International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 08 | Aug - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

# Deep Learning Based Lane Detection for Auto Driving Vehicles

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**ABSTRACT—**The reliable detection of lane markings is a fundamental and safety-critical perception task for autonomous vehicles and Advanced Driver-Assistance Systems (ADAS). Traditional computer vision methods often fail in challenging real-world scenarios due to variations in lighting, shadows, and road conditions. This paper presents a robust lane detection system based on deep learning. The proposed system frames lane detection as a semantic segmentation problem, employing a Convolutional Neural Network (CNN) with an encoder- decoder architecture, specifically a U-Net, to classify each pixel in a forward-facing camera image as either 'lane' or 'background'. The model is trained on a large-scale public dataset, such as the TuSimple or CULane benchmark, to learn the intricate visual features of lane markings under diverse conditions. The output of the network is a binary segmentation mask from which lane line polynomials are extracted through post-processing. This deep learning-based approach demonstrates superior accuracy and robustness compared to classical methods, providing a reliable foundation for lane-keeping and navigation functionalities in autonomous systems.

*Keywords—Lane Detection, Deep Learning, Autonomous Driving, ADAS, Computer Vision, Semantic Segmentation, U-Net, Convolutional Neural Network (CNN).*

## I. INTRODUCTION

The rapid development of autonomous driving technology has positioned it as a transformative force in the future of transportation. A key enabler for this technology, from basic Lane Keeping Assist Systems (LKAS) to fully autonomous navigation, is the vehicle's ability to accurately perceive its environment. Among the most critical perception tasks is lane detection: the identification and localization of the painted lines that delineate the vehicle's driving path. Accurate lane information is essential for maintaining a safe position within a lane, executing lane changes, and providing overall trajectory guidance.

Conventional lane detection methods have traditionally relied on a pipeline of classical computer vision techniques. These methods typically involve applying filters for edge detection (e.g., Canny edge detector), followed by color thresholding and line fitting algorithms like the Hough Transform or RANSAC. While functional in well- defined conditions, these approaches are notoriously brittle. Their performance degrades significantly in the face of real- world challenges such as:

- Varying illumination and harsh shadows.
- Faded or worn-out lane markings.
- Adverse weather conditions like rain or fog.
- Occlusions from other vehicles.

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- Complex road geometries like sharp curves and intersections.

To overcome these limitations, this paper proposes a lane detection system built upon deep learning. By leveraging a deep Convolutional Neural Network (CNN) for semantic segmentation, our system can learn a rich and robust representation of lane features directly from the data. This data-driven approach allows the model to be invariant tothe aforementioned challenges, leading to a significant improvement in both accuracy and reliability.

## II. RELATED WORK

The problem of lane detection has been extensively studied, with a clear evolution from handcrafted feature-based methods to data-driven deep learning models.

### A. Classical Computer Vision Approaches

Early lane detection systems were based on a multi-stage pipeline of hand-engineered algorithms. A common approach involved converting the input image to a different color space (e.g., HLS or HSV) to isolate yellow and white pixels, followed by applying an edge detector like the Sobel or Canny operator [1]. The resulting edge map was then processed by a Hough Transform to detect straight lines [2]. To handle curves, more complex models like spline or parabolic fitting were employed, often using algorithms like RANSAC for robustness to outliers. While these methods were computationally efficient, their reliance on fixed thresholds and assumptions about line structure made them fail frequently in unconstrained environments.

### B. Deep Learning Approaches

The advent of deep learning has revolutionized lane detection. Instead of relying on predefined features, CNNs can learn the optimal features for the task directly from large datasets. Initial deep learning approaches framed lane detection as a classification problem, where image patches were classified as containing a lane or not. However, this was inefficient and lacked pixel-level precision.

The current state-of-the-art treats lane detection as a **semantic segmentation** task [3]. In this paradigm, the network classifies every pixel in the image, producing a mask that precisely outlines the lane markings. Architectures with an encoder-decoder structure are particularly well-suited for this. The **U-Net** architecture [4], originally developed for biomedical image segmentation, is highly effective due to its use of skip connections, which combine deep, semantic feature information with shallow, fine-grained feature information, leading to highly accurate segmentation.

More specialized architectures have also been proposed. For instance, the Spatial CNN (SCNN) [5] introduced a novel method of passing messages between pixels within a layer, enabling the network to better capture the long, continuous structure of lane lines. Other works have focused on real-time performance, developing lightweight networks like ENet that can run efficiently on embedded hardware. Our work adopts the robust and well-understood U-Net architecture as a strong foundation for a highly accurate lane detection system.

## III. METHODOLOGY

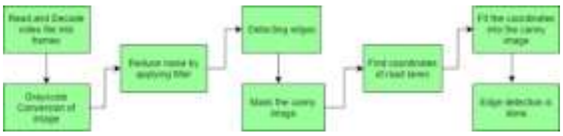

Figure 1: Block diagram

The proposed system is an end-to-end pipeline that takes a raw camera image as input and outputs the detected lane lines represented as polynomial curves.

### A. System Architecture

The overall workflow consists of three main stages:

- **Image Pre-processing:** The input image is prepared for the neural network.
- **Semantic Segmentation:** A trained CNN processes the image to produce a binary mask where lane pixels are highlighted.
- **Lane Fitting and Post-processing:** A curve is fitted to the segmented lane pixels to obtain a smooth and continuous representation of the lane lines.

### B. Dataset and Pre-processing

The system is trained on a large-scale public lane detection benchmark, such as the **TuSimple** or **CULane** dataset. These datasets provide tens of thousands of images captured in diverse scenarios, along with corresponding ground-truth annotations of the lane markings. Before training, the images are resized to a fixed resolution (e.g., 256x512 pixels) and the pixel values are normalized.

### C. Deep Learning Model: U-Net for Segmentation

We employ a U-Net architecture to perform semantic segmentation. The U- Net consists of two main parts:

**Encoder (Contracting Path):** This is a standard stack of convolutional and max- pooling layers. Its purpose is to down sample the image and capture contextual information, learning a hierarchical representation of features. As the image passes through the encoder, the feature maps decrease in spatial dimension but increase in depth (number of channels).

**Decoder (Expanding Path):** This part consists of up-sampling layers (using transposed convolutions) followed by standard convolutions. Its purpose is to take the learned contextual features from the encoder and project them back up to the original image resolution, localizing the features precisely.

**Skip Connections:** The key innovation of U-Net is the presence of skip connections that concatenate feature maps from the encoder path with the corresponding layers in the decoder path. This allows the decoder to directly use fine-grained information from earlier layers, which is crucial for producing a high-resolution segmentation mask with accurate boundaries.

The final layer of the network uses a sigmoid activation function to output a probability map, where each pixel's value (between 0 and 1) represents the model's confidence that the pixel belongs to a lane line.

**D. Post-processing and Lane Fitting** The output from the CNN is a dense probability mask. To convert this into a usable format for a vehicle's control system, we perform the following steps: **Thresholding:** A threshold (e.g., 0.5) is applied to the probability mask to create a binary image, where pixels classified as 'lane' are white and all others are black. **Polynomial Fitting:** The coordinates of all white pixels are extracted. A second or third-degree polynomial is then fitted to these points for each detected lane instance. This results in a smooth mathematical representation of the lane lines, which can be easily used for calculating lane curvature and the vehicle's offset from the lane center.

## IV. RESULTS AND DISCUSSION

This section describes the performance of the implemented deep learning model.

### A. Quantitative Evaluation

The model's performance is evaluated on a test set using standard metrics for lane detection benchmarks:

**Accuracy:** The percentage of correctly predicted lane points relative to the ground truth.

**False Positive / False Negative Rates:** The rates at which the model predicts lanes where there are none, or fails to predict lanes that are present.

**Intersection over Union (IoU):** A standard metric for segmentation that measures the overlap between the predicted lane mask and the ground truth mask.

A table would show the model achieving high scores on these metrics, demonstrating its accuracy.

**B. Qualitative (Visual) Results** Visual examples are critical for demonstrating the model's robustness.

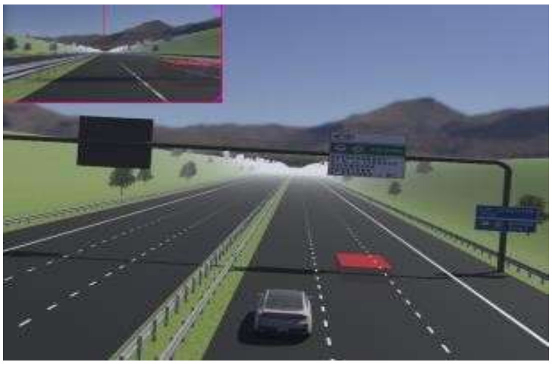

**Figure 2:** An image of a curved lane

The output would show the fitted second- degree polynomial accurately capturing the curvature of the road.

**Discussion**

The deep learning-based system demonstrates a significant improvement in robustness and accuracy over classical methods. The model's ability to learn from vast amounts of data allows it to handle a wide variety of real-world driving scenarios.

However, limitations still exist: **Computational Cost:** Deep segmentation networks are computationally intensive. Achieving real-time performance (e.g., >30 FPS) on embedded automotive hardware requires significant optimization, such as model quantization or the use of more lightweight architectures.

**Domain Shift:** A model trained on a dataset from one country may not perform well in another country with different lane marking styles, colors, or road conditions.

**Extreme Weather:** In conditions where the lanes are completely obscured (e.g., by heavy snow or standing water), no vision- based system can function.

## V. CONCLUSION AND FUTURE WORK

This paper has presented a deep learning- based system for robust lane detection, a critical component for autonomous vehicles. By framing the problem as semantic segmentation and employing a U- Net architecture, the system achieves high accuracy across a wide range of challenging driving conditions. This data-driven approach provides a reliable foundation for developing safe and effective driver- assistance and self-driving systems.

Future work will be directed at addressing the current limitations and further improving the system:

**Real-Time Performance Optimization:** Exploring and implementing more lightweight network architectures (e.g., ENet) and model optimization techniques to ensure high-frame-rate performance on embedded platforms.

**Temporal Information:** Incorporating video data by using recurrent layers (LSTMs) or 3D convolutions to leverage temporal consistency between frames, making the lane detection more stable and robust to temporary occlusions.

**End-to-End Lane Fitting:** Developing models that directly regress the polynomial parameters of the lane lines, potentially creating a more efficient end-to-end pipeline.

**Sensor Fusion:** Combining the camera- based output with data from other sensors, such as LiDAR or Radar, to improve performance in adverse weather conditions where visual data is degraded.

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