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Paper Authors

**P.Vishnu Vardhan Reddy, E.Venkatesh, SK.Mahammad Rasool, Y.Kanuka Lourdhu Reshma**

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# Automated Traffic Light with Yolo V3 and Machine learning

**P.Vishnu Vardhan Reddy, E.Venkatesh, SK.Mahammad Rasool, Y.Kanuka Lourdhu Reshma**

**UG Students, Dept of CSE, Kallam Haranadhareddy Institute of Technology, Ap, India.**

**ABSTRACT**

**One of the major problems in India is traffic congestion, which is especially common in the country's major cities. For example, congested roadways serve as a stark reminder of the lodge's awfulness. Since streets are frequently free for the taking, there is little financial incentive for cars to use them responsibly, leading to traffic jams whenever demand exceeds the ability to pay. Both street estimating and the privatization of interstates have been suggested as possible solutions to reduce traffic through financial disincentives and rewards. Blockage can also happen as a result of one-time parkway events, like a mishap or road construction, which may reduce the street's capacity below normal levels. While congestion is a possibility for all modes of transportation, the majority of the systems focused on vehicle obstruction on open streets. Techniques for image analysis have been widely used in traffic framework management and control. This paper suggests an alternative methodology, an algorithm, that would help distribute traffic fairly while controlling the signal by utilizing HERE maps API in order to eliminate the excess and impracticality of these image preparation frameworks.**

**Keywords—Machine learning, traffic signal algorithm, traffic management, and congestion.**

## 1. INTRODUCTION

India takes pride in being the second-largest social organization in the world. The staggering 5.4 million km still exist in the Indian street networks! As a result, it forms a massive final recommendation for the Indian Government to provide impeccable streets at each stage. Passing through the Indian alleys is undoubtedly a problem that no Indian, whether traditional or modern, might want to experience. Extreme traffic congestion develops as demand approaches a street's limit (or the intersections along the street).

A traffic jam or (informally) a traffic growl up occurs when all moving vehicles come to a full stop for an extended period of time. Drivers who encounter traffic obstructions may become perplexed and engage in street anger. In terms of numbers, a clog is typically thought of as the number of cars that pass through a particular location during a specific period of time or a stream. Some of the common transportation problems include Poor Street quality due to excessive traffic - The outrageous congestion of urban streets due to heavily used

Private vehicles contribute to the degradation of the street environment. This frequently results in constant transportation problems.

Air pollution, particularly in urban areas, and noise other health-harming problems like air pollution and noise pollution are also brought on by the mere size of the traffic problems.

Therefore, we suggest a system that dynamically manages traffic based on a number of key variables, including the time of day, the weather, the state of the roads, etc. The system makes it possible to equally spread the area's traffic congestion.

## 2. LITERATURE SURVEY

The goal of the study is to create an image processing-based system for vehicle recognition and counting. The overall works consist of creating software for a system that needs to record a video frame and stream. The backdrop road is devoid of any moving vehicles, and the frame is filled with moving vehicles. The device is made to distinguish between moving vehicles and determine the quantity of moving vehicles from a video frame. There are four main parts to the system for detecting and numbering vehicles: image acquisition, image processing, object detection and counting, and display result are the first three steps. The following characteristics have been accessed through the experiment: 1) Usability, to demonstrate that the system is capable of detecting and numbering vehicles under the predetermined conditions. 2) Effectiveness, to demonstrate the system's great degree of accuracy. For intelligent traffic management and supervision of the highway, vehicle detection and statistics in highway surveillance video scenes are extremely important. The widespread installation of traffic security cameras has resulted in the collection of a sizable database of video footage for analysis. A farther-off road surface can typically be taken into account from an elevated viewing angle. At this viewing angle, the vehicle's object size varies significantly, and a small object far from the road is less likely to be detected accurately. Effectively resolving the aforementioned issues and then applying them is crucial when dealing with intricate camera situations. The purpose of this article is to address the aforementioned problems and offer a workable solution. We also apply the vehicle detection findings to multi-object tracking and vehicle counting.

Vehicle counting is a crucial technique for estimating traffic flow, which is typically estimated to assess the condition of the traffic in traffic management. With the widespread installation of cameras in metropolitan transportation networks, surveillance footage develops into a significant data source for conducting vehicle counting. The complexity of traffic situations, however, has a significant impact on the effectiveness and accuracy of vehicle counting. In this study, we use the virtual loop technique to enhance the accuracy of the video-based vehicle counting approach. As an example, to enhance the quality of segmenting moving cars, the expectation-maximization (EM) algorithm is combined with the Gaussian mixture model (GMM).

In order to get a better object area, a restoration technique is also intended to remove noise and fill in any holes. The final step is to address occlusion problems using a morphological feature and the color-histogram. The proposed approach can enhance the results of vehicle segmentation and vehicle occlusion detection, according to effectiveness and efficiency experiments. It is also possible to significantly increase and achieve 98% accuracy in vehicle counting. Highlights Better car segmentation is suggested using a Gaussian mixture model based on EM. The vehicle area in the difference image is intended to be restored by a restoration technique. Occlusion is detected by combining a morphological trait with a color histogram. In an effort to advance the current traffic systems, intelligent traffic flow analysis (TFA) systems use sensing and data processing methods. In order to actively improve vehicles and traffic flow, they incorporate additional hardware, such as sensors, digital traffic signs, and cameras, and use cutting-edge processing methods to process the data the hardware provides. For instance, effectively improving the traffic flow and decreasing the delay by changing the timing and phasing of the lights in a traffic light system. The TFA system uses a video stream that includes an image sequence to perform a video-based vehicle counting. This is crucial because the only feasible technology for counting, feature extraction, pattern recognition, projection, and multi-scale signal analysis is digital image processing. To count vehicles more accurately, the system also needs to know their precise position. In essence, the video is split into frames, which are then changed to colored or grayscale frames, and the frames are then provided to the system as inputs. To conduct vehicle counting, the system then uses various kinds of preprocessing, object detection, identification, and tracking algorithms. The tracking focuses on a specific area of an image known as the Region of Interest (ROI), which is thought to be crucial for the gathering of data. Once the system has collected the data, it will make sure not to process or count the same object again. For the same object location, vehicle tracking entails a comprehensive measurement procedure in numerous defined frames.

For the purpose of simulating the operation of inductive loops, a camera-based scheme is suggested for the detection of vehicles at user-defined virtual loops. Combining effective edge recognition with color information reduces false vehicle detections. The experimental results imply that the proposed method may be capable of accurately detecting and counting vehicles at user-defined virtual loops (with an average correct detection rate of more than 98%) while also being more resistant to cast shadows and abrupt changes in illumination than comparable methods that currently represent the state of the art.

Traffic monitoring systems, which are built on a variety of sensors technologies, are used to collect crucial data for traffic management. Systems dependent on GPS, for instance, can be utilized.

Traffic monitoring systems, which are built on a variety of sensors technologies, are used to collect crucial data for traffic management. For instance, a vehicle's position can be predicted using GPS-based systems. Traffic monitoring systems, which are built on a variety of sensors technologies, are used to collect crucial data for traffic management. For instance, GPS-based systems can be utilized to forecast the position of a vehicle.

It is possible to combine several sensors, including cameras and lasers, to produce approximations of a vehicle's localization that are even more precise. Detecting registration plates and classifying vehicles are two additional applications for camera-based systems. Additionally, information provided by statistics on the number of vehicles, their speeds, and the occupancy of streets can help with municipal planning. These days, inductive loop sensors or magnetic sensors are frequently used by traffic monitoring devices to collect traffic data.

However, video camera-based traffic monitoring systems have an edge over other kinds of sensors. In contrast to other sensor technologies, camera-based systems can be used for traffic monitoring and for detecting vehicles at user-defined virtual loops, which can provide more details about the vehicular traffic (such as the kinds of vehicles in circulation, vehicle size, and speed). This study introduces a novel technique for counting and tracking moving objects in video traffic patterns. The suggested technique groups particles in videos using image processing, particle filtering, and motion coherence to create convex shapes that are then examined for possible vehicles. In order to combine or separate the groupings, this analysis takes into account the convex shape of the items and contextual information.

Using the similarity of color histograms on windows centered at the particle locations, a vehicle is recognized and tracked after that. To synchronize traffic lights, assist users in choosing the best routes, and assist governments in planning the growth of the traffic system, information about traffic conditions can be used (e.g., building new roads). For traffic management, information on the number of vehicles, speed, and track occupancy is crucial. Typically, inductive loops, ultrasonic sensors, and microwave are used to acquire such information. Video provides much more information than the methods listed above, including the potential for using already-installed cameras, so computer vision has recently been the subject of extensive research. To enhance traffic control and management, a robust and trustworthy traffic surveillance system is essential. The detection of vehicle movement seems to be a crucial component of the surveillance system. The traffic flow aids in management and control, particularly when there is a traffic jam, by displaying the traffic status at regular intervals. This study describes an efficient traffic surveillance system for locating and monitoring moving vehicles in different low-light conditions. Four stages make up the proposed algorithm: headlight segmentation and detection, headlight pairing, vehicle tracking, vehicle counting, and vehicle detection. To quickly extract bright objects of interest, a segmentation method based on an adaptive threshold is first used.

The findings of the experiments demonstrate that the suggested system can deliver timely and beneficial information for traffic surveillance. The traffic surveillance system has received a lot of attention in recent years because it can deliver important and practical data like traffic flow density, queue length, average traffic speed, and total vehicle in a set time period. The traffic surveillance device typically needs more sensors. Push buttons (used to detect pedestrian demand), loop detectors (used to detect the presence of a vehicle at a specific location), magnetic sensors (magnetometers), radar sensors, microwave detectors, and cameras are some of the prevalent traffic sensors. A video camera is a promising traffic sensor because of its low cost and potential to gather a lot of data (including the number of vehicles, their speed and acceleration, class of vehicles, and their tracks), as well as the ability to infer higher-level data (incidents, speeding, origin-destination of vehicles, etc.).

A computer that handles image/video processing, object recognition, and object tracking is linked to the video cameras (CCD or CMOS). The past few decades have seen a plethora of research projects focused on measuring traffic performance using stationary rectilinear cameras to identify and track vehicles. If they can be made to be sufficiently dependable and robust, vision-based systems are generally acknowledged to be flexible and versatile in traffic monitoring applications. Traffic flow rate, average traffic speed, queue duration, and traffic density can all be used to evaluate traffic conditions, which is the main objective of a traffic surveillance system. When it comes to traffic surveillance systems, where efficient traffic management and safety are the primary concerns, vehicle detection and tracking is effective and important. Detecting vehicle and traffic statistics from video frames is a topic we cover in this paper.

There is still room for improvement in this field, despite the extensive study and numerous methods that have been used. To make changes, it is suggested to create a special algorithm for vehicle data tracking and recognition using blob detection techniques and the Gaussian mixture model. By studying the background, we can first tell the foreground from the background in frames. Here, the object is found using the foreground detector, and the area surrounding each found object is defined using a binary calculation. Some morphological operations have been used to accurately identify the moving object and remove the noise. The ultimate tally is then calculated by following the regions and objects that were discovered. The findings are promising; using the Gaussian Mixture Model and Blob Detection methods, we achieved average detection and tracking accuracy of over 91%. This paper introduces a traffic surveillance-based intelligent vehicle counting technique. The three stages of the proposed algorithm are as follows: Moving object segmentation, fragment analysis, and tracking are the three primary stages of processing. Through the use of blob analysis, a car is modelled as a rectangular patch.

The important characteristics are taken out by analyzing the blob of vehicles. Monitoring the minimal distance between two temporal images and comparing the extracted features allows one to track moving objects. Additionally, by examining blobs of vehicles, it is possible to determine each vehicle's velocity as well as the flow of vehicles through a designated region. The outcomes of the experiments demonstrate the capability of the suggested system to deliver timely and beneficial information for traffic monitoring.

There are various techniques for numbering vehicles, including headlight detection and particle filtering. Despite being the state-of-the-art for modelling video backgrounds, Principal Component Pursuit (PCP) hasn't been used for this job yet. This is primarily due to the fact that the majority of the PCP algorithms currently in use are batch techniques with large computational costs, making them unsuitable for real-time vehicle counting. In this study, we suggest using an innovative incremental

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PCP-based algorithm to determine the number of vehicles in top-view traffic video sequences in real-time.

We put our method to the test on a number of difficult datasets, and the results compare favorably to state-of-the-art techniques in terms of both performance and speed: an average accuracy of 98% when counting vehicles passing through a virtual door, a 91% estimate of the total number of vehicles in the scene, and processing speeds of up to 26 frames per second.

## 3. PROBLEM STATEMENT

This project aims to reduce traffic congestion and unwanted long time delays and provides a better approach to this by calculating the density of the traffic at each part of the road and simultaneously provides the best solution in order to reduce the congestion and in some cases to stop giving a green light indication to some roads where there are less number of vehicles.

## 4. EXISTING SYSTEM

Currently, traffic lights operate on a fixed cycle with predetermined time delays between each signal change. However, this system can lead to significant traffic congestion, particularly in areas with high volumes of vehicles. This is because the traffic signal sequence may allocate a green light to a road section with minimal traffic, while a more congested area remains at a standstill.

## 5. PROPOSED SYSTEM

The proposed project presents a density-based traffic control system using reinforced learning to solve this problem. We bring in a slight change to the traffic signal system by making it priority based when there is a huge amount of traffic and then switching it back to the normal sequence after there is less amount of traffic. The system counts the number of vehicles on each part of the road and after the analysis the system takes an appropriate decision as to how much time is to be given the highest priority and the longest delay for the corresponding traffic light.

This algorithm is used to count, detect, and track the different types of vehicles. It determines the vehicle count earlier and suggests alternative routes to the vehicles.

The object detection algorithm operates in every frame. Finally counting the entire vehicle. If vehicle count is less than the threshold it is normal traffic signal switching otherwise the vehicle count is more suggest alternative routes to reduce the time spent.

The complete block diagram representation:

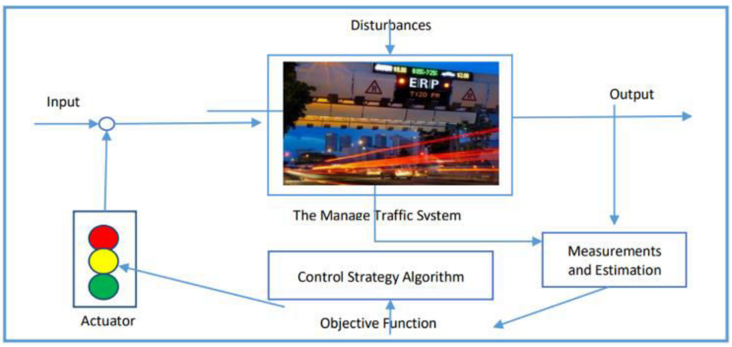


Figure 1: Overall block diagram of proposed system

For each of the vehicles identified in the frame, the model gives the parameters for the location, class, and confidence score. We first locate ROIs in the area for vehicle tracking. We begin tracking a vehicle's position when it is first detected within a ROI and continue to do so until it departs the area. We update the tracking positions of any additional vehicle detections within a ROI that are already being monitored from earlier frames. He events processor module receives all of the results from the preceding module and analyses them to identify important events. Vehicle

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enumeration is one of the event processing module's subtasks.

There is a virtual counting zone within the ROI where the vehicles are counted according to class classification. Other subtasks, like traffic density measurement, accident detection, speed tracking, or traffic flow prediction, can be added to this module to help with traffic management.

## 6. METHODOLOGIES

The majority of image processing techniques apply to video processing, as well as techniques that take advantage of the temporal structure of video data. The objective of the video processing module is to analyze video images from traffic monitoring cameras in order to identify vehicles and then extract information about them, such as their position, class, and direction of travel. It has been used in this study to record videos from on-highway traffic surveillance cameras. The video processing module is then fed the footage to be processed. The first stage is to approach the video frames as images and apply image processing methods to them.

We used OpenCV, an open-source computer vision library created specifically for processing images and video, to read the movie frame by frame. Vehicle detection, Vehicle classification, and Vehicle tracking are the three tasks that make up video processing in this study.

As traffic surveillance applications for vehicle detection rely on quick and precise vehicle detection capabilities, the vehicle detection and classification duties are the most crucial in this framework. As was previously mentioned in the literature analysis, CNN has demonstrated significant improvements in object detection and classification in recent years. In our framework, we used the cutting-edge, real-time object detection system YOLOv3 for this job.

For feature extraction, YOLOv3 employs Darknet-53, a brand-new 53-layer CNN. We required some weights for the feature extraction layers in order to execute the object detection model (convolutional layers). We made use of the weights from a pre-trained model that had been optimized on the COCO dataset [LMB+14] with 80 object classes after being trained on the ImageNet dataset with 1000 object classes.

Although YOLO is very good at classifying and detecting items, it is designed to do so in a single image. The same processes for object detection, classification, and probability scores are repeated for each frame. Its ability to rapidly repeat these steps over a large number of frames gives it an edge over comparable object detection models. The COCO dataset-trained YOLOv3 can analyse 30 frames per second.

We have looked at works in the literature that could perform multi-object tracking because there are multiple vehicles in an image that we need to monitor. The estimation of an unknown number of objects in a film, as well as their individual paths, are both necessary for multi-object tracking.

In order for the traffic surveillance/control system to run securely and dependably, it must automatically detect any events, produce useful data about traffic status, and create or handle alarms. Such a module is crucial to the system's ability to observe and manage events. The vehicle counting sub-module was implemented in this effort, but additional modules may be added in the future.

The centroid of each vehicle's bounding area has been computed and tracked. A vehicle's status is changed from counted = False to tracking = True when it reaches the tracking zone. The subsequent frames track its position after that. Its state is updated to counted = True if it enters the counting zone. a message stating that the car was tallied. Counting of vehicles is done based on type. The vehicle ceases being tracked once it exits the counting zone, and we update its status to tracking = False.

## 7. RESULTS

YOLOv3 is a distinct model created for object recognition using each framework. Bounding boxes are used by the neural network to extract the features and identify the item. The model determines the class of the vehicle from a car, bike, truck, etc. after object recognition. The dynamic traffic signal timer algorithm receives the entire number of vehicles in a lane as input.

The algorithm determines the relativity between the lanes while taking into account the density of every other lane. The green signal timer for a specific lane is determined by the classification of the lane as low, middle, or high vehicle density.

| S.No | Number of vehicles | Green Signal time |
|---|---|---|
| 1 | 15 | 17 sec |
| 2 | 17 | 21 sec |
| 3 | 5 | 6 sec |
| 4 | 20 | 30 sec |
| 5 | 23 | 35 sec |
| 6 | 30 | 43 sec |

## 8. CONCLUSION

This new method makes it easier for cars to move through intersections, which reduces traffic and CO2 emissions, among other benefits. Because video data is so rich, it is crucial to keep up with technological advancements in object detection, classification, and tracking for real-time apps. The development of picture detection methods has been steady, starting with feature descriptors like HOG and ending with deep network-based methods like Faster R-CNN and YOLO. YOLO offers incredibly quick inference speed with a minimal accuracy loss, particularly for lower resolutions and smaller object sizes. Even though real-time inference is feasible, apps that use edge devices still need hardware upgrades for either the architecture or the edge devices themselves. Finally, by using this real-time data from YOLO and sequentially optimizing phases, we have suggested a new algorithm.

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