NUMBER PLATE RECOGNATION

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1. Background

Number Plate Recognition (NPR), also known as License Plate Recognition (LPR), is an advanced computer vision technology used to automatically detect and recognize vehicle license plates. Our project utilizes YOLO (You Only Look Once) for real-time object detection, enabling accurate identification of license plates in images and video streams. This approach, combined with machine learning and data processing tools like Roboflow, allows for efficient localization of plates under various conditions.

While traditional NPR systems rely on Optical Character Recognition (OCR) to extract alphanumeric characters, our focus is on enhancing detection accuracy and real-time performance through deep learning-based object detection. This technology is crucial for applications in traffic monitoring, security, and automation, reducing the need for manual supervision and improving efficiency.

2. Objectives

Aim
Our project focuses on developing an computer vision-powered Number Plate Recognition (NPR) system that can:

•Detect vehicles and license plates in images and video.
•Extract and display recognized plate numbers in real time.

Research Question
How accurately can deep learning models (YOLO) detect vehicles and license plates, and how effectively can extracted text be displayed for real-time applications?

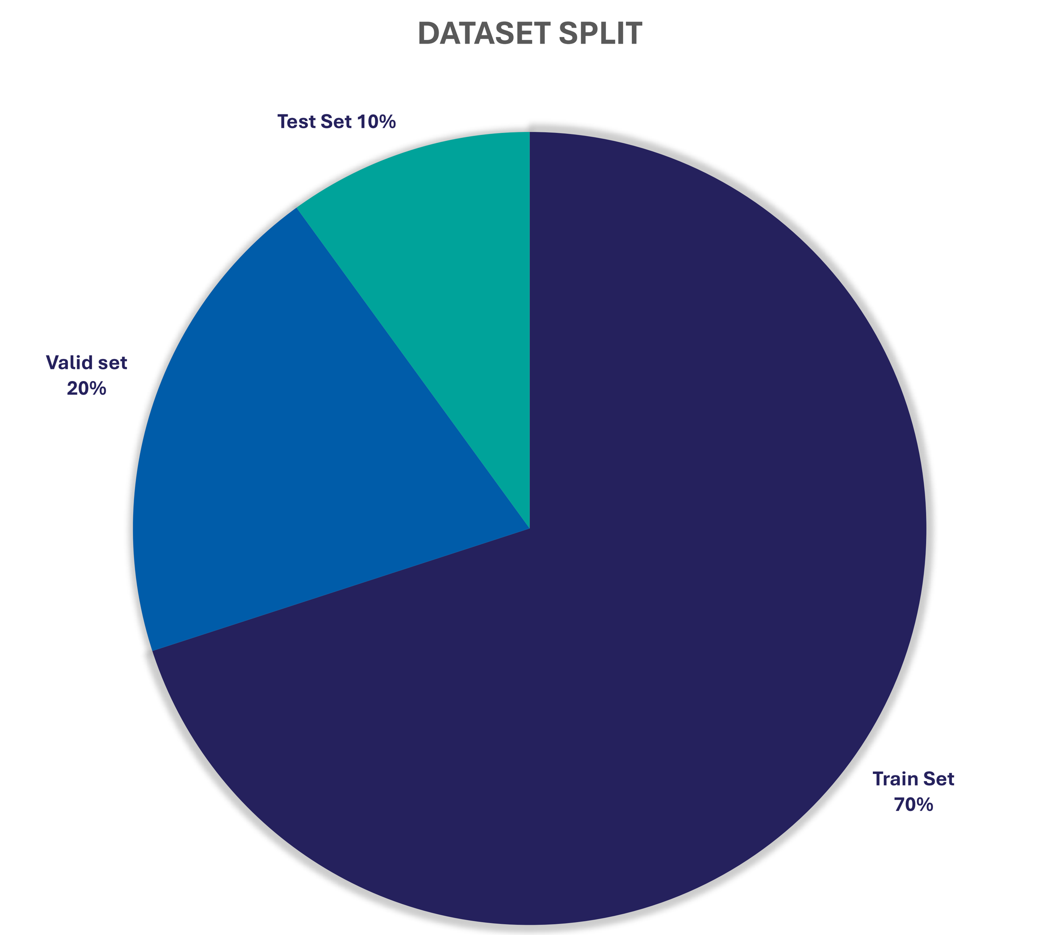
Objective
To create an automated, efficient, and scalable solution for vehicle recognition, enhancing applications in traffic management, security, and smart city systems.

3. Methods

Our project focuses on deep learning-based Number Plate Recognition (NPR) using YOLOv8 for object detection. The system was trained to identify vehicles and license plates in images and video streams. The dataset used for training comes from the Roboflow License Plate Recognition dataset, which contains annotated images of vehicles and plates captured under various conditions. Preprocessing steps included augmentation, resizing, and normalization to improve model performance.

The primary model for detection is YOLOv8 (You Only Look Once), while SVAT was initially considered but later deemed unnecessary. For text recognition, potential integration with OCR was explored to extract plate numbers. The system successfully detects vehicles and license plates in real time, displaying recognized plate numbers with high accuracy. Performance was further optimized through dataset tuning and model fine-tuning, ensuring reliable and efficient recognition.

3a. Dataset



The dataset provides the Train Set (7058 images), Valid Set (2048 images), Test Set(1020 images)

3b. Analysis

The License Plate Recognition dataset from Roboflow Universe provides annotated images designed for training machine learning models in automatic license plate detection and recognition. It includes a diverse range of vehicle license plates captured under different angles, lighting conditions, and environments. The dataset is available in multiple annotation formats, including COCO, VOC, and YOLO, making it compatible with various computer vision frameworks. This dataset is particularly useful for developing YOLOv8-based models for real-time vehicle monitoring, security applications, and smart parking systems.

4. Results

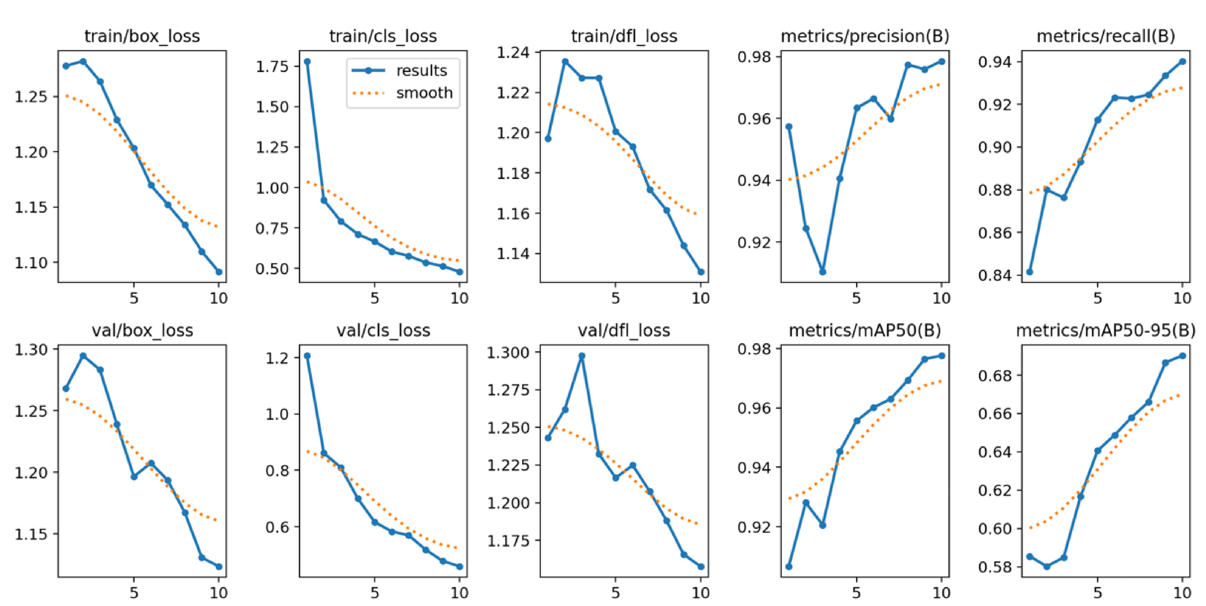


Fig 1. Graphs of YOLOv8 model learning metrics

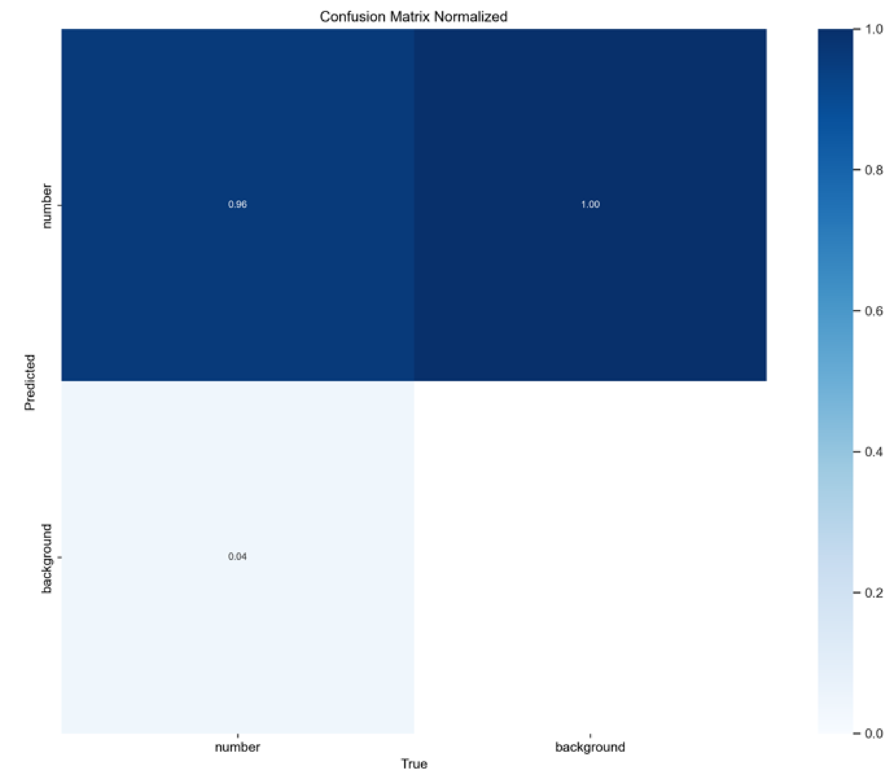


Fig 2. Confusion Matrix Normalized

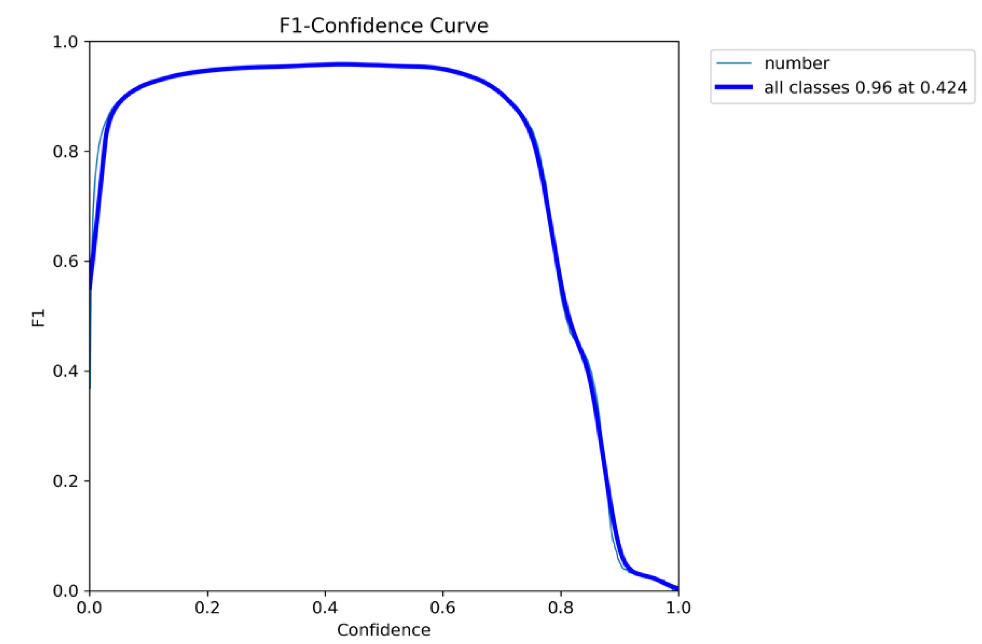


Fig 3. F1- Confidence Curve

Fig 4. Results

The model is learning steadily, and the metrics are improving (fig 1). However, the losses behave less smoothly on the validation data, which may indicate a slight instability or the initial stage of retraining. In general, the model works well, but it remains possible to reduce the 4% loss of numbers (fig 2). The F1-measure graph shows high values over a wide range of confidence, but a slight decrease is observed at high levels (Fig 3).Image analysis with number detection shows that the model successfully finds numbers in various conditions: on different types of cars (cars, buses, police cars), at night, at difficult viewing angles and in a busy environment. However, there are cases when the numbers are determined incorrectly, for example, in conditions of poor lighting or strong reflections. In some images, the model may have mistakenly marked other parts of the car or uncertainly identified the license plate, which may indicate the need for additional optimization (fig. 4).

5. Conclusion

The analysis showed that the developed model for number recognition demonstrates high quality indicators. During the training, there was a steady improvement in metrics, and the final results confirm the effectiveness of the chosen approach. The dataset used included images of cars in various conditions (different angles, lighting, types of cars), which allowed the model to successfully identify the numbers with high accuracy.

Nevertheless, the detected errors in detection on complex frames indicate possible areas of improvement. In particular, additional image processing techniques such as contrast enhancement or glare filtering can improve accuracy in night and illuminated scenes. In addition, balancing the training data and expanding the set of examples with atypical numbers can help the model better adapt to a variety of conditions.

In general, the goal of the work — to build a model capable of effectively recognizing car license plates in real conditions — has been achieved. However, further optimization will improve its stability and accuracy in complex scenarios.

References

Roboflow

Real-Time Automatic Number Plate Detection

Understanding Automated Number Plate Recognition Technology

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