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Lane-lines identification system using CNN

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Abstract - ***In recent times, significant advancements have been made in the realm of road safety due to the alarming increase in accidents with one of the leading causes being driver in- attention. To mitigate the occurrence of accidents and ensure safety it is imperative to explore technological breakthroughs. One such approach involves the utilization of Lane Detection Systems, which operate by identifying lane boundaries on the road and notifying the driver if they deviate from the correct lane marking. Lane detection systems are pivotal components in various advanced transportation systems. However, achieving this objective proves to be challenging due to the diverse road conditions encountered, especially during nighttime or daytime driving. By placing a camera at the front of the vehicle, it captures the road view and detects lane boundaries. Various techniques have been presented for detecting lane markings on the road. In this study, the approach utilized involves partitioning the video image into smaller segments and extracting image characteristics for each segment. These characteristics are subsequently used to detect the lanes on the road. Keywords- lane Detection System, self-driving car assistant, Open CV, Road Accidents, Machine learning.***

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1. Introduction

A Lane Detection System is a critical component of artificial intelligence (AI), machine learning (ML), and computer vision, particularly in intelligent vehicle systems. Its primary objective is to accurately detect lane lines and issue alerts or messages when a vehicle is about to deviate from its lane. Additionally, it incorporates object detection to prevent accidents. Advanced Driving Assistance Systems (ADAS) rely on lane detection to model road lanes and determine the vehicle's position accurately. The development of intelligent vehicles aims to automate driving tasks, enhancing safety conditions. Road detection is important in driving assistance systems as it provides information such as lane structure and vehicle position which helps for drivers to drive safely. Performing lane detection in complex traffic driving scenes presents numerous challenges [1]. A suggestion has been put forward that spatial CNNs can effectively acquire knowledge about the spatial connections between feature maps and the seamless, uninterrupted assumptions of lane lines in traffic situations, surpassing the capabilities of previously developed networks. Despite advancements, vehicle crashes remain a significant concern in Malaysia and other Asian countries with tens of thousands of fatalities and millions of injuries annually mostly on highways. The United Nations has ranked Malaysia among the nations facing considerable challenges in road safety.

1.1 Problem statement

According to the Topic overview, the Lane Detection System is extremely important and essential to gain control over the rising number of accidents and save people's lives. It is widely known that the lack of advanced features in vehicles and the increasing driver drowsiness caused by heightened stress are endangering many lives. Taking this into account, a solution needs to be designed. The existing lane detection systems are not accurate and fail to notify the user in any way. Additionally, the new system should be less time-consuming and more effective. Therefore, this proposed system must be well-developed and responsive.

1.2 Existing System

The existing lane line identification system relies on Convolutional Neural Networks (CNNs) and preprocessing of raw images to extract lane markings. However, its reliance on annotated datasets may limit its performance in diverse driving conditions, where training examples are lacking. Additionally, CNNs may struggle to generalize to new environments, leading to reduced adaptability in varying lighting, road markings, and weather conditions. Despite multiple stages including data collection, preprocessing, training, and evaluation, the system may face challenges in accurately identifying lane lines across real-world driving scenarios [2].

2. Literature Survey

We have done research from different research papers and we have found what methods are used and drawbacks in the existing system.

A. Road Lane Line Detection System by Using Cnn and Rnn Algorithms in Deep Learning.

This paper uses the CNN and RNN algorithms which help in lane detection.

1. The paperwork is concentrated on lane detection by using the Hough line transform method.
2. This system is not working in conditions like low lightning, and poor environmental conditions.

B. A Robust Lane Detection Using Vertical Spatial Features and Contextual Driving Information.

This paper proposed a system that uses consensus (RANSAC) and Hough transform algorithms.

1. For identifying lanes in case of complex traffic scenes based on the CULane and TuSimple lane dataset.
2. Their lane detection system uses techniques like vertical spatial features and contextual driving information for complex traffic scenes.
3. This system cannot fulfill the real-time needs. Does not perform well in the condition of curved roads.

C. Robust Lane Detection for Complicated Road Environment Based on Normal Map.

This paper uses the Normal map techniques for lane detections.

1. Despite encountering numerous significant challenges, particularly in achieving resilience in complex lighting conditions and heavy traffic situations[3].
2. In the proposed system challenges are

   faced like poor visibility lane scratches.
3. In the proposed system challenges are faced like poor visibility lanes scratches.

D. Road Lane-Lines Detection in Real-Time for Advanced Driving Assistance Systems

1. This paper uses pipelines of algorithms like Canny edge detection and Hough transform.
2. The suggested approach merely requires unprocessed RGB images captured by a sole CCD camera positioned behind the vehicle's front windscreen.
3. The proposed system only detects straight lines and not curved lines on the road which is the challenging factor.

3. Proposed System

In the proposed system we are going to use the CNN algorithm for lane detection and the Haar cascade algorithm for object detection. Our proposed system quickly and accurately detects the lanes and objects on the roads.

4. System Architecture

Image Processing: the vehicle's camera captures road images, which are subsequently analyzed for lane detection.

Pre-processing: Before detection, the captured image undergoes pre-processing, converting it into grayscale to expedite computation.

Edge detection module: An edge detector is used to generate an image with defined edges. This is achieved through machine-generated thresholding and the use of a Canny filter to identify edges.

Lane detection module: A line detector is employed to recognize both the left and right portions of the lane boundaries. Identification of yellow and white lanes is achieved through the utilization of RGB color codes. [4]

Implementation of neural networks in the system: To enhance the accuracy of lane detection, a multitask deep CNN detector can be implemented.

5. Algorithms

5.1. CNN Algorithm

The lane lines identification system is the machine learning model that is developed using Python and OpenCV. It's a software toolkit utilized for processing both images and videos. it is an open-source library that is used for creating computer vision applications in sectors like machine learning and artificial intelligence. OpenCV is used to identify the lane lines efficiently

In the realm of deep learning, the Convolutional Neural Network (CNN) stands out as a class of deep neural networks that finds extensive application in the field of image recognition and analysis. The distinguishing feature of CNN lies in its utilization of a unique technique called Convolution. Convolutional layers, which resemble a grid-like structure, are responsible for processing data that exhibits grid-like properties, such as images. An image, essentially a visual representation, comprises a grid of pixels, with each pixel being assigned a value that determines its brightness and color.

The design of Convolutional Neural Networks (CNNs) draws inspiration from the intricate connectivity patterns observed in the human brain, particularly in the visual cortex. In this sector of the brain is important to determine visual information and interpret it. In CNNs, artificial neurons are arranged in a manner that enables efficient interpretation of visual information, thus empowering these models to process entire images. Due to their exceptional ability to identify objects, CNNs are widely employed in computer vision tasks like image recognition, object detection, and even in cutting-edge applications like self-driving cars. CNN algorithm is classified into three layers Convolutions, Pooling and ReLU.

1. Convolutions layers-

The process of convolution involves sliding the kernel across the width and height of the image, gradually covering the entire image through multiple iterations. At every position, the weights of the kernel are used to compute a dot product with the pixel values of the image below it. [5] This process results in generating feature maps or convolved features, each indicating the presence and strength of specific features across various locations within the image. To determine the size of the resulting volume, we can use the following formula when given an input size of N x N x W, many kernels with size F, a stride of S, and a certain amount of padding [6].

2. Pooling layers-

As Convolutional layers extract features from images, Pooling layers work to gradually diminish spatial dimensions in representations, effectively reducing parameter count and computational load. The feature map produced by Convolutional layers is inherently sensitive to object locations within images. If an object shifts even slightly, the Convolutional layer may fail to recognize it. This suggests that the feature map maintains the exact positions of features from the input. Pooling layers, on the other hand, offer "Translational Invariance," making the CNN capable of recognizing features even if the input undergoes translation.[7] Two types of pooling are commonly used:

1.Max pooling: This approach picks the highest value from each pool, thus preserving the most significant features of the feature map, leading to a crisper image compared to the original.

2. Average pooling: This method calculates the mean value within each pool. Average pooling preserves a generalized representation of the feature map.

3.ReLU-

The Rectified Linear Unit (ReLU) is a non-linear function that outputs the input when it's positive; otherwise, it yields 0 as a result. This function, denoted as f(K) = max(0, K), is six times more computationally efficient and reliable compared to sigmoid and tanh functions [8].

ReLU effectively eliminates negative values by setting them to 0, making it beneficial for introducing nonlinearity in models. It also accelerates training and computation speed.

5.2. Haar Cascade Algorithm

Rectangular regions within an image are utilized to extract Haar features. These features are determined by the intensities of the pixels and are commonly calculated using a sliding window technique. The window divides the area into multiple rectangular regions, and the Haar feature is the discrepancy in pixel intensity sums between these regions. To optimize efficiency, the rectangular regions in Haar features are typically aligned with the edges of the image rather than being tilted. Yet, employing diverse sizes and shapes of rectangles is feasible to capture various features and adapt to scale differences within an object. Consequently, Haar features possess the capability to represent three distinct patterns:

1. Edges: These can be vertical or horizontal depending on the orientation of the rectangular region. They are valuable for identifying boundaries between different regions within an image.

2. Lines: Diagonal edges in an image are significant for detecting lines and contours in objects.

3. Center-surrounded applications: It involve the detection of variations in intensity levels between the central region of a rectangular area and its surrounding context. It is handy for identifying objects with distinct shapes or patterns.

To detect objects using the Haar cascade classifier, you can utilize the detectMultiScale() method. For this technique to work, you'll need the following inputs:

1. image: serves as the input for object detection. Ensure the image is either in grayscale format or corresponds to the "V" channel for images in HSV channel format.

2.scaleFactor: It adjusts for the variation in object sizes due to their distance from the camera. It dictates the extent of reduction in image size at each scale level. The scaleFactor value must be greater than 1. A smaller scaleFactor increases detection time but also increases the chances of detection. Typical values range from 1.01 to 1.3.

3. minNeighbors: This parameter specifies the minimum number of neighbors each potential object should have to be considered a valid detection. Greater values yield fewer detections, albeit with superior quality. Conversely, lower values may increase the number of detections, albeit potentially accompanied by false positives. It's a balance between precision and recall.[9]

4. minSize: This parameter sets the minimum size for an object. Any objects smaller than this specified size will be ignored. It's represented as a tuple in the format (width, height).

6. Result/Analysis

The lane detection system's methodology begins with capturing a video of the road surface via a vehicle-mounted camera, followed by converting the video into a series of images to undergo processing.

Fig-1: Input

By utilizing convolution and pooling filters, the process of filtering and pooling is carried out. Once the model training is completed, if the model fails, it is redirected back to the preprocessing stage.

Moving on, after training the model, the next step involves making predictions and detecting lanes. If it is determined that an object or car is crossing the lanes, an alert is triggered. In the case where a car is found within the lane, the process is repeated by inputting the data again.

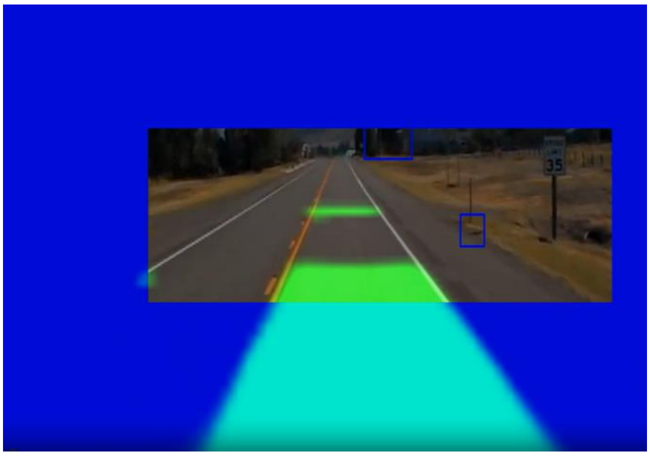

Fig-2: Output

7. Future work

1. Our system will have the capability to identify curved lane markings.

2. The detection of lanes faces a challenge, especially when they are not clearly visible. To address this issue, we will focus on strengthening our model and implementing improvements in the future.

3. Detecting lines on the road can be complex since there are various markings present, including both actual lane lines and other marks such as scratches. To ensure accurate detection of lane lines, we will train our model using precise and relevant information.

8. Conclusion

Intelligent Transportation Systems have demonstrated that lane detection is the most effective method. It appears that in studies on lane detection, many researchers have overlooked the challenges posed by fog, objects, and image noise. The Lane detection system promptly notifies the driver if their vehicle is veering across the lane boundary, thereby assisting in the prevention or reduction of accidents. Similar to other safety features, the developers of this technology claim that it will contribute to a decrease in car accident rates.

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