Lane Detection with Deep Learning and Conventional Approaches

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***Abstract*— In concept of Advanced driver assistance systems (ADAS), lane detection is among the most essential and critical roles in driverless automobiles. Lane identification techniques can be classified into two parts: deep learning and classical approaches. classical approaches for lane detection in automated driving began with image processing technics and manually abstracting the features, Even so, conventional approaches limited to operate in particular driving scene and might not be suited to various driving situations and since the threshold values cannot be altered or suited according to a new surroundings, Several studies have been conducted in higher education and sector to apply deep learning methods to accomplish reliable lane detection. Deep learning techniques are extra stable and accommodative in identifying lanes for various scenarios including seasonal changes, shading, car obstruction, missing marks on the road but the majority of deep learning studies and techniques concentrate on identifying lane detection out of a single frame "picture" that could result to disappointing outcomes. To solve this challenge, a hybrid deep neural network was proposed by integrating recurrent neural networks (RNN) with convolutional neural networks (CNN). This hybrid technique studies the lane in several frames, including earlier frames from data sets.**

I. INTRODUCTION

Most of the incidents are caused by unseen roadways. Enhanced driving assistance will substantially decrease the number of accidents. A technology that alerts the driver can potentially rescue a lot of lives. The identification of road lanes or borders, that are visible in white and yellow lines on roadways, is one of the most difficult jobs in cruising support to accomplish traffic efficiency.

There is a significant improvement of the driverless automobiles market is due to advances in research, large datasets, and increased processing capacity of physical components. Lane recognition is the core of driverless cars. A car will find out its route and location in a lane and adjust its placement continually in a lane absent the requirement of individual involvement after lane parameters are computed and retrieved by computer vision or alternative means like as distance estimation. The goal of this innovation is to guarantee that driverless cars is protected, trustworthy, and pleasant.

Numerous conventional methods, like lane identification with Geometric mapping [1], as well as other classical techniques including, Hough transform[2], curve fitting[3], as an instance lane segmentation, had been released; nevertheless, the usual spot among these suggested techniques is that they restrict lane detection to a separate present shot of the data. As instance, the Hough Transform method is such a procedure and that is why being usually implemented when detecting straight lines on the pathway. In addition to the Hough transform method, a curve fitting model can be created to improve the resilience of lane detection and monitoring for safer driving in this study. To improve the functioning of the lane recognition and following, the Curve fitting concept and associated element operation will be used in our technique to examine the lane and its monitoring. As a result, they may operate improperly under various driving sequences in which instance a lane may not be identified, slightly spotted, or sometimes falsely predicted. Because the road is made up of ongoing lines, every line divided from the other by crushed or robust lines, and the driving scenario is ongoing, there would be an elevated level of common points and intersecting between the present image and numerous previous images.

The paper is organized as follows. Section 2 explains the previous studies and observations on lane detection and its limitations. Section 3 describes both machine learning and traditional methods . In Section 4, the comparisons and the limitations of these methods are mentioned for better understanding of the lane detection concept. Section 5 provides the experimental outcomes. Both software simulation and real data are utilized to evaluate the suggested methods.

II. LITERATURE REVIEW

The deep learning part of this mini project focuses on supervised learning techniques for lane detection, which combines CNN + RNN (hybrid model) as end-to-end neural network. For the purpose of lane detection many different deep learning researches and approaches have been done, during the research phase of this mini project, one of the interested researches is application of light weight CNN for lane detection that implements semantic segmentation and self-attention distillation to enhance the learning process, another interesting research is deep learning approach for lane detection that utilize CNN to mark and extract lanes features, then applying post processing to analyze the detected marks in order to perform polynomial curve fitting to figure out the lane boundaries[4],

meanwhile in the conventional method of the mini project Hough transform is one of the two conventional methods that is used for lane detection, starting with the paper of [5] applied the Hough transform with improved frames to the compiler cells in the ROI in similar and spots lanes with high effectiveness. Although Hough Transform can sense only straight lane, the poor lane identification rate on the curve road has been fixed properly.

[6] projected a new system for colour road picture edge recognition. The actual colour info in RGB colour pattern were changed to among gray scale colour with special image processing. The impact displays that the system has highly reduced the noise and retain improved edges for colour road picture edge recognition than the common methods, on the other hand numerous publications have investigated and presented several lane following algorithms for autonomous cars, however they are unable to resolve the challenges of yellow lane line identification and curved lane line detection in complicated situations. The boundary and colour properties of lane marker pixels retrieved in the image are the most important. The Hough transform approach, Extended Kalman Filter, computation system that analyses route layout by contorting contour line, Window sliding approach and RANSAC algorithm have all been used to identify lanes. [7] suggested an inverted viewpoint approach for obtaining a bird's eye view of route pictures, as well as an adaptable thresholding approach for identifying highway lanes. To eliminate outliers, the recovered lane is processed using RANSAC and adjusted with the cubic spline technique. The sliding window technique was suggested by . In the field of lane projection, one might consider that the pathways start at particular points towards the bottom of the picture. As a result, windows move across the picture in predetermined steps starting these places along a single image dimension.

III. PROPOSED METHOD

In the deep learning part of this project hybrid combination of RNN and CNN is implemented as end-to-end neural network, CNN part contains encoder and decoder section, in the encoder section pooling and convolution performed to the input image for the purpose of feature extraction and abstraction, later in the following decoder section up sampling and deconvolution implemented to get the image information for reconstruction, meanwhile in the RNN (LSTM architecture) part works as a memory to store the previous images or frames in order to perform prediction of current image, mainly CNN will perform feature abstraction and RNN will perform to predict the lane, further more in the conventional methods as all other lane detection process[8], Hough transform require dataset (image / video) capture by the vehicle cameras. To get the result as detected lane there was other pre-process such as filtering, image smoothing etc.

first identity the image channels weather it was colored image or 1 channel gray image then next step is to convert

image into one channel for that applied filter to image which returns grayscale image, further, to remove noise

and obstruction from image here, filter is applied which reduce the computational time and processing time.

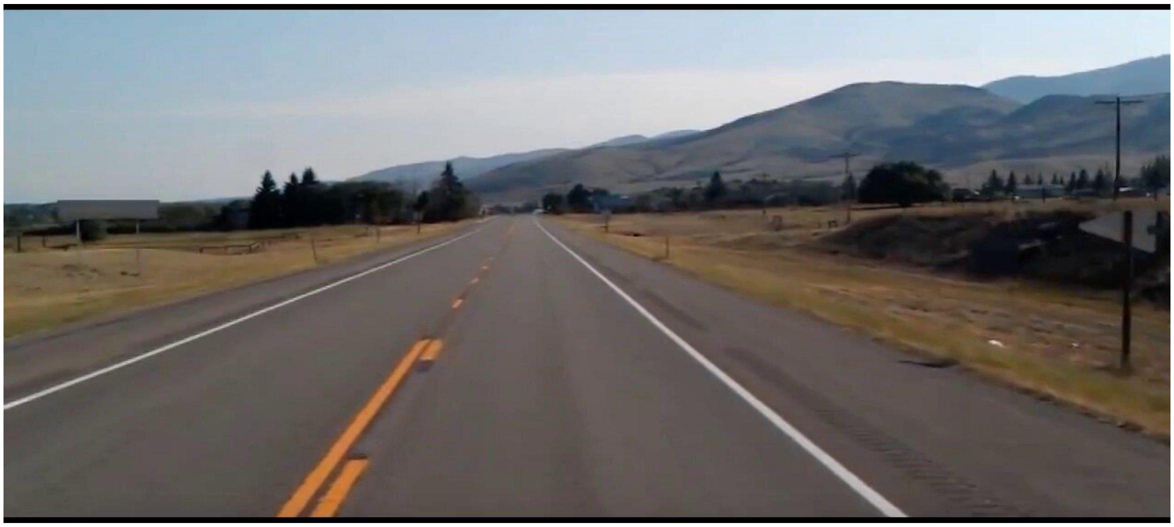
Filter can be any one such as Gabor filter, bilateral filter etc. After getting filtered image main task was performed on image which convert filtered image into binary image so binary image detects each pixel of the image and plot the edge. Moreover, edge detected image goes for the lane recognition by using Hough transform which scan the edge of both side of track and gives the output as a sequence of points in image, at the end, point captured image signify the frame and draw the line on the detected lane[9]. In addition, the other conventional method, which is curve fitting, implementation of the lane detection of curve fitting consists of 6 parts (methods). First process that needs to be done was camera calibration. The reason why this method was used at the first part of the process is to take the image on a correct position. That way, the success rate of the system could be higher. After the calibration, the next process was applying threshold to the image to reduce the noise and make the lanes cleaner and more visible. This procedure is used to turn the road image into pixels. After combining the two binary images (gradient threshold and colour transform), new binary image new image has emerged. Next, as can be seen on the example image, the lines on the road are located at the bottom of the screen. With perspective transform method[10], it can take a certain segment of the road including lane and brings it to the bird view of the screen. This makes the lines easier to work with when detecting the lane. After changing the view of the example image, the next process is to obtain a histogram graph to classify the lane pixels. In the next stage, sliding windows approach is used to allow us to pinpoint where an item is in an image. It can be identified objects in images at numerous magnitudes and areas using this method. In conclusion, the whole lane is twisted back onto the source picture utilizing the reverse of the matrix obtained in the perspective transform phase after the lines have been detected. Then, measurements of the lane lines are gathered, and the amount of curving in the pathway is determined to be displayed on the screen.

IV. CONCLUSION AND LIMITATIONS

The deep neural network hybrid approach comparing the conventional approach was more adaptive to different driving situation such as shadow and bad weather conditions, where accuracy of the hybrid model was 97.8%, precision: 78%, recall: 93% and F_1score 85% , moreover the conventional method requires al handcrafted work for feature extraction and labeling, meanwhile in the deep learning approach features are extracted and abstracted automatically by CNN [11], however the deep learning approaches trained on a GPU and it was computationally expensive to train and run it in real time while the conventional methods does not occupy that much memory and more appropriate to deploy it in real time detection, meanwhile Hough transform is most popular and common technique of conventional method to detect lane. Since it is a traditional method it has several limitations, and it work more accurate for straight lane and ignore curve lane. for this method there are many conditions is still challenging to identify lane in presence of noise. Noise can be anything such as dust on road, tire marks on lane, broken lane, shadow etc.[12]. overall, this method required changes to get accurate result for both straight and curve, in the case of curve fitting.

The model was created by applying the several traditional methods. The research centers on a lane recognition approach for lane line maintenance in various settings based on the Sobel filter and curve fitting approach[13]. Although a good result was obtained in general, the suggested lane detection approach does not perform well in demanding scenarios when it comes to detecting and tracking lane limits. The design is sensitive to a wide range of lighting conditions as well as dispersed reflections. As a consequence, an incorrect threshold can outcome in incorrect lane markings on the path. In the future, we will use a more advanced lane detecting method to increase efficiency.

Comparison between the two conventional methods and the neural network approach on the same image as sown in the following images, figure 1 is the general image (input frame), figures displace edge map and output result of Hough transform, figure 2 thresholding techniques to change the images to reduce the dimension, meanwhile RNN+CNN hybrid neural networks is shown in figure 4 with the binary and labeled results.



(a) *Figure 1. Input Image of conventional method* (b)

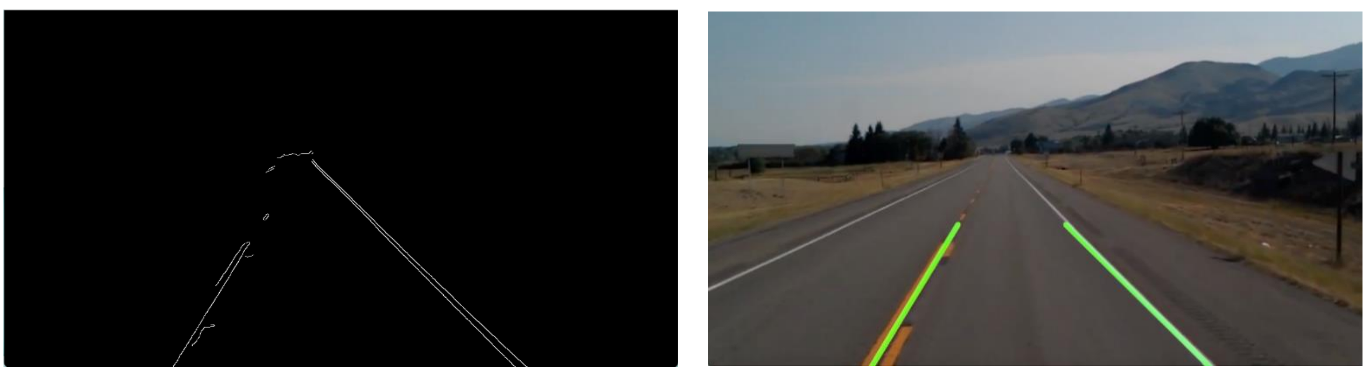


Figure 2.(a) Edge detected image using canny edge detector (b) Output image by using Hough Transform

(a) (b)

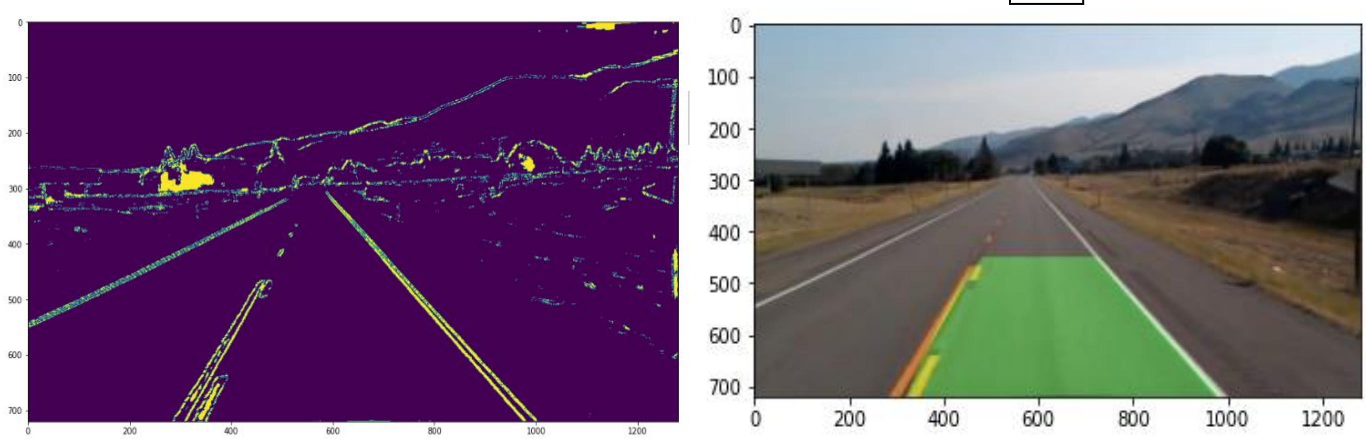


Figure 3.(a) Gradient and color threshold (b)curve fitting

(a) (b)

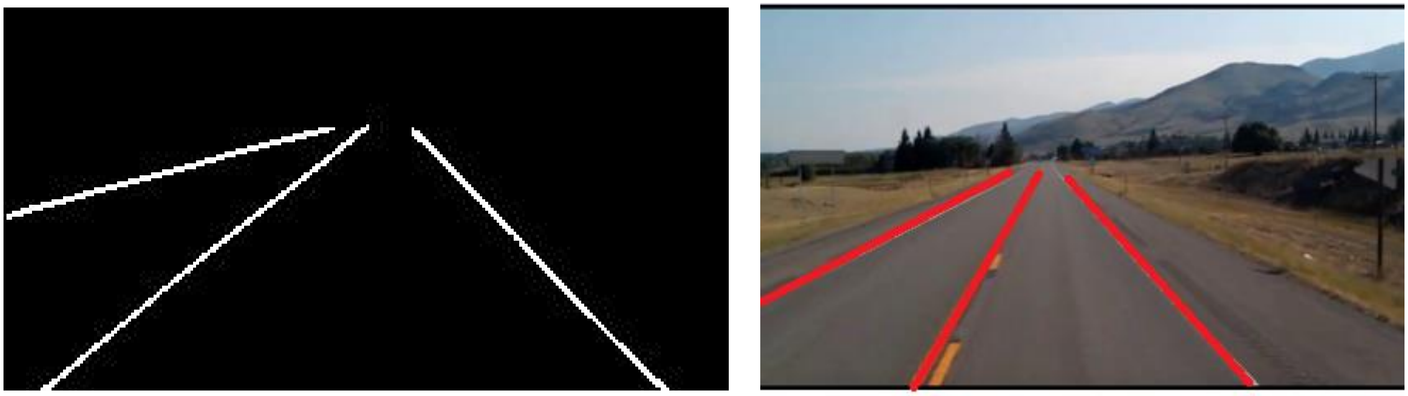


Figure 4. (a) result of the hybrid neural network (b) labeling the input image

V. Comparison

This project mainly was about lane detection with two different approaches, such as deep learning and conventional approaches, In the last decade deep learning approach became more popular than the conventional approach, however each one of the mentioned approaches has its pros and cons, but in general deep learning approached is more reliable, adaptive to different driving situations, it showed processing performance in this mini project.
The following tables showing us the main differences between the traditional and deep leaning approaches

Selection criteria	Traditional Image Processing	Deep Learning
Training dataset	Small	Large
Computing power	Low	High
Feature engineering	Required	Unnecessary
Training time	Short	Long
Annotation time	Short	Long
Algorithm Transparency	High	Low
Domain expertise	High	Low
Priors (Assumptions)	Few	Many
Proprietary material - Risk of exposure	DLLs (Risk – Negligible)	Model files, DLLs (Risk – High)
Deployment flexibility	High	Low
Expenditure (BOM)	Low	High

Table 1. Comparison of selection criteria between traditional and deep learning approaches

As shown in the table 1 above, many different selection criteria to be compared between the two methods, in the training set of deep learning approach more than 70.000 images used to train the neural network, while in the traditional method only one single image used as end to end learning to detect a lane, furthermore the computing power in deep learning was so heavy, especially in the training phase, it took like 17 hours to train the deep leering model for the lane detection[14].

Traditional Image Processing	Deep Learning
Image transformation (Lens distortion correction, view changes)	Image classification (OCR and Handwritten character recognition)
Image Signal Processing (ISP)	Object detection/ identification
Camera calibration	Semantic segmentation
Industrial inspection – Defect detection	Instance segmentation
Stereo image processing	Image synthesis
Automatic panorama stitching	Image colorization
3D data processing	Image Super-resolution
Calculating geometries	Scene understanding

Table 2. Comparison between the techniques of traditional and deep learning approaches

As shown in the table 2 above, one example of the differences between the two methods is in deep learning, semantic segmentations vs camera calibration to process the input image.

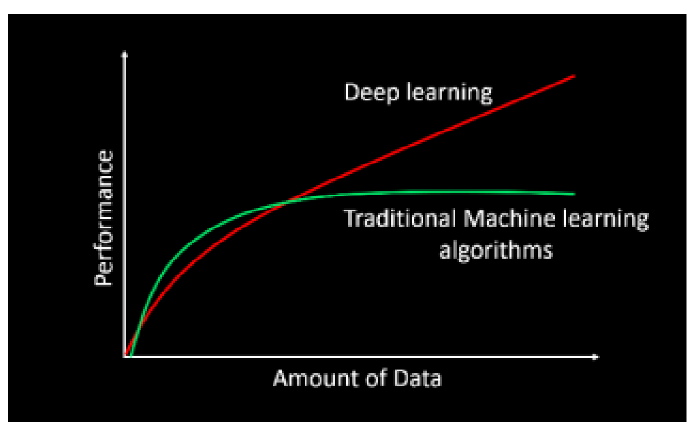


Figure 5. performance VS data amount correlations between deep learning and traditional methods

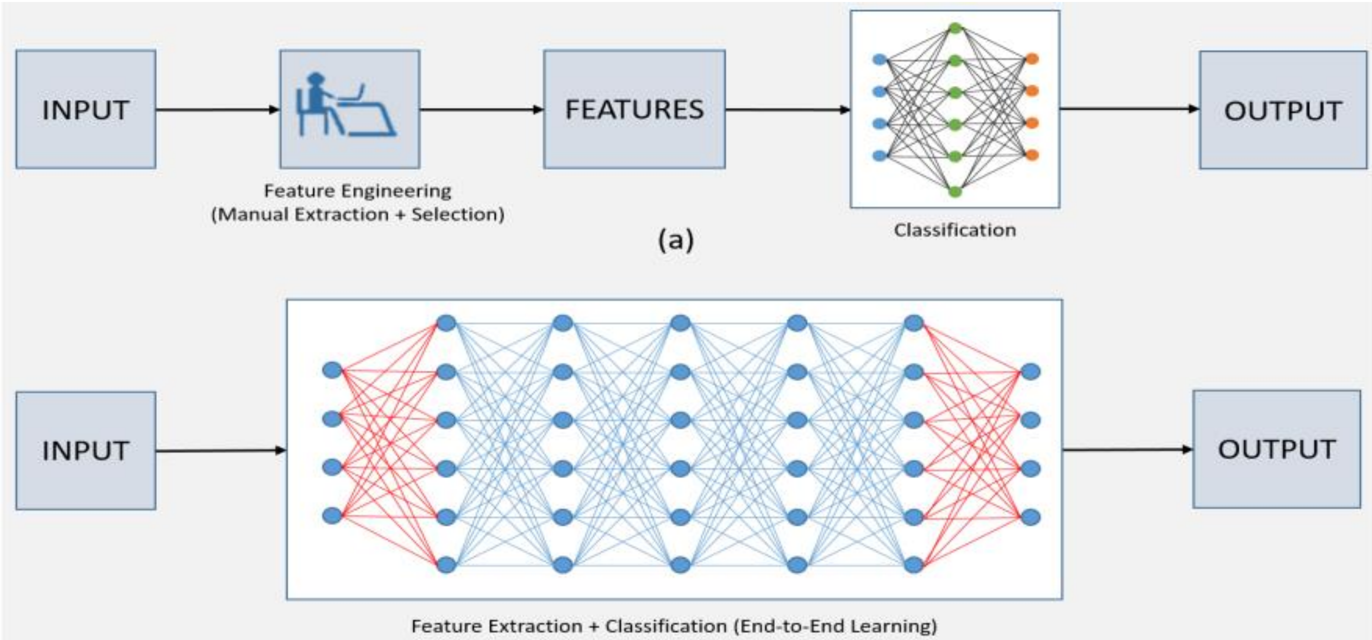


Figure 6.block diagram representing the summarized differences between the two methods

A conclusion section is not required. Although a conclusion may review the main points of the article, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

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Lane Detection Using Hybrid RNN and CNN Approach

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Abstract*— Lane detection in autonomous vehicles is one of the fundamental and crucial functions in terms of ADAS 'advanced driver assistance system', mainly we can classify lane detection methods into two main categories: deep learning based approach and conventional approach. the evolution of lane detection in autonomous vehicle started with conventional methods for lane detection by utilizing image processing techniques and handcrafted feature extraction, however conventional approach performs well only in specific driving scenes and it has no ability to be adapted to different driving scenes due to their fixed threshold values that is already embedded in the system and can not be changed or adapted to a new environment. In recent years many researches done in academia and industry in order to implement deep learning approach to achieve robust lane detection, deep learning approach is more reliable and adaptive in detecting lanes under different circumstances such as bad weather conditions, shadow, car occlusion and mark degradation, however most of the deep learning researches and approaches focus on detecting lane detection from one single frame "image" which is also can lead to unsatisfactory performance of lane detection under different challenging conditions. To overcome such a problem a hybrid deep neural network implemented by combining recurrent neural networks (RNN) and convolutional neural networks (CNN), this hybrid approach investigates the lane in more than one single frame which includes the previous frames of a driving scenes.

***Index Terms*— lane detection, hybrid method, RNN, LSTM, autonomus vehicle, image segmentation**

I. Introduction

THE leap in science, big data and increasing in computational power of hardware devices led to emergence of autonomous vehicles, lane detection is the backbone of autonomous vehicles once lane coordinates are calculated and obtained by a computer vision or any other method like an odometry, a vehicle will figure out its track and position in a lane and correct its position continuously in a lane without the need for human intervention. the purpose of such a technology is to ensure that autonomous driving offers safe, reliable and comfortable travel. In recent years evolution in artificial intelligence systems has encouraged industry and academia to allocate huge amounts of resources in the field of autonomous driving. In this paper a hybrid deep neural network (RNN+CNN) is utilized to achieve its objective and handle different challenging driving scenarios and scenes such as shadow, snowing, illumination variation, mark degradation and so on, meanwhile Many conventional approaches such as lane detection with Geometric modelling [2], and other supervised methods such as lane segmentation[6][9] have been published, however the common point among these proposed methods they limit the detection of lane only in a single current frame of driving scene, Thus the could perform poorly under different driving scenes and scenarios, in this case the lane might not be detected, partially detected of even false prediction of the lane might occur, the main reason behind this fluctuation in their performance is that the information obtained by a single one frame is not sufficient to predict the lane accurately Since a way / road consists of continuous lanes, while each lane is separated from the other line by a dashed or solid lines and the scene of driving is continuous, thus there will be high degree of correlation and overlapping among the current frame and multiple previous frames, by taking advantage of overlapping frames, in this proposed hybrid method, a lane of current frame can predicted by utilizing previous images "frames" of a continuous scenes.

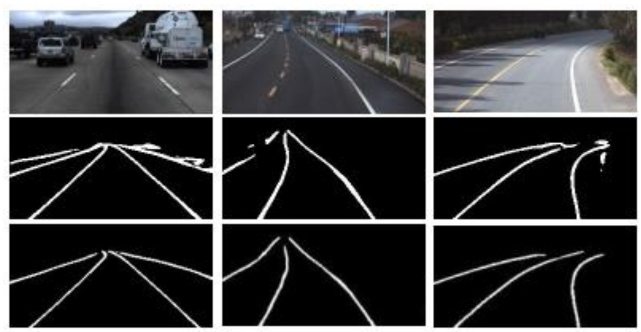


Figure 1. top line scenes of different driving situation middle line detected lane by using a single frame bottom line detected lane by using multiple previous frames

as shown in Figure 1 In the top row we can see challenging cases such as shadow and car occlusion that effects lane detection, the performance of the model is more robust in handling different situation while using multiple frames compared to one single frame. [3]

In this proposed hybrid method recurrent neural networks (RNN) and convolutional neural networks (CNN) is implemented as end-to-end neural networks (considering RNN + CNN as a single trained neural networks), since we have two types of neural networks CNN+RNN and both are functioning together as single neural network, each one of them will have a its own task, mainly CNN abstracts features from the input images or videos, the core task of CNN in this stage is to reduce the dimension of the raw input image by abstracting features that is necessary for lane detection that is acquired during the training the network, for example if the raw image is 420 x 1280 roughly we will have about half a million features of vectors which is not tolerable to use these amount of vectors in the further stages of RNN and it is computationally very expensive, so CNN here reduces the dimension to maintain tolerable operations in the network[4][5]

II. LITERATURE REVIEW

In the last decade using deep learning for many different application became very popular, especially in object detection and recognition, lane detection is one of interesting topic in terms of self driving cars and autonomous vehicle, variety of researches have been done in this field, one of them is published in IEEE 2021 (A Deep Learning Approach for Lane Detection) where CNN was implemented as feature extractor (same thing in my mini project), then a post processing implemnted to detect and analyze the road markings in order to perfrom curve fitting, mainly it consists of main two block as the following.

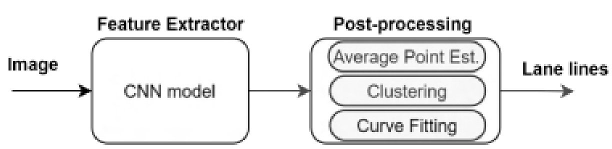


Figure 2. Diagrama of mentioned deep learning approach

Another interesting and enlightening research (Learning Lightweight Lane Detection CNNs by Self Attention Distillation), in this research the fundamental principle is using Self Attention Distillation in order to make a model spontaneously learning by itself without the need to extra labeling or supervision.[6]

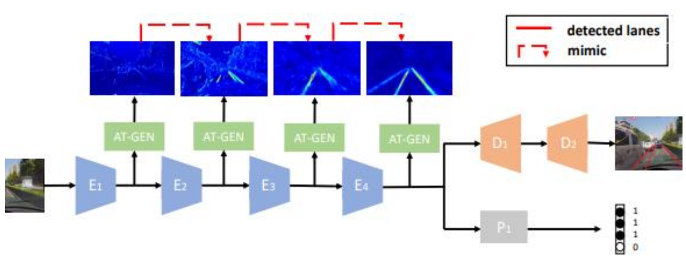


Figure 3. the main block of SAD that mimics the detected lines to enhance learning process

III. PROPOSED METHOD

In this part of the mini project, we will take a look at the hybrid neural network (the combination of convolutional and recurrent neural networks), their network architecture and working principle to achieve the prediction of lane detection task with minimum possible errors.

A. overview of the system

In this proposed method to perform lane detection, mainly we have two type of deep neural networks:

1- Deep convolutional neural network (CNN)

2- Deep recurrent neural network (RNN)

The purpose of CNN is to take the input image or video and perform feature abstraction and extraction on each single image or frame, the idea behind applying CNN as feature extractor is minimize the dimension of the input while maintaining and considering the required information to detect a lane, the importance of minimizing the dimension is crucial step to ensure our network performs appropriately.

For example the dimension of the images used to train the network in this mini project is 256 x 128 which roughly about 3.3k that means our dimension vector or feature is about 3.3k, thus by applying CNN the dimension will be reduced to tolerable levels to enhance the performance of the network and make it computationally less expensive and more reliable

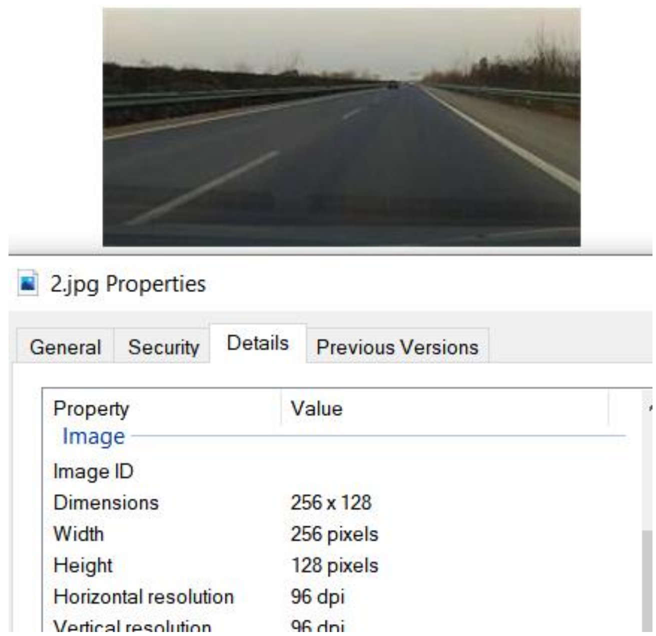


Figure 4. Example of an image used in during the training of the neural network and its dimension

On the other hand since driving scenes are continuous, it is considered as time – series process since the frames of a scene is captured from a video are sequential with respect to time, here emerges the importance of RNN.

RNN is proficient in predicting time - series problems, as a remainder we mentioned already that CNN processes the input images and then RNN predicts current image by analyzing multiple pervious images or frames, explicitly RNN processes input frame recursively by dividing the input into successive parts to build a fully connected layers, meanwhile the type of the RNN used in this mini project is long short memory LSTM

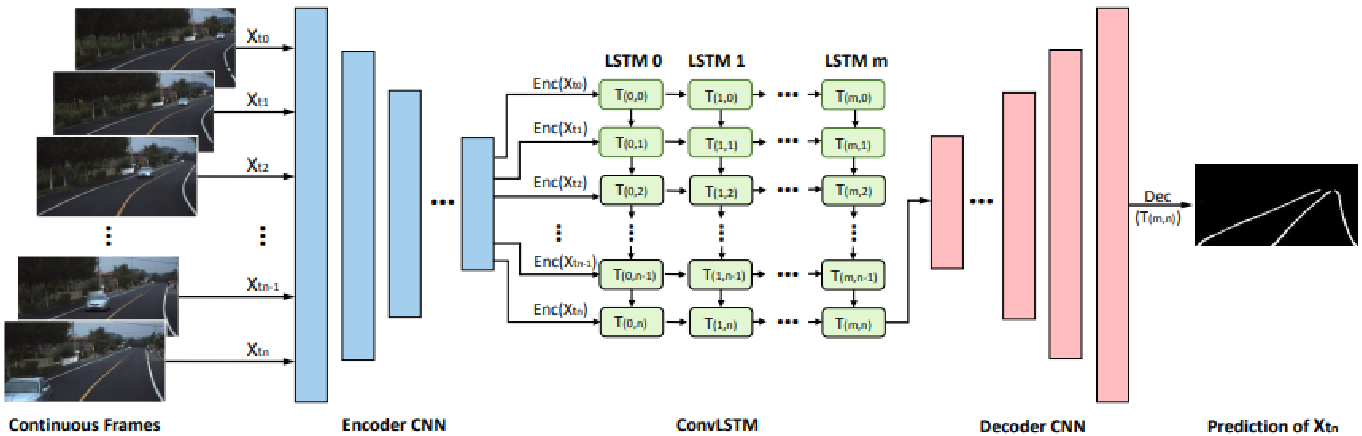


Figure 5. Network architecture of the model

B. Design of the network

The purpose of the proposed method is to take many previous images as input, then predict the current lane by semantic segmentation method, to achieve semantic segmentation a fully convolution (FCN) [smt]network is introduced within the CNN, where many other recursive operations such as pooling and convolution is carried out by the CNN to generate smaller size of feature maps obtained from continuous scenes which is time series problem, that latter will be fed RNN to be processed to predict lane features, the RNN/LSTM generates new frature maps to feed the decoder part of the CNN, operation such is deconvolution and upsampling will performed in the decoder part in order to reconstruct the image into its original size, since the images size was reduced in the encoder part, hence the size of the input image/frame and the output image/frame will be in the same size. meanwhile the architecture of CNN has two main block encoder and decoder (as shown in figure 6)
(both encoder and decoder are fully convolutional network FCN), the encoder of the CNN abstracts the features to be processed in the RNN, as shown in figure 5 the CNN has encoder and decoder blocks and the RNN (LSTM) is embedded between the encoder and decoder of the CNN to process time-series driving scenes.
the encoder and decoder was designed in order to integrate the CNN and RNN as a end to end neural network[7].

Moreover, as shown in figure 5 the RNN(LSTM) is embedded in the network between the encoder and the decoder, LSTM block fed by the encoder, the LSTM has the ability to remember important and forgetting unnecessary features, the task of each cell in LSTM is to check and estimate whether the received features from the decoder is necessary or not.
Convolutional long short memory (LSTM) is utilized instead of conventional fully connected LSTM to reduce to reduce computation power and time, since convolutional long short term memory utilizes convolution process in every cell instead of using matrix multiplication, as shown in the RNN block of figure 5 we have ConvLSTM.
In this mini project two different network designs are used in the LSTM, the first one is SegNet-ConvLSTM and the second one is Unet-ConvLSTM, each single of them has different input and output size, where the input and output sizes depends on the size of the feature map that is generated by the encoder, for SegNet-ConvLSTM the input/output size is 4 x 8 while in the case of Unet-ConvLSTM the input/output size is 8 x 16 and each network convolutional kernel size of 3 x 3 while the one hidden layer with dimension of 64, one hidden layer with dimension of 128, one hidden layer with dimension of 256 and at the end of the network we have two hidden layers with the dimension of 512 as shown in Figure 7 that summarizes the network designs of both SegNet and UNet ConvLSTM.

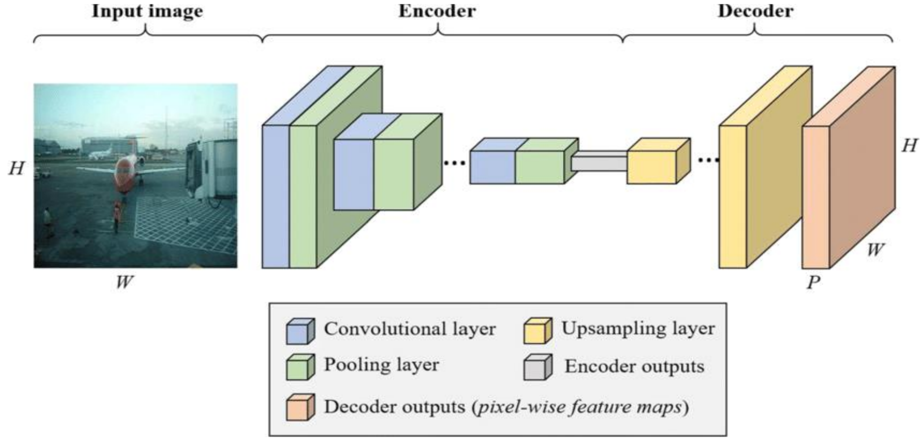
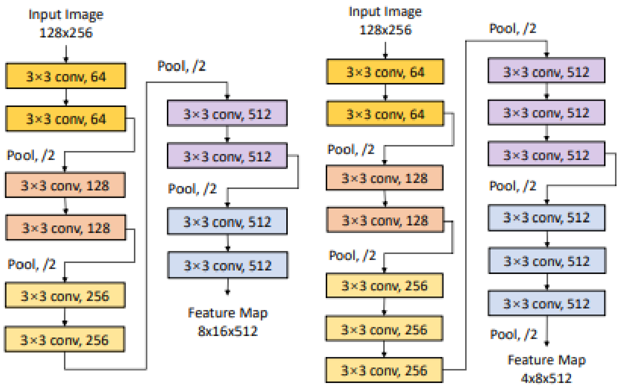


Figure 6. Basic structure of the CNN with encoder - decoder parts



(a) *(b)*

Figure 7. (a) network design of UNet-ConvLSTM and (b) network design of SegNet-ConvLSTM

the fundamentals of ConvLSTM network design is determine the number of convolutional kernels, layers and their sizes.

C. Training phase

One the network is constructed, then it could be trained to predict and detect lane, two different designs of LSTM are built for detection, while the models are trained by using TuSimple lane dataset, which contains more than 3000 packages images of different roads, high ways and rural ways in order to work with comprehensive dataset, where each package contains 20 of continuous image of the same scene and some images are labeled for the purpose of training as show in figure 8. for efficient train, different optimizers chose during different phases of the training, initially started with Adam optimizer, however since Adam optimizer falls in the local minima easily, thus to overcome this problem, training switched to SGD optimizer is after achieving high accuracy with Adam optimizer in order to find the global minima[8][9].

Figure 8. Labeled image from TuSimple dataset

Figure 9.. input image with its result

IV. Results and Conclusion

Two evaluation methods was considered in this proposed method

1- visual evaluation
2- metric evaluation

visual evaluation is the basic method to evaluate a system by observing the results visually, results of visual examination was satisfying as shown in figure 9, meanwhile evaluation metrics is was performed to measure the results in a scientific way, the following evaluation metrics was applied to the Unet-ConvLSTM model.

1- Accuracy, where the formula as the following

$$\textbf{Accuracy} = \frac{\textbf{True Positive} + \textbf{True Negative}}{\textbf{Total Number of Pixels}}$$

the accuracy in the trained Unet-ConvLSTM model was **97.872%**

2- F1 score, where the formula as the following

$$\mathbf{F1} = \mathbf{2} \cdot \frac{\textbf{Precision} \cdot \textbf{Recall}}{\textbf{Precision} + \textbf{Recall}}$$

The F1 score in the trained Unet-ConvLSTM model was **85.1%**

3- Precision, where the formula as the following

$$\textbf{Precision} = \frac{\textbf{True Positive}}{\textbf{True Positive} + \textbf{False Positive}}$$

the precision in the trained model Unet-ConvLSTM was **78.85%**

4- Recall, where the formula as the following

$$\textbf{Recall} = \frac{\textbf{True Positive}}{\textbf{True Positive} + \textbf{False Negative}}$$

The recall in the trained model Unet-ConvLSTM was **93.0%**

As a conclusion, even though the precision is relatively low compared to the other evaluation metrics, the results are satisfying since the test of the model is done on a large dataset including variety of high ways, rural roads and other challenging situations.

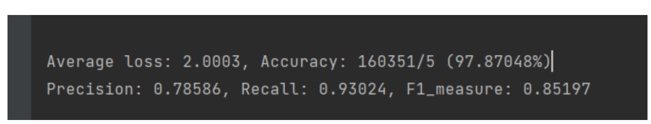


Figure 10. the results of UNet-ConvLSTM obtained after training and testing the model in Python programing language

V. LIMITATIONS

it is obvious that hybrid deep learning performs better under different situations than the conventional method, however there are no perfect system that performs perfectly without any additional drawbacks, every system has its limitation, pros and cons, one of the main problems that I faced while I was working in this mini project was during the training phase, hardware demanding to train a very large dataset, it took me 18 hours to train the UNet-Cnn LSTM model, meanwhile during the training phase my PC was operating at its highest capacity and performance in terms of GPU and RAM, my RAM is 12 GB and my GPU is NVIDIA GEFORCE 940 mx 2 GB model had to run excessively for many hours to train the model with relatively high temperature, my PC during the training hours was not available even to browse an internet page due to the heavy computational power of training the neural network, in the following figure 12 screenshot of the task manager shown.

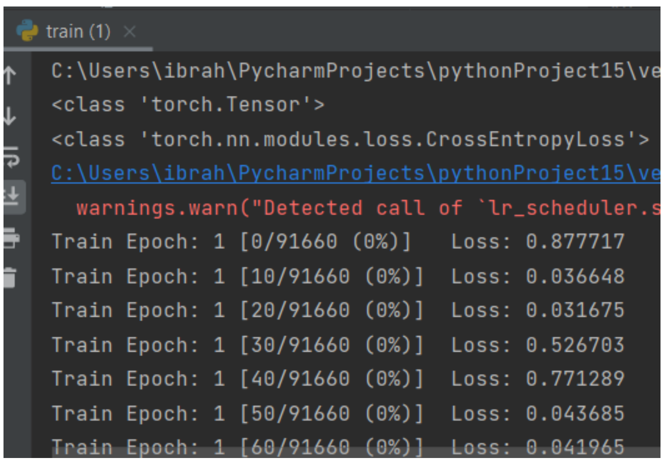


Figure 11. screenshot early stages of the training process

I had to reduce the batch size due to my limitation in the GPU and that caused a very long training time

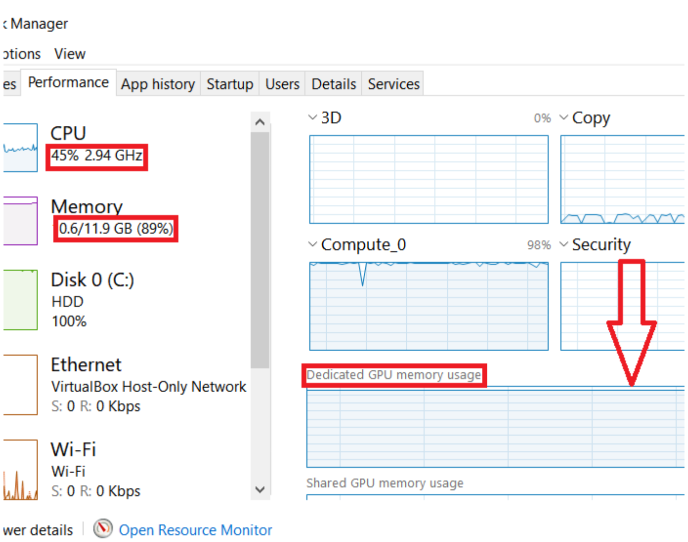


Figure 12.my PC's CPU, RAM and GPU perfprmance during the training phase

Another limitations deep learning working with large dataset even though the dataset is labeled and ready to use I had to pre-process the dataset to adjust the directories of more than 70,000 image including training and testing images, this preprocessing was done by the help microsoft excel, handling very large dataset requires patient and the ability to visualize the dataset. Another limitation is that runing the model on real time is

ACKNOWLEDGMENT

I would thank and express my deepest gratitude for Dr. Ioannnis kypraios and Professor Aladdin ayesh for being a source of motivation for me.

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Lane Detection – A Mini Project

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***Abstract*— Several individuals die in highway leaving crashes. Record of the period, it was due to driver inattentiveness. So LDWS (Lane Departure Warning System) are existence settled for aiding the driver. Lane Detection technique are beneficial in preventing these accidents as security is the key commitment of these systems. Such system develop the aim to identify the lane results and to inform the driver in the situation of vehicle has a movement to leave from lane. Lane detection is an essential element in the enlargement of smart automobiles. Lane detection was a stimulating job because of the noise, visibility etc. The noise can be whatever such as dirt, shades, snowflake, oil marks, tire skid spots, etc. The main emphasis of this article is to assess the breaches in present method and appropriate explanation for the same.**

***Index Terms*—Lane detection, edge detection, Hough transform, computer vision lane detection, image processing.**

I. INTRODUCTION

The yearly growth in car possessions has initiated traffic security to develop an significant aspect affecting the expansion of a city. To a huge range, the repeated incident of accidents was caused by unusual objects associated to the driver, for example drunk, tiredness and inappropriate driving processes. Smart vehicles can exclude these individual aspects to a definite range [1-3]. In latest times, the increase of smart vehicles has progressively fascinated of researchers in associated subjects widespread. Smart vehicles can support individuals execute driving duties established on present traffic data, thereby showing their impact in improving the protection of car driving and delivering individual from boring driving situations [4,5]. Lane detection was an key base in the way of intelligent car enlargement that straight affects the execution of driving performances. Founded on the driving track, responsible a successful driving focus for the smart vehicles and delivering the exact location of the car in the track are promising; these characters provide suggestively near refining the proficiency and driving security of programmed driving [6,7]. Therefore, showing a detailed analysis on this was required.

In turn to reach the eventual aim of self-directed driving in formless locations, sufficient immediate examination of the road landscape is mandatory[8]. Lane detection was the tricky to recognizing road lane borders exclusive of a priori data of road's measurement. A records of picture-built lane detection algorithms have developed from self-directed car research[9]. Highest of the initial techniques focused on organized roads and used a sole graphic cue for instance tint, edge or quality. A programmed lane detection method should provide for both straightforward and rounded lane borders, and a large scale of boundary marks containing solo, paired or destroyed lines, and roadside edges.

An important prerequisite for the lane indicator recognition structure was the simultaneous functionality with hardware and software accomplishment [10]. It is also essential to remark that lane observation is only one of various image processing phases throughout semiautonomous driving. As a outcome, the lane detection method wants to be straightforward and effective enough to adapt the short report time and narrow computational sources [11,12]. The Hough Transform method was such an algorithm and therefore being generally worked when detecting straightforward tracks. Subsequently, the study aim the research on HT-based algorithms. Conversely, this algorithm experiences low lane indications, disturbance, and blockings. It was described that fault proportions of ADAS (Advanced driver-assistance systems) should be various orders of amount reduce for a closed-loop self-driving system [13].

To help actual application, lane border recognition algorithms should be capable to:

(1) focus on shadows generated by road-side plant, construction, etc.
(2) work on highlighted or unpainted road track strokes;
(3) manage curved as well as straightforward roads;
(4) recognize lane borders on either side of the road

II. Literature Review

Many studies has well focused on lane recognition for highway. While city area has different road type and many other situation. Mostly highway contain straight line where city streets are unusual. [14] projected a process which combined various cues, with block filter which has been effective to spot block-shape substances like road track, tint cue, and Hough Transform. To promise the healthy and actual lane detection, element purifying method has been applied. [15] used a multiresolution HT to discover road boundaries. The job, however, does not consider how to manage the discovery of destroyed marks or road boundaries.

III. Lane Detection

The common technique of lane detection was initial take picture of road through the camera built in the car. Then photo was determined in a grayscale photo in demand to reduce the processing time.

Secondly, as occurrence of noise in the picture will obstruct the accurate edge detection. So, filters must be applied to eliminate disturbances such as bilateral filter, Gabor filter, etc. Afterward edge indicator was used to create an edge picture by applying canny filter with programmed thresholding to achieve the edge. Next, edge image was referred to an line detector after spotting the edges which will creates an exact track borderline section. The lane frame scan uses the data in the edge photo discovered by the Hough Transform to implement the scan. The scan deliver a sequence of points on the both side. Lastly, sets of hyperbolas was attached to these statistics plugs to signify the lane frame. For picturing points the hyperbolas are revealed on the actual tint photo [16].

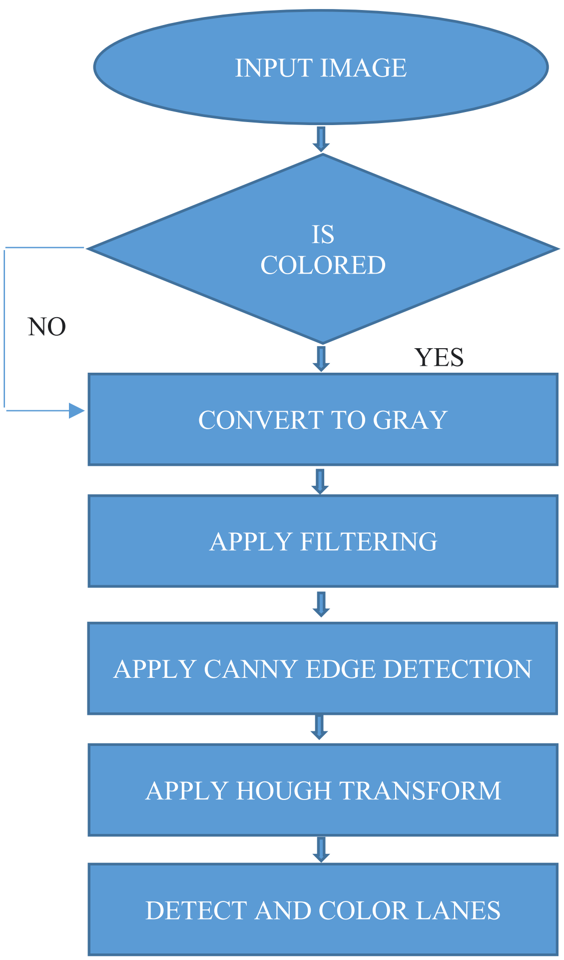

Fig. 1: Work Flow

The process flow go through several transformations and discovery of patterns in the pictures of roads for lanes recognition. Some of the copy are indicated in Figure 2-6. Figure 2, displays the input image.

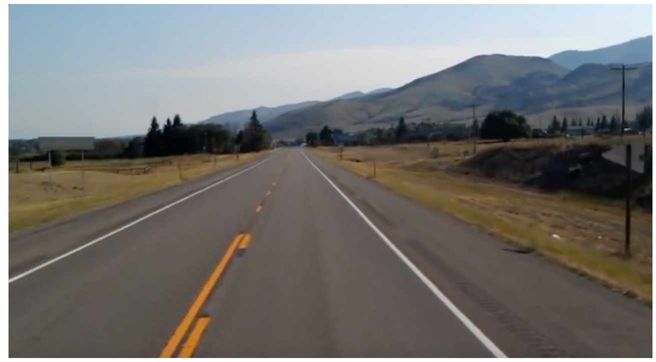

Fig. 2 : Input Image

Figure 3, the input image was transformed to grayscale for decreasing the rendering time.

Fig. 3 : Grayscale Image

Figure 4, the grayscale image converted in blur image for more accuracy to discover accurate lane marks. This image was converted in blur image applying filter such as, Gabor filter etc. here Gaussian filter was used.

Fig. 4 : Blur Image

Figure 5, displays the spotted edges in the picture by the support of canny edge detector.

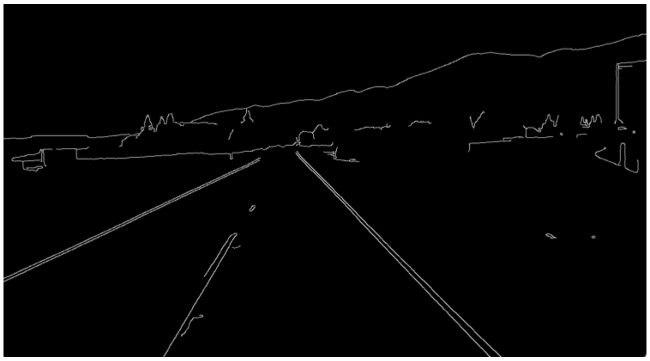

Fig. 5 : Edge Discovered Image

Figure 6, Displays the ROI(Region Of Interest), which contain the certain potion of image that was used to detect lane and give the actual location of the lane in image.

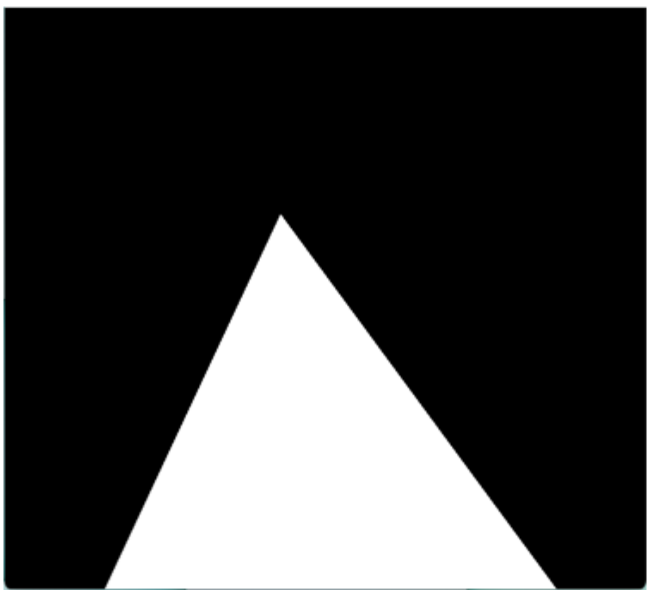

Fig. 6 : ROI Image

Figure 7, shows the portion of image that was used for lane detection and remaining portion was masked and display the region of intrest with detected lane.

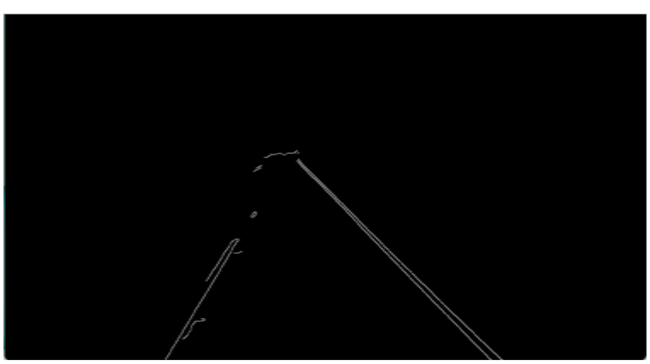

Fig. 7 : Region of Interest Image with Detected Edge

IV. Lane Detection Technique

Hough Transform [17] method was used for obtaining characters that can be used in photo examination and digital image handling. Conventional Hough Transform was essentially used for recognizing strokes in the images. There was a struggle in identifying straightforward lines, rounds etc. in computerized exploration of digital images. The edge indicator has been used in pre-handling step for getting details on image that keep on desired arc but due to certain hitch in image, several of the pixels were omitted on preferred arc. So for resolution this difficulty Hough Transform was used.

Hough Transform was an effective [18] tool for the recognition of straightforward strokes in images, even in the occurrence of interference and obstruction. By calculating exceptional equivalence for each promising mark across point of image, it was capable to discover leading outlines in an image. By picking pixels after image entity set, the edge pixels can be assembled into an entity class.

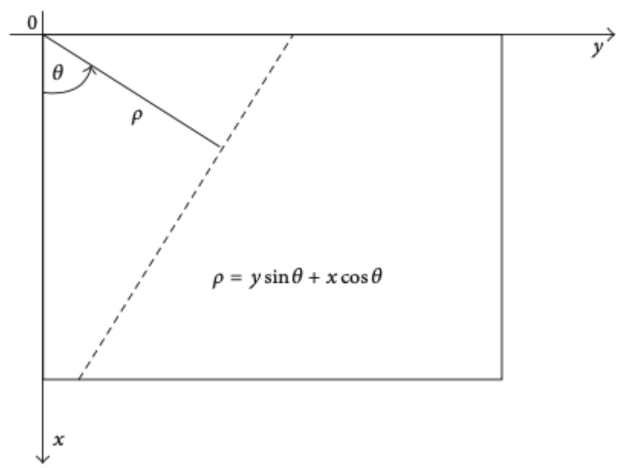

Fig. 8 : Hough Transform

In the close examination image, a straightforward track recognition algorithm was conveyed by using Hough transformation. Hough transform technique examines for lane using the calculation as can be seen in Figure 8.

It was essential to indicate the lengthiest straightforward route from the lines spotted from the Hough transformation. The affected Hough transformation gives the position of an initial point (x1,y1) and the position of the finish point (x2,y2) as can be seen in Figure 9.

Now, the calculation of a traditional mark model equation was described and the factors of the straight road model are computed by using the initial and finish points from every boundary order of near segment image. Formula displays the traditional line model for the road lane discovery as follows:

$$b = \frac{(y2-y1)}{(x2-x1)},$$

$$a = y1 - \frac{(y2-y1)}{(x2-x1)} * x1$$

where b is the slop of the lane discovery model. It noticed that the factors, a and b , used in the straight lane recognition system are also used over in an arched lane detection procedure in the distant vision image plot.

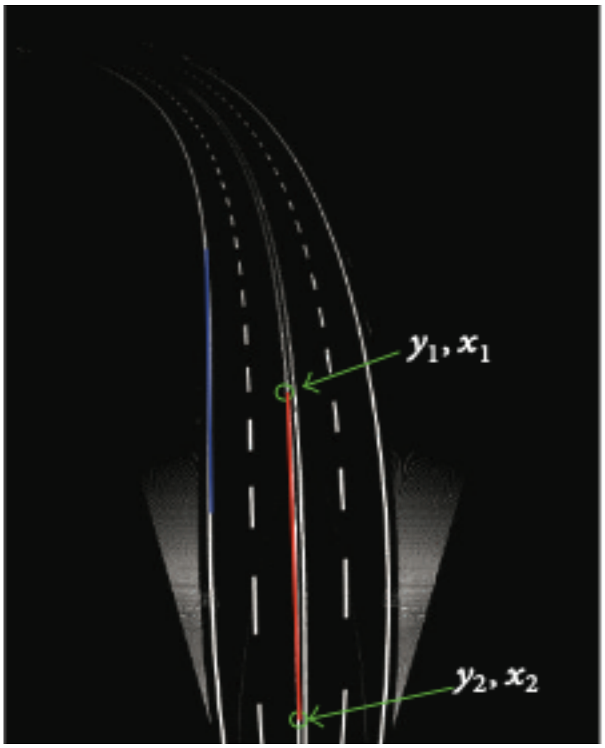

Fig. 9 : Hough Transform Coordinate

V. Result of Hough Transform

Figure 10, shows the detected lane in masked image, which means in result there was no presence of other objects from image, it's gives only the region on intrest oriented output.

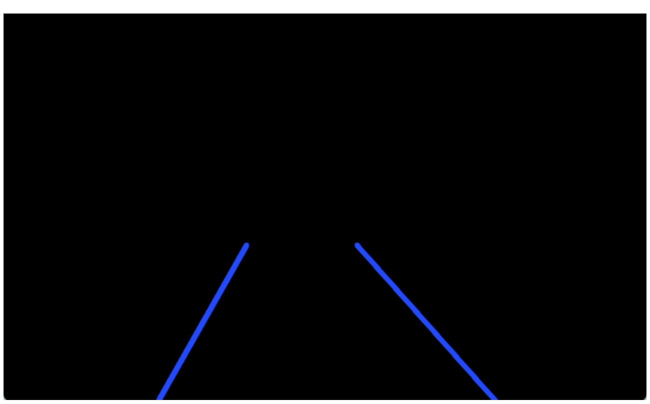

Fig. 10 : Lane Detection in ROI

As a final outcome, Figure 11 shows the combined image of masked image and original input image in which lane detection was performed using Hough Transform.

Fig. 11 : Detected Lanes

VI. Limitation in Existing Work

Most of the work was based on straight lane detection and ignored curve detection. In present system has several problem to detect the right lane in image in by using Hough transform algorithm, because Hough transform algorithm was focused on the straight lane and if is there any object in straight lane or any missing object Hough transform gives false results as can be seen in Figure (11-14).

In Hough transform technique there are many factors available that gives false lane detection such as weather condition (snow, rain), shadow on the lane, dust , tire marks on lane marking, bright light focus on lane, missing lane marking and many more, some of that noticed in the given images below.

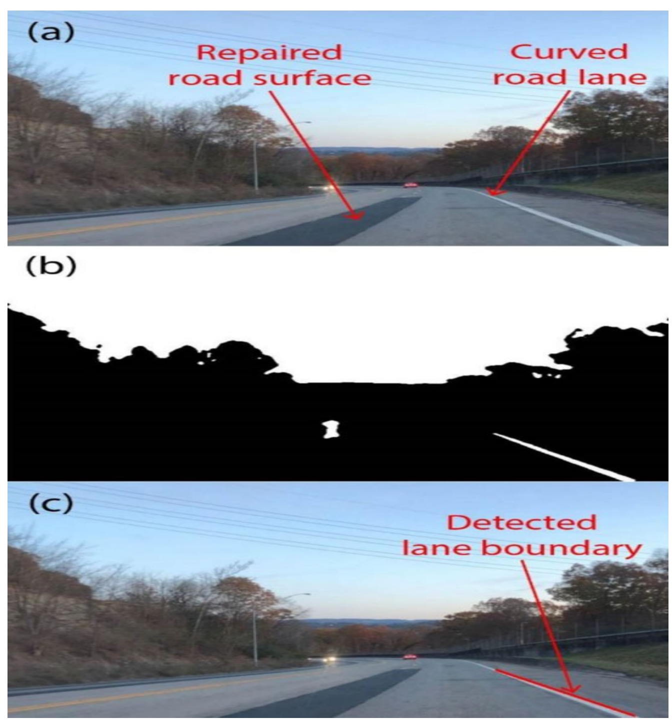

Fig. 11 : Left lane boundary is missing

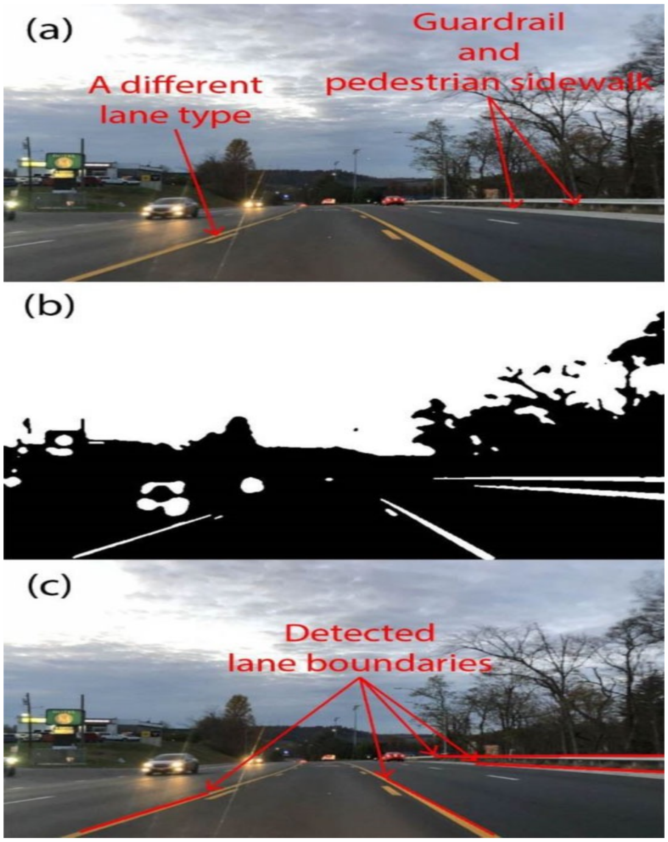

Fig. 12 : Sidewalk incorrectly detected

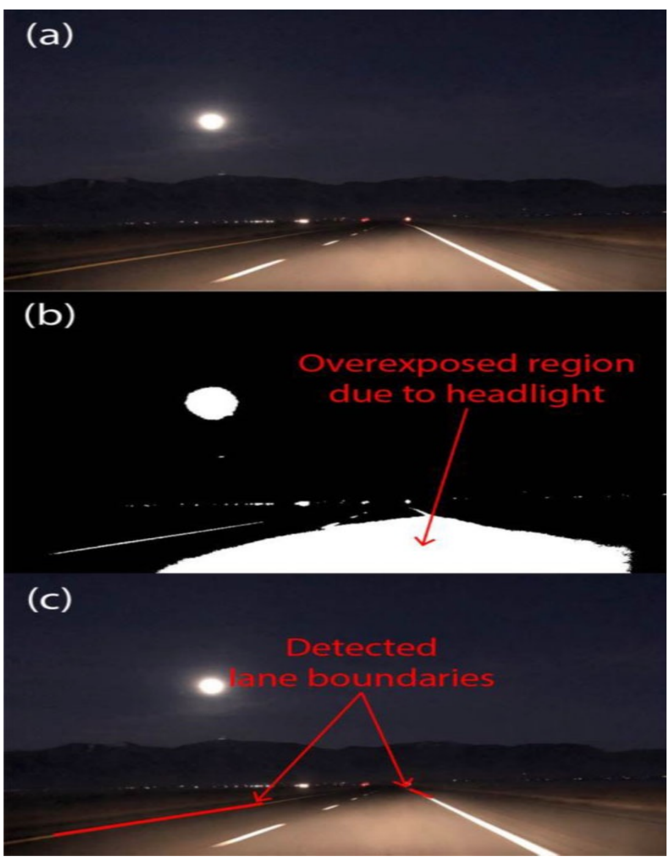

Fig. 13 : Failed to detect the road markings

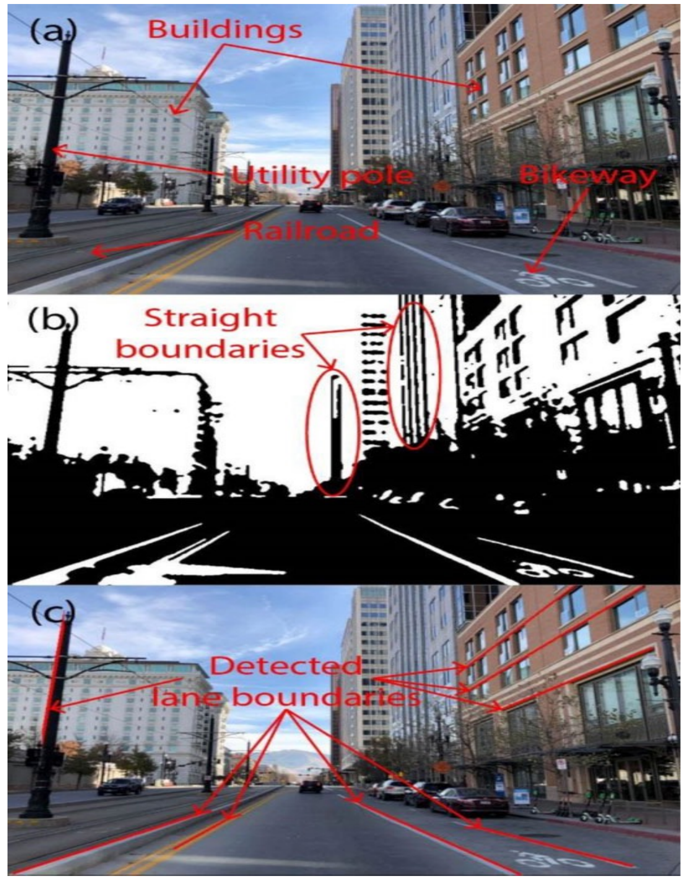

Fig. 14 : Other object identify as lane

VII . Summary and Conclusions

Hough transform based track recognition system was one of the most frequently used process in ADAS. In this paper, lane finding technique have been reviewed for unusual road condition, different location and time(Day-Night). Most of them caused in incorrect outcomes. Overall, the outcomes suggest the vital requirement for increasing road observations, which can help gee-up the field of self-driving cars.

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Lane Detection System – A Mini Project

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***Abstract*— According to the National Highway Traffic Safety Administration (NHTSA) [1], human factor is at blame for 94% of all incidents worldwide. Aggressive driving, having lost the control of the vehicle in severe situations, alcoholic or distracted driving, and a long list of other instances can be provided. One of the most important features that should be in autonomous vehicles is lane recognition and tracking. For that purpose, we suggest designing a lane detection system capable of identifying lane on the road. In addition, this study discusses lane detecting dynamics, as well as strategies, algorithms, and approaches for constructing this system.**

***Index Terms*— Lane detection, NHTSA, autonomous vehicles**

I. Introduction

Lane detection is a crucial component of transportation safety. In an efficient travel network, the lane line is by far one of the most significant traffic indicators in roadway transport, as it can constrain and ensure car movement, ensuring greater levels of protection. Throughout the lane detecting procedure, computer vision is thought to be both efficient and straightforward. In the area of car protection and smart car routing, lane recognition became a fundamental and required operational component that may not prevent the incidence of road incidents dramatically.

Unseen roadway lane lines cause the majority of accidents. Enhanced vehicle assistance can significantly decrease the number of accidents. A driver-warning technology might protect a lot of people's lives. The identification of lanes on the road, that are visible in **yellow and white** colored lines on roadways, are one of the most difficult jobs in **driving assistance** to accomplish traffic safety. We created a **Curve fitting** method to improve the reliability of lane detection and monitoring for safe driving in this paper. In our technique, the Curve fitting model and associated functions can check the lane and its monitoring in order to improve the lane identification efficiency.

II. Background

Numerous publications have investigated and presented several lane following algorithms for autonomous cars, however they are unable to resolve the challenges of yellow lane line identification and curved lane line detection in complicated situations. The boundary and colour properties of lane marker pixels retrieved in the image are the most important. The **Hough transform** approach with canny edge detection method, curve fitting method, computation system that analyzes route layout by curved lines on the road, and thresholding technique have all been used to identify the lanes.

Palach et al. (2014)[2] used the Canny edge technique to detect the edges of roadway limits, wherein margins of the road edge that are greater than the hysteresis threshold result are chosen and linked with a continuous line calculated using a Hough transform vote system. This approach has a sensitivity to lane marker inconsistencies, non - uniform reflections, and changing meteorological circumstances. Mammeri et al. (2016) [3]employed a progressive probabilistic Hough transform paired by maximum stable extreme area (MSER) algorithm, as well as a Kalman filter to accomplish ongoing detection recognize and identify lane lines. The method, unfortunately, doesn't quite operate effectively at dark.

Li et al. (2018)[4], developed a lane identification system that may be used in a variety of challenging traffic circumstances. They didn't create sophisticated lane recognition algorithms, instead, they used the Hough transform to find linear lanes and the Extended Kalman Filter to track lanes. After the specified preparation, they additionally applied the Region Of Interest analysis.

Serov et al. (2021)[5], demonstrated a visual-multisensory odometry solution centered on filters that was used to a self-driving vehicle situation. They implement comparative localization using an Inertial measurement unit, velocity of the car, steering orientation data-driven Unscented Kalman Filter and a graphical position update.

Z. Sun (2020)[6] proposed an innovative novel computer vision-based lane identification approach that integrates the yellow lanes lines in HSV colour space and the white lane line in grayscale colour space. Lane recognition is achieved via canny edge detection, inverse perspective transformation, and a sliding window polynomial fitting technique.

III. PROPOSED METHOD

Camera Calibration

Since many cameras utilize several lenses, sun's beams twist at the borders of these camera lenses owing to diffraction in order to concentrate (nearly all) sunlight beams on the camera and acquire a wider image. The impact of this phenomena distorts the margins of pictures.

The radial distortion [7] phenomenon may be divided into two categories.

- Negative radial displacement results from the **barrel distortion** effect.
- A positive radial displacement correlates to the **pincushion distortion** effect

The symmetrical distortion generated by the lens owing to irregularities in curve whenever the lens was ground is known as radial lens distortion. Radial lens distortion causes defects that are often considerably lower than the scanning resolution of the picture. Applying the data might substantially rises the computation while offering minimal benefit to the outcome. Radial distortion can be represented as follows:

$x_{distorted}=x(1+k_1r^2+k_2r^4+k_3r^6)$

$y_{distorted}=y(1+k_1r^2+k_2r^4+k_3r^6)$

In short, we need to find five parameters, known as distortion coefficients, given by:

Distortion coefficients$=(k_1k_2p_1p_2k_3)$

It is suggested that at least 20 chessboard pictures be utilized in the object points and image points generation procedure. We're set to start calibration once we have both object and image points. The cv2.calibrateCamera() method returns the camera matrix, distortion coefficients, rotation and translation vectors, and other information.

Now, we can take an image and undistort it by using cv2.undistort() function.

Thresholding

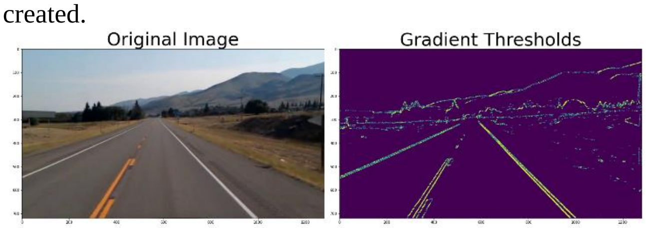
Thresholding is a form of image segmentation in which the pixels of an image are changed to make it simpler to evaluate the image. We turn a colour or grayscale images into binary images by thresholding.

The objective of this stage is to design an image processing pathway in which the program can easily identify the lines on the road. Working with various gradient and colour threshold may lead to a lot of interesting solutions.

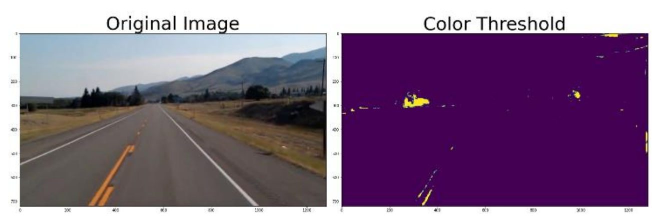
This procedure is used to "pixelize" the road picture. Initially, the sensor produces coloured images, with each colour indicated by three R, G, and B components. It is a common misconception that locating lanes may be accomplished simply by separating yellow and white pixels, however that is not the case. For identical hue might be rendered by multiple RGB values based on the lighting circumstances, necessitating a more sophisticated method. As a result, colour transformations and a gradient threshold were used to make a binary image which catches lane pixels despite of illumination.

The cv2.Sobel() [8] method was used to set the gradient threshold. Sobel is a fascinating way for detecting any pattern in a specific axis, including x and y axis.

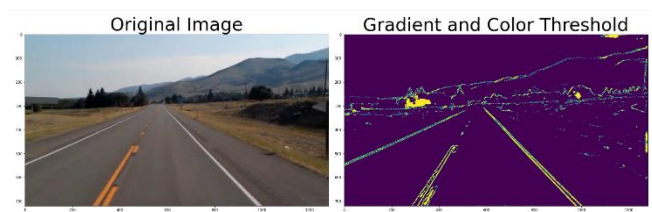
Following the implementation of Sobelx and Sobely, the absolute value of the gradient was found. Next, the gradient magnitude was calculated by using np.sqrt() function. Then, the absolute value of the gradient direction was calculated by calculating the angle between Sobelx and Sobely gradients . Finally, all above threshold were calculated by combining which three thresholds and the binary image result was created.



For colour transformations, first, the image was converted to HLS (Hue, Lightness, and Saturation) style by using cv2.cvtColor [9]. Furthermore, since saturation readings don't really fluctuate as much as RGB (Red, Green, Blue) values based on the illumination, the saturation was extracted: s channel. The pixels that fell under the threshold range that defined for locating the lane pixels were activated. Next, the minimum and maximum color threshold values were set to 170 and 255 and the binary image was returned.

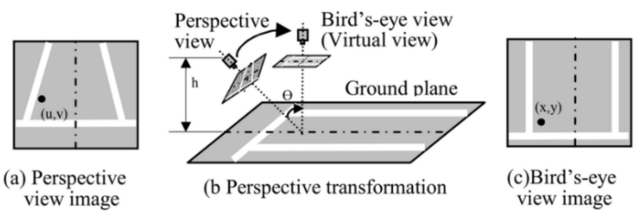


Finally, combined binary image was returned by combining the colour transform and gradient threshold.



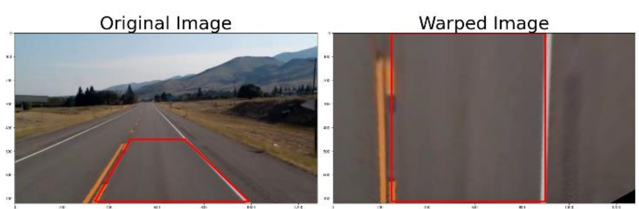
Perspective Transform

Whenever human eyesight view objects that are close to them, they appear larger than when they observe objects that are further off. In a broad sense, this is referred to as perspective. The transition of an item, for example, through one condition to another is called transformation.
Generally, perspective transformation is focused with the translation of a three-dimensional reality into a two-dimensional picture. The identical concept that underpins human sight and that underpins the camera's operation.



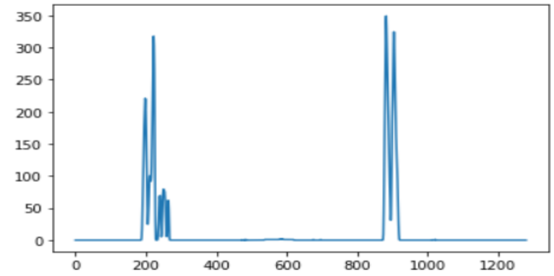
We may modify the viewpoint of an images and videos using Perspective Transformation to have a greater understanding of the content we need. The areas on the picture out of which we wish to obtain content by adjusting the viewpoint must be provided in Perspective Transformation. We must additionally specify the points inside where we wish our picture to be displayed. Next, we wrap the perspective transform around the source image by using the 2 pairs of points.

The src (source) is four points on the corners of a trapezoidal shape, while the dst (destination) is four points on the corners of a rectangular shape. The transform matrix M would be obtained using the v2.getPerspectiveTransform() [10]method. The perspective would then be warped using the cv2.warpPerspective()[11] method.



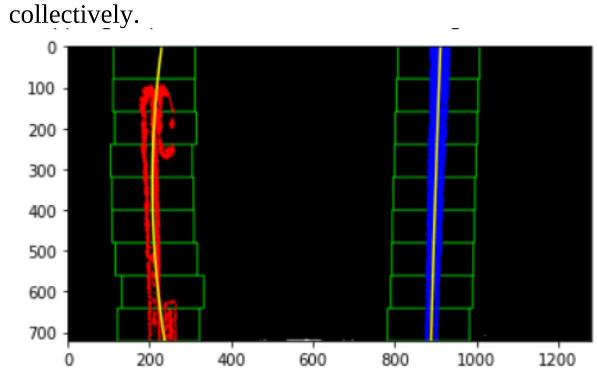
Histogram

To identify lane pixels, It was needed to determine the starting point, which was by determining the highest point of the perspective-transformed image's histogram.

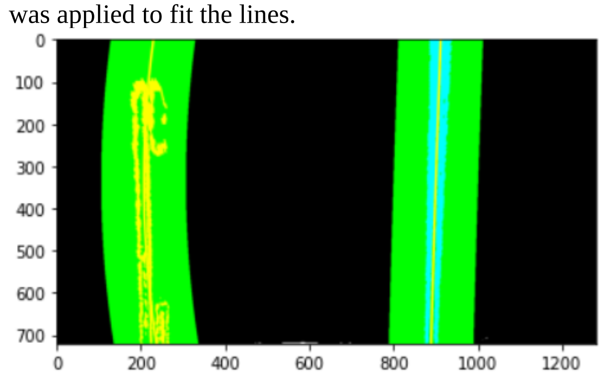


Sliding Window

The sliding window technique was used to apply convolution, which increased the amount of pixels for each panel. To construct the signal, the window is slid across the image sample and any contiguous elements are combined collectively.



The maximum of the convolved wave has the largest pixel overlapping, hence this is the most probable spot for the lane marker. Lane line pixels were detected using algorithms in the rectified binary frame. The lines on the left side and the right side of the image were discovered, and a polynomial function was applied to fit the lines.



Depending on the amount of windows which pixel value within demands a relatively small density and the amount of frames whose pixel value inside demands a minimal crowd, we can anticipate a degree of certainty of detected 'line' to determine if it's a line or not.

Lane Curvature

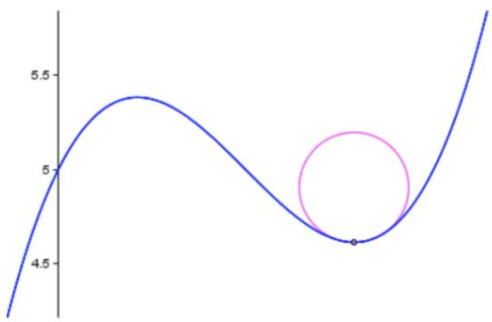
Determining the radius of curvature and the vehicle's position on the road is critical while self-driving. The level of maneuvering required is determined depending on the radius

of curvature detected in the lines and how far the vehicle is from the center of the path.
Readings of the lane lines is collected and how much the route is twisting has calculated, as well as the car's positioning in relation to the lane center.

$$R_{curve} = \frac{[1+\left(\frac{dx}{dy}\right)^2]^{3/2}}{\left[\frac{d^2x}{dy^2}\right]}$$

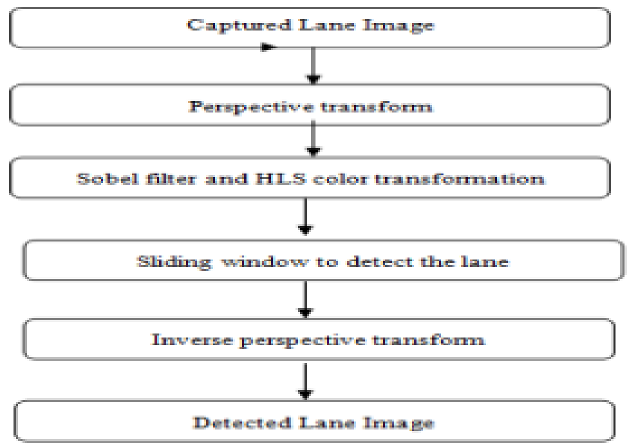
It is believed that the sensor was situated in the vehicle's center. The radius of the smallest circle that can be tangent to our lane lines was also calculated to determine the lane curvature – for a flat lane, the radius would be large. By determining the necessary pixel height to lane length and pixel width to lane width proportions, it needs to be transformed from pixel space to meters.

The pixel-values to meters are converted by multiplying xm_per_pix, and ym_per_pix. These figures are calculated by measuring the distance of the dotted white line to the number of pixels it occupies in the picture. The radius of curvature is determined depending on the poly-fitted lines after transformation.



Final Touches

The whole lane is twisted back onto the source picture utilizing the reverse of the matrix obtained in the perspective transform phase after the lines have been detected.



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IV. Conclusion and Limitations

Under typical illumination circumstances, this method works wonderfully. It must, nevertheless, be enhanced to handle various use scenarios. For example, lanes where a part of the lane is recently resurfaced and has a distinct colour than the other half of the lane, that is an older surfaced road, might be enhanced. The technique also requires to be enhanced in scenarios that the lens has glaring from bright sunshine, and in many other elevated contrast situations where the lane lines seem faded out and are difficult to identify. These problems might be handled by continuously altering the picture intensity to guarantee that the lane lines in the frames are not bleached out and that the technique has a reasonable contrast ratio over all illumination circumstances. It will be challenging to correctly distort the photos in the scenario of curving and sloped roadways, that might present issues for the technique. Establishing a dynamic zone of focus for every captured image can also help with this problem. These are few of the areas we will have to look at further down the road in order to improve the current method and make it more resilient for varied use circumstances.

This lane line detection implies that the vehicle is travelling in the middle of the lane. It would most probably struggle if the vehicle changed lanes since the system isn't built to tackle that kind of a complicated issue.

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