Efficient Lane Detection Using ENet for Autonomous Driving

Sujoy Dutta
Dept. of Geomatics Engineering
sujoy.dutta@ucalgary.ca

***Abstract*—Lane detection is essential for the development of autonomous driving systems. This work implements ENet, a lightweight convolutional neural network designed for real-time semantic segmentation, to detect lane markings in challenging scenarios. Utilizing the TuSimple dataset, the model achieves efficient lane segmentation with low computational overhead, making it suitable for deployment on devices with limited hardware capabilities.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

Lane detection is a cornerstone of advanced driver assistance systems (ADAS) and autonomous driving technologies. Its primary function is to maintain vehicle alignment within designated lanes, enhancing road safety and minimizing accidents caused by lane departures, driver distractions, or adverse road conditions. As the automotive industry increasingly transitions towards semi-autonomous and fully autonomous vehicles, the demand for robust and accurate lane detection systems has grown significantly, highlighting its critical role in modern transportation.

Conventional computer vision techniques for lane detection rely heavily on manually crafted features and predefined assumptions about lane patterns, lighting conditions, and road quality. While effective under ideal circumstances, these methods often falter in real-world scenarios where conditions deviate from standard assumptions. For example, poor lighting during nighttime or under heavy shadows, adverse weather conditions such as rain, fog, or snow, and roadways with worn-out or partially obscured lane markings can severely degrade performance. Additionally, traditional approaches struggle to adapt to the complexities of urban driving environments, including intersecting or merging lanes, uneven road surfaces, and a high degree of variability in lane configurations.

Deep learning has emerged as a transformative solution to these challenges by enabling models to learn and extract features directly from data. Unlike traditional methods, deep learning-based lane detection systems can generalize across diverse scenarios without extensive manual feature engineering. In particular, framing lane detection as an instance segmentation problem has proven highly effective. This approach allows systems to simultaneously identify and differentiate between multiple lanes, adapt to complex road geometries, and handle challenging conditions with improved accuracy and robustness. Such advancements underscore the potential of deep learning to revolutionize lane detection and its applications in autonomous driving systems.

II. Related Work

Deep learning lane detection methods are divided into two categories, two-step and one-step methods. Two-step methods consist of a feature extraction step and data post-processing step. Post-processing steps often work on clustering and fitting. However, the one-step methods directly classify the feature and finish the post-processing method from the image input [1].

In 2014, Jihun Kim and Minho Lee proposed a two-step deep learning lane detection method using three layers of a convolutional neural network (CNN) with the random sample consensus (RANSAC) algorithm. The CNN model consists of eight layers, including three convolutional layers, two subsampling layers, and a multi-layer perceptron (MLP) with three fully connected layers. Before the images are input into the model, a blur and edge detection process using a hat-shaped kernel is applied to strengthen the lane signals. Their model achieved a detection accuracy of 94%. [8]

Unet is a convolution neural network designed for image segmentation. It has the advantage of handling high-resolution images and identifying objects in the pixel level. Since then, Unet has been implemented in many object detection tasks.

L. Zhang, J. Shen, and B. Zhu applied a Unet-based method called CrackUnet for concrete crack detection. They tried models with different number layers and found that the depth of the model didn't affect the performance of the model. However, a deeper Unet model might be overfitting if the dataset is too small. [3]

Sokipriala et al. [4] proposed a deep-transfer-learning method for the reduction of training time, improvement of accuracy, and estimation of the control command steering. Their study integrated VGG16 and long short-term memory (LSTM), where VGG16 extracted features from the real-world Udacity dataset, and these were fed into the LSTM network to predict the steering angle in real time. Kortli et al.

Beyond natural language processing, LSTMs and GRUs have been utilized in a variety of tasks, including general time series classification [5], the classification of ECG signals [6], and time series forecasting [7]. These applications demonstrate their versatility and effectiveness in modeling sequential data across different domains.

RNNs face limitations that impact their accuracy and training efficiency. They require sequentially batched data to maintain hidden state dependencies, which prevents data shuffling—a technique that improves model performance. This constraint can lead to poor learning of infrequent classes. Additionally, RNNs process inputs one at a time, with hidden states and outputs computed at each step, resulting in slower training. In contrast, CNNs avoid these issues by processing entire batches in parallel and allowing data shuffling, making them more efficient for many applications.[8]

III. Materials and Methods

A. Dataset

The model was developed and evaluated using the **TuSimple Lane Detection Dataset**, a widely available and utilized dataset for autonomous driving lane detection tasks. This dataset includes annotated images with lane markings represented as pixel-level labels. The dataset contains more than three thousand high-resolution images of size 1280 $\times$ 720 pixels, with a horizontal and vertical resolution of 96 dpi, and a bit-depth of 24. The dataset was divided into training, validation, and test sets in an 80:10:10 ratio, ensuring a balanced evaluation.

TABLE I
SUMMARY OF THE TUSIMPLE LANE DETECTION DATASET.

Property	Value
Total Number of Images	3000+
Image Resolution	1280 x 720 pixels
Horizontal/Vertical Resolution	96 dpi
Bit Depth	24
Dataset Split	80% Training, 10% Validation, 10% Test

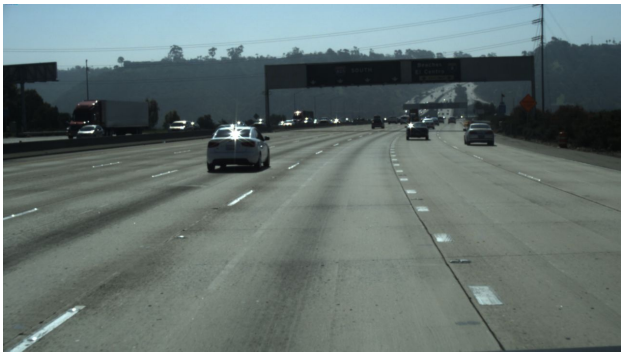

Fig. 1. Sample clip from the dataset

B. Preprocessing

The following preprocessing steps were implemented to prepare the data for training:

- **Resizing:** Images were resized to 512×256 to match the input dimensions of the ENet model, balancing performance and computational efficiency.
- **Normalization:** Input images were normalized to have pixel values in the range $[0, 1]$ for stable training.
- **Data Augmentation:** Techniques such as random cropping, horizontal flipping, and brightness/contrast adjustments were employed to increase data variability and reduce overfitting.

C. Model Architecture

The segmentation model used in this project was**ENet** (Efficient Neural Network) is a deep learning architecture designed for real-time semantic segmentation, particularly in resource-constrained environments like embedded systems. The key innovation of ENet is its ability to achieve high segmentation performance while maintaining low computational overhead. It accomplishes this by introducing a lightweight encoder-decoder structure where the encoder efficiently reduces the spatial dimensions of the input, extracting essential features, while the decoder progressively upsamples the features to restore the spatial resolution. ENet utilizes a combination of bottleneck layers and dilated convolutions to ensure effective feature extraction and resolution recovery with minimal computational complexity.

The architecture of ENet is tailored for speed and efficiency without sacrificing accuracy. The network is designed to work with real-time video processing, making it ideal for applications like autonomous driving and robotics. ENet achieves a significant reduction in model size and computational cost compared to traditional segmentation models by adopting strategies such as early downsampling and using less computationally expensive operations in the decoder. This makes ENet a powerful tool for real-time tasks requiring rapid semantic segmentation, offering a practical solution where performance and speed are both crucial.

In a nutshell, ENet comprises:

1) **Encoder:** Extracts multi-scale spatial and contextual features from input images.
2) **Decoders:**
   - **Segmentation Decoder:** Outputs pixel-wise lane probability maps.
   - **Instance Embedding Decoder:** Produces embeddings for lane instance differentiation.

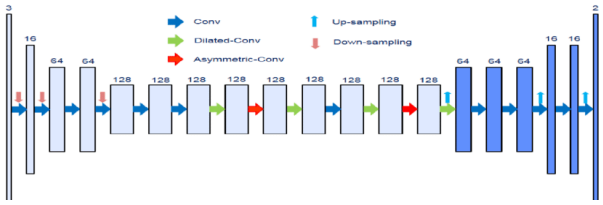

Fig. 2. The complete architecture of the ENet model for nuclear segmentation is shown in terms of layers of convolutional networks. The model includes both encoder (light blue) and decoder (dark blue) parts. The upward and downward arrows indicate up-sampling and down-sampling operations. Right hand arrows show different types of convolution including normal, dilated, and asysmmetric.

D. Bottleneck

The bottleneck is the core building block of ENet, designed for efficiency and versatility. It performs:

- **1x1 Convolutions:** Reduce and restore channel dimensions for efficiency.
- **3x3 Convolutions:** Standard, dilated (to expand receptive field), or asymmetric (5x1 and 1x5) for computational savings.
- **Residual Connections:** Preserve gradient flow and stabilize learning.
- **Downsampling:** Max-pooling with indices and convolution for spatial reduction.
- **Activation & Regularization:** PReLU for non-linearity and dropout for regularization.

E. Encoder

The encoder extracts hierarchical features while progressively reducing spatial dimensions.

- **Initial Block:** Combines convolution and max-pooling to preserve features.
- **Stage 1:** Downsamples input and refines features with five bottlenecks.
- **Stage 2:** Further downsampling with diverse convolutions: standard, dilated, and asymmetric.
- **Stage 3:** Processes features at the same resolution as Stage 2 with similar operations.

Outputs include feature maps and max-pooling indices for upsampling in the decoder.

F. Decoder

The decoder reconstructs a high-resolution segmentation map from compressed features.

- **Upsampling Bottlenecks:** Use max-pooling indices to restore spatial resolution.
- **Stage 4:** Upsamples to Stage 1 resolution and refines features.
- **Stage 5:** Final upsampling to the input resolution with additional refinement.
- **Final Layer:** Transposed convolution produces the segmentation map.

G. Key Features

- Lightweight design enables real-time segmentation.
- Residual connections ensure stability and efficient training.
- Asymmetric and dilated convolutions balance accuracy and speed.
- Reuse of max-pooling indices ensures precise upsampling.

H. Training and Optimization

The training process was configured as follows:

- **Optimizer:** The Adam optimizer was used with a learning rate of 1×10^{-3}.
- **Batch Size:** A batch size of 16 was chosen to balance memory usage and computational efficiency.

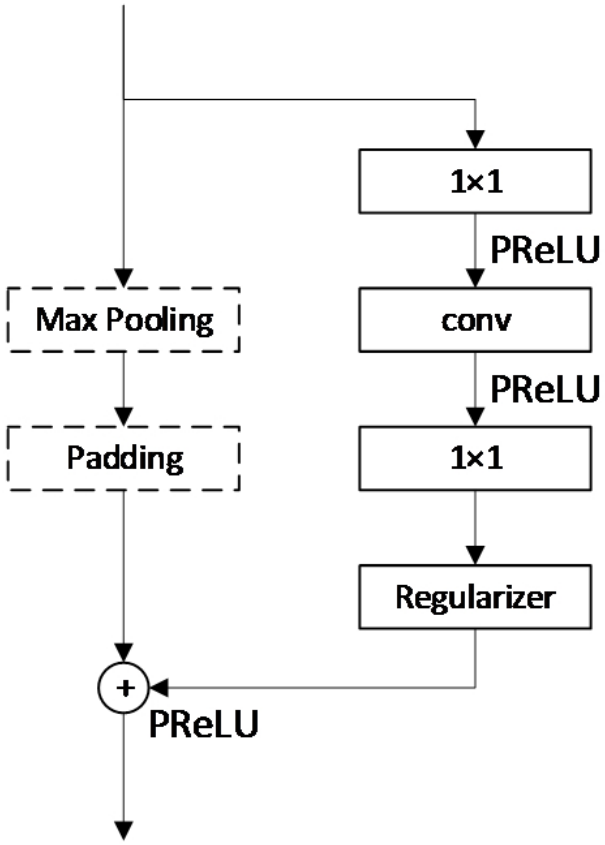

Fig. 3. ENet bottleneck module. conv is either a regular, dilated, or full convolution (also known as deconvolution) with 3 × 3 filters, or a 5 × 5 convolution decomposed into two asymmetric ones.

- **Epochs:** Training was conducted for 10 epochs.
- **Data Augmentation:** Further augmentations, such as rotation and scaling, were applied during training to increase robustness.
- **Validation:** After each epoch, the model's performance was validated on the validation set using Dice Loss as the primary metric.

I. Loss Function

The **Dice Loss** was employed to address class imbalance and prioritize segmentation accuracy. The Dice Loss is defined as:

$$\text{Dice Loss} = 1 - \frac{2 \cdot \text{Intersection} + \text{Smooth}}{\text{Union} + \text{Smooth}}, \tag{1}$$

where the **intersection** represents the overlap between predicted and ground-truth lane pixels, and the **union** is the sum of all predicted and actual pixels. A smoothing factor (1×10^{-5}) was used to ensure numerical stability. The Dice Loss is particularly suitable for lane detection due to its sensitivity to small foreground regions.

J. Hardware Setup

Experiments were performed using the following hardware and software configuration:

- **Hardware:** Google Colab CPU.
- **Software:** Python 3.8 and PyTorch 1.11 with supporting computer vision libraries.
- **Visualization Tools:** Matplotlib was used to plot training loss and evaluate model performance over epochs.

K. Post-Processing

The output of the segmentation model was refined using:

- **Thresholding:** Segmentation outputs were binarized using a threshold to identify lane regions.
- **Non-Maximum Suppression (NMS):** Removed redundant lane predictions to enhance accuracy.
- **Curve Fitting:** A RANSAC-based curve fitting algorithm was applied to smooth lane predictions.

L. Training Performance

The training process involved tracking Dice Loss values over 10 epochs, demonstrating steady convergence. Loss trends were visualized using line plots, showcasing improved segmentation performance as training progressed.

IV. Results and Discussion

The TuSimple lane dataset is currently the only large-scale dataset for evaluating deep learning approaches on lane detection tasks. It comprises:

- **Training Data:** 3626 images.
- **Testing Data:** 2782 images.
- **Conditions:** Captured under good and medium weather conditions.
- **Road Types:** 2-lane, 3-lane, 4-lane, and multi-lane highways, at various times of the day.

For each image, the dataset provides 19 preceding frames, although these are not annotated. Annotations are supplied in JSON format, specifying the x-coordinates of lane points at a series of discretized y-coordinates. The following lanes are annotated in each image:

- Current (ego) lanes.
- Adjacent left and right lanes.
- An additional 5th lane is included during lane changes to minimize ambiguity.

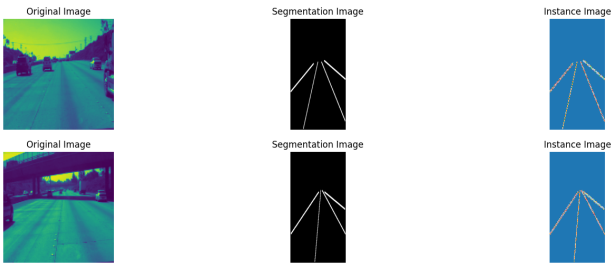

Fig. 4. The comparison between Original Image, Segmentation Image, and Instance Image.

A. Calculate Dice Loss

To evaluate the performance of the model during training, a histogram of the **Dice Loss** values was generated. This histogram provides a visual representation of the distribution of Dice loss across multiple epochs, highlighting the changes in segmentation accuracy over time. As the model learns, the Dice loss should ideally decrease, reflecting improved overlap between the predicted segmentation and the ground-truth lane pixels. The histogram helps in identifying the stability and convergence of the training process, showcasing how the Dice loss fluctuates throughout the training phases. A lower Dice loss corresponds to better model performance, as it signifies a higher intersection between the predicted and true lane pixels, which is crucial for effective lane detection.

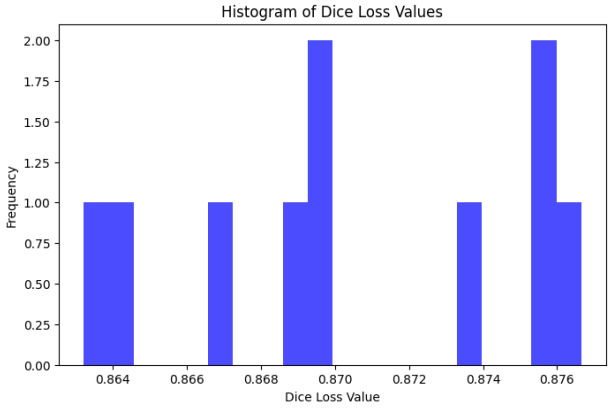

Fig. 5. Visualization of Loss During Training. Dice Loss over training epochs. The model converges as the loss decreases over time.

The **Dice Loss over Epochs** plot was used to monitor the model's performance throughout the training process. As shown in the figure, the Dice Loss value generally decreases with each epoch, indicating that the model is improving in terms of accurately predicting the lane segmentation. Initially, the model struggles with higher loss values due to poor predictions, but as the epochs progress and the model learns, the Dice loss gradually reduces, suggesting that the model is better at identifying the lane markings. The smoother curve of the Dice loss reflects the model's convergence towards an optimal solution, where the intersection between the predicted segmentation and the ground truth becomes larger. This decreasing trend in Dice Loss is a key indicator of the effectiveness of the training process applied.

The ENet model was trained for a total of 10 epochs on the given semantic segmentation task. The model consists of a series of layers, including convolutional layers (Conv2d), batch normalization (BatchNorm2d), activation functions (PReLU), and upsampling layers (ConvTranspose2d), resulting in a total of 359,524 trainable parameters. The model's architecture was designed to efficiently process input images and produce segmentation maps. The input size to the network was $1 \times 4 \times 128 \times 128$, and the output was $1 \times 2 \times 128 \times 128$, representing the two output classes for segmentation.

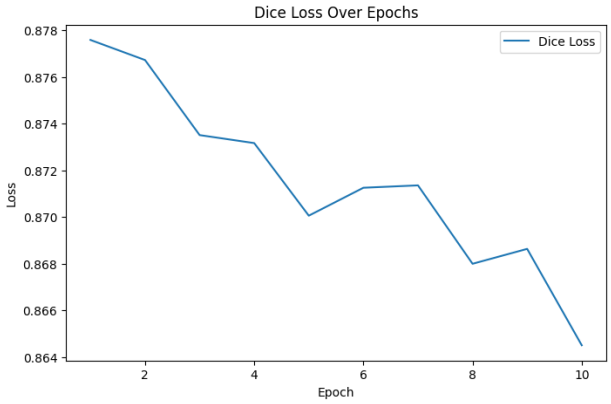

Fig. 6. Dice Loss over Epochs: This plot illustrates the decrease in Dice Loss as the model improves its lane segmentation accuracy over multiple epochs of training. A steady reduction in Dice Loss indicates the model's convergence towards a better solution for lane detection.

The training progress was monitored through the loss function, which showed a slight decrease from 0.8932 at epoch 1 to 0.8777 at epoch 9, with a small increase to 0.8788 at epoch 10. The following table summarizes the training loss at each epoch:

TABLE II
TRAINING LOSS FOR EACH EPOCH

Epoch	Loss
1	0.8932
2	0.8865
3	0.8860
4	0.8860
5	0.8872
6	0.8850
7	0.8802
8	0.8830
9	0.8777
10	0.8788

The model exhibited stability throughout the training, with the loss fluctuating within a narrow range, demonstrating that it was effectively learning to segment the input images. Despite the minor fluctuations in the latter epochs, the overall trend indicates the model's convergence towards an optimal solution.

V. CONCLUSION

The Lane detection project using ENet comprises a semantic segmentation task with a dataset of three thousand images. The model was able to reduce the training loss from 0.8932 in the first epoch to 0.8788 in the final epoch, achieving a satisfactory level of performance in 10 epochs. Given its relatively low number of parameters (359,524), ENet proves to be an efficient model for real-time semantic segmentation, particularly suitable for resource-constrained environments.

The results suggest that the ENet architecture is effective for this task, although further experimentation could involve extending the training to more epochs or applying different optimization techniques such as a higher learning rate and using more GPU's to further improve performance. Overall, the model's architecture and its training results highlight its potential for real-time deployment in practical applications, such as autonomous driving or robotic vision, where computational resources are limited, and processing speed is crucial.

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