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A Review of Lane Line Detection

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ABSTRACT—

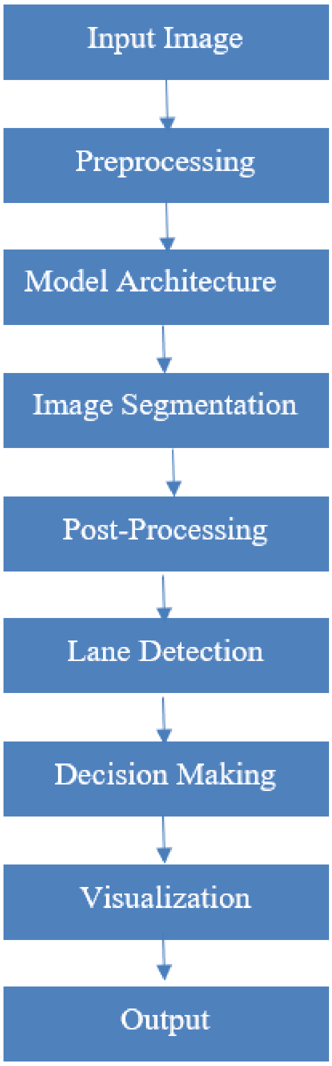
Lane line detection is a critical component for self-driving cars and also for computer vision. This concept is used to describe the path for self-driving cars and to avoid the risk of getting in another lane. In recent years many machine learning algorithms have been deploying but they failed to produce high efficiency and accuracy so in order to improve accuracy and robustness of the lane detection in complex conditions, such as the shadows and illumination changing, we will study on a novel approach that was proposed to detect the road lanes with high precision and accuracy by combining convolution neural networks with line detection (CNN-LD). Convolutional Neural Network-based approach merged with Sobel filters is used to detect the edges from the sample image. Performance is assessed through the generation of experimental results on the dataset. When compared with state-of-the-art lane detection techniques, the proposed technique produced high precision and high efficiency.

Keywords— Machine Learning, Road Lane line detection, Convolution neural networks, Sobel filters.

I. INTRODUCTION

Lane line detection is a main component of modern automotive safety and autonomy systems. It serves as a linchpin in the pursuit of heightened safety standards within the automotive landscape. By utilizing advanced computer vision techniques, vehicles equipped with this technology can precisely identify and interpret lane markings. This precision is paramount in ensuring that vehicles stay within their designated lanes, significantly reducing the risk of accidents. The ability to prevent unintended lane departures not only protects the occupants of the vehicle but also enhances the safety of other road users. This proactive safety feature, rooted in cutting-edge computer vision algorithms, underscores the commitment of the automotive industry to harness technology for the greater good of road safety. Beyond its role in accident prevention, lane line detection contributes substantially to the optimization of traffic flow and overall road efficiency. In congested urban environments, where traffic snarls are commonplace, this technology aids in maintaining orderly lanes, mitigating bottlenecks, and improving the fluidity of vehicle movement. The result is not only a reduction in travel times but also a decrease in fuel consumption and emissions. This dual impact aligns lane line detection with broader sustainability goals by fostering more efficient use of road infrastructure, thereby reducing the environmental footprint of transportation systems. As we usher in an era of autonomous vehicles, lane line detection emerges as a pioneering technology shaping the future of mobility. The seamless integration of this capability allows self-driving cars to navigate complex road scenarios, interpret intricate lane configurations, and adapt to diverse driving conditions. This technology, coupled with sensor integration, forms the bedrock of autonomous navigation systems, providing the necessary data for vehicles to make informed decisions. The trajectory of lane line detection points toward a future where autonomy and human-driven vehicles coexist harmoniously, fostering a transportation landscape marked by increased safety, efficiency, and the realization of smart city visions. In essence, lane line detection stands not only as a technological milestone but as a transformative force driving the evolution of transportation for generations to come.

II. Related Works



The road scene is first recorded by the vehicle-mounted camera and fed into the lane line detecting system. Preprocessing is the first stage, during which methods such as contrast correction, noise reduction, and grayscale conversion are used to improve the quality of the image and get it ready for further examination. The LaneNet architecture, a reliable model built for lane detection, is used at the heart of the system. The model separates the lanes from the background by picture segmentation, which serves as the foundation for further research. In order to improve the accuracy of lane recognition, post-processing stages refine the segmented lanes using methods such as morphological operations, filtering, and curve fitting.

The final lane detection, which highlights the recognized lane lines on the road, is the process's output. After that, the system uses the detected lane lines to inform its decisions. The position of the car within the lane is determined by decision logic, which allows the system to make well-informed decisions regarding vehicle control. The detected lane lines and decision outputs are shown on the original image to facilitate monitoring and study. The lane line detection system's final product is a thorough representation that graphically displays the identified lanes and information relevant to the choice. This constant, real-time iterative process enables the system to adjust to shifting road conditions and guarantee dependable performance in a range of driving situations.

III. LITERATURE SURVEY

Zakaria, N. J., Shapiai, M. I., Ghani, R. A., Yasin, M. N. M., Ibrahim, M. Z., & Wahid, N. (2023) explored the methods employed for lane detection in autonomous vehicles from 2018 to 2021. It reviews both geometric modelling /traditional approaches and artificial intelligence-based techniques. Geometric modelling /traditional methods involve image preprocessing, feature extraction, lane model fitting, and line tracking. Various techniques, including perspective transform, thresholding, and Hough Transform, are used. Artificial intelligence-based methods leverage deep learning and machine learning, with an increasing focus on deep learning in recent years. Some studies use standalone deep learning for lane detection, while others combine deep learning with other techniques or integrate attention mechanisms for improved performance. The paper emphasizes the growing importance of deep learning in lane detection. It also discusses dataset collection and highlights the need for further research in accuracy, speed, and extreme conditions in lane detection for autonomous vehicles.

Chen, W., Li, Y., Tian, Z., & Zhang, F. (2023)

This paper offers a comprehensive overview of recent advancements in image-based 2D and 3D object detection algorithms within the field of computer vision. The primary focus is on the transition from traditional techniques to deep learning approaches, with a particular emphasis on different object detection frameworks. The paper categorizes 2D object detection into three main groups: anchor-based, anchor-free, and Transformer-based methods. Meanwhile, 3D object detection is classified into four categories: monocular-based, stereo-based, pseudo-LiDAR-based, and multi-view-based methods.

Pavel, M. I., Tan, S. Y., & Abdullah, A. (2022) The paper discusses the significant advancements in autonomous vehicle systems (AVS) over the past decade, primarily fueled by artificial intelligence improvements. Despite these strides, mass production of AVS faces challenges due to the high costs associated with sensor fusion and the absence of comprehensive solutions to address uncertainties on roads. To alleviate these issues, the paper proposes deep learning-based approaches as a promising alternative for practical AVS development. The systematic review covers a range of modules, including perception analysis, decision making, end-to-end controlling, prediction, path planning, motion planning, and augmented reality-based HUD. The focus is on research employing RGB camera vision from 2011 to 2021, aiming to reduce sensor dependency and manufacturing costs while enhancing safety. The review analyzes representative outcomes, emphasizing augmented reality-based head-up display applications for early warning systems, road markings, and improved navigation. Overall, the paper contributes a detailed analysis of state-of-the-art deep learning methods relying solely on RGB camera vision, offering insights for the cost-effective and secure development of practical autonomous vehicle systems.

Zhou, H., & Song, X. (2021, April) presents an innovative lane detection algorithm leveraging a Haar feature-coupled cascade classifier to enhance accuracy in complex environments. The methodology involves scaling input images, extracting Regions of Interest (ROI) based on vanishing line positions, and utilizing Haar features for rough lane detection through a cascade classifier. The Line Segment Detector (LSD) method is then employed for precise lane fitting, and optimization strategies such as growth and geometric checking further refine results. Tests on various datasets demonstrate superior robustness and accuracy, reaching up to 96.5%—outperforming existing lane detection methods.

Zhang, Y., Lu, Z., Ma, D., Xue, J. H., & Liao, Q. (2020) focuses on lane line detection, which is essential for ADAS and intelligent driving. We introduce two networks: Ripple-GAN and RiLLD-Net. Prioritizing speed over complexity, RiLLD-Net leverages fast connections and gradient maps to achieve efficient lane line learning. Designed with typical traffic scenarios in mind, it provides a simple yet effective lane line detection solution, enhancing safety during difficult driving conditions.

Lee, D. H., & Liu, J. L. (2023) In order to achieve end-to-end lane recognition and path prediction in autonomous driving, the paper suggests DSUNet, a lightweight variant of UNet. Depthwise separable convolutions (DS) are used to improve both efficiency and accuracy at the same time. The CNN-PP simulation model, developed by the authors, combines convolutional neural networks (CNN) with a path prediction (PP) algorithm for dynamic real-time performance evaluation. Optimized for path prediction and lane recognition, DSUNet outperforms traditional UNet with a 1.61× inference speed improvement and a 5.12× model size decrease. In dynamic simulations, DSUNet-PP performs better than UNet-PP in terms of mean average errors for lateral offset and curvature, as shown by successful trials using a host agent car. The study highlights the significance of accurate lane recognition for advanced driver assistance systems (ADAS) and autonomous vehicles, presenting DSUNet as a workable and effective remedy.

Haris, M., Hou, J., & Wang, X. (2023) highlights the necessity for algorithms managing complicated road circumstances and introduces Convolutional Neural Networks (CNNs) for lane recognition and departure calculation. Asymmetric Kernel Convolution (AK-CNN) is a revolutionary technique that improves on classical CNNs with the goal of increasing efficiency by lowering computing load. The suggested approach, tested on the CULane dataset, demonstrates an astounding 84.5 frames per second real-time detection speed and 80.3% accuracy in complicated settings. The study emphasizes how crucial AI is to improving traffic safety, especially when it comes to ADAS devices like lane departure warning systems.

Yan, G., Luo, Z., Liu, Z., & Li, Y. (2023)research emphasizes alignment with the vehicle coordinate system and highlights how important it is for sensors to be correctly calibrated in autonomous driving. GNSS/INS, millimeter-wave radar, camera, and LiDAR are the four main sensors for which universal calibration methods are introduced by the innovative SensorX2car toolkit, whereas prior approaches concentrate on extrinsic sensor calibration. For quick and useful online calibration during routine driving, unique sensor-specific techniques leverage picture features, 3D LiDAR points, GNSS/INS posture solutions, and radar speed. Hailed as the first open-source toolkit for sensor-to-vehicle calibration, SensorX2car addresses misalignment issues caused by vibrations and operational changes. The study presents different approaches for calibration of each sensor, demonstrating the flexibility of the toolbox in both simulated and real-world experiments. All in all, it improves system reliability by advancing the development of dependable and intuitive sensor calibration tools for autonomous driving.

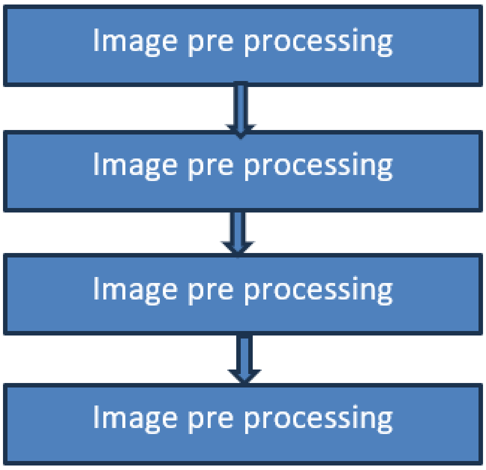
Yang, X., Ji, W., Zhang, S., Song, Y., He, L., & Xue, H. (2023) addressing shortcomings in current lane identification methods, such as too strict feature extraction parameters and edge information loss, the Lane Shape Prediction with Transformers (LSTR) methodology mitigates these problems. Ghost Convolution is used by LSTR to provide a lightweight design that drastically lowers the number of network parameters. A Self-BN module maximizes the use of the original feature information, and an Efficient Channel Attention technique improves the extraction of edge and lane details, resulting in a 0.96% increase in accuracy overall. LSTR shows improved precision, faster detection, and reduced parameter requirements when tested on the TuSimple dataset, making it appropriate for real-time autonomous driving applications.

Singal, G., Singhal, H., Kushwaha, R., Veeramsetty, V., Badal, T., & Lamba, S. (2023) study emphasizes how crucial lane detection is to contemporary transportation, particularly to driver assistance and automated driving technologies. In difficult situations, traditional approaches have difficulties, which has led to a move toward deep learning. Accuracy and hardware deployability are given top priority in the proposed real-time lane detection model, which is based on convolutional neural networks (CNN). Difficulties such as different road conditions are addressed during training on the NVIDIA DGX V100 Supercomputer. The study highlights the possible influence on road safety and promotes the use of standardized databases. All things considered, the model advances intelligent driving systems by providing an effective real-time solution that shows promise in terms of accuracy and execution time.

Chen, Y., Xiang, Z., & Du, W. (2023) research addresses issues such as complex driving circumstances and various lane appearances by introducing a novel approach for robust lane recognition in intelligent vehicle navigation systems. For precise lane curve fitting in bird's-eye perspective, the Homography Prediction Network (HP-Net) adaptively predicts homographic projection matrices. HP-Net improves resilience by adjusting to changes in camera-ground relative posture, in contrast to fixed matrices. Lane parallelism is leveraged for HP-Net training through the use of an annotation-sharing technique. The method delivers state-of-the-art performance on the CULane dataset and a proprietary dataset when integrated with lane instance segmentation. It shows effectiveness in handling a variety of driving circumstances and increases overall lane detection robustness.

Qiao, D., Wu, X., & Wang, T. (2020, April) work addresses the difficult problem of lane detection and highlights the need to use classification in addition to localization. Two approaches are presented: Line-CNN + categorization and LaneNet + Visual Geometry Group Network (VGG). LaneNet + VGG adds lane categorization, and LaneNet converts detection into an instance segmentation problem. For end-to-end detection, the Line-CNN + classification integrates a classification task for several traffic line categories using a Line Proposal Unit. Results from experiments using publicly available datasets show competitive performance in identifying different traffic line groups and forecasting lanes without post-processing. The work advances reliable lane recognition algorithms, which are important for artificial intelligence and automated driving applications.

IV. METHODOLOGIES



Geometric modeling/traditional:

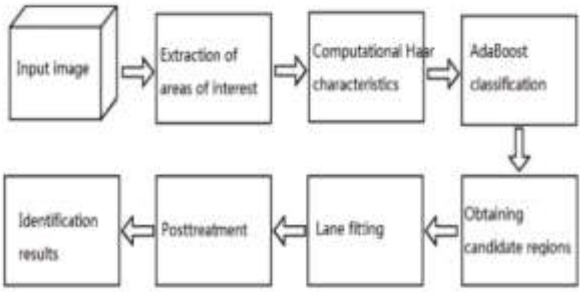
The pipelines used by most traditional detection algorithms comprise image preprocessing, feature extraction, lane model fitting, and line tracking.

- Image preprocessing involves removing noise and defining a region of interest (ROI) for lane detection. Various methods, including perspective transform and vanishing point detection, have been used for ROI creation.
- Feature extraction is crucial for detecting lanes and includes techniques like color analysis, edge detection, and geometric features. Heterogeneous operators and sliding windows help reduce noise and extract lanes.
- Lane model fitting is accomplished using techniques like the Line Segment Detector (LSD) and various fitting-based methodologies, including B-spline, polynomial, and least squares.
- Line tracking, often employing the Kalman filter, is used as a post-processing step to compensate for lighting changes and detect occlusions caused by faulty lane markers. Traditional geometric modeling methods are widely employed in the literature for lane detection. This includes kalam filer, lane classification, parabola equation.

Artificial Intelligence-based techniques:

Machine Learning (ML) and Deep Learning (DL) are the two primary categories that may be used to classify most of the AI approaches used in lane detection. To improve the effectiveness of the network in challenging conditions when it comes to identifying the lane mark DL is integrated with another method ---- DL + geometric modeling, DL + ML, DL + DL and DL with attention mechanism.

Haar Feature Based Coupled Cascade Classifier:



- ROI:

  Establishing ROI reduce computational complexity, reduce complexity and improve detection speed.

- Haar Feature Selection:
  - It is a method used in computer vision and image processing for feature extraction and object detection.
  - Haar-like features are simple rectangular patterns or filters used to represent certain characteristics of an image.
  - Haar features are originally consists of 5 rectangular features. The extended Haar features with rotations are considered but simplified to basic rectangular features for lane detection due to their effectiveness and reduced computational complexity.
- AdaBoost Classification:

  Adaptive Boosting algorithm uses cascade a series of weak classifiers to form a strong classifier.

- Weak classifier design:
  - Set the training set (x1,y1),...,(xN,yN) and there eigen values for each Haar feature
  - Formulae: loss= min(((P2+(N1-N2)),N2+(P1-P2)))
  - Search for the element with the smallest loss value and identify it as the optimal threshold, thus generating the optimal weak classifier.
- Strong classifier design:

Update each weight according to the error rate em and calculates the weight coefficient of weak classifier:

$$\alpha_m = \frac{1}{2}\log\frac{1-e_m}{e_m}$$

$$w_{m+1,i} = \frac{w_{m,i}}{z_m}\exp(-\alpha_m y_i G_m(x_i)), i = 1, 2, \cdots N$$

$$z_m = \sum_{i=1}^{N} w_{mi}\exp(-\alpha_m y_i G_m(x_i))$$

- Lane fitting:

Lane fitting involves scale scaling, gradient analysis, and a seed-based approach. They initialize elements based on gradient values and iteratively find and evaluate potential straight lines within a binary lane candidate area using LSD (Line Segment Detector) to achieve more efficient and accurate lane detection.

- Post-processing operations:

Post-processing operation for refining lane detection results obtained from AdaBoost, addressing issues of disconnected and discontinuous lanes. The process includes growth strategy, lane combination and geometric criteria.

LaneNet + VGG Pipeline:

Instance Segmentation Transformation:

- LaneNet transforms lane detection into an instance segmentation problem.

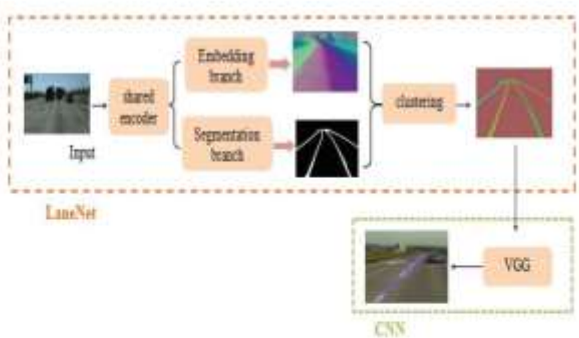
- E-Net serves as the backbone in the LaneNet pipeline.
- Each lane in an image is treated as an instance.

Multi-Branch Task Design:

- Encoder layer is shared, and it divides into two tasks during decoding.
- Lane binary segmentation task.
- Lane embedding task: Groups points belonging to the same lane.
- Tasks are fused to obtain the final segmented image.

Lane Classification Enhancement:

- CNN (VGG16) is added after LaneNet to classify segmentation results.
- Main categories include white solid lines, white dotted lines, yellow solid lines.



Line-CNN + Classification Pipeline:

End-to-End Lane Detection:

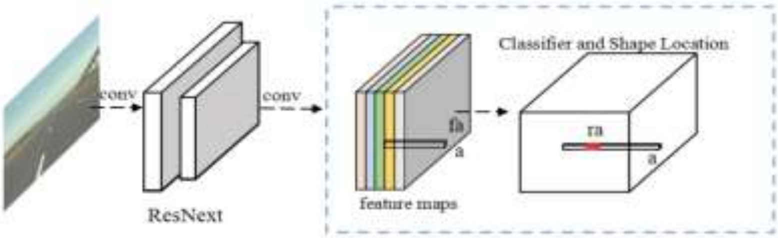
- Line-CNN directly regresses parameters of traffic lines.
- Key component: Line Proposal Unit (LPU) locates entire traffic lines through proposals.

Line Proposal Unit (LPU) Modification:

- LPU adapted from Region Proposal Network (RPN) using straight rays as line proposals.
- Original LPU vs. Improved LPU: Extension of convolutional network sliding to the entire feature map for added details in lane classification.

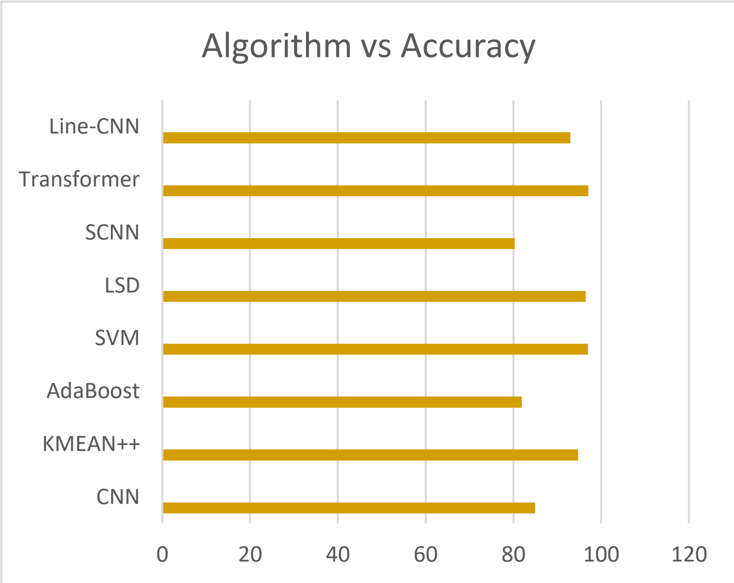
Traffic Line Classification:

- Original LPU sufficient for locating traffic lines.
- Structure modified to capture more details and add lane classification.
- Two additional convolution layers identify categories of lanes.



V. RESULTS AND CONCLUSION

When evaluated under normal circumstances using a self-gathered dataset, a conventional geometric modeling method attains a noteworthy 96% accuracy. When tested on the Caltech-lanes dataset, a Haar Feature Based Coupled Cascade Classifier achieves a high detection rate of 97.1% and an accuracy of 96.5% in a short processing time of 0.02381 seconds. Using both LaneNet+VGG and Line-CNN+Classification, the DT2I model performs well on the TuSimple dataset. While Line-CNN+Classification obtains a 93.8% detection rate, 93.0% accuracy, and a processing time of 0.068 seconds, LaneNet+VGG achieves an 88.1% detection rate with 84.3% accuracy in 0.035 seconds. These results demonstrate the variety of methods and how well they work to solve lane detecting problems.



VI. DISCUSSIONS

This review examines the various frameworks and techniques used in lane detecting studies. Both publicly accessible and self-collected datasets are used as inputs. While machine learning and deep learning are two examples of artificial intelligence (AI) techniques that have attracted a lot of attention, geometric modeling and other conventional approaches remain widely used. Research on deep learning architectures like CNN, FCN, and RNN has increased, and there's a tendency to use attention methods to improve performance. While some studies concentrate on standalone deep learning implementations for single or multiple lane detection, others investigate how to increase efficiency by combining deep learning with other machine learning techniques and traditional methodology. According to the review, there is increased interest in creating lane detection techniques that are more accurate and efficient. This is especially true when combining deep learning with attention mechanisms. The study explores the field of Autonomous Vehicle Systems (AVS) in greater detail than only lane detection, highlighting the critical role that deep learning plays in overcoming conventional constraints. It examines deep learning applications in AVS for navigation, control, prediction, decision-making, path planning, and visualization, highlighting theoretical approaches that call for real-world application in order to advance the field. The research also examines developments in deep learning algorithms for 2D and 3D object detection, assessing their benefits, drawbacks, and patterns. The review emphasizes the continuous trend of improving detection performance, efficiency, and generalization in complex scenes through attention mechanisms, knowledge distillation, and domain adaptation, with particular attention to applications in autonomous vehicles, unmanned aerial vehicles, and intelligent inspection robots. All things considered, it offers a thorough summary of current advancements and potential paths in autonomous systems.

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