Lane Detection Network: Using Artificial Intelligence and Deep Learning

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Abstract - **Lane detection, a pivotal technology in autonomous vehicles, involves the identification and tracking of lane markings on roadways using computer vision or image processing techniques. In this study, we utilize the Yolov8 semantic segmentation model to train our dataset. Our objective is to implement this solution road, with customized data sourced from different roads and highways. The model demonstrates exceptional accuracy, rendering it highly dependable for segmentation tasks. Even across a broader Intersection over Union (IoU) range (0.5:0.9), the model maintains a commendable mAP of 0.842.**

Keywords: Lane Detection, Semantic Segmentation, Yolov8, Autonomous Vehicle, Indian Roadways.

I. INTRODUCTION

Autonomous vehicles, or self-driving cars, operate without human input, utilizing advanced technologies like sensors, cameras, radar, lidar, and AI algorithms to navigate roads safely. They aim to reduce the staggering number of road accidents worldwide, especially in countries with high accident rates like Turkey, Sri Lanka, Japan, and the US. To adapt to diverse road conditions, deep learning models are employed. These models continuously learn from data, improving their ability to handle complex traffic scenarios. Additionally, Advanced Driver Assistance Systems (ADAS) integrate various technologies into vehicles to aid drivers, enhancing safety and comfort.

Deploying autonomous vehicle concepts in India faces unique challenges due to the country's diverse traffic and weather conditions. A project targeting Indian roads utilizes a dataset of 5,000 samples for lane detection, employing a YOLO model renowned for its effectiveness in identifying road lanes and boundaries.

II. LITERATURE REVIEW

Lane Marking Detection (LMD) is a critical aspect of Advanced Driver Assistance Systems (ADAS) to ensure safe navigation on roads. Several research endeavors have focused on enhancing LMD accuracy and robustness across diverse environmental conditions. Mamun A. et al. [1] proposed a semantic segmentation approach integrating U-net and VGG16 architectures, achieving a remarkable 96.4% accuracy rate, surpassing previous state-of-the-art research. Cheng et al. [2] introduced an instance segmentation-based lane detection algorithm employing RepVgg-A0 network and multi-size asymmetric shuffling convolution, achieving an impressive accuracy of 96.7%. Zhang et al. [3] presented a two-stage YOLO v3-based architecture for lane detection, achieving high accuracy rates of 88% on the KITTI dataset and 89% on the Caltech dataset. PINet algorithm [4] integrates key point estimation and instance segmentation, resulting in remarkable accuracy of 96.75% on the TuSimple dataset. Ju Han Yoo et al. [5] developed a robust lane detection approach focusing on vanishing point estimation, demonstrating impressive accuracy rates across different scenarios.

Zhao et al. [6] proposed YOLO-Highway, an enhanced YOLOv3-based model for highway center marking detection, surpassing the performance of the original YOLOv3 with an average precision of 82.79%. Dawam et al. [7] contributed with a YOLOv3-based road surface marking recognition system, enhancing traffic sign recognition for autonomous vehicle safety. Researchers utilized DEEPLABv3 [8] for lane line segmentation, achieving an overall accuracy of 94.6%. Yueen et al. [9] proposed a three-step deep learning approach for vision-based lane detection and model inference. Hu et al. [10] introduced a YOLO-based algorithm for lane and obstacle detection in self-driving cars. Madan et al. [11] presented a lane detection system using OpenCV, incorporating techniques such as Canny Edge Detection and Hough transform.

III. IMPLEMENTATION

A) YOLOv8

YOLOv8, short for "You Only Look Once version 8," is a state-of-the-art deep learning model used for object detection tasks in computer vision. It builds upon previous versions of the YOLO architecture, known for its efficiency and accuracy

in detecting objects within images or video frames. YOLOv8 utilizes a single neural network to predict bounding boxes and class probabilities for multiple objects simultaneously, enabling real-time detection with high accuracy. This model is widely used in various applications, including autonomous vehicles, surveillance systems, and image analysis tasks, due to its speed and effectiveness in detecting objects in complex scenes.

B. Architecture

The architecture of YOLOv8 (You Only Look Once version 8) consists of multiple layers arranged in a deep neural network structure. It begins with an input layer that accepts fixed-size images. These images are then processed through a backbone network, such as Darknet or CSPDarknet, which extracts features from the input images through hierarchical convolutional layers.
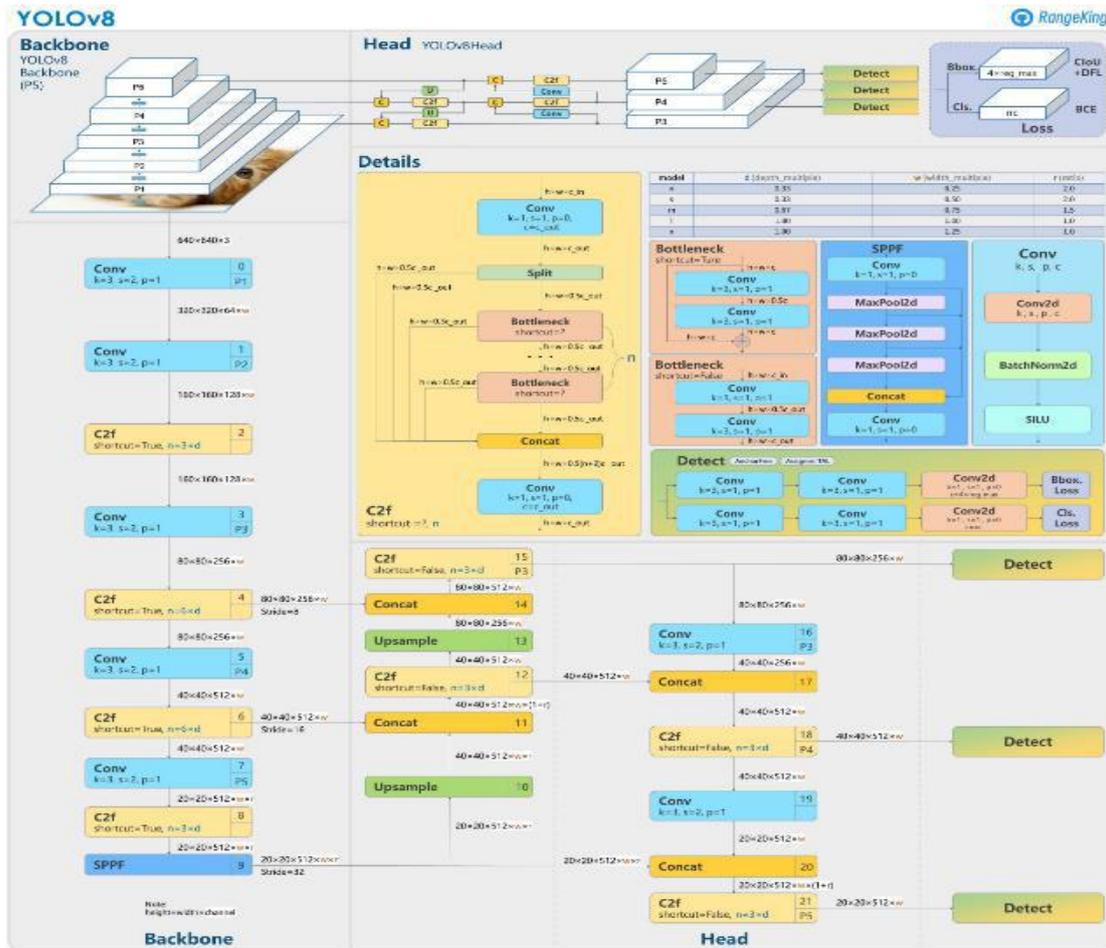

Figure 1: Architecture of Yolov8

Following the backbone network, additional layers may be included to further refine the feature representation. The detection head, comprised of convolutional layers, is responsible for predicting bounding boxes, objectness scores, and class probabilities for detected objects. YOLOv8 employs anchor boxes and multi-scale prediction strategies to enhance accuracy and efficiency in object detection. Finally, the output layer produces the final predictions in the form of bounding boxes along with associated class labels and confidence scores. Overall, YOLOv8 strikes a balance between speed and accuracy, making it suitable for real-time object detection tasks across various applications. Its architecture is optimized for efficient computation, allowing for high-performance operation on both CPU and GPU hardware platforms.

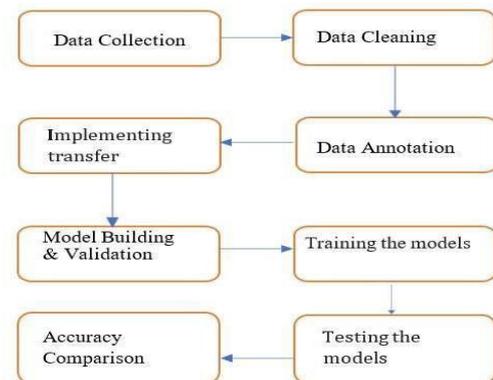**C) Dataset Collection and Annotation**

Figure 2: Data Annotation

This dataset, comprising approximately 1300 images, is a vital resource for the development of a segmentation model. We collected the dataset from online. Similar roads data can be found in different parts of Indian Highways. Each image has been meticulously annotated using object segmentation tools in Roboflow. Roboflow is an open-source platform that provides segmentation tools for computer vision tasks. It is a web-based platform.

D) Model Training

To train our model, we utilized the YOLOv8s architecture and divided our dataset into standard proportions of 8:1:1 for training, validation, and testing. This training process was conducted on a high-performance Google Colab platform, offering free GPU access. The YOLOv8s-seg model underwent 50 epochs of training, with each epoch lasting approximately 39 seconds, totaling 0.524 hours of training time. During training, the memory consumption peaked at 5.1 GB, utilizing a Tesla T4 GPU with 15 GB of available GPU RAM.

E) Output

Figure 3: Model Testing

While YOLO can run on a CPU, optimal real-time performance is achieved with a robust multi-core CPU or, preferably, a GPU. Our setup utilized a Tesla T4 GPU with 15 GB of dedicated GPU RAM on a Windows operating system, leveraging the processing power for enhanced speed. Programmed in Python3, the model showcased exceptional performance metrics, boasting a precision of 1 and a recall of 0.9. Additionally, at an intersection over union (IoU) threshold of 0.5, the model achieved a remarkable mean average precision (mAP) of 0.9. Expanding the IoU range to 0.5:0.9, the reported mAP stands at 0.8, indicating robust performance across various detection scenarios.

IV. DISCUSSION

The research paper focuses on lane detection, a crucial aspect of advanced driver assistance systems (ADAS) and autonomous vehicles. It employs the Yolov8 semantic segmentation model to identify and track lane markings on Indian road systems, utilizing data from the Gandhari New Road in the Kalyan region. Comparable roads in Navi Mumbai and major highways such as NH275 and the Delhi-Mumbai Highway are also considered. The model achieves exceptional accuracy with a mean average precision (mAP) of 0.995, making it highly reliable for segmentation tasks. Even across a broader range of intersection over union (IoU), the model maintains commendable performance. This study underscores the effectiveness of the Yolov8 model for lane detection on Indian roadways, contributing to the advancement of autonomous driving technology.

V. CONCLUSION AND FUTURE SCOPE

In conclusion, the research highlights the efficacy of the Yolov8 semantic segmentation model in lane detection on Indian road systems, achieving a remarkable mean average precision (mAP) of 0.995. The successful application of the model on roads in the Kalyan region and its comparability to roads in Navi Mumbai and major highways like NH275 and the Delhi-Mumbai Highway underscore its versatility and potential for real-world deployment. This study offers valuable insights into improving lane detection capabilities in advanced driver assistance systems (ADAS) and autonomous vehicles, contributing to enhanced road safety and navigation. Moving forward, future research could focus on further validation of the model in diverse road conditions, integration of additional sensor data for improved accuracy, real-time implementation on vehicles, and addressing challenges related to adverse weather conditions and complex road geometries. Such efforts promise to advance the capabilities of autonomous driving systems and elevate road safety standards globally.

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