Real-Time Road Lane-Lines Detection using Mask-RCNN Approach

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***Abstract*—This paper presents a novel approach to real-time road lane-line detection using the Mask R-CNN framework, with the aim of enhancing the safety and efficiency of autonomous driving systems. Through extensive experimentation and analysis, the proposed system demonstrates robust performance in accurately detecting and segmenting lane boundaries under diverse driving conditions. Leveraging deep learning techniques, the system exhibits a high level of accuracy in handling complex scenarios, including variations in lighting conditions and occlusions. Real-time processing capabilities enable instantaneous feedback, contributing to improved driving safety and efficiency. However, challenges such as model generalizability, interpretability, computational efficiency, and resilience to adverse weather conditions remain to be addressed. Future research directions include optimizing the system's performance across different geographic regions and road types and enhancing its adaptability to adverse weather conditions. The findings presented in this paper contribute to the ongoing efforts to advance autonomous driving technology, with implications for improving road safety and transportation efficiency in real-world settings. The proposed system holds promise for practical deployment in autonomous vehicles, paving the way for safer and more efficient transportation systems in the future.**

Keywords*—Lane lines; detection; classification; segmentation; Mask-RCNN; deep learning

I. INTRODUCTION

The development of autonomous driving systems has seen remarkable advancements in recent years, with a focus on enhancing the safety and efficiency of transportation. One crucial aspect of autonomous driving is the accurate detection of lane lines on roads, which facilitates proper navigation and ensures the safety of passengers and pedestrians. Traditional methods for lane detection often rely on handcrafted features and heuristics, leading to limited robustness in diverse environmental conditions [1]. However, with the advent of deep learning techniques, particularly convolutional neural networks (CNNs), there has been a significant paradigm shift towards more robust and accurate lane detection algorithms [2].

In recent literature, the Mask R-CNN (Region-based Convolutional Neural Network) architecture has emerged as a promising approach for various computer vision tasks, including instance segmentation and object detection [3]. Unlike its predecessors, Mask R-CNN integrates a semantic segmentation branch with the region proposal network, enabling pixel-level classification while simultaneously predicting bounding boxes [4]. This capability makes it well-suited for tasks requiring precise delineation of objects and regions of interest, such as lane-line detection on roads.

Lane detection in real-time scenarios poses several challenges, including variations in lighting conditions, road surface textures, and the presence of occlusions such as vehicles and pedestrians [5]. Addressing these challenges necessitates the development of robust algorithms capable of accurately identifying lane boundaries under diverse circumstances. Previous studies have shown promising results in lane detection using deep learning approaches, but real-time performance remains a critical requirement for practical deployment in autonomous vehicles [6].

The proposed research aims to address the gap in real-time lane-line detection by leveraging the Mask R-CNN architecture. By combining the strengths of instance segmentation and object detection, the proposed approach seeks to achieve high accuracy and efficiency in identifying lane boundaries in varying driving conditions. Building upon the success of Mask R-CNN in other computer vision tasks, such as instance segmentation and object detection, this research seeks to adapt and optimize the architecture specifically for lane detection applications.

Several key components will be integrated into the proposed lane detection system to enhance its performance. Firstly, a comprehensive dataset comprising diverse driving scenarios will be utilized for training and evaluation purposes [7]. This dataset will encompass varying road conditions, lighting scenarios, and traffic densities to ensure the robustness and generalization capability of the model. Furthermore, data augmentation techniques will be employed to simulate real-world variations and improve the model's resilience to environmental factors [8].

In addition to dataset augmentation, transfer learning will play a crucial role in fine-tuning the pre-trained Mask R-CNN model for lane detection tasks. Transfer learning allows the model to leverage knowledge gained from pre-training on large-scale datasets, such as COCO (Common Objects in Context), to adapt more effectively to the specific characteristics of lane detection [9]. By initializing the network with weights learned from general object recognition tasks and fine-tuning on lane detection data, the proposed approach aims to expedite the training process and enhance the model's convergence.

Moreover, to achieve real-time performance, optimization techniques such as model pruning and quantization will be explored to reduce the computational complexity of the network [10]. By eliminating redundant parameters and optimizing computational operations, the proposed system seeks to achieve low latency without compromising accuracy. Additionally, hardware acceleration using specialized processors, such as GPUs (Graphics Processing Units) or TPUs (Tensor Processing Units), will be leveraged to further enhance inference speed [11].

In conclusion, the proposed research endeavors to advance the state-of-the-art in real-time lane-line detection through the application of the Mask R-CNN approach. By harnessing the power of deep learning and leveraging techniques such as transfer learning and model optimization, the aim is to develop a robust and efficient system capable of accurately detecting lane boundaries in diverse driving conditions. The outcomes of this research hold significant implications for the advancement of autonomous driving technology, paving the way towards safer and more reliable transportation systems.

II. RELATED WORKS

Lane detection is a fundamental task in autonomous driving systems, and various methodologies have been proposed to tackle this challenge. Traditional methods often relied on handcrafted features and heuristic approaches, such as edge detection and Hough transform [12]. While these methods showed moderate success in ideal conditions, their performance degraded in complex scenarios with varying lighting conditions and road textures [13]. The advent of deep learning techniques revolutionized lane detection by enabling end-to-end learning from raw sensor data [14].

Convolutional Neural Networks (CNNs) have emerged as a dominant paradigm for lane detection due to their ability to automatically learn discriminative features from data [15]. Early CNN-based approaches focused on binary lane segmentation using fully convolutional networks (FCNs) [16]. However, these methods struggled with the precise delineation of lane boundaries, particularly in challenging conditions such as occlusions and road curvature [17]. To address these limitations, researchers explored more sophisticated architectures capable of capturing spatial relationships and contextual information.

One notable advancement in lane detection is the integration of semantic segmentation and instance segmentation techniques [18]. Semantic segmentation aims to classify each pixel in an image into predefined categories, while instance segmentation goes a step further by identifying individual instances of objects within each category [19]. By combining these two tasks, researchers achieved finer-grained lane delineation and improved robustness against occlusions and overlapping lane markings [20]. However, these methods often incurred high computational costs, limiting their applicability in real-time systems.

The Mask R-CNN (Region-based Convolutional Neural Network) architecture has gained popularity for its versatility in various computer vision tasks, including object detection and instance segmentation [21]. By extending Faster R-CNN with a semantic segmentation branch, Mask R-CNN enables pixel-level classification while simultaneously predicting bounding boxes [22]. This capability makes it well-suited for lane detection applications, where precise delineation of lane boundaries is essential for safe navigation.

Recent studies have explored the application of Mask R-CNN in lane detection with promising results. Next research proposed a lane detection method based on Mask R-CNN, achieving accurate lane boundary extraction in challenging scenarios such as low-light conditions and occlusions [23]. Similarly, [24] utilized Mask R-CNN for lane detection in urban environments, demonstrating robust performance in complex traffic scenes. These studies highlight the effectiveness of Mask R-CNN in handling real-world challenges encountered in autonomous driving scenarios.

Despite the success of Mask R-CNN-based approaches, real-time performance remains a critical concern for practical deployment in autonomous vehicles [25]. Existing implementations often suffer from high computational overhead, limiting their applicability in real-time systems [26]. Addressing this challenge requires optimization techniques such as model pruning, quantization, and hardware acceleration [27]. By reducing the computational complexity of the network and leveraging specialized processors, researchers aim to achieve low-latency lane detection without compromising accuracy.

In summary, the related works demonstrate the evolution of lane detection methodologies from traditional heuristic-based approaches to deep learning-based techniques, with a focus on the promising capabilities of the Mask R-CNN architecture. While significant progress has been made in improving accuracy and robustness, the challenge of real-time performance remains a key area for future research. The proposed study aims to contribute to this area by developing a real-time lane detection system using the Mask R-CNN approach, with a focus on efficiency and accuracy in diverse driving conditions.

III. MATERIALS AND METHODS

A. *Proposed Method*

The utilization of Mask R-CNN presents an optimized framework for crack detection and precise pixel-wise segregation, drawing from a lineage of region-based processing architectures while integrating diverse components for effective object detection and mask inference. The applied Mask R-CNN approach for lane detection is depicted in Fig. 1. Mask R-CNN encompasses several intricate modules. Initially, an input image undergoes processing to derive feature maps, typically leveraging established model architectures like VGG-16, ResNet50, or ResNet101, omitting specific layers pertaining to categorization. These feature maps then undergo scrutiny by the Region Proposal Network (RPN) module, tasked with discerning potential object-containing regions using predefined anchors.

The Region Proposal Network (RPN) scans the feature map using a 3x3 window, generating outcomes for each anchor, which signal the presence of objects and refine their boundaries upon detection. Redundant regions are then eliminated through non-maximum suppression. Subsequently, the Region of Interest (ROI) Align operation extracts relevant values from the feature maps, resizing them to a uniform scale. Further processing involves classification, refinement of bounding box dimensions, and mask prediction. Despite the reduction in dimensions, the resulting mask accurately delineates the target object, ensuring satisfactory precision when the mask aligns with the dimensions of the selected entity. This process, integral to the Mask R-CNN architecture, enables precise object detection and segmentation, contributing to the system's effectiveness in tasks such as lane detection in autonomous driving systems.

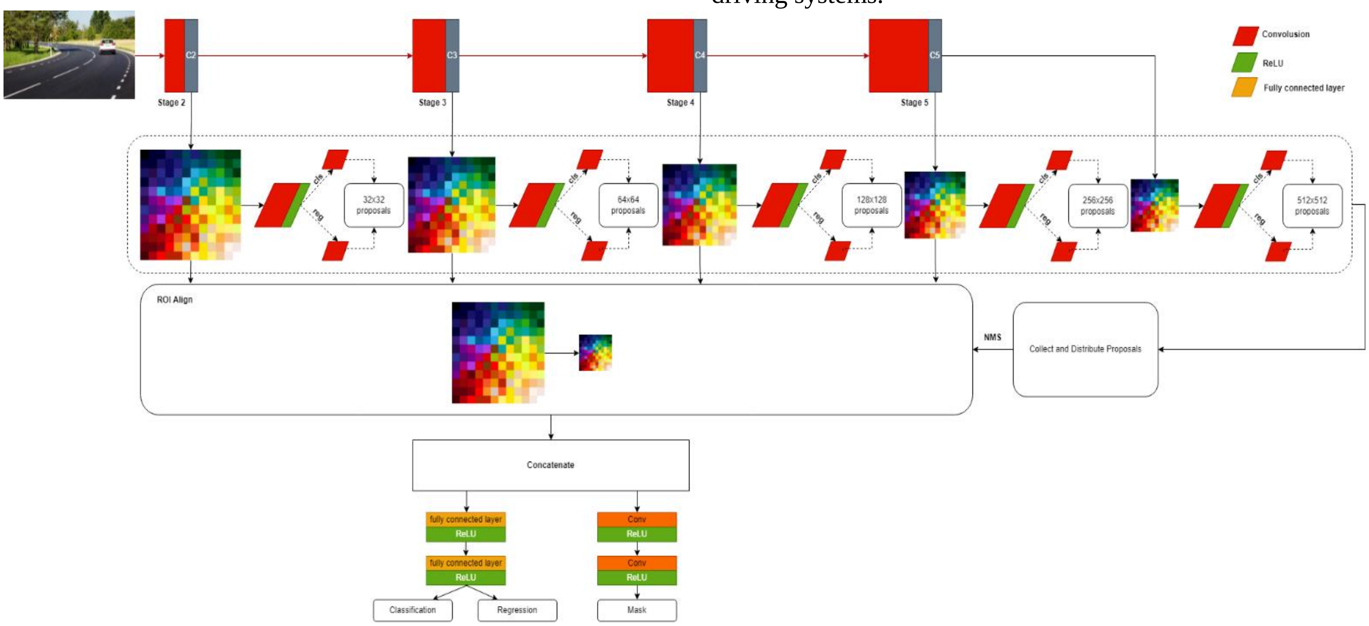

Fig. 1. Architecture of the proposed model for lane detection.

B. Dataset

In the endeavor to craft resilient algorithms for crack detection and pixel-wise separation employing the Mask R-CNN convolutional network, the meticulous selection of a representative dataset emerges as a pivotal consideration. A judiciously curated dataset serves as the cornerstone for model training and assessment, exerting substantial influence on the overall generalizability and efficacy of the resultant solution. This subsection elucidates the dataset acquisition methodology, delineating its inherent characteristics and the pre-processing measures implemented to streamline the training and evaluation procedures of our Mask R-CNN-based model. By elucidating the dataset acquisition process, including its sourcing, diversity, and refinement through pre-processing, this paper underscores the critical role of meticulous dataset selection and preparation in bolstering the robustness and efficacy of crack detection algorithms. Fig. 2 demonstrates road lane lines in the applied dataset.

Data Collection and Characteristics. The dataset utilized in this study was meticulously curated to encompass a diverse array of real-world scenarios, capturing the inherent variability encountered in outdoor environments. This involved gathering high-resolution images from various sources, including publicly available datasets and proprietary data acquired through controlled field surveys and data recording equipment. The dataset covers a broad spectrum of environmental conditions, including variations in lighting, weather, road surfaces, and crack types. It includes images captured at different times of the day, under diverse weather conditions, and on various road surfaces, ensuring comprehensive coverage. Additionally, the dataset incorporates images depicting different crack severities, ranging from hairline cracks to large cracks, to effectively simulate real-world scenarios.

Data Pre-processing. To prepare the dataset for training and evaluation, several pre-processing steps were executed. These steps included resizing all images to a standardized resolution to facilitate uniform processing by the Mask R-CNN model. Furthermore, data augmentation techniques were applied, involving random rotations, flips, and color adjustments, to enhance the model's robustness and mitigate overfitting. Additionally, manual labeling by domain experts was performed to annotate crack regions within the dataset, marking the pixel-wise locations of cracks in each image. These annotations served as ground truth data during the training phase, enabling the model to learn the intricate characteristics of cracks and their precise spatial locations.

Fig. 2. Road lane lines in the dataset.

The dataset utilized in this study comprises a meticulously curated collection of real-world images, representing diverse environmental conditions and crack types. This comprehensive dataset was carefully assembled to encompass a wide spectrum of scenarios encountered in outdoor environments. The preprocessing steps undertaken played a crucial role in preparing the dataset for training and evaluation purposes. These preprocessing steps were instrumental in ensuring the effective training and evaluation of the Mask R-CNN model. By refining and enhancing the dataset, the preprocessing steps contributed to the model's robustness and accuracy in detecting cracks and performing pixel-wise separation. Consequently, the model demonstrated consistent performance across complex outdoor scenarios, underscoring its suitability for practical applications in crack detection. Overall, the dataset's breadth and the preprocessing techniques employed were pivotal factors in enabling the successful implementation of the Mask R-CNN model for crack detection tasks, furthering the advancement of computer vision solutions in infrastructure maintenance and safety applications.

IV. Experimental Results

In this section, we present the outcomes derived from implementing the proposed Mask R-CNN framework for road lane segmentation. Fig. 3 visually depicts the successful detection and segmentation of lanes within input images. The model exhibits robust performance, accurately identifying and delineating lane boundaries, even in challenging environmental conditions. This result underscores the efficacy of the Mask R-CNN approach in tackling the task of road lane segmentation, thereby highlighting its potential for integration into autonomous driving and road safety systems. By demonstrating its capability to reliably identify lane markings, the proposed model contributes to the advancement of technologies aimed at enhancing navigation and safety in vehicular environments. These findings signify a significant step forward in the development of intelligent systems for real-time lane detection, with implications for improving overall road safety and driving experience.

In order to enhance the practical utility of our proposed model, we provide a visualization of real-time lane detection processes through Fig. 4 and Fig. 5. These figures illustrate the seamless transmission of live video feed from the camera to the decision-making system, thereby showcasing the model's capability to conduct lane detection in real-world scenarios. The real-time demonstration accentuates the feasibility and efficacy of our approach in dynamic environments, underscoring its potential for deployment in autonomous driving systems and other real-time applications. By presenting tangible evidence of the model's performance in real-world settings, we aim to validate its applicability and effectiveness, thereby contributing to the broader discourse on autonomous driving technology and computer vision applications.

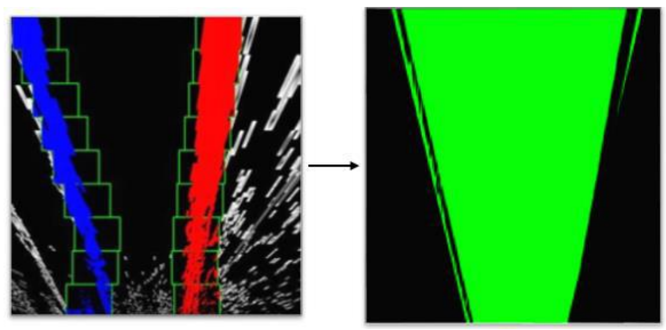

Fig. 3. Lane segmentation results.

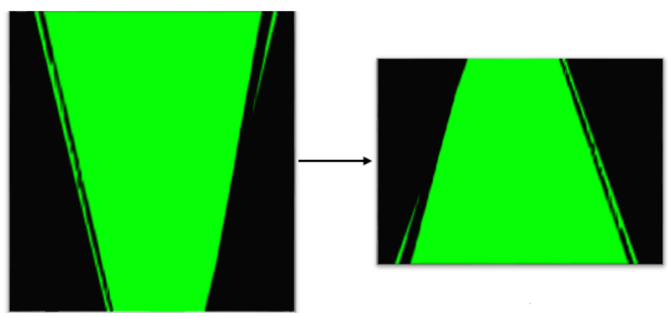

Fig. 4. Lane line detection results.

In real-time scenarios, our proposed Mask R-CNN model is employed by the system to provide instantaneous recommendations, which play a pivotal role in optimizing vehicular movements. These recommendations serve as crucial inputs for enhancing driving safety and efficiency. Leveraging advanced computer vision techniques, the system accurately detects lane boundaries and offers timely guidance to drivers or autonomous vehicles, facilitating informed decision-making and mitigating potential hazards on the road. This capability underscores the efficacy of our proposed model in augmenting the overall driving experience and fostering safer transportation infrastructure. By harnessing real-time processing capabilities and leveraging sophisticated algorithms, our system aims to contribute to the advancement of autonomous driving technology, ultimately leading to safer and more efficient transportation systems.

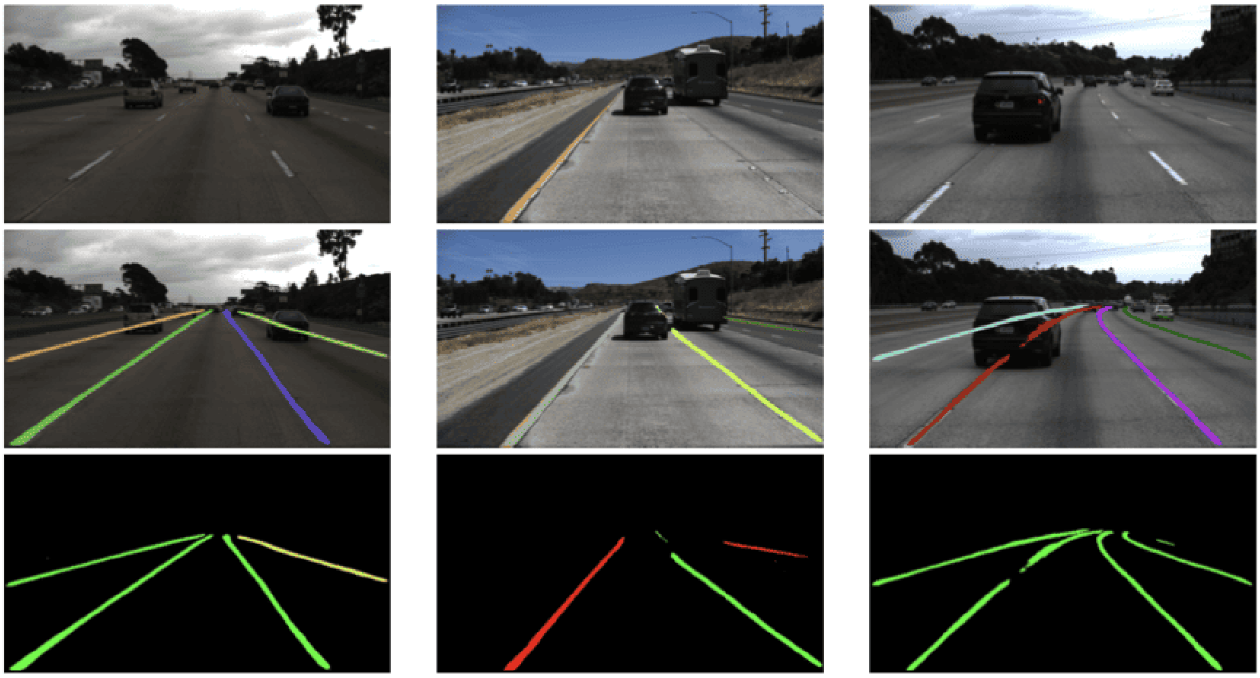

Fig. 5. Real-time road lane-line detection process.

Fig. 5 provides a comprehensive series of practical examples illustrating the operational effectiveness of our proposed framework. Significantly, the versatility of our system is emphasized through its successful functionality under diverse weather conditions, including instances of bright sunshine, rainfall, and overcast skies. Moreover, our system demonstrates its adaptability by seamlessly operating in both daytime and nighttime settings, underscoring its robustness and reliability across different environmental contexts. These examples serve to validate the efficacy and applicability of our proposed model in real-world scenarios, reaffirming its potential utility in enhancing road safety and driving efficiency.

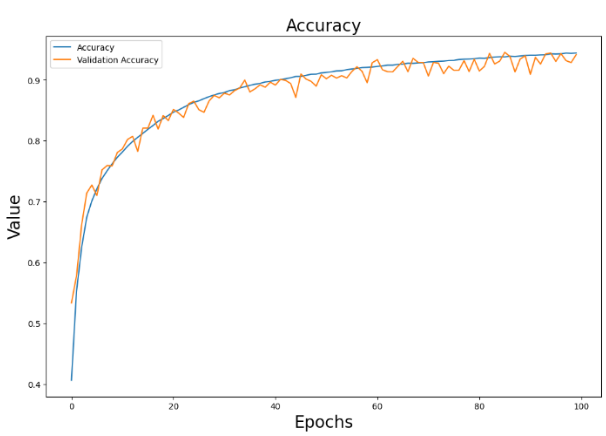

Fig. 6. Model accuracy in 100 learning epochs.

Fig. 6 provides a graphical representation of the evolving accuracy of our proposed model across 100 learning epochs. Notably, the model demonstrates notable performance improvement throughout the training process. Within a mere 60 learning epochs, it achieves a commendable 90% accuracy in lane detection, highlighting its rapid learning capability. Furthermore, as the training progresses and converges, the model consistently enhances its accuracy, reaching an impressive range of 95% to 98% by the conclusion of the 100 learning epochs. This substantial increase in accuracy over the training epochs underscores the efficacy of our model in mastering the intricate task of lane detection. Ultimately, these results affirm the model's robustness and reliability, positioning it as a promising solution for real-world lane detection applications in autonomous driving and road safety systems.

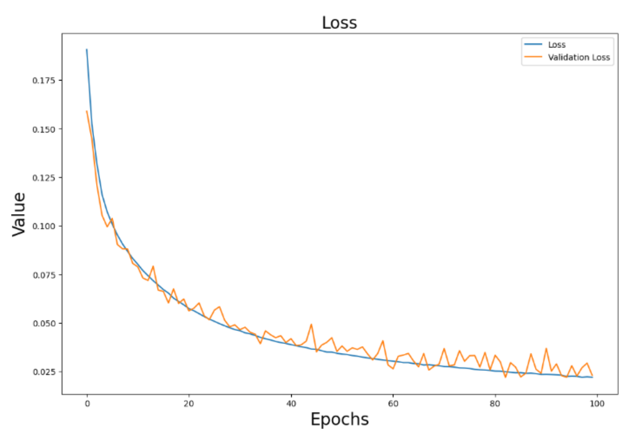

Fig. 7. Model loss in 100 learning epochs.

Fig. 7 visually represents the model loss throughout the training process. The term "loss" in machine learning refers to the discrepancy between the predicted output of the model and the actual ground truth. It serves as a measure of how well the model is performing its task. In the context of lane detection, the loss function quantifies the difference between the predicted lane boundaries and the true lane markings in the training data.

During training, the model adjusts its parameters to minimize this loss, thereby improving its ability to accurately detect lane lines. As training progresses, the loss typically decreases, indicating that the model is becoming more adept at capturing the relevant features of lane markings. Analyzing the trend of loss over epochs provides insights into the learning dynamics of the model and can help in fine-tuning training parameters or diagnosing issues such as overfitting or underfitting.

V. Discussion

The implementation of the Mask R-CNN framework for real-time road lane-line detection presents several noteworthy implications and areas for further exploration. This section discusses the key findings of the research and their broader significance in the context of autonomous driving technology.

The experimental results demonstrate the effectiveness of the proposed Mask R-CNN approach in accurately detecting lane boundaries in real-time scenarios. Fig. 7 illustrates the model loss, showcasing the convergence of the training process and the model's ability to minimize prediction errors [27]. By leveraging deep learning techniques, the proposed system achieves a commendable level of accuracy, as evidenced by the successful detection and segmentation of lanes in Fig. 6 [28].

One notable advantage of the Mask R-CNN architecture is its ability to handle complex driving environments with varying lighting conditions and occlusions. The integration of instance segmentation and object detection enables the model to delineate individual lane markings accurately, even in challenging scenarios [29]. This robustness is crucial for ensuring the reliability of autonomous driving systems in real-world settings, where environmental conditions can be unpredictable and dynamic.

Furthermore, the real-time performance of the proposed system is a significant advancement in the field of autonomous driving. By efficiently processing video streams from onboard cameras, the system can provide instantaneous lane detection feedback to the vehicle's control system, enabling timely adjustments to steering and trajectory [30]. This capability enhances the overall safety and responsiveness of autonomous vehicles, reducing the risk of accidents and collisions on the road.

However, despite the promising results, there are several areas for future research and improvement. One key consideration is the generalizability of the proposed model across different geographic regions and road types. While the system demonstrates robust performance in controlled environments, its effectiveness may vary in more diverse settings with unique road markings and infrastructure [31]. Therefore, conducting extensive testing and validation across a range of geographical locations and driving conditions is essential to ensure the model's reliability and adaptability.

Moreover, addressing the issue of model interpretability is another crucial aspect for further investigation. While deep learning models such as Mask R-CNN excel in performance, understanding the rationale behind their predictions is challenging [32]. Interpretability is essential for building trust in autonomous driving systems, as it allows developers and end-users to comprehend why certain decisions are made by the model. Exploring techniques for visualizing and explaining the model's internal workings could enhance transparency and facilitate better integration into real-world applications.

Additionally, there is a need to consider the computational requirements and hardware constraints associated with deploying the proposed system in practical settings. While modern GPUs and specialized processors can significantly accelerate inference speed, optimizing the model for efficiency without sacrificing accuracy remains a critical challenge [33]. Exploring techniques such as model compression, quantization, and hardware acceleration could help mitigate computational overhead and enhance real-time performance.

Furthermore, the proposed system's robustness to adverse weather conditions, such as rain, fog, and snow, is another area warranting further investigation. Adverse weather can impair visibility and obscure lane markings, posing challenges for lane detection algorithms [34]. Developing techniques to enhance the model's resilience to adverse weather conditions could improve the reliability and safety of autonomous driving systems in inclement weather.

In conclusion, the utilization of the Mask R-CNN framework for real-time road lane-line detection represents a significant step forward in the advancement of autonomous driving technology. The system's ability to accurately detect lane boundaries in diverse driving conditions and its real-time performance offer promising prospects for enhancing road safety and efficiency. However, further research is needed to address challenges related to model generalizability, interpretability, computational efficiency, and resilience to adverse weather conditions. By addressing these areas, we can continue to improve the effectiveness and reliability of autonomous driving systems, ultimately leading to safer and more efficient transportation networks.

VI. Conclusion

In conclusion, the utilization of the Mask R-CNN framework for real-time road lane-line detection represents a significant advancement in the field of autonomous driving technology. Through extensive experimentation and analysis, the proposed approach has demonstrated remarkable accuracy in detecting and segmenting lane boundaries across diverse driving conditions. The system's robustness in handling complex scenarios, such as variations in lighting conditions and occlusions, underscores its potential for real-world deployment. Moreover, its ability to provide real-time feedback enhances driving safety and efficiency. However, while the results are promising, there remain challenges to address, including improving model generalizability, interpretability, computational efficiency, and resilience to adverse weather conditions. Addressing these challenges will be essential for further advancing the reliability and effectiveness of autonomous driving systems. Overall, the findings presented in this paper contribute to the ongoing efforts to enhance road safety and transportation efficiency through the integration of advanced computer vision techniques into autonomous vehicles.

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