Lane Detection on Roads using Computer Vision

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***Abstract:** In recent times many technological advancements are coming in the domain of road safety as accidents has been increasing at an alarming rate and one of the crucial reason for such accidents is lack of driver's attention. Technical advancements should be there to reduce the frequency of the accidents and stay safe. One of the way to achieve the same is through Lane Detection Systems which work with the intention to recognize the lane borders on road and further prompts the driver if he switches and moves to erroneous lane markings. Lane detecting system is an essential component of many technologically intelligent transport system. Although it's a complex goal to achieve because of vacillating road conditions that a person encounters specially while driving at night or even in daylight. Lane boundaries is detected using a camera that captures the view of the road, mounted on the front of the vehicle. The approach used in this paper changes the image taken from the video into a set of sub-images and generates image-features for each of them which are further used to detect the lanes present on the roads. There are proposed numerous ways to detect the lane markings on the road. Feature-based or model-based are the two categories of the lane detection techniques. Down-level characteristics for example lane-mark edges are used by the feature-based functions.*

***Keywords:** Traffic Safety, Lane Detection, Deep Learning, Computer Vision*

I. INTRODUCTION:

The traffic safety becomes more and more convincing with the increasing urban traffic. Exiting the lane without following proper rules is the root cause of most of the accidents on the avenues. Most of these are result of the interrupted and lethargic attitude of the driver. Lane discipline is crucial to road safety for drivers and pedestrians alike. The system has an objective to identify the lane marks. It's intent is to obtain a secure environment and improved traffic surroundings. The functions of the proposed system can range from displaying road line positions to the driving person on any exterior display, to more convoluted applications like detecting switching of the lanes in the near future so that one can prevent concussions caused on the highways.

Actuate detection of lane roads is a critical issue in lane detection and departure warning systems. If an automobile crosses a lane confinement then vehicles enabled with predicting lane borders system directs the vehicles to prevent collisions and generates an alarming condition. These kind of intelligent system always makes the safe travel but it is not always necessary that lane boundaries are clearly noticeable, as poor road conditions, inadequate quantity of paint used for marking the lane boundaries makes it hard for system to detect the lanes with accuracy and other reasons can include environmental effects like shadows from things like trees or other automobiles, or street lights, day and night time conditions, or fog occurs because of invariant lightening conditions. These factors causes problem to distinguish a road lane in the backdrop of a captured image for a person.

In order to deal with above stated problems arising due to changes in lane boundaries. The algorithm followed in this paper is to detect lane markings on the road by giving the video of the road as an input to the system by using computer vision technology and primarily designed with the objective of reducing the frequency of accidents.

System can be installed in cars and taxis in order to prevent the occurrence of accidents due to reckless driving on the roads. In school buses as it will guarantee the safety of the children. Moreover, performance of the driver can also be monitored, Road Transportation Offices can use the setup to check and report the negligence of drivers and lack of attention on the roads.

II. LITERATURE SURVEY

3.1 Lane Detection Techniques: A Review [1]

Paper considers two types of neural network and extends the idea of deep learning in detecting the lanes by developing a multitask deep CNN. Further establishes both the CNN and RNN detectors is effective in detecting lanes.

First a picture of the road is acquired with the assistance of a camera attached on the vehicle. Next one may reduce the processing time by translating the image to a grayscale image.

Next, the existence of disturbance captured in the image will interrupt the accurate detection of the edges, so one can activate filters to get rid of noises. Some of the filters which can be used are bilateral filter, gaussian filter, trilateral filter. There upon in order to produce an edged image, an edge detector can be used which makes use of canny filter to get the edges by using machine generated thresholding. Line detector can then use it for the purpose of detection. It will generate a left side and right side segments of the lane boundary. As a result, yellow and the white lanes are obtained using the RGB color codes.

Techniques that are used for detecting the lanes plays a compelling part in technologically intelligent transport setup. Methods that one may make use of have been studied in this paper. Many of them resulted in inappropriate conclusions. Hence, other enrichments can also be included in the present approach in a way to increase the efficiency of the setup. In the coming future, one can change the current Hough Transformation so that it can sum up curved and straight roads respectively. This approach cannot give accurate results in poor environmental conditions like on hazy, cloudy, rainy and stormy days, therefore one needs to make amendments in it.

3.2 A Layered Approach To Robust Lane Detection At Night [2]

Firstly, we need to reduce out a Region Of Interest (ROI) in the image present originally so that we can omit unnecessary objects such as the sky, street lights, signs, moon, etc. from the image. Cropping also improves both the accuracy and the speed of the lane detection system. The velocity enhancement is obtained from the decrease in the size of the image to be processed. The accuracy can be improved by the alimentation of objects that are present outside the ROI that may have characteristics same as to lanes. In this implementation, the ROI is set manually; whereas, to automatically determine a suitable ROI, camera calibration parameters could be used.

The conversion of a color image into a gray scale image is the only pre- processing used in this lane detection system; consequently, monochrome images can circumvent this step. It is assumed that the accessible colorful picture is present in Bayer format. Firstly it is demised to extract the color of each pixel.

Since the shoulder generally display up as a lengthy and straight line in the image, therefore, for lane detection, the shoulder lane of the road is generally detectable in compared to a traffic lane. Traffic lanes on avenues are dashed lines and, they may be shown as a dot or a short line in the picture, depending on the vulnerability time. In order to expand the traffic lanes and give the presence of a long and continued line, one may use temporal blurring.

The adaptive threshold is used to retrieve the lane markers in the average picture. The adaptive threshold changes depends on the features of its nearby pixels in comparison to a global threshold. This is advantageous as isolated bright objects like street lights and taillights of cars would influence the global threshold, the adaptive method would not be easily altered.

In earlier stage, the binary image that is obtained by application of the adaptive threshold is divided into its left and right halves. Next, a low resolution Hough transformed is calculated on each hal image in order to get the positions of straight lines with respect to lanes.

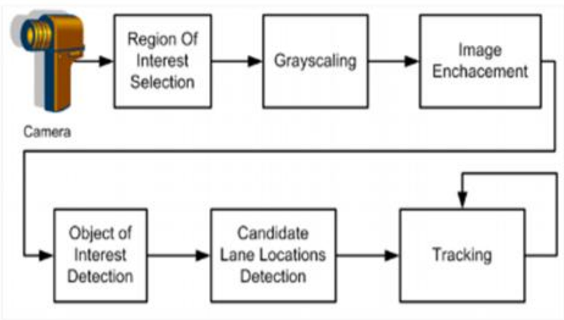

Figure 3.2-Proposed Model for Lane Detection System.

The model which is used for the detection of lanes in this paper is explained with the help of a flowchart in above figure Fig 3.2 and comparisons of accuracy are shown Table 3.1.

Table 3.1-Comparing Accuracy for Lane Detection System

Highway type	Traffic type	Average Accuracy Per Minute		
		Correct	Incorrect	Misses
Isolated	Light	92.27%	6.49%	1.22%
	Moderate	92.14%	4.43%	3.45%
Metro	Light	82.41%	12.6%	4.91%
	Moderate	75.56%	20.17%	8.26%

The arrangements bounded by the type of traffic environment and avenues mentioned atop permit to compute a practical collection of conditions which a person may confront during driving in the darker environment. There are some of the conclusions which are displayed in the above table. It shows the aspects of the proposed lane detection system when checked on a time span of 5 hrs over the acquired video. A simple frame-wise access to permit bendability in conclusions when approved on videos with varying frame rates one can prefer this measurement is preferred over the other measurement techniques. In Table I, the percentage of accurate detections per minute is represented by the correct column whereas, the percentage of inaccurate positives and undetected lanes are represented by Incorrect and Misses column respectively. Efficiency per minute of the system can be measured to check the accuracy of the system. Moreover, neighbouring vehicles and the lightning from their headlights appeared to have very less to no changes on the average efficiency estimation. The high contrast of the lane markers on isolated highways which are culminated in the high detection rates are as shown in Table I.

III. IMPLEMENTATION

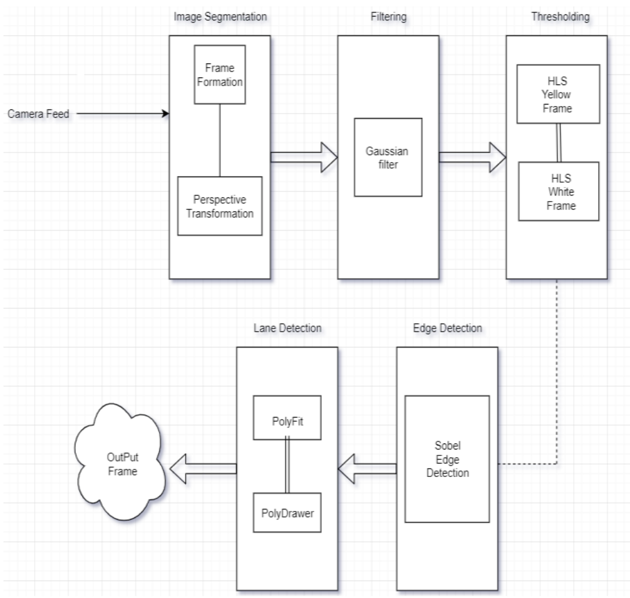

Figure 4.1.– System Design of Classic Approach

Proposed design of the system Fig 4.1.

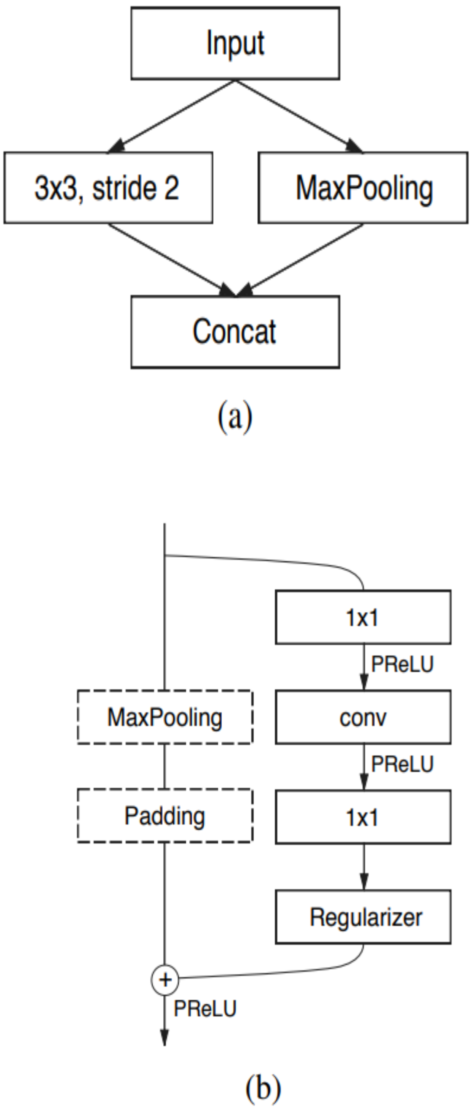

Figure 4.2.– System Design of Deep Learning approach
The system design of the deep learning approach is depicted in the above figure Fig.4.2.

Region Of Interest

A region of interest (ROI) is that area of an image that one want to percolate or allow some other operations on them. One can use the high-level ROI functions in order to create ROIs of many shapes, for example drawpolygon or drawcircle in the library of openCV. The main objective of ROI is to decrease the portion of an image for speedy calculation and also the size of image can be decremented by ROI generation. One can describe several ROI in an image. Generally, ROIs are defined as collections of several contiguous pixels but you can also describe them as ROIs by depth values, where it is not necessarily that the regions must be contiguous. Most general use of an ROI is to generate a binary mask image which is defined as the combination of 0 & 1 in the image file matrix. Pixels that belong to the ROI are set to 1 that is white and pixels outside the ROI are set to 0 that is Black In the mask image.
There are two images shown below which indicates how one's image may look like after we focus only on the region of interest. The original image is as shown below in the Fig 4.3 and in Fig 4.4 the Region of Interest is shown.

Figure 4.3-Original Image

Figure 4.4- Figure Showing Region of Interest

Gaussian Blur

We use **Gaussian blur** which is also known as **Gaussian smoothing,** while refining an image. Typically to reduce image noise and reduce detail, it is an extensively used effect in graphics software. We get the result by making our image hazy using a Gaussian function. This function is named after famous mathematician and scientist Carl Friedrich Gauss. Gaussian smoothing is widely used for pre-processing stage of lane detection in computer vision algorithms. In order to improve image structures at different scales we used the Gaussian Blur.
Mathematically, applying a Gaussian blur to an image is similar as convolving the image with a Gaussian Function. This is also called as a two-dimensional Weierstrass transformation.
The image is convoluted with a Gaussian filter inspite of using the box filter, in Gaussian Blur operation. The Gaussian filter is a low-pass filter that omits the high-frequency components which are being reduced.This operation is being achieved with the help of **Gaussianblur()** function of the **imgproc** category.
Here is an example of what happens after application of the the Gaussian Blur Algorithm on an input image.

Figure 4.5-Original Unfiltered Image

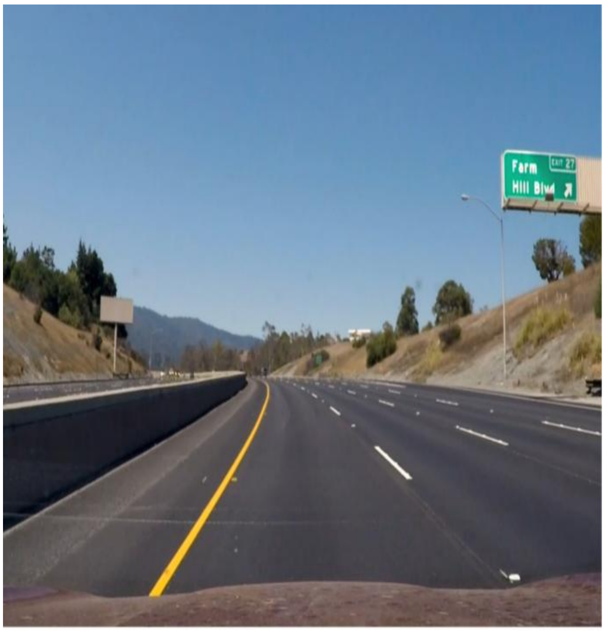

Figure 4.6-Image with Gaussian Blur

Above Figures 3.5 and 3.6 shows the original image and the image after the application of gaussian blurr respectively.

Sobel Operator

There is a discrete differentiation operator called as Sobel Operator. It generally merges Gaussian smoothing and differentiation of an image. It calculates an resemblance of the gradient of an image intensity method. This is also called as Sobel-Feldman operator or Sobel Filter, and is named after Irwin Sobel and Gary Feldman. The image with a small, separable, and integer-valued filter in the horizontal and vertical directions is convoluted with the help of the Sobel–Feldman operator. This operator is not very costly in comparison with other such operators in the circumstances of calculations. Sobel detection indicates calculating the gradient degree of an image using 3x3 filters. A number giving the absolute value of the rate of change in light intensity for each and every pixel is called "Gradient magnitude". It is carried out in a way that it allows to give us the result in the direction which maximizes this number.

Here is the following figure 3.7 that shows the result after applying the Sobel operator.

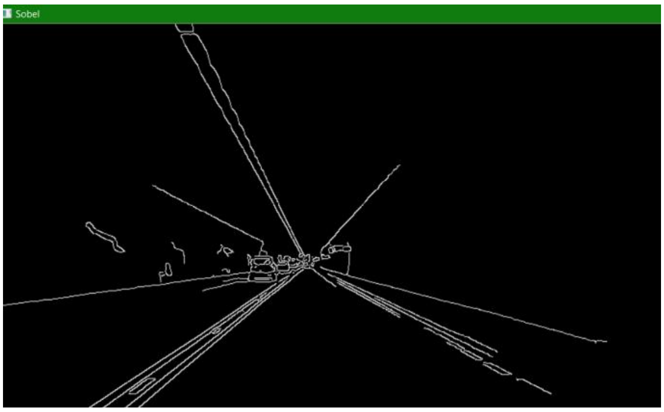

Figure 4.7-Using Sobel Operator in OpenCV

Computational Results of Deep Learning Approach

- Pixel wise semantic segmentation is used for image segmentation.
- Dataset used for the training is taken from Internet sources.
- 30 Classes have been used for segmentation.
- Simple convolution diluted with activation function- Prelu, is used.
- Finding the kernel is the main approach.

Various classes can be used for the purpose of segmentation like:

- Road
- People
- Vehicle
- Terrain
- In this project we need the road class for segmentation.

Below Table 3.1 depicts the model of Enet pipeline schema.

Table 3.1-Enet Model Pipeline Schema.

Name	Type	Output size
initial		$16 \times 256 \times 256$
bottleneck1.0	downsampling	$64 \times 128 \times 128$
$4\times$ bottleneck1.x		$64 \times 128 \times 128$
bottleneck2.0	downsampling	$128 \times 64 \times 64$
bottleneck2.1		$128 \times 64 \times 64$
bottleneck2.2	dilated 2	$128 \times 64 \times 64$
bottleneck2.3	asymmetric 5	$128 \times 64 \times 64$
bottleneck2.4	dilated 4	$128 \times 64 \times 64$
bottleneck2.5		$128 \times 64 \times 64$
bottleneck2.6	dilated 8	$128 \times 64 \times 64$
bottleneck2.7	asymmetric 5	$128 \times 64 \times 64$
bottleneck2.8	dilated 16	$128 \times 64 \times 64$
Repeat section 2, without bottleneck2.0		
bottleneck4.0	upsampling	$64 \times 128 \times 128$
bottleneck4.1		$64 \times 128 \times 128$
bottleneck4.2		$64 \times 128 \times 128$
bottleneck5.0	upsampling	$16 \times 256 \times 256$
bottleneck5.1		$16 \times 256 \times 256$
fullconv		$C \times 512 \times 512$

Retrieval Number: A94256109119/2019©BEIESP
DOI: 10.35940/ijeat.A94256.109119

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Assumptions:

The following assumptions were made in preparing the Project Plan:

- The Road should be in good Quality
- The Lane Paint in the road should be visible
- Yellow Lane Colour define the left side of road beginning
- White Lane Colour define the right side of road ending
- All road Constructed should meet the highway authority standards
- We assume that the weather will be sunny with adequate lighting on the road
- Assuming the system used for lane detection is sufficiently fast and memory is not limited.

Dependencies :

Resource-based planning dependencies:

1. For training of data , high GPU computational power is required , so time for training is directly connected to system raw power.
2. Output from the camera mounted on the moving vehicle will have great impact on detection result
3. Lane visibility in weather condition will also have high impact of model accuracy for lane detection.

Logical planning dependencies:

1. Python Libraries should be pre-installed for working of this module.
2. All operating System files should be updated.
3. System should have sufficient Memory for module operation.

4.3. Implementation Details

Following images have been used for test cases in our project. There are two input images. One which is used for classic approach and the other is used for deep learning in our project.

Figure 4.1-Input Image for Classic Approach

Figure 4.2-Input Image for Deep Learning Approach

Above figures Fig 4.1 and Fig 4.2 are the examples of test cases that are used by us in order to implement our project. There are two approaches for detection of the lanes – one is the **classic approach** and other is the **deep learning approach.**

- **CLASSIC APPROACH**

Figure 4.3 and 4.4 depicts the results after the blurring is done in the below figures respectively.

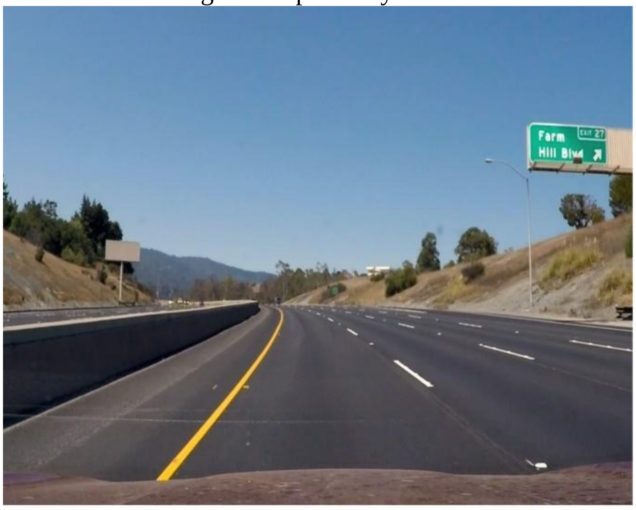

Fig 4.3- Originally Captured Image

Fig 4.4-After application of Gaussian Blurring

Figure 4.3 is the figure displaying only that region that is to be focussed on i.e. Region of Interest.

Fig 4.5- Region Of Interest

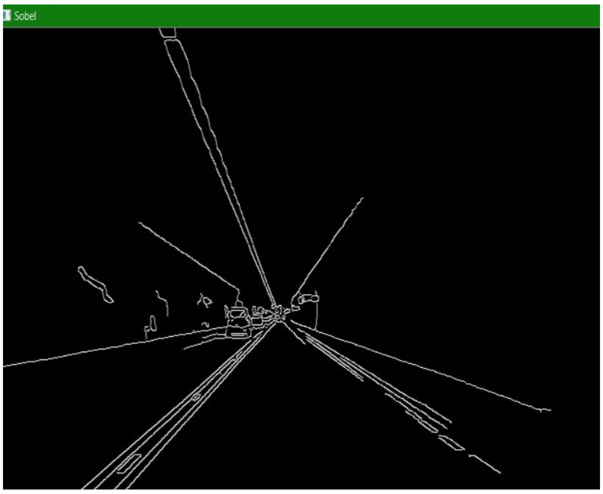

Fig 4.6 – After applying Sobel Operator

Figure 4.6 shown above is the result of application of sobel operator.

DEEP LEARNING APPROACH

Fig 4.7 -Input Image for Deep Learning

Figure 4.7 and 4.8 show the original and the output generated by deep learning approach respectively.

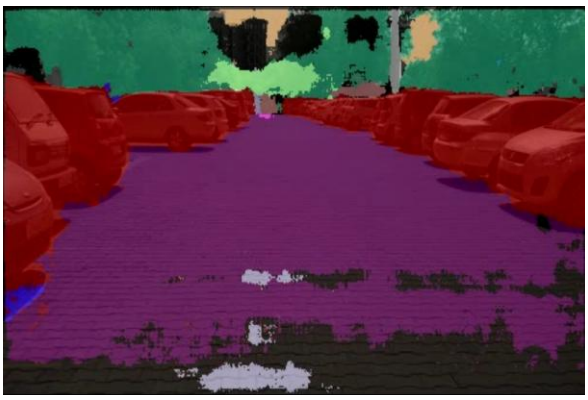

Fig 4.8 -Output generated by Enet Model

Several colour codes used in the output generated are as shown below in figure 4.9:

Fig 4.9-Colour Code Image

IV. FUTURE WORK:

This model can be updated and tuned with more efficient mathematical modelling, whereas the classical OpenCV approach is limited and no upgrade is possible as the approach is not efficient

It is unable to give accurate results on the roads which do not have clear markings present on the roads. Also it cannot work for all climatic conditions

This technology is increasing the number of applications such as traffic control, traffic monitoring, traffic flow, security etc.

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