohamed et al., 2021). This technique enables an image to be broken down into uniform regions, making it easier to distinguish between different objects and their background (Hurtik et al., 2022). A common example of this technique is binarization, where the image is segmented into two distinct sets of pixels, often used to clearly separate objects from the background. The main objective of image segmentation in our study is to extract significant objects present in images (Ghosh, 2021). This involves dividing images into semantic regions, making it easier to identify and count vehicles. Segmentation simplifies and clarifies image analysis, isolating elements of interest (in our case, vehicles) from the rest of the image. In our specific study, image segmentation was applied to video captured at the Bouskoura traffic circle. As illustrated in figure 4, this segmentation enabled us to clearly distinguish vehicles from the rest of the urban environment. By segmenting the image, we can focus our analysis on vehicles, improving counting accuracy and providing more reliable data for traffic flow assessment.

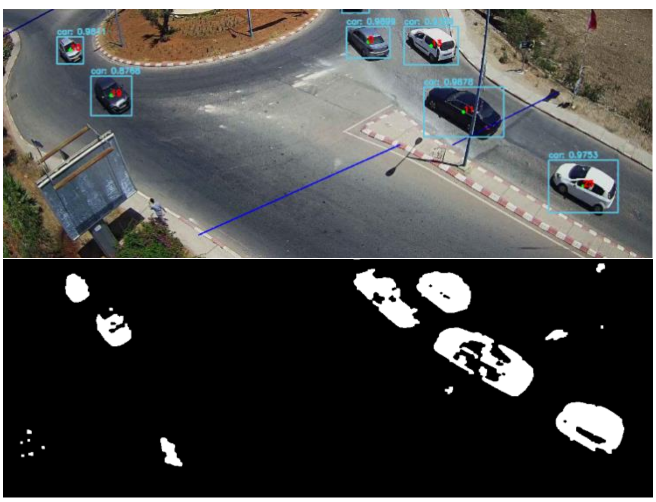

Figure 4: Segmentation by objects

3.4 Methodology

Our system, illustrated in figure 5, consists of two main functional blocks: the detector and the counter. Initially, the user selects the data source, typically a recorded video. The detector processes this video to generate bounding boxes around the identified vehicles, which are then used as input for the counter. The counter then analyzes the data in the buffer, counts the vehicles and displays the final result. This methodology enables efficient video processing, guaranteeing accurate detection and counting of vehicles within our system. The detailed workings of these blocks and their interaction will be explored in the following subsections of the article.

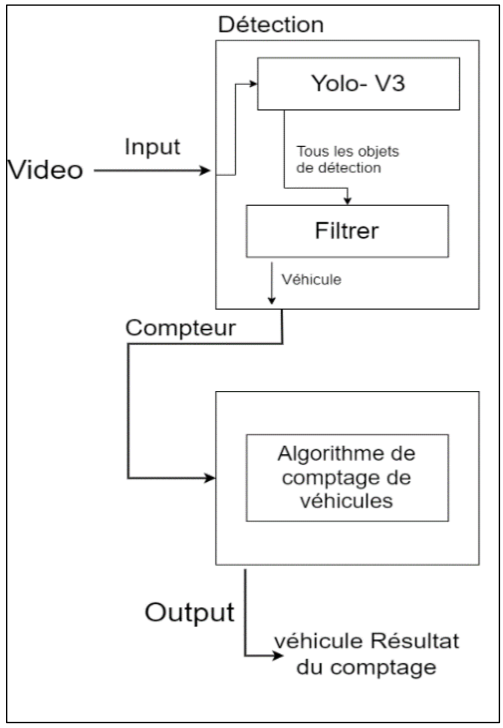

Figure 5: Methodological flowchart

4. ALGORITHMES

4.1 Structure of Yolo network model

YOLO (You Only Look Once) is an open source algorithm for object detection and classification, distinguished by its use of a convolutional neural network (CNN) (Lee and Kim, 2020). Unlike conventional CNNs, which generate regional predictions to propose bounding boxes, YOLO takes a unique approach. It evaluates the entire image at once, enabling the simultaneous prediction of the objects present and their locations. The method is characterized by the creation of spatially separated bounding boxes around the detected objects. The process begins with the scoring stage, during which YOLO assigns scores to the different bounding boxes based on the probability of objects being present. This is followed by duplicate correction and removal, where less relevant or redundant bounding boxes are eliminated. YOLO then re-evaluates all remaining bounding boxes, based on the objects identified. The image region with the highest score is considered detected, as shown in figure 6.

YOLO main advantage lies in its ability to analyze the entire image via a single neural network, facilitating fast and efficient object detection based on predicted regions. This global approach enables not only high processing speed, but also greater precision in locating and classifying objects in the image (Radovic et al., 2017).

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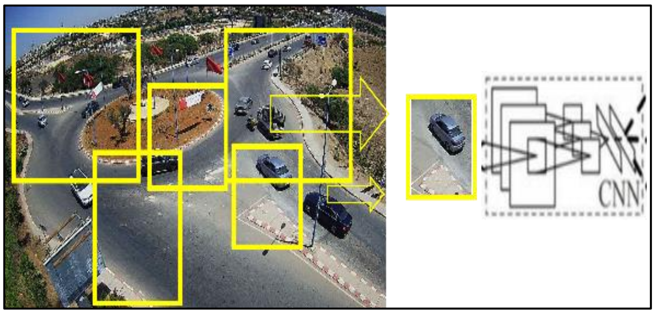

Figure 6: YOLO workflow diagram

YOLO structure, based on convolutional neural networks, adopts an innovative method for object detection (Figure 7). The input image is initially divided into an SxS grid, where each cell of this grid is responsible for detecting objects. YOLO works on the assumption that a single grid cell is responsible for estimating an object. For each cell, bounding boxes are generated, and each of these boxes is assigned a confidence score reflecting the likely presence of an object (Ahmad et al., 2020).

Each bounding box is characterized by five variables: x, y, w, h and C. 'x' and 'y' determine the center of the box, while 'w' and 'h' represent the width and height of the box respectively. In addition, for each grid cell, YOLO calculates 80 conditional class probabilities (C), indicating the probability that the detected object belongs to a specific class (Redmon and Farhadi, 2017).

The confidence score, a crucial element in the YOLO process, combines the object's classification probability with the confidence of its location. A special feature of YOLO is that the confidence score of a grid is set to zero if no object is detected on it. The final output of the YOLO algorithm is represented by a tensor S x S x (B x 5 + C). In the YOLO approach, a single CNN network is designed to estimate this tensor. The system selects and uses bounding boxes whose confidence score exceeds a predefined threshold, usually set at 0.25, for more accurate object identification (Ahmad et al., 2020).

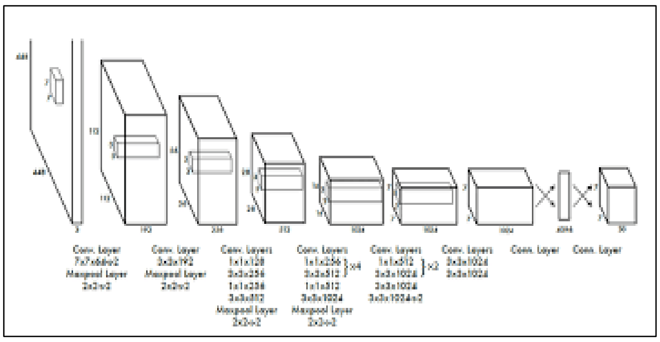

Figure 7: The architecture of YOLO

4.2 OpenCV Tracking Algorithms

OpenCV, a renowned open-source library, plays a pivotal role in computer vision, machine learning, and image and video processing. This versatile library is utilized in a multitude of applications, ranging from object detection and recognition to automated surveillance, autonomous driving, and medical image analysis. Its ability to integrate with other libraries, such as NumPy, and to process visual data makes it indispensable in artificial intelligence, especially for architectures based on convolutional neural networks (Deshpande et al., 2020). OpenCV is also prized for its object tracking functionalities, offering various trackers like MIL, CSRT, GOTURN, and MediandFlow, each with specific advantages depending on the intended application. This functional richness, combined with compatibility with multiple programming languages, makes OpenCV a tool of choice in the field of computer vision.

5. RESULTS

5.1 First "Detection" Block

The detector serves as the first critical processing step in our system, activated immediately after the video is input. This block is tasked with performing initial extraction and preliminary processing of the video for subsequent uses. In our setup, the pretrained YOLO model forms the backbone of the detector's architecture (Chandan et al., 2018). It's noteworthy that we have tailored YOLO to specifically suit the needs of our study. In practice, the camera captures various moving objects, including bicycles, people, and animals. However, our focus is exclusively on vehicles for counting purposes (Lin et al., 2014). The YOLO model is capable of identifying up to 80 types of objects using the weights trained by the COCO dataset. For our vehicle counting system, we limited the processing to the following categories: cars, buses, motorcycles, and trucks. Therefore, we modified the original YOLO code to filter and display only the coordinates of these four vehicle types. Other moving objects captured by the camera are masked or ignored in our analysis, as shown in Figure 8. This customization allows our system to focus solely on relevant vehicles, thereby optimizing the efficiency and accuracy of the counting process.

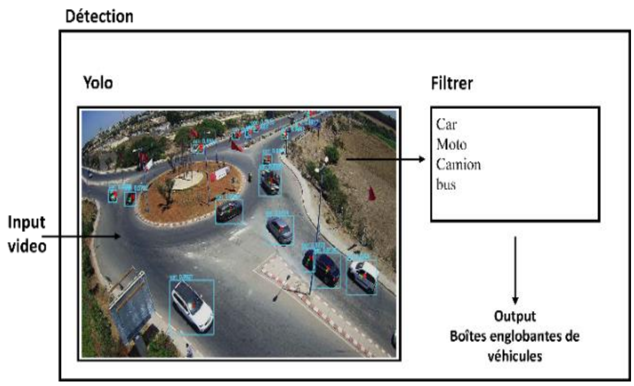

Figure 8: Detection

5.2 Second "Counter" Block:

Before initiating the vehicle counting process, it is crucial to establish a tracking system, which significantly contributes to the accuracy of the count. Tracking in this context refers to monitoring an object's movement and trajectory, a process essential for pinpointing its location. The use of video tracking extends beyond counting and includes applications in augmented reality, surveillance, video compression, editing, interaction between humans and computers, and traffic management. The key goal of tracking in videos is to consistently identify and follow target objects through consecutive frames. This task becomes particularly challenging when objects move quickly, potentially outpacing the video's frame rate, or when they change direction over time. To address these challenges, video tracking systems often utilize a motion model that captures the appearance of the target object from various angles and orientations. In our study, we adopted centroid tracking. This method involves linking the centroid of a bounding box surrounding a detected object in one frame to the centroid in the next, using a proximity measure like Euclidean distance. Although performing detection frame-by-frame is computationally demanding, the greater challenge lies in setting a reliable threshold to ascertain whether consecutive centroids represent the same object. Factors influencing this threshold include the object's size and the video's frame rate and resolution. For the purpose of tracking vehicles, the center of each bounding box, marked with a green dot during detection, serves as the point of reference. As depicted in Figure 9, when a vehicle is detected, it is represented by a numeral, such as '5', which corresponds to the total number of vehicles counted.

Figure 9: Vehicle counting

5.3 Counting vehicles on each road

The next step in our study, following the implementation of vehicle tracking, was to assess the specific vehicle flow for each lane around the roundabout. This roundabout is served by three roads, each comprising two distinct lanes: one for entering and the other for exiting the roundabout. To ensure accurate analysis, I began by defining specific regions of interest for each lane using tailored masks. For each road, I set up two separate tracking systems - one for vehicles entering and another for those exiting the roundabout. A pixel thresholding method was utilized to effectively distinguish vehicles in each lane. This technique ensured that data related to vehicles in each lane were accurately attributed to the corresponding tracking system. The approach is based on the use of virtual lines (represented in green in Fig. 10) drawn on each lane. A vehicle's passage is recorded when the center of its bounding box crosses one of these virtual lines. This process thus reliably tallies the number of vehicles traveling on each lane, whether entering or exiting the roundabout.

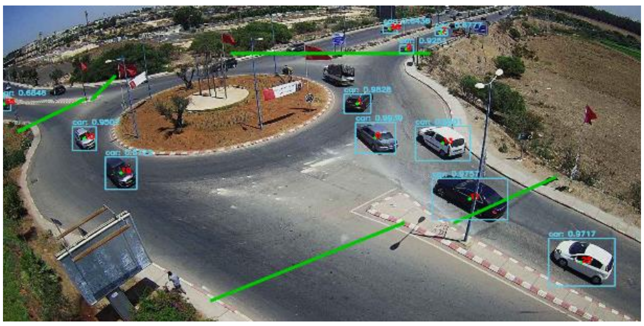

Figure 10: Virtual line for communication in each road

5.4 Discussion

Figure 11 illustrates the final phase of our application, which integrates the detection, tracking and counting of vehicles in each lane. One of the main advantages of our vehicle counting system is its ability to assess the demand and capacity required for electric vehicle charging stations. The system helps determine how many charging stations are needed and where they should be installed. It also helps to identify which roads require the most charging stations compared to others, enabling more efficient and targeted planning of charging infrastructure based on actual traffic needs.

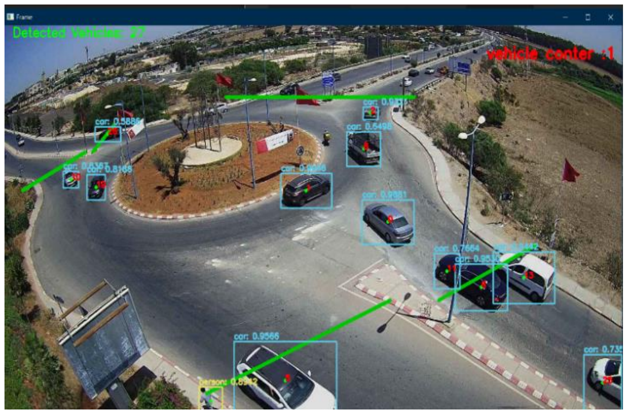

Figure11: Vehicle counting system

Our vehicle counting system is applied to a roundabout served by three roads, each comprising two lanes: one for entering and one for exiting. The detailed analysis of vehicle flow for each road provides valuable insights for planning electric vehicle charging infrastructures. For the first road, we observed 42 vehicles entering and 25 exiting. On the second road, there were 27 vehicles entering and 37 exiting. As for the third road, the count was 16 vehicles entering and 23 exiting. These data reveal distinct traffic patterns for each road, which is crucial in determining where the need for charging stations is most significant. The advantage of our system is that it allows for precise understanding of the demand and required capacity for charging stations. By identifying roads with heavier traffic, we can strategically target the location of new charging stations, prioritizing roads with a higher number of entering or exiting vehicles, as needed.

6. CONCLUSION

This study demonstrated an innovative approach using the YOLO v3 model for precise vehicle counting in an urban setting, specifically applied to a roundabout in Casablanca. Our method, successfully integrating detection, tracking, and vehicle counting, provided detailed traffic data for each incoming and outgoing lane on three different roads. It's important to emphasize that our application is a prototype, showcasing significant potential for broader implementation, particularly at city entrances and exits. Such an application would allow for analysis and understanding of the traffic volume circulating in the city, offering crucial insights for urban planning and mobility management. The results reveal the effectiveness of our system in identifying and counting vehicles, key elements in planning electric vehicle charging infrastructures. The analysis highlighted significant variations in traffic flow between different roads, indicating potential areas for increased demand for charging stations. This research contributes significantly to the field of urban mobility and energy management, proposing a technological solution to support the transition to more sustainable mobility. The implications of this study are extensive, opening possibilities for future applications in urban planning and traffic management, especially in the context of increasing use of electric vehicles.

In conclusion, our study illustrates how the integration of advanced deep learning technologies can play a crucial role in addressing contemporary urban mobility challenges and establishing a more efficient and needs-based electric vehicle charging infrastructure.

7. ACKNOWLEDGEMENTS

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