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Real-Time Vehicle Identification for Improving the Traffic Management system- A Review

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Abstract

Due to the increasing number of cars on the road and the exponential growth of traffic throughout the globe, regulating traffic has become crucial in the most industrialized countries. The development of technology has led to the current state of traffic management systems that comes with the ability to count, monitor, and predict the speed of vehicles in order to improve the transportation planning. This has also reduced the number of accidents that occur due to worsen traffic conditions. Road traffic surveys have been carried out manually for a long time since automated measures were not often employed due to the difficulty of installation. Machine learning in image processing is widely recognized as a significant approach for real-world applications such as traffic monitoring. The primary benefit of automated vehicle counting is that it allows for the management and evaluation of traffic in the urban transportation system. There are many methods employing distributed acoustic systems on intelligent transportation systems, including YOLO v4 and the Normalized Cross-correlation algorithm, which uses ultrasonic sensors and the algorithms ALPR, YOLO, GDPR, and CNN. The simplest method for identifying a vehicle is to gather information from sensors such as cameras, vibration detectors, ultrasound detectors, or acoustic detectors. These sensors are combined with the proper microcontrollers to determine the amount of traffic using the most recent data and theory. This review article is a quick reference for researchers working on safety-related traffic management systems.

Keywords: Traffic Management System, Signal Processing, Safety, Communication, Data Processing, Neural networks

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1. Introduction

Nowadays one of the major issues contributing to public discontentment is traffic congestion, particularly in large cities. The main causes of congestion are an increase in population, expanding roadways and infrastructure, and an increase in vehicle density. The technological developments to manage the traffic is still underway. Outdated systems with static traffic signals, unmanaged power supplies, and random turning on and off of the traffic management system are in use even today causing difficulties in managing the traffic properly. The research put forth by "D. K. Soundra" suggests an IoT-based system for autonomously counting autos that is linked to the Node-Red Platform through the MQTT protocol. A low-cost device with a normalized cross-correlation algorithm integrated and an efficiency of 89.90% was developed using ultrasonic sensors and a microcontroller linked to the internet. This study may be used to the development of smart traffic lights. One of the problems is when two or more cars are approaching because the signals are confused and cause errors in computations [1].

An essential component of city planning is the detection, counting, and speed monitoring of vehicles. It assists in supplying details like the overall vehicle count, traffic in a specific location, and the vehicle-mileage per unit of time. The most common method of measuring speed is by using the radar speed detector, although this method has the drawback of only being able to measure the speed of one vehicle at a time. The research work [2] detects automobiles using the Background Subtraction approach. As soon as a vehicle enters the virtual detection zone, the vehicle counter is updated. The median filter, a nonlinear filtering method, is used to reduce the video's noise. The suggested system has certain drawbacks, including the fact that it performs worse on windy days. It also experiences 30% accuracy loss in the absence of adequate light.

Automatic vehicle counting allows the evaluation and management of the necessary traffic conditions for the urban transportation system. For improving the traffic signalling system, automobile counts are thus most important and advantageous. New, integrated networks for smart cities have been created using cutting-edge technology like the Internet of Things (IoT) and computer vision to replace the outdated legacy systems. The approach put forth [2] has the advantages of better decision-making, more security, improved traffic flow, and conservatively applied maintenance job scheduling. In this paper, the authors suggest a novel low-cost embedded vehicle counter system that uses a Jetson Nano and the Telegram app to connect to a smartphone and communicate via computer vision and the Internet of Things. The Internet of Things application delivers hourly reports to a smartphone for all automobiles that enter and leave the city. The suggested technique may be utilized for artificially managing park lots or for traffic congestion analysis [3].

Due to their lower cost than four-wheeled vehicles, motorcycles are becoming more and more popular in developing countries. The dependence on motorcycle-based services, which have seen a large increase in popularity, has resulted in a significant increase in the number of motorbikes on the road today. Worldwide, 1.3 million people die as a result of traffic accidents. Pedestrians and cyclists account for more than half of all traffic-related fatalities. Road safety is improved with the use of traffic management systems. The dataset has two classes added to it: motorbike and vehicle, thanks to the COCO Annotator tool. The Python package OpenCV was used to count the number of objects per class using real-time object detection while the YOLOv4 model was trained using the GPU provided by Google Collab [6].

Using image processing from a CCTV camera together with traffic scenario classification, a universally reliable system with vehicle recognition capabilities will be created. Using the YOLOv5 algorithm, this research was able to develop a strong, universal method for identifying automobiles and recognising them in CCTV video. With few modifications, the vehicle classification produced average accuracy of 90% for vehicle classification and 97% for vehicle type identification [7].

The technology is designed to find the triple riders and riders who are not wearing helmets. The real-time tracking of the incidences of triple riding and helmet-less riders has been the primary emphasis of this study. The COCO dataset was utilised and found to be effective [8].

A method called License plate detection (LPD) uses increasingly sophisticated machine vision capabilities to automatically detect and identify the number on a vehicle's number plate. To track, monitoring, and analyse further, this cutting-edge intelligent transportation system delivers vehicle number information. By using the Sobel operator(3x3), this research study has suggested a reliable licence plate identification approach. Otsu's thresholding is performed to binarize the image, and the HSV and RGB values of 75-D are utilised to extract features for the purpose of classifying the licence plate using a featured vector neural network classifier. With a 98% accuracy rate, the neural network classifier's results are highly promising for application in real time. The suggested approach yields reliable and effective results instantly [9].

This study examines a distinctive ITS data source based on an optical fibre that serves as an uninterrupted length of virtual sensors using the distributed acoustic sensor (DAS) technology. To fully use the potential of DAS in ITS systems, the authors suggest using an additional data source to help with the labelling. With a mean accuracy of 94%, the approach correctly identifies one of the five automobile types utilized in the controlled experiment. The same technique is used to determine if a vehicle is Small or Large using a binary classification. With an average accuracy of 95%, the findings are promising. The results of this ground-breaking study show how rich DAS signals are and how essential these signals are for recognizing overground mobility in a way that respects privacy [10].

Traffic lights are essential for preserving traffic order and safely guiding both vehicles and pedestrians through junctions. Traffic accidents may be significantly reduced by following traffic rules while passing the junctions with traffic signals. However, in reality, there are still a lot of traffic accidents and traffic jams caused by failing to obey traffic signals in certain locations because of the unusual or impolite driving conduct of vehicle drivers. Using the YOLOv5 model and YOLOv5+DeepSort, this research primarily investigates traffic light detection and identification. The data samples should first be expanded using the random clipping procedure to include all 3000 images in the training set. The DeepSort method is compared to the YOLOv5 target identification algorithm on the basis of tests, and the enhanced approach significantly raises the model's mAP [11].

There are numerous traffic issues occurring right now.. Humans are too impatient to wait. It is very common in many countries to ignore the traffic signal. At the railway crossing, accidents happen frequently. some of the major cause that leads to the traffic congestion are, wrong side parking, travelling in the wrong direction etc. . This research work improves the system efficiency and the speed using the YOLO Objects, OCR, and Vision Assistant [12-15].

This review article's primary goal is to;

- Examine the multiple technology developments used recently in the area of traffic management systems.
- Compare and evaluate the workings of completed products based on efficiency, errors, and usability.

2. Methodology

To explain and examine the many operating principles, this section has been separated into five sections. By dividing according to several categories, one may quickly comprehend the significance and utilize the appropriate technique to execute in their task.

a. Traffic Analysis with Vehicle Counting based on Image Processing

The term "preprocessing" refers to the process of breaking down a movie into individual visual frames. Nonlinear filtering methods are employed to enhance the video's quality. The noise is reduced using a median filter [2]. The backdrop reduction procedure, which helps to discriminate between stationary and non-stationary items must be used. Second, the Mixture of Gaussians (MoG), a density model containing certain Gaussian function components, for the first background subtraction is utilized. Third, the object detection model to forecast the tracking circumstances are applied. Fourthly, the centroid tracking technique to track each vehicle. Figure 1 shows the data acquisition process of the proposed system with image processing [3]. The best model with the greatest accuracy using the same datasets was chosen after a thorough comparison to ensure the best overall result could be obtained. In the model selection procedure, the three models Faster RCNN, SSD, and YOLOv5 were compared. Vehicle counting keeps track of and retains a list of the detected cars' center coordinates. Along with detection and counting, colour identification was also done. The cropped, BGR-to-HSV converted photos of the identified automobiles were used for colour identification [5-8].

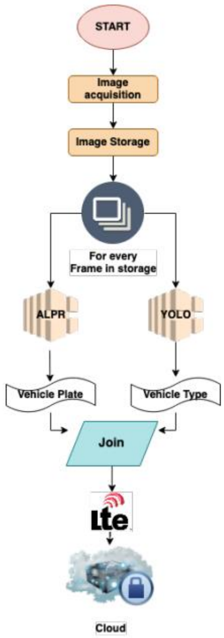

Figure 1. Flowchart for Data Acquisition Process [5].

b. Ultrasound sensor and Normalized Cross-Correlation Algorithm (NCCR)

Comparing time with itself at various times is known as cross-correlation. The sensors used in this study are ultrasonic sensor, which may operate day or night and are not light-dependent. Additionally, these sensors are inexpensive, making it possible for those living in dense populations to readily access the job. A microcontroller is linked to the internet via the MQTT protocol, and an ultrasound sensor is attached to it. The platform Node-Red receives data that has been processed in parallel. The NCCR algorithm depicted in Figure 2 is executed on the Raspberry Pi 3B+, which helps to lighten the workload and improves the efficiency and accuracy of the proposed task. In order to conduct the experiment, a MEMS-based ultrasonic sensor is used and combined with microcontrollers and single board computers, such as the Raspberry Pi computing board [1].

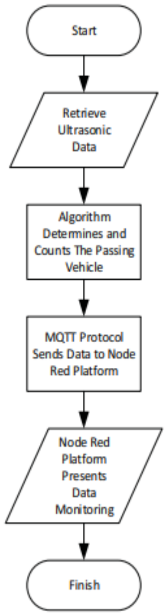

Figure 2. Flow diagram of Ultrasound Sensor with Cross-Correlation Algorithm [1].

c. Vibration sensor and Machine Learning

No investigation has been done before that uses a single sensor to both identify and categorize cars based on the vibrations of the road. In this research, a system using a single vibration sensor and machine learning paired with Support Vector Machine and Random Forest, accomplishes vehicle recognition and vehicle type classification for vibrations of passing cars. By taking measurements over a 12-hour period at two different sites, the algorithm mentioned in Figure 3 is implemented. Piezoelectric elements are used to capture vibration data by translating applied vibrations into a voltage. To avoid manipulation during measurement, a traffic cone has been placed over the sensor. For model training and assessment, a video camera is mounted on the traffic cone near the vibration sensor's center to identify vibration peaks with real-world data [4]. Figure 4 shows the vibration sensor employed in this work.

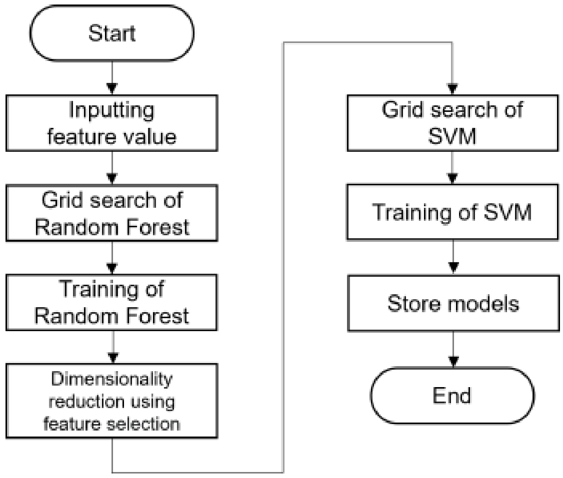

Figure 3. Flowchart using Vibration Sensor Paired with Machine Learning [4].

Figure 4. Vibration Sensor [4].

d. License Plate Detection (LPD) using Neural Network Classifier

The alphanumeric rectangular plate that serves as a license plate. For vehicle identification, it is fastened to the vehicle. The main problem in identifying the owner of a car is the vast majority of automobiles that are typically on the road. By extending the Sobel operator, the study effort suggests a brand-new method of detecting license plates. The flow diagram of the suggested work is depicted in Figure 5 and the step-by-step execution in Figure 6. Numerous functions that are used in everyday life are provided by this LPD (License Plate Detection) system, including parking lots, border checks, toll collecting, and traffic monitoring. Image of the vehicle is the input for the proposed LPD system. photos are captured using a digital camera with a high-resolution of 1082 x 728 pixels; the pre-processing technique removes the noisy, inconsistent, and incomplete data from the acquired input photos. Preprocessing is required for higher-quality vehicle images. To remove the extra pixel, the image's original size, 1082 x 728 pixels, was reduced to 256 by 256 pixels. By extending the Sobel operator, the preprocessed image is then edge detected. The 'Trainscg' is used as a training function with a 5 hidden layer network in the suggested technique. By using the scaled conjugate gradient back propagation approach, the Trainscg network training function changes the weight and bias parameters [10].

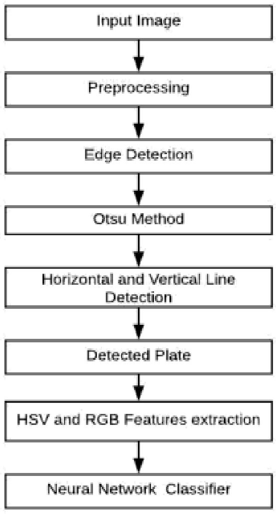

Figure 5. Flow Diagram of the License Plate Detection using Neural Network [10].

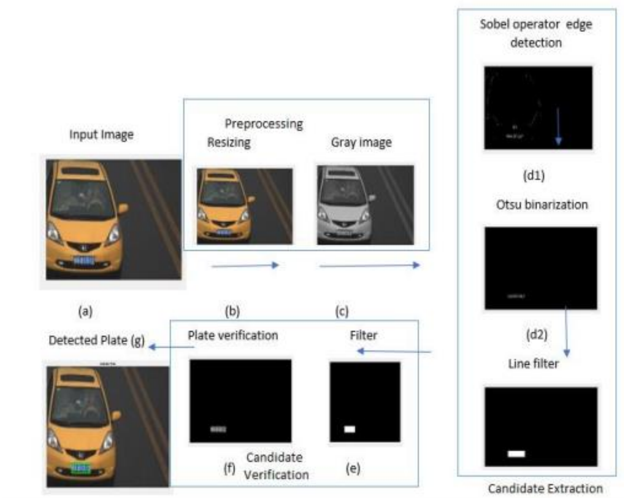

Figure 6. Step-by-Step Process of Segmentation and Classification [10].

e. Distributed Acoustic Sensor-based Classification

The method is based on optical time domain reflectometry (OTDR), in which a fiber is regularly pulsed with coherent light, a portion of which is reflected back by the Rayleigh (elastic) scattering process, and the remainder is detected by a photodetector. A basic DAS system is depicted in Figure 7. There are thirteen layers employed in the 1D-CNN of the reviewed article [11]. Convolution, batch normalization, and average pooling are the three layers that make up a CNN block. Backpropagation (BP) is used to optimize kernels throughout the model training process.

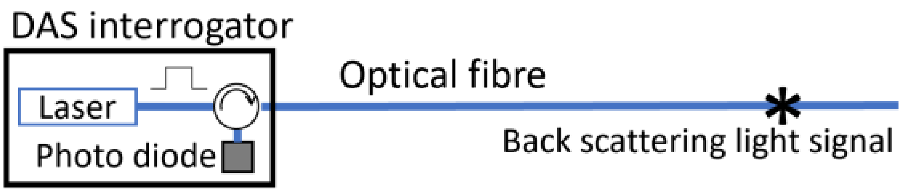

Figure 7. Distributed Acoustic Sensor System [11].

3. Comparison of the Reviewed Articles

a. Traffic Analysis with Vehicle Counting based on Image Processing

The algorithm being utilized is successfully identifying all of the cars in the input movies, and the vehicle counter is producing flawless results. Vehicle detection is accomplished using the background subtraction technique. When using triple axis to estimate a vehicle's speed, the accuracy attained with dual axis rises to 94.4% [2]. By creating a low-cost car counter with an integrated Jetson Nano based on computer vision and an Internet of Things application, the mobile application was built using the suggested system to identify automobiles in real-time. The recommended system uses the Python programming language and libraries. The identification of cars is aided by a computer vision model [3]. A total of 195 automobiles out of a total of 300 specified vehicles from the initial video were spotted, while 105 went unnoticed. Only 65% of targets were accurately detected by the system [7]. Table 1 explicates the performance metrics of the works which are employed for Traffic Analysis using Image Processing.

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Table 1. Performance Metrics of Traffic Analysis using Image Processing

Cited Work / Parameters	**[2]**	**[3]**	**[7]**
Objective of the cited work	Vehicle detection, Speed Estimation	Vehicle Counting	Classification of 7 different vehicles
Accuracy (%)	94.4	90	85
Error rate (%)	5.6	10	15
Hardware employed	Raspberry Pi, Rpi Camera	Nvidia Jetson Nano, low-cost web-camera	No additional hardware, CCTV data (video) from traffic utilised.
Algorithms / Software req.	Open CV, YOLO	MoG algorithm	YOLO v5
Network Connectivity	No	Yes	No

b. Ultrasound Sensor and Cross-Correlation Algorithm

Both non-correlation algorithm-based and non-correlation algorithm-free techniques have been validated using the ultrasound data. It produced a 10% inaccuracy. Traffic jams and signal confusion are the main factors leading to this. It has been possible to go in this direction thanks to the use of two boards, Wemos and Raspberry Pi 3B+, and the effective integration of sensors and software [1]. Table 2 explicates the performance metrics of the work employed in Traffic using Ultrasound sensor and NCCR algorithm.

Table 2. Performance Metrics of Traffic Analysis using Ultrasound Sensor and NCCR

Cited Work / Parameters	**[1]**
Objective of the cited work	Vehicle Counting and segregation based on size of the vehicles
Accuracy (%)	89.91
Error rate (%)	10.09
Hardware employed	Ultrasound sensor, Raspberry Pi
Algorithms / Software req.	Normalized Cross-Correlation Algorithm (NCCR)
Network Connectivity	Yes

c. Vibration Sensor and Machine Learning

Two genuine road sites were used for data gathering and three distinct types of verification were carried out. using Linear Discriminant Analysis (LDA) to classify data and Mel-frequency cepstral coefficients (MFCCs) to extract features. The human measurement errors for small cars were 3%, big vehicles were 9%, and total vehicles were 3% during the actual execution of the traffic census, which took into account the wet weather. Huge cars are mistakenly classified as small vehicles which accounts for a portion of the reason why there are fewer measurements of huge vehicles [4]. Table 3 explicates the performance metrics of Traffic Analysis using Vibration sensor and Machine Learning (ML).

Table 3. Performance Metrics of Traffic Analysis using Vibration Sensor and ML

Cited Work / Parameters	**[4]**
Objective of the cited work	Vehicle Counting and segregation based on the vibration magnitude recorded with the sensor.
Accuracy (%)	91
Error rate (%)	9
Hardware employed	Vibration sensor
Algorithms / Software req.	LDA, MFCC, Fourier Transforms
Network Connectivity	No

d. License Plate Detection using Neural Network Classifier

The LPD suggested approach was implemented in MATLAB 2020a using a CPU running at 2.53 GHz and 4 GB of RAM. The image's green rectangle indicates that the license plate was correctly detected. The categorization of the license plate is done using a job classifier. The neural network classifier's 94% accuracy rate is highly promising for application in real-time. The suggested strategy delivers reliable and effective results in real-time. This suggested solution still has some drawbacks for challenging circumstances like reflecting glare from license plates [10].

Table 4. Performance metrics of Traffic Analysis using Neural Network Classifier

Cited Work / Parameters	**[10]**

Objective of the cited work	License Plate detection
Accuracy (%)	94
Error rate (%)	6
Hardware employed	-
Algorithms / Software req.	Multiclass Support Vector Machine (MSVM)
Network Connectivity	No

e. Distributed Acoustic Sensor-Based Classification

It ought to be stated that the data evaluated in this study was gathered under controlled circumstances; hence, the acquired conclusions cannot be directly extrapolated without more investigation. This was made feasible by the properly labelled data that was based on previous information about the desired automobile and speed. A unique and untainted DAS signature of a target automobile would be required prior in the absence of such information. Applications where a specific vehicle must be identified, such as those at factories, power plants, airports, and similar locations, need for a list of allowed vehicles that has been meticulously collected, as opposed to an indeterminate list in general metropolitan areas [9].

Table 5. Performance Metrics of Traffic Analysis using Distributed Acoustic sensor.

Cited Work / Parameters	**[11]**
Objective of the cited work	Vehicle Counting and segregation based on size of the vehicles
Accuracy (%)	95
Error rate (%)	5

Hardware employed	Distributed Acoustic sensor, Nvidia A-100-PCIE-40GB GPU
Algorithms / Software req.	1-D CNN (13 hidden-layers)
Datasets	40,000
Execution time (s)	46.77
Epoch size	100
Network Connectivity	No

4. Discussions

This section discusses the tactics that were looked at along with the advantages and disadvantages of different works. A quick comparison of the most current studies is provided in Table 6.

Table 6. Comparison of Works based on Several Criteria

Citation Number	Methodology (Dataset/Realtime)	Advantages	Disadvantages
1	Realtime	Uses MEMS based ultrasonic sensor coupled with Arduino, WESMOS and Raspberry Pi with data being uploaded to Cloud. Works during both day and night with no interferences from light.	When two vehicles are closer this system is unable to identify the vehicles due to signal mixing / interferences.
2	Realtime	Usage of Image processing is an advantage with low-cost hardware for maximum utilisation of a Raspberry Pi board. Works with high efficiency during day time.	Since the camera is a low-cost one, it fails to be employed in night time. The system is redundant during low-light conditions.

3	Realtime	The hardware employed is similar to [2], although there is distinct variation in the algorithm employed. MoG algorithm employed on Nvidia Jetson board, which allows for faster computation.	The system remains redundant during low-light conditions.
4	Realtime	This work uses vibration sensor to classify vehicles. This is a new approach to identification of vehicles in urban areas. Can be used in both day and night conditions.	Fails to differentiate small and large vehicles with error percentage of 9%.
5	Realtime	Application of Image processing with APLR and YOLO for vehicle plate detection and vehicle type detection with parallel processing and data merging at different sites.	The system is redundant for low-light conditions.
6	Realtime	Application of Image processing with YOLO v4, with Katipunan Avenue Southbound Dataset. This system identifies motorcycles and 4 wheeled vehicles with highest accuracy.	This system is redundant during low-light conditions.
7	Realtime	This work employs Image processing approach with YOLO v3. The recorded data is stored in an excel sheet and is used for detail extraction.	The system is redundant during low-light conditions.
8	Dataset	PKU dataset is employed for detection of license plates with application of Neural Network Classifier. 4000 images are processed with least amount of delay.	The system is redundant during low-light conditions.
9	Realtime	Distributed Acoustic sensor is employed. This system has the capability to work in both day and night time.	The sensors used are expensive, with dependency of optic fibre. Incase of sensor tampering, repairing

			the sensor is difficult. Also, this work is carried out in a controlled environment due to which the accuracy varies if deployed in real-time.
10	Dataset	This work utilises Image processing for detection of Traffic lights with application of Deep Learning based on YOLOv5 and YOLOv5+DeepSort. The resulting data can be used in Intelligent Transportation systems for autonomous driving.	There are certain drawbacks with the system recognising the taillamps of vehicles and classifying them as traffic lights. More research is required in sorting and analysis after data acquisition.

By analyzing various techniques for various parameters, working, based on sensors, microcontrollers and algorithms used, it is found out that majority of the systems with Image processing as the base in Real-time face the issues of unable to perform in low-light conditions. This issue contributes to majority of the systems, as the night-vision camera are expensive. Also, utilization of data from night vision camera is a new direction which needs extended research. On comparison of techniques employing Ultrasound sensor and Distributed Acoustic sensors it is found that these systems do not require light for carrying out the specific task, and can be employed anywhere at any time. This comes with a disadvantage of being unable to identify vehicles in close proximity and the latter being unable to identify large vehicles and small vehicles at some occasions.

5. Conclusion

This study examines different vibration sensors, ultrasonic sensors, acoustic sensors, microcontrollers, CNNs, RNNs, and DAS algorithms used in traffic management systems. For this review article, the most current works published in IEEE were taken into consideration as it guarantees the accuracy of the original work.

In the present world, technology's importance to the traffic control system is essential. Without strong traffic regulations, there might be a variety of issues, such as accidents, air pollution, and reckless movement of people that could endanger lives and create mayhem.

Finding answers to these issues has included exploring discussions based on a variety of variables. A variety of methods are investigated, from the study using image processing as their foundation and using ultrasound, vibration, and acoustic sensors.

The image processing approach works best and most accurately during the day time. The systems continue to be redundant since the camera struggles in low light. Because night-vision cameras are so expensive, only inexpensive cameras are employed for the experiments. When automobiles are too close to one another, signal mixing also happened in the ultrasonic sensor-based method, causing confusions and mistakes in the resultant data. Experiments are carried out in a controlled environment with a limited number of cars, and data in DAS systems is restricted to a small number of vehicles.

By taking into account a variety of factors and the quality of the work that was done, it can be concluded that, even when not employed in low-light situations, image processing still offers increased safety, high precision, and the shortest amount of delay with improvisation at each level. Few research work is carried out based on the cloud connected system using the MQTT (Message Queuing Telemetry Transport.). Additionally, it is discovered that the camera-based technique is more affordable and is used considerably more often in the real-time environment when comparing costs with camera and other sensor-based approaches.

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