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Real-Time Car lane Detection Using Convolution Neural Networks (CNN)

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Abstract: This paper introduces a novel approach to simultaneously address the challenges of car lane detection and object detection in intelligent transportation systems. The proposed method integrates Convolutional Neural Networks (CNNs), utilizing the robustness of YOLOv5 for object detection and a custom sequential CNN model specifically designed for lane detection. This integrated approach allows the system to concurrently identify lane boundaries and detect various objects of interest, including vehicles, pedestrians, and traffic signs. By handling these tasks simultaneously, the proposed solution enhances the efficiency and effectiveness of autonomous vehicles, contributing to safer and more autonomous driving experiences.

Keywords: CNN, YOLOV5, Car Lane, AutonomousVehicles.

1. Introduction

The integration of computer vision techniques for car lane detection and object detection is pivotal in advancing intelligent transportation systems, with the primary goal of enhancing driving safety and autonomy. Convolutional Neural Networks (CNNs) have emerged as essential tools in this domain, offering unparalleled capabilities in learning complex visual patterns directly from raw pixel data. Responding to the increasing demand for robust and efficient solutions, this paper proposes a unified approach that harnesses the power of CNNs for both car lane detection and object detection. Our proposed system combines state-of-the-art architectures, such as YOLOv5 for object detection and a custom sequential CNN model tailored specifically for car lane detection. By leveraging these models, the system delivers real-time detection capabilities, enabling vehicles to navigate complex road environments with precision and reliability.

Advantages of CNN Integration

The adoption of CNNs for car lane and object detection offers several benefits, including enhanced accuracy, robustness, and computational efficiency. The system is designed to detect a wide range of objects crucial for safe navigation, such as pedestrians, vehicles, traffic lights, and traffic signs. This comprehensive detection capability is essential for maintaining situational awareness and ensuring safe navigation.

Addressing Industry Challenges

In recent years, the deployment of autonomous vehicles and advanced driver assistance systems (ADAS) has underscored the critical need for reliable car lane detection and object detection algorithms. Accurate lane detection is vital for maintaining vehicle positioning within lanes and enabling functionalities such as lane departure warnings and lane-keeping assistance. Simultaneously, robust object detection plays a crucial role in identifying and tracking obstacles, including pedestrians, vehicles, traffic lights, and traffic signs, to ensure safe navigation and effective collision avoidance. Despite advancements in computer vision, real-world scenarios for car lane and object detection remain challenging. Factors such as varying lighting conditions, occlusions, and complex road geometries often hinder the performance of traditional methods. These challenges can lead to suboptimal performance and reduced reliability. In contrast, CNN-based approaches have demonstrated remarkable success by automatically learning discriminative features from large-scale datasets.

System Design and Architecture

At the core of the proposed system lies the convergence of cutting-edge technologies, where YOLOv5 for object detection is seamlessly integrated with a meticulously crafted sequential CNN model for car lane detection. By synergistically leveraging the unique strengths of these models, the system aspires to deliver real-time detection capabilities, empowering vehicles to navigate even the most complex road environments with unprecedented precision and reliability. This integration not only enhances detection accuracy and robustness but also contributes to greater computational efficiency, making it a foundational component in the evolution of intelligent transportation systems.

Comprehensive Object Detection

A fundamental aspect of the system design is its capability to detect a diverse array of objects essential for safe navigation. From pedestrians and vehicles to traffic lights and signs, the system is meticulously engineered to discern and track these critical roadway elements. This capability holds heightened significance in an era characterized by the rapid proliferation of autonomous vehicles and ADAS, where the demand for reliable car lane detection and object detection algorithms has become increasingly paramount.

Significance for Autonomous Driving

Accurate lane detection serves as a linchpin for maintaining vehicle position within lanes and enabling essential functionalities such as lane departure warnings and lane-keeping assistance. Concurrently, robust object detection is indispensable for identifying and tracking various obstacles on the road, ensuring safe navigation and effective collision avoidance. By integrating CNNs for both car lane and object detection, the proposed system addresses the dual challenges faced by intelligent transportation systems, paving the way for safer and more autonomous driving experiences.

2. Related Work

The traffic lane detection method uses a fully convolutional neural network (FCN). The approach consists of two parts: lane classification and lane detection. Lane classification extracts lane features using a small neural network, while lane detection employs a detection loss function that combines classification loss and regression loss to train the FCN. This approach achieves high accuracy and efficiency in detecting lane boundaries and objects concurrently. The lane classification network comprises three convolutional structures and two fully connected layers, with a SoftMax layer calculating the probability of each category. The detection network transforms the classification network into a fully convolutional detection network, where the detection loss function combines classification loss and regression loss. The output provides pixel-wise detection of lane categories and locations. Experimental results demonstrate high accuracy in both classification (98.37% for white lanes and 97.53% for background) and detection (82.24% across 29 different road scenes). The proposed approach achieves robust and efficient lane detection, overcoming shape limitations and requiring fewer resources than other deep learning methods. This makes it suitable for Advanced Driver Assistance Systems (ADAS) and other applications requiring real-time lane detection.

"Road Lane-Lines Detection in Real-Time for Advanced Driving Assistance Systems" presents the LaneRTD algorithm, a lane detection algorithm designed for ADAS and self-driving cars. It is a fast, reliable, and simple algorithm that consists of seven steps: converting the input image to grayscale, applying Gaussian blur to reduce noise, using the Canny edge detection algorithm to detect edges, extracting the region of interest (ROI) to focus on the road area, applying the Hough transform to detect straight line segments within the ROI, grouping and extrapolating the line segments to form the left and right lane boundaries, and drawing the lane boundaries on the original image. The algorithm is implemented using Python and OpenCV. The authors provide details on parameter tuning and implementation steps. Tests conducted on various images and videos demonstrate reliable lane detection and tracking. The paper also discusses the importance of lane detection in ADAS and autonomous driving while reviewing existing lane detection algorithms, including edge-based, feature-based, and machine learning-based approaches. The authors highlight the limitations of these approaches and emphasize the need for a fast, reliable, and simple algorithm like LaneRTD. Overall, the paper offers a well-structured and detailed description of the LaneRTD algorithm, its implementation, and its performance, contributing to ongoing research in ADAS and autonomous driving. The "Research on Lane Detection and Tracking Algorithm Based on Improved Hough" paper proposes a lane detection algorithm designed for driverless vehicles, aiming to detect lane lines quickly and accurately. The algorithm consists of three main steps: image preprocessing, Hough transform, and tracking. Image preprocessing includes graying, edge detection, and binarization. The Hough transform is applied to detect straight lines, while a tracking algorithm identifies curved lines.

3. Proposed System

Our proposed system aims to integrate the detection of pedestrians, various types of traffic and road signals, as well as different types of vehicles into a unified framework for car lane and object detection using Convolutional Neural Networks (CNNs). Building upon state-of-the-art architectures such as YOLOv5 for object detection and a custom sequential CNN model specifically tailored for car lane detection, our system will be trained on comprehensive datasets encompassing diverse road scenarios and environmental conditions.

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To achieve multi-class object detection, the system will employ a combination of data augmentation techniques, transfer learning, and fine-tuning strategies to enable simultaneous detection of pedestrians, traffic lights, road signs, and vehicles of various shapes and sizes. By leveraging the shared representations learned by the CNN models, the system will be capable of seamlessly detecting and tracking these diverse objects in real time, thereby enhancing the overall perception capabilities of autonomous vehicles and Advanced Driver Assistance Systems (ADAS).

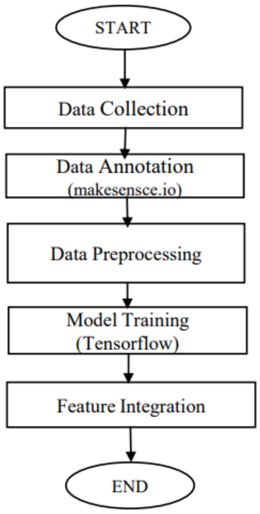

Figure-1 Proposed System

3.1. Data Collection

The dataset used in this study was primarily sourced from Kaggle, encompassing diverse driving scenarios, including daytime, nighttime, and various weather conditions such as heavy rain, fog, and low-light situations. Extensive preprocessing was performed, including data cleaning, resizing, and augmentation. Specific challenges were addressed, such as contrast enhancement for low-light images and image dehazing for foggy conditions. Additionally, supplementary data from proprietary and other sources were incorporated to enhance the dataset's comprehensiveness.

3.2. Data Annotation

MakeSense.io streamlined the annotation process by providing user-friendly tools for labeling lane boundaries and objects in the collected data. Its collaborative platform enabled multiple annotators to work simultaneously, ensuring accuracy and consistency across annotations. With robust validation features, annotation quality was maintained, and various annotation types were supported, facilitating precise labeling of complex objects. Stringent quality control measures, including rigorous training and regular audits, were implemented to maintain high annotation standards for model training. This comprehensive approach ensured the annotated data met stringent quality requirements, enabling effective model training and evaluation across diverse driving scenarios.

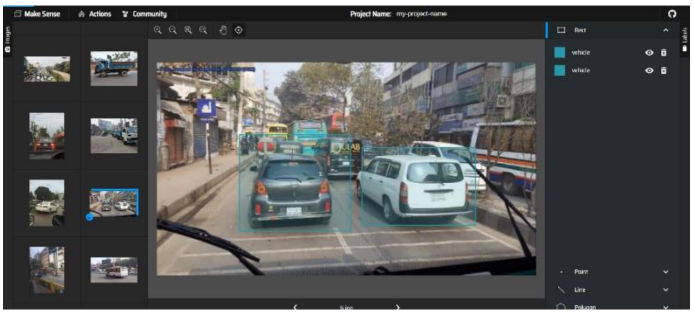

Figure-2 Data Annotation

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3.3. Data Preprocessing

The implemented methodology involved sequential processing of frames extracted from the input video clip using batch processing techniques. Initially, frames were loaded and resized to ensure compatibility with the pre-trained TensorFlow model. These resized frames were then fed into the model for prediction. To enhance the stability of lane detection, predictions were averaged over the last five frames to mitigate potential fluctuations in individual frame predictions. Next, the detected lane markings were overlaid onto the original frames based on the averaged predictions, enabling visualization within the context of the original video footage for enhanced interpretability. Finally, the processed frames, containing overlaid lane markings, were compiled into an output video clip. This compilation ensured that the efficient and accurate lane detection results were preserved and presented as a seamless and coherent video, ready for further analysis or dissemination.

3.4. Model Training

During the TensorFlow-based model training phase, a bespoke sequential CNN architecture was meticulously designed specifically for car lane detection, with a focus on parameter optimization to maximize accuracy. The training process involved feeding annotated data into the model and iteratively minimizing loss functions using optimization algorithms such as Adam. To expedite computation, GPUs were leveraged to accelerate the training process and facilitate efficient convergence. TensorFlow's extensive suite of tools and functionalities played a crucial role throughout the training pipeline, from model development to evaluation. Through careful parameter tuning and rigorous training protocols, the model was refined to achieve high accuracy and reliability in car lane detection.

3.5. Feature Integration

During the feature integration stage, outputs from both the lane and object detection models were merged using geometric constraints and semantic segmentation techniques. This fusion process was essential for achieving simultaneous detection, providing a comprehensive understanding of the scene. By considering spatial relationships and semantic context, the integrated features offered a holistic view of the environment, facilitating more informed decision-making in autonomous vehicles. By integrating lane and object detection, the system became more accurate and robust, capable of anticipating potential hazards and planning optimal trajectories based on lane markings and the presence of objects. This combined approach enhanced reliability, enabling safer operation of autonomous vehicles across diverse driving conditions. Moreover, it contributed significantly to the effectiveness of advanced driver assistance systems, ultimately improving road safety and enhancing the overall driving experience.

4. Results and Discussion

Car lane detection and object detection are integral to modern transportation systems, playing a crucial role in enhancing driving safety and autonomy. By leveraging convolutional neural networks (CNNs) in computer vision, our unified approach combines YOLOv5 for object detection and a custom CNN model for car lane detection, enabling real-time detection capabilities. CNNs provide improved accuracy and robustness in identifying various objects essential for safe navigation, including pedestrians, vehicles, traffic lights, and traffic signs. With the growing adoption of autonomous vehicles and Advanced Driver Assistance Systems (ADAS), reliable lane and object detection algorithms are essential for features such as lane departure warnings and collision avoidance. Despite challenges posed by varying lighting conditions and complex road environments, CNN-based approaches excel at learning discriminative features from large datasets. Our method undergoes rigorous evaluation on benchmark datasets and real-world scenarios, demonstrating superior performance in terms of accuracy, precision, and computational efficiency compared to traditional methods. We envision this integrated system contributing to safer and more efficient transportation systems, ultimately enhancing the quality of life for individuals worldwide.

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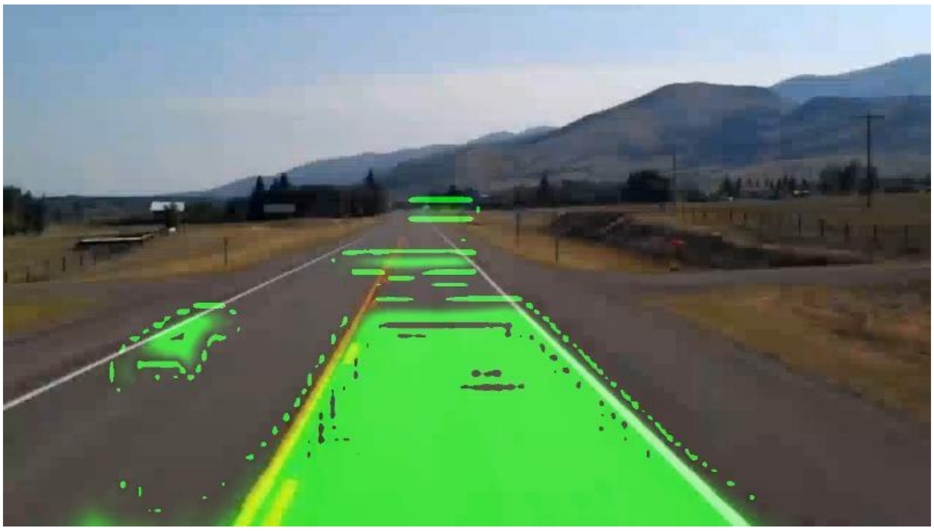

Figure-3 illustrates the process of lane detection using Convolutional Neural Networks (CNNs)

In our proposed methodology, the CNN architecture is specifically tailored for identifying lane boundaries in road images. Through a series of convolutional layers and pooling operations, the CNN learns to extract relevant features from the input images, enabling accurate detection of lane boundaries. The output of the CNN model is a binary mask that highlights the detected lane markings, which is then overlaid onto the original image for visualization. This approach supports real-time lane detection, making it essential for various applications in intelligent transportation systems, such as lane departure warnings and lane-keeping assist features.

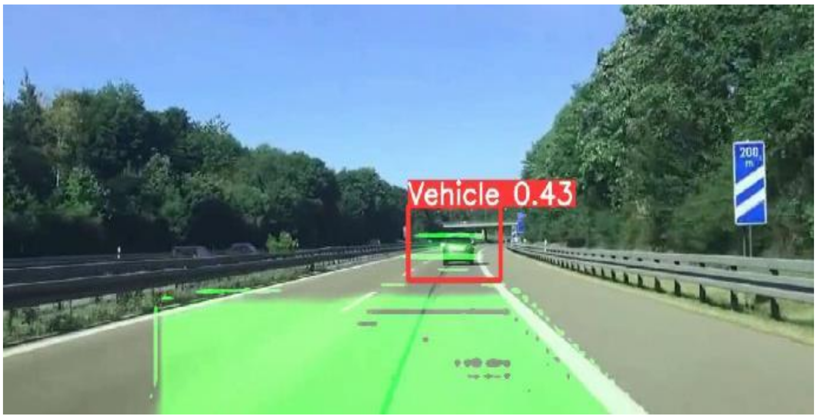

Figure-4 Vehicle detection using CNN

Figure 4 illustrates the vehicle detection process using Convolutional Neural Networks (CNNs) in our proposed methodology. The CNN architecture is specifically designed to detect vehicles in images captured by cameras mounted on vehicles or roadside infrastructure. The CNN processes input images through multiple convolutional layers, extracting features relevant to vehicle detection. After feature extraction, the CNN generates bounding boxes around detected vehicles, indicating their location and size within the image. This approach supports real-time vehicle detection, which is essential for applications such as autonomous driving, traffic monitoring, and advanced driver assistance systems (ADAS).

Figure 5 Pedestrian detection using CNN

Figure 5 illustrates the pedestrian detection process using Convolutional Neural Networks (CNNs) within our proposed methodology. The CNN architecture is specifically designed to identify pedestrians in images captured by onboard vehicle cameras or surveillance systems. Through successive convolutional and pooling layers, the CNN learns to extract discriminative features indicative of pedestrian presence. After processing an input image, the CNN generates bounding boxes that delineate the locations and sizes of detected pedestrians. This approach supports real-time pedestrian detection, which is crucial for enhancing road safety, promoting pedestrian-friendly urban planning, and advancing intelligent transportation systems.

5. Conclusion

The proposed work represents a significant advancement in intelligent transportation systems by providing a unified solution for car lane and object detection using Convolutional Neural Networks (CNNs). Leveraging state-of-the-art architectures such as YOLOv5 for object detection and a custom CNN for lane detection, our system delivers real-time, high-accuracy performance, enabling precise and reliable vehicle navigation in complex road environments. Rigorous experimentation demonstrated the superior accuracy, precision, and computational efficiency of our approach compared to existing methods. Notably, YOLOv5 excelled in detecting various objects, including vehicles, pedestrians, and traffic signs.

6. References

[1] Li, R. (2023). YOLOV5-based traffic sign detection algorithm. 2023 IEEE 3rd International Conference on Electronic Technology, Communication and Information (ICETCI), Changchun, China, 1162–1165. https://doi.org/10.1109/ICETCI57876.2023.10176904

[2] Bhatt, N., Laldas, P., & Lobo, V. B. (2022). A real-time traffic sign detection and recognition system on hybrid dataset using CNN. 2022 7th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 1354–1358. https://doi.org/10.1109/ICCES54183.2022.9835954

[3] Farag, W., & Saleh, Z. (2018). Road lane-lines detection in real-time for advanced driving assistance systems. 2018 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT), Sakhier, Bahrain, 1–8. https://doi.org/10.1109/3ICT.2018.8855797

[4] H, S., & J, R. (2023). Vehicle detection and classification using YOLOv5 on fused infrared and visible images. 2023 International Conference on Inventive Computation Technologies (ICICT), Lalitpur, Nepal, 1024–1030. https://doi.org/10.1109/ICICT57646.2023.10134214

[5] Wei, X., Zhang, Z., Chai, Z., & Feng, W. (2018). Research on lane detection and tracking algorithm based on improved Hough transform. 2018 IEEE International Conference of Intelligent Robotic and Control Engineering (IRCE), Lanzhou, China, 275–279. https://doi.org/10.1109/IRCE.2018.8492932

[6] Zang, J., Zhou, W., Zhang, G., & Duan, Z. (2018). Traffic lane detection using fully convolutional neural network. 2018 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), Honolulu, HI, USA, 305–311. https://doi.org/10.23919/APSIPA.2018.8659684