Real-time Automated Traffic Management Scheme Using Blockchain Based on Unmanned Aerial Vehicles

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Abstract. The drones or Unmanned Aerial Vehicles (UAVs), will be crucial for addressing issues in airspace and developing traffic management. This paper's goal will provide a review of recent research, which focuses on the development of the system based on four requirements: accuracy of position, system quality, power consumption, and user interface. Additionally, upgrades in computer vision algorithms will be implemented to capture specific information from UAVs that have captured video and images, facilitating communication with other research endeavors. On enhancing traffic flow prediction and analysis methods, addressing the challenges posed by increased numbers of UAVs (multi-UAVs) and how to overcome roundabouts and obstacles, in conjunction with their consequences. This paper will summarize all methods used in mining data and leveraging it to identify the most suitable way to reduce accidents and enhance monitoring. We focused on the YOLO (You Only Look Once) algorithm and compared all versions. It was observed that the eighth version is considered the best, and students can benefit from it in projects related to computer vision. Then, the YOLO output can be passed to the Queuing theory for time control, specifically for side applications.

1 Introduction

Year after year, the number of vehicles increases as technology advances, which led to the emergence of drones. Drones can gather various traffic and road data information conditions via aerial photography and videos from around the area. The current control solution doesn't provide the necessary functionality for a future autonomous transport system. To achieve full autonomy in transport drones this required developing and advanced algorithms for the path planning. Today, most UAV flights are conducted within the visual line-of-sight (VLOS) of the operator. But, limited range. So, depends on the beyond-line-of-sight (BVLOS) of an operator in real-time operation [1]. In the same year 2020, other research suggested improvements to infrastructure based on the offload/shared method. The results show the drone can share information under 3D aerial mobility. But, still faces high delay. To overcome this limitation, fog computing with an edge server is used to provide the most efficient and optimal solution [2].

In recent times, the wide-scale deployment of UAVs has been used to advance rapidly with the help of computer vision to solve problems related to capturing video images [3]. On the other hand, depending on the Beidou satellite positioning, Lora's communication,

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also, yolov3 technical. Where, the outcome displays that in the surveillance of vehicles and prediction, position accuracy was achieved at 80% [4]. The traffic video data acquired through UAV needs to be effectively processed for the intended traffic analysis to take place. The processing framework considers five steps pre-processing, stabilize, geo-registration, detection, path monitoring, and control. Subsequently. The processing module is undertaken and determines which dataset will used for input [5]. Since UAV has inherent characteristics and flexible mobility in 3D space, it is based on new technology such as 5G/B5G. Where the results show the UAV has high coverage and the data rate is guaranteed to be 100 Mbps [6]. Multiple UAVs are connected. Consequently, must support the types of infrastructure network. Vehicular Ad hoc Networks (VANET) and Flying Ad hoc Networks (FANET) are used. Both of them are effective peer-to-peer (p2p) for transferring data among all network nodes [7]. Another study proposed to enhance the security-based blockchain technology, it enhances data privacy and enables decentralized methods to uphold network integrity in a simplified manner[8]. Recently, used blockchain-based federate learning. This technology relies on decentralization with traffic flow prediction and is unable to model to update. While preventing unreliable [9].

To enhance confidentiality, integrity, and authentication of the drones. The studies support both autonomous and hybrid drone operations. The results show the data is immutability and network stable with the ecosystem [10]. In [11], the authors combine beyond-line-of-sight (BLOS) with Unmanned Traffic Management (UTM-chain) to offer security between the base station (BS) and UAVs. The simulation results of the UTM-chain provide tamper-resistance data, security practices for UTM, safe and effective reliable. Nevertheless, the count of accidents keeps rising. So, developed certain systems through 5G technology such as the SAHER system in Saudi Arabia [12]. Video capture by UAVs can be enhanced based on the Intelligent Transpiration System (ITS) where drones are employed to record high-quality video footage of traffic flow in congested areas [13]. Others have proposed utilizing a blockchain-powered Internet of Drones (IOD) ecosystem designed for 5G to alleviate congestion transmission of the data within this system depending on beyond-visual-line-of-sight (BVLOS) [14]. But at the same time, other studies focused on the type of drones. Where, discovered that the fixed-wing was considered the best speed and could fly for several hours. Furthermore, a hybrid (fixed-wing hybrid) is a Vertical Takeoff and Landing (VTOL) and long-endurance flight [15]. While UAVs cover limited distances, other studies proposed to use of aerial base stations (BS) of wireless networks. Such as cellular-connected UAVs to provide high coverage, capacity, and reliability [16].

The blockchain must be efficient it relies on the consensus mechanism, where this mechanism can solve the Byzantine general problem that is accurate in the distributed system. The blockchain reaches a single agreement to decide on the network that isn't dependent on authority. So, the nodes must agree between them based on VANET [17]. Blockchain operated by UAV is not directly. It needs fog nodes that help the blockchain achieve encryption [18]. On the other hand, to avoid conflict between drones-based TMS. It will use two algorithms rise- and -avoid and Stop-and-wait conflict resolution [19]. Physical unclonable function (PUF) has been ingrained in the UAV [20]. Or UAV cluster [21]. Traffic light systems (TLSs) within intersections and displayed to decrease accidents and urban traffic congestion [22]. A tiny drone is supplied in the establishment of micro-electromechanical systems [23]. The security mechanism is applied between UAV-UAV and UAV-GCS and Air traffic control (ATC) [24, 25]. On the other hand, vehicular fog computing provides real-time traffic management and position accuracy [26]. Each group of (unmanned aircraft systems) UAS provides various providers based on UTM service providers (UASSPS) [27]. This technique makes UAVs able to execute multiple tasks in limited capacities [28]. Drone battery consumption rate (BCR) is a technique that can be accommodated between time and battery consumption during the flight [29]. For this, the image on the BS needs to process the image based on the deep neural network (DNN), which can be classification/regression tasks [30].

Table 1. A summary of the most important methodology, problem statement, constraints, and Evaluation

Methodology	Problem Statement	Constraints	Evaluation
1. BVLOS and the current state-of-the-art of UTM	Air traffic control may be ill-equipped to deal with the expected number of vehicles	Lack of standardized system for UAV traffic management.	keeping the system scalable to thousands of vehicles per node
2. UAV can offload/share Nash equilibrium	Utilize small unmanned aerial vehicles without integrated cameras to enhance packet	Limited resource device, delayed response.	Drones can be used in collaboration with other devices to achieve the desired results.
3. UAV wide-scale, Computer vision algorithm	Progress in the use of drones in transportation safety, and traffic monitoring.	Limited view, Poor connectivity.	he drones are used to capture footage and photographs that are then used to reconstruct accident scenes using vision algorithms
4. Lora, beidou satellite position& yolov3	Its idea is to integrate the real-time operation of people, vehicles, roads, and traffic involved in the traffic	Yolov3 output in 3scales. Sample Images contain the same object with the same color	to solve the application short board of Wi-Fi, ZigBee, GPRS, and other common wireless communication in-vehicle monitoring systems, and improve the low range, low cost.
5. employ a rational approach to assess the effectiveness of roundabouts	Multirotor drones have become increasingly for a vast variety. efficient traffic data collection and extraction of various flow parameters	The limited flight time and battery capacity of UAVs restricted the duration and range of data collection. Weather conditions	provided sources is the use of UAVs for traffic analysis at urban roundabouts.
6. 5G/B5G satellite technology massive Multiple Input Multiple Output (MIMO)	UAVs aren't fully autonomous in an ecosystem environment and cannot accomplish different missions.	Drones are mobile and require wireless support, that can provide licensed or unlicensed	Use for wide range (3D) operation and intelligent placement of higher coverage and connectivity, ultra-reliable low latency communication (URLLC), support for massive (mMTC), greater bandwidth and

			throughput
7. Multi_UAV communication. networking systems	Multi-drone requires a high level of coordination and collaboration to perform tasks.	Limited B.W, High mobility Intermittent connectivity, Bound transmission range, Unpredictable noisy	Can be used for elasticity, adaptability, workability, and plasticity.
8. cryptosystem (blockchain).	Privacy protection of drone big data, security and safety	Doesn't work without a consensus mechanism	Blockchain-based method for securing UAV big data has efficient cryptography
9. Consortium blockchain-based federated learning. Noise-adding mechanism (ITS)	privacy exposure risks associated with traffic flow prediction methods based on centralized machine learning.	Centralized model coordinator, Scalability, Computational overhead, Real-world implementation.	blockchain-supported distributed learning with no central authority and miner-validated vehicle model update
10. The Internet of Drones (IoD) distributed ledger-based technology.	Establishing confidence in a hostile setting and the high amount of network actions needed for coordination	Limited parameters without specifying what these parameters are and how they were measured	Reliable and safe network assistance is the most important need in the IoD environment
11. beyond-line-of-sight UTM-Chain consensus mechanism	. Security becomes harder when they are online as their data flow is vulnerable to attacks.	In the consensus mechanism, data cannot be edited or erased. UTM chain limited by software simulator loop.	It can observe, recognize, locate, and track the UAVs, which are drones, in real-time, meaning without any delay or lag.
12. SAHER system UAVs using 5G	limitations and loopholes that allow drivers to avoid fines and detection. Common violations include excess speed and abrupt deceleration.	Limited flight time and range, weather conditions affecting UAV operations, and potential privacy concerns. integration and coordination of UAVs with the existing traffic monitoring.	(5G) communications network has already caused a radical change in the industry, especially the IoT-based industries, which concentrate on latency, power usage, and network range.
13. Intelligent Transportation Systems (ITS) and used high-quality cameras.	traffic data that rely on either stationary sensors or GPS devices with limited spatial coverage rates	Small scale, indicating that the implementation of this approach on a larger scale may face additional challenges.	This capture traffic flows in a mixed-mode crowded situation over a city area using a group of drones.
14. BOD5-IOD by using 5G	The drones use unsafe wireless	The simulation result was a low	The 5G technology was introduced in 2020 to

	communication channels to talk to other components in the system	efficiency of 34.4% and 23.3%	support ultra-fast Internet with higher bandwidth and reliability.
15. Swarm drones	The process happens on the more efficient server or even in the cloud	Expensive and requires skill training to operate.	Swarming drones ensure safety and security rules and supervision
16. Drones enable various key potential uses in wireless systems.	UAV-enabled wireless networks including 3D deployment, performance analysis, channel modelling, and energy efficiency	Energy consumption of UAVs, flight constraint	UAVs can work as airborne mobile devices within a wireless network. Such wireless-linked UAVs.
17. Consensus mechanism POW	The importance of self-driving vehicles has created a demand for safer road traffic data	Energy consumption, cost constraints.	Enhance performance and reduce bandwidth overhead.
18. authentication for UAV based on blockchain	Hackers can easily intercept information on UAVs and hijack it.	Scalability, environment impact, interoperability.	It guarantees that information can be transmitted and exchanged instantly between UAV and UAV, UAV and GCS
19. hyper ledger fabric, Integrity, and Availability (CIA)	Traffic congestion, security, authentication, trust, and accountability, provide a predictable path	Energy supply, -any interruption causes a UAV network that cannot be controlled	This method organizes and avoids drone flight routes, enabling secure movement in busy airspaces
20. lightweight authentication scheme based on physical unclonable function (PUF).	Information sharing is carried out via public channels.	PUFs rely on the inherent manufacturing variations in hardware components, which can result in inconsistent behavior, sensitivity to environmental	Provide mutual authentication between UAVs. PUF is used to make each UAV have its fingerprint
21. UAV cluster & blockchain (FCFS)	UVA has the inherent characteristics of wireless networks,	Managing a large number of UAVs in the cluster can become complex.	enhanced efficiency and fault tolerance, making reliable computing
22. Network traffic light system (NTLS), (VDAS) vehicle detector	Cybercriminals are targeting critical infrastructures.	Small data and calculation expenses compared to the simple methods	Collaboration between multiple traffic light systems in different regions

authentication scheme			
23. FANET (flying ad hoc network).	single UAVs are not efficient for multi-tasks compared with multi-UAVs	Not offer a thorough analysis of user and network quality of a wireless network that supports both UAVs and users	FANET can be built to offer dependable and steady situation-based networks
24. Lightweight scheme based on PUF for UAV-GCS & UAV-UAV.	UAVs face many security risks in open and wireless settings	PUF does not store any secret information on the UAV.	Present a formal security analysis as well as old-fashioned cryptanalysis and show that our protocol provides various security features.
25. BVLOS UAV.	How UAV controlling over long distance & how coverage over a long distance.	Traffic systems that don't currently exist and consider different actors and a multitude of risk	MTU can applied to any geographical area and identify missing links.
26. Vehicular fog computing (VFC) &(VPC)	Instant traffic control for small towns using fog computing & vehicle networks	vehicles can be arranged for intensive computing to lower the process latency	aiming to attain instant and position-based network reactions
27. Conflict detection resolution (CDR) & UAS service providers (UASSPs).	Conflict avoidance in multi-agent route planning (MARP) for UAV traffic control	Schedule conflict, data integrity, and conflict decision-making.	to resolve conflicts among their UAV operations—without centralized UTM directives
28. CDR, UASSPs, and first come first	UAVs limited capacities to execute a	Communication infrastructure in real-time	Analyse air traffic topology of deliveries
29. battery consumption rate (BCR), mixed integer linear programming problem (MILP)	Creation of a package delivery system using drones, especially concentrating on long-term planning	Minimizing the number of drones, data accuracy and availability, operational constraints, and dynamic environment.	The outcomes show the effect of adding the BCR in drone planning, 3 out of 5 (60%) flight routes are not possible if the BCR is ignored
30. Deep neural networks (DNNs)	DNNs solved that released on classification, and regression to acquire data from image or video.	High dimensional data, sequential data, large scale data, non-linearity.	Remote sensing offers insight into the current state of the art.

2 System Requirements

2.1 Accuracy of Position

Accuracy of the position refers to the ability of a device or system to accurately determine and track its physical location in space. The vehicle terminal must be able to accurately determine and track its physical location with an error or deviation of no more than 10 meters. This is important for applications, such as GPS navigation, fleet management, and location-based services. To achieve this level of accuracy, the vehicle terminal may use various positioning technologies, such as Global Position System (GPS), Global Navigation Satellite System (GLONASS), or Galileo, and may also incorporate other sensors and algorithms to improve accuracy and reliability [4].

2.2 Quality of the system

By using Long Range (LoRa) communication, it is also possible to collect information from the vehicles, such as their location, speed, and other relevant data. This information can be used to monitor the vehicle fleet, optimize routes, and improve overall efficiency. Additionally, by reducing the number of nodes required to transmit data, the system can be made more cost-effective and easier to deploy. The maximum distance that can be achieved with Long Range (LoRa) depends on various factors, such as the signal strength, the environment, and the number of obstacles in the transmission path. However, in ideal conditions, Long Range (LoRa) technology can provide communication ranges of up to several kilometers [4].

2.3 Power Consumption

Overall, reducing power loss is an important goal for technical systems, and can provide a range of benefits, including improved energy efficiency. costs, reduce reliability and improve cost performance.

2.4 User Interface

The software used on a computer for tracking vehicles must be easy to interface and operate. This means that the user interface should be intuitive and user-friendly, with clear and concise instructions. Additionally, the software should be designed to work seamlessly with other applications and systems, making it easy to integrate with existing workflows and processes. As UAV big data becomes more important in various fields, ensuring the privacy protection of this type of work is crucial. It is essential to provide data protection that ensures the exchange of UAV large data In general, the big data that is transmitted between drones has become a more important issue because drones collect data from a large area and then share this data with different sensors and actuators in another area. As such, various data protection mechanisms can be used to achieve security for data sharing, especially when this data is applied to applications [8].

3 System Components

3.1 Data

Since drones deal with 3D images, this is a condition for the image to be 3D for it to be sensed by these types of cameras Moreover, the data means the video or image that the drones can capture from the environment, subsequently, the data can be customer data which the police station can determine the data captured. On the other hand, can determine the network in which the drones are used to capture the goal and send them to the police station. As shown in Figure (1).

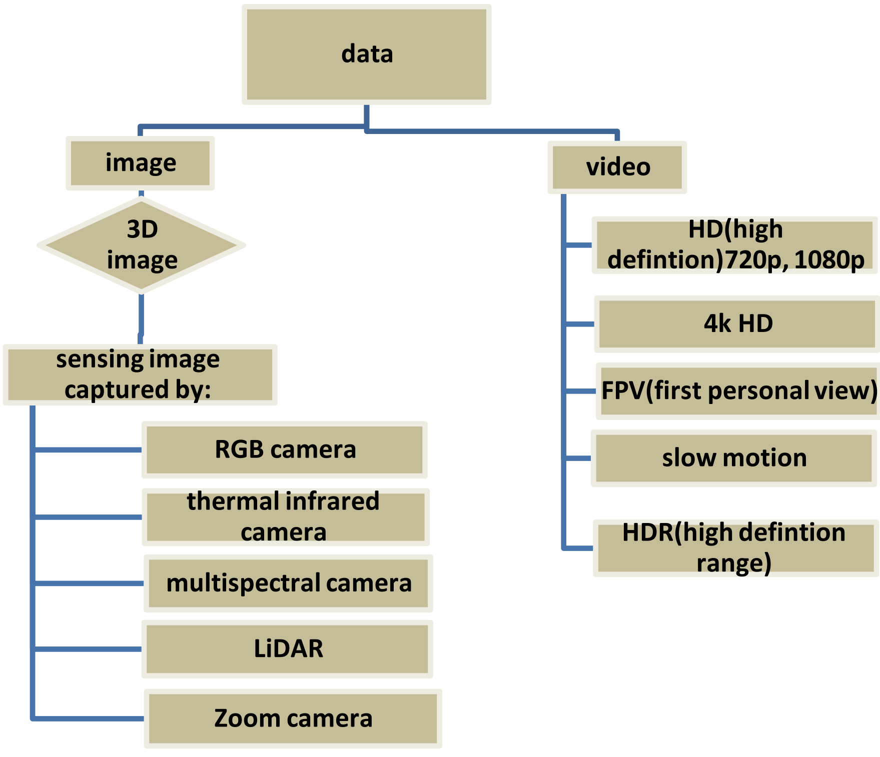

Fig. 1. Data captured from drones and types of cameras and videos.

In this figure, we can notice that the drone works with 3D images or videos to classify them in three coordinates: x, y, and z, this provides the police station with more accurate information about objects and can improve the quality of security. An RGB camera is a type of camera that works with three colors: Red, Green, and Blue. A thermal infrared camera is a device that captures infrared radiation emitted by objects and converts it into a visible image. A multispectral camera can work with a wide range of areas. Light Detection and Ranging (LiDAR) is based on laser light. A zoom camera provides more details for each object. The first type of video is used for high definition, with resolutions of 720p and 1080p to increase the number of pixels. First Person View (FPV) provides precision control, enhances security, and is used for aerial photography and videography. Slow motion is used for tasks that require a high number of frames in a video. Finally, High Dynamic Range (HDR) increases the number of pixels within a high range.

3.2 Techniques

Line-of-sight (LOS) involves high-coverage, point-to-point radio waves. But it is influenced by the ecosystem. Visual line-of-sight (VLOS) has been introduced to enhance this method, which advances speed and coverage. But it faces some obstacles. Where it doesn't consider operation in the urban area. Finally, the advancement beyond visual line-of-sight (BVLOS) [1]. Also, drones are based on communication and sensing tools and technology.

In [2] optimize the system performance, based on the offload/shared technical. Also, the Nash Equilibrium is used to predict the auto-come of the drone's decision. Overcome the collision and risks, depend on the retrieval of vehicle paths using drones. Depended on the data from the video to analyze compulsory lane change collision risk at freeway merging zones [3]. Also, a special type of computer vision, called Kanda-Lucas-Tomasi (KLT), is used for tracking, and selecting features in a sequence of images or videos. In [4]Utilizing Beidou satellite positioning technology and Lora communication to address the limitations of Wireless Fidelity (Wi-Fi), ZigBee, General Packet Radio Service (GPRS), and other wireless communication technologies in-vehicle monitoring applications furthermore, machine learning algorithm yOLOv3 A real-time object detection algorithm that recognizes particular objects in videos, live feeds, or images is the YOLO machine learning algorithm. It leverages features acquired through a deep convolutional neural network to identify objects. To enhance the management of circular intersections or roundabouts, one of these is to Augment the number of cameras/sensors or employ additional manual observation. Additionally, Innovative Technology Solutions Intelligent Transportation Systems (ITS), and the field of view (FOV) are utilized [5].

In [6], the others proposed to use 5G and wireless network communication. We need new networking models when multiple UAVs are used. Therefore, others have proposed enhancing the infrastructure of networks based on Mobile Ad hoc Network (MANET) and Vehicular Ad hoc Network (VANET) [7]. blockchain that helped a consensus mechanism, p2p, and encryption algorithms achieve high security and privacy for data [8]. On the other hand, blockchain-based federated learning provides a mechanism for real-world values, while another technology adds noise, introducing random noise into the data[9]. Distributed ledger technology and blocks are linked together in chronological order, forming a chain [10]. In [11], the others are based on the same technology in the paper one but the UTM-chain, lightweight blockchain-based using hyperledger fabric. One of the systems that enhance traffic monitoring is the SAHER system based on the 5G technology [12]. Intelligent Transportation System (ITS) and pNEUMA provide the dataset needed to identify congestion [13]. Blockchain-enabled AKA scheme in the IOD network using 5G [14]. As well as other studies, which focus on swarm drones and the nature of autonomy [15]. Optimization theory is utilized for resolving issues about deployment and route mapping, stochastic theory, optimal theory, and machine learning [16].

In [17- 22], all authentication and identification theories need the drones to be within a specific cluster. Therefore, this cluster must be organized based on a specific network, determining the location of each drone, according to a specific routine [23- 27]Improving your routing results in the execution of previously limited tasks, enhancing drone planning through BCR algorithm and deep learning [28-30]. The main idea of the drone with the blockchain is to overcome traffic congestion [31]Analyses audio and video recordings [32]. Finding solutions for low and heavy vehicles [33]. Size of vehicles [34]. Or resize the speed of vehicles to get perfect management [35]. Consider the microscope is one of the best simulations used to measure the speed of vehicles [36]. In [37- 39], to improve the allocated time for each vehicle or adapt to changes in each flow can be based on the intelligent transportation system (ITS).

4 YOLO (You Only Look Once)

The drone will be mounted using traffic signal poles, and then it will capture a video or image that will be sent to the base station (police station), then make object detection and tracking will be performed on the video or image using the YOLO (You Only Look Once) algorithm. Which running process takes half of a minute [40]. The best version is yolov3, which consists of Darknet53 layers and each image passes through these layers. Furthermore, the size of the image is 416*416 considered constant for each version [41-42]. In 2022, Intersection Over Union (IOU) was developed into Distance Intersection Over Union (DIOU) to calculate the distance between predictions and ground truth within a set of bounding boxes [43]. The training process takes place on the spatial pyramid pooling (SPP) model, in which the accuracy has reached 99% [44]. In 2023, to enhance detection efficiency with lower energy consumption, the training process relied on YOLOv3, YOLOv4 tiny, and YOLOv7 tiny based on a huge dataset [45].

YOLOv4 is generally used to improve detection accuracy by incorporating scale-sensitive intersection over union (SIOU) to alleviate the loss of information present in based Convolutional Neural Network (R-CNN) and Single Shot Multi-Box Detector (SSD), whose accuracy reached 93.74% to 98.6% [46- 47]. And based on OpenCV with Google Colab [48]. Later on, they relied on the yolov5 covering detection over 100km by leveraging a two-model approach adaptive attention module (AAM) and feature enhancement module (FEM). which combines the backbone and head in a structure called the neck. The backbone consists of several convolution layers with Kerman filters (3x3) that process the images [49]. Also, it used the COCO dataset [50]. Another author, in 2023 developed YOLO by relying on another type of dataset Intelligent & Safe Automobiles Traffic Sign (LISA) [51].

The development involves various types of intersection over union (IOU), including Distance IOU (DIOU), Complete IOU (CIOU), and Generalized IOU(GIOU) to optimize the running process [52]. Or employed technique for balancing difficult and simple samples is the EIOU (Efficient Intersection over Union) [53]. The images are resized from 640x640 to reach the final module, which is the Spatial Pyramid Pooling Fusion (SPPF). This module contacts with the head of the YOLO structure by up sample layer to complete another part of the process. The process is based on the currently available and dependable YOLO environment Notebooks with free GPU, Deep Learning VM, and Ultralytics that contain Pytorch package with version 1.7. The dataset is uploaded via Roboflow., the detection process can be used manually in real time after that, it will do the tracking process at the same time or OpenCV to make detection, tracking, and counting with ROI calculation [54- 56].

When comparing all versions of YOLO in terms of Mean Average Precision (MAP) accuracy, it's important to consider the specific use case and the specific dataset being used with the mean camera sensor and by openCV [57- 58]. Generally speaking, newer versions of YOLO tend to have better accuracy, but the difference may not always be significant enough to warrant upgrading. It's always a good idea to experiment with different versions and see which works best for your specific task for the 2023 year only [59- 62]. In YOLOv5 the resulting Mean Average Precision (mAP) after training on the GTSDB dataset is 91.5% [63]. We will notice that the seventh version of the dataset was expanded [64- 66] Comparison accuracy for some versions of YOLO are Illustrate in figure (2).

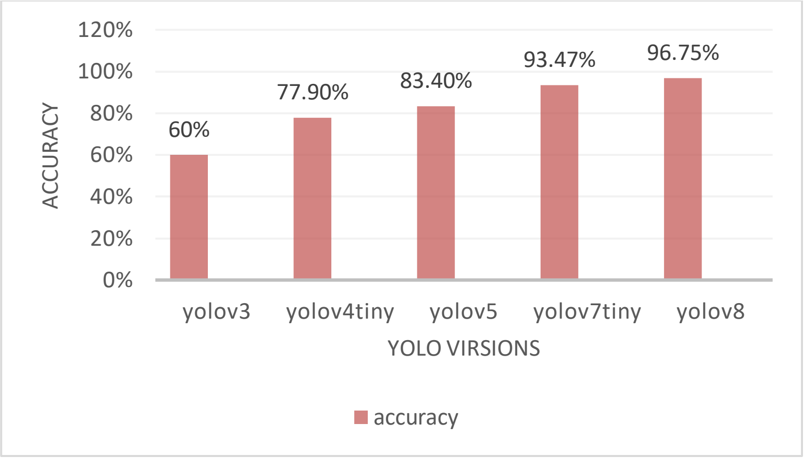

Fig. 2. Comparison of accuracy for some versions of YOLO.

From this comparison, we can notice that YOLOv8 is considered the best in terms of accuracy, while the least accurate is YOLOv3. YOLOv4 achieves slightly higher accuracy than YOLOv3 but is more advanced. YOLOv5 benefits from advancements in the architecture of YOLO. In YOLOv7, the dataset's range of accuracy is broader, with a slight increase in accuracy. Finally, in YOLOv8, the dataset is open source and achieves very high accuracy. After the detection and tracking process using recorded video footage from drones with the utilization of the YOLO algorithm, the second stage proceeds through the quaternion theory at the police station Also depends on Kalman Filter.

5 Queuing theory

Queuing theory supplies a mathematical structure for evaluating and modeling the actions of waiting lines or queues [67]. It can calculate the horizontal distance between vehicles and the specific time for travel links in a network [68]. Or shack wave to calculate the queuing length [69] furthermore, quality of services (QoS) [70]. Through this method, it is possible to determine the arrival time [71]. Several vehicles [72], also, can determine the direction of traffic and location relays on Global Positioning Systems (GPS) [73]. Mathematically can decrease the average waiting time on the road. As shown in the equation:

$$W=\frac{1}{\wedge}\sum\frac{\lambda i}{\mu i-\lambda i} \tag{1}$$

Where the summation from i=1 to M

λ: Rate of transportation on the road

W: waiting time

μ: Rate of transport on another road [74].

6 Discussion

Moreover, based on the pipeline structure [75]. The data is transferred from the drones to the base station through the protocol type, one of which is used for this purpose (Transport Control Protocol) TCP protocol through the network [76]. where it operates within the cluster routing [77]. It can randomly detect traffic and vehicles or with TCP protocol to re-transmit the data [78]. Quick recovery [79].Guarantee transport of data [80]. Determine end-to-end delay by Ad hoc Distance Vector (AOVD) protocol [81]. So, the TCP protocol is considered the best and easiest for this research. Developing a plan to ensure the safety of passengers using public transportation on roads is crucial [82]. To reduce accidents and save the lives of people with private information for each vehicle [83].

Generally, it can be employed in some applications on the mobile phone to alleviate traffic M/M/1 queuing is a method based on waiting time, probability, and average time that can cause traffic [84]. It is suggested that the SNMP protocol may be needed [85]. Markov decision is utilized by processing random data in this method [86]. It relies on a single server [87] and manages small objects, utilizing the first in first out (FIFO) theory[88]. Performance assessment can be done using the stochastic model. This research aims to decrease the impact of accidents and optimize traffic for urban systems[89]. Additionally, it can assess the performance of UAVs with low power wide area networks and sensor sensing that are managed by blockchain for security. UAV traffic management solutions for BVLOS and fully autonomous flight control need for scalable autonomously in developed airspace. So, offload/sharing is shared of the computational task with a nearby UAV. This alleviates computational Expense in terms of time lag and energy consumption. Moreover, shared with nearby UAVs could give good performances for tasks with moderate.

Developing software with cloud computing helped to extract information from UAVs. Vehicle monitoring and traffic prediction models are necessary to detect kinds of traffic. but at the same time, the methods of deep learning are Unable to fulfill the real-time processing demands for vehicles based on priority rules, in roundabouts, this priority of rules can order and ensure traffic operation with accurate of data. Efficient of the system may be limited by the type of communication UAV-assisted cellular, cellular-assisted, and UAV-UAV communication. This method may be used for Radio Frequency (RF) signals in bands such as High Frequency (HF) and Ultra High Frequency (UHF). Flying ad hoc network (FANET) they consider the best topology on which drones can depend on it. Where nodes have very high mobility, mobility models are random or regular under special conditions and 3D. Deep learning is needed for the central server to predict the data and connect with the drones, so this isn't supported sometimes, as the failure of the server causes the system to crash. Finally, collecting the traffic data with vehicles can achieve high coverage and accuracy with large-scale networks.

7 Conclusions

UTM traffic management can be advanced to achieve full monitoring, surveillance, and tracking beyond visual line of sight (BVLOS) with the help of computer vision and advanced software on the ground control station (GCS). Additionally, each drone on the network can be connected to other drones through radio frequency identification (RFID), which provides long-distance coverage, less delay, and lower computational costs. Furthermore, connecting the Global Position System (GPS) on each drone helps to accurately determine their location in urban environments, which is made possible by the 5G network. The drones can capture videos and simultaneously record information about the traffic, which is then sent to the ground control station for processing. Currently, YOLO is considered the best algorithm applicable to drone-based applications due to the precision of drones in capturing images or videos. The primary data, essential for YOLO, is derived from drone-captured content and serves as the basis for further processing. Subsequently, any additional algorithm can be integrated with YOLO to enhance its capabilities.

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