

Intelligent Lane Detection and Path Prediction for Autonomous Driving in Varied Weather

by

Ashik Adnan
22166003

A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
M.Sc. in Computer Science

Department of Computer Science and Engineering
Brac University
January 2025

© 2025. Brac University
All rights reserved.

Declaration

It is hereby declared that

1. The thesis submitted is my own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

Student's Full Name & Signature:



Ashik Adnan

22166003

Approval

The thesis/project titled “Intelligent Path Prediction Technique in Varied Weather Conditions for Autonomous Driving” submitted by

1. Ashik Adnan (22166003)

Of Fall, 2024 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of M.Sc. in Computer Science on December, 2024.

Examining Committee:

Examiner:
(External)



Dr. Md. Abdus Samad Kamal

Associate Professor
Graduate School of Science and Technology
Gunma University

Examiner:
(Internal)



Dr. Muhammad Iqbal Hossain

Associate Professor
Department of Computer Science and Engineering
BRAC University

Supervisor:
(Member)



Dr. Md. Khalilur Rahman

Professor
Department of Computer Science and Engineering
BRAC University

M.Sc. Coordinator:
(Member)



Dr. Md Sadek Ferdous

Professor
Department of Computer Science and Engineering
Brac University

Head of Department:
(Chair)

Dr. Sadia Hamid Kazi

Chairperson and Associate Professor
Department of Computer Science and Engineering
Brac University

Abstract

Rapidly advancing intelligent and autonomous driving systems demand reliable computer vision-based perception technology, particularly for safe path detection in various weather and road conditions, essential for efficient vehicle navigation. This paper proposes a novel lane detection technique utilizing a pre-trained Keras-based CNN model capable of identifying the path ahead under challenging lighting and weather situations, such as nighttime and heavy rain, using videos acquired with a monocular camera. Furthermore, we address the issue of lane detection when lines are illuminated by vehicle headlights or streetlights, even under severely reduced visibility conditions caused by heavy rainfall, using a color filtering technique. We propose a path projection technique that integrates the widely used slope calculation method with convolutional neural networks (CNN). The Keras model facilitates the detection of lane lines, enabling the calculation of the center trajectory based on the identified road lanes. The projection technique demonstrates effective performance in low visibility and adverse weather conditions. The experimental results show that the presented algorithms effectively detect road lanes and predict paths in multiple weather conditions.

Keywords: Lane Detection, Lane Center Point, Path Projection, Artificial Intelligence, Driver-less Vehicle

Dedication

This study is entirely dedicated to Sir Fazle Hasan Abed KCMG, a pioneer of social development in our esteemed country, renowned for promoting the socioeconomic empowerment and rights of millions of impoverished and marginalized individuals through the establishment of BRAC, in response to the dire circumstances of nascent Bangladesh.

Acknowledgement

First and foremost, I express gratitude to the Almighty for bestowing His blessings on me throughout this research effort, which enabled its successful completion.

I extend my sincere gratitude to my research supervisor, Dr. Md. Khalilur Rahman for granting us the opportunity to conduct the study and for his invaluable guidance throughout the process. He has profoundly impressed us with his dynamism, vision, authenticity, and ambition for success. Working and learning under his guidance was a significant honor and privilege. I appreciate his kindness, empathy, and exceptional sense of humor.

In addition, I was perpetually grateful to my parents for their steadfast dedication to our education and future well-being, manifested by their boundless love, prayers and concern for us. Our journey could not have been completed without the continuous support of these individuals. I am deeply grateful to the Department of Computer Science and Engineering at BRAC University, whose lecturers diligently and selflessly equipped me for this significant opportunity at my graduation.

Gratitude is extended to Md Abdus Samad Kamal and Koh Yamada for their indispensable assistance and support in the completion of this research.

Table of Contents

Declaration	i
Approval	ii
Abstract	iv
Dedication	v
Acknowledgment	vi
Table of Contents	vii
List of Figures	ix
List of Tables	x
Nomenclature	xi
1 Introduction	1
1.1 Background	1
1.2 Problem Statement	1
1.3 Preface	2
2 Related Work	4
3 Road Lane Detection	7
3.1 Data Source	7
3.2 Detection methodology and model description	7
3.3 Path Projection	10
3.3.1 Lane Boundaries Detection	10
3.3.2 Lane Center Calculation	12
3.3.3 Moving Average Smoothing	12
3.3.4 Polynomial Fitting (Savitzky-Golay)	12
4 Results Visualization and Conclusion	13
4.1 Result Analysis	13
4.2 Visualization	15
4.2.1 Detection in different light and weather conditions	15
4.2.2 Lane center prediction in different light and weather conditions	17
4.2.3 Detection in multi lane scenario	17

4.2.4	Detection in Bangladeshi roads	17
4.3	Conclusion	20
	Bibliography	24

List of Figures

3.1	Represents the sample image data of three different weather and ambience scenarios.	8
3.2	Processing steps of an input image for detection.	9
3.3	Architecture of the proposed sequential CNN model for lane and path detection.	10
4.1	Comparison of lane detection models	14
4.2	Detected lanes in (a) day, (b) night, and (c) rainy day.	16
4.3	Predicted road centre path over the detected lanes in (a) day, (b) night, and (c) rainy day.	18
4.4	Detected road lanes in multi lane scenario.	19
4.5	Detected road lanes of Bangladeshi roads.	19

List of Tables

3.1	Comparison of My Dataset with Benchmark Lane Detection Datasets	8
3.2	Model architecture summary	11
4.1	Comparison of Lane Detection Models	14

Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

ADAS Advanced Driver Assistance Systems

AV Autonomous Vehicle

CNN Convolutional Neural Network

DTHDI Deformable Transformer with high-order Deep Infomax

FPGA Field-Programmable Gate Array

ROI Region of Interest

SCNN Sequential Convolutional Neural Network

SDC Self Driving Car

Chapter 1

Introduction

1.1 Background

A report from the World Health Organization (WHO) published in June 2022 states that more than 1.3 million people die each year as a result of road traffic accidents[3]. Human drivers frequently encounter difficulties in maintaining proper lane positioning and sufficient following distance from the vehicle in front, necessitating sustained attention to the roadway. Additionally, individuals are prone to driving fatigue, sleepiness, inattention, and drowsiness. The use of technologies in automobiles, such as smartphones, entertainment, and navigation systems, can distract drivers and compromise safety during vehicle operation. The societal costs of road traffic accidents are significant in terms of human injury and economic loss. The development of passive and active safety systems in automobiles has arisen from the previously mentioned issue. Seat belts and airbags serve as examples of passive safety mechanisms[3]. These were developed to reduce the risk of injury to both the driver and passenger resulting from collision impacts. These systems have established themselves as the standard safety equipment for automobiles, yet their application is limited to post-accident scenarios; it would be more desirable to completely prevent casualties. As a result, active safety solutions have become a central focus for manufacturers and researchers[2]. The inception of autonomous vehicle development occurred in Europe in 1986. Numerous automotive manufacturers and research institutions have initiated various vehicle safety initiatives and studies to address urban traffic challenges effectively. The European Union launched the Generic Intelligent Driver Support (GIDS) project within the framework of the Dedicated Road Infrastructure for Vehicle Safety in Europe (DRIVE) initiative. This comprehensive Intelligent Vehicle initiative aims to assist drivers in identifying and evaluating road hazards, followed by the implementation of a system to mitigate specific dangers. The main aim of the developing system in an autonomous vehicle is to assist drivers in identifying driving hazards while improving safety and comfort for both the driver and passengers.

1.2 Problem Statement

The implementation of autonomous vehicle (AV) systems has unique obstacles in many socio-economic and infrastructural environments, including Bangladesh and

Japan. Although both nations aspire to progress vehicle automation, their distinct traffic dynamics, infrastructure, and cultural norms pose differing challenges.

In Bangladesh, cities have small, one-lane roads that are often crowded with cars and are in bad shape. People who drive often don't follow the rules of the road, which can cause unpredictable actions like sudden lane changes, passing at high speeds, and parking illegally. This problem is made worse by the fact that public transportation is not controlled, drivers are not trained, and unsafe driving habits like long hours, drug use, and cell phone use are common. These things make settings that are hard to predict for AV systems that depend on traffic moving in a smooth, rule-based way. Additionally, the lack of high-quality, location-specific datasets like road layouts, lane markings, and real-time traffic trends makes it harder for AVs to navigate, find their way around, and avoid accidents. The risks of using autonomous systems are also increased by problems with infrastructure like roads that aren't well maintained, crossings that aren't marked, and vehicles that don't meet safety standards (for example, gas tanks that are too old).

Japan, on the other hand, has problems because its traffic is very organized and uses a lot of technology. Because Japan's population is getting older, there is a lot of interest in self-driving cars to help older people get around. A lot of people living in cities, complicated road networks with many levels, and a lot of walking and bike traffic are, however, big problems. Even though Japan has good infrastructure and follows traffic rules, AV systems need to work smoothly in places that need to be very precise. For example, Japan's use of high-definition maps and vehicle-to-infrastructure (V2I) communication systems sets the bar for how well AVs work together and how accurate they are. Also, it can be hard for AVs to work consistently in rural places where the road network may not be as well developed or mapped.

Another problem is that it's hard to compare things. For instance, in Bangladesh, the lack of data, especially in cities, makes it hard to build strong AV systems. In Japan, it's still hard to make sure that modern systems are in sync with each other in real time, even though data access is better. Driver Behavior and Traffic Rules: Bangladesh's driving culture is very different from Japan's, which means that AV algorithms need to be able to react to both types of traffic. The infrastructure and the rules: Japan has a very modern infrastructure that makes it possible to use AVs, but there are still gaps in rural areas. In Bangladesh, on the other hand, road upkeep and enforcement of the law need a lot of work.

1.3 Preface

Autonomous driving technology has emerged as a significant topic in the field of intelligent transportation in an effort to mitigate traffic accidents. Autonomous driving systems aim to improve the self driving capabilities of automobiles continuously [23], [26]. For this, researchers are developing various technologies related to Intelligent Driving Systems[16]. Specifically, autonomous cars need to be able to estimate traffic lanes since each lane offers distinct visual signals that govern travel in addition to serving as a spatial barrier.

Accordingly, lane detection is an essential and crucial part of Intelligent Driving Systems and Autonomous Vehicles[24]. Modern automobiles and autonomous vehicles rely heavily on advanced driver assistance systems (ADAS)[9], [31]. Regarding lane detection, the two main schools of thought are deep learning and conventional

computer vision[22]. In order to handle what seems like an endless number of driving scenarios, settings, and unforeseen impediments, the traditional computer vision paradigm necessitates extensive feature engineering, road modeling, and special case handling[16], [34], [27]. In recent years, significant advancements have been made in the deep learning paradigm’s ability to address these challenges. Various ambient and meteorological conditions are another important and challenging part of lane detecting[14], [5]. The environment is naturally varied; for example, it could be a freeway with a lot of traffic or a quiet neighborhood. Driving through these areas can also be affected by a variety of lighting circumstances[8] likely day, night, dawn, tunnels, etc., and weather conditions likely rain, snow, sunshine, etc. Any weather should not be a problem for the car.

Active driving assistance, lateral and longitudinal controls, and path prediction rely on self-driving vehicles’ center-line projection. The individual vehicle’s speed and steering angle, the road’s shape, and the proximity of other vehicles in the area are only a few variables that affect traffic and road conditions. This also incorporates the ego vehicle’s sensory[7], [4], [29], perceptual, and control systems. The center line projection[1], [15] is both an easier and more precise technique to use the detected lane lines. Even though perception and control are closely related to this issue, the existing literature is incomplete and disjointed. Projecting the trajectory[18], [13] for one thing, using our previous work on lane detection in various environments and climates.

This research presents a new lane line detection method capable of identifying road lanes under both standard weather conditions and challenging environments, including nighttime and normal rainfall. At night, the roads are illuminated by headlamps, resulting in the images having a low color temperature. During heavy rain, the visibility of road lanes significantly decreases. The proposed technique employs a pre-trained Keras-based CNN model and tests it using primary video data captured through a smartphone camera mounted on a vehicle. We present a path projection method that combines the widely utilized slope calculation technique with convolutional neural networks (CNN). This approach effectively detects lanes and projects the center path, even in low visibility and adverse weather conditions.

Chapter 2

Related Work

For autonomous driving lane recognition and path prediction, Lee D et al.[20] present DSUNet, a lightweight UNet using depth-wise separable convolutions. They create a simulation model using PP and CNN. Compared to UNet, DSUNet-PP is faster and lighter, outperforming UNet in path planning and lateral error. MatchNet is a deep learning submodule-based solution to autonomous driving lane detection by Sapir K et al.[34]. MatchNet substitutes label assignment with a submodule network in a cutting-edge lane detection network like CLRNet. CLRmatchNet, the integrated model, improves curved lane circumstances while retaining or improving other parts. This improves lane detection confidence. Gao R et al.[29] introduced the Deformable Transformer with high-order Deep Infomax (DTHDI) learning model for hard environment lane detection. It preserves lane line shape variation by combining local and global contextual information. Row categorization and mutual information maximization reduce computing complexity in the model. State-of-the-art lane detecting approaches are outperformed by the model in difficult settings. Nalcakan Y et al.[31] present a framework utilizing contrastive representation learning to detect hazardous cut-in maneuvers near autonomous vehicles. The encoder network undergoes training utilizing contrastive loss, further refined through datasets labeled with cut-in/lane-pass scenarios and simplified scenes. The most effective model exceeds the leading fully supervised model by approximately 2%, achieving an accuracy of 92.52%.

Yang C et al.[35] offer a polynomial regression-based deep learning model for lane detection that outperforms PolyLaneNet and achieves state-of-the-art performance on TuSimple and VIL100. The model uses temporal information to improve real-time accuracy and practicality. Wang J et al.[11] use a monocular camera to study an unstructured campus road. We choose the best preprocessing approach utilizing cutting means and Canny operator. Hough transform identifies lane lines. A lane departure warning model is created from angles and vehicle axis positions. Simulations verify the detection technique and model. Piao et al.[17] propose a new network for detecting unstructured lanes, including rural and urban roadways, using WS-P2PNet as the backbone and SCNN for message passing. The technique performed well in CULane and other tests of the lane detecting system. Tabelini L et al.[22] propose a novel method for lane detection that utilizes a forward-looking camera image and deep polynomial regression to model lane markings. The method is comparable to current techniques in the TuSimple dataset and sustains an efficiency of 115 FPS. The source code and trained models facilitate the replication of

outcomes, a distinctive characteristic in contemporary methodologies.

For self-driving cars (SDCs) to maintain their right lane position, Mahersatillah A. A. et al.[19] focus on road detection. With HSV color space segmentation, it discovers unstructured highways and gives automobiles lane center position data. The technology uses Hough transform to designate roadside limits and curbs. The results show an average accuracy of 99.59% with 98.84% recall and 99.49% precision. Technology also marks roadside edges with 99.27% precision. For semantic lane segmentation, Chen T M C et al.[12] uses Global Convolution Networks for classification and localization. Color-based segmentation, residual-based boundary refinement, and Adam optimization are used. Sharing training sessions across cars is proposed using real-world video transfer.

Cheng H Y et al.[6] propose hierarchical lane detection for structured and unstructured roads. Environment classification uses Eigenvalue Decomposition Regularized Discriminant Analysis, while lane recognition uses feature points from lane-marking pixels. The technique locates lane edges on diverse roadways in varied weather conditions. Cheng W et al.[28] introduces instance segmentation-based lane line recognition for complex traffic scenarios. A RepVgg-A0 network encodes road images, a multi-size asymmetric shuffling convolution model for sparse lane lines, an adaptive upsampling model for pixel-level classification, and a Jetson Nano embedded platform for half-precision acceleration. The approach outperforms current algorithms with 96.7% accuracy and 27 fps/s detection. Using FPGA for verification, Wang Z et al.[11] improves detection algorithm accuracy and real-time performance, and lane line detection. The research reviews these algorithms' merits and cons, studies their detection feasibility, and enhances them.

For assistance navigation, Lei Y et al.[25] evaluates pedestrian lane identification systems in unstructured environments. Conventional and deep learning, semantic segmentation, and road detection are covered. An experimental evaluation on a large benchmark dataset is also conducted. The goal is to inform assistive technology researchers and facilitate urgent vision-impaired research. An end-to-end method and big dataset for drivable region road recognition and steering angle estimate on unstructured roadways are introduced by Rasib M et al.[21]. The approach estimates steering angle by extracting drivable road sections and quantifying lane interception. A thorough qualitative and quantitative examination proves these methods work. Kim J et al.[15] describes an FPGA-based stereo camera-based real-time road and lane recognition system that separates roads from urban settings for accurate self-driving car detection. Experimental findings are promising. A multi-task-based strategy for autonomous driving lane detection is proposed by Liu P et al.[10]. Decoders segment road and lane marks. An iteration-specific training technique trains only one branch. A segmentation-lane marking fusion algorithm combines findings. Cities and TuSimple datasets show accurate and robust lane recognition in numerous traffic situations.

Xu Z et al.[32] introduces CenterLineDet to detect lane centerlines for automatic HD map creation. With vehicle-mounted sensors, the imitation learning method can detect centerline graphs. Lane intersections and other complex graph structure are supported. On the massive public dataset NuScenes, the technique proves superior. In an attempt to lower traffic accidents and air pollution, Kebbati Y et al.[30] writes a technical overview of research on autonomous vehicle lateral control, outlining obstacles and constraints for future progress. Lin C et al.[1] examines onboard

path prediction in autonomous vehicle control and active safety systems. It uses a linearized two-degree of freedom vehicle handling model, steady-state Kalman filter, and piecewise constant-in-time model to exhibit path prediction accuracy. An approach to describe path prediction uncertainty is also proposed. A monocular vision-based perception pipeline for autonomous vehicles to recognize road lines, maintain proper lane trajectories, and estimate car relative pose is proposed by Cudrano P et al.[18]. For lateral control, the system collects road lines equation, centerline, heading, and lateral displacement with exact geometric ground truth data. Yaw acceleration serves as a predictor for vehicle trajectories in adaptive cruise control, as demonstrated by Lee et al.[16]. The estimation of vehicle routes utilizing a clothoidal cubic polynomial curve model requires the curvature rate, yaw rate, and longitudinal velocity. The state-space model estimates yaw acceleration based on noisy yaw rate measurements. The constant acceleration model is employed to ascertain relative distance and velocity within a multirate longitudinal control framework to enhance performance.

Chapter 3

Road Lane Detection

3.1 Data Source

A recognized dataset is essential for developing a lane or detection technology using machine learning methods. Existing datasets show a scarcity of rural and hilly tracks in Japanese road conditions. This location is crucial for autonomous vehicles to accurately detect lanes, as GPS data in these areas is often unreliable due to noise level, and network communication systems may not function effectively. Thus, creating a dataset for this category of roads from the ground up was essential. The data we have collected is fundamentally primary. While traversing the roadway adjacent to Gunma University in Kiryu, Japan, we recorded footage of the lanes and passing automobiles in April to July 2024. We generated a dataset [33] using our driving videos. This dataset offers real-time driving statistics for many weather conditions, including Normal Day, Normal Night, and Rainy Day. The videos were recorded on rural and hilly roads in Japan, utilizing an iPhone 13 camera affixed to the author's vehicle. This dataset has 15 minutes of video footage categorized into three distinct weather and lighting conditions. Typical Day, Typical Night, and Rainy Day. Each condition has 20 video files, each with a duration of 15 seconds. The video is encoded in H.264 format and has a resolution of 1920 x 1080 pixels. The films were recorded at a speed range of 30 to 60 km/h. From the video data another image dataset has been made. Which contains ten thousands images in each weather and ambiance category and they have been split into training, test and by 70%, 15% and 15% respectively. At the below figure, the sample data at different scenario is represented.

The below table compares my dataset with renowned benchmark datasets for lane detection.

3.2 Detection methodology and model description

This study employed a pre-trained sequential CNN model. The model is intended for image segmentation, with a particular focus on lane line detection. We will examine the detection technique utilized by the model. The process begins with preprocessing, during which the model receives the image input and transforms the frame into grayscale. The process involves applying Gaussian blur to diminish noise,

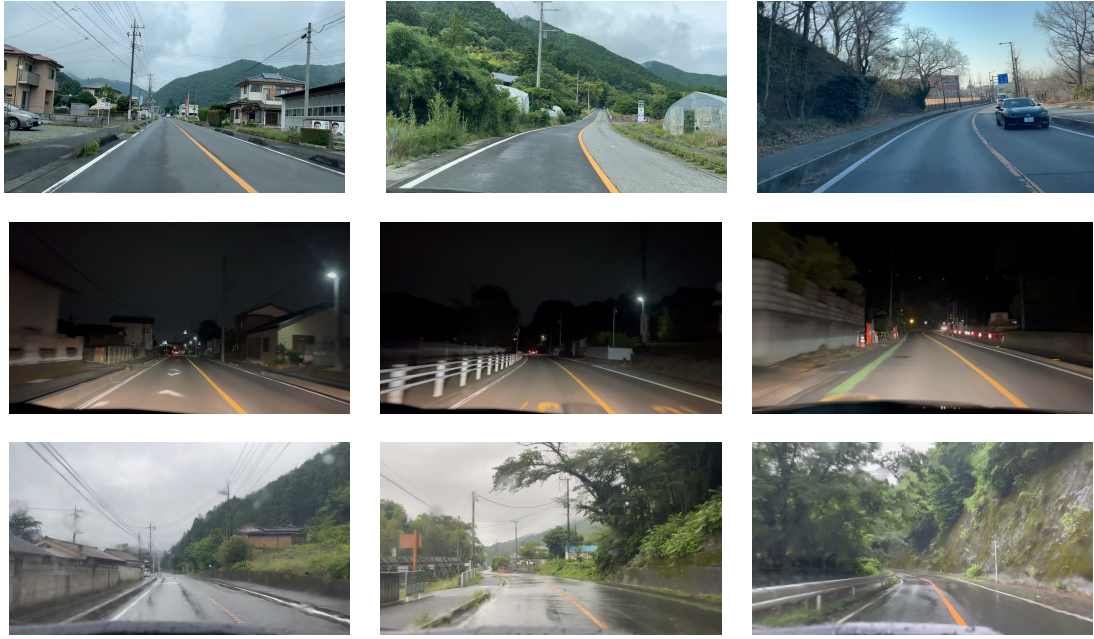


Figure 3.1: Represents the sample image data of three different weather and ambience scenarios.

Table 3.1: Comparison of My Dataset with Benchmark Lane Detection Datasets

Aspect	My Dataset	CULane	Tusimple	BDD100K	Cityscape
Dataset Size	40,000 images	55,000 images	6,000 images	100,000 images	5,000 images
Weather Conditions	Normal day, normal night, rainy day	Mostly clear weather, limited rain/night	Mostly clear weather, limited rain/night	Clear, rain, fog, night scenes	Mostly clear, limited rain/night scenes
Road Types	Japanese urban roads, multi-lane, hilly roads	Urban multi-lane roads	Primarily highway roads	Urban, highway, rural roads	Urban, structured roads
Geographical Context	Japanese roads	Chinese roads	US highways	US and global roads	European urban roads
Lane Complexity	Multi-lane, hilly, varying structures	Urban multi-lane, less complex	Simple highway lanes, mostly straight	Variety of lane complexity, less hilly roads	Urban roads with structured lane markings
Unique Features	Focus on hilly roads, varied weather conditions	Focus on urban roads	Focus on highway roads	Diversity in road types and conditions	Primarily urban roads, less weather diversity

followed by the implementation of a Canny edge detection algorithm to identify the edges of the road lanes. Following edge detection, the process identifies the region of interest to determine the appropriate lane area for detection, subsequently applying Hough Transformation to identify the lanes. The model computes the mean slope and intercept for the left and right lanes across the input image. It subsequently establishes two points, Y1 and Y2, on the y-axis, with Y1 representing the height of the image and Y2 denoting 60% of Y1. The pixel points are utilized to compute the x-axis values corresponding to Y1 and Y2. Subsequently, it delineates lines on a black image and superimposes these lines onto the original image. Subsequently, an additional function analyzes each frame of the image to generate the video. This study refines Gaussian blur and color filtering to enhance algorithm performance under poor lighting and adverse weather conditions. Figure 3.1 shows the lane detection mechanism in step by step.

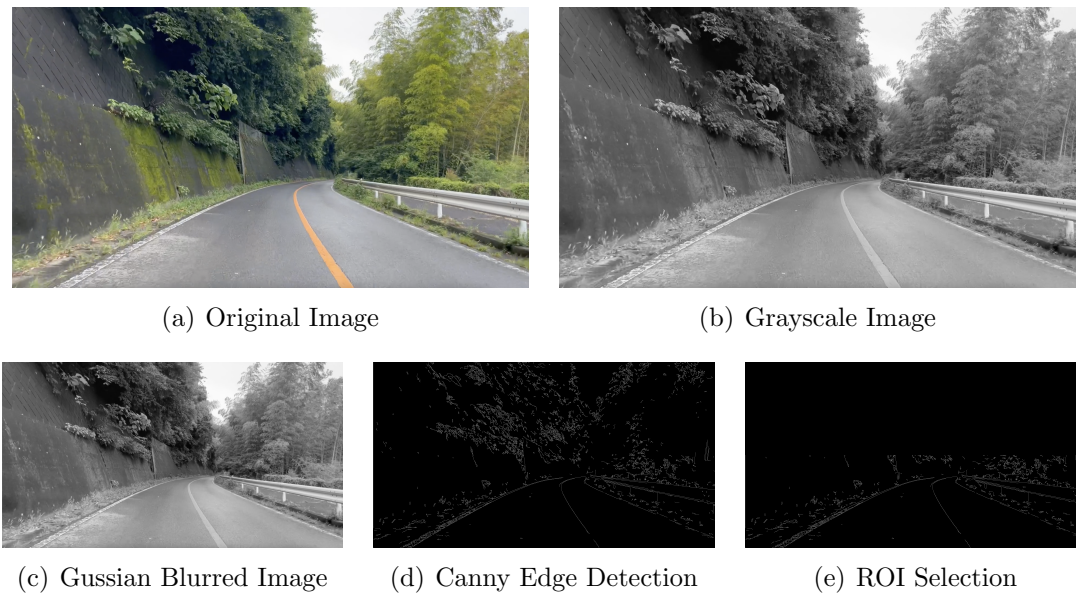


Figure 3.2: Processing steps of an input image for detection.

The model initiates with an input image measuring 80x160 pixels and comprising three color channels (RGB). The process initiates with a batch normalization layer that standardizes the input data, enhancing both training speed and stability. Each block comprises a convolutional layer succeeded by a ReLU activation function. Decreases the spatial dimensions of the feature maps. Randomly deactivates a portion of the input units during training to mitigate overfitting. Augments the spatial dimensions of the feature maps before transposed convolution. Resize the feature maps to match the original image dimensions. The output image is generated with detected lane markings, resulting in a single-channel image of dimensions 80x160x1. The figure below illustrates the architecture of the sequential CNN model employed in this study.

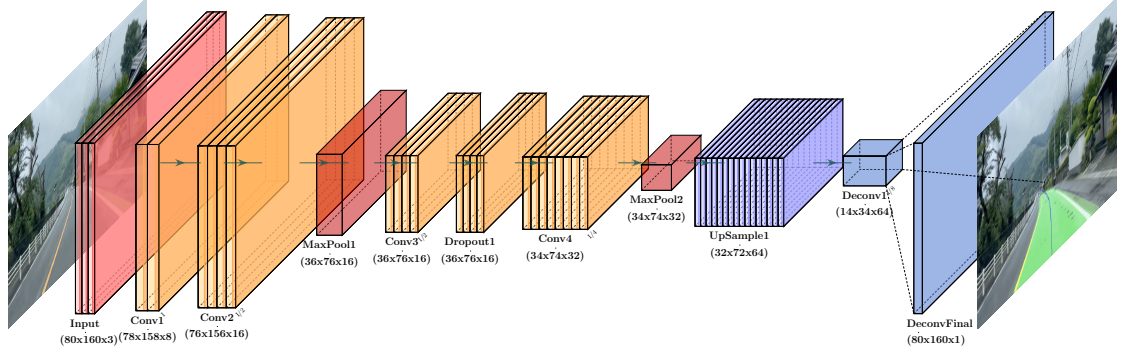


Figure 3.3: Architecture of the proposed sequential CNN model for lane and path detection.

3.3 Path Projection

At the beginning of the path projection technique, we start with the Region of Interest (ROI) selection technique. After lane detection, the video is sent to the path projection pipeline, where it first creates a mask with the same shape as the input image for ROI selection. Then it checks if the input image has more than two color channels; if there are any, it ignores them by setting the ignore mask to white (255, 255, 255); otherwise, it is set to 255. For representing the vertices, we take four vertices of the polygon. The vertices of the polygon are defined as bottom left, top left, top right, and bottom right, and they are filled with the colour value of ignore mask to calculate the projection line. Now comes the Hough transformation, which calculates the distance resolution, angle resolution, minimum number of votes, minimum length of a line, and maximum gap between lines. After calculating all these, the values are sent to another function for the average slope intercept calculation. Here, it takes input of lines and stores them as left and right lanes, respectively. Based on the slope interception value, it defines the line, whether it is the left or right one, and then stores them, respectively. Based on the slope and intercept points, it calculates the midpoint and projects the line over the video. The following equations elucidate the computation of the center and the prediction methodology.

3.3.1 Lane Boundaries Detection

For each row y in the image, the leftmost and rightmost lane boundary points are determined as:

$$x_L(y) = \min\{x \mid \text{lanes_image}(y, x, 1) > 0\} \quad (3.1)$$

$$x_R(y) = \max\{x \mid \text{lanes_image}(y, x, 1) > 0\} \quad (3.2)$$

where:

- $x_L(y)$ is the left lane boundary at row y .

Table 3.2: Model architecture summary

Layer Type	Number of Units/Neurons
Input	3
Batch Normalization	3
Conv2D	8
Conv2D	16
MaxPooling2D	16
Conv2D	16
Dropout	16
Conv2D	32
Dropout	32
Conv2D	32
Dropout	32
MaxPooling2D	32
Conv2D	64
Dropout	64
Conv2D	64
Dropout	64
MaxPooling2D	64
UpSampling2D	64
Conv2DTranspose	64
Dropout	64
Conv2DTranspose	64
Dropout	64
UpSampling2D	64
Conv2DTranspose	32
Dropout	32
Conv2DTranspose	32
Dropout	32
Conv2DTranspose	16
Dropout	16
UpSampling2D	16
Conv2DTranspose	16
Conv2DTranspose	1

- $x_R(y)$ is the right lane boundary at row y .

3.3.2 Lane Center Calculation

The lane center at row y is computed as:

$$x_C(y) = \frac{x_L(y) + x_R(y)}{2} \quad (3.3)$$

where:

- $x_C(y)$ is the estimated lane center.

3.3.3 Moving Average Smoothing

To reduce noise, a moving average filter over the last N frames is applied:

$$\bar{x}_C(y) = \frac{1}{N} \sum_{i=1}^N x_C^{(i)}(y) \quad (3.4)$$

where:

- $x_C^{(i)}(y)$ is the lane center for the i -th frame.
- $\bar{x}_C(y)$ is the smoothed lane center.

3.3.4 Polynomial Fitting (Savitzky-Golay)

To further smooth the lane path, a polynomial of degree d (e.g., $d = 3$) is fitted using the Savitzky-Golay filter:

$$\hat{x}_C(y) = ay^3 + by^2 + cy + d \quad (3.5)$$

where:

- $\hat{x}_C(y)$ is the predicted lane center.
- a, b, c, d are polynomial coefficients obtained from least squares regression.

Chapter 4

Results Visualization and Conclusion

4.1 Result Analysis

Among various lane detection models, SCNN emerges as the most dependable option for challenging driving circumstances. In contrast to models like UltraFast and ENet-SAD, which are effective solely on structured highways with distinct lane lines, SCNN demonstrates superior performance in unstructured situations, rendering it the optimal selection for rural and hilly regions in Bangladesh and Japan. The main benefit of SCNN lies in its deep semantic segmentation methodology, allowing for lane detection even when markings are deteriorated, fragmented, or entirely missing. This is especially advantageous in mountainous areas, where curving roads and limited lane visibility render traditional lane identification algorithms ineffective. SCNN's capacity to deduce lane configurations, even when partially obscured, ensures the operational efficacy of autonomous driving and ADAS systems in intricate, real-world traffic circumstances in Bangladesh.

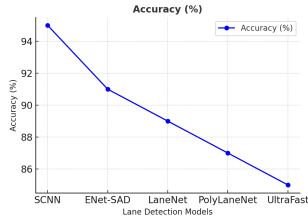
Another rationale for using SCNN is its exceptional performance in adverse weather and nighttime circumstances. In Bangladesh and Japan, monsoon rains frequently obscure lane markings due to accumulation of water and reflections, hindering the correct performance of edge-based models such as UltraFast and PolyLaneNet. At night, headlight glare on roads can lead to inaccurate lane predictions; nevertheless, SCNN, through its sophisticated feature extraction, and our color filtering techniques can sustain lane tracking despite these challenging conditions. Although SCNN has a longer inference time of 50ms relative to swifter models such as UltraFast at 5ms, its superior accuracy of 95% surpasses speed concerns, particularly in rural, mountainous, and inadequately signed roads where safety and reliability are paramount. In Bangladesh, where several highways are devoid of adequate lane markers, SCNN is the optimal selection owing to its unparalleled precision and resilience.

The data indicates that SCNN is the most precise model, rendering it suitable for inadequately designated lanes, adverse weather conditions, and nocturnal driving. Although UltraFast is the quickest model, it falters in difficult situations, rendering it inappropriate for the unstructured roadways of Bangladesh. ENet-SAD achieves a compromise between velocity and precision; nonetheless, it is inadequate in rural and hilly landscapes, where SCNN excels remarkably.

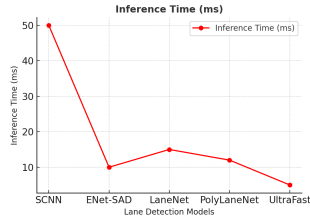
The graphs present a comparative analysis of five lane detection models: SCNN,

Table 4.1: Comparison of Lane Detection Models

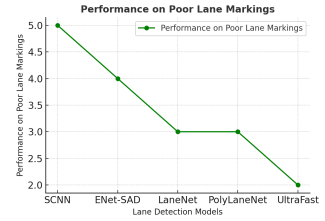
Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Inference Time (ms)	Strengths	Weaknesses
SCNN	95	92	94	93	50	Good for challenging lane markings	Higher computational cost
ENet-SAD	93	91	90	90.5	10	Fast and lightweight	Less accurate on complex roads
LaneNet	90	89	88	88.5	15	Performs well on curves	Struggles with occlusions
PolyLaneNet	88	86	85	85.5	20	Polynomial fitting method	Less robust to occlusions
UltraFast	92	90	91	90.5	5	Extremely fast inference	Sacrifices some accuracy



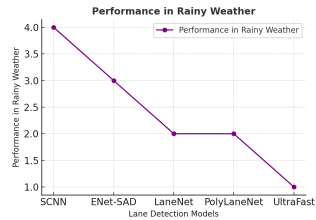
(a)



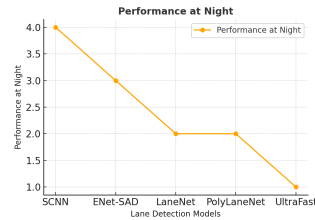
(b)



(c)



(d)



(e)

Figure 4.1: Comparison of lane detection models

ENet-SAD, LaneNet, PolyLaneNet, and UltraFast. The analysis focuses on key performance metrics, including accuracy, inference time, performance on poor lane markings, rain performance, and night performance. SCNN attains the highest accuracy of approximately 95%, establishing it as the most dependable model for lane detection. Nonetheless, it exhibits the longest inference time (approximately 50ms), indicating that it is slower than UltraFast, which, while the fastest, is less accurate. SCNN demonstrates superior performance in challenging conditions, including faded lane markings, inclement weather, and low-light scenarios, rendering it the most appropriate option for rural roads in Bangladesh, where lane visibility is frequently compromised.

The accuracy of each model is determined using the following equation:

$$Accuracy = \frac{\text{Correctly detected lane pixels}}{\text{Total lane pixels in ground truth}} \times 100 \quad (4.1)$$

The evaluation of Performance on Poor Lane Markings, Rain Performance, and Night Performance is conducted using the equation:

$$P = \frac{TP}{TP + FN + FP} \times 100 \quad (4.2)$$

where:

- TP = True Positives (Correctly detected lane pixels)
- FN = False Negatives (Missed lane pixels)
- FP = False Positives (Incorrectly detected lane pixels due to noise)

In this context, "TP" denotes correctly detected lane pixels, "FN" refers to missed lane pixels, and "FP" encompasses incorrectly detected lane pixels attributed to noise. These metrics facilitate a thorough assessment of lane detection models, especially under real-world conditions where lane visibility is limited. The findings demonstrate the superiority of SCNN, establishing it as the optimal option for rural, hilly, and inadequately marked roads in Bangladesh.

4.2 Visualization

The next part shows graphic depictions of the segmented lane marks under several light and environmental conditions. The figure allows one to deduce several interesting observations. The model shows excellent control of difficult illumination and weather conditions, including overexposure, poor vision and low light, which obscure lane marks.

4.2.1 Detection in different light and weather conditions

Figure 4.2(a) illustrates the identified lane lines under normal weather and lighting conditions while the vehicle operates on hilly rural roads at a maintained speed limit of 40 km/h. In this scenario, lane markings are detected accurately, with both white and yellow lane lines present. The detection of lanes occurs for both straight and curved road configurations. Figure 4.2(b) depicts the detection of road

lanes under normal weather conditions during nighttime. The roads are illuminated by HID headlamps, which accounts for the low color temperature in these videos. In this scenario, the proposed technique accurately detects white and yellow lane lines on both straight and curved roads. Figure 4.2(c) depicts the detection of road lanes under normal lighting conditions and during rainy weather. Where lanes are obscured by water and not entirely discernible. Additionally, rainwater and the motion of the windshield wipers further reduce visibility. Under critical weather conditions, the proposed approach effectively detects white and yellow lane lines with precision on both straight and curved roads through image tuning and sharpening.



(a)



(b)



(c)

Figure 4.2: Detected lanes in (a) day, (b) night, and (c) rainy day.

4.2.2 Lane center prediction in different light and weather conditions

Figure 4.3(a) illustrates the path predicted for the center of the road across the identified lanes under normal weather and ambient conditions. The road center path prediction technique presented in this study demonstrates effective predictive capabilities for both straight and curved roads. Figure 4.3(b) depicts the predicted road center path across the identified lanes under normal nighttime conditions with low temperature of color. The road center path prediction technique is capable of predicting paths on both straight and curved roads with minor noise. Figure 4.3(c) presents the predicted road center path across the identified lanes under rainy conditions. Rainwater obscures lane lines, reducing visibility and complicating lane line detection and center path prediction. Despite certain difficulties, our algorithm successfully overcame them and accurately predicted the lane path. It operates effectively on both curved and straight roads.

4.2.3 Detection in multi lane scenario

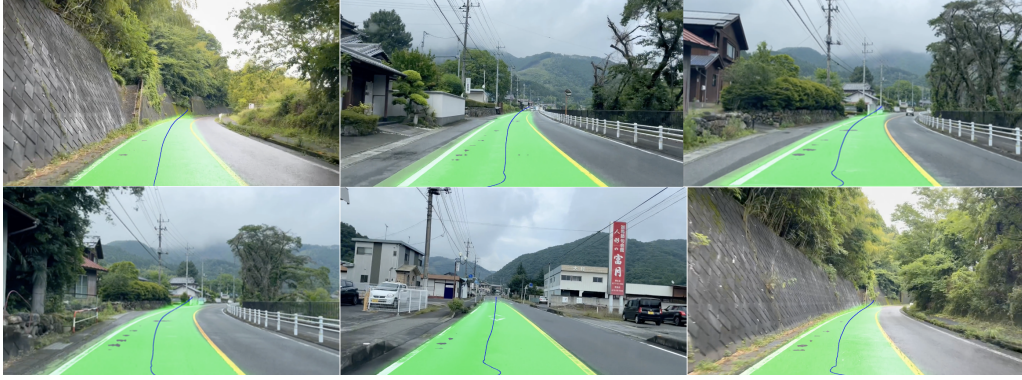
The picture 4.4(a) illustrates the detected lane in nighttime conditions, indicating that the vehicle is positioned in the right lane, with an adjacent lane on the right side. The model identifies the lane solely in the vicinity of the vehicle. Figure 4.4(b) depicts the identified lane under night-light conditions, where two unoccupied lanes flank the vehicle, which is positioned in the central lane, and the detection is exclusively focused on this middle lane. Another vehicle is present in the same lane, keeping the standard distance, and the model can accurately detect the lane in this situation. In figure 4.4(c), the vehicle maintains its position in the middle lane while the vehicle ahead approaches, and the detection stays flawless.

The subsequent image 4.4(d) shows identifying the lane during evening and low light conditions. In this scenario, the lane is curved, with the test car positioned in the left lane and an unoccupied lane on the right. Figures 4.4(e) and 4.4(f) illustrate lane detection under normal daylight conditions, with the test vehicle positioned in the left lane and an approaching car in the right lane. In this situation, the model can accurately determine the lane.

4.2.4 Detection in Bangladeshi roads

Figures 4.5(a), 4.5(b) and 4.5(c) illustrate the identified road lane markings under typical weather and ambient circumstances, featuring numerous lanes and vehicles. This data is collected from the Padma Bridge in Bangladesh, where the roadways may be accurately identified in this context.

Figure 4.5(d) depicts a Bangladeshi roadway characterized by imprecise and indistinct lane markings, compounded by diminished visibility due to light fog. In this situation, the model can quite accurately detect the lane markings. Image 4.5(e) depicts a multi-lane road in Bangladesh, featuring a bus in the left lane, with imperfect lane markings; still, lane detection is extremely effective in this scenario. Finally, figure 4.5(f) depicts the identified lane of a Bangladeshi road during nighttime. The road is illuminated solely by car headlights, and although the lane curves, detection remains effective.



(a)



(b)



(c)

Figure 4.3: Predicted road centre path over the detected lanes in (a) day, (b) night, and (c) rainy day.



Figure 4.4: Detected road lanes in multi lane scenario.

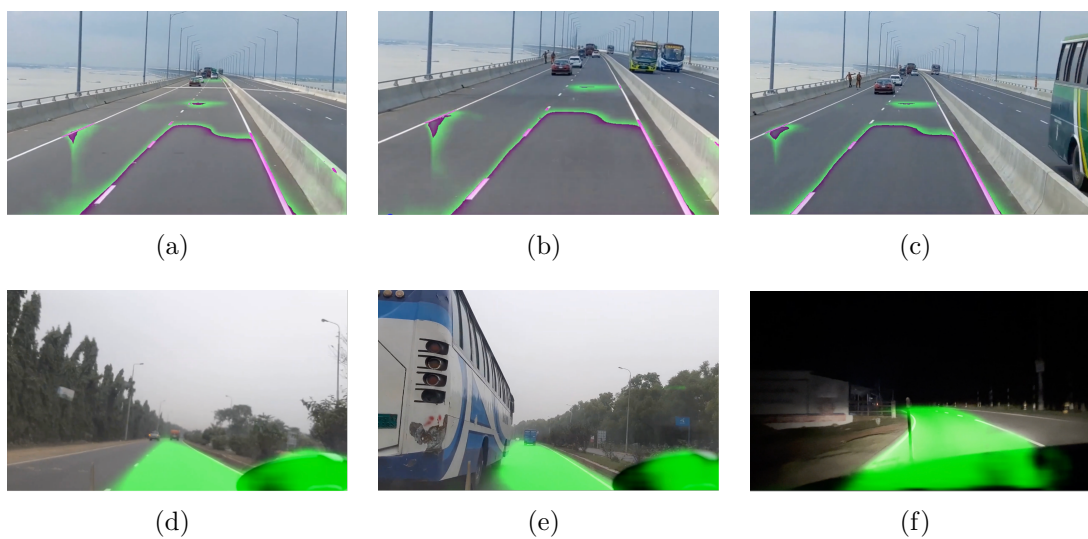


Figure 4.5: Detected road lanes of Bangladeshi roads.

4.3 Conclusion

Utilizing Artificial Intelligence and Convolutional Neural Networks, we have developed a lane detecting system operational under three distinct lighting and weather circumstances. This research employs an algorithm that utilizes a model to identify road lanes under three specific weather conditions and illumination environments: Normal Day, Normal Night, and Rainy Day. The system effectively detects road lanes under all specified weather conditions. Detection technology can also accurately identify curved road lanes without any difficulties. During inclement weather, visibility decreases, making road identification using color filtering somewhat challenging. We trained the model and implemented the algorithms using our primary data collected using a smartphone camera mounted on a car. We subsequently estimated the lane center points from the pixel values of the identified lane lines, considering the curvature of the lanes, and projected the central path of the lanes based on these center point values.

In the future, we will incorporate additional weather conditions into our detecting technology, specifically Rainy Night and Light Snow.

Bibliography

- [1] C.-F. Lin, A. Ulsoy, and D. LeBlanc, “Vehicle dynamics and external disturbance estimation for vehicle path prediction,” *Control Systems Technology, IEEE Transactions on*, vol. 8, pp. 508–518, Jun. 2000. DOI: 10.1109/87.845881.
- [2] Z. Sun, G. Bebis, and R. Miller, “On-road vehicle detection: A review,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 5, pp. 694–711, 2006. DOI: 10.1109/TPAMI.2006.104.
- [3] C.-Y. Chan, “Trends in crash detection and occupant restraint technology,” *Proceedings of the IEEE*, vol. 95, no. 2, pp. 388–396, 2007. DOI: 10.1109/JPROC.2006.888391.
- [4] Q. Gao, Q. Luo, and S. Moli, “Rough set based unstructured road detection through feature learning,” in *2007 IEEE International Conference on Automation and Logistics*, 2007, pp. 101–106. DOI: 10.1109/ICAL.2007.4338538.
- [5] J. Huang, B. Kong, B. Li, and F. Zheng, “A new method of unstructured road detection based on hsv color space and road features,” in *2007 International Conference on Information Acquisition*, 2007, pp. 596–601. DOI: 10.1109/ICIA.2007.4295802.
- [6] H.-Y. Cheng, C.-C. Yu, C.-C. Tseng, K.-C. Fan, J.-N. Hwang, and B.-S. Jeng, “Hierarchical lane detection for different types of roads,” in *2008 IEEE International Conference on Acoustics, Speech and Signal Processing*, 2008, pp. 1349–1352. DOI: 10.1109/ICASSP.2008.4517868.
- [7] Q. Li, L. Chen, M. Li, S.-L. Shaw, and A. Nüchter, “A sensor-fusion drivable-region and lane-detection system for autonomous vehicle navigation in challenging road scenarios,” *IEEE Transactions on Vehicular Technology*, vol. 63, no. 2, pp. 540–555, 2014. DOI: 10.1109/TVT.2013.2281199.
- [8] L. Nguyen, S. L. Phung, and A. Bouzerdoun, “Efficient vanishing point estimation for unstructured road scenes,” in *2016 International Conference on Digital Image Computing: Techniques and Applications (DICTA)*, 2016, pp. 1–6. DOI: 10.1109/DICTA.2016.7797037.
- [9] J.-G. Kim, J.-H. Yoo, and J.-C. Koo, “Road and lane detection using stereo camera,” in *2018 IEEE International Conference on Big Data and Smart Computing (BigComp)*, 2018, pp. 649–652. DOI: 10.1109/BigComp.2018.00117.
- [10] P. Liu, M. Yang, C. Wang, and B. Wang, *Multi-lane detection via multi-task network in various road scenes*, 2018. DOI: 10.1109/CAC.2018.8623762.

- [11] J. Wang, H. Ma, X. Zhang, and X. Liu, “Detection of lane lines on both sides of road based on monocular camera,” in *2018 IEEE International Conference on Mechatronics and Automation (ICMA)*, 2018, pp. 1134–1139. DOI: 10.1109/ICMA.2018.8484630.
- [12] W. Zhang and T. Mahale, *End to end video segmentation for driving : Lane detection for autonomous car*, 2018. arXiv: 1812.05914 [cs.CV]. [Online]. Available: <https://arxiv.org/abs/1812.05914>.
- [13] C. Badue, R. Guidolini, R. V. Carneiro, *et al.*, *Self-driving cars: A survey*, 2019. arXiv: 1901.04407 [cs.R0]. [Online]. Available: <https://arxiv.org/abs/1901.04407>.
- [14] T. Huang, Z. Wang, X. Dai, D. Huang, and H. Su, *Unstructured lane identification based on hough transform and improved region growing*, 2019. DOI: 10.23919/ChiCC.2019.8865870.
- [15] J.-G. Kim and J.-H. Yoo, “Hw implementation of real-time road lane detection in fpga-based stereo camera,” in *2019 IEEE International Conference on Big Data and Smart Computing (BigComp)*, 2019, pp. 1–4. DOI: 10.1109/BIGCOMP.2019.8679333.
- [16] D.-H. Lee, K.-L. Chen, K.-H. Liou, C.-L. Liu, and J.-L. Liu, *Deep learning and control algorithms of direct perception for autonomous driving*, 2019. arXiv: 1910.12031 [cs.LG]. [Online]. Available: <https://arxiv.org/abs/1910.12031>.
- [17] C. Piao and C. Lu, “Lane detection of unstructured roads based on wsp2pnet,” in *2019 International Conference on Intelligent Computing, Automation and Systems (ICICAS)*, 2019, pp. 596–599. DOI: 10.1109/ICICAS48597.2019.00130.
- [18] P. Cudrano, S. Mentasti, M. Matteucci, M. Bersani, S. Arrigoni, and F. Cheli, “Advances in centerline estimation for autonomous lateral control,” in *2020 IEEE Intelligent Vehicles Symposium (IV)*, vol. 10, IEEE, Oct. 2020, pp. 1415–1422. DOI: 10.1109/iv47402.2020.9304729. [Online]. Available: <http://dx.doi.org/10.1109/IV47402.2020.9304729>.
- [19] A. Mahersatillah, Z. Zainuddin, and Y. Yusran, “Unstructured road detection and steering assist based on hsv color space segmentation for autonomous car,” in *2020 3rd International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, 2020, pp. 688–693. DOI: 10.1109/ISRITI51436.2020.9315452.
- [20] D.-H. Lee and J.-L. Liu, *End-to-end deep learning of lane detection and path prediction for real-time autonomous driving*, 2021. arXiv: 2102.04738 [cs.CV]. [Online]. Available: <https://arxiv.org/abs/2102.04738>.
- [21] M. Rasib, M. A. Butt, F. Riaz, A. Sulaiman, and M. Akram, “Pixel level segmentation based drivable road region detection and steering angle estimation method for autonomous driving on unstructured roads,” *IEEE Access*, vol. 9, pp. 167 855–167 867, 2021. DOI: 10.1109/ACCESS.2021.3134889.
- [22] L. Tabelini, R. Berriel, T. M. Paixão, C. Badue, A. F. De Souza, and T. Oliveira-Santos, “Polylanenet: Lane estimation via deep polynomial regression,” in *2020 25th International Conference on Pattern Recognition (ICPR)*, 2021, pp. 6150–6156. DOI: 10.1109/ICPR48806.2021.9412265.

- [23] S. Waykole, N. Shiwakoti, and P. Stasinopoulos, “Review on lane detection and tracking algorithms of advanced driver assistance system,” *Sustainability*, vol. 13, no. 20, 2021, ISSN: 2071-1050. DOI: 10.3390/su132011417. [Online]. Available: <https://www.mdpi.com/2071-1050/13/20/11417>.
- [24] A. Adnan, G. M. Mahbubur Rahman, M. M. Hossain, M. S. Mim, and M. K. Rahman, “A deep learning based autonomous electric vehicle on unstructured road conditions,” in *2022 IEEE 12th Symposium on Computer Applications Industrial Electronics (ISCAIE)*, 2022, pp. 105–110. DOI: 10.1109/ISCAIE54458.2022.9794498.
- [25] Y. Lei, S. L. Phung, A. Bouzerdoun, H. Thanh Le, and K. Luu, “Pedestrian lane detection for assistive navigation of vision-impaired people: Survey and experimental evaluation,” *IEEE Access*, vol. 10, pp. 101 071–101 089, 2022. DOI: 10.1109/ACCESS.2022.3208128.
- [26] A. Rahman, “Computer vision based road lane line detection,” *SSRN*, no. 2, 2022. DOI: 10.2139/ssrn.4189852. [Online]. Available: <https://ssrn.com/abstract=4189852>.
- [27] T. Zheng, Y. Huang, Y. Liu, *et al.*, “Clrnet: Cross layer refinement network for lane detection,” *Arxiv*, 2022. arXiv: 2203.10350 [cs.CV].
- [28] W. Cheng, X. Wang, and B. Mao, “Research on lane line detection algorithm based on instance segmentation,” *Sensors*, vol. 23, no. 2, 2023, ISSN: 1424-8220. DOI: 10.3390/s23020789. [Online]. Available: <https://www.mdpi.com/1424-8220/23/2/789>.
- [29] R. Gao, S. Hu, L. Yan, *et al.*, “High-order deep infomax-guided deformable transformer network for efficient lane detection,” *Signal, Image and Video Processing*, vol. 17, pp. 1–8, Apr. 2023. DOI: 10.1007/s11760-023-02525-y.
- [30] Y. Kebbati, N. Ait-Oufroukh, D. Ichalal, and V. Vigneron, “Lateral control for autonomous wheeled vehicles: A technical review,” *Asian Journal of Control*, vol. 25, no. 4, pp. 2539–2563, 2023. DOI: <https://doi.org/10.1002/asjc.2980>. eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/asjc.2980>. [Online]. Available: <https://onlinelibrary.wiley.com/doi/abs/10.1002/asjc.2980>.
- [31] Y. Nalßakan and Y. Bastanlar, “Cut-in maneuver detection with self-supervised contrastive video representation learning,” *Signal, Image and Video Processing*, vol. 17, pp. 1–9, Mar. 2023. DOI: 10.1007/s11760-023-02512-3.
- [32] Z. Xu, Y. Liu, Y. Sun, M. Liu, and L. Wang, *Centerlinedet: Centerline graph detection for road lanes with vehicle-mounted sensors by transformer for hd map generation*, 2023. arXiv: 2209.07734 [cs.CV]. [Online]. Available: <https://arxiv.org/abs/2209.07734>.
- [33] A. Adnan, M. Kamal, and K. Yamada, *Driving video for lane detection (various weather)*, 2024. DOI: 10.34740/KAGGLE/DSV/8771644. [Online]. Available: <https://www.kaggle.com/dsv/8771644>.
- [34] S. Kontente, R. Orfaig, and B.-Z. Bobrovsky, *Clrmachnet: Enhancing curved lane detection with deep matching process*, 2024. arXiv: 2309.15204 [cs.CV]. [Online]. Available: <https://arxiv.org/abs/2309.15204>.

- [35] C. Yang, Z. Tian, X. You, *et al.*, “Polylanenet++: Enhancing the polynomial regression lane detection based on spatio-temporal fusion,” *Signal, Image and Video Processing*, vol. 18, pp. 1–10, Jan. 2024. DOI: 10.1007/s11760-023-02967-4.