Computer Vision-Based System to Study Parking Utilization

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***Abstract* – Parking studies are commonly used to evaluate the use of parking lots by determining peak usage days and times, balance of lots usage, and similar other aspects. These studies have traditionally depended on human labor with researchers walking through a series of parking lots at scheduled times to record the number of occupied parking spaces. The recent availability of camera-equipped unmanned aerial vehicles (aka drones), together with the advancements in computer vision and deep learning techniques made it possible to replace the human labor-based approach with a more efficient, cost-effective, high accuracy automated approach.**

In this paper, we present an end-to-end computer vision-based solution that was developed and tested in parking utilization studies on our university campus. A drone, programmed to travel on a flight path over the parking lots of interest, captures images at different times. The images are processed and fed into a pre-trained deep learning model that detects the locations of vehicles in the images. A Python script counts and reports the number of vehicles parked in the various sections in each lot at every time. The results show that the system was able to successfully report the number of vehicles with a 100% accuracy rate.

I. Introduction

Parking management has become a critical aspect of our urban infrastructure. With the rapid growth of urban populations and vehicle ownership, efficient parking management became a pressing concern for municipalities, universities, hospitals, and other similar campuses. To that end, parking studies are commonly used to assess the use of parking lots and may include a number of goals: determining peak usage day and time, balance of lot usage at sites with multiple lots, and evaluate the effects of policy changes on parking demand. Traditionally, these studies were performed manually, where the researcher walks or drives through a series of parking lots at scheduled times of the day and notes the number of occupied parking spaces. In lots with more than one allowed parking classification, the number of occupied spaces by category is also noted. This type of study is useful in determining the maximum occupancy rate of the lots and can highlight the peak usage time of day. An example of the data collected for a parking lot (Lot 5 – Commuter) on our campus, is shown in Figure 1. As can be seen in this figure, the study span over the duration of two days (Tuesday and Wednesday) with four data points measured for each of the days, which is typical in a study of this kind. The manual collection of data for this one parking lot takes approximately 10 minutes for each data sample. A similar plot is developed for each parking lot and each permitted parking category.

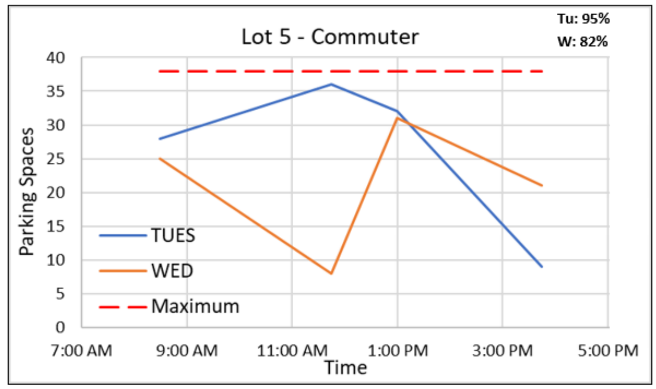

Figure 1. Sample of parking occupancy rate for a parking lot on our university campus.

In recent years, advancements in computer vision technology have opened up new possibilities for understanding parking usage patterns in urban environments. Computer vision techniques enable the automatic extraction of valuable information from images or video streams, offering a scalable, efficient, and cost-effective alternative to the traditional method. Being quicker and simpler, data can be collected more frequently throughout the day, creating a more accurate plot of parking lot occupancy throughout a day. The ease of data collection also means data can be collected on more than two days, potentially allowing longitudinal analysis of parking across the entire semester – sampling data over multiple weeks instead of the one, as is currently being done.

Visual data can be captured either from cameras installed on every floor of a multi-level parking structure or from a camera that is mounted on a drone that periodically flies over open parking lots. For open parking lots, the drone solution is desirable because one camera on a drone can replace a multitude of cameras on the different floors. The only downside of drone data collection is the inability of the drone to fly in high winds or during precipitation. In those cases, manual data collection can be used as a last resort to avoid interrupting a study. The analysis of the visual data can be used to classify the parking spots as "empty" or "occupied" to count the number of available spots and potentially direct incoming drivers to the closest "available" spot [1], or to count the vehicles that are parked in a lot to gain insights into parking occupancy, duration, turnover rates, and collective user behaviors [2]. The latter is our application of interest in this work.

This paper presents a system that is developed to take in a set of drone-captured images of a parking lot and automatically generate an occupancy report of said parking lot. The rest of the paper is organized as follows: section II is a literature review of similar works. Section III introduces the deep learning Neural Network-based YOLO model that is used to detect the positions of the vehicles in an image. Section IV presents our proposed end-to-end solution for the problem. Section V discusses the obtained results and the paper is concluded with a summary in section VI.

II. Literature Review

Many researchers have previously studied parking management techniques. These techniques can be categorized into sensor-based techniques (such as RFID, Magnetometers, or ultrasonic sensors) and image-based techniques that use computer vision algorithms [3]. Among the image-based techniques, some of the previous works have used fixed camera based images, showing oblique angles of parked cars, versus vertical, drone captured images showing predominately top-down views of vehicles.

Among the drone-related works, Jausevac, et al. [4] used drone captured imagery for their study, coupled with a Convoultional Neural Network (CNN) for real-time monitoring of parking. Using 128 x 128 pixel images an 100 training epochs they were able to achieve an accuacy of 87.%5 with relatively rapid processing. Sayani et al [5] also used drone captured images and a CNN process for their analysis. The drone was flown at a unifom 10 meter flight level, with individual images captured of each parking space. This process relsulted in an overall accuarcy of 95.8%. Regester and Paruchuri [6] used individual images taken from drone video captured at a 400 foot flight level to determine the number of parking spaces in a parking lot, but did not determine vehicle occupancy. Acharya et al [7] used fixed-base camera images to determine parking lot occupancy by using a pre-trained CNN system (ImageNet-VGG-f) which then passed the processing on to a Support Vector Machine (SVM) classifier. This system produced an overall accuracy of 96.6%. The accuracy of the system noticeably dropped, however, in late afternoon and was attributed to changing light conditions and shadows. Amato et al [8] also used a CNN based system on fixed based camera acquired images for parking lot occupancy determination. They also noted higher error rates due to changes in weather, including sunlight reflections on puddles and vehicles.

III. The YOLO Vehicle Detection Model

To study the occupancy in a parking lot, we must be able to identify vehicles in an image. For this purpose, we used the pre-trained YOLO [9] computer vision model. YOLO (You Only Look Once), is a popular object detection and image segmentation model that was developed at the University of Washington and launched in 2015. YOLO is known for its high speed and accuracy. For our case, we used a YOLO version 8 (YOLOv8) roboflow version [10] that was fine-tuned on 2001 drone images of intersections with 80,474 annotations. The model has precision and recall scores of 95.9% and 94.3% respectively.

The fine-tuned YOLOv8 uses a deep learning neural network that is trained to take in aerial view images and return bounding boxes around the vehicles. Each box has a percentage figure that indicates the model's confidence that the box actually contains a vehicle. Figure 2 shows a sample parking lot input picture and Figure 3 shows the corresponding output picture processed by the model.

IV. The Proposed System

Our proposed system is an end-to-end solution that takes in a time-domain sequence of drone-captured aerial images and return an occupancy report of the parking lots on our campus. A block diagram of the whole system is shown in Figure 4. The system starts with a set of images of a parking lot over the time duration of the study. Because of the time-domain nature of the study, occupancy data must be reported with the time and date of measurement. This is accomplished by extracting the time and date stamps encoded in the images. In our case, the images include the date and time data in the EXIF [11] format. The Python Pillow library [12] is used to extract this EXIF data and decode the corresponding segment to record the separate date and time fields.

As can be seen in Figure 3, the YOLOv8 model detected two vehicles that are not "parked" in a parking spot. This is not a surprise since the model is trained to detect vehicles, regardless of their location. This, however, can be problematic in our solution because it results in counting vehicles that are driving through lots or even driving on nearby roads that appear in the picture frame. This may significantly reduce the accuracy of the system and degrade the quality of the study.

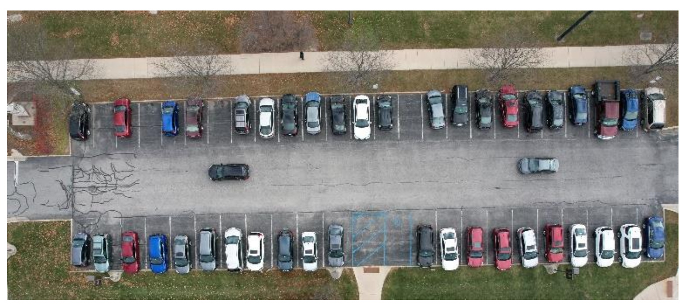

Figure 2. A sample aerial picture of a parking lot

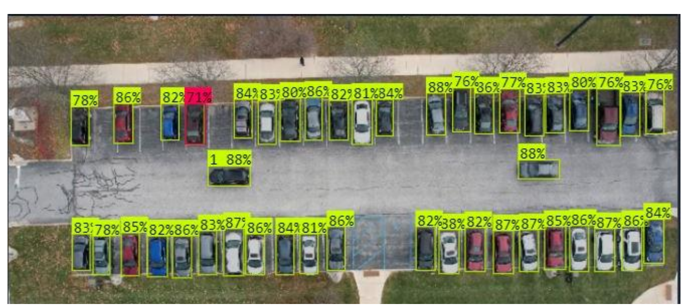

Figure 3. The output of the YOLO classification model when the image shown in Figure 1 is used for input.

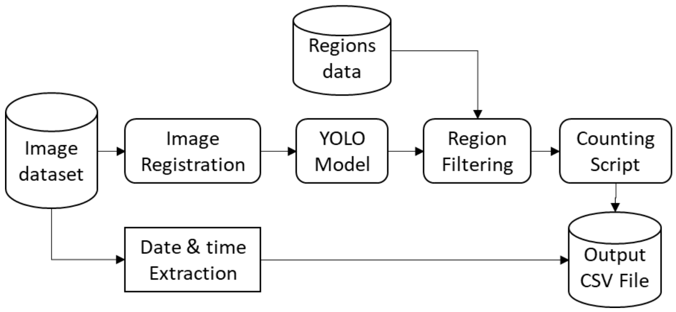

Figure 4. The block diagram of the suggested system

Furthermore, the parking lots on campus include areas with various designations. Different sections of a parking lot, can be designated to faculty and staff, commuter students, on-campus resident students, or visitors. Since the project aims to study the occupancy for the different parking sections, we need to identify those different sections and also process specific areas of an image. This problem, together with the aforementioned "non-parked" vehicles problem are addressed by creating a "Regions.json" data file containing the various designations and the bounding pixel coordinates of each parking section. This file is used to perform region filtering to focus exclusively on the region of interest in an image.

In order for the region filtering to work correctly, the regions data must consistently point to the same location in all the pictures of a certain parking lot. Despite the image-capturing drone being programmed on a Global Positioning System (GPS) controlled flight path, we still observed some inconsistencies in the positions and the angles from which the various pictures are taken. This meant that the pixel coordinates used to identify the parking regions are not going to be consistent in the pictures taken at different times. In order to address this issue, the system designates the first image of each parking lot as the "base" image. All the other images are then aligned with the base image through a registration process. This is done by first using the "Oriented FAST and Rotated BRIEF" (ORB) algorithm [13] in the Python OpenCV library to detect key features between the images. Then, a brute force matcher with hamming distance as measurement mode is used to match these features and create a homography matrix. The image is then transformed using the matrix to align with the base reference. Figure 5 shows a sample image that was misaligned and Figure 6 shows the post-registration version of the same picture.

Once the images are all registered, the YOLOv8 model is implemented to identify the vehicles and store the pixel locations of each of them. The regions pixel information is then used to perform region filtering and isolate regions of interest. The counting script then counts the number of vehicles located in each region of interest. At the end of the process, the count results are written to a CSV file. The exported data is a table with the rows being different dates and times and the columns being various parking designations.

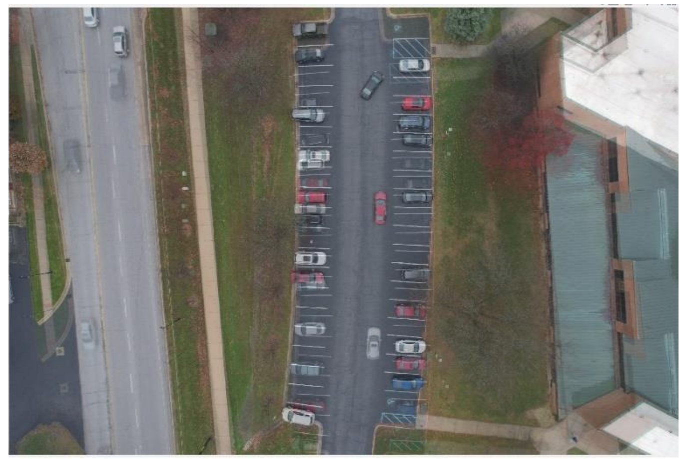

Figure 5. A pre-registration sample image (misaligned with the base image)

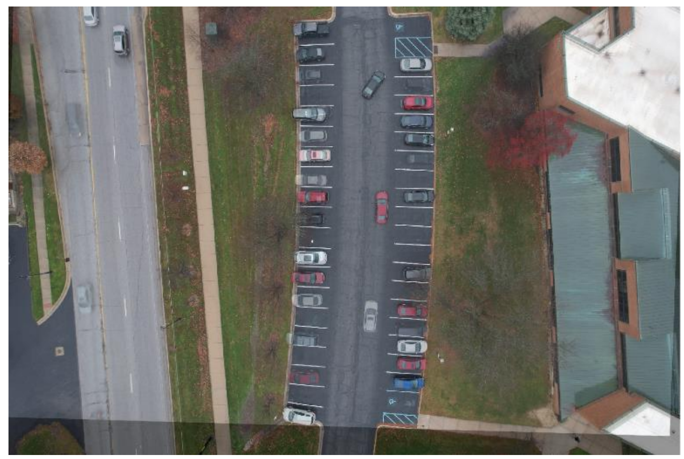

Figure 6. The image shown in Figure 5 after registration (aligned with base image)

V. Results

For the sake of comparison, the first trial was run with the assumption that the images correspond to a uniform parking lot (without parking designations). Therefore, image registration and region filtering are not necessary and were not used. A drone flight path was created for the lot of interest and three flights were performed at various times in the day. The vehicles in the photos were also manually counted to obtain the actual occupancy for validation purposes. For each of the three pictures, Table I shows the number of vehicles detected by the system, the actual number of vehicles (counted manually), and the percentage error of the system. In these tests, we used a confidence threshold of 50%. In other words, the YOLOv8 model detected a vehicle if it was, at least, 50% confident it was a vehicle. This threshold value was selected by a trial and error process. Lower confidence values caused electrical transformer boxes and other "car-like" objects to be false positives. Higher confidence intervals meant darker or slightly obscured vehicles would not be detected.

Table I. The performance results of the first trial of the system

Date	Time	Detected	Actual	Error
12/1/23	10:03	23	19	21.05%
12/1/23	12:17	32	31	3.23%
12/1/23	14:58	21	17	23.53%

As can be seen in Table I, the system exhibited a significant error rate. This is mainly due to counting non-parked vehicles driving through the lots or on roads picked up in the pictures. For example, in the image corresponding to the 10:03 am measurement, shown in Figure 7, two cars driving through the center of the parking lot were erroneously detected and counted as parked vehicles. Additionally, this picture includes a nearby busy road. In this picture, two cars were driving by on this road and therefore were also erroneously counted as parked vehicles. In some other extreme cases, it is possible for rectangular objects like electrical transformer boxes or parts of buildings to also be erroneously detected as vehicles. Hence the importance of always including the image registration and region filtering in the system, even if the parking lot has a uniform designation.

A second trial was performed, on the same images, this time knowing that the parking lot has two distinct regions. In this test, the image registration and region filtering steps were implemented. The same confidence threshold of 50% was used for the YOLOv8 model. Figure 8 shows the detected vehicles for an image that was registered and region filtered to focus on region 1 (the parking row shown to the right side of the image). The system accurately detected all 6 vehicles that are parked in that region (marked with a green dot at their centroids) and accurately skipped over a vehicle that was driving adjacently to region 1. A sample CSV file that was produced by the system is shown in Figure 10.

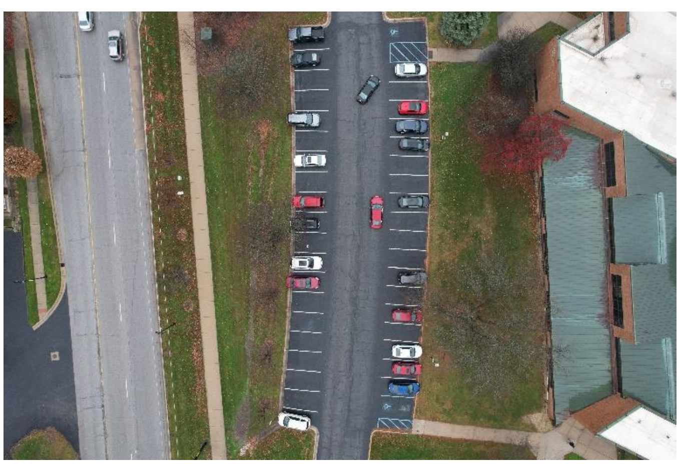

Figure 7. The image corresponding to the 10:03 measurement in the non-registered, non-filtered image test.

Similarly, Figure 9 shows the results of the same image that was registered and region filtered to focus on region 2. In this case, all of the 11 vehicles in that region are detected and marked without detecting any of the vehicles driving on the nearby road. The overall results of the test are shown in Table II. The test includes 3 different images of the same parking lot taken at 3 different times. The table shows that the system had a 100% accuracy rate for both regions and across all 3 images.

Figure 8. The detected vehicles in the 10:03 image filtered to focus on region 1.

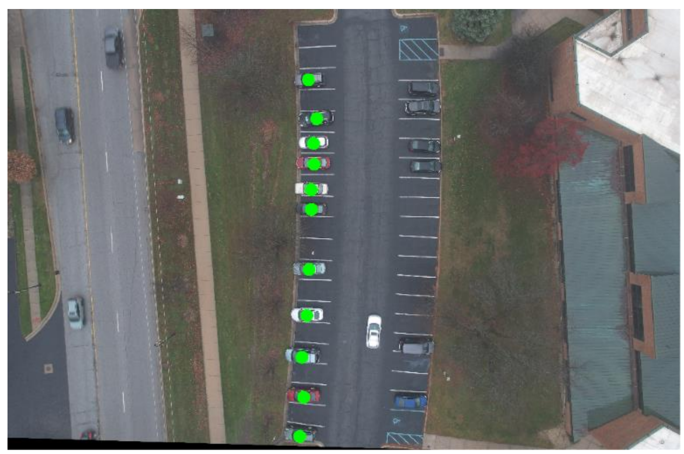

Figure 9. The detected vehicles in the 10:03 image filtered to focus on region 2.

Table II. The performance results of the second trial

		Region 1			Region 2		
Date	Time	Detected	Actual	Error	Detected	Actual	Error
12/1/23	10:03	10	10	0%	9	9	0%
12/1/23	12:17	16	16	0%	15	15	0%
12/1/23	14:58	6	6	0%	11	11	0%

datetime	commuter	faculty
12/1/2023 10:02	9	12
12/1/2023 12:18	10	11
12/1/2023 14:58	5	4

Figure 10. A sample CSV file output of the system

VI. Summary

In this paper, we presented a solution to fully automate parking studies. The system uses computer vision techniques with a pre-trained deep learning model to count the cars in drone-captured images. The results show that the full implementation of the system can determine the number of vehicles in a parking lot with an accuracy of 100%. It is roughly estimated that a round-trip drone flight over a parking lot takes roughly 1 minute while it takes around 10 minutes for a human to walk around the lot to manually count the vehicles. In other words, the proposed system delivers 100% accuracy with 90% time saving.

VII. References

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