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Application of Object Tracking for Intelligent Transport Systems

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Abstract **– Effective road network operations require maximizing the available capacity especially in congested urban road networks. One of the ways of improving traffic flow and optimizing road network capacity, especially in peak periods, is by utilizing reversible lanes. This involves utilizing real-time road traffic information to reduce congestion. This study applies the video processing techniques of object detection and object tracking to feed traffic data into a database (PostgreSQL). The data is pre-processed and analyzed and the information is used to assign directions to vehicles through an indicator. The prototype design uses a three-lane model and assigns the middle lane for traffic in either direction depending on the acquired traffic information.**

Keywords-Traffic management; Intelligent Transport Systems (ITS); Object Tracking; OpenCV; Deep Learning, Object Detection; Single Shot Multibox Detection (SSD)

I. INTRODUCTION

A functional and integrated transport system is important in the economic development of a country as it enhances the quality of life and enables the seamless movement of goods and services in the country [1]. This seamless movement can be achieved by the use of an Intelligent Transport System (ITS) which integrates information, communications, computers and other technologies to construct an integrated system of people, roads and vehicles by utilizing advanced data communication technologies [2]. ITS can help make the transition from the underutilization and overutilization of road to its optimal utilization. To accomplish this, an intelligent transport system utilizes advanced technology to provide drivers with a real-time road information and convenient services to reduce traffic congestions and to maximize the road capacity [2] [3]. The provision of accurate data and useful information on congested routes, available alternative routes and anticipated travel time can be possible if two important components of any ITS, traffic data collection and data evaluation, are functioning successfully [3]. The data collection can be performed using loop detectors or cameras or a combination of both mounted on the roadway sections of interest [3]. In the data evaluation component, the trend is in performing a real-time traffic control by using a high-speed real-time traffic simulator [3]. As an important function in ITS, the detection of vehicles also provides information that facilitates count of vehicles, vehicle speed measurement, road accident identification and traffic flow predictions.

Traffic congestion is a problem in metropolitan areas, and most of these areas have deployed traffic lights to control traffic. These traffic management systems are limited in their abilities to adapt to real-time traffic conditions. Recent traffic management systems have seen the introduction of loop detectors and cameras for real-time traffic control [4]. In some developing countries, the effect of a poor transport infrastructure and ineffective traffic management systems have resulted in frequent traffic congestion and sometimes road accidents. Nigeria, for example, recorded 2,080 road crashes resulting in about 855 fatalities between the months of April and June 2020 [5]. With ITS and a real-time traffic management integration, it is expected that these statistics can be reduced significantly.

Traffic signal timing systems are usually programmed based on historical traffic data and therefore are not flexible and cannot be adapted to cater for unusual events such as road accidents and road repairs. On the other hand, an object tracking system integrated into an ITS as stated in [3] uses traffic simulation models that also need calibration for actual and prevailing traffic conditions using data collected by the ITS data collection component. The increased benefit attached with a real-time traffic monitoring and management system has led to the need for a dynamic traffic control system.

A greater application of a real-time traffic management system is in its integration in reversible lanes to handle special road occurrences such as scheduled construction or maintenance activity on the road [6]. Reversible lanes are also important during times of adverse weather or natural disaster, as the evacuation process is hastened [7].

In this paper, we present an intelligent traffic control system for a reversible lane on a 3-lane road that seeks to allocate the middle lane dynamically to reduce traffic congestion. This traffic control system logs the present state of the road and the corresponding time of the day, density of traffic as well as the flow of both expected and unexpected traffic, thereby, reducing the relative travel time as much as possible.

II. USE OF OBJECT TRACKING FOR TRANSPORT SYSTEMS

A. *Moving Object Detection*

Moving object detection is the first step in the process of moving object tracking. Object detection are usually performed with the use of sensors.

In road transportation, depending on the location of the sensor, traffic flow sensors can be classified into in-road sensors and on-road sensors. In-road sensors such as the inductive loop detector (ILD) sensor and magnetic detectors have been used for collecting data on traffic flow, vehicle's occupancy, length, and speed. ILD is best suited for allocating parking slots for vehicles with the disadvantage being the high cost of installation [8] [9] [10]. In general, in road sensors have high detection accuracy with ILDs and magnetic sensors having accuracies of up to 92% and 99% respectively [11]. On the other hand, camera-based systems have been reported to have accuracies of 94.5% [12].

Li, et al. used magnetic sensors to construct a model to determine linear length measurements at signalized intersections. The design of a single sensor-based approach proposed in the research is simple and economical making it ideal for large-scale deployment and application.

A study on piezoelectric road sensor technology showed that piezoelectric sensors can detect vehicles at high speeds (speed range of more than 112 km/h) moving over a sensor (ILD) through a change in the sensor's voltage [13]. This is especially useful in monitoring over-speeding road users as piezoelectric sensors can monitor up to four lanes. Piezoelectric systems are usually composed of piezoelectric sensors and ILD sensors.

An example of the on-road sensor system is the video image processor (VIP) system. It involves the use of a video camera, a computer for processing images and a sophisticated algorithm-based software for interpreting the images and translating them into traffic data. In addition, the VIP system can be employed to detect cracks on roads [11]. Maria, *et al.*, presented a car detection system prototype using VIP within an experimental project which was tested with a desktop PC and an embedded system to analyze video streams recorded by drones flying over an urban environment. The end result of the project was the automatic provision of useful information, such as available parking spaces and level of traffic congestion [12].

Object detection has evolved from detecting objects of concern in an image to objects in a video. Image object detection involves two stages: (1) hypothesis generation and (2) hypothesis verification [11] [12]. Object detection from video uses motion-based method of hypothesis generation and verification [14].

The output of object detection from video is the set of moving objects separated from the background. Different object detection methods have been used over time. The frame difference method operates by calculating the difference between consecutive images [15]. Though this approach is simple and keeps track of all the changes in a frame, it is difficult to obtain a complete caption of the moving object. The main concept of the subtraction method [16] lies in detecting the moving objects from the difference of a current frame and a reference frame, often called the 'background image' which is a representation of the scene with no moving objects. This background must be regularly updated to adapt to varying conditions.

The optical flow method uses the vector characteristics of the moving object which changed over with time to detect moving objects in image sequences [16]. The method can be applied to dynamic scenes, but its calculation is complex and anti-disturbance ability is poor which can't meet the requirements of real-time video processing.

Several other algorithms are: Gaussian mixture model (GMM), Kanade-Lucas-Tomasi, Horn-Schunck, Single Shot Detection (SSD), and Farneback [17].

In this work, we have used the SSD algorithm which is based on feature fusion for the object detection process.

B. *Object Tracking*

Object detection is the fundamental step in video analysis. Object tracking and detection are used concomitantly. All tracking methods require an object detection process either in every frame or on the first appearance of the object in the video [18]. Object detection manages the segmentation of moving objects from stationary background objects. The features used for object tracking are edges, color, centroid and texture.

Object tracking is the act of keeping track of an object(s) over time by locating its position in all instances of a video surveillance system's frame [18]. Tracking involves matching detected foreground objects between successive frames using different features of the object like velocity, color, texture, motion [18]. The technique used for object tracking in this paper is the block matching technique for object tracking in traffic scenes [19]. The technique employs a motionless airborne camera, or camera suspended in mid-air on a platform (a bridge, a pole) used for video capturing [20].

There are different methods of object tracking: point, silhouette and kernel tracking [19, 21]. Silhouette tracking is used when the complete terrain of an object is needed. Complex object such as human body, hands, and the head can be tracked. For this reason, only both Point and kernel tracking methods were evaluated in this work with Kernel tracking showing better accuracy for 2-D and 3-D object video tracking. In the tracking approach, the objects are represented with appearance models, points or shapes [22, 18]. The model selected to represent the object shape limits the type of motion. In this paper, the object of interest (vehicles) is represented with square boxes (kernel tracking) with thick outlines.

C. *Reversible Lanes*

Some of the works carried out on reversible lanes studied the application status, control, management measures, evaluation methods of reversible lanes, and concluded that although there was no unified planning and well-established standards, the concept of reversible lanes still achieved set goals and were generally accepted [23] [20]. According to Mao, *et al*., the road conditions for the implementation of a reversible lane must stick to the following: the existing number of lanes on the road must be at least three in both directions and in mega cities with large traffic flow, the number of lanes on the road should be greater than six or no less than 5 to ensure room for the reversible lanes; immovable traffic infrastructures such as trolley tracks or central separation zones should not be installed in roads with reversible lanes [20].

Also, the traffic conditions for the implementation of a reversible lane are: the main condition is that reversible lane area must have a stable traffic flow with clear traffic imbalance, a phenomenon premise to set the reversible lane; after the inculcation of the reversible lane, the capacity of the road still has to meet the actual road demand [20] and the traffic capacity of the road can be increased to accommodate more traffic, of about 20% increase on average [21]. Also, efficient installation facilitates the evacuation of a particular area especially during accidents or special events [19].

III. VEHICULAR TRACKING MODEL

The vehicular tracking model used consists of three sub modules:

A. *Object Detection*

A typical object detection model takes a frame as its input and returns an array of objects containing the classes of objects detected and their respective bounding boxes [24]. This stage involves the prediction of objects present in a frame and the wrapping of a bounding box [25] around the match as shown in Fig. 1. The accuracy of the entire architecture depends solely on the model used for this stage. Object detection model with low accuracy would be greatly discouraged because the object detection will fail through too many frames causing estimation errors and distortions [22].

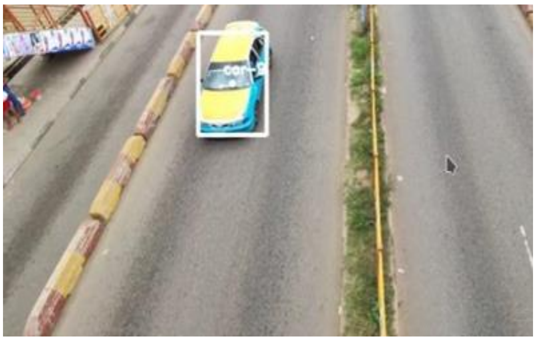

Figure 1. Sample object detection captured from study location

B. *Motion Path Analysis/ Estimation*

This stage uses the stored coordinates from the object tracking stage to plot the motion path, using vector analysis, and the speed, using the time taken to move through the video frame. For example, the direction of an object could be measured by the subtraction of the start and end coordinates of the object path (if the object moves linearly i.e., cars).

The camera path is analyzed using Fig. 2. The speed calculation algorithm is a linear mathematical expression (1). The algorithm is utilized considering the time taken for an object to move through 70% of the frame in any direction; 30% of the video frame movement is ignored covering 15% at both the beginning and the end of the video frames. This is done to reduce speed estimation errors that could arise due to partial object detections as vehicles enter and exit the video frame.

$$\text{Speed}=\frac{K \times D}{T} \quad (1)$$

Where the constant of proportionality (K) is the ratio of the portion of road covered by the camera (meters) to the camera resolution (pixels), D is the distance travelled by the centroid through the frames and T is the time taken. K is a crucial parameter in estimating the speed of vehicles. It varies depending on the position of the camera, the camera's focus, camera color sensor and/or the camera manufacturer. Alternatively, if the camera's viewing angle is known, then K could be computed using the length of the road in the camera's view and could be measured as:

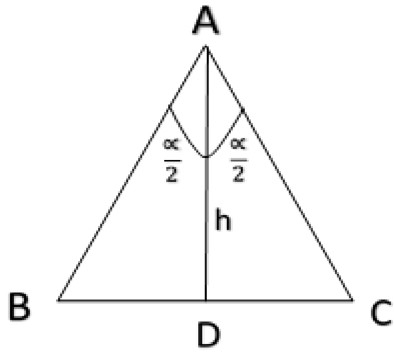

Figure 2. Camera Motion Path Analysis

Where

$$R = 2h \tan \frac{\alpha}{2} \quad (2)$$

Hence;

$$K=\frac{R}{x} = \frac{2h}{x} \tan \frac{\propto}{2} \quad (3)$$

Where;

A = Camera position,

$\overline{BC}$ = R = the length of the road covered (meters), h = the perpendicular height of the camera above the road (meters),

α = the viewing angle of the camera (degree), and

x = the pixel resolution of the image (width) fed to the SSD model

IV. METHODOLOGY

The study was carried out at Oja Oba, Akure South Local Government Area, Ondo State. Final tests were performed and data acquisition was also at the same location. The location was selected because heavy traffic and anomalous situations often arise there.

A. System Implementation

A Raspberry pi V4 equipped with a Sony 8-megapixel 1080p camera module, two USB 3.1 Gen 1 Type A ports at its end and a cooling fan, all enclosed in a plastic case. It also consists of a microcontroller with a 64-bit processor, a 1.4GHz processor, Wi-Fi and its own Bluetooth module. The Raspberry pi system has a PostgreSQL database installed in it. Raspberry pi v4 has a RAM of 4GB, and a processor speed of 1.4GHz which is important for real-time image processing speed. Light Emitting Diodes (LEDs) were used on the indicator board to communicate with car drivers.

Fig. 3 shows the indicator circuitry of the system where the inputs to the transistor switching circuit is from the microcontroller. The red LED is used to denote “STOP”; the green LED is used to denote “GO”; and the yellow denotes “SLOW DOWN”. The indicator circuit is connected to the Raspberry pi V4 and the timing allocations are controlled from the software.

B. System Overview and Architecture

The processes can be separated into two dependent processes which are; tracking vehicular movements, and assignment of the reversible lane based on the state of traffic flow.

Fig.4 shows the flowchart of the developed system. The microprocessor CPU is loaded with an Ubuntu OS. The system uses a Raspberry pi v4 with camera modules interfaced in an inclined position to give feedback to the microprocessor. The received real-time video feeds are cut into frames and the vehicular tracking algorithm is used to extract features like the direction and estimated speed. If the estimated speed on a lane is lower than a given threshold, the algorithm assigns the reversible lane after a specified delay.

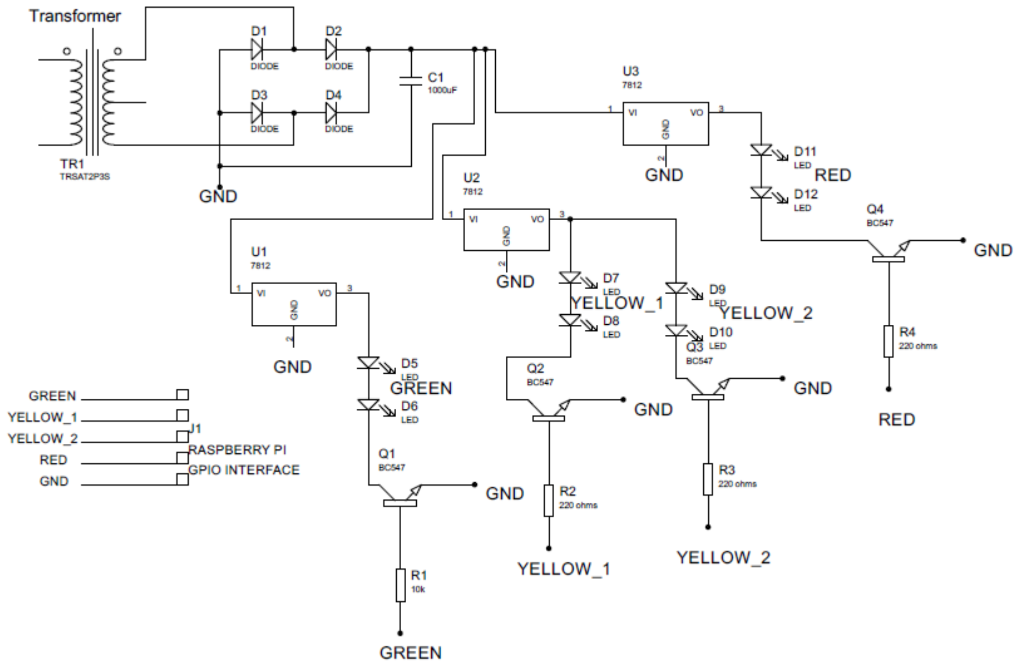

Figure 3. Indicator circuit diagram showing the power supply circuit and switching circuit for the red, green and yellow LED indicators.

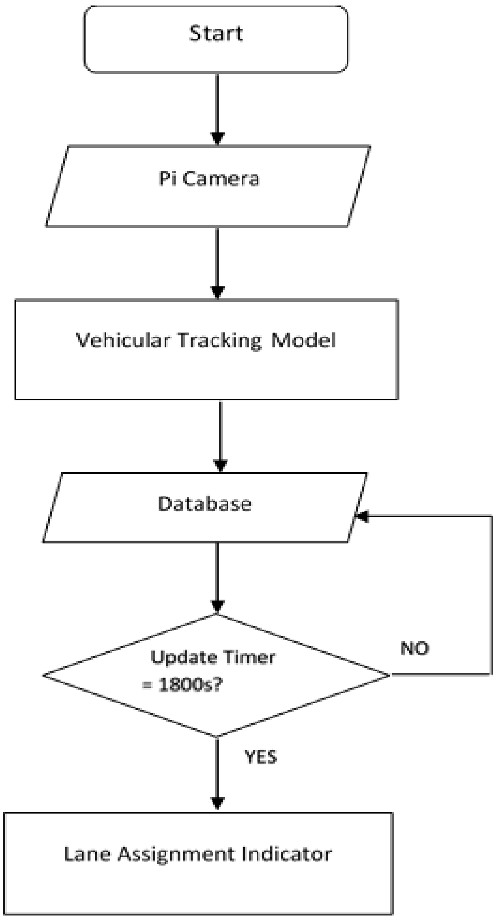

Figure 4. Flowchart of the developed system

C. *Algorithm Used*

The proposed system uses a pre-trained single shot detection (SSD) model. The SSD model is a relatively fast and accurate object detection model. The model was pre-trained using XYZ dataset.

The SSD network is an associate degree object detector that conjointly classifies detected objects. The SSD pre-trained model was loaded with the required object to be tracked. This model is fast for object classification because it skips the region proposal stage when classifying unlike other popular models like Raster- Convolutional Neutral Network (RCNN) and Rough-Fuzzy C-Means (R-FCM).

The live feed from the camera module is generated using open-source computer vision (OpenCV) library. Its video capture function was used to create the video capture object for the purpose of detection. When an object enters the view of the camera, an instance is created with the current coordinates of the object in pixels. As the images move through the frame, the current position of the object is updated and is appended to the property of the instance called history.

The SSD model undergoes some procedures when a color image is fed into the input layer: It begins with the extraction of feature maps at different points after an image is passed through a large number of convolutional layers. Then at every location in each feature map, a 4x4 filter is used to linearize and score a small default box. The prediction of the bounding box offset for each box is then made.

Also, the prediction of the class probabilities for each box is made. Depending on the intersection over union (IOU), the valid boxes are matched with the predicted boxes.

The result exploits the best-assured loss for each default box rather than exploiting all negative samples.

D. *Object Tracking Database Query*

The algorithm used for the lane assignments is a query-based decision algorithm which involves querying the data added over the last 30 mins and comparing the vehicular count and estimated speed. For the lane 2 assignment decision, a unit less threshold factor of 1.5 (configurable) was set. If the estimated speed per vehicle count for either lane 1 or lane 3 with respect to each other exceeds the threshold significantly, then lane 2 is assigned to the lane with the lower estimated speed per vehicular count to aid traffic flow.

E. Data Collection

The designed data acquisition system requires little or no change to road infrastructure during integration. It uses a camera for video and image data extraction. The data from the vehicular tracking model are stored directly in the PostgreSQL database on Raspberry pi v4.

The tracking model is designed such that data are collected and processed in real time, that is, the cameras provide regular feeds without a time lag and these feeds processed simultaneously and loaded into the PostgreSQL database, collected and analyzed. The analyzed data is used to indicate the direction of the reversible lane. The collected data consists of results of performing the operations of object detection, object tracking and motion path estimation. The sequence of operation is shown in Fig. 5.

V. RESULTS AND DISCUSSION

The daily variations in traffic data were collected and used to set the timer control for reallocation of the reversible lane. Fig. 6 shows a pie chart of the daily vehicle count within the study period of 9:00am to 9:30am over a span of 3 weeks. The total weekly vehicle count is 2132.

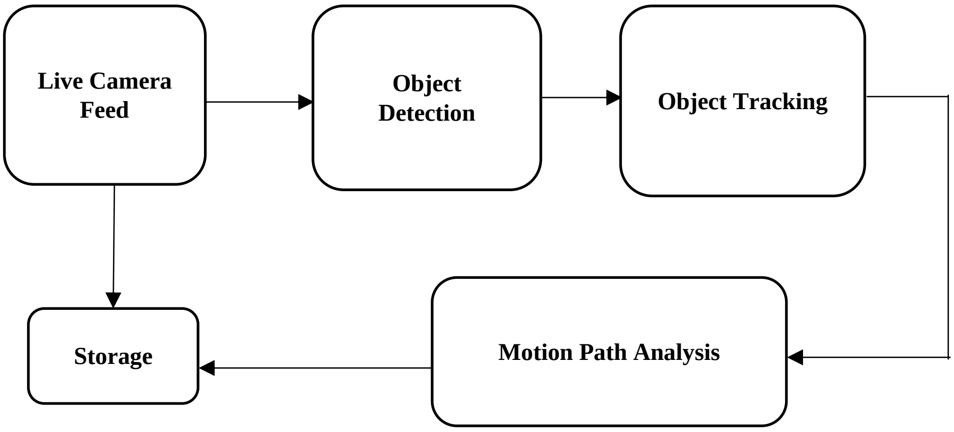

Figure 5. Block diagram of the vehicular tracking model

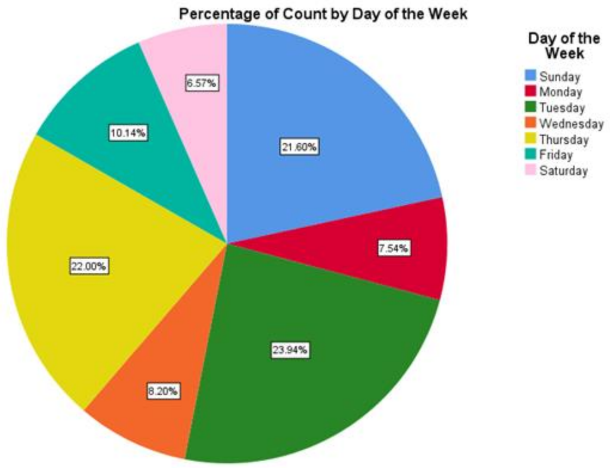

Figure 1. Pie chart showing the percentage of vehicle count within sample timeframe per day

This depicts the existence of variations in daily traffic flow and confirms the fact that traffic flow is influenced by the day of the week as observed in the pie chart.

The point object tracking application was found to be accurate and useful only in the 2-D video tracking experimentations. The points were mis-assigned during 3-D video analysis. However, kernel tracking was found to be accurate both in 2-D and 3-D experimentation and was used in this work.

The trained system has a recognition time of 20 milliseconds and a recognition accuracy of 95% and is able to process about 6.2 frames per second on 300×300 resolution. Fig. 7 shows the capture complexity of the tracking algorithm. It is able to capture the vehicles alongside their directions. The hardware parts of the implemented system is shown in Figs. 8 and 9.

Figure 2: Detected vehicle and direction information from the tracking algorithm using video feeds from the surveillance camera at the study location.

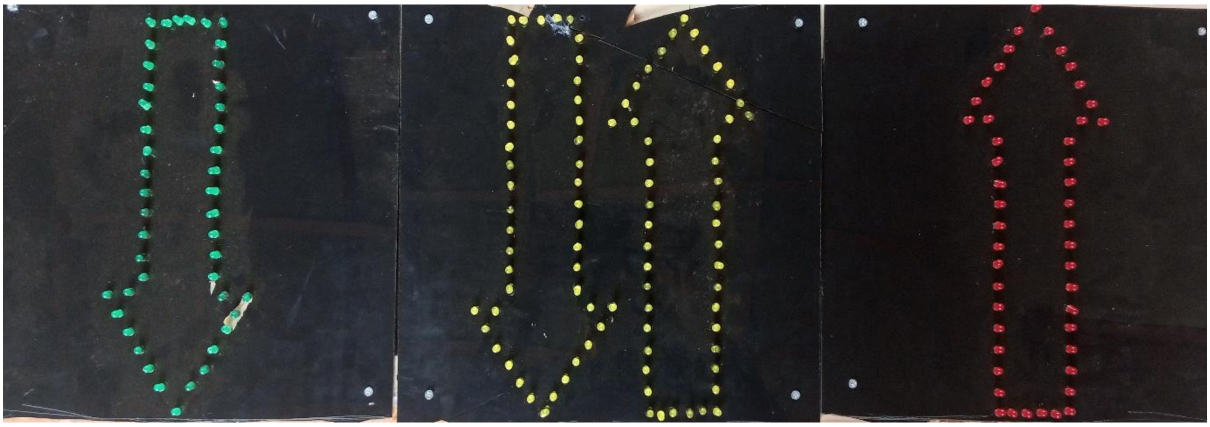

Figure 3. The developed indicator board consisting of green, yellow and red arrows. The yellow arrows are used for the reversible lane.

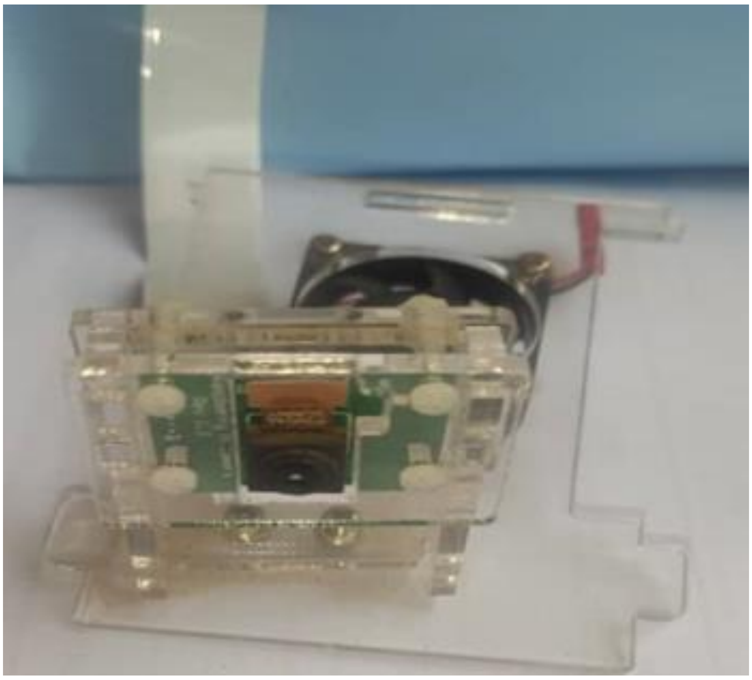

Figure 4. Pi Camera

CONCLUSION

We have developed an intelligent traffic control system for the implementation of a reversible lane using measured real-time traffic data. The system uses video-based sensors in combination with artificial intelligence for road traffic control. The SSD model is used in this work for object detection while the block matching technique is used for object tracking. The trained system has a recognition time of 20 milliseconds and a recognition accuracy of 95%. Direction and speed information are obtained from motion path analysis and the results compared to a threshold. The developed system was shown to have the capability to perform a vehicular count, acquire speed and direction information and assign a reversible lane respecting set thresholds. Further work may involve creating an interconnected system of smart traffic systems bots fitted with object tracking that can do more than change lanes of vehicles but also suggest routes as it interacts with vehicle sensors.

REFERENCES

[1] J. Aworemi, and J. Ajayi. "Impact of Integrated Transport System (ITS) on the Productivity of Smes in Selected South-Western States of Nigeria", Journal of economics and Sustainable Development, vol. 4, no. 8, pp. 1-6, 2013.

[2] A. Koźlak, "The Role of the Transport System in Stimulating Economic and Social Development," *Research Journal of the University of Gdansk. Transport economics and Logistics*, vol. 72, pp. 19–33, 2017.

[3] D. O. Melinte, A. Travediu, and D. N. Dumitriu, "Deep Convolutional Neural Networks Object Detector for Real-Time Waste Identification," Applied Science, vol. 10, no. 20, pp. 7301, 2020.

[4] K. Nellore and G. P. Hancke, "A survey on urban traffic management system using wireless sensor networks," Sensors, vol. 16, no. 2, pp. 157, 2016.

[5] Nigerian Bureau of Statistics, "Road Transport Statistics," 2020 (Q2).

[6] Z. Bede, G. Szabó, and Tamás Péter, "Optimalization of road traffic with the
Application of reversible direction lanes," *Periodica Polytechnica Transportation Engineering*, vol. 38, no. 1, pp. 3-8, 2010.

[7] M. W. Hancock, B. Wright, A Policy on Geometric Design of Highways and Streets (AASHTO, 2013).

[8] V. Paidi, H. Fleyeh, H. Johan and R. G. Nyber, "Smart parking sensors, technologies and applications for open parking lots: a review," *IET Intell. Transp. Syst., vol. 12, no. 8, pp. 735-741, 2018.*

[9] K. Mouskos, M. Boile and Parker, "Technical solutions to overcrowded park and ride facilities," *Tech. Rep.*, 2007.

[10] S. Shaheen, "Smart parking management field test: a bay area rapid transit (bart) district parking demostration," Institute of Transportation Studies, California, 2005.

[11] H. A. Oliveira, F. R. Barbosa, O. M. Almeida and A. P. Braga, "A Vehicle Classificaion BAsed on Inductive Loop Detectors Using Artificial Neural Networks," in *Industry Applications (INDUSCON), 2010 9th IEEE/IAS International Conference, pp. 1-6*, 2010.

[12] S. Y. Cheung, S. Coleri, B. Dundar, S. Ganesh, C. W. Tan and P. Varaiya, "Traffic Measurement and Vehicle Classification with Single Magnetic Sensor," *Transp. Res. Rec. J. Transp. Res. Board, vol. 1917, pp. 173-181, 2005*.

[13] Y.-K. Ki and D.-K. Baik, "Vehicle-Classification Algorithm for Single-Loop Detectors Using Neural Networks," *IEEE Trans. Veh. Technol., vol. 55, no. 6, pp. 1704-1711, Nov. 2006*.

[14] B. Bargagli, G. Manes, R. Facchini and A. Manes, "Acoustic Sensor Network for Vehicle Traffic Monitoring," in *Proc. International Conference on Advances in Vehicular Systems, Technologies and Applications*, Venice, Italy, pp. 1-6, 2012.

[15] A. M. Husein, Calvin, D. Halim, R. Leo, and William, "Motion detect application with frame difference method on a surveillance camera," *J. Phys. Conf. Ser.*, vol. 1230, no. 1, pp. 0–10, 2019, doi: 10.1088/1742-6596/1230/1/012017.

[16] J. Guo, J. Wang, R. Bang, Y. Zhang, Y. Li. A New Moving Object Detection Method Based on Frame-difference and Background Subtraction IOP Conference Series: Materials Science and Engineering Volume 242, 2017.

[17] A. Makhmutova, I. V. Anikin and M. Dagaeva, "Object Tracking Method for Video monitoring in Intelligent Transport Systems," *2020 International Russian Automation Conference (RusAutoCon)*, pp. 535-540, doi: 10.1109/RusAutoCon49822.2020.9208032. , 2020.

[18] K. A. Joshi and D. G. Thakore, “A Survey on Moving Object Detection and Tracking in Video Surveillance System,” International Journal of Soft Computing and Engineering, vol. 2, no. 3, pp. 44-48, 2012.

[19] The Vehicle Detector Clearinghouse, “A Summary of Vehicle Detection and Surveillance Technologies Used in Intelligent Transportation System,” FHWA, 2017.

[20] G.-I. Juan, Z. Sherali and C.-C. Juan, “Sensor Technologies for Intelligent Transportation Systems,” *Sensors, vol. 18, no. 4, 2018*.

[21] G. Shen, “Road crack detection based on video image processing,” in *2016 IEEE International Conference on Systems and Informatics (ICSAI)., pp. 912-917, 2016*.

[22] X. Hu and J. Zheng, “An Improved Moving Object Detection Algorithm Based on Gaussian Mixture Models,” no. July, pp. 449–456, 2016.

[23] B. Morris and M. Trivedi, “Real-time Video Based Highway Traffic Measurement and Performance Monitoring,” *Proc. IEEE Conf. Intell. Transp. Syst.*, pp. 59-64, 2007.

[24] A. Alaiad and L. Zhou, “Patients Adoption of WSN-Based Smart Home Healthcare Systems: An Integrateed Model of Facilitators and Barriers,” IEEE Trans. Prof. Comun, vol. 60, no. 1, pp. 4-23, 2017.

[25] A. A. Khamukhin and S. Bertoldo, “Spectral Analysis of Forest Fire Nation for Early Detection Using Wireless Sensor Networks,” in Proceedings of the International Siberian Conference on Control and Communications (SIBCON), Moscow, 2016.