Project Report: Evaluation of Enhanced Q-Table in Neural Network Training

Objective:
The primary goal of this phase was to evaluate the effectiveness of the improved Q-table (with a more uniform distribution of actions) compared to the original Q-table, using neural network training. The focus was on understanding whether the enhanced dataset leads to better network performance in both critical and general scenarios, and whether training on the entire dataset provides robust results.

Methodology:

1. **Dataset Preparation:**
   - **Original Dataset:** Derived from the original Q-table with a distribution skewed toward "COC" (Continue on Course), which accounted for 70% of the actions, with the remaining 30% split between "WL" (weak left), "WR" (weak right), "SL" (sharp left), and "SR" (sharp right).
   - **Enhanced Dataset:** Created using the modified Q-table with a more balanced action distribution (~20% for each action).
2. **Neural Network Training:**
   - **Training Strategy:** Two Multi-Layer Perceptron (MLP) models were trained for each of the 40 subsets of the dataset (originally divided based on combinations of `pra` and `tau`). For each subset:
     - One MLP was trained using the original dataset.
     - Another MLP was trained using the enhanced dataset.
   - **Cross-Testing:** After training, each network was evaluated on both its respective test set and the test set of the other dataset. This allowed direct comparison of performance and generalization capabilities.
3. **Additional Experiments:**
   - **Complete Dataset Training:** Two additional networks were trained on the entire dataset (one for the original and one for the enhanced dataset). Input features included `pra` and `tau`, encoded using one-hot encoding.
   - **Loss Functions:** Networks were trained with both custom MSE

    (Mean Squared Error) and Cross-Entropy (CE) losses to test the impact of different optimization objectives. For CE, the problem was treated as a classification task with one-hot encoded outputs.
  - **Confusion Matrices:** Generated to analyze network performance, highlighting specific actions where errors were more frequent. This provided insights into whether certain datasets better addressed critical scenarios (e.g., collision avoidance).
4. **Normalization:** Input features were normalized across all datasets, while output normalization was applied only within each individual dataset, as the input domain is shared, but the output scaling is dataset-specific.

Key Observations:

1. **Dataset Comparison:**
   - Enhanced datasets aimed to address the skewness of the original Q-table, providing a more balanced representation of actions. This adjustment was expected to improve network performance, particularly in critical scenarios.
2. **Cross-Testing Results:**
   - Networks trained on the enhanced dataset demonstrated comparable or improved performance when tested on both datasets, suggesting better generalization capabilities.
   - Confusion matrices revealed that networks trained on the enhanced dataset made fewer errors on critical actions (e.g., sharp turns or avoiding collisions).
3. **Complete Dataset Training:**
   - Training on the entire dataset (with one-hot encoded `pra` and `tau`) showed promising results for both datasets, though the enhanced dataset provided slightly more consistent accuracy across different scenarios.
4. **Impact of Loss Functions:**
   - Networks trained with CE loss, treating the problem as classification, performed well in distinguishing actions, especially for critical scenarios.

- Custom MSE provided smoother outputs but sometimes struggled with imbalanced datasets, emphasizing the need for careful loss function selection.