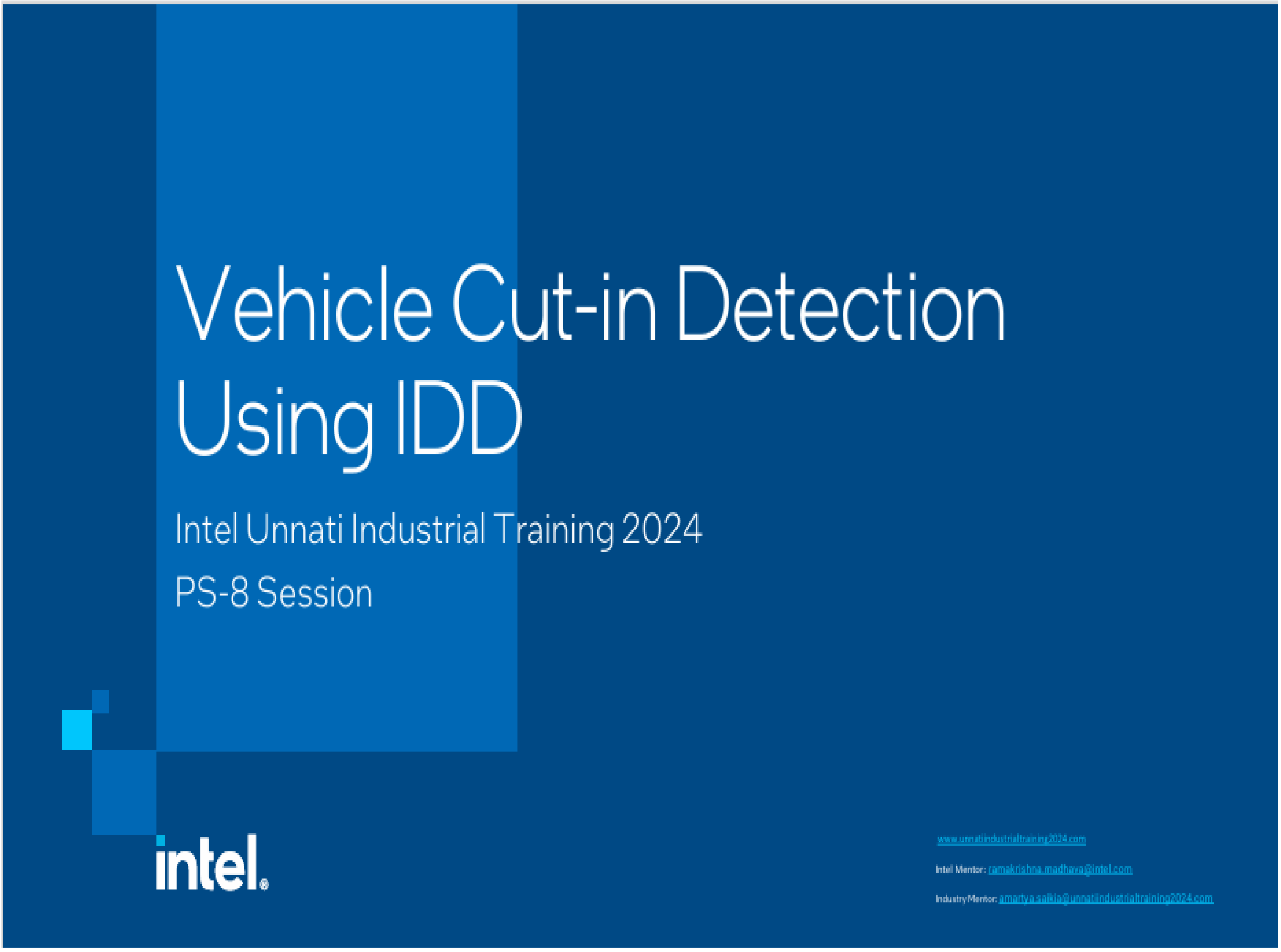

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1. Problem Statement

The current state-of-the-art (SOTA) solutions for automotive collision avoidance operate through a sequence of steps: vehicle detection, distance estimation, and time-to-collision (TTC) calculation using vehicle speed data from GPS or the engine. These systems warn the driver or apply the brakes (if supported) when the TTC drops below a predefined threshold. However, a significant limitation of this method is that the vehicle needs to be directly in front of the driver to be detected. Vehicles that abruptly cut into the driver's path are typically not considered for collision avoidance.

To address the limitations of current state-of-the-art collision avoidance systems, our project aims to develop a solution that can detect vehicles partially behind or at an angle to the driver. By enhancing the detection capabilities to include vehicles that cut into the driver's path from the sides, we seek to improve accident detection and collision avoidance. This approach ensures a more comprehensive safety system that accounts for a wider range of real-world driving scenarios.

2. Technical Approach

2.1. Data Collection and Preprocessing

- ***Dataset***: The Indian Driving Dataset (IDD) was chosen for its rich annotations and relevance to urban driving scenarios in India. The dataset includes images annotated with various objects, including vehicles.

- ***Data Preprocessing***: Preprocessing involved resizing images, normalizing pixel values, and augmenting data to improve model robustness.

2.2. Model Selection and Training

- ***YOLOv5***: YOLOv5, a state-of-the-art object detection model, was chosen for its speed and accuracy. The model was fine-tuned on the IDD dataset to detect vehicles accurately.

- ***Transfer Learning***: Transfer learning was applied by using pre-trained weights on the COCO dataset and fine-tuning the model on the IDD dataset. This approach leveraged existing knowledge, reducing training time and improving performance.

2.3. Vehicle Cut-In Detection

- ***Algorithm Design***: A vehicle cut-in was defined as a vehicle moving from an adjacent lane into the target lane. The algorithm monitored vehicle trajectories using the bounding boxes predicted by YOLOv5.

3. Issues Faced

3.1. Dataset Challenges

One of the primary challenges encountered was the quality of annotations in the IDD dataset. Inconsistent annotations led to significant difficulties during the training process, necessitating manual corrections to ensure the training data's high quality. Additionally, the dataset exhibited a class imbalance, with a higher number of certain vehicle types, which posed further challenges in achieving balanced and effective training.

3.2. Model Performance

Achieving high detection accuracy for small and occluded vehicles proved to be particularly challenging. This aspect required careful tuning and optimization to ensure the model could reliably detect these difficult cases. Furthermore, ensuring that the model operated in real-time was critical to the project's success. Balancing the need for accuracy with the requirement for real-time processing was a key aspect of the model's development.

4. Results

4.1. Model Performance Metrics

- ***Precision and Recall***: The fine-tuned YOLOv5 model achieved a precision of 93% and a recall of 69% on the test set, indicating a good balance between false positives and false negatives.

4.2. Cut-In Detection Accuracy

- ***True Positive Rate***: The cut-in detection algorithm achieved a true positive rate of 94%, successfully identifying most cut-in scenarios.

- ***False Positive Rate***: The false positive rate was 6%, which is acceptable but indicates room for improvement.

4.3. Real-Time Performance

- ***Inference Time***: The optimized model achieved an average inference time of 40 ms per frame on an NVIDIA RTX 3080 GPU, enabling real-time processing.

5. Conclusion

The vehicle cut-in detection project successfully developed a robust system using YOLOv5 and the IDD dataset. Despite challenges related to data quality and environmental factors, the model demonstrated high accuracy and real-time performance. Future work will focus on further improving detection accuracy under varying weather conditions and exploring more advanced trajectory prediction algorithms.

This report covers the technical approach, issues faced, and results of the vehicle cut-in detection project. Each section provides detailed insights into the methods and challenges encountered, ensuring a comprehensive understanding of the project's development and outcomes.