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Original Article

Revolutionary Enhanced Lane Departure Detection Techniques for Autonomous Vehicle Safety using ADAS.

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Abstract *- This paper introduces an Enhanced Lane Departure Warning System (ELDWS) leveraging cutting-edge vision technology to boost road safety for ADAS enabled vehicles. Our novel approach utilizes a combination of Phase Stretch Transform for edge detection, Curved and Straight Lane Detectors for accurate lane Detection, and a modified Kalman Filter for dynamic lane tracking, collectively aimed at improving vehicle safety through precise lane departure estimation. Unlike traditional systems that rely heavily on clear lane markings and favorable environmental conditions, our model excels in various lighting and road scenarios, including curved paths and challenging weather conditions. The research demonstrates the system's efficacy in real-world simulations, where it outperforms existing technologies in detecting and alerting potential lane departures. Through meticulous integration of advanced image processing techniques and machine learning algorithms, our model offers a significant leap towards achieving robust lane-keeping assistance in autonomous and semi-autonomous vehicles. Furthermore, the paper discusses the system's ability to adapt to different environmental conditions and road types, making it a versatile tool for enhancing driving safety. By addressing the limitations of current LDWS technologies, such as sensitivity to weather conditions and the reliance on high-contrast lane markings, our approach sets a new standard for safety in the autonomous driving domain. This paper shows that by overcoming the problems of older lane departure warning systems, like their struggle with bad weather and dependency on clear road markings, our system sets a new standard for keeping cars safely within their lanes, especially in self-driving and semi-self-driving cars. We offer a detailed solution that combines new detection methods with advanced tracking techniques for better accuracy and reliability. The accuracy of our ELDWS is quantitatively measured using a custom dataset, revealing impressive results. During daytime conditions, our system achieved a high accuracy rate of 95.81%, correctly detecting lanes in 7665 out of 8000 frames. This demonstrates the system's robustness in optimal lighting conditions. The accuracy remains commendable in left and right departure scenarios during the day, with rates of 83.26% and 84.83%, respectively, showcasing the system's capability to recognize lane departures effectively. This research is important for making cars safer and provides useful information for developing better driving assistance systems in the future.*

Keywords *- ADAS, Curved and Straight lane detector, Enhanced lane departure warning system.*

1. Introduction

In road transport systems, accidents can be avoided with the Advanced Driver Assistance System (ADAS). This usually involves combining different sensors, including Radar, Lidar, Vision Cameras and Ultrasonic sensors. These are used to sense the environment around the vehicle, and the information gathered is fed to the vehicle's control system to give the driver real-time information and/or alarms. Aid systems can be categorized into various levels. Level 1- Systems that control a single operation, such as cruise control and lane departure warning. Level 5- Systems that take full control of the vehicle and can operate the car in all situations without requiring any human input. ADAS systems refer to complex computer systems that are integrated into automobiles for the purpose of improving the driving experience by assisting the main driver in numerous ways. ADAS plays a crucial role in monitoring the driver's condition, such as detecting signs of fatigue or distraction and consequently issuing timely warnings[1]. These systems are also equipped to evaluate and advise on driving performance. A notable feature of ADAS is its ability to assume control in response to perceived threats, thereby aiding in simple operations like cruise control or more complex tasks such as overtaking and parking maneuvers[2]. The ADAS systems lead to an enhanced exchange of information, which is crucial for improved vision, accurate localization, and more strategic planning and decision-making for the vehicles, thereby significantly contributing to safer and more efficient driving[3].

In the literature [4], ADAS systems are categorized into two primary types based on functionality: comfort-oriented functions and vehicle centric safety functions. Comfort-oriented functions are designed to alert the driver through various mechanisms, such as visual signals (flashing lights), auditory alerts (sounds), tactile feedback (vibrations), or subtle guidance (gentle steering suggestions). These notifications serve to enhance the driving experience by providing timely and user-friendly warnings. In contrast, safety functions proactively intervene in vehicle operations when the driver fails to respond to hazardous scenarios. This intervention can manifest in several forms, including pre-charging the brakes, readying the safety belts, raising the hood, executing automatic braking, and implementing evasive steering maneuvers. These actions are critical in mitigating the risk of accidents and enhancing overall road safety. Recently, there has been an extension of ADAS technology called the Safety Driving Assistant System (SDAS), which is increasingly catching the public's attention and becoming a part of daily life. During typical driving scenarios, if a sudden accident occurs, this smart assistant driving system can instantly provide support through services like emergency braking, driving assistance decisions, or urgent warnings. This significantly enhances the safety and stability of driving while also reducing the financial impact and human toll of traffic accidents. It also assists in collision avoidance by analyzing the surroundings and providing real-time navigation support to evade potential hazards with other vehicles, pedestrians, or obstacles. This system also includes traffic sign recognition capabilities, ensuring drivers are aware of important road information like speed limits or no-entry signs. Additionally, the system enhances side collision prevention through blind spot detection, alerting drivers to unseen vehicles or objects. Within this system, the Lane Departure Warning System (LDWS) is gaining growing interest as an important subsystem. The LDWS is one of the subsystems of the Safety Driving Assistant System (SDAS) that significantly enhances vehicular safety and the overall driving experience through lane departure alerts. LDWS vigilantly monitors the vehicle's position, alerting drivers if they unintentionally drift out of their lane, a crucial feature to counteract inattention or drowsiness. The vital role of LDWS helps to augment road safety, reduce accident rates, and elevate the driving experience.

The LDWS is a safety system in today’s cars that assists the driver in reminding the driver that the car is drifting away from the lane it is in, except if the driver has signalled a turn. This system employs some detectors, most of which are cameras, to detect the lane markings on the road. If the system recognizes the fact that the vehicle is moving towards the lane markings without turning indicators being engaged, it alerts the driver. This warning can be in the form of an icon on the car’s display, sound or haptic feedback, such as vibration in the steering wheel or seat. The LDWS includes several fundamental benefits. First of all, it helps to keep drivers in their lane while driving with the help of a camera that recognizes the lane markings. Secondly, when the vehicle is near the markings mentioned above and is likely to swerve out of the lane, a vibration is felt in the steering wheel. Thirdly, the system goes into a dormant state when it detects lane lines on its left and right sides, and the green LED light on the dashboard blinks.

LDWS come in two main types: Road Infrastructure-Based and Vehicle-Based. Road Infrastructure-Based LDWS: These systems rely on road infrastructure to monitor a vehicle's position. They use sensors to detect ferromagnetic signals embedded in the road. By measuring the signal strength, the system can determine the vehicle's position within the lane. Vehicle-Based LDWS: In contrast, these systems are built into the vehicle itself, using onboard sensors to keep track of the vehicle's lane position independently of any special road infrastructure. The road infrastructure-based LDWS relies on infrastructure modifications, such as embedding magnets or wires under roads, which vehicles detect to determine their lateral position within a lane. This method, though accurate, is expensive due to the need for road alterations. The limitations of road infrastructure-based Lane Departure Warning Systems (LDWS) include high installation and maintenance costs due to the need for physical modifications to the road infrastructure. Additionally, their effectiveness can be compromised in areas where such infrastructure updates are not feasible.

Vehicle-based Lane Departure Warning Systems (LDWS) primarily rely on machine vision and image processing to detect the position of lane markings. These systems rely on cameras mounted on vehicles to capture and analyze road images, identify lane markings and assess the vehicle's position. A typical vision-based Lane Departure Warning System (LDWS) has three main components: lane detection, lane tracking, and lane departure warning. An onboard camera mounted high on the windshield captures sequences of road images. If the system detects a potential lane departure, it alerts the driver to prevent unintentional dangerous driving situations. The primary advantage of using image information is its ability to adapt to different environmental conditions and road types. This adaptability, powered by advanced image processing and machine learning algorithms, allows the system to function effectively in various lighting and weather conditions, making it a versatile and essential tool for modern driving safety. Vehicle-based Lane Departure Warning Systems (LDWS) primarily use vision sensors to detect lane edges, lane markings, and road contours. These systems are most effective on highways with clear lane markings. However, they can struggle with poor visibility, varying lane conditions, and image resolution issues. Additionally, the road conditions can sometimes render the system ineffective. Detecting lanes using onboard sensors remains a challenging task despite significant research and advancements. Because environmental factors often hinder the accurate identification of lanes, there is a need to develop a new framework for lane departure estimation. This new approach would aim to improve the system's robustness and reliability in handling these challenges.

Numerous researchers and organisations have investigated several vision-based approaches for the Lane Departure Warning System (LDWS). In the last thirty years, traditional methods have mainly dealt with image processing and computer vision. However, these traditional algorithms are not efficient enough to meet the needs of industrial systems. Recently, there has been more focus on the development of enhanced techniques. Some of the techniques include the three-dimensional processing algorithms that employ multiple sensors as well as the semantic segmentation that employs deep learning and neural networks. These newer methods are faster and better suited to the more current LDWS.

The technique used by [5] for detecting and identifying lane departure events in vehicles is as follows. First, a Piecewise Linear Stretching Function (PLSF) is used to improve the contrast of images within the Region of Interest (ROI). The ROI is then divided into two subregions, and then the Hough transform is applied to each of the subregions separately. This segmentation approach really helps in the efficient detection of the lanes as it minimizes the time required for the process. Lane departure identification is made by calculating a distance-based measure for every frame that indicates the degree of departure from the lane. Should this measurement be beyond a specified limit, the system issues a warning to the driver.

In [6], a vision-based Lane Departure Warning System (LDWS) that targets both day and night environments has been designed. Their system includes two main components: lane detection and the calculation of the lateral offset ratio. The lane detection process has two stages: Pre-processing and detection, which are another challenge because they involve identifying the features of an image that need to be extracted and analyzed, as well as determining the presence of objects or anomalies in a video stream.

Pre-processing involves converting the color space of the image, cropping the area of interest, and isolating the lane markings. In the detection stage, the Hough transform is employed to determine the position of lanes. Last of all, the system is able to determine the lateral offset ratio by finding the X coordinates of the lower part of each of the lane boundaries in the picture. The above-stated ratio is then used to create a lane departure warning.

In [7], the author proposed a method that consists of three primary components: Firstly, we employ a voting map to determine a disappearing point and then construct an adjustable Region of Interest (ROI) area to decrease the computational load. Secondly, it effectively utilizes the different colors of lanes to solve the problem of illumination invariance in lane candidate detection. Last but not least, using a clustering approach, we decide on the primary lane out of the potential ones. While the vehicle moves out of the lane, the technology provides a driver alarm signal. The results of the experiment show a satisfactory level of performance at different light conditions with an average detection rate of 93%. In addition, the overall operation is completed in 33 milliseconds per frame.

In [8], the author presents an approach for lane detection using a road module and extended Kalman filter, which includes the following steps. The first operation is to define the road Region of Interest (ROI) from the input image. The road ROI is again divided into different partitions, and a model of the road structure is developed based on the width of the lane and the distance between the lanes. The extended Kalman filter is then applied to estimate the lane parameters, which include the position of the lane, lane width and lane curvature. The lane model is then employed to identify the lane boundaries through an adaptive edge detection method. Last, the lanes are delimited more accurately through post-processing in which false positives are eliminated, and gaps in the lane detection are closed.

This model proves to be insensitive to variations in lighting conditions and the types of road surfaces, which makes it ideal for real-life implementation. Nevertheless, the model can fail to identify lanes in complex traffic situations, for instance, at intersections or roundabouts, where lanes are not well marked or even missing. However, the model will not be able to accurately identify the lanes in particular weather conditions, such as rainy or snowy weather, which causes the lanes to be barely visible. Nevertheless, the proposed model seems to have the capability to enhance the performance of the lane detection system and, consequently, the safety of self-driving cars.

In [9], the author suggests a model that comprises LDWS alongside a frontal collision warning system that is functional both day and night. This system employs a fixed camera that is mounted on the windshield of the car. The algorithm starts with the generation of the bird’s eye view of the road through Inverse Perspective Mapping (IPM). Then, the Hough transform is applied to this IPM to find out the points that might belong to the lane. The RANSAC Bezier spline fitting is used to identify the lanes precisely. For vehicle detection, the Hough transform is used again to find the horizontal lines that are likely to be vehicles. To increase the overall speed and optimize the use of resources, the model employs multithreading.

In [10], the learning-based method was proposed to detect the possible off-lane deviations and the probability of drivers straying back to the intended lane. This method involves two main steps: The approach begins by developing a personalized driver model that incorporates both a Gaussian mixture model and a hidden Markov model. This model describes the driver's lane departure and lane-keeping activities. Online Prediction Algorithm: Based on this model, an online prediction algorithm is designed to predict the future motion of the vehicle. The algorithm determines whether the driver is likely to maintain the current position or change lanes. Also, they provided a warning strategy built on the prediction algorithm. This strategy makes certain that the alerts given by the lane-departure warning system are given in a way that will be acceptable to the drivers based on the predicted trajectory.

In [11], the author developed a lane detection and tracking method based on monocular vision that was specifically designed for urban environments. This system integrates a Lane Departure Warning (LDW) to determine the car's position relative to lane boundaries. The process involves several key steps: First, the system establishes the Region of Interest (ROI) by identifying and highlighting relevant sections of the road images. Then, it preprocesses the data by reducing image noise with a Gaussian filter and enhancing lane boundaries using the Canny edge detector. For lane boundary extraction, the system utilizes color information and performs image segmentation with histogram thresholding and the Hough transform to achieve high accuracy in detecting lane boundaries. The system continuously monitors the vehicle's position and detects any drifting from the lane. When a lane departure is detected, it alerts the driver with a warning message, thus contributing to road safety.

In [12], the author introduced a method for identifying and categorizing lane markers using a linear parabolic model. This approach leverages the fact that the intensity of pixels associated with lane markers is generally higher than that of pavement pixels. The system distinguishes between lane markers and pavement by analyzing small rectangular patches to derive statistical values. In each frame, each pixel within these patches is compared against a distribution of pavement pixels to differentiate between asphalt and lane marker pixels. After detecting the lane markers, a cascade classifier is utilized for identification. Four binary classifiers are then employed to categorize the identified lane markers into five classes: dashed, dashed-solid, solid-dashed, single-solid, and double-solid.

In [13], the author has worked on an in-vehicle system that can detect and inform drivers of the lane markings. In order to detect and recognize lane markings, such as lines and pictograms, the system utilizes the combination of the MSER technique and the Hough transform. The system operates through the use of the MSER method to get to the relevant areas of interest. An enhancement processing algorithm of three stages refines the MSER results and erases unnecessary data, such as trees and vehicles. In real-time detection, the Progressive Probabilistic Hough Transform technique is employed for the detection of line markings. After that, the system identifies the color and type of line markings using the MSER results for the left and right lines. From the MSER regions, another algorithm can identify High-Occupancy Vehicle pictograms. Last but not least, a Kalman filter is used to track both ends of each of the detected line markings.

In [14], the author used a method with Bayesian inference theory to enhance lane detection. Their approach uses Rao-Blackwellized Particle Filters (RBPF) to deal with the linear and nonlinear properties of the road model. This approach helps to minimize the number of samples that the particle filters use as compared to other standard sampling techniques. They employed real-time cameras to capture images at 30Hz on an embedded computer. The Rao-Blackwellization process is divided into two stages. The first is the linear part, which consists of defining the position of the vehicle in the transversal direction. Nonlinear Part: The particle filters the hypotheses about the road curvature and generates the new hypotheses. Their system is capable of handling difficult situations, including rapidly fluctuating lighting, night vision, absence of clear references and the existence of other cars. It is highly accurate but is a disadvantage as it entails numerous hypothesis calculations.

In [15], the author proposes a solution which begins with converting the front view into a bird’s eye view. The transformed image is then subjected to selective 2D Gaussian spatial filters to smoothen it. Then, a simple and faster Hough transform is used to determine the number of lines present in the image. The RANSAC algorithm is used to estimate the better lines for the given input data. These lines are then passed through a more refined RANSAC that not only outputs the points on the line but also outlines a region around the line and fits a Bezier curve to the points in the region. It is possible to state that the algorithm has a high degree of accuracy. But there are some problems while driving on the right side of the road. If the right lane marking is not present, the algorithm may identify a ghost line.

Most of the papers reviewed in the literature reveal that they used Hough transformation and its extension, such as Progressive Probabilistic Hough Transform" (PPHT) based approaches for lane detection. These techniques primarily utilize probabilistic methods for detecting lane lines in images. These techniques are efficient in environments with clear lane markings but may struggle with complex road geometries, varying weather, and lighting conditions. Another drawback of these techniques is that they failed to detect fully oriented curves and were successful for small orientation curve lanes. Hence, in this paper, we propose to employ a Curved and Straight Lane detector (C&S Lane Detector) to detect fully oriented and straight lanes. This method significantly enhances lane departure analysis, particularly in challenging environments and complex road scenarios. The proposed method is best suited to overcome the limitations of the PPHT method by providing better performance even in different conditions, better real-time tracking and thus more efficient lane departure warnings. To implement LDWS, a vision-based LDWS is proposed in this paper for estimating the lane departure event by capturing the video from a vision sensor mounted on a vehicle for different lighting conditions and different road types, such as straight and curved roads.

The main contributions of the paper for the lane departure warning system are given below.

1. The novel edge detector, such as Phase Stretch Transform, is employed to detect edges, which overcomes the drawback of the Canny Edge detector.
2. We proposed employing a Curved and Straight Lane detector (C&S Lane Detector) to detect fully oriented curved and straight lanes.
3. The modified Kalman filter is employed for lane tracking.
4. The estimation of lane departure distance by calculating the Euclidean distance of the midpoint of the ROI and midpoint of the left and right lanes with the intention of enhancing vehicular safety.

2. Proposed Model

The proposed model presents a novel integrated approach for enhancing the functionality of lane departure warning systems in vehicles aimed at reinforcing road safety. The model's first step is to gather visual input through images or video feeds, capturing the vehicle's immediate driving environment. This input is then meticulously pre-processed to improve the visual clarity and minimize any interference, ensuring that the subsequent edge detection is both precise and reliable. Utilizing the Phase Stretch Transform (PST) algorithm[16], the model excels at detecting the lane edges by highlighting critical structural features within the images. To further refine the detection accuracy, a Curved & Straight (C&S) Lane Detector algorithm is applied, which is adept at distinguishing and classifying lane boundaries with high precision. The model's sophistication is evident in the Modified Kalman Filter for Lane Tracking, which predicts and follows the lane's position dynamically, adapting to the vehicle's manoeuvres and external environmental variations. The culmination of this process is the Enhanced Lane Departure assessment, which scrutinizes the lane tracking data to evaluate if the vehicle is veering off course. If such a deviation is detected, the system promptly initiates alerts, thus enabling the driver to take swift corrective measures. The strength of this proposed model is that the proposed workflow is integrated and comprehensive and employs the most advanced image processing techniques coupled with efficient detection and tracking methodologies in order to keep the vehicle within the intended lane while at the same time enhancing the safety of the driving experience. The flow diagram of the proposed method is depicted below in Figure 1.

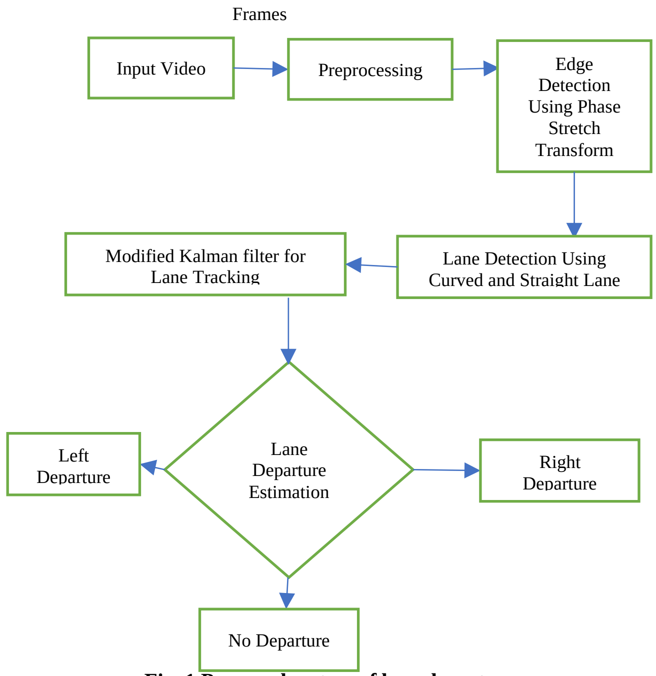


Fig. 1 Proposed system of lane departure

2.1. Pre-processing of Input Image/Input Video

When images are taken in less-than-ideal conditions such as low light, excessive brightness, or adverse weather like rain or fog, they can end up with much noise. This noise can significantly lower the quality of the images and make it harder to process them effectively. To tackle this, a preprocessing step is employed to clean up the images. This involves smoothing out the noise without losing important details in the image, which helps recover lost information and enhance image details. However, when an image is not only noisy but also lacks sharpness, a sharpening technique is applied to make the details pop and improve the overall look of the image. But there is a catch: sharpening a noisy image can make the noise more pronounced.

Dehazing methods are used to blur images affected by fog or haze, which can blur them and reduce contrast. Several techniques have been developed, including some based on the premise that the contrast should be higher in clear conditions than in foggy ones and that light attenuation due to fog varies smoothly with distance. One notable method is the Dark Channel Prior (DCP) algorithm proposed by [17], which has shown promise in addressing the limitations of earlier dehazing techniques by focusing on the natural properties of haze-free images. There is also a method tailored for traffic videos that speeds up dehazing but still is not fast enough for real-time application, highlighting the ongoing challenge of making these methods faster and more universally applicable.

To enhance contrast and reduce noise further, filters such as median or Gaussian are used on the images. This is followed by converting the images from RGB to grayscale, which simplifies the images and reduces processing time. The grayscale images are then segmented into binary images, setting the stage for smoother, clearer images that are ready for the next steps in processing for Edge Detection.

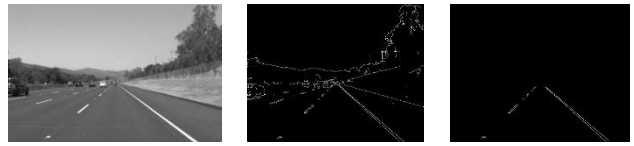
(a) (b)

Fig. 2 (a)Left: Original image, (b) Right: Pre-processed image.

2.2. Edge Detection Using Phase Stretch Transform (PST)

Edge detection is the process of identifying and pinpointing abrupt changes in an image. It may identify regions with strong intensity contrasts. It is the area where the image's intensity or contrast significantly changes. Because edge detection helps emphasize and bring forth information about a picture, it is used. These details include object identification and highlighting, as well as the size, shape, sharpening, and augmentation of the image. It can also be used as an instrument for segmenting images, which modifies their intensity. An edge is a shift in intensity between adjacent pixels in a continuous picture.

Many researchers have used the Canny Edge detection method for lane detection. It is used in these multi-level algorithms to distinguish one edge from the other in the given image. It is mainly applied for boundary detection and intensity change detection in numerous computer vision-related tasks. Should the gradient amount of a pixel be higher than the gradient amount of the pixels on both sides in the direction of change of intensity, this approach identifies the pixel as an edge. To eliminate this noise, the image must be smoothed. Subsequently, the region of interest with spatial derivatives is identified through the picture gradient. After identifying these areas, any pixel that does not have this value is set to zero. Hysteresis is currently showing more losses in the angle it presents at the given point in time. Hysteresis is performed to detect the remaining suppressed pixels. In hysteresis, there are two levels known as the upper and the lower[18]. The extend is set to zero (made a non-edge) at the point where it is below the main edge. Size turns into an advantage as soon as it reaches the high edge. Furthermore, if no path can be traced from this pixel to another pixel with a slope greater than the second threshold, greatness is set to zero when it is between two thresholds. From the above process, we can deduce that Canny is one of the most complex edge detection systems that require much time on the computer in order to accomplish its objectives.



(a) (b) (c)

Fig. 3 Result of edge detection (a) Pre-processed image (b) Result of Canny edge detection (c) Result of PST edge detection.

Steps to compute PST Edge Detection for Pre-processed Images:
Given a pre-processed image $I(x, y)$, where x and y are spatial coordinates, the PST edge detection can be represented by the following steps:

1. Calculate the Fourier Transform $F(u, v)$ of the image:
$$F(u, v) = \mathcal{F}\{I(x, y)\} \tag{1}$$

2. Apply a phase function $\phi(k)$ to the Fourier Transform, where k is the spatial frequency:
$$\phi(k) = \log(k) \tag{2}$$
$$F_\phi(u, v) = F(u, v) \cdot e^{i \cdot \phi(k)} \tag{3}$$

3. Perform the Inverse Fourier Transform $I_\phi(x, y)$ of the phase-modified Fourier Transform:
$$I_\phi(x, y) = \mathcal{F}^{-1}\{F_\phi(u, v)\} \tag{4}$$

4. Apply a non-linear thresholding function T to extract edges:
$$\text{Edge}(x, y) = T\{I_\phi(x, y)\} \tag{5}$$

Abbreviations:
$I(x, y)$: Original image in spatial domain

$F(u, v)$: Fourier Transform of the original image

$\phi(k)$: Phase function applied to Fourier Transform

$F_\phi(u, v)$: Phase-modified Fourier Transform

$I_\phi(x, y)$: Image after applying Inverse Fourier Transform to $F_\phi(u, v)$

Edge (x, y): Final edge-detected image

$\mathcal{F}$: Fourier Transform operator

$\mathcal{F}^{-1}$: Inverse Fourier Transform operator

T : Non-linear thresholding function

1. Fourier Transform (FT): Perform the Fourier Transform on the input image to transform the image from the spatial domain to the frequency domain.
2. Phase Function Application: Apply a phase function $\phi(k)$, typically a logarithmic function, to the Fourier

Transform. This function is used to modify the phase information of the transformed image.

3. Inverse Fourier Transform (IFT): Apply the Inverse Fourier Transform to the phase modified Fourier image to convert it back into the spatial domain.
4. Non-linear Thresholding: Finally, apply a non-linear thresholding function to highlight the edges.

The Phase Stretch Transform (PST) is used in edge detection by transforming an image to highlight transient features like edges and texture. The Phase Stretch Transform (PST)[19] can be more effective than the Canny edge detector in certain scenarios due to its unique approach to edge detection. While Canny uses gradient-based techniques, PST focuses on the phase congruency of an image, which is less sensitive to changes in illumination and contrast. This allows PST to detect edges in conditions where the Canny method might fail, particularly in low-contrast images or where the edge information is subtle. PST's ability to capture finer details and texture in images makes it a powerful tool in scenarios requiring high fidelity edge detection, like complex road lighting scenarios.

The PST works mathematically by applying a phase function to the Fourier transform of an image. This function is typically a logarithmic function, represented as φ(k) = log(k), where k is the spatial frequency. The transformed image is then inverse Fourier transformed, and a nonlinear thresholding is applied to extract edges. This approach emphasizes the edges in images, making PST particularly effective for detecting fine features in images where traditional edge detection methods might struggle. This method is beneficial for applications like lane detection in autonomous driving, where clear edge delineation is crucial.

2.3 Curved and Straight Lane Detector (C&S Lane Detector)

The traditional Hough Transform approach computes ρ and θ. And transforms the Cartesian coordinates (x, y) into (ρ, θ) space. It helps to detect straight lines but fails to identify curved lines. In the C&S Lane Detector approach, we compute $\rho_{\text{curvature}}$ along with ρ and θ. And we transform the Cartesian coordinates (x, y) into $(\rho, \theta, \rho_{\text{curvature}})$ tuples. We discretize ρ, θ and $\rho_{\text{curvature}}$ values to fit in the accumulator array. In our method, we increment the corresponding cells for $\rho_{\text{curvature}}$ in the accumulator array. Therefore, this new approach helps to detect both curved and straight lines. The goal is to accurately identify and extract lane lines, which can be either straight or curved, to facilitate tasks such as autonomous driving or lane departure warning systems.

The algorithm starts by defining the parameter space ranges for ρ (distance from the origin to the line), θ (angle of the line), and an additional parameter ρ_curvature, which represents the radius of curvature for curved lines. An accumulator array is created to store votes for different combinations of (ρ, θ, ρ_curvature) tuples. For each edge pixel (x, y) in the input image, the algorithm iterates through a range of θ values (typically from -90° to 90°). For each combination of (x, y) and θ, it calculates ρ using the equation ρ = x * cos(θ) + y * sin(θ). The algorithm checks if the calculated ρ value falls within a predefined limit (ρ_max) to avoid capturing excessively long lines. If ρ is within the limit, the algorithm proceeds to discretize ρ, θ, and ρ_curvature values to fit them into the accumulator array and increments the corresponding cell to vote for that line. A threshold value is set to determine which cells in the accumulator array are considered potential lines.

Fig. 6 Results of BDD100K benchmark datasets
(a) Straight line detection (b) Curved line detection

For each cell in the accumulator array that exceeds the threshold, the algorithm converts the (ρ, θ, ρ_curvature) indices back to (ρ, θ, ρ_curvature) values. The list of detected lines is sorted based on the accumulator values in descending order. The algorithm iterates through the list and retains only those lines that are not too close to each other in the parameter space (ρ, θ, ρ_curvature). This step helps eliminate redundant detections. For each remaining (ρ, θ, ρ_curvature) tuple in the list of detected lines, the algorithm converts these parameters into Cartesian coordinates:

For straight lines, the formula is used.

$$y = -(\cos(\theta) / \sin(\theta)) * x + (\rho / \sin(\theta)). \quad (6)$$

Table 1. The lane detection results of the proposed model under different road conditions using our Custom dataset

Video Sequence	Road Geometry	Total Number of Frames	True Positive	False Negative	Accuracy Rate	Detecting Time
1	Straight road in the day	600	587	13	97.83%	20 ms
2	Structured road with Curves	600	584	16	97.33%	22 ms

For curved lines, it employs the appropriate curvature formula based on the method used for curvature estimation, i.e., $= 1/r$, Where R = the radius calculated using the radius of curvature.

$$\text{Radius of Curvature Formula } (R) = \frac{\left[1+\left(\frac{dy}{dx}\right)^2\right]^{\frac{3}{2}}}{\left|\frac{d^2y}{dx^2}\right|} \quad (7)$$

The algorithm then draws the detected line or curve on the original image using the calculated points shown in Figure 4 for both the curved lane and straight lane.

(a)	(b)

Fig. 4 Result of C&S lane detector
(a) For curved line detected (b) For Straight line detected

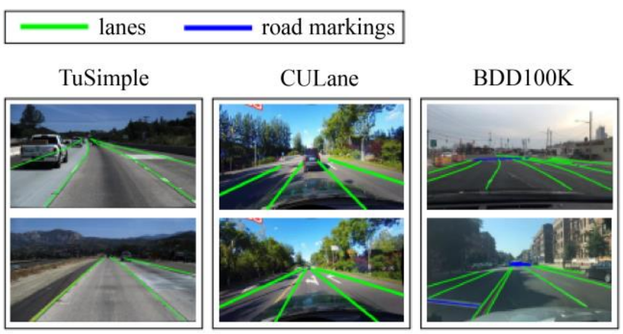


Fig. 5 Images of TuSimple, CULane and BDD100K datasets

In this research, we randomly selected 600 frames from the custom dataset that depict a variety of scenarios for our lane detection experiments using the proposed algorithm. To confirm the effectiveness of our methods, we conducted quantitative assessments. The primary measure of evaluation was accuracy, which determines the algorithm's overall capability in correctly classifying images. Similarly, we randomly chose 1000 images from the BDD100K dataset, reflecting different conditions, to conduct lane detection tests with our algorithm. The outcomes of these tests, as indicated by the performance metrics with the BDD100K dataset, are displayed in Table 3 . Table 2 evaluates the algorithm's performance, and the following formulas are used in lane detection.

In the context of lane detection, these abbreviations refer to the outcomes of predictions made by a detection algorithm compared to the actual situation. They help in evaluating the algorithm's accuracy and performance.

True Positive (TP): This occurs when the algorithm correctly identifies a lane that is actually there. In other words, the algorithm positively detects a lane, and in reality, the lane is present.

False Positive (FP): This happens when the algorithm identifies a lane that is not actually there. The algorithm makes a positive prediction (thinks it has found a lane), but this prediction is incorrect because no lane exists in that spot.

True Negative (TN): This is when the algorithm correctly identifies that no lane is present. Although not as common in lane detection contexts (since the focus is usually on detecting the presence of lanes rather than their absence), it essentially means the algorithm correctly predicts the absence of a lane.

False Negative (FN): This occurs when the algorithm fails to identify a lane that is present. The algorithm negatively predicts (thinks there is no lane), but this prediction is incorrect because there actually is a lane.

These metrics are crucial for understanding how well a lane detection system is performing. High TP rates indicate good detection of actual lanes, while low FP rates indicate that the system is not mistakenly identifying non-lanes as lanes. High TN rates would be relevant in systems that also specifically identify areas where lanes are not present. Low FN rates indicate that the system effectively recognizes most of the lanes that are present.

As Shown in Table 3, a comparative study on the effectiveness of various lane detection methods used in structured road environments. It details an experiment involving 1000 frames for each method calculated to identify the accuracy of lane detection and compare their performance in accurately detecting lanes.

The methods analysed include the Spatial Ray Feature extractions, Hough transform, and a Proposed Method labelled as C & S (Curved & Straight) lane Detector.

Table 2. Evaluates the algorithm's performance, and the following formulas are used in lane detection

Sl. No.	Metrics	Formula *
1	Accuracy(A)	$A = \frac{(TP+TN)}{(TP+TN+FP+FN)}$
2	Detection rate (DR)	$DR = \frac{(TP)}{(TP+FN)}$
3	False positive rate (FPR)	$FPR = \frac{(FN)}{(TP+FN)}$
4	False negative rate (FNR)	$FNR = \frac{(FN)}{(FN+TP)}$
5	True negative rate (TNR)	$TNR = \frac{(TN)}{(TN+TP)}$

Table 3. Comparison of our results with existing literature

Methods	Road Geometry	Total Number of Frames	Total Number of Detected Lanes	Accuracy Rate
[17] Spatial Ray Feature extractions	Structured road	1000	889	88.9%
[18] Hough transform	Structured road	1000	897	89.7%
Proposed Method (C & S lane Detector)	Structured road	1000	941	94.1%

Spatial Ray Feature extractions technique [19] showed improvement over the traditional approach, with an accuracy rate of 88.9%, successfully detecting 889 lanes. This method utilizes spatial ray features for more effective lane detection. [20] Hough transform method further enhanced detection capabilities, identifying 897 lanes with an accuracy rate of 89.7%. This approach is known for its effectiveness in detecting straight lines, which is beneficial for lane detection on structured roads. The proposed Method (C & S lane Detector) achieved the highest accuracy rate of 94.1%, detecting 941 lanes. This method combines techniques for detecting both curved and straight lines, indicating a significant advancement in lane detection technology.

The progress in lane detection methods also underlines the proposed method's superiority in handling structured road scenarios. Additionally, it references several studies and proceedings that have contributed to the development of these methods, including works by [21][22]., which provide a theoretical foundation and empirical evidence supporting the evolution of lane detection technology. This comparative analysis offers a clear view of how lane detection techniques have evolved, emphasizing the proposed method's potential to enhance road safety through improved lane detection accuracy significantly.

2.4. Modified Kalman Filter for Lane Tracking

Kalman filtering can be used to track objects, including tracking lanes on the road. Lane tracking typically involves estimating the lane's position and orientation over time. The standard Kalman filter is a mathematical approach used to estimate the state of a dynamic system in the presence of noise and uncertainty. It involves two steps: prediction and correction. Lane tracking estimates the position and orientation of lanes on the road by using a state vector, state transition matrix, control input, and measurements. The standard Kalman filter is ideal for linear systems with Gaussian noise. The standard Kalman Filter has limitations, particularly in handling non-linear systems, as it assumes a linear relationship between the state and the measurements. It also presumes that the process and measurement noise are Gaussian, which might not be the case in real-world scenarios. Modified Kalman Filters address these limitations by incorporating non-linearities into the state and measurement models. They use different methods to approximate the state distribution, allowing for more accurate state estimation in complex scenarios where the standard Kalman Filter might fail to provide a precise solution [23].

A modified Kalman filter, on the other hand, includes adjustments or extensions to the standard Kalman filter equations to handle better the specificities of the lane tracking problem, which may include non-linearities or non-Gaussian noise. Such modifications often aim to improve the accuracy of the lane tracking system, especially in challenging scenarios like curved roads or rapid lane changes, by better accounting for the vehicle's dynamics and the environment's unpredictability. These improvements might involve more sophisticated models for state transition or measurement noise or the inclusion of additional control inputs that influence the system's state. It starts by initializing various matrices and vectors that represent the system's state, such as the lane's position and orientation and the expected noise in the system. For each time step, it predicts the future state based on the current state and control inputs like acceleration. It then updates this prediction using new sensor measurements to correct the state estimate. The Kalman gain is calculated to minimize the estimation error. The updated state and covariance matrices are then used in the next time step, continually refining the vehicle's lane position and orientation estimates. This process helps determine if a vehicle is departing from its lane, enabling the system to alert the driver accordingly.

Prediction Step:

Predicted state estimate:

$$\text{Predicted\_State\_Estimate } \mathbf{x}[k \mid k-1] = \mathbf{F}[k]\mathbf{x}[k-1] + \mathbf{B}[k]\mathbf{u}[k]. \quad (8)$$

Predicted covariance estimate:

$$\text{Predicted\_Covariance\_Estimate } \hat{\mathbf{P}}[k \mid k-1] = \mathbf{F}[k]\mathbf{P}[k-1]\mathbf{F}[k]^{\top} + \mathbf{Q}[k]. \quad (9)$$

Update Step:

Measurement matrix: $\mathbf{H}[k]$

Measurement noise covariance: $\mathbf{R}[k]$

Measurement update: $\mathbf{z}[k]$

Kalman gain:

$$\mathbf{K}[k] = \hat{\mathbf{P}}[k \mid k-1]\mathbf{H}[k]^{\top}\left(\mathbf{H}[k]\hat{\mathbf{P}}[k \mid k-1]\mathbf{H}[k]^{\top} + \mathbf{R}[k]\right)^{-1} \quad (10)$$

Updated state estimate:

$$\mathbf{x}[k \mid k] = \hat{\mathbf{x}}[k \mid k-1] + \mathbf{K}[k](\mathbf{z}[k] - \mathbf{H}[k]\hat{\mathbf{x}}[k \mid k-1]) \quad (11)$$

Updated covariance estimate:

$$\mathbf{P}[k \mid k] \stackrel{\downarrow}{=} (I - \mathbf{K}[k]\mathbf{H}[k])\hat{\mathbf{P}}[k \mid k-1] \quad (12)$$

In a lane departure system, mathematical equations are used in a modified Kalman filter algorithm for lane tracking. The state vector x[k] at each time step k contains the position of the vehicle in the lane and the orientation of the lane. The prediction step uses the state transition matrix F[k] and control input u[k] along with the control input model B[k] to project the current state into the next time step. The process noise covariance Q[k] takes into consideration any variability in the prediction process. The Kalman gain K[k] is computed during the update step with the help of measurement matrix H[k] and measurement noise covariance R[k].

This gain determines how much the predictions should be corrected based on the new measurement's z[k]. The state vector and covariance matrix are then updated to yield x[k|k] and P[k|k], which are better estimates of the position and orientation of the lane. This process goes on iteratively, and the vehicle's position with respect to the lane is adjusted at each step. These steps are performed recursively as more measurements are taken, making it possible for the Kalman filter to predict and update the lane's position and orientation in relation to the car while taking into account noise and uncertainty involved in the process and measurements. The modified Kalman filter provides a way to estimate the state of a system recursively (in this case, the vehicle's lane position and orientation) over time, taking into account both the uncertainty in the system dynamics (process noise) and the uncertainty in the measurements (measurement noise). This is particularly useful for lane tracking as it allows the system to filter out noise and inaccuracies in sensor data, providing a more reliable and accurate estimate of the vehicle's position relative to the lane.

2.5. About Lane Departure Estimation

In [24], the author proposed a reliable lane departure approach utilizing the distance of the vehicle from the lane by employing the PLSF algorithm. In the study described here, advanced computer vision methodologies are used to design a system that can identify lanes and avoid road accidents by providing lane departure alerts. This approach employs the Canny edge detection method to find the edges of the roadway and the median strip, while the Hough transform method provides better detection. The distance of the vehicle from the central divider is calculated using the lateral distance formula, which is the Euclidean distance. When this measurement is used together with the PLSF (Phase Line Segment Fitting) algorithm, it improves accuracy for various illumination conditions.

The proposed model for the lane departure estimation includes the C&S Lane Detector and a Modified Kalman Filter to determine the lateral position of the vehicle with respect to the lane. The identification of lane lines and their coordinates is critical to determining the likelihood of lane departure. The assessment employs the Euclidean Distance (ED) to measure the transverse movement of the vehicle with reference to the lane markings. The ED between the midpoint of the vehicle's front axle is projected onto the Region of Interest (ROI). The midpoints of the detected lane lines are computed as follows: The ED between the midpoint of the vehicle's front axle projected onto the Region of Interest (ROI) and the midpoints of the detected lane lines is computed as follows:

$$\lambda = \sqrt{(H_0^x - mp_1^x)^2 + \left(H_0^y - mp_1^y\right)^2} \quad (13)$$

Where:
$\boldsymbol{\lambda}$: Euclidean distance between midpoints.
H_0^x, H_0^y : Horizontal and vertical coordinates of the vehicle's projected midpoint within the ROI for x and y.
mp_1^x, mp_1^y : Horizontal and vertical coordinates of the midpoint of the identified lane line for x and y.

To determine a potential lane departure, the EDs for both the left and right lane lines are monitored over time. A predefined threshold θ is established to gauge significant lateral shifts. If the ED to either lane line falls below θ, a lane departure event is flagged:

- Left Departure: $\lambda_{\text{left}} < \theta$
- Right Departure: $\lambda_{\text{right}} < \theta$

The thresholds can be dynamically adjusted based on vehicle speed, road conditions, or driver behavior to enhance the accuracy and sensitivity of departure detection. By incorporating threshold values along with the C&S Lane Detector and Modified Kalman Filter analysis, the system achieves a more nuanced detection of lane departure events, which is essential for the activation of safety mechanisms in autonomous vehicles and Advanced Driver-Assistance systems (ADAS).

2.6. Lane Departure Estimation of Enhanced Lane Departure Warning System (ELDWA)

Algorithm: Enhanced Lane Departure Warning System (ELDWA)
Input: Lane detection output (η)
Output: Lane deviation angle and direction
Procedure ELDWA(η):

1. Highlight the vehicle's travel path within the detected lane from η.
2. Perform C&S Lane Detector along with modified Kalman filter on η to obtain right (Pr) and left (Pl) lane boundaries.
3. Identify the lane's midpoint (ρ) using the positions of Pr and Pl.
4. Construct right triangles using the lane boundaries (Pr, Pl) and midpoint ρ.
5. Calculate angles ω (relative orientation to the right boundary) and θ (relative orientation to the left boundary) from the triangles.
6. Determine lane deviation direction:
   a. If lane_deviation (ϕ > ω) and lane_deviationRange(ρ - Zr < ρ - Zl), then vehicle will deviation towards the left.
   b. If lane_deviation (ϕ > ω) and lane_deviationRange (ρ - Zl < ρ - Zr), then vehicle will deviation towards the right.
   c. If lane_deviation (ϕ > θ) and lane_deviationRange (ρ - Zr < ρ - Zl), then vehicle will deviation towards the left.
   d. If lane_deviation (ϕ > θ) and lane_deviationRange (ρ - Zl < ρ - Zr), then the vehicle will deviation towards the right.
   e. Else, the vehicle is within the lane trajectory.
7. Calculate the offset from ρ on the side of deviation.
8. Determine the departure angle indicative of deviation severity.

End Procedure

The Enhanced Lane Departure Warning System (ELDWA) utilizes advanced computational methods to ascertain lane departure. The core mathematical model involves the calculation of lane boundaries Pr and Pl using the C &S Lane Detector alongside a modified Kalman filter. The midpoint ρ is calculated as the average position between Pr and Pl.

Geometrically, right triangles are constructed using these points to derive angles ω and θ, representing the vehicle's orientation to the lane boundaries. The decision to flag a deviation is based on comparing these angles to a critical angle ϕ, with conditions such as $\phi > \omega$ indicating deviation. Specifically, the algorithm evaluates if $\rho - Zr < \rho - Zl$ for leftward deviation or the inverse for rightward. The offset from ρ on the deviated side is calculated, leading to the determination of the departure angle, which quantifies the deviation's severity. This mathematical approach allows for precise and dynamic monitoring of lane discipline, significantly enhancing vehicular safety.

The mathematical conditions in the Enhanced Lane Departure Warning System

(ELDWA) algorithm is crucial for determining the vehicle's lane position and detecting deviations. These conditions involve comparing calculated angles ω and θ against a predefined threshold angle ϕ. The conditions for detecting a deviation are as follows:

Table 4. Deviation conditions for lane detection

Leftward Deviation:	If ϕ > ω and the distance from the midpoint to the right boundary (ρ - Zr) is less than that to the left boundary (ρ - Zl), it indicates a leftward deviation.
Rightward Deviation:	Conversely, if ϕ > ω and ρ - Zl < ρ - Zr, a rightward deviation is indicated. The algorithm also considers θ similarly to ω for enhanced accuracy in detecting the direction of deviation.
No Deviation:	If none of the above conditions are met, the vehicle is considered to be moving within the lane trajectory.

These mathematical evaluations enable the system to precisely identify when and in which direction the vehicle deviates from its lane, enhancing the safety features of autonomous and semi-autonomous vehicles.

3. Results and Discussion

There are many datasets available for lane detection. In most of the Benchmark datasets, they have provided images of road scenarios. Using images makes it difficult to calculate departure. As it requires videos that contain the left and right departure of the driving vehicle, in order to evaluate the performance, we are using the Custom dataset to evaluate the performance of the proposed model.

The algorithm underwent testing on a custom dataset under three different scenarios. The outcomes include the identified lanes and their respective vehicle offsets. This custom dataset includes videos taken during the day, at night and under foggy conditions.

Accuracy = Detected Correctly / Total Number of Frames.

Table 5. Daytime departure accuracy

Conditions	Total Number of Frames	Detected Correctly	Accuracy
Total Frames	8000	7665	95.81%
Left Departure	478	398	83.26%
Right Departure	554	470	84.83%

Table 6. Night-time departure accuracy

Conditions	Total Number of Frames	Detected Correctly	Accuracy
Total Frames	1078	912	84.6%
Left Departure	200	130	65%
Right Departure	150	97	64.66%

The algorithm will be tested on a custom dataset across three distinct scenarios: daytime, nighttime, and foggy conditions. This approach aims to evaluate the model's effectiveness in various driving environments. The evaluation metric used is accuracy, calculated as the ratio of correctly detected lanes to the total number of frames.

Daytime Departure Accuracy (Table 5): This table shows the model's performance during the day across different conditions, including total frames, left departures, and right departures. Out of 8000 total frames, 7665 were correctly detected, resulting in an accuracy rate of 95.81%. For left departures, 398 out of 478 frames were accurately identified (83.26% accuracy), and for right departures, 470 out of 554 frames were correctly detected (84.83% accuracy).

Night-time Departure Accuracy (Table 6): This table presents the model's performance at night. The total number of frames was 1078, with 912 correctly detected, yielding an accuracy rate of 84.6%. The accuracy for left departures was lower, with 130 out of 200 frames detected correctly (65% accuracy), and for right departures, 97 out of 150 frames were accurately identified (64.66% accuracy).

These tables collectively illustrate the proposed model's capability to detect lane departures under varying conditions accurately. It is evident that the model has a high degree of accuracy throughout the day but has a slightly lower performance at night due to the difficulties arising from poor visibility. The analysis of the performance, depending on the type of departure, gives insights into the model's performance in different lighting conditions and reveals its weak points. This evaluation underscores the importance of comprehensive testing across various conditions to ensure the reliability and robustness of lane detection models.

3.1. Limitations of the Proposed System

1. Firstly, the system's reliance on high-quality image and video data may pose challenges in extremely adverse weather conditions or scenarios where visibility is severely compromised, such as heavy fog, torrential rain, or blizzard conditions. These situations can hinder the system's ability to accurately detect lane markings, potentially reducing its effectiveness.
2. Additionally, the complexity and computational requirements of the proposed algorithms, including the Phase Stretch Transform for edge detection and the Modified Kalman Filter for lane tracking, may limit the system's real-time performance on less powerful hardware. Optimizing these algorithms for faster processing without sacrificing accuracy remains a crucial area for future research.
3. Another limitation stems from the inherent variability in road conditions and markings. The system's performance in regions with poorly maintained roads, faded lane markings, or unconventional road layouts could be less reliable. Furthermore, the adaptation to different global road standards and conditions presents an additional layer of complexity that requires extensive validation and customization.

4. Conclusion

This research presents a comprehensive study on the development and evaluation of an Enhanced Lane Departure Warning System (ELDWS) using cutting-edge vision technology. The system, designed to improve road safety for ADAS-enabled vehicles, incorporates a novel approach utilizing Phase Stretch Transform for edge detection, Curved and Straight Lane Detector for precise lane detection, and a modified Kalman Filter for dynamic lane tracking. These integrated technologies collectively aim to improve vehicle safety through precise lane departure estimation. Our system was rigorously tested under various lighting and road conditions, including challenging weather scenarios and curved paths, demonstrating its superior performance and robustness compared to existing technologies. The evaluation conducted using a custom dataset and the BDD100K dataset, a general-purpose benchmark for lane detection, showcases the system's high accuracy rates: 95. The main goal of this paper is to identify the critical factors that affect the performance of SMEs in the context of their interactions with key suppliers. 81% in daytime conditions. These findings support the viability of ELDWS when used in practice and its ability to operate in various environmental settings and road surfaces. The advancements introduced in this paper are useful for autonomous driving and establish a new safety benchmark by overcoming the flaws of current LDWS technologies. In this way, the proposed system can help to provide safe lane-keeping assistance in both full- and high-level self-driving cars while considering factors like sensitivity to meteorological conditions and reliance on proper striping. Apart from this, this research reveals the possibilities of utilizing the various image processing algorithms and the application of machine learning in developing better driving assistance systems. Ultimately, the Enhanced Lane Departure Warning System marks a significant step towards achieving safer autonomous driving, offering a detailed and effective solution that enhances the accuracy and reliability of lane detection and departure warnings. As we move forward, the insights and methodologies developed through this research will undoubtedly play a crucial role in shaping the future of vehicle safety and driving assistance technologies.

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