Comparative Analysis for Vehicle Detection and Counting System Using Machine Learning

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Abstract : This paper describes a system for detecting and counting the number of vehicles on roads and highways using multiple techniques for extracting image or video features. Globally, the system merely requires a video clip captured by a multitude of static cameras mounted on roads and highways. The ability to recognise and identify a car in a video has proven to be the most difficult and presents numerous difficulties. Some issues may be associated with image processing, such as determining the number of vehicles in an image without human intervention. Where some vehicles can be excluded temporarily or permanently by other vehicles, making detection challenging or impossible. The four phases of the system described are: 1. The variable background subtraction 2. picture segmentation 3. vehicle detection a count of vehicles The need for this in vehicle detection and counting is particularly beneficial for traffic surveillance and many other purposes. Important system capabilities include the ability to identify and count vehicles. The capacity to demonstrate that the system will deliver output with the highest degree of accuracy.

Keywords : Traffic Surveillance, Feature Extraction, Background Subtraction, Segmentation, Detection, Counting, Computer Vision, and Computer Vision.

I. INTRODUCTION

These vehicles' surveillance systems were analysed in this study. The classification of vehicles is an essential component of traffic management software. Then, it is prudent to identify the detected vehicle, as this permits multiple questions to be asked when the vehicle is look over, such as "When did this vehicle pass by or where did it go?" Due to these numerous factors, vehicle classification has numerous applications for traffic flow control, including vehicle counting, vehicle type detection, etc.

In recent years, the number of surveillance systems has increased due to technological advancements and decreased production costs, and the video cameras in these systems have a very high level of intent. As a result, enlarge video sources generated a staggering amount of data that must be reviewed, analysed, and interpreted, but the volume of data is too great for human operators to examine. Consequently, the analyzers are likely to use intelligent image processing technology, which is a crucial component of the artificial intelligence system used to interpret the environment. Before using this environmental data, it must always undergo the interpretation processes required for artificial intelligence. In general, these steps consist of assembling the data, i.e., image, video, etc., analysing it, and transferring it to various forms so that the computer interpreter or computer vision can understand it.

II. LITERATURE SURVEY

Multiple Intelligent vehicle detection and counting systems have been developed as a response to daily traffic congestion issues. The various techniques for blob analysis, background subtraction, image enhancement, sensor-based systems, and image segmentation. [1] Consequently, neural networks are used for object detection and pedestrian counting in order to determine their speed with static cameras and their number with neural networks.[3] night vision functionality [4] Additionally, numerous nations have installed pedestrian detection cameras. [5] To count the number of vehicles, we must create software that accepts video as input and processes video files efficiently. [6] In addition to video frame and image segmentation, vehicle counting and detection are also supported. [7] the application of blob analysis to traffic surveillance. [8] A convolution neural network, an alternative method for counting and detecting vehicles, would yield the most accurate results in real time. [9] In addition to virtual coils and CNN, it may be possible to achieve accurate results.[10] Due to the aforementioned research, the detection and counting of vehicles has reached a very precise level. [11] In addition to the virtual collector and morphological operation, vehicle detection and counting on roads and highways requires background subtraction.

III. ARCHITECTURE OF THE SYSTEM

This section will outline the steps necessary to create a system that is capable of detecting and counting vehicles in a video clip. Let's analyse the system's flow and learn about each component and the various techniques we employ.

A. Architecture

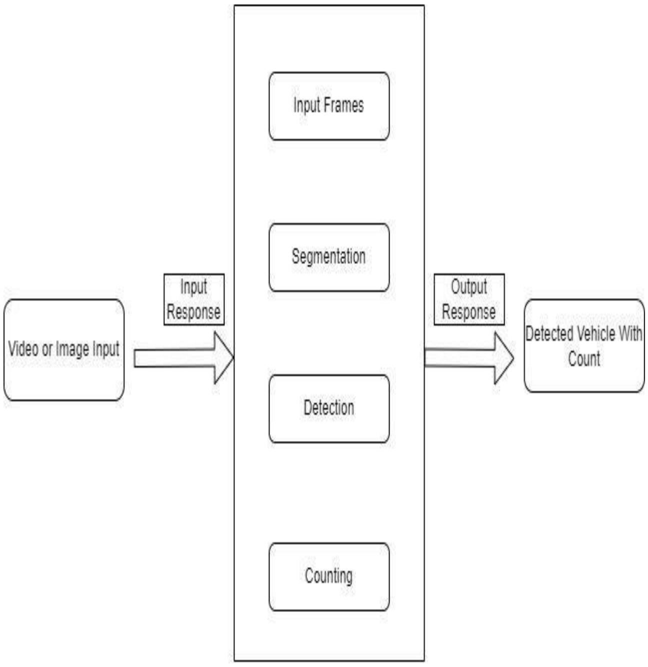

Figure 1. Flow chart for vehicle detection and counting

When the system reads the video input, multiple segmentation techniques are applied. Figure 1 provides an overview of vehicle counting and detection from a video frame. The system consistently utilises existing video frames. The reference frame of a video is always the initial frame. Frames that follow are considered input frames. After comparing the images, the backgrounds are removed. If the vehicle exists within the input frame, it will be kept. Utilizing techniques such as the adaptive background method, a vehicle can be detected. In the background subtraction algorithm, we assume that the first frame of each video clip represents the background. Figure1 depicts the proposed architecture of the system. The Video sequence is then read and converted into individual frames. Initially, the difference between frames is calculated using two distinct variables. Next, the differences are compared, and then pixels with identical values are eliminated. Post-processing is the fourth phase of vehicle detection, performed on the image received in the third and fifth steps. And the final step is vehicle counting.

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B. Background Subtraction

Background Subtraction is a technique for removing moving things from a video and replacing them with the foreground image. Foreground detection, also known as background subtraction. It is an indispensable image processing technique. Using background subtraction, it is possible to identify the location and details of objects. The foreground image is then created by subtracting the background, as shown in figure b. The classification method that utilises machine learning can be divided into three categories. First, the classification features must be eliminated, then the classification algorithm must be chosen and the model must be executed. Numerous researchers have developed numerous techniques for background subtraction, but their practical applications are not terrible.

C. Foreground extraction

After applying the background subtraction technique to a video, Figure b depicts an empty road. The colour image is converted to grayscale. As depicted in figure b, hole editing, binary image, and adaptive background subtraction will be utilised to remove the grayscale from each pixel of the video clip's background image. Compilation of the entire output occurs in a separate image known as the difference image.

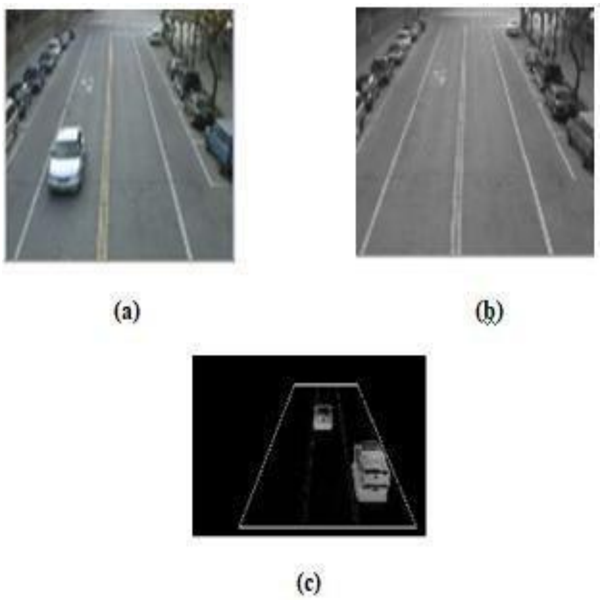

Figure a. video frame b. Fore grounded mask c. differenced image.

IV. VEHICLE DETECTION

The input video sequence is read, converted to frames, and the threshold operation is applied to the differenced image to differentiate the foreground and background images. As shown in Figure a, the differenced image is masked using foreground masking. Moreover, numerous morphological operations are carried out on the frames. Similar to erosion and expansion as depicted in figures b and c. Morphology is required to draw the vehicle's forms and boundaries. Each frame comparison is made between the output image and the identical frame of the transmitted input image. Dilation

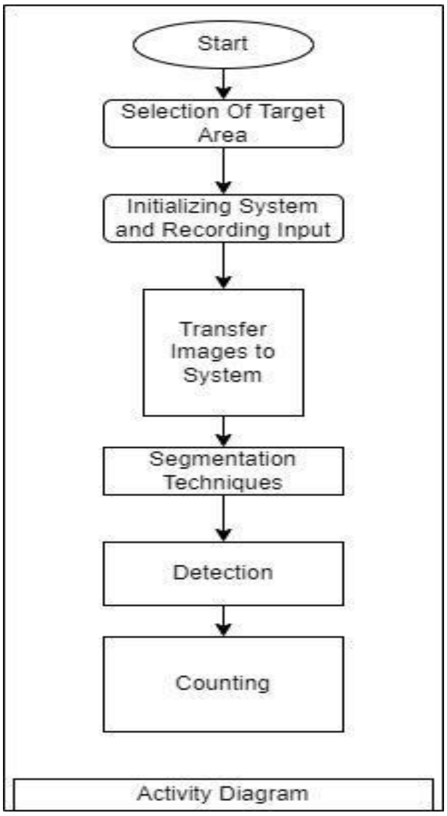

Figure. Activity Diagram for vehicle detection and counting

will add the image's edges to the detected objects; therefore, dilations will add the image's edges. We utilise a variety of morphological operations in order to obtain highly accurate results under adverse weather conditions or in response to a variety of interpretive factors, such as wind, rain, etc. Using the contours, the

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sizes of the squares and rectangles used to calculate each vehicle's area are fixed. Car dimensions are configured as 5x5, and truck dimensions are configured as 11x11. The values derived from the image differences exceed the values set to one. If the differenced images result in a smaller value, the value will be set to zero. In addition, we can use dilation and erosion to remove objects from images and smooth the border region. Counting vehicles is the subsequent step.

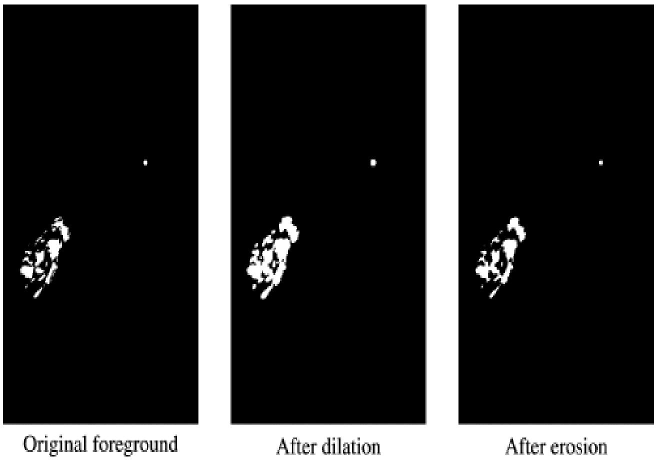

Fig a. Foreground masking b. Dilation c. Erosion

V. VEHICLE COUNTING

Image mask 1 serves as the counting input image. The image is then analysed from top to bottom to detect the vehicle's presence. count and counts registered countreg are maintained to store vehicle registration information from the video. When a new vehicle is encountered, it is first scanned to determine if it has been previously recorded in the buffer; if not, it is considered the most recent vehicle and the count value is incremented; otherwise, it is considered the last vehicle type and its appearance is ignored. The hypothesis is applied to each image, and the most recent vehicle count is stored in the variable count. An accurate level of counting is attained. Occasionally, Two automobiles are merged and regarded as a single entity due to an obstruction. Once contours have been appealed as depicted in figure c, the component is computed for each vehicle and a value of one is displayed if the vehicle is present. Each vehicle identification number increments this counter. If no vehicle is detected, the value of the variable is reset to zero and frame detection continues. As shown in the illustration, once the vehicle count is complete, the area portion will be displayed on the output screen. As given in figure b. After a vehicle crosses the red line, the inputted clip is used as the portion of engrossment, and the centroid is used to calculate the portion of each vehicle. Then, differentiations are applied to the total number of vehicles. Following the crossing of the blue line, a vehicle count will be conducted.. It would operate in both prescribed ways. The corresponding binary image is set to zero if certain vehicles are not
detected.

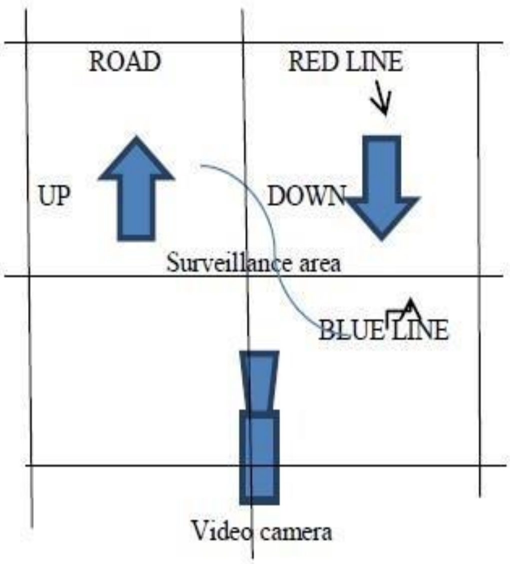

Figure. Diagram for vehicle detection and counting.

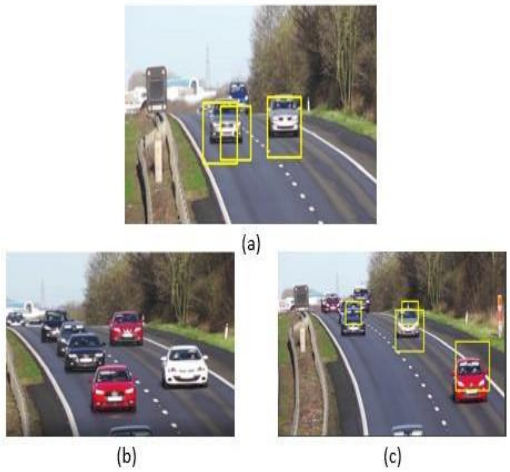

Figure. Experimental results and discussions

We have utilised the roadside cameras to record approximately four to five videos. We captured footage between noon and dusk. We have utilised 1280 x 720 pixels and 30 frames per second throughout the entire presentation. Computer vision was used to execute the Python programming language method. When the video sequence is input into the system, the required method will produce more accurate results than manual counting. The alternative method is compatible with all laptops with core i3 to core i7 processors and 4GB to 8GB of random-access memory. The outcomes are presented in table A. The implemented method has achieved between 92% and 96% accuracy. The majority of vehicles in all input videos have been counted and identified with a precision of 96.95%. Based on the number of precise vehicles, the table will contain an integrant, such as r.

Table a. Experimental Results

No. of videos	Vehicles which Traverse The Red Line	Vehicles which Traversed The Blue Line	Accuracy
1	122	106	92.1%
2	78	64	94.8%
3	87	92	94.4%
4	73	59	93.05%
5	65	79	94.18%
6	105	114	96.54%

VI. CONCLUSION

The article described the vehicle counting and detection system used to identify and count the number of vehicles within a stationary camera's captured video frame sequence. Initially, using a virtual detector and the well-known technique of background subtraction. In addition, foreground masking, contour detection, motion analysis, and edge detection techniques have been implemented. Thirdly, by employing contour method techniques for detecting and counting vehicles within the captured streamed sequence by stationary cameras.

The vehicles and their entangled regions are utilised to determine the area and detect the vehicle. Open computer vision techniques such as dilation, erosion, morphological operations, etc. are utilised to remove objects from video frames and smooth the edges while ignoring noise. The preferred method has a mean accuracy of 96.54 percent, according to exploratory findings.

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