SMART TRAFFIC SIGNAL CONTROL SYSTEM FOR TWO INTER-DEPENDENT INTERSECTIONS IN AKURE, NIGERIA

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Abstract: The increasing growth in urban population and vehicular volume coupled with inefficient traffic management results in traffic congestion on road networks. In this work, a smart/intelligent traffic signal control system was developed for two inter-dependent intersections in Akure, Nigeria. The system developed in this work uses deep learning and computer vision techniques to estimate the density of traffic and uses this information to adaptively switch traffic signals based on the traffic density estimated. Simulation results show that in 30 minutes of simulation, 32 signal cycles can be achieved and 967 vehicles can move at these two inter-dependent intersections.

Keywords: Traffic signal control, Intersection, Smart transport systems, Computer Vision, Vehicle Detection, You Only Look Once (YOLO)

1. INTRODUCTION

Transportation has grown to become an important part of everyone's daily life. A good transportation system facilitates the social and economic development of a society and as such, careful consideration should be given to ensure its efficiency. Traffic congestion is one of the major problems that has plagued transportation systems around the world and several solutions have been proposed to reduce and maybe eventually eliminate the problem of traffic congestion. [1] claims that the current estimated worldwide car count is above 1.2 billion, and that this number is expected to climb above 2 billion in 2035 or 2040, according to research. According to [2], the growth in traffic in many regions of the world can be attributed to an increase in global population, which in turn causes an increase in the number of vehicles on the road. Ineffective capacity management (e.g., improper traffic light timing), inadequate infrastructure, crises, work zones, unconstrained needs, special events, and so on are all causes that contribute to traffic congestion.

Wireless communication technologies, deep learning, and computer vision, as well as vehicular network standards, have prepared the way for the use of Intelligent Transportation Systems (ITS), also known as Smart Transportation Systems. An Intelligent Transportation System is defined as the application of advanced sensors, cameras, computers, electronics, telecommunication technologies, and strategies for management in an integrated way to ameliorate the safety and efficacy of the transportation system [3]. The foremost aim of Intelligent Transportation System is to develop, evaluate, analyze and integrate sensors and concepts of information communications technologies make efficient traffic flow thereby improving environmental quality, saving energy, conserving time such that the comfort of drivers, pedestrians, and other traffic groups is enhanced [4]. [5] describes the

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characteristics of an intelligent transportation system as a system that can detect, control, and reduce congestion based on available and accessible data that depict patterns in traffic such as traffic density, travel speed, travel time, the position of vehicles geographically, and the current time.

Two intersections are described as inter-dependent when the distance between them is relatively small (usually less than 200 m) and the traffic activities around these intersections are mutually dependent i.e., the activities of vehicles around one intersection affect the flow of vehicles at the second intersection [6]. The control of traffic at inter-dependent intersections is complex in comparison to single intersections and independent intersections and as a result, traffic control at inter-dependent intersections requires meticulous planning and application of intelligent transportation systems.

[7] developed an intelligent traffic monitoring and traffic light management system using a wireless sensor network (WSN). Sensor nodes were utilized to detect the vehicular presence, and traffic lights were dynamically organized based on data from the sensor nodes using a self-organizing protocol (Alg5).

A smart traffic light controller that uses was designed by [8]. Infrared sensors mounted at road sides were used to detect the presence of vehicles. This data serves as input to the Smart Traffic Control (STC) unit which generates the Red, Green, and Yellow signal timings. The STC system also gives information on an alternative route to the road used if present traffic is heavy. A software API was also developed to provide an easy interface to the administrator.

Embedded systems with sensor networks were used by [9] to design an intelligent traffic light controller. The Red, Green, and Yellow timings of lights at each road crossing were intelligently determined depending on the overall traffic on all neighboring roads. Comparison with existing fixed-time traffic signal shows the system is more efficient.

A smart traffic controller that uses real-time image analysis was proposed by [10]. Edge detection algorithms, Gaussian Mixture Models (GMM), and Detector Blob analysis were used to track and count vehicles. This information was used to control traffic using available low-cost components and was used for various traffic streets.

The intelligent traffic light controller developed by [11] combines sensor networks and embedded technology. The developed system consists of 4 infrared (IR) sensors that were used to sense the presence of vehicular objects. These data were saved in a MySQL database as a log of vehicle count per instance of time. A clustering algorithm (K-Mean) was used to intelligently control the traffic signal by getting the count of vehicles from different intersections.

[12] proposed an intelligent traffic control system based on WSN deployment in their paper. There are two modules in this system. The first module is the Traffic Density Monitoring Module (TDMM), which makes use of an ultrasonic sensor to determine the length of the queue created by a crowd of vehicles, and the second module is the Traffic Management Module (TMM), which is computer software that allows traffic lights to be controlled based on data collected by various sensors.

Similarly, [13] designed an intelligent adaptive traffic light control system using magnetic sensors put in the ground along all approaches that make up an intersection. The data collected by the magnetic sensors are used by the base station, which uses an algorithm to detect the level of traffic congestion in each lane, allowing the traffic lights at the road intersection to be dynamically managed.

Using an Atmega 32 microcontroller and infrared sensors for the implementation of a traffic system, a microcontroller-based smart traffic control system was designed by [14]. The simulation was performed using Proteus 7.7 Professional software and implementation was done by constructing a test rig.

[15] used image processing technology to create a prototype. The technology uses pictures and lives video to detect vehicles. The scenes in the image were captured using closed circuit television (CCTV) cameras stationed at the traffic light. The collected images were matched sequentially using image matching, and edge detection was performed using the Prewitt edge detection operator, with images of all the vehicles serving as the reference image. Finally, traffic light durations are modified based on the proportion of matching. The Raspberry Pi board was used to process images and regulate traffic signals.

Object detection and object tracking were utilized to feed traffic data into a database (PostgreSQL) in [16]. The Single Shot Multibox Detection (SSD) technique is used to detect vehicular object. The data is preprocessed and analyzed, and the results are used to give directions to vehicles via an indicator. The prototype employs a three-lane model, with the center lane being assigned to traffic in either direction based on the information gathered.

[6] designed and implemented a small-scale model of an 8-pole microcontroller-based traffic light control system to reduce traffic jams and congestion at Oloko and Roadblock/Orita-Obele inter-dependent intersections. The traffic light control system was designed using PIC16F877A microcontroller, and light emitting diodes (LEDs) as the traffic lights. Eight positions were selected for the placement of poles bearing the traffic lights. Fixed times were set for all the poles and the microcontroller was programmed using Micro C compiler and Proteus software according to the determined logic. A simulation was conducted, and bread-boarding was carried out to ensure that result matches the expected result. The circuit was assembled on a printed circuit board (PCB) and encased. The designed and implemented system uses pre-timed control and does not take into account the current volume of vehicles at these intersections to control the traffic situation. This limitation necessitated the need to develop a Smart Traffic Control System (STCS) which takes into account the volume of vehicles at the inter-dependent intersections to intelligently control traffic situations. This work is an improvement over the limitation of [6].

In this work, an algorithm to control traffic signals at Oloko and Roadblock/Orita-Obele interdependent intersections in Akure, Nigeria in teal-time was developed. Video data were collected at the selected interdependent intersection and used to develop a vehicle detection and counting model using deep learning based object detection (YOLOv3) and computer vision techniques. Information from the VDC model is used to dynamically set green signal time at each leg of the intersections.

2. MATERIALS AND METHODS

2.1. The Study Area

The study area is two inter-dependent intersections of Oloko and Roadblock/Orita-Obele intersections in Akure, Nigeria. Figure 1 shows the schematic of the road network. [6] describes the intersections as two close intersections located along the Ilesha-Akure dual carriageway. Oloko intersection is located on latitude 7.28996 and longitude 5.16167 while Roadblock/Orita-Obele intersection is located on latitude 7.29115 and longitude 5.16054. The road is one of the most important links that serve different users namely: travelers, daily commuters, tourists, and commercial drivers to and from Akure. The road also links the South Eastern and the Northern parts of Nigeria. Thus, the vehicular interaction at the two Tee-intersection is enormous which results into serious conflicting road uses. The two intersections are staggered Tee intersections with a distance of less than 50 m between them. The intersections are controlled by traffic wardens through yield signs which lack adequate coordination. As shown in Figure 2, there are 9 conflicts possible at a Tee intersection – 3 are as a result of merging, 3 as a result of diverging and 3 as a result of crossing. In the study area, conflicts among road users will be about 18 and this could lead to accidents and serious traffic congestion thereby creating delays for road users, air pollution, and increase in fuel consumption. Traffic volume study conducted during weekdays at these intersections revealed that an average of 776 vehicles per hour. Of these vehicles, 63 are motorcycles, 649 are cars, 39 are buses and 25 are trucks.

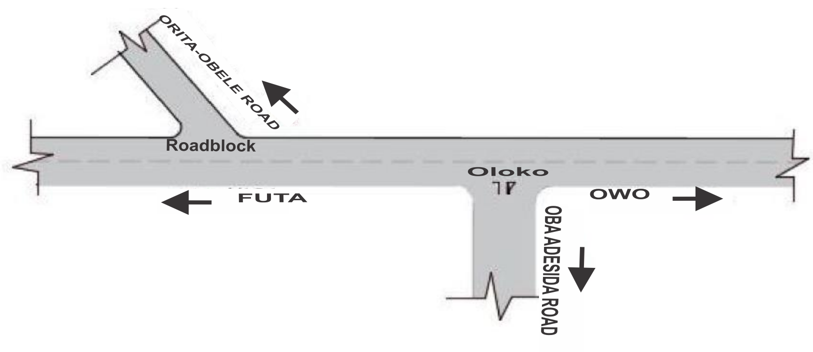

Fig. 1. Schematic diagram of the Oloko and Roadblock/Orita-Obele intersections [6].

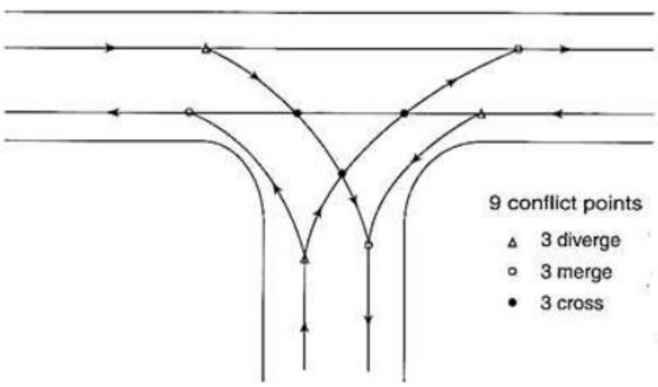

Fig. 2. Typical Conflict Points at Tee Intersection [17].

In order to ascertain the warrant for designing traffic signal for any intersection, traffic volume and delay study are apparent. In this study, data on traffic volume and delay collected by [18] through video recording was used. The data is made up of hourly video recording of the morning peak-period and evening peak-period for five working days at the selected intersections. To observe automobile movements, a video camera was put at an elevated viewing point from the roadside of the selected intersections. At the designated intersections, two cine cameras were employed to provide complementary views, and they were hidden from the drivers so that they would not be distracted from their typical behavioral patterns. The video data were processed in the laboratory by playing several times to extract needed data such as traffic volume count and the length of time it takes a vehicle to wait at a given approach before getting right of way was used to calculate traffic delays. On the subject approach, the cars were split into five categories: cars/taxis, motorcycles, buses, 2-axle load, and 3-axle load trucks for the traffic count while the average time delay at the selected intersections was determined using Equation (1).

$$TD = \frac{\sum(t_d - t_o)}{n} \tag{1}$$

where TD is the average delay time, t_0 is the subject approach vehicle's arrival time at the line of reference, t_d the subject approach vehicle's departure time, and n the total number of delays detected.

2.2. Proposed System

2.2.1. Traffic Control Pattern

The proposed system aims to use real-time data from CCTV cameras at the traffic intersections as inputs to evaluate the traffic density using object detection and computer vision techniques. As shown in Figure 3, the vehicle detection and counting algorithm use You Only Look Once version 3 (YOLOv3) to calculate the number of vehicles of each class such as motorcycles, cars, buses, and trucks detected. This is used to estimate the traffic density. The ATSSA uses this information along with other factors to set the green signal time (GST) for each lane at the selected intersections. To prevent any lane from becoming starved, the GST was limited to a maximum value. This will also prevent excessive cycle lengths

To control traffic signals at the selected intersections, 6 strategic positions were selected for pole placement. They are labeled TS1, TS2, TS3, TS4, TS5, and TS6 respectively as shown in Figure 4. This position matches the Traffic Flow Pattern (TFP) and Traffic Transition Pattern (TTP) - observed at the selected intersections. The TFP refers to the way in which vehicles move from an approach of one of the two inter-dependent intersections to another approach of the other intersection while the TTP refers to the method by which traffic lights change colors from green to yellow to red on the poles for the six traffic signal poles. Table 1 shows the relationship between the TFP and TTP at the selected intersection and Figure 4 shows the positioning of the traffic signal poles proposed. Eight poles were recommended in [6] but the poles are reduced to six in this work.

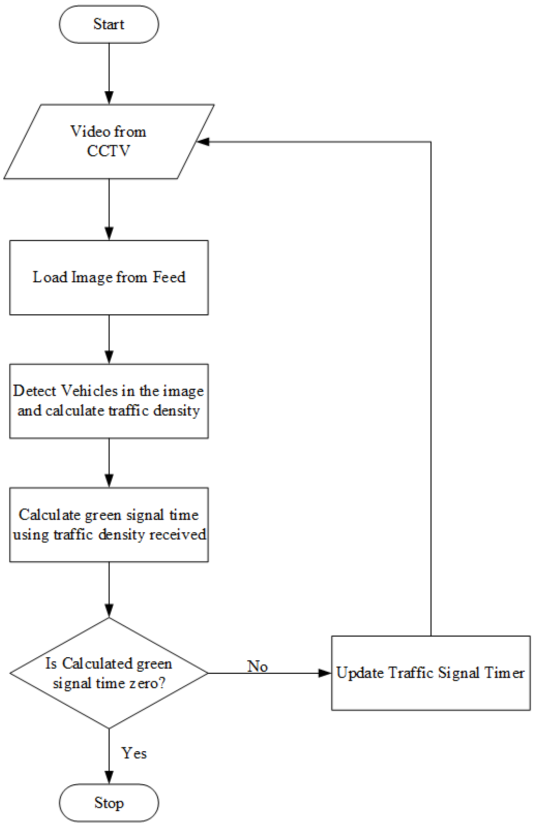

Fig. 3. Proposed System Flow Diagram.

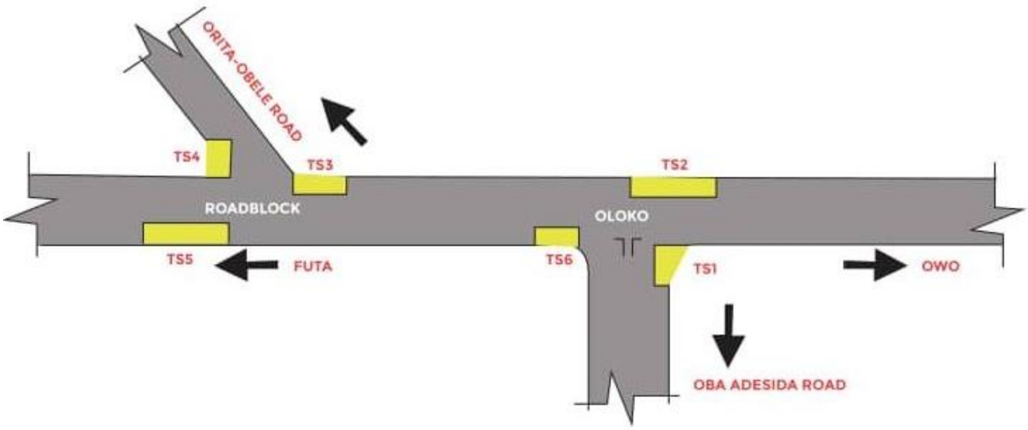

Fig. 4. Proposed Pole Numbering and Placement of Traffic Signals at the Two Intersections.

From Table 1, the instances of the traffic flow pattern are assigned TFP-1, TFP-2, TFP-3, and TFP-4 while the traffic transition pattern are designated TTP 1-2, TTP 2-3, TTP 3-4, and TTP 4-1. In the first instance i.e., TFP1, TS1 lights green, TS3 is also green while other traffic signals are red. This will allow the movement of vehicles from the Oba Adesida approach to move in three directions - some can cross the intersection and move towards FUTA, some can cross and divert movement towards Orita-Obele Road while others vehicles can divert and move toward Owo road.

For the TFP-2, TS1 and TS3 are light green while other traffic signals are red. This allows vehicles from the Owo approach to move in three directions either crossing the intersection and heading towards Oba Adesida Road or moving straight towards FUTA o divert and move towards Orita-Obele Road.

Table 1. Relationship between traffic signal colour pattern, traffic flow pattern and traffic transition pattern at oloko and roadblock/orita-obele intersections.

Traffic Flow Pattern (TFP) and Traffic Transition Pattern (TTP)	**TRAFFIC SIGNAL COLOUR PATTERN**						
	POLE NUMBER	TS1	TS2	TS3	TS4	TS5	TS6
	TFP-1	G	R	G	R	R	R
	TTP 1-2	Y	R	G	R	R	R
	TFP-2	R	G	G	R	R	R
	TTP 2-3	R	Y	Y	R	R	R
	TFP-3	R	R	R	G	R	G
	TTP 3-4	R	R	R	Y	R	G
	TFP-4	R	R	R	R	G	G
	TTP 4-1	R	R	R	R	Y	Y

In the third instance i.e. TFP-3, TS4 and TS6 lights green while other traffic signals are red. Vehicles coming from the Orita-Obele approach are able to move either towards FUTA, Oba Adesida Road or Owo.

For TFP-4, TS5 and TS6 lights green making other traffic signals red. Movement of vehicles from FUTA approach is possible and the vehicles can move towards Orita-Obele Road, towards Oba Adesida Road or towards Owo.

2.2.2. Vehicle Detection and Counting (VDC) Module

The proposed system uses YOLOv3 for vehicle detection. A custom YOLOv3 model was trained to detect vehicles of various classes such as cars, motorcycles, buses, and trucks. YOLOv3 is a real-time convolutional neural network (CNN) based algorithm for object detection. It is an improvement over YOLO and YOLOv2 and was developed in [19]. It separates an image into regions, predicts bounding boxes and their probabilities for each region, and then applies a solitary neural network (NN) to the image. YOLOv3 has 24 convolutional (conv.) layers and 2 fully connected layers, with some convolutional layers constructing ensembles of inception modules with 1 x 1 reduction layers followed by 3 x 3 conv layers. This allows the network to process images in real-time at a rate of 45 frames per second (FPS), which is more accurate than most existing real-time object detectors. Using Darknet-53, an open-source neural network framework developed in C and CUDA, the backbone CNN used in YOLO can be reduced to improve processing time. It is quick, simple to set up, and supports both CPU and GPU computations [20].

The dataset used for model training was put together by video recording through semi-automatic method in the study area. These videos were converted to image frames and manually annotated using LabelImg, a graphical annotation tool for images by [21]. At the end of the annotation, 2208 images were annotated. The object instances observed in this dataset are 17841 cars, 6692 motorcycles, 1859 buses, and 2433 trucks. The dataset was split into training and validation sets. The training set contains 1766 images representing 80 % of the dataset while the validation set contains 442 images representing 20 % of the dataset.

The vehicle detection model was trained using pre-trained Darknet-53 weights downloaded from the YOLO website. The configuration of the .cfg file utilized was also adjusted in accordance with our model's specifications. In the last layer, the number of output neurons was fixed to be the same as the number of classes the model is supposed to detect. In this case, 4 viz. Car, Motorcycle, Bus, and Truck classes. 5 (5+number of classes) = 45 was used to calculate the number of filters needed and this was changed in the configuration file accordingly. The training of the model was done on Google Colab - an online-based research Collaboratory platform with powerful Graphic Processing Unit (GPU). When it was determined that the loss had been considerably decreased and that no further reduction appeared to be possible, the training was stopped and the weights were updated in accordance with the stated requirements. The weight was imported with Python 3.7.3 and used for the detection of vehicles with the aid of OpenCV library. The minimum level of confidence required for successful detection is set as a confidence threshold and non-maximum suppression (NMS) was used to remove overlapping bounding boxes. The drawing of bounding boxes on images, corresponding classes, the probability/confidence level, and coordinates of the bounding boxes were achieved with OpenCV.

2.2.3. Adaptive Traffic Signal Switching Algorithm (ATSSA)

Based on the traffic density given by the VDC module, the GST is determined using the adaptive traffic signal switching algorithm, and the red signal time (RST) of other traffic signals are adjusted correspondingly. The algorithm uses the information about the vehicles identified by the VDC module as input. This is used to determine how many vehicles of each class are present in the image parsed. The traffic signal's GST is computed and allocated, as well as the time value for the next red signal is adjusted accordingly. To develop this algorithm, the following factors were considered:

i. Number of lanes at each leg of the selected intersections;
ii. Total number of vehicles of various classes present, such as cars, motorcycles, buses, and trucks;
iii. Traffic density calculated from ii;
iv. Average traffic delay observed from traffic volume study of the selected intersections;
v. Average speed of vehicles of each class at start up;
vi. Maximum green signal time to mitigate starvation and excessive cycle length.

Based on the factors above, GST is calculated using Equation (2).

$$GST = \sum_{C} \frac{NV_C x TD_C}{NL} \quad (2)$$

where NV_c is the number of vehicles of each class detected by the VDC module on the leg of the selected intersection, TD_c is the average delay time for that class of vehicle at the intersection as observed in the traffic delay study. The number of lanes at the intersection leg is denoted by NL.

Adaptive Traffic Signal Switching Algorithm

Start
Repeat
Get input from VDC module for Oba Adesida approach
Set GST for TS1 and TS3 according to equation (3), and count down.
Set yellow signal time (YST) for TS2 and count down.
Get input from VDC module for Owo approach
Set GST for TS2 and TS3 according to equation (3) and count down.
Set yellow signal time (YST) for TS4 and TS6 and count down.
Get input from VDC module for Orita-Obele approach.
Set GST for TS4 and TS6 according to equation (3) and count down
Set yellow signal time (YST) for TS5 and count down.
Get input from VDC module for FUTA approach.
Set GST for TS5 and TS6 according to equation (3) and count down
Set YST for TS1 and TS3 and count down
Until *VDC module returns zero for all approaches*
Stop

To evaluate the performance of the vehicle detection model and the effectiveness of the ATSSA, new videos were recorded at each leg of approach at the two inter-dependent intersections. The videos are 30 minutes long each and were captured during the evening peak hour. A script was written in Python 3.7.3 using PyCharm Community integrated development environment (IDE) to process these videos in OpenCV while embedding the VDC module and the ATSSA into it. This script serves as our simulation and was run for a period of 30 minutes to observe how efficient our algorithm is.

3. RESULTS AND DISCUSSION

The efficiency of the vehicle detection model after fine-tuning is shown in Figure 5. This is the model loss curve. The loss curve shows the deviation between the predicted classes of the model and the real classes based on the training and validation sets. As shown in Figure 5, the loss curve of both the training sets and the validation sets have a downward trend and began to reduce significantly after training the fourth epoch. After the fourth epoch, the value of the loss reduces slowly with increasing number of training epochs. From the curve it is observed that the vehicle detection model learns at optimum level without overfitting and underfitting. In order to avoid overfitting, the training was stopped after the 20th epoch.

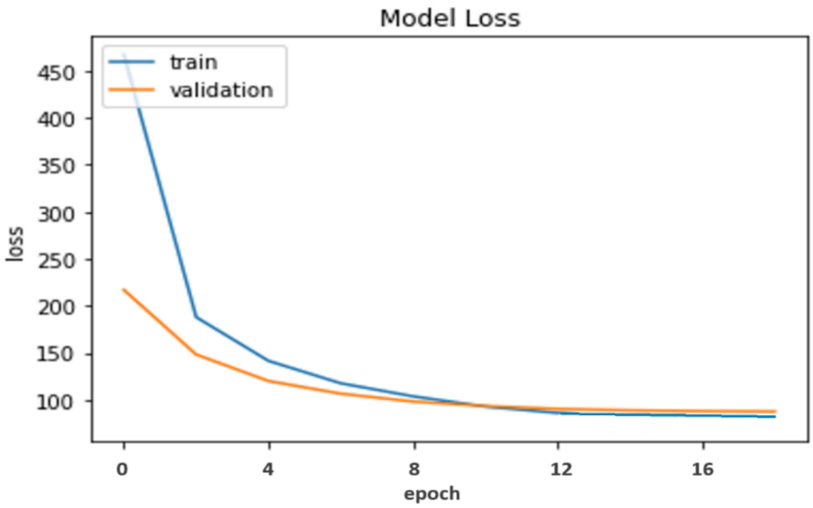

Fig. 5. Vehicle Detection Model Loss Curve for Train and Validation Sets.

The vehicle detection model was applied to test images in Figure 6. The original image is on the left side of Figure 6, while the output on the right side shows bounding boxes, associated classes, and confidence of detection following detection. The variation in the confidence of detection of different objects shown in Figure 6 is as a result of the proximity of the objects in the image to the stationed camera and occlusion from other objects in the image.

The result obtained after running the Python script with the VDC and ATSSA embedded into it for 30 minutes is presented in Table 2. From Table 2, the distribution of vehicular movement at the two intersections from each approach is 310 vehicles from Oba-Adesida approach, 232 vehicles from Owo approach, 172 vehicles from Orita-Obele approach, and 253 vehicles from FUTA approach with Oba Adesida approach having the highest vehicular movement and Orita-Obele has the lowest.

Also, the distribution of vehicles according to their classes is 79 motorcycles, 798 cars, 38 buses, 52 trucks with vehicles of the class car having the highest and vehicles of the class bus with the lowest. It is observed that 32 signal cycles (i.e., complete switching through all the traffic signals) can be realized in 30 minutes if the proposed system is implemented.

Table 3 presents the GST for each of the six traffic signal poles at the two intersections for the first and second signal cycles during the course of simulation. Figure 7 presents the simulation while it is being run in PyCharm Community IDE. It shows an image captured from the video stream recorded at one of the legs of the two inter-dependent intersections (Owo Approach) with VDC module in place as well as the GST calculated for TS2 and TS3 as well as the RST calculated for TS4.

Table 2. Simulation result of the ATSSA.

	Oba-Adesida Approach	**Owo Approach**	**Orita-Obele Approach**	**FUTA Approach**	**Total**
Motorcycles	15	23	26	15	79
Cars	287	174	123	214	798
Buses	7	11	15	5	38
Trucks	1	24	8	19	52
	310	**232**	**172**	**253**	**967**

Fig. 6. Vehicle detection results.

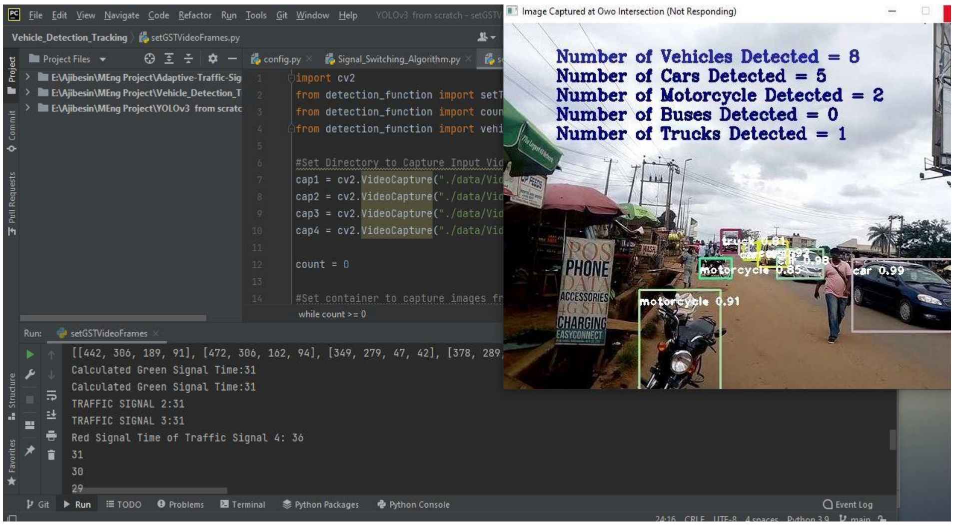

Fig. 7. ATSSA script running in PyCharm Community IDE.

Table 3. Time allocation for two different signal cycles during simulation.

<table>
<tr><th colspan="7">TRAFFIC SIGNAL COLOUR PATTERN</th></tr>
<tr><th>POLE NUMBER</th><th>TS1</th><th>TS2</th><th>TS3</th><th>TS4</th><th>TS5</th><th>TS6</th></tr>
<tr><td></td><td colspan="5">First Signal Cycle</td><td></td></tr>
<tr><td>TFP-1</td><td>G.34s</td><td rowspan="2">R. 39s</td><td rowspan="3">G.56s</td><td rowspan="4">R. 61s</td><td rowspan="6">R.92s</td><td rowspan="4">R. 61s</td></tr>
<tr><td>TTP 1-2</td><td>Y.4s</td></tr>
<tr><td>TFP-2</td><td>R</td><td>G.17s</td></tr>
<tr><td>TTP 2-3</td><td>R</td><td>Y.4s</td><td>Y.4s</td></tr>
<tr><td>TFP-3</td><td>R</td><td>R</td><td>R</td><td>G.31s</td><td rowspan="3">G.60s</td></tr>
<tr><td>TTP 3-4</td><td>R</td><td>R</td><td>R</td><td>Y.4s</td></tr>
<tr><td>TFP-4</td><td>R</td><td>R</td><td>R</td><td>R</td><td>G.24s</td></tr>
<tr><td>TTP 4-1</td><td>R</td><td>R</td><td>R</td><td>R</td><td>Y.4s</td><td>Y.4s</td></tr>
</table>

<table>
<tr><th colspan="7">Second Signal Cycle</th></tr>
<tr><td>TFP-1</td><td>G.20s</td><td rowspan="2">R. 24s</td><td rowspan="3">G.55s</td><td rowspan="4">R. 60s</td><td rowspan="6">R.91s</td><td rowspan="4">R. 60s</td></tr>
<tr><td>TTP 1-2</td><td>Y.4s</td></tr>
<tr><td>TFP-2</td><td>R</td><td>G.31s</td></tr>
<tr><td>TTP 2-3</td><td>R</td><td>Y.4s</td><td>Y.4s</td></tr>
<tr><td>TFP-3</td><td>R</td><td>R</td><td>R</td><td>G.26s</td><td rowspan="3">G.71s</td></tr>
<tr><td>TTP 3-4</td><td>R</td><td>R</td><td>R</td><td>Y.4s</td></tr>
<tr><td>TFP-4</td><td>R</td><td>R</td><td>R</td><td>R</td><td>G.40s</td></tr>
<tr><td>TTP 4-1</td><td>R</td><td>R</td><td>R</td><td>R</td><td>Y.4s</td><td>Y.4s</td></tr>
</table>

The number of vehicles transiting any of the approach of the intersections is known in real-time in this work. This is an improvement over the work done in [6] which is not capable of estimating the number of vehicles for which GST is set. Also, the deep learning based vehicle detection model developed in this work outperforms the Prewitt edge detection image processing algorithm used in [15] in processing time as our model is capable of processing at a rate of 45 frames per second. The use of computer vision techniques eliminates the problem of high failure rate of wireless sensor networks, infrared sensors, and magnetic sensors used in [11, 12, 13].

4. CONCLUSIONS

This work has been able to develop a smart traffic control system for selected two inter-dependent intersections in Akure, Nigeria. The developed system uses deep learning and computer vision techniques to estimate the traffic density at each leg of approach at the intersections to adaptively determine the GST for the traffic signal at each approach. Simulation results show that in 30 minutes of simulation, 32 signal cycles can be achieved and 967 vehicles can move at these two inter-dependent intersections. The breakdown of the result according to different vehicle classes shows that cars are the most prevalent vehicular class at these intersections with a total of 798, following cars are motorcycles,79 then trucks 52, then buses 32.

The authors believe that the problem of traffic congestion at the selected interdependent intersections which leads to high fuel consumption and increased pollution can be solved. By working in real-time, the system is capable of dynamically setting the GST for the selected intersection which is an improvement over previously proposed system. Also, this eliminates the need for human traffic controllers at the two inter-dependent intersections. With a little adjustment, the smart traffic signal control system algorithm developed in this work can be adapted to any intersection.

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