Smart Parking Solution for Multi Building Campus

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***Abstract*— Locating parking spaces is becoming a serious problem as more and more employees prefer to switch to personal commutes due to the prevailing pandemic situation across the globe inside the office campus. Particularly, where there is multiple building inside the main campus, and it is quite challenging to keep track of car parking inside a given building. Without parking availability information, commuters must shuttle around builds to find parking spaces during peak hours, and this will be a loss of time as well as frustration to the commuter. There are quite a few options companies follow like physically counting cars at certain intervals and updating the dashboard, installing badge readers at entry and exit and people must punch cards at both places, sensors have been installed in certain parking lots allowing management to track when cars enter and exit, install Radio Frequency Identification (RFID) tags and reader at entry and exit to track the capacity. All these methods will bring in the burden on additional resources and high cost of installation of reader & necessary barricade systems respectively. Also, will add to regular maintenance of the overall system. This project details Deep Learning (DL) implementation to create a vehicle counting system by using video from a camera installed at the entry and exit paths of the vehicles. The pretrained model of YOLOv4 is used for object detection, vehicle tracking with Euclidean distance, and counting. Since vehicle movement is considerably slow in a pathway, the performance of the model tested is 96.8% to 100% for varied frame rates of the video in parking capacity tracking.**

Keywords*— *Deep learning, Yolov4, Object detection, Vehicle counting, RFID, Parking

I. INTRODUCTION

It is challenging to keep track of available car parking spaces inside a given building. There are multiple buildings on the main campus. Offices or buildings with separate entry and exit or single entry & exit. Post-pandemic, employees prefer to use personal commutes than public. Without parking availability information, employees must shuttle around builds to find parking spaces during peak hours, and this will be a loss of time as well as a frustrating experience for the commuter. In recent years, numerous proposals have been made for improved parking occupancy systems along with guidance. There are benefits and drawbacks to each of these modern systems. A method of determining whether or not a car is entering or exiting a given space is essential to all of these systems. This mechanism could be anything from a straightforward ultrasonic sensor that detects a vehicle at a threshold distance to a sophisticated optical sensor that activates dependent on distance. The presence of a vehicle or other object is detected by these sensors. Much research has been conducted for traffic management applications based on image and video processing approaches. The analysis of traffic video data includes detection or recognition of vehicles, measurement of vehicle's speed, generation of tracking trajectory, counting of vehicles, congestion of traffic, and collisions of vehicles. These applications have become popular recently due to the availability of low-cost cameras and embedded devices. Thus, video data analytics is one of the prime research projects focused on computer vision and big-data areas. This work proposes an easy-to-use system for counting vehicles based on the deep learning algorithm. A well-known pretrained YOLOv4 DL architecture is known for its excellent accuracy in object detection and its moderate computation compared to other DL architectures. Vehicle tracking with Euclidean distance and counting entry and exit vehicles for accuracy for parking capacity tracking.

II. LITERATURE REVIEW

The counting of vehicles is often performed by splitting the scene into a moving foreground and a stationary background. Background subtraction (BS) and blob analysis [1], BS combined with Gaussian Mixture Model (GMM) based BS [2] [3], and particle filter-based tracker [3] [4] are used to achieve this goal. Frame averaging, the Gaussian mixture model, and principal component images are common methods for achieving BS, However, when dealing with traffic data, the background removal method has its limits. Partial occlusion in processed picture data causes vehicles to merge, and inaccurate bounding box predictions are made. Additionally, car shadows lead to erroneous detection. The results are enhanced by combining a Gaussian mixture model and an expectation maximization to create the background model. The moving vehicles are then retrieved from the background using subtraction. Morphological features and colour histograms are used to deal with the occlusions. One application of Computer Vision (CV) technology is in traffic monitoring systems, which can be used to keep tabs on things like vehicle speeds, parking lot occupancy rates, and traffic violations. The first step in every one of the aforementioned chores is finding where each car now resides. Therefore, an object detection method is so important. Pre-processing techniques like grayscale picture scaling, binarization of images, and background reduction [5] [6] or even edge detection are required by the traditional Machine Learning approach to accomplish this task. There are, of course, drawbacks to this method; for example, if the vehicle's shadow is present in the image, the detection may be less accurate. Changes to the road surface, such as road maintenance, road damage, or any barriers on the road, can also cause inaccurate detection since they can disrupt the image subtraction process. Although it is computationally expensive and requires a considerable amount of data to train the networks, the Deep Learning (DL) methodology provides more adaptable performance without the requirement to pre-process the image and extract the feature using multiple methods. There are even more advanced DL architectures available, which have been trained with millions of data points, making the creation of CV systems much simpler. It is well-known that the Convolutional Neural Networks (CNN) architecture of Deep Learning (DL) performs exceptionally well in Computer Vision (CV), particularly in the tasks of object detection and categorization. Regional-based CNN (R-CNN), Fast R-CNN, Faster R-CNN, Region-based Fully CNN (R-FCN), Single Shot Detector (SSD), Mask R-CNN, YOLO, YOLOv2, YOLOv3, and YOLOv4 are only some of the CNN-based architectures used in CV for object recognition and categorization. For this experiment, YOLOv4 was chosen as the best model to utilize because of its high accuracy and fast computation time in real-time compared to the other object identification methods.

III. Problem Statement

Locating parking spaces is becoming a serious problem as more and more employees prefer to switch to personal commutes due to the prevailing pandemic situation across the globe in office campuses. Particularly, where there is multiple building main campus, and it is quite challenging to keep track of car parking inside a given building. Without parking availability information, employees must shuttle around builds to find parking spaces during peak hours, and this will be a loss of time, productivity as well as frustration to the commuter. There are a few options companies follow like physically counting cars at certain intervals and updating the dashboard, installing badge readers at entry and exit and people have to punch cards at both places, sensors have been installed in certain parking lots, allowing management to track when cars enter and exit., install Radio Frequency Identification (RFID) tag on each employee vehicle and reader at entry and exit in order to track the capacity. Very few or negligible companies have installed simple ultrasonic sensors at each parking space, and these are hardwired to the centralized system to detect parking occupancy. All these methods will bring in a burden on additional resources and high cost of installation of reader & necessary barricade systems respectively. Also, will add to regular maintenance of the overall system.

IV. Objectives of the Study

This project proposes to use advancement in deep learning robust method You Only Look Once (YOLO) which treats object detection as a regression problem to map pixels into bounding boxes with class probabilities. Moreover, it computes everything in a single evaluation. Euclidean distance methodology for object tracking and boundary line to count entry or exit of the vehicle in a single frame of the video to capture the parking availability in each building. The primary objective of this study is to implement the customized smart parking solution for multibuilding campus offices. Having multibuilding it is extremely important to let the employees know where the parking space is available, especially during peaking hour. A dashboard at each building entrance encompassing overall occupancy and available status will greatly help the employee peacefully approach the building where parking is available. The secondary objective of the study helps in the selection of optimal video modes for better accuracy for vehicle detection and counting.

V. Project Methodology

The vehicle counting system which was built in this work has three main modules, i.e., Object Detection Module, Vehicle Tracking Module, and Counting Module as given in Fig. 1. The first module reads every single frame from the video and does vehicle detection using YOLOv4 algorithm. This module results in the location of every detected vehicle, i.e., the bounding box coordinates. The second module tracks a vehicle by its centroid location between frames to frame using Euclidean distance by checking centroid distance between frames is within the threshold, to ensure the same object is being tracked and the third module counts the number of vehicles that crossed the road depending on the coordinates or position of the vehicles. So, the result of the object detection module plays a vital function in this system, since if the vehicle is not spotted, then it will not be counted. The video containing the entry and exit of the vehicle from a single camera is used to demonstrate the proposed solution.

A. *Flowchart of the proposed methodology*

The workflow in the proposed approach discussed in the previous section is shown in Fig. 1.

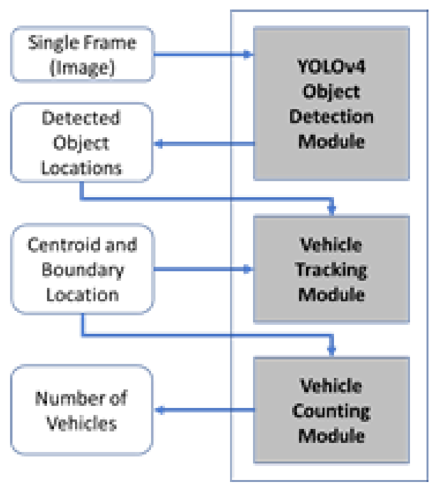

Fig. 1. General architecture of the vehicle counting system.

B. *Dataset*

Data for the proposed solution is implemented using video from a surveillance camera having 81 seconds video with 1280 x 720 pixels having 30 frames per second frame rate and the same video is converted to 15 frames per second frame rate for the study. This video has two-way traffic by which both entry and exit of vehicle data have been extracted to run through the model. In both directions, 48 cars will pass on entry and exit paths each. Specifically, video of different frame rates is taken because more the frame rate means higher storage capacity of storage for surveillance. Hence most of the companies record the video at a lower frame per second to reduce the storage space and the cost associated with it. A Snap of the video is shown in Fig. 2.

Fig. 2. Single image from a video

C. *Experimental setup*

The proposed solution is implemented using OpenCV 4.5.2 and PYTHON 3.8.5 in a machine with Intel(R) Core i5-10210U, CPU of 2.10GHz processor with 16GB RAM. Even though this engine is not as fast as the GPU-enabled system, but sufficient to run deep learning.

D. *Module processing flow*

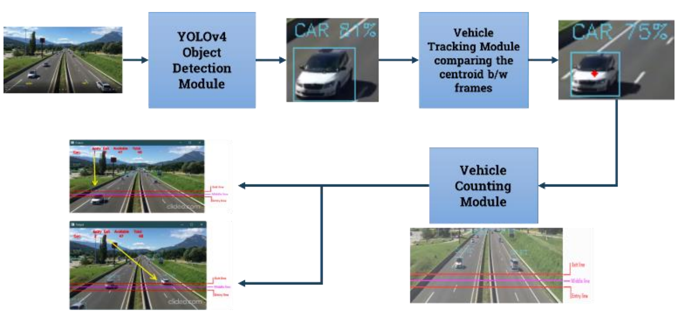

Fig. 3. Output flow from each module

VI. Result and Analysis

The vehicle counting system developed in this work is tested using two different videos as described in the previous section. Since the proposed solution used a pretrained YOLOv4, there is no training phase in this work. In the first testing scenario, the system uses video with 1280 x 720 resolution, 30 frames per second, and a total has about 2460 frames. In the second scenario, the same video with 15 frames per second was used. Both videos have 48 cars passing on entry and exit paths each. Differences between the actual number of vehicles and the number counted by the system are used to evaluate the system's efficiency. The resultant accuracy of the method is mentioned in TABLE I.

TABLE I. Accuracy result of model

	Entry		**Exit**		**Entry Accuracy**	**Exit Accuracy**	**Overall Accuracy**
	Actual	***Predicted***	***Actual***	***Predicted***			
Video with 30fps	48	48	48	48	100%	100%	100%
Video with 15fps	48	48	48	45	100%	93.8%	96.9%
						Average Accuracy	98.45%

VII. Conclusion and Future Work

Smart parking solution which is developed by employing vehicle counting system at both entry and exit which process live or video feed has been developed using YOLOv4 for object detection, tracking by calculating Euclidean distance between the centroid of a vehicle between frames and counting is simply executed by evaluating the distance between the vehicle's centroid to the borderline. It successfully achieved the highest accuracy of 100% when using a 30fps video feed as discussed in the previous section. The frame rate of the video affects performance since it symbolizes the information integrity of the data that the system processes. Overall, this work was successfully finished with a positive outcome and the accuracy of the model is presented in TABLE I. A dashboard with the status of available car parking can be placed at the main entrance of each building on campus along with the parking status of the rest of the other buildings within the campus so that it helps employees proceed to the building where parking space is available without having to shuttle across building to find the space predominantly during peak hour. Selection of the frame rate can be made based on the storage capacity or a non-storage live feed can be used for high accuracy and to avoid additional costs on storage. The proposed solution can further be extended to count other objects like motorcycles, bicycles...etc. With a higher-resolution camera, the same method can be applied to extract license plate information as well. Also, dashboard data can be made available to the employees over the cloud or employee portal so that they can be well informed.

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