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VEHICLE DETECTION, TRACKING, COUNTING AND CLASSIFICATION USING DEEP LEARNING

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Abstract
This paper explores vehicle counting system, which is a crucial component of building a robust transportation management system (TMS) that proffers solution to various challenges facing transportation systems in modern cities around the world. Although there are existing approaches such as the manual vehicular counting and hardware-based systems but they are plagued with various limitations such as being intrusive on roads, difficult to scale and also very expensive to maintain. Hence, there are not enough viable solutions to the current complex and diverse traffic challenges. This paper focused on the development of a vehicle counting system designed to capture and read video in real-time from a camera placed strategically to capture traffic scenes and thereafter counts and classify the vehicles as they cross a detection line. A visualization of the results is displayed onscreen in real-time and the count data for all vehicle classes are saved in a database for future analysis. The counting and classification obtained accuracy is greater than 80%. This research achieved a software-based video counting system that runs on computer vision algorithms and presents an accurate, inexpensive, flexible, scalable and non-intrusive approach to obtaining vehicle count on highways.

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1.0 INTRODUCTION
The unprecedented level of urbanization presently being experienced has triggered high levels of development necessitating the construction of new infrastructures to accommodate the drastic changes. Among such infrastructures are the transportational facilities such as roads and railways which are the majors in moving people from one location to another [9].

Travelling by road is still the most popular form of transportation, however it has been plagued with incessant heavy traffic causing traffic congestions and jams especially in the cities [9]. [7] observed that the major hindrance on road is due to heavy traffic flow during peak hours especially when people commute to work. The total number of vehicles exceeds its capacity and hence causes blockage for emergency vehicles such as fire fighter and rescue vehicles. Furthermore, wastage of fuels adds to the environmental pollution which is not sustainable for a country's economic growth [7]. [10] postulated that traffic congestion imposes a heavy toll on the economy, health, safety, life span, time, education and social life. Such deleterious effects constitute a plague on urban dwellers. Thus, contending with traffic congestion has become part of the reality of life in our cities.

To develop a safer, more efficient, and cleaner transportation system, it is crucial to advance toward automation in road traffic monitoring [6]. Transport agencies worldwide are actively seeking cost-effective and efficient ways to obtain real-time road data and respond to incidents swiftly. One foundational aspect of this is automated traffic counting, a critical tool for managing congestion, informing infrastructure development, and enhancing road safety [2]. Traffic counting involves the enumeration of vehicles traveling on a roadway section or intersection. During the early days and before the advent of some automated systems, machine learning, deep learning, and artificial intelligence, the process of vehicle counting was carried out manually. It was usually performed by someone who would stand by the roadside, observing and using an electronic device to record the traffic data using a tally sheet. In some cases, the person may do the counting by observing video footages captured by city cameras or closed-circuit television (CCTV) placed above the road or highway [1].

According to an investigation by [12], manual vehicle calculation provides high accuracy, however it requires a great deal of human resources to be accomplished. Besides, it tends to be error-prone, especially on high traffic flow and multiple road lanes. As a result of these limitations, manual calculations are usually performed with only a small sample data, and the results extrapolated for a year, a season or other long-term forecasts. Technically, apart from the manual approach, most vehicle counting methods are characterized into either hardware or software-based systems [8]. Inductive loop detectors, microwave radar and infrared sensors are examples of hardware systems used till date. Although, there are hardware-based systems and technologies today that can be used to count vehicles precisely but these are very expensive systems plagued with many limitations such as being intrusive on roads, very expensive to maintain, usually non flexible and difficult to scale [3].

These limitations drive the need for an automated approach, enabling traffic agencies to gather timely and accurate data across various road types and conditions [11]. In recent years, video-based systems have gained traction due to advancements in deep learning and computer vision, which enable more sophisticated techniques for vehicle detection, tracking, and counting [5]. Computer vision brought about a paradigm shift by providing vision for identifying objects belonging to different classes such as a vehicle, a person or any other object in a video as the case may be. The essence of object detection in computer vision paradigm is to provide solution to real world challenges in areas like image search and video surveillance to detect a vehicle, a person or any other object [7].

Surveying and Geographic Information Systems (GIS) play a pivotal role in enhancing the accuracy and functionality of vehicle monitoring systems. Surveying techniques provide precise geospatial data, which is essential for mapping road networks, defining traffic zones, and calibrating surveillance cameras to align with real-world coordinates [10]. This study leverages state-of-the-art computer vision and deep learning techniques for vehicle detection, tracking, counting, and classification using input from low-cost surveillance cameras. Such systems aim to address growing transportation and urban planning challenges, including traffic monitoring, accident prevention, vehicle theft detection, parking management, and general road security threats [6]. The recent advancements in deep learning, object detection, and tracking systems, however, offer a promising software-based approach that addresses these limitations.

Despite these advancements, existing literature identifies certain limitations in prior methods. For example, traditional frame-differencing, detection-based, and motion-based counting methods often struggle in complex traffic scenes with occlusions or low frame-rate videos, compromising accuracy [2]. Density estimation methods, while promising for simpler scenes, lack robustness in high-perspective or large-vehicle scenarios and are limited in object tracking capabilities. Meanwhile, deep learning techniques using convolutional neural networks (CNNs) have shown considerable progress but still face challenges with vehicle re-identification across lanes and in dense traffic settings [4]. Therefore, this study fills a critical gap by employing a CNN-based approach that integrates real-time tracking and classification, aiming to provide a more scalable, non-intrusive solution to traffic monitoring and road safety.

2.0 METHODOLOGY

The developed system involves passing the real time captured video to the computer vision module so as to process the frames from the video in a sequential manner. The frames are then converted into blobs after which the individual pixels are read and the object detection model called on for each of the blobs. The trained model detects objects in the blobs and creates bounding boxes for each of the detected objects. The recognized objects are then passed to the tracker for tracking and once the tracking of vehicles is completed, the detection line method is used to achieve vehicle counting and classification also done accordingly. The procedure and methodology that is employed are:

i. Oneplus 8 smartphone camera is used to capture traffic video in real-time and transmitted wirelessly for a good degree of freedom.
ii. OpenCV (Open Computer Vision Python module by Intel) is used to capture the video directly from the camera.
iii. YOLO (You Only Look Once); a fast, effective and efficient deep learning algorithm for object detection is used to detect vehicles in video frames.
iv. Deep SORT which is multiple objects tracking algorithm is used for tracking the vehicles and hence, determines the direction of detected vehicles in sequential frames of the video.
v. A computer algorithm is written to count vehicles and classify them accordingly.
vi. The real time video, result from the classification and total vehicle counts are displayed as output all in real-time.

The implementation is illustrated in the methodology flow diagram (Figure 1).

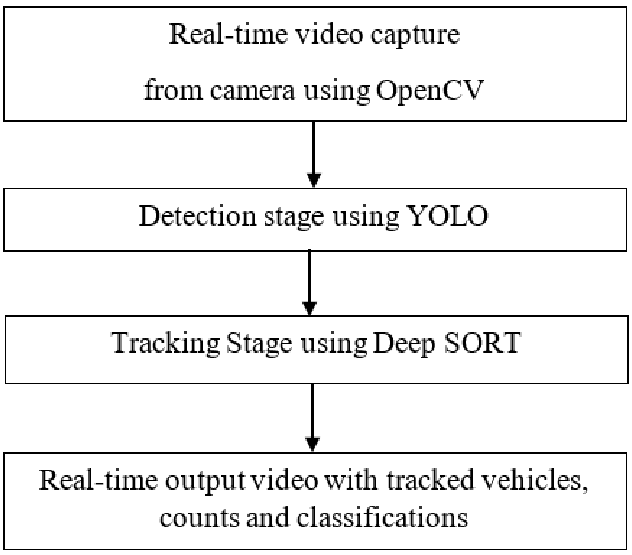


Figure 1: Methodology flow diagram

The above system is implemented using Python programming language. The system entails a convolutional neural network (CNN) which is a type of artificial neural network specifically designed to process pixel data in images and videos. The system is used to detect, recognize and track the vehicles in the sequence of video frames. YOLO with convolutional neural network (CNN) is used for detecting moving objects in real-time and object tracking is done with deep SORT algorithm in OpenCV. Thereafter, vehicle classification is carried out in accordance with their sizes in different classes. Details of each step is discussed below:

Video Capture: The Oneplus 8 smartphone's high resolution 48 megapixels camera is employed because of its Wi-Fi connectivity capability which is leveraged and used as a real-time wireless remote camera. This is achieved using Irium Webcam, a software which enables the use of a compatible smartphone as a wireless remote camera in real-time. The OpenCV Python module is then used to capture video frames directly from the camera and also for some processing on the captured video.

Vehicle Detection: Object detection with a computer is a very complex task which involves several stages for object recognition, localization, and classification. Each of these stages entails complex computer algorithms to achieve the ultimate goal of object recognition with a computer and especially to run those algorithms continuously in real-time which is the aim of this project [1].

Vehicle Count and Classification: After the rigorous tracking process and the center coordinates of the tracked vehicles have been determined, a list, which is an abstract data structure and a container used to store a sequence of values in a specific order is created for each of the vehicle class names where the IDs of counted vehicles will be saved by appending the list. The following procedure is used for vehicle counting:

i. The Detection Line technique is used to achieve vehicle counting. This approach involves drawing a reference line across the video using two sets of (x,y) coordinates which denote exact pixel points.
ii. After drawing the reference line, an algorithm is written to determine when the center point trajectory of any tracked vehicle intersects or crosses the pixels of the drawn reference line then the class track ID is automatically saved in the corresponding list created for each of the vehicle classes accordingly. This list is appended on each reference line intersection and new track ID added on each instance.

3.0 RESULTS AND DISCUSSION

3.1 Results

The developed vehicle counting system is made up of three different and independent programming modules which work together synergistically in order to achieve the counting and classification of vehicles from videos in real time. The output is shown in Figure 2.

The three modules are: (i) detector, (ii) tracker and (iii) counter and classification modules.

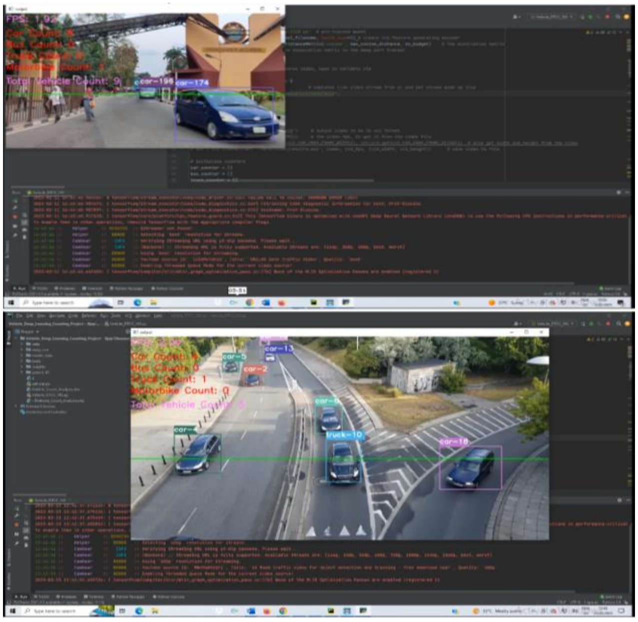
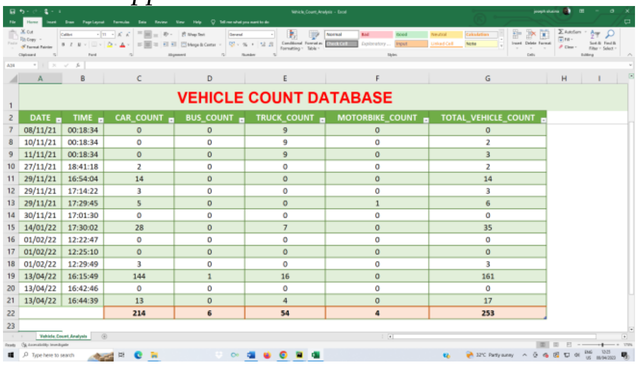


Figure 2: Video frames showing the count of various vehicle classes. This location is UNILAG main gate junction, Akoka, Lagos, Nigeria, chosen because of its frequent vehicular traffic. The geospatial coordinates were acquired using GPS receiver.

3.2 Analysis of Results

The database result on vehicle count and classification is shown in Table 1.

Table 1: *App* Traffic Database



VEHICLE COUNT DATABASE

	DATE	TIME	CAR_COUNT	BUS_COUNT	TRUCK_COUNT	MOTORBIKE_COUNT	TOTAL_VEHICLE_COUNT
7	08/11/21	00:18:34	0	0	9	0	0
8	10/11/21	00:18:34	0	0	9	0	2
9	11/11/21	00:18:34	0	0	9	0	3
10	27/11/21	18:41:18	2	0	0	0	2
11	29/11/21	16:54:04	14	0	0	0	14
12	29/11/21	17:14:22	3	0	0	0	3
13	29/11/21	17:29:45	5	0	0	1	6
14	30/11/21	17:01:30	0	0	0	0	0
15	14/01/22	17:30:02	28	0	7	0	35
16	01/02/22	12:22:47	0	0	0	0	0
17	01/02/22	12:25:10	0	0	0	0	0
18	01/02/22	12:29:49	3	0	0	0	3
19	13/04/22	16:15:49	144	1	16	0	161
20	13/04/22	16:42:46	0	0	0	0	0
21	13/04/22	16:44:39	13	0	4	0	17
22			**214**	**6**	**54**	**4**	**253**

Results from the system were analysed and validated in order to ascertain the level of its accuracy. This was done by testing video of traffic scenes with certain number of frames fed into the developed system and the final results compared with manual counts from the video stream. The results from the analysis are presented in Table 2:

Table 2: Vehicle counts by the developed system with accuracy rates

Number of input video frames	Number of vehicles	Vehicles Detected	Vehicles Tracked	Vehicles Counted	Detection Accuracy (%)	Tracking Accuracy (%)	Counting Accuracy (%)
300	5	5	5	5	100.00	100.00	100.00
750	12	13	13	13	91.67	100.00	91.67
1500	22	24	23	23	90.91	95.83	95.45
2400	29	32	30	30	89.66	93.75	96.55
3150	41	44	43	42	92.68	97.73	97.56
3750	45	50	48	46	88.89	96.00	97.78
4050	52	57	54	55	90.38	94.74	94.23
				AVERAGE	**92.03**	**96.86**	**96.18**

From the above table, the number of input video frames shows the number of continuous frames of traffic video that is captured before running the analysis on them. The number of vehicles is the actual number of vehicles counted via manual approach for accuracy since the manual counting approach is still the most accurate method of vehicle especially when properly and carefully done which is the case here as the vehicle counts were observed and counted with the utmost care.

The detected vehicles are the number of vehicles that were actually recognized as vehicles by the system's deep learning vehicle detection algorithm while the tracked vehicles are those vehicles tracked across several video frames consistently after being detected until they leave the video frame. The vehicles counted is the total number of vehicles counted by the system after the detection and tracking of the said vehicles. The detection, tracking and counting accuracies are thus calculated and the average computed to give an overall insight on the counting results.

The results from the experimental analysis above show that the developed system achieved an average vehicle detection accuracy of 92.03%, vehicle tracking accuracy of 96.86% and overall vehicle count accuracy of 96.18%. This is impressive considering the fact that this is a simple and non-intrusive approach to obtaining vehicle counts on highways.

4.0 CONCLUSION

This project explores the vehicle counting system which is a crucial component of building a robust transportation management system (TMS) that can withstand the various challenges facing transportation systems in modern cities around the world. The importance of the vehicle counting system in TMS cannot be overemphasized as it provides vehicular traffic-flow information on roads which is an indispensable input for optimizing the transportation system as well as planning for the future. This is such an invaluable tool for the various transportation agencies around the world whose major aim is to optimize the current transportation system for an effective and efficient movement of people and goods from place to place and making future developmental plans.

Although there are existing approaches such as the manual counting and hardware-based systems but they are plagued with various limitations such as being intrusive on roads, difficult to scale and also very expensive to maintain hence not viable enough solution to the current complex and diverse traffic challenges. This study proposes a software-based video counting system run on computer vision algorithms presenting an accurate, inexpensive, flexible, scalable and non-intrusive approach to obtaining vehicle counts. There are still improvements to be made in order to make the system cheaper, faster and even more accurate though as it demands a lot of computing power for processing however, a great relief is the ever-increasing computing capabilities and the continued development and recent successes in computer vision techniques and algorithms hence this system will continue to benefit immensely from these developments and eventually replace the older systems for vehicle counting and obtaining traffic-flow information on our highways.

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