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A Study For Self-Driving Car Analysis

Rasha I. Ahmed[1], Rana M. Zaki[2], Matheel E. Abdulmunim[3]
[1,2,3] *Department of Computer Science, University of Technology, Baghdad, Iraq*
[1]*rasha.i.ahmed@uotechnology.edu.iq*, [2]*rana.m.zaki@uotechnology.edu.iq*,
[3]*matheel.e.abdulmunim@uotechnology.edu.iq*

Abstract— *Computer vision has demonstrated itself to be a key component of recent technological advancements. Among computer vision applications, the self-driving automobile. The self-driving cars is one of the most significant developments in the automotive sector. Also Currently, artificial intelligence, especially neural networks, has contributed greatly to the field of automated driving. This paper presents an overview of the use of artificial neural networks for lane detection and demonstrates how this technology has become a key component of vision-controlled autonomous vehicles. Convolutional Neural Networks (CNN) are used for lane detection, which contributes to the car's autonomous operation. Also, the convolutional Neural Networks model gives the vehicle the ability to learn from various road conditions and weather conditions weather rainy, sunny, night or day, granting it the capability of direction prediction so that it can handle any scenario arise which will help the driver to make the right decision and avoid accidents.*

Index Terms— *Self-Driving Car, Deep Learning, Deep Neural Networks, Computer Vision, Lane Detection.*

I. INTRODUCTION

With the rising growth of civic traffic, road safety has become increasingly substantial. changing lanes is accountable for over 30% of all highway accidents, with the majority of these accidents are caused by the driver's distraction or exhaustion. As a result, a system that can alert the drivers of an impending hazard has the potential to salvage a substantial number of lives. Advanced Driver Assistance Systems (ADAS) are technologies that are designed to assist the driver while driving. ADAS includes an assortment of systems like as collision avoidance, adaptive cruise control, blind spot recognition, night vision, and traffic sign detection [1]. This category also includes lane departure systems. This system's purpose is to recognize lane’s markings and the driver a warning if the vehicle is drifting out of its lane. The technique of lane markings on roads locating then presenting these locations to an intelligent system is known as lane detection system. Intelligent vehicles and smart infrastructure work together in intelligent transportation systems [2] to create a safer environment and better traffic conditions. A lane detecting system's applications can range from as simple as pointing out lane locations to the driver on an external display to more difficult jobs like forecasting a lane shift in the near future to avoid collisions with other vehicles. Cameras, laser range pictures, Light Detection and Ranging (LIDAR), and Global Positioning System (GPS) devices are some of the interfaces used to detect lanes [3]. Lane detection in many suggested systems [4] consists of the localization of specified primitives such as road markers on the painted road surface. Various obstacles, such as parked and moving vehicles, poor quality lines, tree shadows as shown in *Fig. 1,* buildings and other vehicles, sharper curves, irregular lane shapes, merging lanes, writings and other road markings, unusual pavement materials, and dissimilar slopes, all contribute to lane detection issues. Lane detection has been the subject of current study, with a wide range of algorithms, representations, detection and tracking strategies, and modalities presented [5].

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FIG. 1. ILLUSTRATES THE DIFFICULTIES ENCOUNTERED IN LANE DETECTION, AS REFERENCED IN SOURCE [6].

Lane detection has been addressed using several methodologies. The initial approach utilizes computer vision and can be categorized into two distinct types: model-based or feature-based [7, 8]. Feature-based algorithms for lane recognition utilize low-level characteristics, such as lane-mark edges [9] and [10]. The feature-based techniques significantly depend on distinct lane markers and are susceptible to inadequate lane markings, noise, and obstructions. Lanes are characterized in model-based techniques as a specific form of curve model that can be defined by a small number of important geometric factors. The user's text consists of two references, [11] and [12]. Unlike feature-based methods, model-based methods are more resistant to weak lane appearance cues and noise. Nevertheless, the model constructed for a certain setting may not be effective in another, hence reducing its adaptability. Furthermore, achieving the most accurate estimation of model parameters necessitates a repetitive process of reducing errors, which can be time-consuming [13]. The second approach employs deep learning techniques. The subsequent sections of the paper are structured in the following manner: Section II introduces various lane-detection models. Section III provides a comprehensive review of existing literature on lane detection using computer vision and deep learning techniques. The conclusions are presented in Section IV.

II. LANE DETECTION mODELS

There are two approaches to lane detection, in this section the algorithms for lane detection models are introduced.

A. Image Processing Based Lane Detection Algorithms

The most common method for lane detection involves using a car-mounted camera to capture an image of the road.

Subsequently, to speed up processing, the image is transformed into a grayscale representation. Moreover, precise edge detection will be hampered by the noise in the image. Use filters, such as the bilateral, Gabor, and trilateral filters, to lessen or completely remove undesirable noise. Subsequently, the edge detector is utilized to produce an edge picture through the application of the Canny filter and automatic thresholding for edge isolation. After receiving the edges that are identified, the lane detector creates distinct segments for the borders of the left and right lanes. The lane boundary scan utilizing the Hough transform edge image is demonstrated in *Fig. 2*. Both the left and right sides of the scan produce a number of points. In the end, the scan precisely corresponds with these data.

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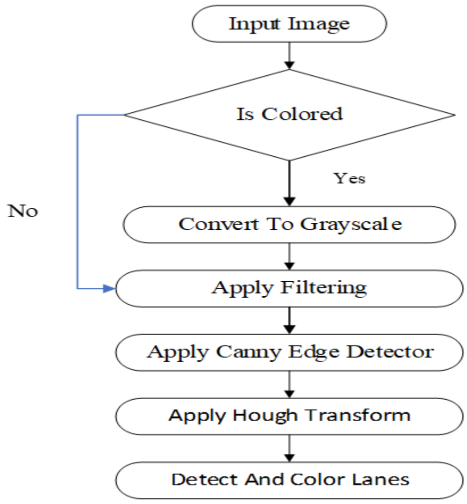

FIG. 2. LANE DETECTION ALGORITHM [2].

For determining lanes, the system goes through a series of adjustments and pattern detection in road images. *Fig. 3-6* depicts some of the photographs. The input image is shown in *Fig. 3a*. The filtered image of *Fig. 3.a* is shown in *Fig. 3.b*. then the filtered image is converted to a grayscale image as shown in *Fig. 4.a* to reduce processing time. The image then segmented to create a binary image (4.b). This is done in order to locate the lanes in the image that has been recorded.

a b

FIG. 3. DISPLAYS TWO IMAGES: A) THE ORIGINAL IMAGE AND B) THE FILTERED IMAGE AFTER USING A SMOOTHING TECHNIQUE.

a b

FIG. 4. PREPROCESSING IMAGES A) GRAYSCALE, B) BINARY.

Fig. 5.a depicts the smoothed image, whereas *Fig. 5.b* depicts the image's discovered edges using the Canny edge detector.

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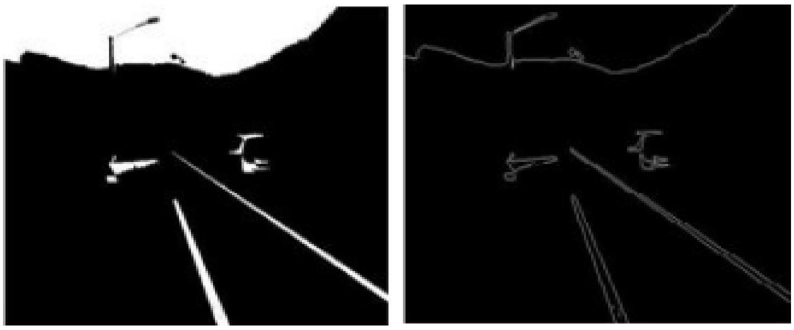


a b

FIG. 5. EDGE DETECTED IMAGE A) SMOOTHED IMAGE, B) EDGE DETECTED IMAGE.

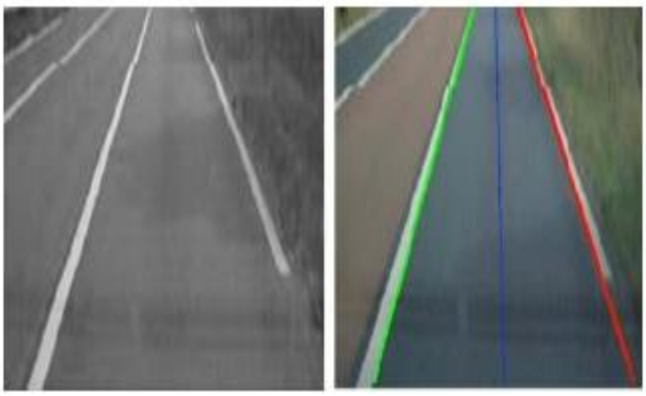
The smoothed image is shown in *Fig. 6.a*, and the output image is shown in *Fig. 6.b*.

a b

FIG. 6. RESULT IMAGE A) SMOOTHED IMAGE, B) OUTPUT IMAGE.

A. 1. Results by applying Hough Transform

An algorithm for lane mark recognition, lane mark attribute recognition, and travel direction determination was proposed by Mariut et al. [1]. The popular Hough transform was applied to identify potential lines in the pictures. To guarantee accurate lane mark identification, they developed a system that extracts the inner lane border. As *Fig. 7* illustrates, the process of creating the magnitude image highlights the edges.



a b

FIG. 7. DETECTED LANES A) INPUT IMAGE, B) DETECTED LANES.

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A. 2. Results by Applying Hough Transformation and Filters

T.T Tran et al. [15] suggested an adaptive lane marking detection approach based on the Hue, Saturation, and Intensity (HSI) color model. They start by converting an image from RGB-based color scheme to an HSI-based color scheme. However, a tweak in the method to calculate the intensity (I) component from RGB images enhanced the HSI color model. Then, after acquiring color shots of the road scene in HSI color space, use the limited domain of colors. This procedure utilized the components H, S, and I. This proposed approach can precisely label the location of lane markings, as shown in *Fig. 8.*

a b

FIG. 8. DETECTED LANES BY HIS COLOR MODEL A) INPUT IMAGE, B) DETECTED LANES.

A. 3. Results: Utilizing H-Maxima and the Improved Hough Transformation

Ghazali et al. [4] introduced a new approach that is faster and more capable of detecting unexpected lane changes. They generated a new technique for lane detection based on an improved Hough transform algorithm with the H-MAXIMA transformation. In order to minimize the area to be searched, the enhanced Hough transform method initially establishes the region of interest from the input image and partitions it into a close field of view and a distant field of vision, taking into account the physical attributes of the road lanes.

Fig. 9 demonstrates the application of the Hough transform for lane marker detection in the near field of view following image noise filtering.

a b

FIG. 9. RESULT OF LANE DETECTION A) SHADOWS, B) VEHICLES.

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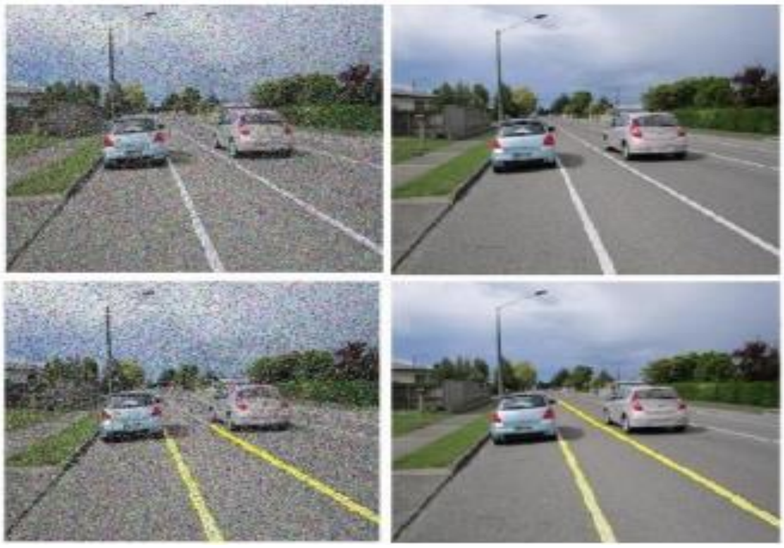
A. 4. Results of lane detection using the HSI model are shown in Section:

In this study, S. Srivastava et al [2] illustrated an efficient reduction method of image noise by employing various filtering approaches. The major goal was to design, improve, perform, and then simulate an efficient lane detecting system that would result high-quality results even when the signal was noisy. The median, Wiener, and hybrid median filters were among the comparison filters used as show in *Fig. 10.*

a b



c d

FIG. 10. THE PROCESS OF IMAGE FILTERING. A) ORIGINAL IMAGE, B) PROCESSED IMAGE, C) UNFILTERED IMAGE, D) RESULTANT IMAGE.

B. Machine Learning of Lane Detection Algorithms:

Researchers are currently prioritizing the utilization of distinct machine learning and deep learning techniques for the detection of lane markers, as opposed to conventional approaches based on image processing. The advancement of deep network theories, parallel computing techniques, and the availability of extensive datasets have all played a role in this. Deep learning has emerged as a prominent and popular field of study over the last decade.

When compared to traditional approaches, several deep learning algorithms demonstrate significant improvements in computer vision tasks, with much improved detection and identification performance. The Convolution Neural Network (CNN) is a frequently used methodology in object recognition research.

CNN has a number of benefits, such as comprehensive end-to-end identification, automated feature learning, and accurate detection accuracy. Some academics have recently employed CNN and other deep learning techniques to successfully apply lane detection. Using the CNN model significantly improved the accuracy of lane detection from 80% to 90% when compared to conventional image processing techniques. [16], [17].

III. LITRATUAE REVIEW

This section presents an illustrated review of the existing literature. The analysis of road boundary and lane detection incorporates references to significant literature from multiple sources. The authors utilized the most popular methods for road lane detection, which are based on computer vision and deep learning. We present these strategies in this section.

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A. Lane Detection using Computer Vision

This literature review aims to investigate and assess the advantages of lane-detecting algorithms in addition to the many drawbacks of existing methods and algorithms. This literature review's primary goal is to identify gaps in existing research and methodology and suggest potential solutions to close these gaps. The RALPH system was presented by D. Pomerleau et al. in 1996 with the purpose of controlling a vehicle's lateral position independently. A matching technique is utilized to find the lane's curvature and lateral offsets. With this method, a template is adaptively aligned and adjusted to the average intensity profile of the scan line. The GOLD system was developed in 1998 by Broggi et al. [19] and uses an edge-based method to identify.

C. Kreucher et al. (1998) [20] presented a deformable template technique in the LOIS algorithm. All possible ways that lane borders could appear in the image are included in the parametric family of forms. The degree of resemblance between a set of lane creation parameters and the pixel data in an image is directly proportional to the function's value. Finding the ideal lane form that enhances the present image's functionality is known as lane identification. The B-Snake spline was used by Y. Wang et al. (2004) [8] as a geometric representation of the route in their investigation. He then used Canny/Hough Estimation of Vanishing Points (CHEVP) to extract the parameters of the geometric model from the images.

AURORA is a system designed in 2004 by M. Chen et al. that uses a color camera directed downward and mounted on the side of an automobile to track lane markers on well-maintained highways. To locate the lane markers, a single scan line is used in each image. The number of lanes on a road was ascertained by C. R. Jung et al. (2005) [22] using edge detection, square angular estimate, and the Hough transform. The algorithm he developed to achieve the results is described in this publication. The technique works incredibly well, except in situations when there are shadows or other obstructions on the road.

In 2008, M. Aly introduced a very reliable technique that can process data in real time and identify road lanes on metropolitan streets. The method identified the lanes on the road by first capturing an aerial view of the image, filtering it using Gaussian kernels, and then utilizing line detection and a novel RANSAC spline fitting technique. In multiple circumstances, this algorithm was able to accurately identify each lane in static photos of city streets. This strategy has several issues due to passing cars, stop lines at junctions and crosswalks, and sloppy writing.

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A reliable method for recognizing and tracking lanes in difficult circumstances, such as curved lanes, faded lane markers, lane shifts, and the existence of emerging, ending, merging, and splitting lanes, was presented by Kim (2008) [5]. Techniques for filtering, consensus, and random sampling were included in the program.

The method was designed to produce a significant number of hypotheses in real time, more than previous algorithms could provide. In 2009, Khalifa et al. presented a system that uses video sequences taken by an automobile traveling on a highway to recognize lanes in real-time. When there are variations in the amount of light and shadow, this approach yields exceptional effects. The Hough transformation method made it easier to find lanes in a constrained search area. No matter what kind of weather is in the area, this approach can be applied to painted or unpainted roads with straight sections and few curves.

This technique has proven to be resilient and efficient in comparison to other methods, which qualifies it for real-time requirements. Automobiles travel on roads that are either straight and level or gently curved. When there are shadows present or abrupt shifts in direction, this strategy is unsuccessful. Meuter et al. (2009) presented a robust approach that uses camera-based lane identification for lane

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detection and tracking systems. Meuter et al. used the Interacting Multiple Models (IMM) technique to integrate the detection system with a tracking strategy that included two extended Kalman filters.

The method showed robustness against noise and weak markers, and it behaved linearly in terms of time. The method can be used to ascertain the position and inclination of lane segments. S. Zhou et al. [24] introduced a geometric model and software for road recognition based on Gabor filters for marked roads in their 2010 study. This algorithm can be utilized in conjunction with an additional driving aid such as a Lane Departure Warning System (LDWS). The starting location, lane original orientation, lane width, and lane curvature were the four characteristics that made up the lane geometrical model.

To determine pixel orientation and apply a filtering procedure to the image along the lane model line, the Gabor filter is utilized. When there are obstructions in the way of edge detection, including shadows cast by trees or people walking on the road, this technique can successfully handle problems related to universal lane detection. The approach performed better in terms of accuracy and showed resilience to noise and other interferences, such shadows.

Lin et al. (2010) [13] presented a lane recognition system that uses realtime vision to identify and categorize lanes in every video frame. This method successfully integrated edgelink and lane-mark features to establish and validate a lane hypothesis. The lane mark candidate search phase utilizes an enhanced edge linking method with directed edge gap closure to provide more comprehensive edge connections The chance of lane continuation is computed using a Bayesian probability model. There were no particular requirements for background models, camera settings, or additional road surface models with this method. As a result, the algorithm demonstrated increased adaptability to different types of road conditions.

Teng et al. [25] presented a method in their 2010 paper that used several cues, including the Hough transform, a color cue, and a bar filter for precise detection of bar-shaped objects like road lanes. Accurate and fast lane detection was achieved by using particle filtering technology. The accuracy of lane identification on both straight and curved highways was improved by this technique. It has proven useful in a wide range of difficult driving situations. This technique is not useful for tracking pathways when used as a particle filter in an environment with dashed lanes. In their research.

An method that makes use of the Hough transform was created by F. Mariut et al. (2012) [1] in order to automatically improve lane markings and distinguish them from digital photographs. This method may identify features of lane markings and ascertain the direction of traffic. A method that extracts the inner edge of the lane is used to produce effective lane mark detection. While the algorithm performs well on straight highways, there are situations in which it becomes unworkable when dealing with curved roadways. A vision-based technology-based lane departure warning system was introduced by N. Phaneendra et al. in their 2013 study. [26].

The objective of this model was to develop an image processing system capable of detecting lanes on roadways and generating a written alert when a lane became empty. The acquired picture coordinates are utilized to determine the distance between lanes and the center of the bottom. This information is then used to make decisions regarding lane switching, requiring a reduced number of parameters. The Kalman filter provides superior lane detection results in comparison to the conventional Hough transformation technique. This paradigm has demonstrated its efficacy and pragmatism when compared to alternative models. In instances where the road conditions are more intricate, our technology becomes inadequate for accurately detecting the lanes. Table I is a concise summary of the data from multiple study studies.

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TABLE I. EXISTING RESEARCHES RELATED TO LANE DETECTION BASED ON COMPUTER VISION

Author Name	Year	Topic	Remarks
Mariut et. al [1]	2012	Lane Mark Detection Using Hough Transform.	The article introduces an algorithm using the Hough transform to highlight lane marks and automatically recognize them from digital images.
S. Srivastava et. al [2]	2014	An effective algorithm for lane detection with several filtering techniques.	A highly efficient approach for reducing noise in photos involves the utilization of various filtering techniques.
T.T Tran et al. [3]	2010	An adaptive method is used to detect lane markings based on the HSI color model.	The adaptive approach utilizes the HSI color model for the purpose of identifying lane markings.
K. Ghazali et al. [4]	2012	Road Lane Detection Using H-Maxima and Improved Hough Transform.	An improved and quick algorithm with the ability of detecting sudden lane changes.
D. Pomerleau et al [5]	1996	Rapidly Adapting Machine Vision for Automated Vehicle Steering.	An autonomous vehicle uses the RALPH system to control its side position.
B.M. Broggi et al [6]	1998	GOLD is a parallel real-time stereo vision system designed for detecting obstacles and lanes in a generic manner.	The GOLD system employs an algorithm for detecting lane boundaries based on edges.
C. Kreucher et al [7]	1998	The LOIS Lane Detection Algorithm serves as the foundation for a driver warning system.	The LOIS algorithm is a method that utilizes deformable templates.
Y. Wang et al [8]	2004	Lane detection and tracking using B-Snake.	The B-snake spline is a mathematical model that accurately represents the shape of a road.
M. Chen et al [9]	2004	AURORA is a road departure warning system that relies on vision-based technology.	developed system called AURORA.
C. R. Jung et al [10]	2004	Lane switching and lane following, using a Linear-Parabolic Model.	proposed system can fit lane boundaries in the presence of several image artifacts, such as sparse shadows, lighting changes and bad conditions of road painting.
M. Aly [1]	2008	Real time Detection of Lane Markers in Urban Streets.	efficient, real time, and robust algorithm for detecting lanes in urban streets.
Z. Kim [11]	2008	Robust Lane Detection and Tracking in Challenging Scenarios.	The researchers showcased a resilient system for detecting and tracking lanes.
O. O. Khalifa et al [12]	2009	Lane Detection using Vision-Based for Autonomous Artificial Intelligent Vehicles.	The lane detection system employs video sequences obtained from a mobile car traversing a roadway in real-time.
s. M. Meuter et al [13]	2009	An innovative method for detecting and tracking lanes.	Presented a novel and resilient methodology for utilizing cameras to identify and monitor lanes in lane detection and tracking systems.
S. Zhou et al [14]	2010	A unique approach to lane detection utilizing the Gabor filter and a geometrical model.	proposed a road detection algorithm.
Q. Lin et al [15]	2010	Real-time lane departure detection based on extended Edge-Linking algorithm.	Presented a novel real-time lane detection system utilizing computer vision techniques to accurately identify the location and classification of lanes in every individual video frame.
Z. Teng et al [16]	2010	Real-time lane recognition is achieved by utilizing numerous cues.	proposed an algorithm which integrated multiple cues.
N. Phaneendra et al [17]	2012	Accident Avoiding System Using Lane Detection.	proposed a vision-based lane departure warning system.

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B. Lane Detection Based on Deep Learning

Nowadays, Deep learning techniques are employed, which rely heavily on training data. Many datasets comprising traffic situational data have emerged as a result of deep learning's application to intelligent driving. This part includes an overview and comparison of the dataset's features, six sizable datasets for diverse intelligent driving tasks, and a few datasets specifically designed for lane marker detection.

B.1. Traffic Scene Datasets

Vision-based autopilot comprises various subtasks in addition to lane marker identification, such as traffic scene semantic segmentation, pedestrian detection and road sign detection. Below a list of some of the most important traffic scene databases.

KITTI [18] is the most extensive dataset available for evaluating performance in several computer vision tasks related to autonomous driving, including as optical flow, visual range, and 3D object detection and tracking. KITTI acquires authentic data from urban, rural, and highway environments. Each image exhibits several levels of opacity and truncation, together with up to 15 cars and 30 pedestrians. Tables II, III, and IV exhibit a selection of the scenes that can be observed when driving in this dataset.

TABLE II. PRESENT SURVEYS PRIORITIZE THE IDENTIFICATION OF LANE MARKINGS (LPY =MOST RECENT PUBLICATION YEAR)

Publication Year	Covered papers (LPY)	Keywords	Notes
[19](2013)	186	Detection System	handcrafted based methods and related hardware platform discussed.
[20](2014)	65	Functional building blocks	Concentrated on perceiving different modes of senses and a comprehensive detecting system.
[21](2018)	112	Algorithms, integration and assessment	The lane marking identification methods rely on deep learning techniques. Concisely presented.
[22](2018)	91	Lane leaving warning	The recognition of lane markings is dependent on the utilization of deep learning techniques. Presented succinctly.
[23](2020)	96	Lane marking detection	Sorted algorithms according to network structure.
[24] (2021)	114	Detection of Lane marking	This study conducts a thorough examination and detailed evaluation of algorithms used for detecting lane markings. It also addresses the main challenges and provides an overview of the datasets used in this field.

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TABLE III. COMPARATIVE ANALYSIS OF LANE MARKING DATASETS

	No. of images	Year	Multiple scenes	Multiple cites	Multiple weather	Multiple moments	Multiple line type	Lane marking labeling	Citation (in this survey)
KITTI road	579	2013	Yes	No	No	No	Yes	Yes	[25] [26] [27] [28]
BDD100K	100,000	2018	Yes	Yes	Yes	Yes	Yes	Yes	[42] [43] [29] [52]
CityScape	5,000	No	No	No	No	No	No	No	none
ApolloScape	143,906	2018	No	No	Yes	No	No	Yes	[30]
Mapillary	19,035	2017	Yes	Yes	Yes	Yes	No	Yes	None
CamVid	182	2008	No	No	No	No	No	Yes	[20]
Caltech Lanes	1,225	2008	No	No	No	No	No	Yes	[31] [28]
Tusimple	6,498	2017	No	No	No	No	No	Yes	[32] [33] [34] [35] [28] [36]
CULane	133,235	2017	No	No	Yes	Yes	No	Yes	[32] [33] [37] [38] [39] [40]
VPGNet	21,097	2017	No	No	Yes	Yes	Yes	Yes	[41]
LLAMAS	100,042	2019	No	No	Yes	Yes	Yes	Yes	[42] [30]
CurveLanes	150,000	2020	Yes	No	Yes	Yes	Yes	Yes	[36]
DET	5424	2020	Yes	No	No	No	Yes	yes	None

TABLE IV. SETTING COMPARISON OF LANE MARKING DATASETS

	Collection Device	Resolution	Annotation
KITTI road	Grayscale cameras Color cameras Laser scanner	1242 x 375	Pixel level + rectangle coordinates
BDD100K	Color cameras	1280 x 720	Key point coordinates
CityScape	Color cameras	1248 x 1024	Pixel level
ApolloScape	Color cameras + Laser Scanner	3384 x 2710	Pixel level
Mapillary	Color cameras	900 million (average)	Pixel level
CamVid	Color cameras	960 x 720	Pixel level
Caltech Lanes	Color cameras	640 x 480	Key point coordinates
Tusimple	Color cameras	1280 x 720	Key point coordinates
CULane	Color cameras	1640 x 590	Key point coordinates
VPGNet	Color cameras	640 x 480	Key point coordinates

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LLAMAS	Color cameras + LiDAR Maps	1276 x 717	Pixel level
CurveLanes	Dynamic Color Cameras Sensor	2560 x 1440	Key point coordinates
DET	Vision	1280 x 800	Pixel level

There are some lane markings in KITTI, but the segmentation labels are missing.

BDD100K [43] is a comprehensive open-sea driving dataset, boasting over 100 million frames across 100,000 movies, making it the largest and most diversified of its kind worldwide. A total of 100,000 images are acquired and classified by extracting crucial frame samples from the 10th second of every video. The package comprises the road target, traversable territory, road target classes, and lanes of many cities. Data on lane markings is available for several types of roadways and under different lighting situations.

CityScape [44] is a dataset for semantic segmentation that specifically aims to comprehend urban streetscapes.

It includes street views from 50 different cities in various seasons. For semantic segmentation at the pixel, panorama, and instance levels, CityScape provides a variety of metadata (front and rear video frames, GPS, stereo, and car odometers). The training set contains 5,000 images with high-quality annotations and 20,000 images with coarse annotations. On the other hand, the lane marking has no distinct label.

ApolloScape [45]: This dataset surpasses the accuracy of KITTI, CityScape, and BDD100K due to its utilization of a mobile LiDAR scanner to collect point clouds from Reigl, resulting in a very exact and densely populated point cloud. ApolloScape comprises street images captured during daylight hours in various weather conditions, collected from four regions in two cities in China. The photographs recorded challenging traffic and environmental conditions. The dataset includes not only lane markers but also images categorized by semantics, such as perception, road network data, and simulation sceneries.

Mapillary [46] features 25,000 high-resolution streetscape images that represent a wide range of weather conditions (sun, snow, rain, haze, fog) and illumination variations throughout the day (dawn, day, dusk, night). It includes lane markers and has five times as many fine annotations as CityScape.

CamVid [47] is the inaugural compilation of videos that includes metadata and semantic tags for object classes. While it does provide annotations for lane markings at the pixel level, its dataset is significantly smaller compared to the previously stated databases.

B.2. Datasets for Lane Marking Detection

Occasionally, common traffic scene datasets are insufficient for lane marking detection. Consequently, researchers have created various datasets specifically for lane marking detection.

Caltech Lanes [31] consists of four movie shots taken at different times of the day on roadways around Pasadena, California. This is an early dataset for lane marking detection. The image quality is low, and the scale is small.

Tusimple [48] This dataset outperforms the Caltech dataset in terms of image resolution and size. There are 3,626 image sequences. The content is collected from the driving environment on the highway; it contains various levels of lane markers, occlusions, and road conditions. In temperate weather, there is a collection of traffic conditions throughout the day. Short videos, each containing 20 frames per second, register the lane marking. In the 20th frame, each sequence represents the ground truth. The difficulty level of detection is average.

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CULane [32] This is the world's largest and most difficult dataset for lane marking detection. It is more than 20 times larger than the Tussimple dataset. The dataset encompasses traffic conditions in Beijing during different times of the day. It contains eight difficult lane marking detection scenarios, including shadow occlusion, traffic congestion, lane marking missing, and curved lane lines, in addition to various weather conditions and lighting levels.

VPGNet [41] This dataset contains images with varying degrees of rainfall, as well as images captured at night.The methods for predicting lane markings. The system accurately delineates a variety of lane markings and road signs, in addition to vanishing point labels. Severe weather and challenging lighting conditions

LLAMAS [49] is a dataset of lane markings that does not require supervision and emphasizes optimizing samples to improve the accuracy of labels. The system use automatically generated maps to project markers onto the visual space. The LLAMAS dataset stands out for its higher level of complexity and accuracy compared to other datasets. This is due to the fact that the number of pixels designated on each lane marker is quite small and varies depending on the distance and position of the markings.

CurveLanes [54] features more than 90% of images with curve lane lines, which makes up for the earlier dataset’s absence of curve scenes.

DET [50] For traffic scene data gathering, a dynamic vision sensor (DVS) is used, which produces data with minimal latency and a high dynamic range. DVS properties (road surface, sky, etc.) ensure that images are free from the effects of lighting changes and redundant backdrops. Most cars equip themselves with color cameras instead of DVS, limiting the dataset's application breadth [51] and [52].

B.3. Dataset Summary

Table III summarizes the properties of the above-mentioned datasets and their citations, with further technical details in Table IV to assist the reader in selecting relevant datasets based on various task needs.

Most of the traffic scene datasets that are currently available are from actual driving scenarios and feature a range of difficult conditions such as incomplete lane marking information, complex lane marking distribution, road texture interference, and shadow occlusion. Nevertheless, datasets for lane marking detection are scarce in inclement weather. We expect the need for more tough datasets, even though there are plenty of rainy traffic scenarios in VPGNT and many dark driving situations in Culane. These datasets ought to cover a wide range of challenging traffic scenarios, such as severe weather, scenes with variable visibility, fluctuating amounts of snow, rain, and fog, and various times of the day, such night and dusk [23].

IV. CONCLUSIONS

This paper implements lane detection for a self-driving car using both deep neural networks and conventional methods. In conventional image processing depend on users manually tuned parameters so, it very sensitive to environmental factors like lighting variations either deep neural network depends on data driven/automatic. Performance of conventional methods are faster, but less robust either deep learning-based approaches slow promising detection accuracy, but computationally intensive. Importance of lane detection and the challenging are highlighted lane detection is well defined but challenging problem due the environmental factors. When compared to conventional methods, using the deep learning model significantly improved lane detection accuracy from 80% to 90%.

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