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A Review of Convolutional Neural Network-Based Automatic Lane Detection Methods on the TuSimple Dataset

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ABSTRACT

This review explores and compares various automatic lane detection methods, shedding light on their strengths, weaknesses, and advancements. The study analyzes a diverse range of techniques, including model-based and deep learning-based approaches, employed in road lane detection. The review highlights the advantages and disadvantages of each method, providing a nuanced understanding of their performance metrics, accuracy, and applicability under different scenarios. It dives into the evolution of lane detection algorithms, emphasizing recent breakthroughs in the field. The comparison section systematically evaluates the effectiveness of these methods, considering factors such as computational efficiency, robustness in challenging conditions, and adaptability to diverse environments. It aims to guide researchers, practitioners, and developers in choosing suitable lane detection methods based on specific use cases and requirements. Ultimately, this review contributes to the ongoing discourse in the area of autonomous driving, intelligent transportation systems, and computer vision, offering valuable insights for the continuous improvement of automatic lane detection technologies.

Keywords: Autonomous Driving, Computer Vision, Deep Learning, Lane Detection, TuSimple Dataset

1 INTRODUCTION

Autonomous vehicles are at the forefront of technological innovation, bringing a future where transportation advances beyond automation to achieve greater levels of safety and efficiency. Lane detection plays a crucial role in this transformation, enabling vehicles to perceive and navigate complex road networks [1]. The goal of autonomous driving is not merely to replicate human driving but to surpass it in precision, adaptability, and safety. To achieve this, effective lane detection is essential, allowing self-driving cars to maintain lane discipline, interact seamlessly with diverse road environments, and respond to varying conditions [2].

Lane detection is the process of identifying and tracking lane markings, providing autonomous vehicles with a spatial reference for positioning and trajectory planning. This capability is fundamental for higher-level decision-making tasks such as path planning and obstacle avoidance, ensuring safe and reliable navigation [3]. Traditional rule-based lane detection methods relied on handcrafted features and heuristics but struggled with challenging conditions such as occlusions, shadows, and poor lighting. The integration of deep learning, particularly Convolutional Neural Networks (CNNs), has significantly improved lane detection performance by enabling models to learn robust and adaptable feature representations [4].

The evolution of lane detection has progressed from simple rule-based techniques to sophisticated deep learning approaches. Early methods used edge detection and Hough Transform-based algorithms, forming the foundation for more advanced learning-based techniques. The adoption of CNNs has transformed lane detection by allowing models to extract complex spatial patterns from images, improving accuracy and robustness. However, lane detection remains challenging due to the variability in road conditions, including different lane markings, environmental factors such as weather and lighting, and real-world constraints like road occlusions and wear [5]. Standardized datasets such as TuSimple have played a pivotal role in advancing research by providing benchmark datasets for evaluating lane detection algorithms in real-world scenarios [6].

This paper provides a comprehensive review of automatic lane detection methods based on CNNs using the TuSimple dataset. It analyzes the evolution of lane detection techniques, highlighting the transition from traditional approaches to deep learning-based methods. The paper evaluates the performance and robustness of various CNN-based lane detection models on the TuSimple dataset, offering insights into their effectiveness across diverse and challenging environments. Additionally, it compares different CNN architectures, discussing their strengths and limitations in real-world lane detection tasks. A structured evaluation framework is proposed, focusing on key performance metrics such as accuracy, efficiency, and adaptability to varying road conditions. Finally, the paper discusses the implications of CNN-based lane detection advancements for autonomous driving, emphasizing future research directions and potential improvements.

2 MATERIAL AND METHODS

This section presents the research problems that we intend to address in this paper. In addition, we will explain about the TuSimple database, the history of automatic lane driving and the evaluation metrics that are used in this review.

2.1 Datasets

The TuSimple dataset is an important resource for computer vision and autonomous driving research. It contains 6,408 road images captured on US highways, each with a resolution of 1280×720 pixels. This dataset is essential for training and testing algorithms, especially in the fields of lane detection and autonomous navigation. The dataset contains 3,626 images for training models to adapt to different road scenarios. The remaining images are for testing how well-trained models perform in real-world situations. TuSimple Lane, an extension of TuSimple, adds an extra layer of complexity with 14,336 annotations that focus on lane boundaries. Annotations are crucial for improving the dataset's usefulness for algorithms that detect lanes. Polylines are used to annotate lane markings, providing detailed spatial information about the lanes. The TuSimple dataset is a benchmark for computer vision tasks, with its rich composition and detailed annotations, and will help advance lane detection algorithms and contribute to the development of autonomous vehicles [6].

2.2 History of Automatic Lane Detection

Lane detection methods have evolved significantly from rule-based systems to advanced machine learning and deep learning techniques. Early lane detection relied on handcrafted algorithms using image processing methods like edge detection and Hough transforms, which struggled with real-world variability such as changing lighting and road surface conditions . As computing power grew, enhancements such as region-based segmentation and color information improved accuracy, but these methods still lacked adaptability [5].

The integration of machine learning marked a turning point, with algorithms like support vector machines and decision trees offering better adaptability by learning from annotated data . This shift allowed for more flexible and robust lane detection, moving beyond the limitations of rigid rule-based systems. Machine learning techniques could autonomously identify relevant features from raw input data, improving performance across diverse conditions [7].

The real breakthrough came with deep learning and Convolutional Neural Networks (CNNs), which excel at capturing hierarchical features and performing well under varied driving conditions. Deep learning introduced end-to-end learning, simplifying the detection pipeline and integrating lane detection into broader autonomous systems [8]. Semantic segmentation networks like U-Net and Fully Convolutional Networks (FCNs) enhanced accuracy by providing pixel-level precision. Recurrent Neural Networks (RNNs) addressed the temporal aspect of lane detection, improving context understanding over time [9].

Further advancements include multi-sensor fusion and attention mechanisms, combining information from different sensors for a more comprehensive road perception [10]. This review will focus on evaluating deep learning architectures for lane detection using the TUSimple dataset, which presents diverse and complex scenarios for testing these models.

2.3 Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a fundamental element of automatic lane detection in computer vision. CNNs excel at processing and analysing visual data, making them particularly effective for tasks such as image classification, object detection and segmentation. In the context of lane detection, CNNs play a key role in automatic feature extraction through convolutional layers, capturing intricate details such as edges, textures and patterns [11]. The spatial hierarchy created by the pooling of layers helps to create a layered representation that progresses from basic features to more abstract and complex lane-related information. CNN consists of various layers and each layer has several neurons. There are no fixed rules to determine the use and apply differently to each data to be processed. In a CNN there are four main types of layers which is: convolution layer, activation layer, subsampling layer, and fully connected layer [12].

2.3.1 Convolution Layer

The Convolution Layer performs a convolution operation on the output of the previous layer. This layer is the main process that underlies a CNN. Convolution is a mathematical operation for feature

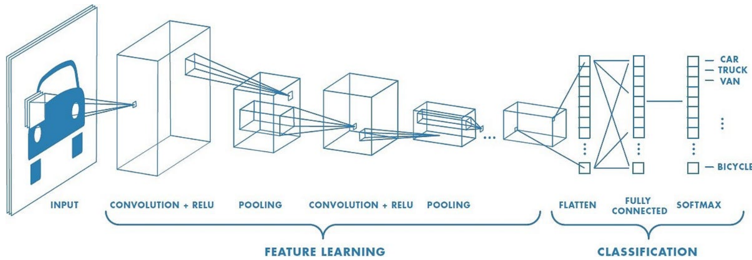

Figure 1 : Illustration of Convolutional Neural Networks

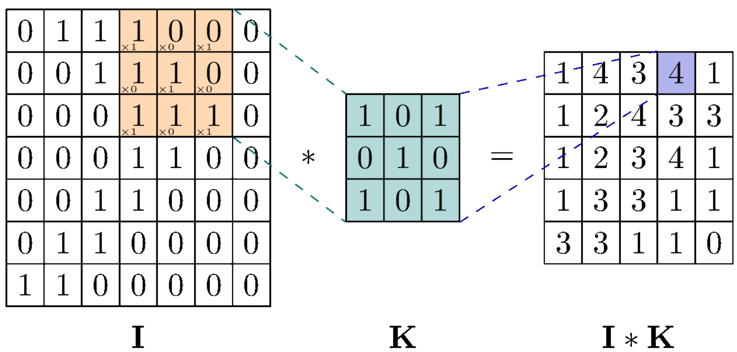

Figure 2 : Illustration of Convolution Layer

extraction [13]. Convolution involves sliding a filter (also known as a kernel) over an input image to compute a dot product at each position. This operation allows the network to detect patterns and features like edges, textures, or more complex structures in the input data [14]. Convolution can be defined as:

$$X(i,j) = I(i-m, j-n) \tag{1}$$

$$A(i,j) = X(i,j) \cdot K = \Sigma_m \Sigma_n A(i-m, j-n) \cdot K(m,n) \tag{2}$$

with I is the original matrix, A is output matrix, and K is augmentation kernel,

2.3.2 Activation Layer

In a CNN, the convolutional layers are responsible for learning features and patterns from the input data. However, these operations are linear in nature, meaning they can only capture linear relationships between input and output [15]. To model more complex, non-linear relationships in the data, activation layers will be used. The purpose of the activation layer is to add non-linearity by applying an activation function to the output of the previous layer. This non-linearity is crucial for the network's ability to learn and generalize from the training data [16]. Activation Layer that are being used in this research is Rectified Linear Unit (ReLU), that are defined as:

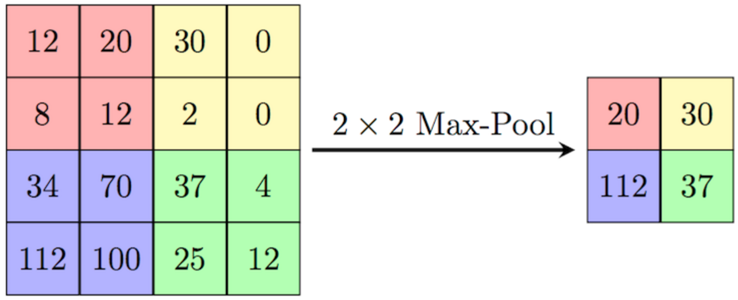

Figure 3 : Illustration of Pooling Layer

$$f(x) = max(x) \tag{3}$$

In simple terms, ReLU replaces all negative values in the feature map with zero, leaving positive values unchanged. This introduces non-linearity because the output is now dependent on whether a certain value is positive or negative [16] [15].

2.3.3 Subsampling Layer

Subsampling is a layer that functions to reduce the size of an incoming image data, in image processing, subsampling also functions as an increase in feature position invariation [17]. In this study, the subsampling method used is Max pooling, Max pooling will divide the convolution layer output into several smaller grids, which are then taken the maximum value for each grid to be arranged in a smaller matrix [18]. The above process can be shown in figure 3

2.3.4 Fully Connected Layer

This layer has a flattening layer to convert output of pooling layer to vector, and output layer or known as a dense layer, is a type of layer in a neural network where each neuron or node in the layer is connected to every neuron in the previous layer and every neuron in the next layer. Fully connected layers are located at the end of a CNN architecture. Prior to the fully connected layers, convolutional and pooling layers are commonly used to extract features from the input data. The fully connected layers then take these high-level features and use them to make predictions [19]. Function that are used is defined by:

$$y_{jk}(x) = f(\sum_{i=1}^{n_H} w_{jk}x_i + w_{j0}) \tag{4}$$

with y as output factor, f as activation function, and w as weight matrix

The synaptic weights, represented by w, play a crucial role in determining the strength of connections between neurons and are evaluated through optimization techniques such as gradient descent.

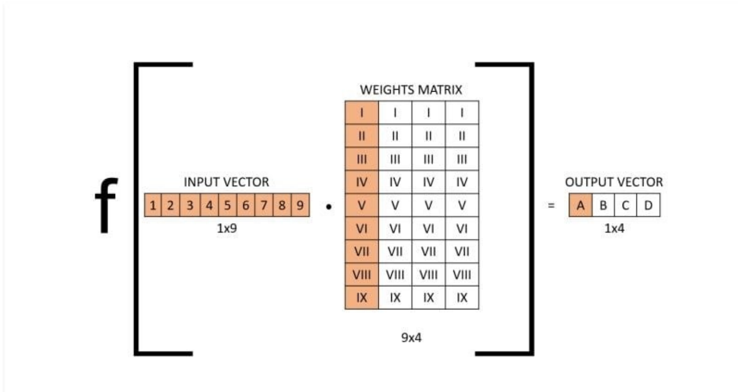

Figure 4 : Illustration of Fully Connected Layer

Initially, these weights are randomly assigned and iteratively updated based on the loss function, which measures the difference between predicted and actual outputs. The backpropagation algorithm calculates the gradients of the loss function concerning each weight, allowing the model to adjust them in a way that minimizes error. This iterative process ensures that the neural network learns to map input data to the correct output more accurately over time. [20]

2.4 Evaluation Metrics

Accuracy and F1 Score are two of the most widely used evaluation metrics for lane detection, each providing different insights into model performance. While accuracy gives a general measure of correctness, F1 Score is particularly useful in assessing the balance between precision and recall, especially in cases where the dataset may be imbalanced [21].

Accuracy is a fundamental metric that evaluates the proportion of correctly classified pixels (or instances) relative to the total number of pixels (or instances) in the dataset. It is calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FT + FN} \tag{5}$$

where TP (True Positives) are pixels correctly classified as lane markings, TN (True Negatives) are pixels correctly classified as non-lane regions, FP (False Positives) are non-lane pixels incorrectly classified as lane markings, and FN (False Negatives) are lane pixels incorrectly classified as non-lane regions [22].

A high accuracy score suggests that most lane pixels and non-lane pixels have been correctly classified, making it a useful metric for evaluating overall model performance. Since lane detection involves distinguishing lane pixels from the background, accuracy provides an effective measure of how well the model differentiates between these classes. Additionally, it offers a straightforward way to compare different methods and track improvements in lane detection models [23].

F1 Score provides a more balanced measure by considering both precision and recall. It is defined as:

$$F_1 Score = \frac{TP}{TP + 1/2(FP + FN)} \tag{6}$$

Alternatively, F1 Score can be expressed as:

$$F_1 Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{7}$$

where Precision (Positive Predictive Value) measures how many of the predicted lane pixels are actually lanes, given by:

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

and Recall (Sensitivity or True Positive Rate) measures how many of the actual lane pixels were correctly detected, given by:

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

F1 Score is particularly valuable for lane detection because it accounts for both the accuracy of lane pixel detection and the completeness of lane predictions. A high F1 Score indicates that the model correctly identifies lane markings while minimizing incorrect classifications. This makes F1 Score a crucial metric for assessing the reliability of lane detection methods, especially in autonomous driving applications where precise lane boundary estimation is essential. Both accuracy and F1 Score play an important role in evaluating lane detection models. While accuracy provides a general measure of correctness, F1 Score offers a more detailed assessment of lane pixel classification performance. Combining these metrics allows for a comprehensive evaluation of lane detection methods, ensuring that they perform well in various driving conditions [24].

3 RESULTS AND DISCUSSION

This section explores the latest developments in deep learning-based lane detection methods, demonstrating the ongoing development automatic lane detection. The basis of these methods lies in the representation of line shapes, leading to a categorisation into four distinct approaches: segmentation-based methods, anchor-based methods, row-wise detection methods, and parametric prediction methods. Each category uses unique strategies to interpret and identify lane markings in different road scenarios.

3.1 Segmentation-based Methods

Segmentation-based methods use image segmentation techniques and deep neural networks like U-Net and FCN for pixel-wise classification to identify lane markings. These methods offer strengths such as instance-level segmentation and semantic understanding, distinguishing between different objects [25]. However, they also have weaknesses, including high computational complexity affecting real-time performance and challenges in accurately defining lane boundaries in obstructed or complex road conditions [26].

3.1.1 Cluster for Proposal-Free Instance Segmentation (March 2018)

The Cluster for Proposal-Free Instance Segmentation (CPFIS) method introduce a novel approach to instance labelling and pixel-wise clustering by training a fully convolutional network (FCN) in an end-to-end manner. The method formulates a unique learning objective that uses pairwise relationships between pixels as supervision, guiding the FCN to perform pixel-wise clustering and assign cluster indices to individual pixels. To handle an unlimited number of instances, the method incorporates graph colouring theory by injecting a colouring strategy into the objective, allowing the FCN to assign different indices for neighbouring instances while reusing indices for objects that are far apart. This facilitates the recovery of individual instances through connected component extraction. The end-to-end learning approach simplifies the pipeline, and the performance of the method in real-world scenarios proves its effectiveness. However, limitations include the restriction on the number of instances due to the available cluster indices, potential issues with the sampling strategy during training, and the complexity of the learning objective and network architecture, which require significant computational resources and expertise for implementation and training [27].

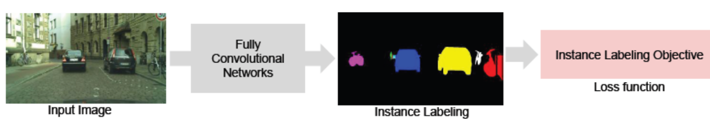

Figure 5 : Illustration of Cluster Instant Segmentation Method

3.1.2 Agnostic Lane Detection (May 2019)

Agnostic Lane Detection (AgLD) method introduces a multi-task learning paradigm and instance segmentation approach to enhance the use of structural and contextual information in driving scenarios. First, the model generates a binary segmentation map to distinguish between lanes and background. It then classifies each lane pixel into a lane instance, allowing the model to adapt to varying numbers of lanes and changing scenarios. This adaptability is a significant improvement over traditional methods that assume a fixed number of lanes. The use of the lightweight ENet network as the backbone and the feature pyramid architecture contribute to the real-time performance, and other enhancements include driveable area detection and lane point regression for improved use of structural information. However, the method may face challenges in terms of complexity, potentially affecting training and optimisation. The inclusion of multiple tasks and architectures may reduce the representability of the model, and further evaluation on diverse real-world datasets is essential to comprehensively assess its robustness and generalisation [28].

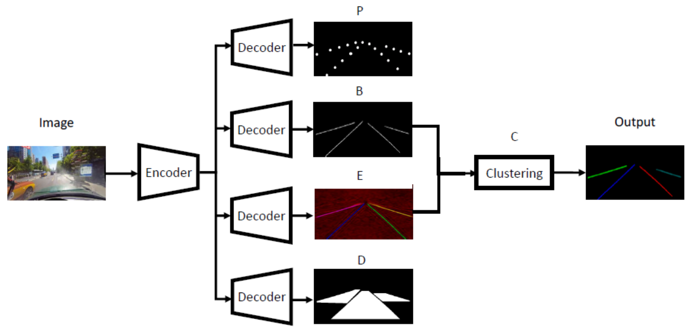

Figure 6 : Illustration of Agnostic Lane Detection

3.1.3 Cascaded CNN's (July 2019)

This method introduces a sophisticated two-stage approach using Cascaded Convolutional Neural Networks (CCNN's) to improve both lane detection and classification. In the first stage of instance segmentation, the ERFNet (Efficient Residual Factorized ConvNet) model is chosen for its real-time efficiency and high accuracy. The network is trained on the TuSimple dataset to detect lane boundaries rather than lane markings, using a specific loss function to prevent clustering during post-processing. The method then extracts descriptors for each detected lane boundary, followed by classification using a second CNN. This phase aims to distinguish between different lane boundary classes, such as dashed and continuous, with the network trained to identify boundaries that may or may not be crossed. The system is optimised for real-time performance and runs efficiently on an NVIDIA Titan Xp GPU. The end-to-end deep learning approach eliminates the need for post-processing and clustering algorithms, streamlining the workflow. The integration of a descriptor extraction strategy provides flexibility, allowing instance segmentation and classification to be combined without relying on two-stage detection networks. Furthermore, the availability of code and pre-trained models promotes accessibility and facilitates further exploration and implementation by the community. However, limitations include the method's specialisation in lane detection and classification, which may hinder its applicability to broader computer vision tasks. Concerns about dataset limitations, particularly in terms of diversity and size, and the trade-off between detection accuracy and GPU RAM raise considerations for potential improvements [29].

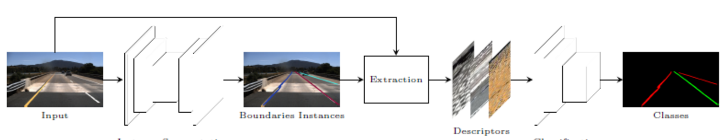

Figure 7 : Illustration of Cascaded CNN's Method

3.1.4 Self Attention Distillation (August 2019)

The Self Attention Distillation (SAD) method introduces a unique approach to lane detection network training, enabling self-reinforcement of representation learning without additional labels. By using attention maps derived from its own layers as distillation targets for lower layers, SAD overcomes the challenges associated with sparse annotations for lane detection. This method is motivated in particular by the observation that attention maps from different layers capture different contextual information related to lanes when a network is adequately trained. Unlike traditional methods, SAD does not require external supervision or a labels, and its ability to enhance representation learning by using attention maps for diverse contextual information. It complements segmentation-based supervised learning and offers a new way to address the challenges posed by sparse annotation. However, SAD has limitations. Its effectiveness relies on empirical evidence, and its performance may vary across different architectures and datasets. In addition, implementing SAD may require a deep understanding of attentional mechanisms, which may be challenging for some practitioners [30].

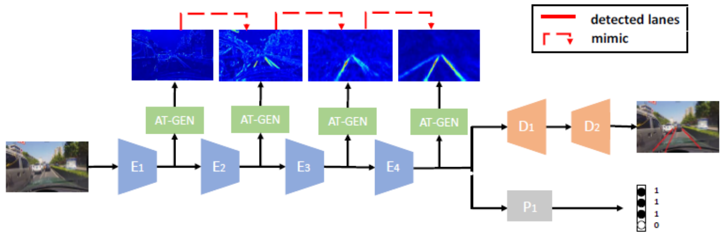

Figure 8 : Illustration of SAD Method

3.2 Anchor-based Methods

Anchor-based methods like YOLO and SSD use predefined anchor boxes for identifying lane markings, making them well-suited for real-time applications and scalable for different lane sizes. However, these methods can be inflexible due to fixed anchor shapes, which may struggle with varying shapes and curvatures of lane markings, especially in complex road environments. Additionally, detection accuracy can be challenged by deviations from standard lane marking shapes or orientations [31] [32].

3.2.1 LaneATT (November 2020)

LaneATT is a single-stage, real-time, deep lane detection model that incorporates an anchor-based attention mechanism for optimal accuracy and efficiency. The model uses a backbone network for feature extraction, followed by a detection head that predicts lane position and shape. The attention mechanism collects global information from feature maps using anchor points, enabling focused detection on relevant lane features while ignoring noise. LaneATT improves efficiency through a unique anchor selection strategy based on anchor utility, which significantly reduces the number of anchors during training and inference. The strength of LaneATT lies in its real-time efficiency, achieving high frames per second and reducing multiply-accumulate operations compared to previous state-of-the-art models, making it suitable for applications such as autonomous vehicles. It excels in accuracy, outperforming existing methods in complex real-world scenarios. The anchor-based attention mechanism proves effective in detecting lane boundaries, even under challenging conditions such as occlusion and missing lane markers. The method is extensively evaluated in different scenarios, demonstrating its effectiveness and efficiency on widely used lane detection datasets. However, LaneATT has certain weaknesses. The anchor selection process adds complexity to the model and requires careful tuning for optimal performance. The impact of the number of anchors and input size on training time may affect the practicality of training on large datasets, this requires balance between number of anchors, input size and overall efficiency, so factors such as these need to be carefully considered in practical implementation. While LaneATT achieves real-time efficiency, the complexity introduced by the attention mechanism and anchor-based pooling may require additional computational resources compared to simpler models [33].

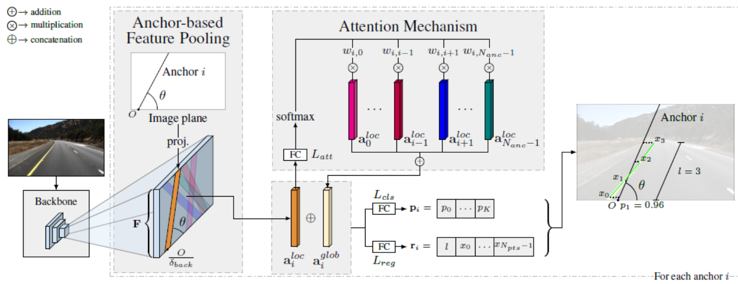

Figure 9 : Illustration of LaneATT Method

3.2.2 *Self Lane Identification and Inter-Lane Correlation Network (March 2022)*

The paper proposes an anchor-based CNN method for lane detection called SIIC-Net, which operates in the eigenlane space. First, it constructs the eigenlane space using Singular Value Decomposition (SVD) to obtain eigenlanes—data-driven lane descriptors that compactly represent structurally diverse lanes, including curved ones. Then, lane candidates are generated by clustering training lanes in this space. SIIC-Net consists of a self-lane identification (SI) module, which classifies and refines lane candidates, and an inter-lane correlation (IC) module, which evaluates compatibility between detected lanes. Non-Maximum Suppression (NMS) and Maximum Weight Clique Selection (MWCS) are used to select the optimal lanes. The method achieves superior detection performance, particularly for complex and highly curved lanes, compared to traditional anchor-based approaches [34].

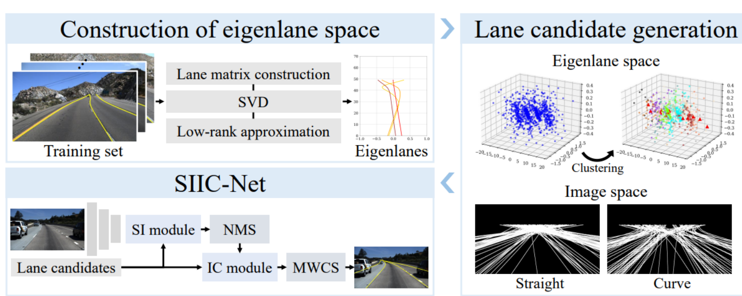

Figure 10 : Illustration of SIIC-Net Method

3.2.3 *Curved Guide Line Network With Adaptive Decoder (April 2023)*

Curved Guide Line Network With Adaptive Decoder (CANet), is an new approach to the challenges of lane detection in complex on-road scenarios. The method introduces the ”guide line” principle, which uses a U-shaped curve to constrain lane origins, which is particularly beneficial for improving detection in challenging scenarios such as bends. CANet's adaptive decoder dynamically adjusts anchors during inference, allowing global pixel comparison and flexible post-processing operations based on the activation shapes of the instance heatmaps. The use of heatmap monitoring further contributes to dynamic post-processing, eliminating the need for additional classifiers and adapting to activation shapes for optimal performance. CANet's strength lies in its remarkable lane detection performance, achieving high results in F1-score, precision and recall on diverse lane detection datasets. The adaptive decoder and heatmap monitoring mechanisms contribute to improved adaptability and dynamic post-processing, enhancing the effectiveness of the method in complex scenarios. The guide line principle introduces a novel approach to constraining lane origins, which is particularly useful in challenging scenarios such as bends. However, potential weaknesses include the complexity of the method, increased computational cost (despite the reduced cost of CANet-S), and sensitivity to hyper-parameters, which require careful tuning for optimal performance [35].

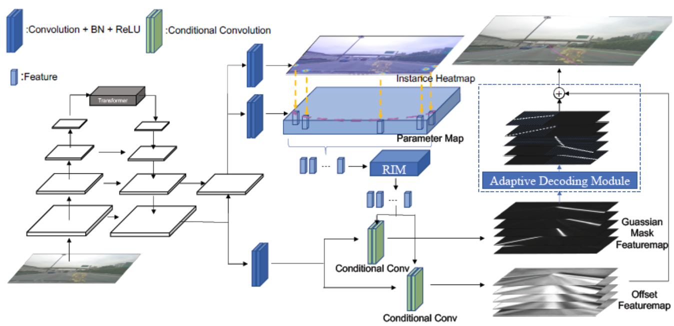

Figure 11 : Illustration of CANet Method

3.2.4 Dynamic Anchor Line Network (August 2023)

The paper proposes DALNet, which introduces a dynamic anchor line mechanism instead of using predefined anchor lines. This approach dynamically generates anchor lines for each lane instance based on the input image, making detection more accurate and efficient. The dynamic anchor line generator predicts the starting point, offset, and slope of the anchor line, which then serves as a reference for precise lane localization. DALNET achieves state-of-the-art results in both accuracy and efficiency, outperforming existing anchor-based methods like LaneATT while reducing computational redundancy and the need for non-maximum suppression (NMS) [36].

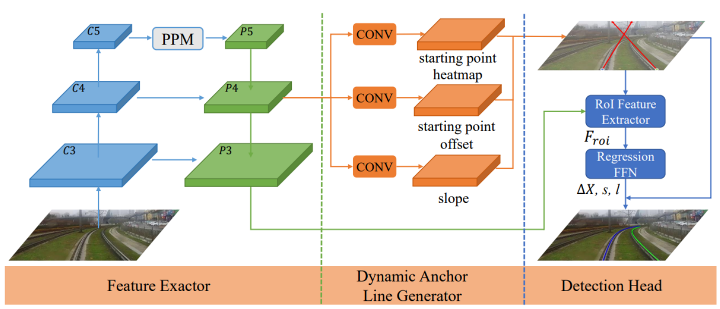

Figure 12 : Illustration of DALNet Method

3.3 Row-wise Detection Methods

Row-wise detection methods, like SCNN, predict lane mark locations row by row, using the shape prior of lane markings. This approach improves accuracy by incorporating expected lane structures and allows efficient detection of continuous markings. However, these methods rely on consistent lane shapes, limiting adaptability to diverse configurations, and the post-processing needed to connect row-wise predictions can impact real-time performance [37] [38].

3.3.1 End-to-End Row Wise Classification (May 2020)

The End-to-End Row Wise Classification (E2E-LMD) method for end-to-end lane detection by row-wise classification offers a streamlined approach by dividing an image into rows and directly predicting lane marker positions using a CNN. This eliminates the need for complex post-processing steps. The network architecture includes shared and lane marker-wise horizontal reduction modules (HRMs) to compress and model horizontal components for both shared representation and individual lane marker modelling. During testing, lane marker vertices are estimated by argmax operations and final positions are determined based on existence confidence thresholds. However, certain weaknesses are identified. The method may struggle in scenarios with severe curvature or obstruction, as evidenced by failures in experiments. The limited number of training images in the TuSimple dataset could lead to overfitting of the network. In addition, the proposed method could face challenges in the presence of reflections over the car hood, affecting its ability to locate lane markers [39].

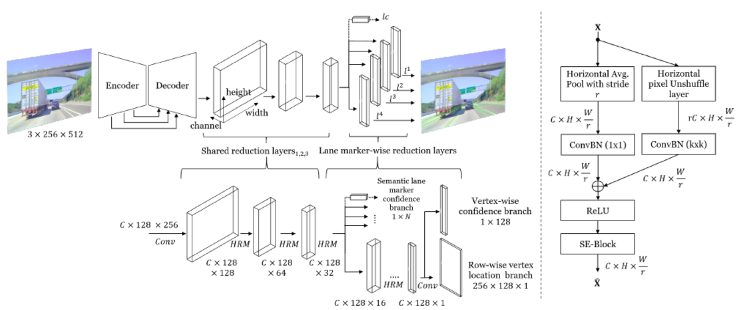

Figure 13 : Illustration of E2E-LMD Method

3.3.2 Recursively Estimating and Summing Aggregator (March 2021)

The Recursively Estimating and Summing Aggregator (RESA) method introduces an innovative approach to the aggregation of information within feature maps, improving the efficiency and detection of spatial relationships in lane detection. Its key mechanism is to slice the feature map vertically and horizontally, allowing each sliced feature to receive an adjacent sliced feature at a given step. This parallelized information transfer significantly reduces the time cost compared to conventional methods such as Markov Random Field (MRF) or Conditional Random Field (CRF). In addition, RESA's flexibility allows it to be seamlessly integrated into other networks. RESA's strength lies in its computational efficiency, achieved through parallel information passing, making it a compelling alternative to more time-consuming methods. The module's effectiveness is further enhanced by its ability to capture feature information without loss during transmission, contributing to more accurate and robust lane detection results. The acquisition of spatial relationships, facilitated by the aggregation of information with different steps, enhances RESA's ability to produce less noisy results, emphasising its utility in real-world applications. RESA's are designed to address challenging scenarios such as severe occlusion and ambiguous lanes, however there may be specific real-world situations where its performance may be limited. Integrating the RESA module into existing networks may require careful consideration of compatibility and potential trade-offs due to complexity and adaptability [40].

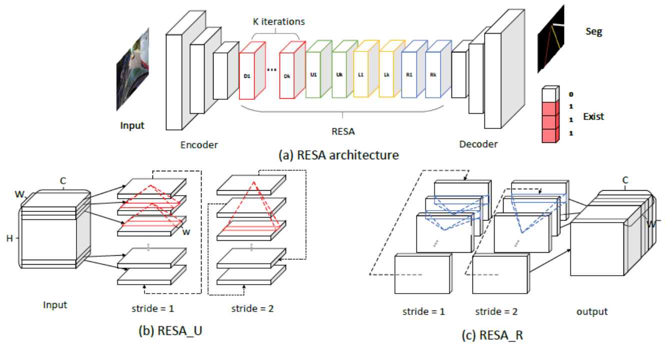

Figure 14 : Illustration of RESA Method

3.3.3 Multi Lane Detection with Affinity Field (August 2021)

Multi Lane Detection with Affinity Field (LaneAF) is a feed-forward CNN designed for lane detection, focusing on the prediction of binary lane segmentation masks and per-pixel affinity fields. The model predicts two affinity fields, the horizontal affinity field (HAF) and the vertical affinity field (VAF), which act as vector fields mapping 2D locations to unit vectors. The HAF points to the centre of the lane in the current row, allowing clustering of lanes of different widths, while the VAF encodes the direction of the next set of lane pixels above. The use of affinity fields allows lane identification regardless of the number of lanes present, increasing the flexibility of the model. It demonstrates robustness and consistency, with low false negatives and low standard deviation of accuracy across training runs. The clustering approach improves interpretability and analysability compared to alternative methods. However, LaneAF has notable weaknesses. A significant amount of training data and computational resources are required to achieve optimal performance. Affinity field clustering can struggle with heavily occluded or overlapping lanes, affecting accuracy. The model's performance may falter in challenging lighting or weather conditions, limiting its applicability. In addition, generalisation to different road types or environments may be a potential limitation [41].

3.3.4 CondLaneNet (February 2023)

CondLaneNet employs a unique conditional lane detection strategy based on conditional convolution and row-wise formulation. This strategy, which includes instance detection and shape prediction, excels in instance-level segmentation, which is critical for accurate lane detection in complex scenarios with dense or forked lines. The Recurrent Instance Module (RIM) plays a key role in handling complex features, improving the accuracy of the suggested points and increasing the overall accuracy of the lane lines. Its real-time efficiency positions CondLaneNet as a suitable solution for applications requiring rapid lane detection, such as autonomous driving and advanced driver assistance systems (ADAS). In addition, the framework demonstrates state-of-the-art performance, confirming its effectiveness in accurately predicting lane instances and line shapes. However, potential weaknesses include the complexity of the method, particularly with conditional convolution and RIM, which may pose challenges for implementation and understanding in certain computing environments.

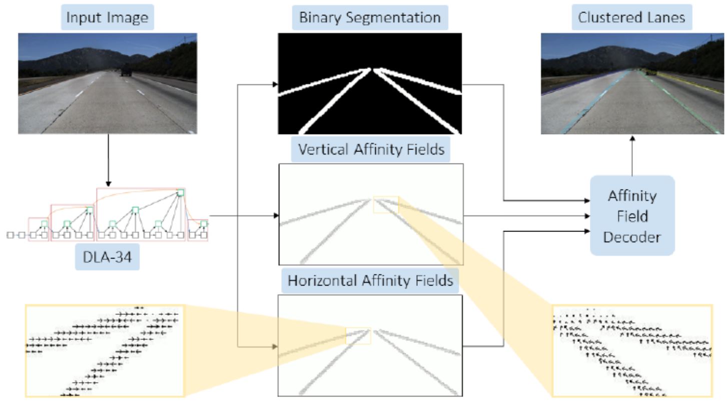

Figure 15 : Illustration of LaneAF Method

Sensitivity to proposal points, although improved with the RIM, and the need for more extensive comparative analysis with other methods are also considerations for further refinement [42].

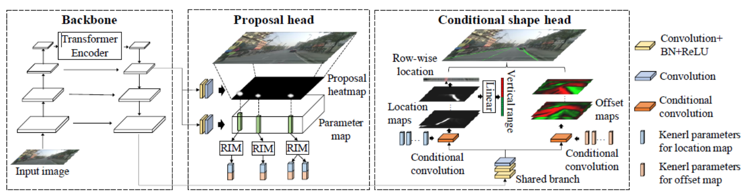

Figure 16 : Illustration of CondLaneNet Method

3.3.5 ElasticLaneNet (April 2024)

The method used in the paper follows a row-by-row approach with a novel lane representation called the Elastic Lane Map (ELM). Lanes are modeled as zero-contours of the ELM, which evolves during training under the guidance of an Elastic Interaction Energy (EIE) loss. Unlike traditional row-wise methods that rely on coarse confidence maps, this implicit representation allows for greater geometric flexibility and smooth lane predictions. The network architecture, ElasticLaneNet, consists of an Encoder-Transformer-FPN pipeline, where lane positions are extracted row by row from the predicted ELM. The EIE loss ensures that lane predictions are smoothly guided towards ground truth lanes through long-range attraction forces. This approach effectively integrates global context and local features, achieving superior lane detection performance, especially in complex road scenarios with high curvature, Y-shaped lanes, and dense lane distributions [43].

3.4 Parametric Prediction Methods

Parametric prediction methods, like LSD and Hough transform, use parametric models (e.g., polynomial curves or splines) to describe lane markings. These methods fit a model to detected lanes and predict position and curvature, offering structured, model-based representations and robustness to noise and outliers. However, they face challenges due to assumptions in the models, which can lead to inaccuracies with complex lane shapes, and the computational complexity of fitting models, impacting real-time performance in resource-constrained environments [44].

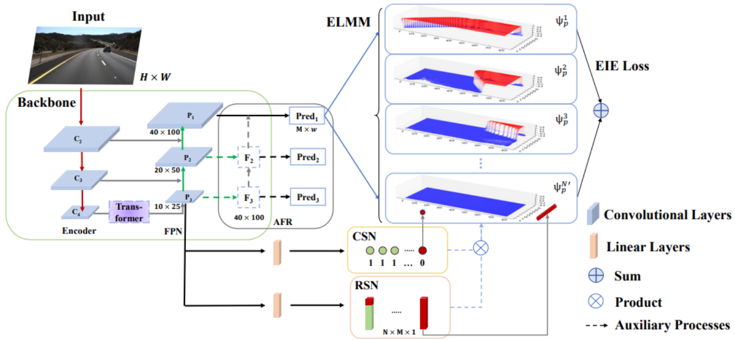

Figure 17 : Illustration of ELasticLaneNet Method

3.4.1 PolyLaneNet (July 2020)

PolyLaneNet method works by processing images captured by forward-facing cameras in vehicles, using deep polynomial regression to output polynomials that represent each lane marker in the image in detail. The architectural backbone of PolyLaneNet is a sophisticated combination of a feature extraction network and a fully connected layer responsible for lane marking prediction. A distinctive feature is the adoption of a polynomial representation for lane markings, as opposed to a set of points. This decision proves to be crucial in enabling both efficiency and accuracy in the detection process. The polynomial representation allows PolyLaneNet to capture the nuanced shapes of lanes in a more compact and efficient manner, potentially contributing to more robust and accurate predictions. While PolyLaneNet has remarkable strengths, it's weaknesses could affect its performance under certain conditions. In particular, there may be variations in accuracy for lane markings closer to the horizon, a challenge attributed to potential imbalances in the dataset. Furthermore, the reliance on public datasets for both evaluation and training leads to concerns about the generalisability of the method to the rich diversity of real-world driving scenarios. Another notable consideration is the trade-off between input image size and processing speed, which leads to differences in adaptability to various hardware and environmental settings [45].

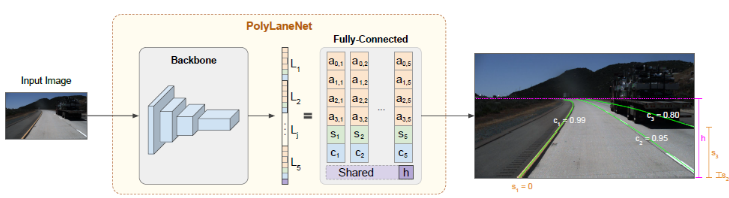

Figure 18 : Illustration of PolyLaneNet Method

3.4.2 End-to-end Lane Detection with Transformers (November 2020)

The End-to-end Lane Detection with Transformers (LSTR) method introduces an approach that combines a lane shape model and a transformer-based network. The parameters of the lane shape model, which directly reflect road structures and camera pose, provide explicit physical meanings. This model contrasts with traditional polynomial coefficients provides a more meaningful representation. The transformer-based network, designed to capture non-local interactions and global context, employs a soft attention mechanism for richer feature extraction. The method's output reframing includes the prediction of lane shape model parameters, and is trained end-to-end with a Hungarian loss for accurate mapping. The strengths of the method lie in its efficiency, capture of global context, use of a meaningful lane shape model, and demonstration of adaptability to different scenarios. Despite its strengths, the proposed method has limitations. The evaluation, while comprehensive on benchmark datasets and a self-collected dataset, lacks investigation on large-scale real-world scenarios. In addition, the interpretability of the transformer-based network may be less straightforward compared to traditional methods, highlighting a trade-off between complexity and interpretability in the approach [46].

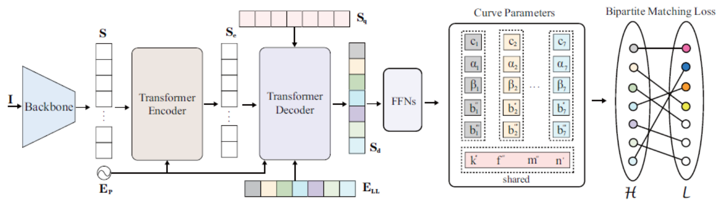

Figure 19 : Illustration of LSTR Method

3.4.3 Cross Layer Refinement Network (March 2022)

The Cross Layer Refinement Network (CLRNet) introduces a comprehensive approach to lane detection, emphasising the importance of both low-level and high-level features in achieving accurate results. The network first performs detection in high-level semantic features for rough lane detection, followed by a refinement process based on low-level features to improve accuracy. This dual use of features allows CLRNet to exploit rich contextual features while improving the accuracy with detailed lane features. To address challenges related to non-visible lane, CLRNet incorporates the ROIGather mechanism, which captures global contextual information by establishing relationships between the ROI lane feature and the entire feature map. This addition enhances the feature representation of lanes, contributing to improved detection accuracy. In addition, CLRNet introduces the Line IoU (LIoU) loss function, specifically tailored for lane detection, which represents the lane as a whole unit and significantly improves detection accuracy. However CLRNet require a significant amount of training data for optimal performance, which poses a challenge in applications with limited annotated data. In addition, the computational complexity resulting from multiple layers and mechanisms could impact real-time performance in certain scenarios. Finally, the suitability of CLRNet for lane detection in complex environments with obstructions or harsh lane conditions depends on the assumption of clear lane markings, suggesting potential limitations in such scenarios [47].

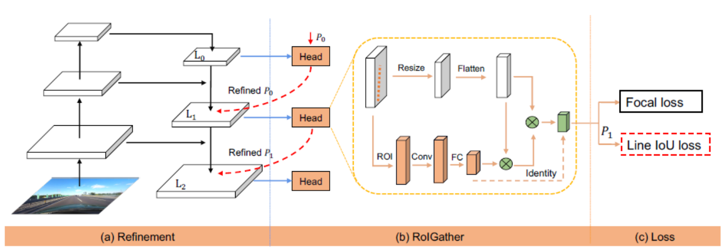

Figure 20 : Illustration of CLRNet Method

3.4.4 Fuzzy Inference System (February 2024

The paper proposes a hybrid lane detection method that enhances CNN-based models by integrating an adaptive preprocessing framework using a fuzzy inference system (FIS). The method dynamically adjusts parameters in geometric-based image processing functions, specifically in edge detection, to improve lane visibility under varying weather conditions. The preprocessing pipeline includes noise reduction, edge detection, region of interest (ROI) selection, and line detection, with FIS tuning the edge detection thresholds based on detected line counts. This approach refines the input fed into CNNs, improving their robustness and generalizability, particularly in challenging weather conditions. Experimental results show significant improvements in detection accuracy, especially in rainy weather, across multiple CNN models [48].

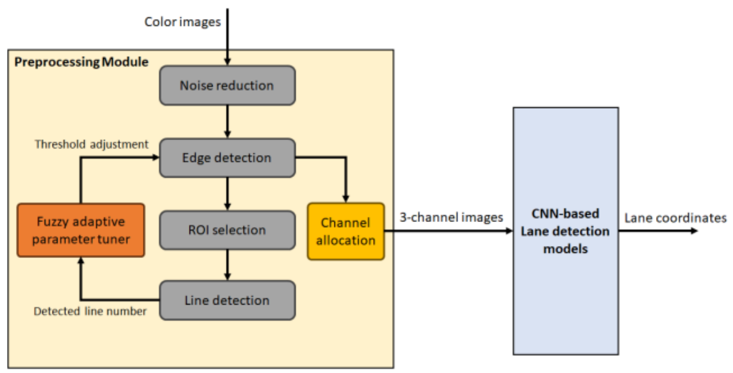

Figure 21 : Illustration of FIS Method

3.4.5 LanePTRNet (March 2024)

The paper proposes LanePtrNet, a novel lane detection method that utilizes a parametric approach based on convolutional neural networks (CNNs). It treats lane detection as a point voting and grouping problem by predicting curve-aware centerness, which assigns the most probable center points for lane markings. The method uses a Centerness-Farthest Point Sampling (C-FPS) algorithm to select key points and a grouping module that clusters lane points using local neighborhood features and cross-instance attention [49]. This approach eliminates complex post-processing, improving efficiency and adaptability to various real-world scenarios. The framework is flexible, allowing integration with point-based models like PointNet++ and extension to 3D lane detection tasks [50].

3.5 Comparison of CNN-Based Lane Detection Methods

Table 1 shows a comparison of some Automatic Lane Detection Methods in TUSimple Dataset based on their accuracy, F1 score, and including their publication year, also their lane detection approach.

Based on their approach, segmentation-based methods, represented by CPFIS, AgLD, CCNN's, and SAD, consistently demonstrate high levels of accuracy, ranging from 95.24% to 96.64%, with SAD achieving the highest accuracy and F1 score among them. Row-wise detection methods, including E2E-LMD, RESA, LaneAF, CondLaneNet, and ElasticLaneNet, show competitive performance,

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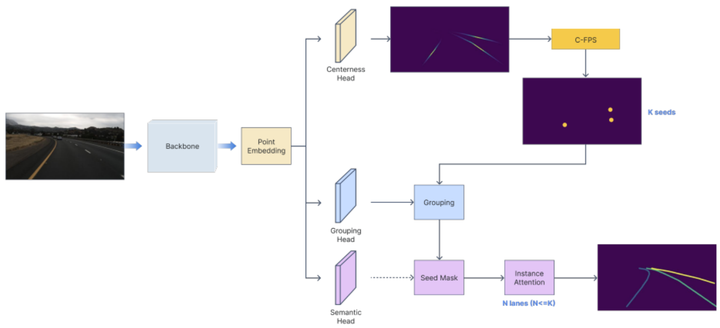

Figure 22 : Illustration of LanePTRNet Method

Table 1 : Comparison between Automatic Lane Detection Methods in TUSimple Dataset

Methods	Year	Approach	Accuracy	F1Score
CPFIS	2018	Segmentation	96,50%	94,31
AgLD	2019	Segmentation	96,29%	95,23
CCNN's	2019	Segmentation	95,24%	90,82
SAD	2019	Segmentation	96,64%	95,92
E2E-LMD	2020	Row-wise	96,22%	96,58
PolyLaneNet	2020	Parametric	93,36%	90,62
LaneATT	2020	Anchor	96,10%	96,06
LSTR	2020	Parametric	96,18%	96,68
RESA	2021	Row-wise	96,82%	96,93
LaneAF	2021	Row-wise	95,64%	96,49
CLRNet	2022	Parametric	96,90%	97,82
SIIC-Net	2022	Anchor	95.62%	-
CondLaneNet	2023	Row-wise	96,54%	97,24
CANet	2023	Anchor	96,76%	97,77
DALNet	2023	Anchor	96.68%	97.52
FIS	2024	Parametric	96.64%	-
ElasticLaneNet	2024	Row-wise	96.48%	97.05
LanePTRNet	2024	Parametric	96.10%	-

with accuracy levels ranging from 95.64% to 96.82%, where RESA achieves the highest accuracy and CondLaneNet has a strong F1 score of 97.24.

For parametric prediction methods, PolyLaneNet, LSTR, CLRNet, FIS, and LanePTRNet display accuracy values ranging from 93.36% to 96.90%, with CLRNet achieving the highest accuracy and F1 score among them. Meanwhile, anchor-based approaches such as LaneATT, SIIC-Net, CANet, and DALNet demonstrate strong accuracy levels, ranging from 95.62% to 96.76%, with CANet and DALNet achieving the highest F1 scores among this category.

The temporal trends from 2018 to 2024 indicate continuous progress in lane detection methods, with recent approaches (2022-2024) showing notable improvements in accuracy and F1 scores. The highest accuracy recorded is 96.90% (CLRNet), while the highest F1 score is 97.82 (CLRNet). Methods developed in 2023 and 2024, such as CANet, DALNet, and ElasticLaneNet, have also achieved competitive performance, reinforcing the dynamic evolution of lane detection techniques.

In conclusion, the field of lane detection is evolving rapidly, with segmentation, row-wise detection, parametric prediction, and anchor-based methods each contributing to advancements in accuracy and reliability. The continuous innovation in this area supports the growing demands of intelligent transportation systems and autonomous vehicles.

4 CONCLUSION

Recent advancements in automatic lane detection have been driven by deep learning-based approaches, particularly convolutional neural networks (CNNs). These methods fall into four main categories: segmentation-based, anchor-based, row-wise detection, and parametric prediction. While segmentation-based methods provide high-resolution lane detection, they suffer from high computational costs. Anchor-based approaches improve efficiency but struggle with complex lane geometries. Row-wise detection methods offer structured lane predictions but face challenges with non-standard lane configurations. Parametric prediction methods, such as CLRNet, provide structured representations with high accuracy but are constrained by model assumptions and computational demands.

Among the evaluated methods, CLRNet demonstrated the highest accuracy (96.90%) and F1 score (97.82%), highlighting the effectiveness of parametric approaches in structured lane representation. CANet and DALNet also achieved competitive F1 scores (97.77% and 97.52%, respectively), reinforcing the importance of anchor-based methods in balancing accuracy and efficiency. Despite these advancements, challenges remain, particularly in handling adverse weather, occlusions, and inconsistent lane markings, which significantly impact model robustness. Furthermore, the computational demands of deep learning-based methods limit real-time deployment on resource-constrained automotive hardware.

To address these challenges, future research should focus on improving model generalization through domain adaptation techniques and self-supervised learning. Optimizing architectures for real-time performance on embedded systems is crucial for practical deployment. Integrating multi-modal sensor data, such as LiDAR and radar, could further enhance lane detection accuracy by providing complementary depth and spatial information. Additionally, expanding benchmark datasets to include diverse road conditions will be essential for improving robustness and adaptability in autonomous driving applications. By addressing these limitations, future research can pave the way for more reliable and scalable lane detection systems.

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