Automatic Number Plate Recognition & Traffic Red-Light Running Violation Detection

Mid-term Project Report - Group 5

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***Abstract*—This project aims to develop an Automatic Number Plate Recognition and Traffic Red-Light Running Violation Detection system, addressing the need for enhanced traffic monitoring and law enforcement tools. Our methodology encompasses a comprehensive approach, beginning with the collection and manual labeling of a diverse dataset of vehicle images. We then proceed to select and implement a deep learning model tailored for accurate number plate recognition. Up to the midterm phase, we have focused on assembling a robust dataset, manually annotating images for training, and choosing an appropriate deep learning model based on ResNet for its accuracy in static image analysis. Testing of the model has shown promising results in identifying number plates from various types of vehicles under different conditions. This work lays a solid foundation for future phases, which will explore real-time detection capabilities and further enhancements.**

***Index Terms*—ANPR, Traffic Violation Detection, OCR**

I. Introduction

The development of Automatic Number Plate Recognition (ANPR) and Traffic Red-Light Running Violation Detection systems represents a significant leap forward in using technology to enhance road safety and enforce traffic laws. Our project aims to integrate these technologies to identify and report vehicles violating red-light signals automatically. Achieving this goal involves leveraging advanced computer vision and deep learning techniques to ensure high accuracy and reliability under diverse conditions.

Our methodology includes collecting a diverse set of vehicle images, manually annotating them, choosing an effective deep learning model, and then training and testing this model. Until the midterm, our efforts have concentrated on data preparation and the initial selection and testing of a ResNet-based model, chosen for its proven accuracy in image recognition tasks. This work establishes the foundation for the next project phase, focusing on real-time detection capabilities.

This report outlines our progress, including the challenges faced and the preliminary results obtained, setting the stage for future developments in real-time ANPR and violation detection systems.

II. Problem Statement

In urban environments, traffic violations, particularly running red lights, significantly contribute to accidents and traffic congestion, posing a challenge for law enforcement agencies in monitoring and enforcing traffic laws effectively. Traditional methods rely heavily on manual observation and are both labor-intensive and prone to human error, leading to inconsistent enforcement and limited coverage. The need for an automated solution is evident, one that can accurately detect and record traffic violations in real-time, thereby enhancing road safety and traffic flow. However, developing such a system entails overcoming technical challenges, including accurate vehicle and number plate recognition under various environmental conditions, and the seamless integration of these technologies into a real-time monitoring framework. Our project addresses these challenges by proposing an automated system capable of efficient and reliable detection of traffic red-light running violations, alongside automatic number plate recognition.

III. Related Literature Review

The domain of Automatic Number Plate Recognition (ANPR) and traffic violation detection has witnessed considerable research and development efforts, aiming to leverage computer vision and deep learning techniques to automate the monitoring of traffic regulations. Several studies have demonstrated the efficacy of deep learning models, such as Convolutional Neural Networks (CNNs), in achieving high accuracy in number plate recognition tasks. Notably, the ResNet architecture has been highlighted for its deep residual learning framework, which significantly improves the performance in image classification tasks, making it a suitable choice for ANPR systems

In parallel, the challenge of detecting traffic violations, particularly red-light running incidents, has been approached by integrating vehicle detection technologies with real-time traffic signal status recognition. Studies have explored the use of the YOLO (You Only Look Once) framework for its real-time object detection capabilities, allowing for the simultaneous detection of vehicles and traffic lights in video streams

However, while these technologies provide a solid foundation, their integration into a cohesive system that operates effectively in diverse and dynamic urban traffic environments remains a challenge. Issues such as varying lighting conditions, diverse vehicle types, and occlusions pose significant hurdles. Moreover, the need for real-time processing and decision-making in traffic violation detection demands efficient computational models that balance speed and accuracy.

Our project builds upon these foundations, aiming to address the identified gaps by developing a hybrid system that combines the accuracy of ResNet-based models for image-based ANPR with the real-time detection capabilities of YOLO for monitoring traffic violations. This dual approach seeks to harness the strengths of each model to create a robust and efficient system for traffic law enforcement.

IV. Methodology

A. Data Collection

In the initial phase of our project, a focused effort was made to collect a comprehensive and varied dataset of vehicle images, crucial for training our deep learning models with high precision and generalisability. This collection process involved two primary sources:

- **College Main Gate**: We captured several images of vehicles at different times of the day at our college's main gate. This setting provided us with a range of vehicle types, lighting conditions, and vehicle movements, offering a realistic and challenging dataset for our system.
- **Online Datasets**: To augment our collected data and ensure a broader diversity in our dataset, we also incorporated images from existing datasets available on the web. These datasets were selected for their relevance to our project goals, including a variety of number plate designs, vehicle models, and environmental conditions.

This dual-source approach to data collection ensures that our model is exposed to a wide range of scenarios, enhancing its ability to accurately detect and recognize number plates under different conditions.

Fig. 1. Original Image

B. Model Selection: Inception-ResNet-v2

For the pivotal task of number plate recognition within our project, we have chosen the Inception-ResNet-v2 model as our cornerstone. This decision is underpinned by the model's proven capability to handle complex image classification tasks with remarkable accuracy. Inception-ResNet-v2, a convolutional neural network, benefits from training on over a million images from the ImageNet database, covering 1000 diverse object categories. This extensive training has endowed the model with rich feature representations, making it adept at recognizing a wide array of images. The architecture elegantly combines the Inception structure, known for its efficient handling of information at various scales, with Residual connections that alleviate the degradation problem inherent in deep networks. This synergy not only ensures robustness in recognizing intricate patterns within images but also enhances the model's training efficiency. The Inception-ResNet-v2's depth and its ability to integrate multiple sized convolutional filters through residual connections make it an ideal choice for our application, promising high accuracy in detecting and classifying number plates from varied images captured in our dataset.

Fig. 2. Labeled Image

C. Training the model

To adapt the Inception-ResNet-v2 model for our number plate recognition task, we began by preprocessing our images and labels for optimal input into the model, which involved resizing images and normalizing values. The dataset was divided into training and testing sets to ensure effective learning and evaluation. We customized the model by adding dense layers tailored for predicting bounding box coordinates around number plates. The model underwent training with adjustments for loss function and optimizer to enhance performance, followed by saving the trained model for subsequent application.

```
1. Preprocess images and labels:
   a. Resize images to 224x224 pixels.
   b. Normalize image pixel values.
   c. Normalize bounding box labels relative to
      image dimensions.

2. Split dataset into training and testing sets
    (80/20 split).

3. Adapt Inception-ResNet-v2 model:
   a. Load InceptionResNetV2 with pre-trained
      weights, exclude top layers.
   b. Append custom dense layers for bounding
      box prediction.

4. Compile the model:
   - Loss function: Mean Squared Error (MSE).
```

```
    - Optimizer: Adam with learning rate 1e-4.

5. Train the model:
    - Batch size: 10.
    - Epochs: 180.
    - Use TensorBoard for training metrics
        visualization.

6. Save the trained model.
```

*1) **Testing the model:*** In the testing phase, we assess the model's ability to accurately detect number plates in new images. This involves loading the trained model, making predictions on unseen images, de-normalizing the bounding box coordinates, and visually verifying the detection accuracy by drawing bounding boxes on the images. To facilitate this, we developed a pipeline that automates these steps, streamlining the process from image input to detection output.

```
# Load the trained model
model = load_model('object_detection.h5')

# For testing with a new image:
- Load and preprocess the image to fit model
    input requirements.
- Make predictions to obtain normalized bounding
    box coordinates.
- De-normalize these coordinates to fit the
    original image dimensions.
- Draw bounding boxes on the original image to
    denote detected number plates.

# To create a streamlined testing pipeline:
Define a function that:
  - Accepts an image path.
  - Performs preprocessing, prediction, and
      postprocessing.
  - Draws bounding boxes around detected number
      plates.
  - Returns the processed image and coordinates
      for further analysis.
```

Fig. 3. Output Image

V. Future Work

As we progress toward the final term phase of our project, our focus will shift towards enhancing and expanding the capabilities of our Automatic Number Plate Recognition and Traffic Violation Detection system. The following key areas will be addressed to fulfill our project objectives comprehensively:

- **OCR (Optical Character Recognition)** The next critical step involves integrating Optical Character Recognition (OCR) technology into our system. This addition will enable the extraction and interpretation of alphanumeric characters from the detected number plates in the images. By leveraging advanced OCR techniques, we aim to achieve high accuracy in number plate recognition, facilitating the identification of vehicles involved in traffic violations.

- **Web Application Development** To make our system accessible and user-friendly, we plan to develop a web application that allows users to upload images for number plate detection and recognition. This web interface will serve as a platform for users to interact with our system, providing an intuitive and efficient way to process images and view detection results.

- **Extending to Real-Time Detection with YOLO** To enhance our system's applicability in real-world scenarios, we will explore the integration of the YOLO (You Only Look Once) model for real-time number plate detection. YOLO's capability for fast and accurate object detection in video streams will allow our system to identify and track vehicles in live traffic conditions, marking a significant advancement in our project's functionality.

- **Traffic Rules Violation Detection** Building on the foundation laid by the number plate recognition and real-time detection capabilities, our final goal is to implement a mechanism for detecting traffic rules violations, specifically focusing on red-light running incidents. By analyzing the real-time video feed, our system will identify vehicles that cross traffic signals when the light is red, automatically flagging them for traffic violations. This feature aims to contribute to road safety and traffic law enforcement efforts.

VI. Conclusion

Throughout the midterm phase of our project, we have successfully laid the groundwork for an innovative Automatic Number Plate Recognition and Traffic Violation Detection system. By meticulously collecting and labeling a diverse dataset, selecting and training a deep learning model based on the ResNet architecture, and preparing for the integration of real-time detection capabilities, we have established a strong foundation for the next stages of our project. The promising results from our initial model testing underscore the potential of our approach to contribute significantly to enhancing traffic monitoring and law enforcement strategies through technology.

Looking ahead, our focus will shift towards refining our system's accuracy and usability. The integration of Optical Character Recognition (OCR) for alphanumeric extraction from number plates, the development of a user-friendly web application for image processing, and the extension of our model to accommodate real-time video analysis using YOLO are critical milestones. Moreover, implementing a mechanism for detecting traffic rule violations, particularly red-light running, will mark the culmination of our efforts. By achieving these objectives, our project aims to deliver a comprehensive solution that not only advances the field of automated traffic monitoring but also supports the broader goals of road safety and efficient traffic management.

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