# Identification of Vehicle Through Video Motion using Haar Cascade Classifier

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***Abstract***

*To reduce the congestion in the road and to make improve the traffic parameters in the road lanes. Smarter ways are developed for analysing traffic and to take a appropriate solution. Analysis of traffic is the process to identify or to count the number of vehicles in a particular time period. So peoples are developing the solutions for the problem but most of them were involved by sensors. Even though this gives a good solution but this are not budget friendly one. This paper the methodology followed here is counting the number of vehicles from the video ,this involves three process they are analysing ,identifying and counting the result. For this the algorithm we proposed is Haar Cascade Classifier for identifying vehicles. The identification can be done in straight lane ,cross lane and in the T-junction traffic areas.*

***Keywords:*** *Vehicle identification,Traffic analysis,Haar Cascade Classifier.*

## 1. Introduction

Vehicle recognition and measurements in parkway observing video scenes are of extensive hugeness to heavy traffic the board and control of the expressway. With the famous establishment of traffic observation cameras, a huge database of traffic video film has been gotten for investigation. For the most part, at a high review point, a progressively far of street surface can be considered. The item size of the vehicle changes significantly at this survey edge, and the location precision of a little article far away from the street is low. Even with complex camera scenes, it is fundamental to successfully take care of the above issues and further apply them. Right now, center around the above issues to propose a reasonable arrangement, and we apply the vehicle identification results to multi-object following and vehicle counting. In this first the video is taken and then converted it into frames using the open cv. After this then the prediction process is done by, So as to check vehicles we first should have the option to identify them in a

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picture.. Be that as it may, on the off chance that we think about that as a picture is only a variety of numbers (one worth for every pixel), we might have the option to utilize this to figure out what a vehicle resembles and what we'd hope to see when there isn't a vehicle there. We can utilize OpenCV to take a gander at how the estimation of specific pixels changes for these two conditions, as appeared in the picture underneath. We would then be able to utilize this data to figure out what is foundation and what is a vehicle, insofar as we have a reasonable foundation picture ie a variant of our scene without any vehicles in it. For the situation appeared here it is hard to acquire an unmistakable picture, anyway we can utilize OpenCV to average between a few casings and make our experience picture. Since we have a foundation picture, or a variety of default/foundation esteems, we can utilize OpenCV to distinguish when these qualities go over a specific worth (or 'limit esteem'). We accept this happens when there is a vehicle inside that pixel, thus use OpenCV to set the pixels that meet the edge criteria to most extreme splendor (this will make recognizing shapes/vehicles simpler later on). The pictures above show the pixels that meet the edge criteria (left) and the subsequent shapes in the wake of setting those pixels to greatest worth/splendor (right). Likewise featured (green) is holes in our items where dull territories (windscreens, barbecues and so on) may not meet our edge criteria. This could cause an issue later on so we attempt to fill in these holes utilizing the disintegration and expansion capacities from the OpenCV library. When we are content with the shapes made, we should then check the shapes (or forms) to figure out which are generally similar to be vehicles before expelling those that are most certainly not. We can do this actualize a condition where we are possibly keen on the distinguished forms in the event that they are over a specific size. Note that this wilsssl change contingent upon the video feed. The kept forms would then be able to be passed to the Vehicle Counter (HCC) and then final target can be identified.

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## 2. Proposed Work

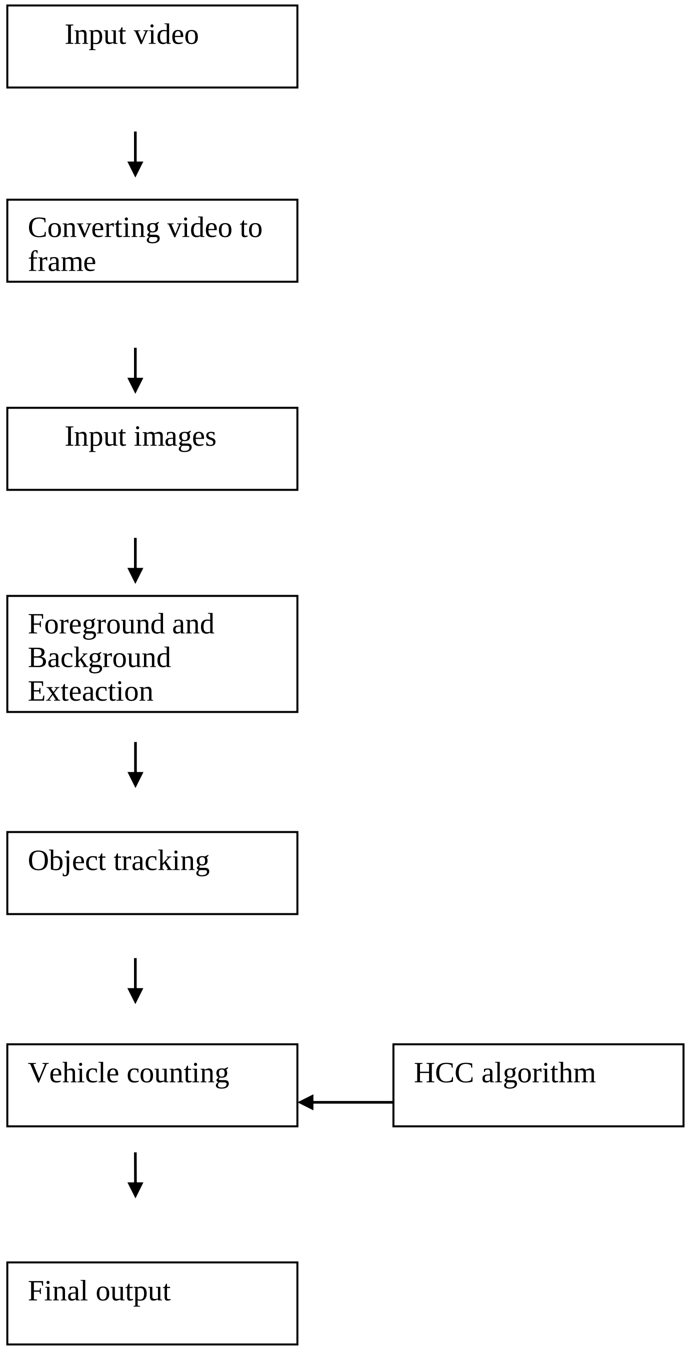


**Figure 1. Proposed Architecture**

The imposed method for vehicle counting system uses the video data input as a standard from the traffic surveillance camera. Performing the operation over the processed frames obtained from the video to find the number of vehicles in the scene. In every frame Gaussian mixture model is used to find the background subtraction by tracking the objects in the target region.


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## 3.Methodology

### 3.1. Vehicle counting process:

The target vehicle counter process consist of two class objects, one has named Vehicle which is used to separate every target vehicle object, and the next one is Vehicle Counter which identifies or finds out which 'vehicles' are considerable for subjecting to the process before identifying them. Vehicle are designed with the patterned shapes and provides data about each separate item, for example, a continuous in each edge, how many number of edges it has identified in, regardless of what we have verified the vehicle yet . We can moreover procure the last position and the circumstance before that to calculate several characteristics inside our Vehicle Counter computation. Vehicle Counter is progressively unusual and fills a couple of requirements. We can use it to choose the vector advancement of each followed vehicle from edge to plot, giving a marker of what improvements are legitimate and which are fake matches. We do this to guarantee we're not erroneously organizing vehicles and as needs be getting the most accurate check possible. At the present time, simply expect vehicles going from the most noteworthy purpose of the image to the base right hand corner, or the pivot. This suggests we simply have a particular extent of permissible vector improvements reliant on the point that the vehicle has moved –this can be seen from the pictures underneath. The object identification on the left side shows the normal vector improvement and the object identified on the left shows a graph of difference moved slightly to that point - those taken as permissible improvement.

#### 3.1.1. Tracking:

The main task of the vehicle tracking is not to take over the time consuming process on the certain frames of image. In this our tracking algorithm is to detect the target images (ie)o objects from the image frames F(i).At the frame F(i+1) we only track the objects o. In order to make this method efficient we define the window size in the defined contour. The following activity can be completed in the following K outlines after t outline, $K \geq 1$. In the wake of following through K outlines, the Road Model and vehicle discovery framework can be applied to picture outline t+K+1 once more. The pattern of identification and following can be rehashed all through the whole picture. grouping. Nonetheless, so as to abstain from missing new approaching vehicles into the scene, the following ought to be applied rarely and K ought to be little.

#### 3.1.2. Background identification and removal:

Shadows may cause significant issues in video- based vehicle recognition and classification.Since shadows keep a similar development design as per that of vehicles, shadows stretched out to neighboring paths can without much of a stretch produce bogus positives. Besides, shadows cast more than a few vehicles can bring about misclassification of vehicles because of the blending moving masses of these vehicles. Consequently, shadow ID and evacuation is among the couple of most significant issues for vehicle recognition and order. Albeit many shadow recognition appraoches were proposed, they were generally compelled by administration conditions in practicality. Therefore, the creators built up another shadow distinguishing proof and evacuation approach for vehicle identification and classification. The significant commitment of the new calculation is to use

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the semitransparent qualities of shadows in consistent picture groupings to separate shadow-strong highlights and afterward, viably segregate them from vehicles. Rather than attempting to recognize the shadow locale dependent on grayscales of pixels, this strategy distinguishes regions with not many edges or edges with high similitude to the foundation edges in a moving mass as shadow areas. The Canny edge identification technique is used to create an edge picture of each moving mass.

#### 3.1.3. Applying harr cascade:

The framework created includes three fundamental advances. Right off the bat, the fundamental vehicle targets are created with Haar-course classifier.Only the applicants that go through all the stages are delegated positive what's more, the ones that are dismissed at any arrange are named negative. The advantage is that most of the beginning applicants are really negative pictures, which for the most part can't pass the initial barely any stages. This beginning time dismissal accordingly significantly diminishes the generally speaking registering time After the principal organize is finished, the target approval is utilized, which is based on vehicle light component. Since there can be a few bogus positives inside the pictures yield by the main phase of the framework, which originates from the restriction of the preparation set. To lessen the bogus alert rate, the calculation utilizes the before referenced vehicle light component. Notwithstanding the shape, surface or shade of the vehicle, they all offer a normal element – they all have red lights in the back. Along these lines expecting that the vast majority of the bogus positives identified by the main stage don't have such a include, the outcome would thus be able to be refined. Finally, the outcomes are additionally refined by Kalman following of the items. The 5 principle thought of this progression depends on a three- organize speculation following. Right off the bat, on the off chance that a recently distinguished zone shows up and goes on for in excess of a specific number of steps, a theory of the article is produced. At that point it is anticipated where the following area of the article ought to be.

## 5. Result and Discussion

#### Performance metrics:

After completing the usual Feature work, Selection, and of course, implementing a part and getting some output in forms of a appropriate value, the next step is to find out how accurate is the model based on some metric test datasets. Different performance metrics are used to evaluate different Algorithms. For now, we will be focusing on the ones used for Classification problems. We can use classification performance metrics such as Accuracy, Precision, efficiency.

#### Precision:

Precision, or the positive predictive value, refers to the fraction of relevant instances among the total retrieved instances.. We can easily calculate it by confusion matrix with the help of following formula.

#### Efficiency:

We can calculate the efficiey by the formula


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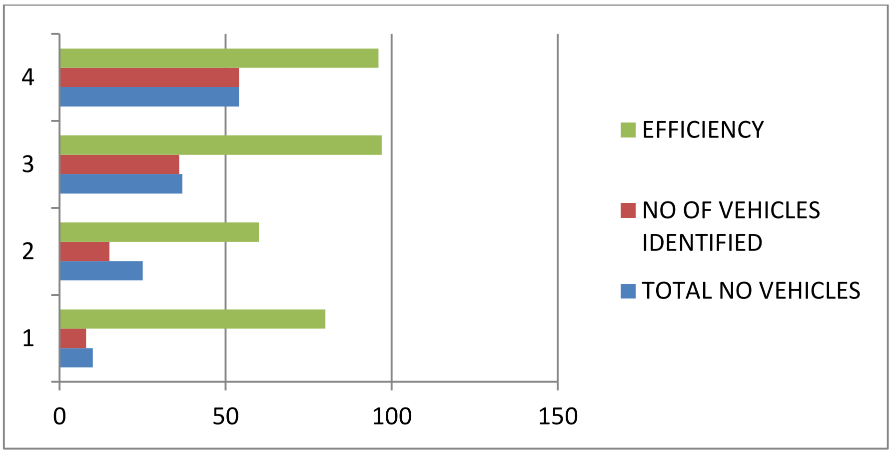
$$E = \frac{TI}{T} x100$$

E-Efficiency

TI-Total number of target vehicle identified

T-Total number of vehicle in the dataset

| S.NO | TOTAL NO OF VECHICLES | TOTAL NO OF VECHICLES IDENTIFIED | EFFICIENCY |
|---|---|---|---|
| 1 | 10 | 8 | 80% |
| 2 | 25 | 15 | 60% |
| 3 | 37 | 36 | 97% |
| 4 | 54 | 52 | 96% |




## 6. Conclusion

Our underlying exploratory outcomes shows that the created strategy (i.e.identifying vehicle and afterward following it) is successful for finding the objective vehicles however it is tedious one. The most exceedingly awful issue with KCF is by all accounts its time consuption. Thus, we plan to build up another calculation approach in which following is done in a productive mannner. We are additionally taking a shot at upgrades of the following step dependent on abusing the criticism originating from a few significant level guidelines. With respect to vehicle discovery, there can be still a few over-division impact when vehicles are too large as for square size. Models aretransports or, at the point when pictures are essentially influenced by point of view, vehicles near the cameras. To manage this issue we are actualizing a point of view calculation so as to evaluate movement accurately if there should arise an occurrence of far and approach vehicles. Also, our future work will address vehicle recognition and

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following in night pictures.

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## References

[1] J. Zhang, F.-Y. Wang, K. Wang, W.-H. Lin, X. Xu, and C. Chen, ''Datadriven intelligent transportation systems: A survey,'' IEEE Trans. Intell. Transp. Syst., vol. 12, no. 4, pp. 1624– 1639, Dec. 2011.
[2] A. M. Pereira, ''Traffic signal control for connected and non-connected vehicles,'' in Proc. Smart City Symp. Prague (SCSP), Prague, Czech Republic, May 2018, pp. 1–6.
[3] Y. Liu, B. Tian, S. Chen, F. Zhu, and K. Wang, ''A survey of vision-based vehicle detection and tracking techniques in its,'' in Proc. IEEE Int. Conf. Veh. Electron. Saf., Jul. 2013, pp. 72–77.
[4] L. Juan and O. Gwon, ''A comparison of SIFT, PCA-SIFT and SURF,'' Image Process. Pattern Recognit., vol. 3, no. 4, pp. 143–152, 2009.
[5] N. Dalal and B. Triggs, ''Histograms of oriented gradients for human detection,'' in Proc. CVPR, Jun. 2005, pp. 886–893.
[6] L.D.Pizzo,P.Foggia,A.Greco,G.Percannella,andM. Vento,''Counting people by RGB or depth overhead cameras,'' Pattern Recognit. Lett., vol. 81, pp. 41–50, Oct. 2016.
[7] "Rich feature hierarchies for accurate object detection and semantic segmentation" in 2014 IEEE coference by Girshick, R., Donahue, J., Darrell, T., Malik, J.
[8] "Object tracking using sift and shift features" in Proc.Lett by Zhou,H,.Yuan,Y.,Shi.
[9] "Traffic-sign detection and classification in the wild".In 2016 IEEE conference by Zhe, Z., Liang, D., Zhang, S., Huang, X., Hu, S.
[10] "Cascade object detection with deformable part models", In IEEE Conf in 2017 by P. F. Felzenszwalb, R. B. Girshick, D. McAllester.
[11] "You only look once: Unified real-time object detection" in IEEE conference by J. Redmon, S.Divvala, R. Girshick, A. Farhadi.
[12] "Soft-NMS—Improving object detection with one line of code" in IEEE conference by N. Bodla, B. Singh, R. Chellappa, L. S. Davis.
[13] "Image-based vehicle tracking and classification on the highway," in ICGSC in 2017 by L. Jin- Cyuan.
[14] "A model-based vehicle segmentation method for tracking," in IEEE international conference in 2016 by S. Xuefeng and R. Nevatia.

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