Software System Design

VIROC [Vehicle Identification OCR]

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Author:	Noah Gardner

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Introduction

This document outlines the system design for **VIROC [Vehicle Identification OCR]**. It details the architectural decisions, components, data models, and operational considerations for the project.

Overview

The purpose of the VIROC system is to provide a platform for vehicle license plate OCR that allows users to submit images that contain license plates and receive back result license plate text and associated confidence scores. It is intended for use in an application stack that requires reading license plate data from live camera views to enhance customer experience and operational efficiency.

Goals and Objectives

- **Goal 1:** To provide a scalable platform for vehicle license plate detection and OCR.
- **Goal 2:** To ensure high accuracy in license plate recognition.
- **Goal 3:** To deliver a user-friendly interface for data submission and results retrieval.

Non-Goals

Model training is out of scope for this project. The system will utilize pre-trained models for license plate detection and OCR.

Glossary

- **API:** Application Programming Interface
- **OCR:** Optical Character Recognition

Requirements

This section details the functional and non-functional requirements that the system must satisfy.

Functional Requirements

Describe the specific behaviors and functions of the system. Use a numbered list for clarity.

1. **Submission API** - The system must provide an API endpoint for users to submit images containing vehicle license plates returning JSON formatted results.

Problem Cases

The system should handle clear images of:

- **Case 1:** a single license plate.
- **Case 2:** multiple license plates.

The system may not be able to handle images with:

- **Case 3:** no license plates.
- **Case 4:** low resolution or poor lighting conditions.
- **Case 5:** obscured or damaged license plates.
- **Case 6:** licenses not attached to vehicles, such as those on a wall or in a parking lot.

High-Level Architecture

This section provides a bird's-eye view of the system's architecture.

Architectural Diagram

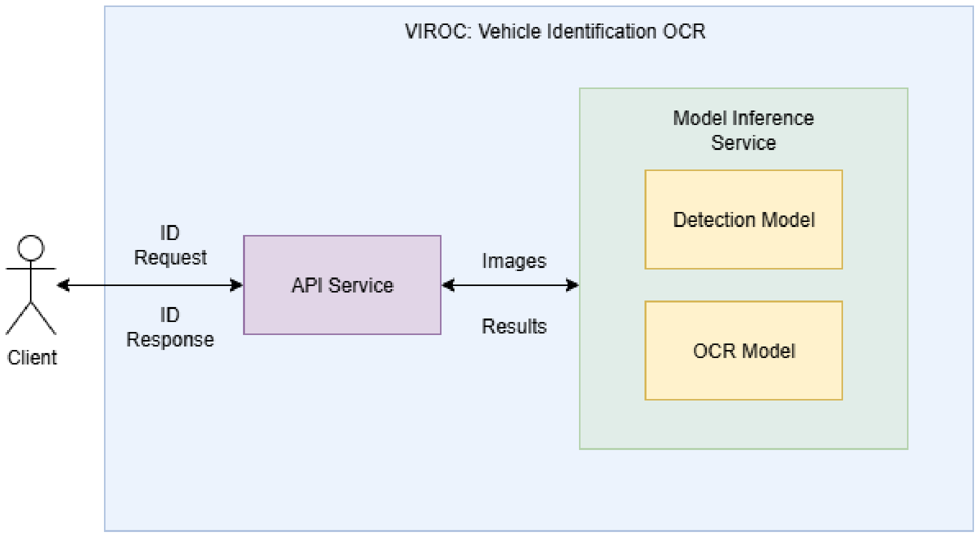


Figure 1: High-Level System Architecture.

System Components

- **API Service:** A FastAPI service that handles incoming requests, processes images, and interacts with the model inference service.
- **Model Inference Service:** A service that uses NVIDIA TritonServer to perform inference on pre-trained models for license plate detection and OCR.
- **Detection Model**: A model that detects license plates in images.
- **OCR Model**: A model that performs OCR on detected license plates to extract text.

Technology Stack

- **Backend:** Python, FastAPI
- **Model Inference:** NVIDIA TritonServer, Models from HuggingFace (GOT OCR v2, YOLOv5 [fine-tuned for license plates])
- **Infrastructure:** Docker

Results

I made a benchmark using 1000 images from the CCPD2019 dataset, which contains license plates from China. Results saved in ‘results/benchmark_results.csv’. I analyzed the results with for the metrics of prediction time (latency), accuracy, and Levenshtein ratio (a similarity measure between two strings). Accuracy measures the percent of time the model predicted the exact license plate (the model is able to detect the middle dot in the license plate ·, so it was removed for analysis). There was no mention of using the CCPD2019 or other license plate datasets for the training of the GOT OCR v2 model in the original paper.

Metric	**Value**
Average Prediction Time (ms)	1647.23
Accuracy	64.90%
Average Levenshtein Ratio	90.25%

Limitations and Potential Improvements

I did not finish implementation for the case where no license plate is visible. Confidence scores and thresholds would help here, but the parameters were tuned for performance on the stitched image test case.

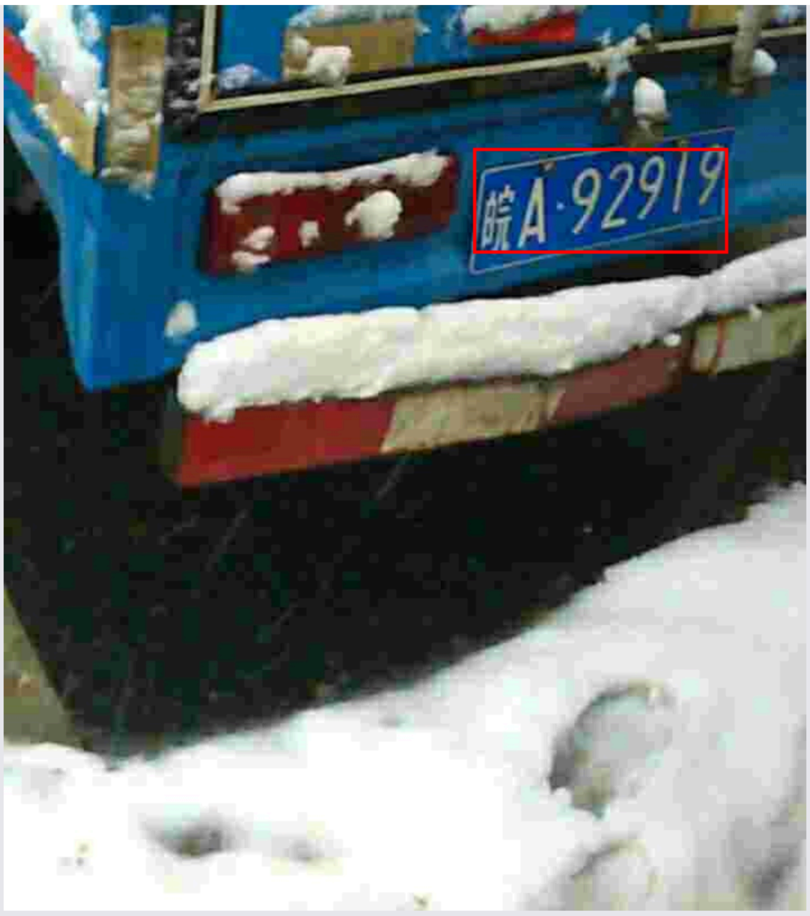
Bigger benchmarks are required to determine the performance of the system under load and also to determine production accuracy. Tracing and other metrics would be useful. Benchmarks would also allow us to compare and contrast different OCR models on our metrics, especially with access to production data.

I was unable to deploy the OCR model to the Triton server. If I was building this application for production I would take the time to find a model that I can deploy more easily, but this is good for a proof of concept.

The detection model is fast (less than 50ms per image) but the OCR model is slow (around 1 second per detected license plate).

Multi-plate detection does not use a very good algorithm (seeing if the corners of boxes are within a certain range of other boxes), needs more research. Also the parameters are not tuned for dataset performance, rather it was tuned to pass the test case for the stitched image.

Successes



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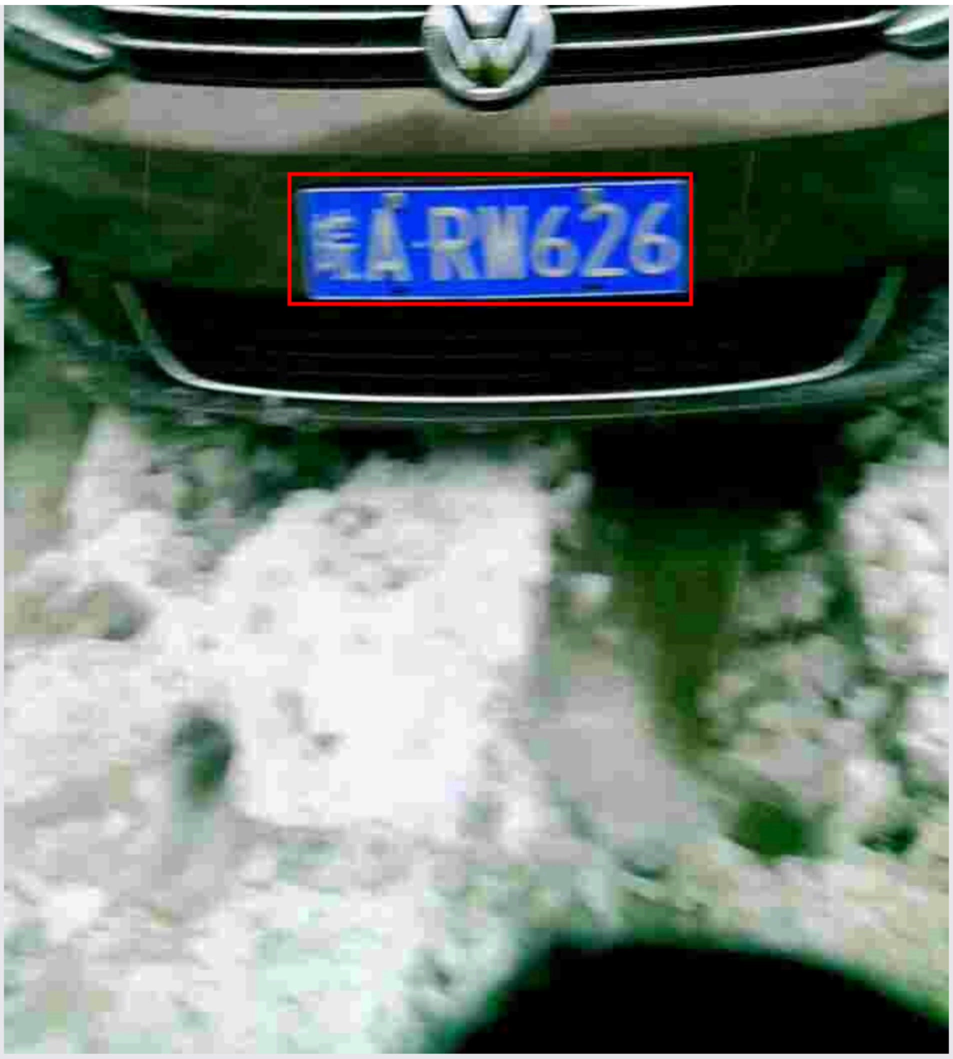
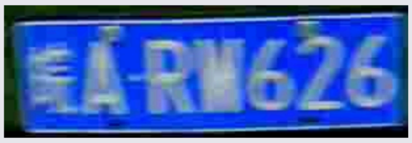
Failures





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AI Usage Disclosure

Gemini 2.5 Pro generated the initial file for the system design template.

Github Copilot autocomplete was used during development of python scripts.

Claude generated “decode_ccpd_labels.py”