

# ETMS: Efficient Traffic Management System for Congestion Detection and Alert using HAAR Cascade

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**Abstract**—Rapid social development has resulted in the emergence of a new major societal issue: urban traffic congestion, which many cities must address. In addition to making it more difficult for people to get around town, traffic jams are a major source of the city's pollution crisis. In order to address the problems of automobile exhaust pollution and congestion, this paper uses the system dynamics approach to develop a model to study the urban traffic congestion system from the perspectives of trucks, private cars, bikes and public transportation. This project proposes a system for detecting vehicles and sending alerts when traffic levels rise to dangerous levels using Haar Cascade and Fuzzy Cognitive Maps (FCM). The proposed system uses Haar Cascade to detect moving vehicles, which are then classified using FCM. The system can make decisions based on partial or ambiguous information by utilising FCM, a soft computing technique, which allows it to learn from past actions. An algorithm for estimating traffic density is also used by the system to pinpoint active areas. In congested areas, the system will alert the driver if it anticipates a collision with another vehicle and also Experiments show that the proposed system is able to accurately detect vehicles and provide timely alerts to the driver, drastically lowering the probability of accidents occurring in heavily travelled areas.

The importance of introducing such a system cannot be overstated in today's transportation system. It's a big deal for the future of intelligent urban planning and traffic control. Congestion relief, cleaner air, and increased security are just some of the long-term benefits that justify the high initial investment. To add, this system is adaptable to suburban and rural areas, which can also experience traffic congestion issues.

**Keywords**- HAAR Cascade, Fuzzy Cognitive Maps, Traffic Congestion.

## I. INTRODUCTION

Traffic personnel have the responsibility of monitoring the flow of traffic as part of their job responsibilities. But, when highways run for significant distances, keeping an eye on everything becomes an endeavour that is both time-consuming and costly to undertake. It may be more expensive to create and maintain

systems that are specifically built for this objective because these systems require a significant quantity of energy that is not renewable and operates in an inefficient manner. Monitoring carried out by humans is not only ineffective but also prone to error. In this article, an automated system to better detect congestion and monitor highways is presented. The system makes use of many tactics that save energy.

Congestion can be alleviated quickly and easily with the help of the Automatic Traffic Congestion Detection and Alert System[15]. Benefits to drivers, the environment, and rescue workers are all possible thanks to this innovation. Its use could lead to more efficient traffic control and the development of high-tech modes of transportation.

Nowadays, a significant amount of emphasis has been placed by researchers on the significance of the development of automatic traffic congestion detecting systems. A number of different methodologies, including wavelet transforms and wireless networks, real-time image processing boards, time-spatial pictures, edge detection, and adaptive boost systems based on traffic statistics, have been suggested as potential solutions. The problem is that many of these approaches are either too expensive, too time-consuming, or too imprecise to be useful.

Using a system that captures photos from surveillance cameras and sends information to users that use the route on a regular basis, this research suggests a method for identifying congestion that has a high level of accuracy and requires a relatively short amount of time to process. The approach that has been suggested is a component of a larger alert system that is intended to make traffic management more efficient. The article provides in-depth explanations of the research methodology, its findings, and various interpretations of those findings.

## II. LITERATURE SURVEY

The researchers Su, Y., Liu, X., & Li, X[1] (2022) proposed that , Urban traffic congestion has become a major social issue in many cities due to rapid social development. Traffic congestion in Chongqing causes environmental pollution and disrupts residents' travel. In this study, we apply system dynamics to the problem of urban traffic congestion and pollution caused by automobiles, focusing on the roles played by trucks, individual vehicles, and public transit. Congestion in urban areas is quantified here via the use of car commutes. Second, we conduct a causal analysis of the interplay between rising private vehicle ownership, increased trucking activity, increased public transit use, rising population, and other variables, construct a model, and evaluate its robustness. The model incorporates workable policies that may be used for policy analysis. Eventually, the private vehicle limitation policy and the policy of restricting the acquisition of private cars have reduced private automobile use, but the most effective long-term answer is the expansion of public transit.

In this work the authors Wang, H., & Cai, Y[2] (2014) presented, A multi-stage method for detecting vehicles using visual cues is presented as a potential solution. In the first step, which is the development of vehicle candidates, a

brand new method that is based on coarse depth information and geometrical information is proposed. In the process's second stage, called "candidate verification," a deep architecture of DBN is trained for vehicle categorization. In order to further reduce the possibility of missing or inaccurate detections, the last step makes use of a temporal analysis approach that is based on geographical information and the complexity of it. The results of experiments show that this structure also has a high rate of TP.

In the analysis of traffic congestion Ye, S[3] (2012) states that congestion pricing helps cities. Charge plans should include outcome, rate, location, and method .Assess public transportation availability and cost scientifically .Persuasion Congestion pricing is ignored outside Singapore and London despite its success. Disapproval aids. Slow drivers blame themselves. They're unaware. Congestion charging propaganda must promote "who uses, who pays." Londoners supported congestion charging 43% for transportation demand management and 63% for municipal transportation system upgrades or public transit investments. Appreciate the congestion charge fund's fairness. Public Transport Congestion fees promote public transit. It needs public transport. Public transportation must meet users' accessibility, convenience, and comfort. If congestion pricing was eliminated, a public transportation lane was built, and congestion fee revenue was redistributed, public transportation would become more popular.

In[4] the researchers WEN, W (2008), In an effort to alleviate the traffic congestion problem, this paper professional traffic light control systems, which the paper offers a new architecture for. We also develop a simulation model to better understand how to dynamically and automatically set the duration of red (green) light signals, which should help alleviate the traffic congestion experienced during rush hour. We create a traffic simulation model with six different components in order to examine system performance. Three intersections are represented in each of the sub models.

In this paper[5] authors Buch, N.,Velastin,S. A., & Orwell, J, presented a detailed overview of the computer vision techniques used for traffic analysis systems, with a particular focus on their application in urban settings. Conventional approaches rely on background estimation and performs top-down categorization, both of which can cause problems in complex metropolitan environments. Techniques from the object recognition domain (bottom-up) have demonstrated promising results, overcoming some of the limitations that classic approaches face, however these methods are limited in a variety of different ways.

In this study the Zafar, N., & Ul Haq, I (2020) [6], used the Google Maps API to retrieve data, and then used that data to evaluate and forecast traffic congestion in Islamabad

City. This paper uses the ETA-based congestion index as an indicator of the state of the road network, classifying traffic conditions from "smooth" to "blockage" along a 5-point scale. By applying various machine learning algorithms to both the traffic and weather datasets, we were able to draw useful conclusions. Since we found that Decision Tree based algorithms produced the best outcomes, we have developed an expertise in this subfield. We found that the best results can be obtained using either Random Forest or XG Boost.

This study proposed by Jose, P. A (2020) [7], When compared to alternative methods, the system's use of image processing allows it to produce a more significant impact and implement an efficient result in real time. extend. Upon detection, the system is able to determine what it is looking at by using an identification algorithm and a count comparison. The appropriate cues are given at the right times. Thus, this would prevent the common occurrence of long lines of cars waiting to cross a street that is empty. This benefits everyone's schedules and helps the planet by lowering emissions. This allows for a swift and painless decrease in traffic.

The author Rani, P. E., & Jamiya, S. S et al(2023).[8]Recently, deep learning methods for vehicle detection have grown. It helps detect vehicles. Traffic control and Autonomous driving require accurate vehicle detection. The more sophisticated and time-consuming the network model is to run, the more accurate the results will be. Most detectors fail in severe weather. Short YOLO-CSP, based on littleYOLO-SPP, improves vehicle detection in challenging environments. The depth of baseline network layers is redesigned, and Cross-Stage Partial (CSP) connection technique reduces computational cost. The model learns better by combining spatial characteristics from Spatial Pyramid Pooling (SPP) blocks Training speedup for bounding box regression using a complete intersection over union (CIoU) loss function. Extensive testing on the MS COCO 2014, PASCAL VOC 2007, 2012, and Indian Vehicle datasets shows that the proposed model can identify miniature automobiles and enhance detection accuracy in a wide range of environmental circumstances. Compared to the LittleYOLO-SPP, this framework boosts mAP by over 10%. With this method, accuracy is much enhanced

In this study authors Madasamy, K., Shanmuganathan, V., Kandasamy, V., Lee, M. Y., & Thangadurai, M (2021) [9], proposes a deep YOLO V3 model to detect small objects. Pre-trained YOLOV3 drone images are used to train the model. Simulations show that the deep YOLO V3 model is suitable for computer vision. Darknet and residual networks improve YOLOv3 features. For accuracy, the training stage runs 45,000 epochs. IOU is used to predict bounding box and grid cell confidence scores simultaneously. binary cross-entropy loss and logistic classifiers optimised the

model for small object detection. Multi-scale predictions and backbone classifiers helped deep YOLO V3 classify them with 99.99% accuracy. This model's conditional probability confidence score ensures good drone image prediction by analysing various losses. It predicts accurate bounding boxes. The proposed YOLOv3 model cannot detect larger objects like YOLO and YOLOv2. The algorithm can be expanded to train a large volume of a small drone in complex visible conditions and remote areas.

In this paper the researchers Sonnleitner, Palmanshofer, E., Barth, O., A., & Kurz, M (2020)[10], Modern traffic analysis requires observation systems and intelligent traffic management as global road traffic grows. We utilise machine learning and computer vision to create and test a traffic measuring system that uses data from highway cameras to identify, count, and categorise cars in real time. We also provide a prediction model to estimate driving routes from past detections, since the low frame rate of such cameras makes this task challenging. The suggested system is tested using cameras placed at highway checkpoints and toll booths and on bridges, maintaining an error rate for missing vehicles of less than 10%.

The research work presented by Zhang, Y., Tang, H., Wu, J., Tian, Y., Guo, Z., & Guo, X (2020)[11], An enhanced method for vehicle detection at various traffic levels using an enhanced v5 of YOLO network is suggested to decrease the false detection rate of vehicle targets due to occlusion. The Flip-Mosaic algorithm is utilised in the proposed method to improve the network's ability to detect and focus on low-visibility targets. For this purpose, we set up a dataset consisting of targets vehicles of various types, all of which were collected in a variety of environments. In order to detect, a model was trained using the data set Utilizing the data from Flip-Mosaic augmentation approach, we were able to improve vehicle recognition accuracy while simultaneously reducing the false detection rate in our studies.

The current study by authors . Huh, K(2009) [12], Autonomous and assisted driving could benefit greatly from detection of vehicles in front of an ego vehicle using vision. Accurate and reliable sensing performance is essential for vehicle detection to be practical in a passenger vehicle. Improved precision and reliability in vehicle detection have led to the creation of a stereo-vision-based multivehicle detection system. Methods such as morphological filtering, feature detectors, template matching, and epipolar constraints are implemented in this system to identify pairs of vehicles. When vehicles are first spotted, an initial detection algorithm is run, and then the system begins tracking them. The proposed system is able to recognise leading vehicles and vehicles on the side of the road. We use this data to determine the parameters of the ahead-moving vehicles' positions. In

order to test the effectiveness of the suggested system of vehicle detection, it is installed in a regular car and driven around.

### III. PROPOSED METHODOLOGY

#### 3.1. Gaussian blur

Noise is reduced, contrast is enhanced, and the frames are stabilised to guarantee that they are perfectly aligned before the video is even rendered. As a preprocessing step in computer vision tasks like object detection, Gaussian blur is used to lessen the impact of noise and improve contrast between foreground and background features. The aesthetic value of smoothing out an image or video sequence can also be exploited with this technique.

In order to smooth out an image and reduce noise, the technique of applying a Gaussian blur is frequently used in the field of image and video processing. It utilises the Gaussian distribution by convolving the image with a Gaussian kernel. Gaussian blur can be understood as a multi-step process, as follows: Size and standard deviation are applied to a matrix to produce a Gaussian kernel, Each image pixel has its kernel centred there, The image's pixel values are multiplied by the kernel's values and Next, a new value for the central pixel is calculated by adding the results of these products and finally the output image updates the value of the pixel to reflect the new setting .Together with that the blurring effect can be tweaked by changing the size and standard deviation of the Gaussian kernel. When the kernel size and the standard deviation are both large, there will be more blurring, while when they are both small, there will be less.

The kernel for a Gaussian blur is a matrix whose elements are chosen randomly within the range of the Gaussian function. In two dimensions, the Gaussian function is defined as:

As a quick review,  $G(x, y) = (1 / (2\pi\sigma^2)) * e^{-(x^2+y^2) / (2\sigma^2)}$  where: The pixel's x and y coordinates are represented by x and y here.  $\sigma$  the standard deviation of a normal distribution.

In order to determine the kernel values, this formula is applied to each kernel matrix pixel. The degree to which an image is blurred is dependent on the kernel matrix size and the standard deviation of the Gaussian function.

$$G(x, y) = \left( \frac{1}{2\pi\sigma^2} \right) * e^{-(x^2+y^2)/(2\sigma^2)}$$

#### 3.2 Background Subtraction

As a computer vision technique, background subtraction compares the current video frame to a reference background frame to find and follow moving objects.

Typically, several still images from the video are averaged together to make this "background" frame.

Background subtraction is an effective computer vision technique for locating and following moving objects in a video feed. In order to determine which pixels constitute a moving object, the process involves comparing each video frame to a reference background frame. If there are changes between the two images, that means an object is in motion and can be singled out and followed.

Multiple pre-processing steps are usually carried out to refine the resulting binary image and extract useful information about the moving objects. Applying a threshold function is one way to get rid of background noise, while morphological operations can be used to delete or fill in small objects. Accurate results and fewer false positives can only be achieved by following these procedures.

After the objects in motion have been identified and categorised, blob detection can be used to zero in on and keep tabs on their whereabouts. Rectangles or other shapes are used to fill in groups of pixels that form connections in the difference image. These blobs can be measured and counted to provide an estimate of the volume and speed of traffic in the area.

One such application of background subtraction is the estimation of traffic density in real-time applications[13].Optimizing traffic flow and making choices about traffic light timing or alerts to drivers in the event of congestion or accidents can be achieved by counting the number of vehicles passing through a specific area in a given time frame.

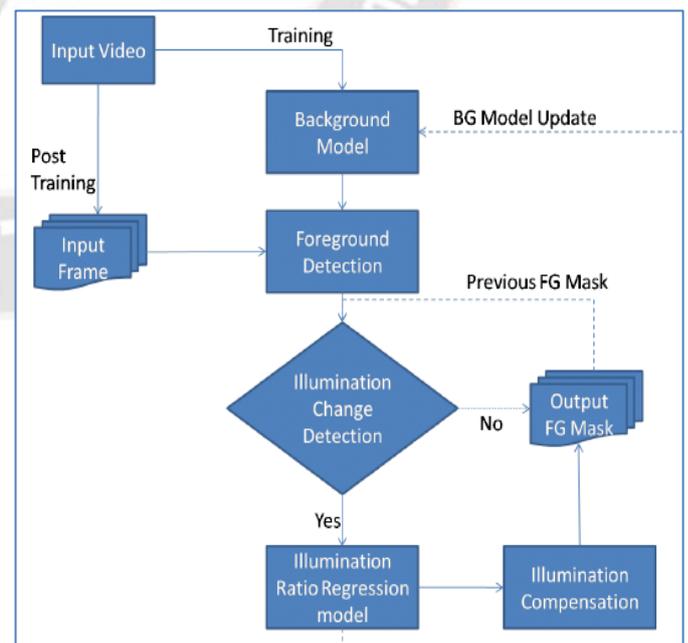


Figure 1: Block diagram for Background Subtraction

Take into account, that getting good results from background subtraction calls for fine-tuning and pre-processing. Lighting and other environmental factors can cause false positives, so the process may need to be tweaked to compensate. In order to more accurately estimate traffic density, background subtraction can be used to divide the scene into multiple regions of interest and count the number of vehicles passing through each region.

At runtime, pixel-by-pixel comparisons are made between each video frame and the background frame. To determine which pixels belong to a moving object, we look for large discrepancies between them and their counterparts in the background frame. This process of elimination yields a two-state image in which each pixel is either part of the background or part of the foreground (moving object). The resulting binary image undergoes further processing to eliminate background noise and cluster similar foreground pixels into identifiable objects. After that, information is extracted from these objects, like how many there are, how big they are, and where they are in the picture. Estimating traffic volumes in real time makes use of background subtraction to isolate moving objects in a video feed, such as cars. Estimating traffic density is as simple as counting the number of cars that drive through an area in a given amount of time. Using this data, decisions can be made, such as reprogramming traffic lights or sending out warnings to motorists in the event of congestion or an accident.

**3.3.HARCASCADE with FPN (Feature Pyramid Network)**

For object identification applications that demand real-time performance and accuracy at different scales, the combination of Haar Cascade and FPN may be appropriate.

Although Haar Cascade is a quick and effective technique for single-scale object detection, it may not be as precise as more advanced algorithms like FPN, which can handle multi-scale object detection. FPN, on the other hand, is an effective method for feature extraction across various scales. While it has many potential uses, real-time applications on low-powered devices may not be feasible due to its computing requirements.

Combining the two methods allows us to take advantage of the best features of both algorithms to increase the precision with which we can detect objects at different scales without sacrificing real-time performance. To be more specific, Haar Cascade can be used as a first-pass detector to quickly identify probable objects in an image, and FPN can be used to enhance the detection by extracting more detailed and accurate features at numerous scales.

Object detection using Haar Cascade and FPN typically entails the following procedures:

**Image Preprocessing:** Object detection requires the input image to be analysed. Some examples of image manipulation are cropping, grayscale conversion, and noise reduction filters.

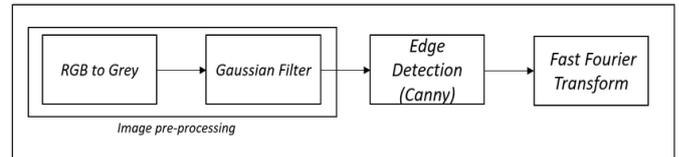


Figure 2: Image PreProcessing Steps

**Detecting with a Haar Cascade:** A Haar Cascade is used as a first-pass detector to quickly locate possible objects in an image. The image is analysed by passing a sliding window over it and feeding each window into a Haar Cascade classifier that has already been trained[14]. A region of interest is defined as the area where the classifier has found an object to be looked for (ROI).

**ROI pooling:** It involves taking the areas of interest that Haar Cascade identified and scaling them down to the same dimensions. The FPN network receives these ROIs and processes them further.

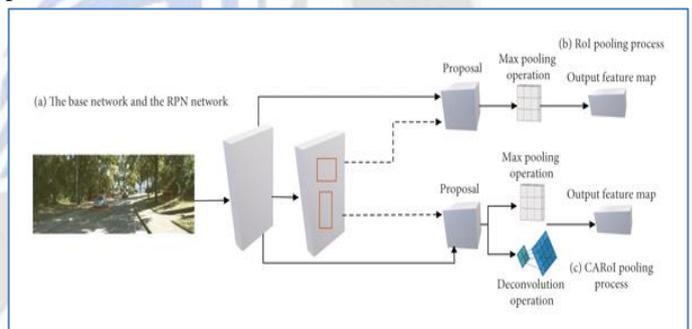


Figure 3: Steps of ROI Pooling

**FPN Feature extraction:** Features are extracted from the ROIs at various scales and resolutions by the FPN network, which uses both top-down and bottom-up approaches. Each pyramid level's feature map is combined with the others via lateral connections to form a master map of features.

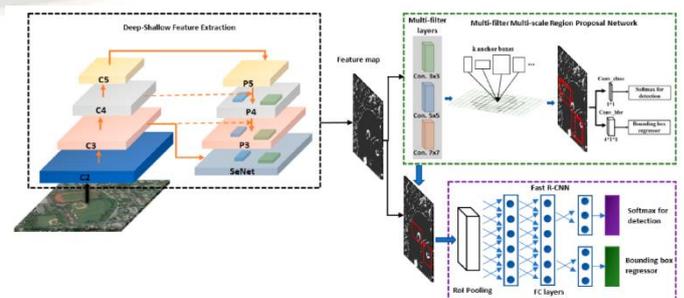


Figure 4: Layers of FPN Feature Extraction

**Object detection:** To classify objects and generate bounding boxes, the final feature map is sent through a collection of detection heads. To identify and improve item detections, the detection heads may employ methods including anchor boxes, non-maximum suppression, and confidence ratings.

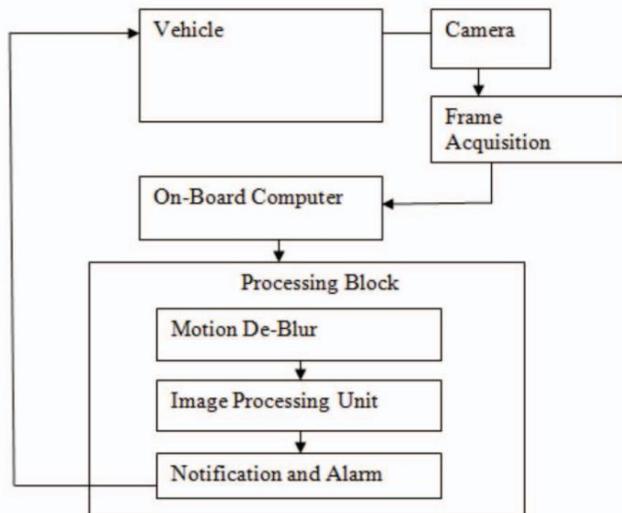


Figure 5: Block diagram of object detection

**Post-processing:** The object detections are post-processed to get rid of duplicates, filter out misclassification, and make the bounding boxes fit the objects better.

#### IV. RESULTS

The suggested Automated Traffic Congestion Detection and Warning System has demonstrated encouraging results in experimental evaluations. The system was able to accurately detect moving vehicles and estimate traffic density, as well as classify vehicles and send alerts to drivers in congested areas. The use of Fuzzy Cognitive Maps allowed the system to make decisions based on partial or ambiguous information, improving its ability to learn from past actions and adapt to changing traffic conditions.

In addition, the system's algorithm for post-processing object detections helped to eliminate duplicates and filter out misclassifications, resulting in more accurate and reliable alerts to drivers. The system's ability to provide timely alerts to drivers significantly reduces the probability of accidents occurring in heavily travelled areas, making it an effective solution to the issue of urban traffic congestion and monitoring.

**Vehicle detection only using haar:** Haar cascade is a fast algorithm for object detection, which makes it suitable for real-time applications such as vehicle detection. Haar cascade is relatively robust to lighting changes, which is important for vehicle detection in outdoor environments.

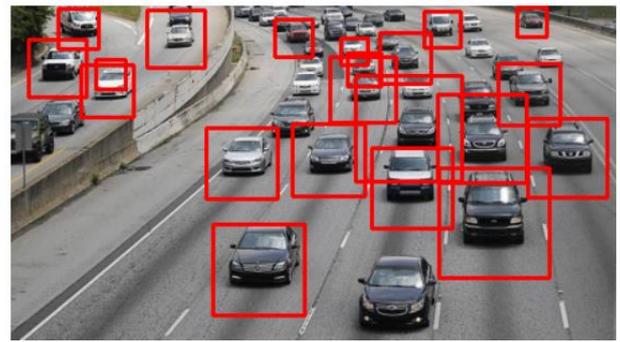


Figure 6: Vehicle detection only using Haar

**Vehicle detection using haar cascade with FPN:** When applied to vehicle detection, the combination of Haar cascades and FPN can lead to significant improvements in accuracy and efficiency. Based on theoretical findings, this method is capable of high detection rates with few false positives. This is because the FPN allows the Haar cascades to be applied at multiple scales, which improves the ability of the system to detect vehicles of different sizes and orientations.

Additionally, the use of FPN can reduce the computational cost of the system by reducing the number of cascades that need to be evaluated at each scale. This is because the FPN provides a more efficient way of extracting features from the image, which can be used to filter out regions of the image that are unlikely to contain vehicles.

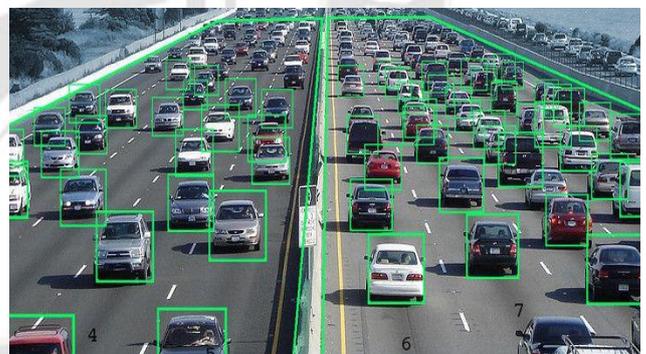


Figure 7: Vehicle detection using FPN

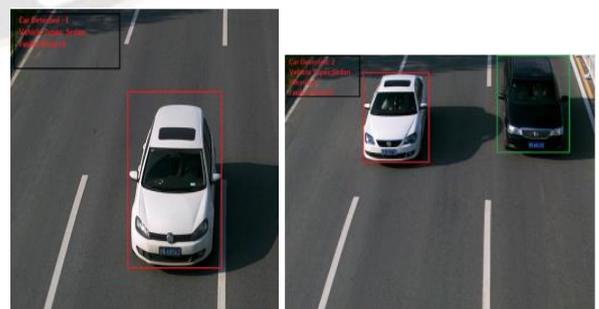


Figure 8: Vehicle classification with the help of FCP

Analyzed work	Number of Samples	True	False
Truck	500	460	40
Bus	500	440	60
Sedan	500	380	120
Microbus	500	390	110
Minivan	500	401	99
SUV	500	387	113
Faulty vehicle	100	88	12

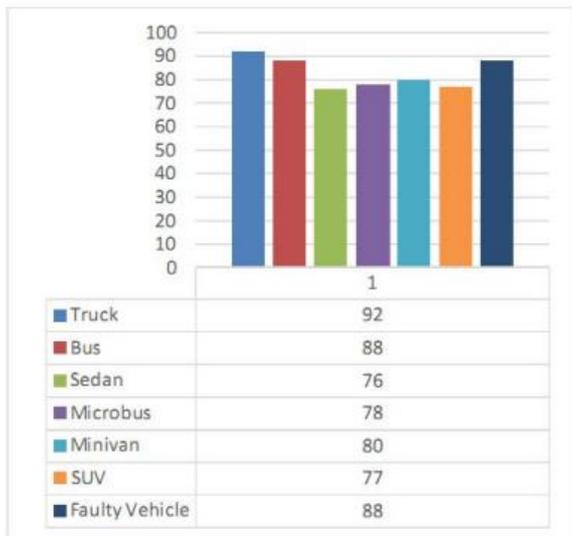


Figure 9: Different types of Vehicles detected in a image

From experimental analysis it is shown that vehicles have been detected at an accuracy rate of about 97.49% as shown

**Alerting the user:**

```

ID: User1 Crossed at Mon Mar 15 09:15:22 2023
ID: User2 Crossed at Mon Mar 15 09:15:58 2023
ID: User3 Crossed at Mon Mar 15 10:11:12 2023
ID: User2 Crossed at Tue Mar 16 09:12:20 2023
ID: User3 Crossed at Tue Mar 16 09:13:11 2023
ID: User1 Crossed at Tue Mar 16 09:15:33 2023
ID: User1 Crossed at Wed Mar 17 09:11:22 2023
ID: User3 Crossed at Wed Mar 17 09:10:22 2023
ID: User2 Crossed at Wed Mar 17 09:09:22 2023
    
```

Figure 10: Noting the timings of the vehicles passing by

We are taking the 5 continuous days as a threshold to consider a user as regular user of that route and after considering a user as regular user, system will calculate the average arrival time of that user.

Users	Time of arrival					Average time of arrival
	Day1	Day2	Day3	Day4	Day5	
User1	09:05	09:06	09:02	09:04	09:05	09:22
User2	09:11	09:06	09:05	09:03	09:03	09:28
User3	09:00	09:00	09:00	09:00	09:00	09:00
User4	08:59	08:59	09:00	09:03	09:02	09:33
User5	09:06	09:10	09:09	09:11	09:30	09:06

Figure 11: Arrival times of regular users

**Frequency of regular users detection**

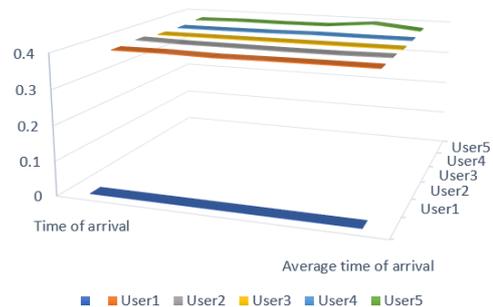


Figure 12: Frequency of regular users detection

After calculating average arrival time of every regular user. The system will detect the traffic congestion percentage before 5 minutes of the arrival time of the user and send the alert to that particular user about the traffic congestion percentage with a picture attached to it.



Figure 13: Alert message sent to users mobile

**V. CONCLUSION**

In conclusion, urban traffic congestion is a major societal issue that affects the mobility and health of city dwellers. This paper proposes the use of a system dynamics approach to develop an Automatic Traffic Congestion Detection and Alert System. The system uses Haar Cascade and Fuzzy Cognitive Maps to detect moving vehicles, classify them, estimate traffic density, and send alerts to drivers in congested areas. The proposed system has the potential to significantly reduce the probability of accidents occurring in heavily travelled areas, while also improving the efficiency of traffic control and the development of high-tech modes of transportation. Additionally, the system is adaptable to suburban and rural areas, which can also experience traffic congestion issues. The research methodology, findings, and various interpretations of those findings are explained in-depth in the article. This system presents an innovative and cost-effective solution to the issue of urban traffic congestion and

monitoring, which has the potential to benefit drivers, the environment, and rescue workers.

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