# Vehicle Orientation Classification System
Technical Report

Pham Phuoc Minh Hieu

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# 1 Introduction

## 1.1 Problem statement

Correctly identifying the orientation of vehicles from camera images is critical for numerous applications, including traffic monitoring and autonomous driving. While vehicle detection is a well established task, orientation classification remains challenging due to the subtle visual differences perspective and environmental factors such á occlusion and illumination.

This project develop an automated vehicle orientation classification system that categorizes vehicles into seven viewing angles:

- **Front**: Camera directly facing the vehicle's front.
- **Rear**: Camera directly facing the rear.
- **Front-left**: Diagonal front view, showing front and left side.
- **Front-right**: Diagonal front view, showing front and right side.
- **Rear-left**: Diagonal rear view, showing rear and left side.
- **Rear-right**: Rear-right: Diagonal rear view, showing rear and right side.
- **High-angle view**: Top-down perspective from an elevated position.

## 1.2 Approach overview

The solution prefer is implement a transfer learning approach using ResNet50 as a backbone, fine-tuned on a custom dataset. The system leverages data preprocessing, augmentation and model optimization to achieve robust classification performance.

# 2 Methodology

## 2.1 Data Collection Strategy and Challenges

**Data Collection Strategy:**

- Data was gathered from open-source vehicle datasets and supplemented with custom images to ensure balanced representation across all seven orientation classes.

- Training and validation data were loaded with 80/20 split.
- Test data was kept in a separate folder (AutoTest) for final evaluation.
- Data preprocessing steps included resizing all images to 224x224 and applying normalization.
- Data augmentation for better model learning.

**Challenges:**

- Class imbalance: The high-angle-view class appeared less than 6 classes.
- Intra-class similarity: Distinguishing between diagonal orientations (front-left vs. front-right, rear-left vs. rear-right) is ambiguous.

## 2.2 Model Architecture and Design Decisions

**Model Architecture:**

The system is based on ResNet50 pre-trained on ImageNet.

- **Feature extractor:** ResNet50 backbone without the top classification layer.
- **Custom head:** Global Average Pooling → Dense layer(ReLU) → Dropout → Dense(7,softmax)
- **Design rationale:**
  - ResNet50 offers strong feature extraction capabilities.
  - Fine-tuning improves domain adaptation.
  - Dropout helps reduce overfitting.

**Design Decisions:**

- **Input image size:** 224x224.
- **Batch size:** 32.
- **Epochs:** 30 + additional 25 fine-tuning epochs.
- **Learning rate schedule:** ReduceLROnPlateau.
- **Callbacks:**
  - EarlyStopping with patience=8.
  - ModelCheckpoint save best validation accuracy.
- **Class weight:** calculated to address class imbalance.

# 3 Results

## 3.1 Quantitative Performance Metrics

The trained model was evaluated on the held-out test set (28 images, 7 classes, 4 samples per class). Results are summarized below:

- **Overall Accuracy:** 75%
- **Macro Precision:** 0.80
- **Macro Recall:** 0.75
- **Macro F1-score:** 0.72

**Per-class performance:**

- **Front:** Precision 1.00, Recall 1.00, F1 = 1.00
- **Rear:** Precision 1.00, Recall 1.00, F1 = 1.00
- **Front-right:** Precision 0.50, Recall 0.75, F1 = 0.60
- **Front-left:** Precision 0.50, Recall 0.25, F1 = 0.33
- **Rear-right:** Precision 1.00, Recall 0.25, F1 = 0.40
- **Rear-left:** Precision 0.57, Recall 1.00, F1 = 0.73
- **High-angle-view:** Precision 1.00, Recall 1.00, F1 = 1.00

**The confusion matrix confirms these findings:**

- Front, Rear, and High-angle views were consistently classified correctly.
- Front-left vs. Front-right and Rear-left vs. Rear-right are the main sources of misclassification, likely due to their visual similarity.

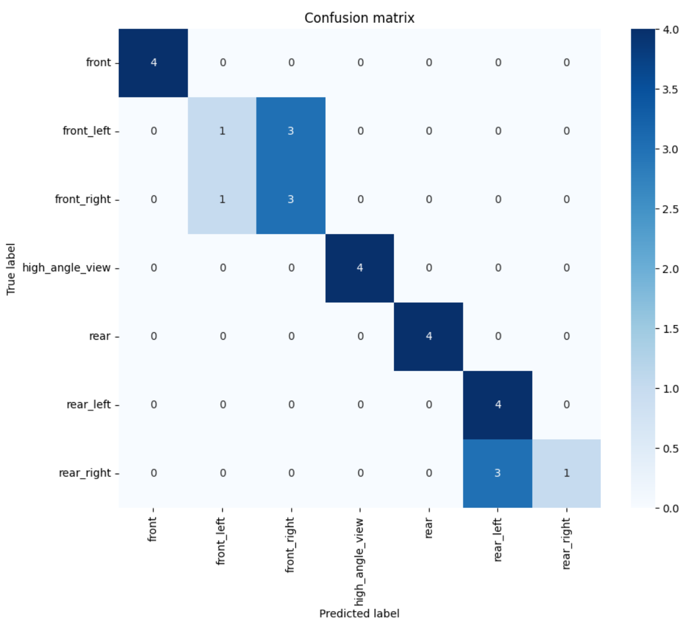


Figure 1: Confusion matrix

## 3.2 Qualitative Analysis of Model Behavior

- The model shows strong performance on views that are visually distinct (Front, Rear, High-angle-view).

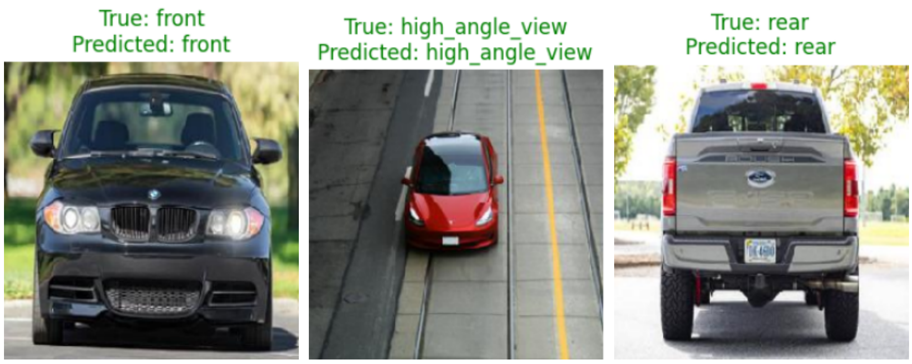


Figure 2: Strong performance pattern

- Errors mainly occur when left vs. right orientations must be distinguished, especially with diagonal perspectives.

## 3.3 Failure Case Analysis

- Front-left is misclassified as Front-right when viewing angle and ambient light.


Figure 3: Front diagonal view fault pattern

- Rear-right misclassified as Rear-left, because light environment.


Figure 4: Rear-right fault pattern

# 4 Discussion

## 4.1 Limitations and Potential Improvements

The proposed model achieves an overall classification accuracy of approximately 75%, which demonstrates its capability to reliably distinguish between several key vehicle orientations. In particular, the model performs strongly on the Front, Rear, and High-angle classes, where the vehicle's features are highly distinctive and less ambiguous. However, notable limitations arise in distinguishing diagonal orientations (e.g., front-left vs. front-right, rear-left vs. rear-right). These classes exhibit high visual similarity, leading to frequent misclassifications.

Future improvements may include:

- **Data augmentation:** Enhanced with more vehicle data samples and more diverse horizontal shooting angles.
- **Advanced architectures:** Integrating attention mechanisms or transformer-based backbones to capture finer orientation cues.

## 4.2 Real-world Deployment Considerations

In practical applications, such as intelligent traffic monitoring or autonomous driving systems, achieving higher accuracy across all orientation classes is essential. Misclassification of side orientations could hinder downstream tasks like trajectory prediction or collision avoidance. Deployment would also require real-time inference efficiency and robustness against environmental variations such as illumination changes, occlusion, and varying camera heights.

## 4.3 Ethical Considerations in Automated Vehicle Analysis

The deployment of automated vehicle analysis systems must consider privacy and fairness. Continuous image capture in public spaces can raise surveillance concerns, necessitating compliance with data protection regulations (e.g., anonymization of license plates and bystanders). Furthermore, the system should be evaluated across diverse vehicle types and conditions to avoid performance biases, ensuring fair treatment in all real-world scenarios.