Cs 512 Project Proposal

- **Title:** Improving Confidence of Lane Detection With LaneIoU

- **Team Members:**
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- **Reference Paper:** CLRerNet: Improving Confidence of Lane Detection with LaneIoU. This paper was authored by Hiroto Honda & Yusuke Uchida and published by Computer Vision and Pattern Recognition (CVPR) in 2022.

- **Description of the Problem:**
- **Misaligned Confidence Scores**: Existing anchor-based lane detectors (like CLRNet) often predict correct lane positions. However, their confidence scores don't align well with the overlap (IoU) between predictions and ground-truth lanes.
- **Weak IoU Metrics**: Metrics like LineIoU (used in training) fail to capture geometric details—especially for tilted or curved lanes, leading to poor learning of confidence scores.
- **Suboptimal Training**: Because confidence scores are used for training sample assignments, misleading similarity measures result in inefficient or incorrect assignments between predicted and ground-truth lanes.
- **Underperformance on Complex Lanes**: These issues reduce performance, especially on challenging lane types (e.g., curves or extreme angles), limiting generalization and accuracy on benchmarks like CULane and CurveLanes.

- **Approach to the Problem:**

1. **Design a Better Similarity Metric (LaneIoU)**
   Introduce LaneIoU, a novel IoU metric that adjusts for lane tilt and curvature. Unlike prior methods (e.g. LineIoU), LaneIoU computes row-wise overlaps while accounting for lane angles, making it more aligned with real segmentation-based IoU.
2. **Integrate LaneIoU into the Training Pipeline**
   Use LaneIoU in three key parts of the training process:

- As a loss function to directly supervise lane shape prediction
- As a cost function during sample assignment
- To calculate dynamic-k, i.e., how many predictions should be assigned to each ground-truth lane

  This improves training accuracy and better confidence in learning.

3. **Train the Model to Learn Meaningful Confidence Scores**
   Modify the model (CLRNet → CLRerNet) to learn confidence scores that reflect actual IoU.

This leads to more reliable lane detection, especially when predictions are close to ground truth but tilted or curved.

4. **Benchmark with Strong Protocols**
Ensure evaluation fairness by using multi-seed training, 5-fold cross-validation, and a consistent method to select the optimal confidence threshold. This provides reliable, reproducible results and demonstrates the real-world effectiveness of LaneIoU and CLRerNet.

- **Datasets:**
  1. CULane
  2. CurveLanes
  3. TuSimple
- **Responsibilities of the Members:**
  - Riddhi Das: Model Implementation and Presentation.
  - Madhur Gusain: Testing Analysis and Training.

- We will be implementing the original paper in our project to get the desired results.

- **References:**

Reference Papers:

1. Main Paper – CLRerNet: Improving Confidence of Lane Detection with LaneIoU.
2. Supporting Paper – Laneformer: Object-aware Row-Column Transformers for Lane Detection.

Software & Frameworks

- Python – Main programming language.
- PyTorch (assumed based on Transformer and CNN-based architecture usage)
- Deformable DETR for transformer-based object detection.
- Faster R-CNN as a base object detector (for person/vehicle detection)
- ROIAlign from `torchvision.ops` for ROI feature extraction
- ResNet (18, 34, 50) as CNN backbones