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Vehicular Flow Characterization: An Internet of Video Things-Based Solution

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Abstract- **Intelligent transportation systems (ITS) have emerged as the optimal solution to address urban mobility challenges. However, to effectively implement ITS, detailed traffic flow statistics are imperative. Various solutions have been proposed, including intrusive/non-intrusive sensors and compute vision-based solutions. However, these solutions have limitations in the number of measured traffic flow parameters, cost or performance under different traffic conditions. To overcome these limitations, we propose an Internet-of-Video-Things (IoVT) based solution. The sensor node (fabricated using Raspberry Pi Zero W, Pi camera, power bank, and Wi-Fi device) can live-streaming roadside traffic video to a remote Dell server located at our lab with Camlytics (commercially available traffic analysis software) installed. The proposed solution was field tested with a 45-minute live-streamed video of 720p at 25 frames per second. Results show that the proposed solution can measure more traffic flow parameters than intrusive and non-intrusive sensors, with an accuracy of 84.3% for vehicle count and speed estimation. Other parameters were also calculated, such as time/distance headway, spatial/temporal densities, heat maps, and trajectories. Additionally, the proposed solution can count pedestrians with an accuracy of 76.3%.**

Index Terms-- **Traffic flow characterization, Raspberry Pi Zero W, Video streaming, intelligent transportation system, IoVT.**

I. INTRODUCTION

Urbanites' share of the world population is projected to increase from 55% to about 68% by 2050 [1, 2]. With this increasing urbanization, the efficient movement of people and goods has become the most pressing challenge in achieving liveable smart cities. Challenges associated with urban mobility range from ambient air pollution, traffic congestion, accidents, and lost productivity, to name a few. For example, 29% of greenhouse gas (GHG) emissions are attributed to the transport sector [3, 4]. These air pollutants, such as carbon dioxide, carbon monoxide, nitric oxides, sulphur dioxide, and particulate matter (PM), exacerbate health problems such as pulmonary, cardiovascular, respiratory, and cancer. Resulting in about 4.2 million premature deaths in 2016 alone [5]. Furthermore, inefficiencies in road networks, such as traffic congestion, are the root cause of psychological health problems such as driver stress, fatigue, and aggressiveness. As an example of lost productivity, it was reported that an average USA commuter wastes about 42 hours and 19 gallons of fuel each year stuck in traffic congestion. Costing each commuter about $960 per year or about $38400 over a 40-year career [6].

A. RESEARCH CONTEXT

To overcome these challenges, intelligent transportation system (ITS) based solutions are being proposed for efficient planning, designing, and managing road networks. One of the basic building blocks for providing ITS-based solutions is real-life vehicular flow characterization. Vehicular flow characterization is traffic parameters estimation categorized as either microscopic (vehicle count, speed, classification, time/distance headway, and spacing) or macroscopic (traffic volume, speed, density, heat maps, and trajectories). These parameters provide insight into local traffic flow behaviour (such as speed vs flow, density vs speed, and density vs flow, to name a few). Furthermore, these parameters are imperative for calibrating and validating mathematical traffic flow models and simulation software for better road network design and management [7, 8, 9, 10, 11]. In the existing literature, varying solutions have been proposed for vehicular flow characterization and are categorized as either intrusive or non-intrusive sensors [12, 13]. Though these solutions have marked improvement over manual counting, they have limitations.

Second-generation intrusive sensors (inductive loops, pneumatic tubes, piezoelectric and magnetic sensors) are expensive and crumb some to install and maintain [12]. As the name suggests, these sensors are embedded in the road surface, thus damaging it and causing traffic disturbances during installation and operations. Intrusive sensors, though highly accurate, can only measure traffic count and are thus severely limited in their scope. In the complex configuration of multiple sensors, intrusive sensors can classify vehicle types. However, accuracy under sensors cannot detect pedestrians and animals\human driven in congested and heterogeneous traffic conditions is severely hindered by intrusive carts [13].

Third-generation non-intrusive sensors provide more granular traffic flow data than intrusive sensors with fewer limitations [12]. Non-intrusive sensors are inherently wireless sensor networks based on different sensor technologies (such as accelerometer, acoustic, ultrasonic, infrared, radar, LIDAR, Bluetooth, and Wi-Fi) [12,13]. These sensors are a marked improvement over intrusive sensors with their ability to provide more traffic flow parameters such as vehicle count, speed, classification, and lane occupancy. However, their performance is severely compromised under congested and heterogeneous traffic conditions. Furthermore, their performance is affected by varying environmental factors such as temperature variation, wind, snow, fog, rain, and sunlight intensity [12]. Non-intrusive sensors cannot detect pedestrians, bicycles, and animal/human-driven carts.

These solutions can measure detailed traffic flow parameters under all (congested, uncongested, homogeneous, and heterogeneous) traffic conditions. Furthermore, compared to non-intrusive sensors, the impact of environmental factors on computing vision-based solutions is less detrimental. Both edge and distributed compute vision-based solutions have been proposed in the existing literature. However, compute vision-based edge computing solutions are limited because of resource-constrained embedded computing boards. These proposed solutions can measure at most two traffic flow parameters, either count\classification or count\speed [14].

B. OVERVIEW AND SCOPE

To overcome the limitations of intrusive, non-intrusive sensors and compute vision-based edge computing solutions, we have proposed a low-cost and real-time internet of video things (IoVT) based solution for traffic flow characterization. Salient features are its low-cost, reliability, energy efficiency, easy installation, and maintenance. The sensor node of the proposed solution is fabricated using Raspberry Pi Zero W (RPi ZW), Pi camera, power bank, and Wi-Fi device. Utilizing the sensor node, roadside traffic video is captured, encoded, and live-streamed to a Dell desktop located at our university's lab. Camlytics, a commercial traffic monitoring software installed on dell desktops, is employed for traffic flow characterization in real-time. The proposed solution can operate under all traffic conditions (such as congested, uncongested, homogenous, and heterogeneous). Furthermore, it can measure detailed traffic flow parameters such as vehicle count, speed, volume, temporal\spatial density, time/distance headway, heat maps, and trajectories with 84.3% accuracy. As opposed to intrusive and non-intrusive sensors, our proposed solution has the added capability to count pedestrians with an accuracy of 73.6%.

The rest of the paper is organized such that section II summarizes related work. The system architecture of the proposed solution is detailed in section III, with results presented in section IV. Lastly, the conclusion and future work are presented in section V.

II. RELATED WORK

An overview of IoVT solutions for vehicular flow characterization proposed in existing literature has been presented in this section. As summarized in this section, to the author's knowledge, no solution can provide as many traffic flow parameters as the solution proposed in this work.

In [15], a solution was proposed for vehicle counting and classification under congested traffic conditions. Using two vision systems (each fabricated using an RPi and Pi camera) a 3D point cloud point was generated. Machine learning algorithms K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) were used for vehicle classification into two types (cars and motorcycles). Reported accuracy is relatively high (95.8% for both SVM, and KNN), with SVM performing better in the case of motorcycle classification. Balakrishna et al. proposed a real-time IoVT-based solution for traffic flow characterization [16]. The proposed system consisted of RPi 3B and USB camera, streaming video to a cloud platform through Wi-Fi. Traffic flow was characterized using an algorithm developed in Simulink, MATLAB 2016A.

In [17], a UAV (Unmanned Air Vehicle) based solution was proposed for emergency management. The proposed system was capable of live video streaming to a cloud platform for better and faster decision-making in emergencies. RPi ZW and Pi camera-based platforms were employed for video streaming, with end-to-end latency below 200 milliseconds (ms) per frame. An autonomous UAV-based solution was proposed for static on-ground vehicle counting, classification, and pedestrian counting [18]. Live video streaming to a laptop for image processing was achieved through RPi ZW and Pi camera over Wi-Fi. In field testing, accuracy varied from 88.9% to 96%. Reasons attributed to this limited accuracy were (1) the limited accuracy of the UAV's GPS and (2) the inability of the UAV to stay on the flight path under windy conditions. In [19], a UAV-based IoVT solution for vehicular flow characterization was proposed. The proposed solution can estimate speed and traffic volume. Kanade–Lucas–Tomasi feature tracker and Cascade Haar were employed with neural network methodology for object tracking.

In [20], an IoVT base solution was proposed with the capability to measure vehicle count, speed, density, time headway, time-space diagrams, and trajectories. The sensor node was fabricated using RPi 4 and Pi camera while employing Wi-Fi for live video streaming. Before streaming, the video was compressed using the H264 compression method. The sensor node's power consumption and fabrication cost were estimated at 900 mA per hour and $50, respectively.

An IoVT-based solution for vehicular flow characterization has been proposed in this work. The novelty of our proposed solution as compared to already proposed solutions in existing literature are:

- Unlike intrusive\non-intrusive sensors, the proposed solution can operate under all (including congested and heterogeneous) traffic conditions. Furthermore, the proposed solution can measure more traffic flow parameters with easier installation and maintenance [22].

- Capability to provide detailed (eight) traffic flow parameters as compared to proposed solutions in existing literature such as [15, 18, 16, 20, 19]. The measured parameters are traffic count, speed, flow, time/distance headway, spatial\temporal densities, heat maps, and trajectories with an accuracy of 84.3%.
- As opposed to existing solutions, the proposed solution has the added capability to count pedestrian crossings and their impact on traffic flow. Pedestrians' counting accuracy was measured at 76.3%.
- With fabrication costs under $40, the proposed solution is low-cost (monetary and data bandwidth) compared to other solutions [15, 16, 20]. This provides the option to scale it to form a wireless sensor network.
- Compared to the most power-efficient solution in existing literature [20], the proposed solution's current consumption has been optimized. This optimization was achieved by employing Raspberry Pi Zero W, thus increasing operational time by fourfold.

III. SYSTEM ARCHITECTURE

In this work, an IoVT-based solution has been proposed, which can be mounted anywhere over a road to characterize traffic flow parameters such as vehicle count, speed, volume, time/distance headway, spatial\temporal densities, heat maps, and trajectories. The proposed solution has the added capability to count pedestrians and the effect of their crossings on traffic flow. The objective in the design phase was to propose a low-cost and real-time solution that works under all (congested, un-congested, homogeneous, and heterogeneous) traffic conditions.

The proposed solution can be subcategorized into four modules: (1) Sensor Node, (2) Video Streaming, (3) Current Consumption, and (4) Camlytics. The system architecture of the proposed solution is detailed in Fig. 1.

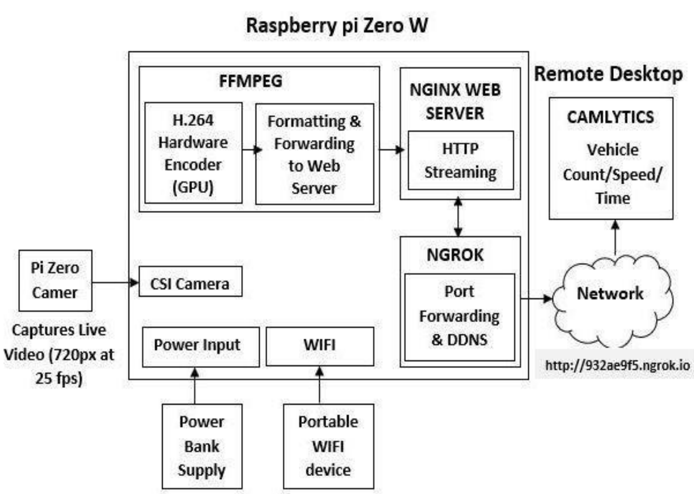


FIGURE 1. System Architecture of the proposed IoVT based solution

The internal working of the proposed system can be understood in Fig. 1. The raw video footage is captured through Pi Camera integrated with the RPI ZW through CSI Connector. The roadside video of 720p at 25 fps is then fed into the FFMPEG software, configured to encode the captured video using the H264 hardware encoder of the RPi Zero W. Using FFMPEG software, the resultant compressed H.264 video is formatted to Flash Video (.flv) and forwarded to the NGINX web server hosted by the RPi ZW.

The NGINX web server is configured to accept the incoming feed from FFMPEG and make it available for streaming using the HTTP protocol. However, as the NGINX web server is hosted locally on RPI ZW, it cannot be accessed remotely from outside the local area network. It necessitates port forwarding and assignment of a unique IP address using DDNS. This is achieved using NGROK tunnel service, which provides a secure HTTP link for video streaming to Dell Desktop with Camlytics installed for traffic flow analysis.

A. SENSOR NODE

Although in existing literature, RPi-based video streaming solutions for traffic flow characterization have been proposed [15, 16, 20]. However, to keep overall costs (both monetary and power consumption) low, RPi ZW [21] has been employed in the proposed solution. RPi ZW is a small, compact single-board computer costing about $18, and its salient features are a 1GHz single-core ARMv6 CPU, 512MB RAM, CSI camera, and 802.11n wireless LAN support.

Pi Camera Module v2 has been integrated with RPi ZW through a specifically designed CSI port for roadside video capturing. The Pi Camera Module v2 has a high-quality Sony IMX219 8-megapixel image sensor, with custom designed add-on board for RPi. It can capture 3280x2464 pixels static images while providing support to capture videos of 1080P @30 fps (frame per second), 720P @60 fps, and 640x480 @ 60/90 fps.

FIGURE 2. System hardware (a) Sensor Node (b) Sensor Node installed over the pedestrian bridge for evaluation

B. VIDEO STREAMING

For circumventing resource-constrained embedded boards, IoVT based solutions are emerging as optimum solutions for different applications. These applications range from smart cities, surveillance, remote sensing, healthcare, and traffic flow characterization. These connected devices are known as the "Internet of Video Things" (IoVT). With 80% of internet traffic consisting of multimedia data, it is estimated that this share will grow even further as the number of IoVT will grow to 13 billion by 2030 [23].

In the existing literature, low end-to-end video streaming for time-critical applications employing resource-constraint hardware is few [24]. Most proposed solutions are cloud-based, using centralized cloud services providers such as Amazon web services, Azure, and google cloud. However, a fully distributed P2P (Point-to-Point) communication approach has been employed in this work. The most important consideration was low-latency video streaming, as communication is directly between source and sink, thus making unnecessary proxying at intermediates nodes redundant. However, barriers must be overcome to achieve P2P video streaming over the internet to ensure lag-free and low-latency streaming. Contrary to common belief, most of the video streaming delay can be attributed to video capturing, encoding, and decoding, with only 10% of the delay attributed to the choice of an intermediate IoT platform [24].

For this work, efforts have been made to propose a low latency, power, and data-optimized video streaming solution, as can be seen in Fig. 2. For better understanding, this section has been subcategorized into (1) FFmpeg, (2) Encoding, and (3) IoVT streaming platform.

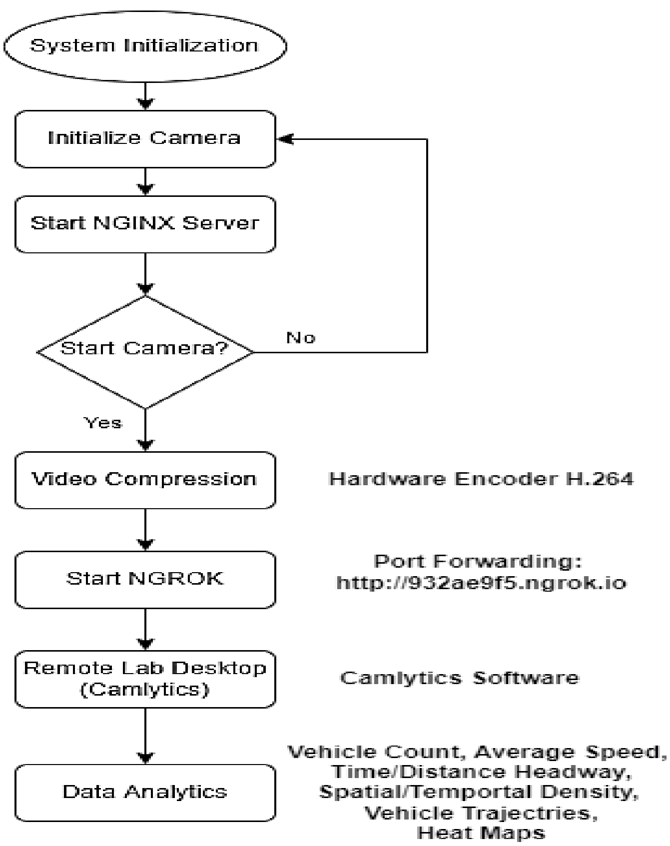


FIGURE 3. Flow chart of the proposed system.

a) FFMPEG

FFmpeg [25] is a free and open-source suite of libraries for handling audio, video, and multimedia streams. FFmpeg libraries, through command-line instructions, can edit, encode, decode, transcode and stream multimedia over the internet. It can convert between arbitrary sample rates and resize video on the fly with a high-quality polyphase filter. In this work, FFmpeg is configured to capture a live video stream through a Pi camera integrated with RPi ZW using the following command.

```
ffmpeg -f v4l2 -re -video_size 1280x720 -r 25 -vsync 1 -i /dev/video0 -c:v h264_omx -b:v 10000k -f flv "rtmp://localhost/live/stream"
```

Using the above command, the video is captured and resized to 1280x720 pixels at 25 fps. The video is then encoded using RPi ZW inbuilt hardware H264 encoder. Using RPi ZW's inbuilt Wi-Fi module, the encoded video is streamed to the web server in .flv video format.

b) VIDEO ENCODING

The most pressing limitation while employing an IoVT-based solution for traffic flow characterization is the bandwidth requirement for video streaming. However, this limitation can be mitigated using video encoding, as demonstrated in this work. Video encoding is video transformation through changes in the format and applying compression techniques. It is essential for efficient transmission over the internet in terms of quality, energy, and data bandwidth consumption.

From a video encoding perspective, H.264 and MJPEG are two of the most common compression standards. However, H.264 has replaced MJPEG because of its improved coding efficiency, high quality, and reduced frame losses [26, 24].

The main difference between the two is that MJPEG compresses individual frames. H.264 compresses video across the frames, thus saving a significant amount of bandwidth. H.264 provides up to 80% and 50% reduction in data bandwidth requirement compared to MJPEG and MPEG4 [26]. In this work, a forty-five-minute-high quality roadside video encoded with H.264 encoder was live streamed. The total bandwidth required to stream the video was measured at 600 Megabytes. This is a marked improvement over MJPEG and MPEG codecs, as seen in Fig. 4. Locally, the 60 gigabytes internet data plan costs about $12.04. Further breakdown of the internet data plan means it costs $0.2007 to stream 1 gigabyte. In our work, the total cost to stream a one-hour video was estimated at $0.283 as seen in Fig. 4.

FFmpeg [25] is a free and open-source suite of libraries for handling audio, video, and multimedia streams. FFmpeg libraries, through command-line instructions, can edit, encode, decode, transcode, and stream multimedia over the internet. It can convert between arbitrary sample rates and resize video on the fly with a high-quality polyphase filter. In this work, FFmpeg is configured to capture a live video stream through a Pi camera integrated with RPi ZW using the following command.

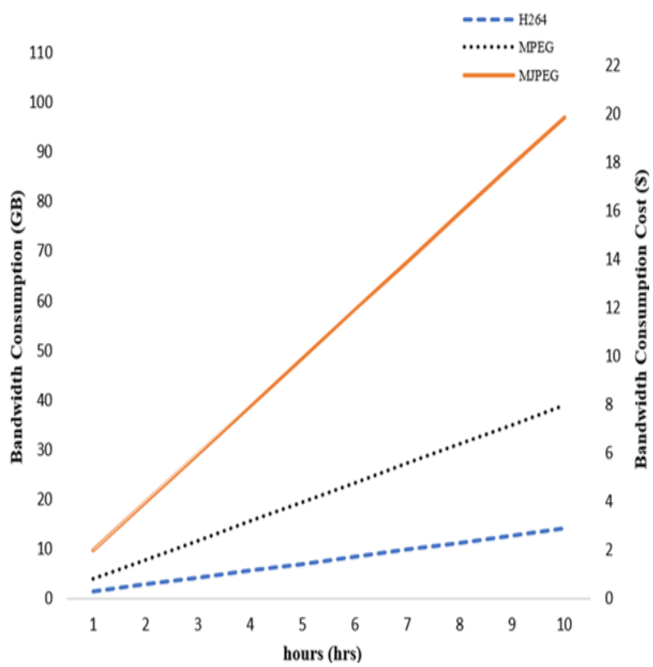


FIGURE 4. Data bandwidth requirement and cost per hour for live-streamed video using different Codec standards

Though a more advanced standard for video compression HEVC (High-Efficiency Video Coding/ H2.65) has become available. However, H.264 standard is chosen because RPi ZW provides inbuilt hardware H.264 compression capabilities. Hardware encoding is more efficient than software encoding in terms of computation resources. For example, Mori et al. reported that encoding a video of 640x480 resolution @ 30fps with RPi ZW's hardware H.264 encoder results in 58 times less current consumption than software encoding [23].

c) IOVT STREAMING PLATFORM

As reported in [24], about 10% of video streaming delays are attributed to an intermediate IoT platform choice. Hence employing a fast web server and IoT platform is paramount for real-time low-latency video streaming. For this work, we have chosen NGINX, a free and open-source IoT platform for web serving, caching, reverse proxying, load balancing, and multimedia streaming [27]. It is known for its high performance, stability, rich feature set, simple configuration, and low resource consumption for live-video streaming. After video compression using the H.264 standard, FFMPEG streams the video to NGINX, as shown in Fig. 2. A local host address inside a local area network can access this live video feed.

However, NGROK has been employed to make the live video stream accessible outside the local area network. NGROK is a multiplatform tunnelling, reverse proxy software that establishes secure tunnels from a public endpoint, such as the internet, to a locally running network service. Through NGROK, a secure tunnel to the local host of the web server was established, thus making redundant port forwarding and dynamic DNS. Global access to a live video stream became possible through NGROK's link on port 80. The most pressing limitation while employing an IoVT-based solution for traffic flow characterization is the bandwidth requirement for video streaming. However, this limitation can be mitigated using video encoding as demonstrated in this work. Video encoding is the transformation of video through both changes in the format and applying compression techniques. It is pretty much essential for efficient transmission over the internet in terms of quality, energy, and data bandwidth consumption.

C. CURRENT CONSUMPTION

Power management is a basic consideration while designing embedded systems to keep them operational with minimum human intervention. In this context, the sensor node was fabricated with RPi ZW to keep overall current consumption low. Furthermore, unnecessary RPi ZW modules such as HDM and LED are kept turned off. As reported in [23], H.264 hardware encoder consumes 58 times less energy than software-based H.264 encoders. Hence, an inbuilt H.264 hardware encoder was employed for video encoding to conserve the current consumption of the sensor node. The sensor node's current consumption breakdown is tabulated in Table 1 and verified using the Keweisi USB tester.

RPi ZW consumes 100 mA current (with HDMI, LED, and Wi-Fi modules turned off) when fully operational. Pi camera's current consumption was measured at 60 mA when turned on and captured 1280x720 resolution @ 25 fps video. RPi ZW's Wi-Fi module consumes a further 60 mA when streaming video over the internet. Overall, the sensor node's current consumption is measured at 220 mA as seen in Table I.

TABLE I
SENSOR NODE'S CURRENT CONSUMPTION BREAKDOWN

RPi ZW State	Current Consumption
Idle (HDMI off LED off Wi-Fi off)	100 mA
Pi Camera	60 mA
Wi-Fi ON (Video Streaming)	60 mA
Total Power	220 mA

The sensor node is powered through a 10,000 mAh Anker Power Core (model number A1263) power bank with a 5V/2.1A output port. Hence the total operational time of the sensor node is estimated at:

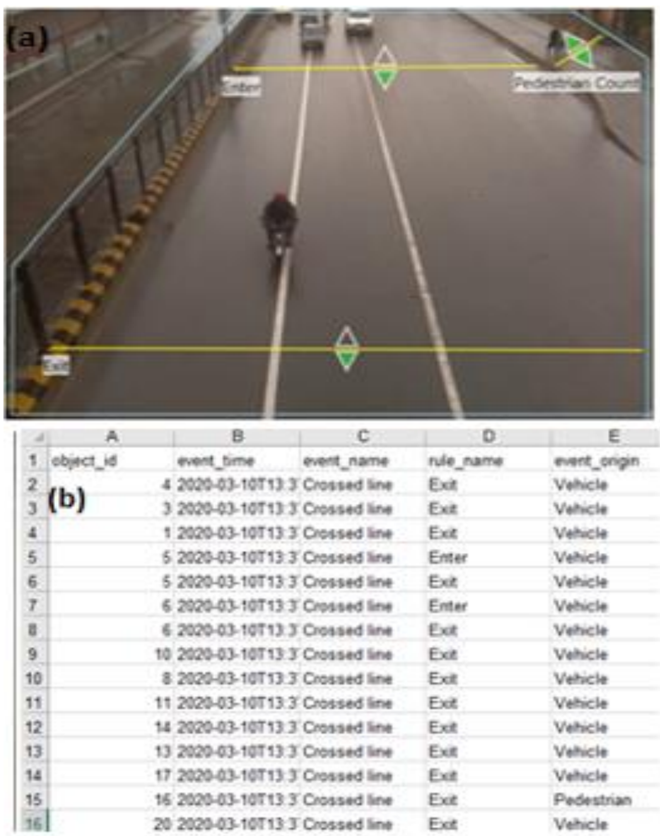
Sensor node's Operational time = 10,000 mAh / 220 mA = 45.4 hours.

D. CAMLYTICS SOFTWARE

Camlytics is a multi-camera traffic flow analytic software available commercially [28]. Salient features of Camlytics range from vehicle and pedestrian counting to traffic analytics, motion alarms, and traffic event recording to name a few. Camlytics uses APIs to send the information extracted from input video feed or streaming link to an excel-sheet file. Since it is commercial software, computer vision algorithms are proprietary. Camlytics is a low-budget and lightweight software, able to work on Windows-installed PCs. The minimum system requirements required to run Camlytics are 2 GB of Ram, 200 GB of Hard Drive Space, and at least a Core i3 Processor to run 4 cameras simultaneously.

IV. RESULTS

In this work, we have proposed a real-time and low-cost IoVT solution for measuring microscopic (count and speed) and macroscopic (road density, flow, time/distance headway, spatial/temporal densities, heatmaps, and trajectories) traffic flow parameters. For field testing, a sensor node was installed on a pedestrian bridge overlooking the main thoroughfare "University Road" in Peshawar, Pakistan, as can be seen in Fig. 5. This road was chosen because of its status as the main arterial road in Peshawar city with major universities, hospitals, and governmental agencies located on it. The real-time roadside video was live-streamed through an installed sensor node to a Dell desktop with Camlytics software. The live-streamed video was 45 minutes from 5:00 PM to 5:45 PM on Saturday, February 29th, 2022, as can be seen in Fig. 5. Camlytics was running on a Dell desktop (i5 quad-core processor, 4 GB RAM) with Windows 10 operating system.



	A	B	C	D	E
1	object_id	event_time	event_name	rule_name	event_origin
2	4	2020-03-10T13:3	Crossed line	Exit	Vehicle
3	3	2020-03-10T13:3	Crossed line	Exit	Vehicle
4	1	2020-03-10T13:3	Crossed line	Exit	Vehicle
5	5	2020-03-10T13:3	Crossed line	Enter	Vehicle
6	5	2020-03-10T13:3	Crossed line	Exit	Vehicle
7	6	2020-03-10T13:3	Crossed line	Enter	Vehicle
8	6	2020-03-10T13:3	Crossed line	Exit	Vehicle
9	10	2020-03-10T13:3	Crossed line	Exit	Vehicle
10	8	2020-03-10T13:3	Crossed line	Exit	Vehicle
11	11	2020-03-10T13:3	Crossed line	Exit	Vehicle
12	14	2020-03-10T13:3	Crossed line	Exit	Vehicle
13	13	2020-03-10T13:3	Crossed line	Exit	Vehicle
14	17	2020-03-10T13:3	Crossed line	Exit	Vehicle
15	16	2020-03-10T13:3	Crossed line	Exit	Pedestrian
16	20	2020-03-10T13:3	Crossed line	Exit	Vehicle

FIGURE 5 (a). Snapshot of streamed video in Camlytics installed on a Dell desktop. (b) Events generated during video analytics by Camlytics

Camlytics provides simple generation lines and zones for traffic analysis, as seen in Fig. 5(a). Camlytics provides the capability to create these event generation lines and zones through drag-and-drop functionality. For traffic analysis, two event generation lines (denoted as Enter and Exit, as seen in Fig. 5(a)) were drawn 14 m apart. These event generation lines can be assigned directions to generate an event for traffic flow analysis. As shown in Fig. 5(a), the green inward and outward arrows on Enter and Exit lines generate events whenever a vehicle enters or exits these two event generation lines, respectively. A third event-generating line, "Pedestrian Count," was created to count pedestrians on the walkway, as can be seen in Fig. 5(a). Green inward and outward arrows on the "Pedestrian Count" event generation line count pedestrians crossing in either direction.

An event is generated every time an object (vehicle or pedestrian) crosses one of the event generation lines. Event Id, line type (Enter or Exit), and the time of line crossing are logged into a ".CSV" file, as can be seen in Fig. 5(b).

A. VEHICLE COUNT AND TEMPORAL DENSITY

During 45 min of live-streamed video, Camlytics detected 843 vehicles, as seen in Fig. 5(b). To check the accuracy of the proposed solution, manual counting was undertaken in the same live-streamed video. In manual counting, a total of 1000 vehicles were detected. Thus, the proposed system performed with 84.3% accuracy. Pedestrian detection was undertaken in the same video as in Fig. 5(a). A total of 158 pedestrians were detected through Camlytics, whereas a total of 207 were detected in manual counting. Thus, the proposed solution's accuracy rate for the pedestrian count was 76.3%. The underlying reasons were observed for miss-detected vehicles and pedestrians:

1. Some undetected vehicles were counted at the 'Enter' line but not at the 'Exit' line or vice versa.
2. Some of the miss-detected vehicles were moving above speed limits.
3. Two vehicles or pedestrians passing exactly at the same time over event generation lines were counted as one.

Compared to intrusive and non-intrusive sensors, this accuracy rate may seem low. However, image processing-based solutions can count all vehicles (such as bicycles, bikes, three-wheelers, and animal/human-driven carts) and pedestrians. As image processing techniques evolve, this accuracy will improve further still.

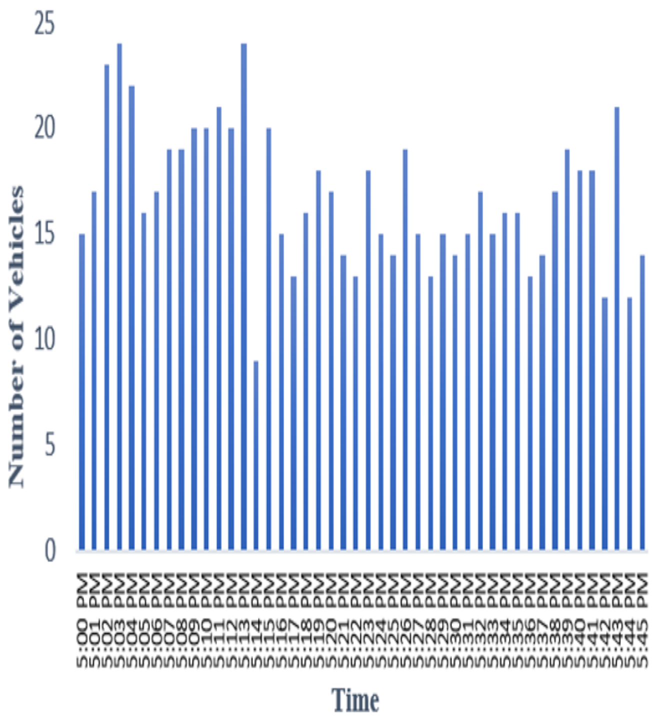
For accuracy, miss-detected vehicles were not considered in vehicle count, temporal/spatial densities, time/distance headway, and trajectory calculations, as reported in the rest of this section. Temporal density is the number of vehicles per unit of road length at specific intervals. The 45-minute vehicular temporal density on the 14 m road segment has been divided into 1 min time segments, as can be observed in Fig. 7. It was observed that the highest temporal density of 24 vehicles/min was recorded at 5:03 PM and 5:13 PM. At the same time, the lowest temporal density was observed at 5:14 PM, as shown in Fig. 6.

B. AVERAGE SPEED

Individual vehicle speed is the time required to traverse a unit distance, given by the following equation.

$$Indivisual\ Vehicle\ Speed = \frac{Distance}{Exit_{Time} - Enter_{Time}} \quad (1)$$

FIGURE 6. Temporal density on 14 m road section on Saturday, February 29th, 2022.



Where EnterTime represents the time when a vehicle crosses the 'Enter' event generating line represented as "Enter" in Fig. 5(a). ExitTime represents the time when a vehicle crosses the "Exit" event generation line as can be seen in Fig. 5(a). Distance represents the distance between these two-event generator lines (Enter, Exit), which in our experimental setup is 14 m. To find the average speed, the following equation has been employed.

$$Average\ Vehicle's\ Speed = \sum_{1}^{N} \frac{S_i}{N} \qquad (2)$$

The subscript' i' denotes the vehicle number, while N is the total number of vehicles during each minute of the observed period. Fig. 7 represents the average vehicular speed on the 14 m road segment under observation. As shown in Fig. 7, the lowest average speed recorded at 5:28 PM was 5.05 m/s, while the highest average speed recorded at 5:12 PM was 12.27 m/s.

C. TRAFFIC FLOW

Road density (K) is the number of vehicles (N) per unit of the road segment. The following equation represents it.

$$K = \frac{N}{L} \qquad (3)$$

In this work, the unit length of the road segment is 14 m. This is the distance between two event-generating lines (Enter & Exit), as seen in Fig. 5. In the existing literature, different time segments are considered when counting vehicle numbers (N). For this work, 45 min live streamed video is divided into 1 min time segments.

Traffic Flow rate (Q) is the rate at which vehicles pass a reference point on a given road segment. It is expressed in vehicles per unit of time and is a product of traffic density and average vehicle speed. The following equation represents Traffic Flow.

$$Q = K * S_A \qquad (4)$$

According to the fundamental flow-density relationship, when the number of vehicles increases on a road segment under observation, density also increases along with the traffic flow. Similarly, a reduction in density results in a reduction in flow, as demonstrated in Fig. 7. However, if the number of vehicles keeps on increasing per unit length, it reaches a condition where the speed drastically reduces and is jam density (maximum density). The highest density measured during the 1-min time segment was 1.71 veh/m at 5:03 PM, while the lowest density was 0.64 veh/m at 5:14 PM, as shown in Fig. 8.

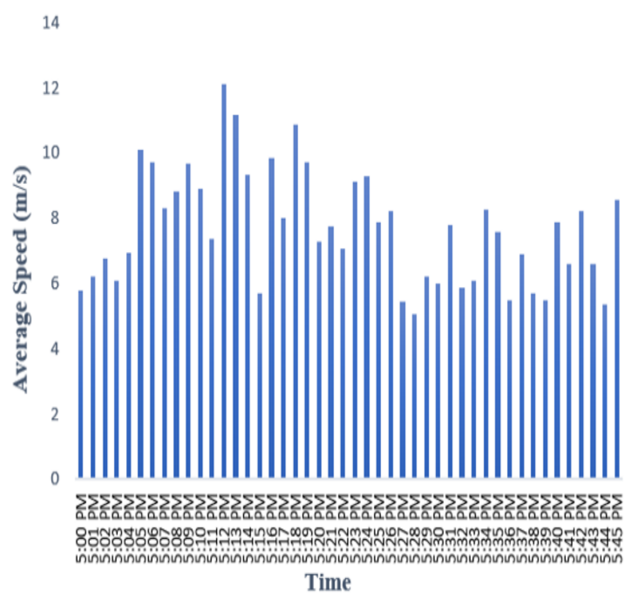


FIGURE 7. Average vehicle speed on 14 m road section on Saturday, February 29th, 2022.

Speed-flow relationship describes that when traffic flow increases, average speed also increases until it reaches the critical flow. Beyond this, when flow increases, the average speed decreases. The highest average speed observed during the 1-min time segment was 12.11 m/s at 5:12 PM, while the lowest average speed was observed at 5:28 PM at 5.05 m/s as can be observed in Fig. 8. Similarly, the highest traffic flow measured during the 1-min time segment was 19.13 veh/s at 5:13 PM. The lowest traffic flow at 4.60 veh/s was observed at 5:44 PM, as shown in Fig. 8.

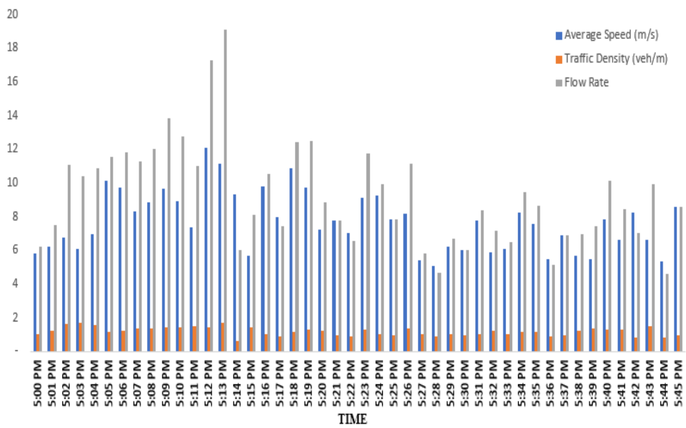


FIGURE 8. Traffic flow versus average speed versus road density on a 14m road section on Saturday, February 29th, 2022.

D. AVERAGE TIME AND DISTANCE HEADWAY

Average time headway is the time difference between the arrival of two vehicles at a reference point on a roadway. Average time headway has an inverse relationship with traffic flow, and is given as:

$$Average\ Distance\ Headway = \frac{1}{K} \qquad (5)$$

Average distance headway is the difference in position of two vehicles in meters. It has an inverse relationship with density (K), and is given as:

$$Average\ Time\ Headway = \frac{1}{Q} \qquad (6)$$

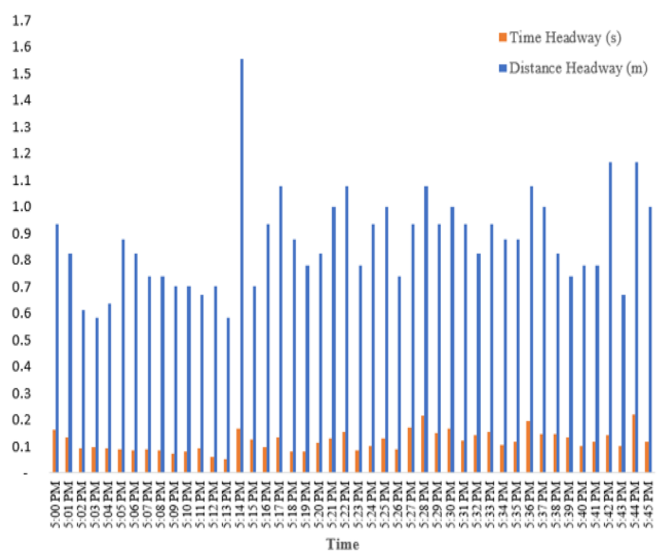


FIGURE 9. Average Time and distance headway on 14m road section on Saturday, February 29th, 2022.

The average time and distance headway of traffic flow on the under-observation road segment is shown in Fig. 11. The highest time headway at 5:44 PM was 0.22 s while the lowest time headway at 5:13 PM was 0.05 s. The largest average distance headway at 5:14 PM was 1.55 m while the lowest average distance headway was observed at 5:03 PM and 5:13 PM as 0.58 m as shown in Fig. 9.

E. AVERAGE TIME AND DISTANCE HEADWAY

Vehicle trajectories measurements (tracks map) are the trajectories of all passing vehicles on a road segment. These are helpful in the detection of abnormal/unsafe driving behaviors and quantification of road-vehicle-driver system dysfunctions. All detected vehicle trajectories are aggregated on observation 14 m road segment and can be seen in Fig 10(a). These trajectories are useful for analyzing the directional flow of vehicles and pedestrians on a road.

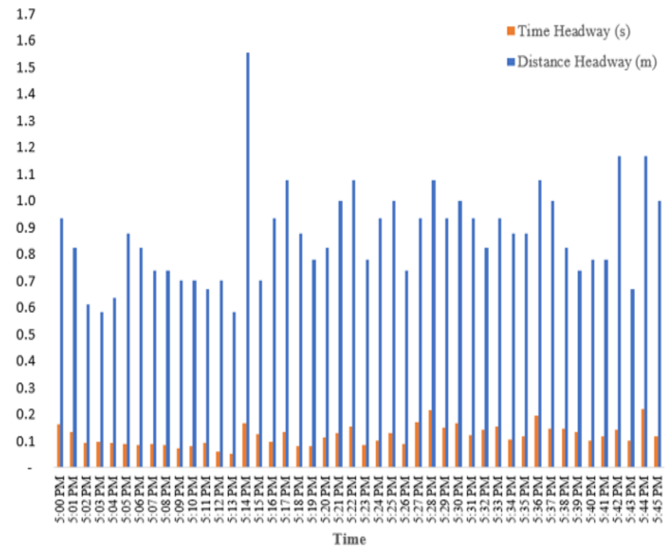


FIGURE 10 (a). Vehicle trajectories on the 14 m road section on Saturday, February 29th, 2021. (b) Heat map of 14m road section on Saturday, February 29th, 2022.

F. DENSITY MAPS

Density maps can provide an effective visual summary of traffic flow on a given road segment. It can synthesize traffic flow data in pictorial form, thus identifying parts of road segments with the highest concentration of vehicles and pedestrians. This concentration is depicted through colour schemes (red, yellow, and green), with red representing the highest concentrated areas and green colour with the lowest concentration of objects. In other words, red represents the road segment with the highest activity and green with the least, as shown in Fig. 10(b). Fig 10(b) presents the heterogeneous traffic behaviour with the highest activity in the leftmost lane.

V. CONCLUSION

This work proposes a low-cost and real-time IoVT-based solution for traffic flow characterization. The following are the main points concluded in this work.

- The sensor node is fabricated using RPi ZW, Pi camera, Wi-Fi device, and 10,000 mAh power bank with an overall cost of $40. The sensor node can live stream roadside traffic video to a Dell desktop at our lab with Camlytics installed.

- To conserve the sensor node's current consumption and overall data bandwidth requirements, streamed video is encoded using RPi ZW built-in hardware H.264 encoder.
- The proposed sensor node can operate for 45.4 hours without human intervention, with data bandwidth (video streaming) cost per hour at $0.283.
- For field evaluation, traffic flow parameters were measured on a main arterial road with an accuracy of 84.3%. Unlike intrusive/non-intrusive sensors and edge computing solutions, detailed traffic statistics (such as vehicle count, speed, flow, time/distance headway, spatial\temporal densities, heat maps, and trajectories) were measured under congested and heterogeneous traffic conditions.
- The true novelty of the proposed solution is its capability to count pedestrians with an accuracy of 76.3%.

In the future, we plan to install multiple sensor nodes in a connected network. Data analytics will analyze traffic behaviour at complex road configurations (intersections, roundabouts, and junctions). Transportation engineers can employ analyzed data for better planning, designing, and managing urban road infrastructure.

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CONFLICTS OF INTEREST

The authors declare they have no conflicts of interest to report regarding the present study.

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