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# Improved YOLOv8 algorithm for vehicle image target detection based on learning rate optimisation strategy

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**Abstract.** Vehicle image target detection is of great significance in the field of computer vision, which is mainly applied in the fields of traffic safety, intelligent traffic management and automatic driving. This study adopts a learning rate decay strategy for the YOLOv8 algorithm, which achieves the purpose of dynamically adjusting the learning rate. Through the analysis of model confusion matrix, F1 confidence, precision confidence, accuracy, recall, and recall confidence curve, the results show that the YOLOv8 algorithm adjusted by the learning rate attenuation strategy is able to efficiently and accurately detect and identify the car target in the image, and all the evaluation indexes have reached the optimal level. Comparison of the target detection results with the labels in the test set verifies that the optimised learning rate YOLOv8 algorithm achieves 100% prediction accuracy, successfully identifying and labelling the car target in the image. In conclusion, the learning rate optimised YOLOv8 algorithm performs well in vehicle image target detection and provides an effective solution for efficient and accurate car recognition.

**Keywords:** YOLOv8, Learning rate optimisation strategy, Target detection.

## 1. Introduction

Vehicle image target detection is an important research direction in the field of computer vision, and its background mainly stems from the needs of traffic safety, intelligent traffic management, automatic driving and other applications [1]. With the acceleration of urbanisation and the increasing penetration of cars, problems such as traffic congestion and frequent accidents are becoming more and more prominent, so accurate and fast recognition and monitoring of vehicles have become particularly important. Traditional rule-based or feature engineering methods have limited effect in complex scenes, and the rise of deep learning algorithms provides new ideas and technical means to solve this problem [2].

Deep learning algorithms play a crucial role in vehicle image target detection. Firstly, deep learning algorithms have powerful feature learning capabilities, which can automatically learn more abstract and advanced feature representations from a large amount of data, which helps to improve the accuracy and robustness of target detection [3,4]. Secondly, deep learning models such as convolutional neural networks (CNN) and other structures perform well in processing image data, and can effectively capture feature information such as different scales, shapes, and poses in the image, thus achieving accurate detection of diverse vehicle targets [5]. In addition, deep learning algorithms can directly optimise the

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target detection model through end-to-end training, which simplifies the model design and tuning process to a certain extent.

In recent years, with the continuous development and improvement of deep learning technology, more and more vehicle image target detection methods based on deep learning algorithms have been proposed and achieved significant results. For example, models based on Regional Convolutional Neural Networks (R-CNN), Fast Regional Convolutional Neural Networks (Fast R-CNN), Faster Regional Convolutional Neural Networks (Faster R-CNN), and Single Stage Detectors such as YOLO (You Only Look Once) have made great progress in terms of accuracy and efficiency [6,7]. These methods can not only achieve efficient and accurate vehicle detection in static images, but can also be applied to real-time monitoring of vehicle position, driving trajectory and other information in video streams.

Deep learning algorithms play an important role in vehicle image target detection and continue to promote the technical level of this field. With the increasing hardware computing power, expanding dataset size and continuous optimisation of algorithms, it is believed that deep learning will achieve even more outstanding achievements in the field of vehicle image target detection in the future, bringing more innovative applications and development opportunities for intelligent transportation systems, autonomous driving technology and other fields. In this paper, target detection and recognition of vehicles in traffic images based on the parameter-optimised YOLOv8 model provides a certain research basis for subsequent research.

## 2. Data set sources and data analysis

The dataset used in this paper is from the Kaggle public dataset, including the original images as well as the image labels, and some of the data images are shown in Figure 1.

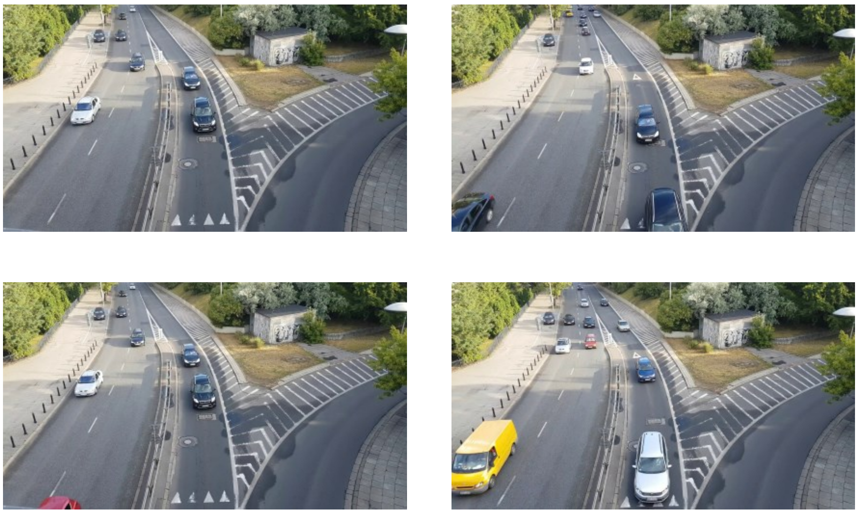

**Figure 1.** Selected data sets.
(Photo credit : Original)

After acquiring the data, the data images are firstly unified in format and size, while the images are standardised, and finally the dataset is divided according to the ratio of 7:3, with 70% of the data used for training and 30% of the images used for testing.

## 3. Method

YOLOv8 (You Only Look Once version 8) is a deep learning based model in the field of target detection, which has high efficiency and accuracy in the task of target detection.The principle of the YOLOv8 model is mainly based on the design idea of a single-stage target detector, i.e., an end-to-end convolutional neural network model is used to perform target detection directly on the input image. which simultaneously achieves higher speed and better detection accuracy.The structure of the YOLOv8 model is shown in Fig. 2.

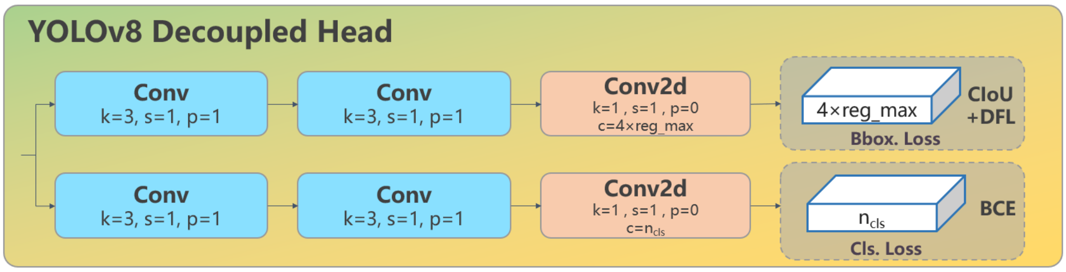


**Figure 2.** YOLOv8 model.
(Photo credit : Original)

Firstly, the YOLOv8 model adopts a backbone network as a feature extractor, and some classical convolutional neural network structures such as Darknet and ResNet are usually chosen. These backbone networks can effectively extract rich feature information from the input image and gradually abstract the features through multi-layer convolutional operations for better target detection by subsequent network layers [8,9].

Second, the YOLOv8 model introduces a multi-scale prediction mechanism. By performing target prediction at different layers, the feature information of targets at different scales can be effectively captured. This multi-scale prediction mechanism helps to improve the model's ability to detect small-size targets and long-range targets, which makes the model's performance more stable and reliable in complex scenes.

In addition, YOLOv8 employs an attention mechanism to enhance the focus on important regions. By introducing the attention mechanism, the model can focus on the most representative and important regions in the image in a targeted manner, thus improving the accuracy of target localisation and classification. This approach can effectively reduce the influence of redundant information on the final result, making the model more accurate in recognising and locating the target [10].

In addition, YOLOv8 also combines data enhancement, hardware optimisation and other technical means to further improve the model performance. Data enhancement technology can expand the size of the training dataset and enrich the diversity of data samples, thus enhancing the model generalisation ability; hardware optimisation can accelerate the training and inference process by using GPUs, TPUs, and other computing devices to improve the efficiency and speed of the whole system.YOLOv8, as a state-of-the-art target detection model, integrates a variety of cutting-edge technologies in its design, and improves them through continuous optimisation to achieve more efficient and accurate vehicle image target detection task.

## 4. Result

The experimental setup section of this paper includes the environment parameter settings and device parameters for the YOLOv8 model. Before conducting the YOLOv8 experiments, the environment parameter settings include Python version 3.7, PyTorch version 1.10.0, CUDA version 11.2, and cuDNN version 8.2.1. As for the device parameters, the experiments are conducted using a workstation equipped with an NVIDIA GeForce RTX 3090 GPU, an Intel Core i9- 12900K processor and 64GB RAM for the experiment.

In this experiment, during the training process, this paper uses a learning rate decay strategy for YOLOv8 to dynamically adjust the learning rate. Using a larger learning rate in the initial stage can accelerate the convergence speed of the model, and the subsequent gradual reduction of the learning rate is used to refine the parameter adjustment to avoid oscillating or falling into the local optimal solution during the training process.

In terms of output parameters, the output parameters of YOLOv8 include confusion matrix, F1 confidence, precision confidence, accuracy, recall, and recall confidence. The confusion matrix is an N × N matrix used to compare the relationship between the model predictions and the actual labels. In the target detection task, the confusion matrix can show the model's prediction for each category, including the number of true cases, false positive cases, true negative cases, and false negative cases.F1 confidence: the F1 confidence is a metric that combines precision and recall to measure the overall performance of the model.Higher F1 scores indicate that the model's accuracy and completeness in detecting a target is better. Precision Confidence: precision confidence indicates the degree of confidence that the model has in the accuracy of the prediction for detecting a positive example. A higher value indicates more reliable identification of positive examples by the model. Accuracy is the proportion of all cases predicted to be positive by the model that are truly positive. Higher precision indicates that the model is more reliable in determining the presence of a target. Recall is the proportion of the number of positive examples successfully found by the model to the number of all actual positive examples. A high recall rate indicates that the model is able to capture the target effectively. Recall confidence: recall confidence indicates how reliable the model is in terms of the recall rate of detecting positive examples. A higher value indicates that the model is more comprehensive in target detection.

Epoch is set to 50, batch size is set to 32, F1 confidence, precision confidence, precision, recall, and recall confidence are shown in Fig. 3, label of the test set is shown in Fig. 4, and the output results of target detection for the test set are shown in Fig. 5.

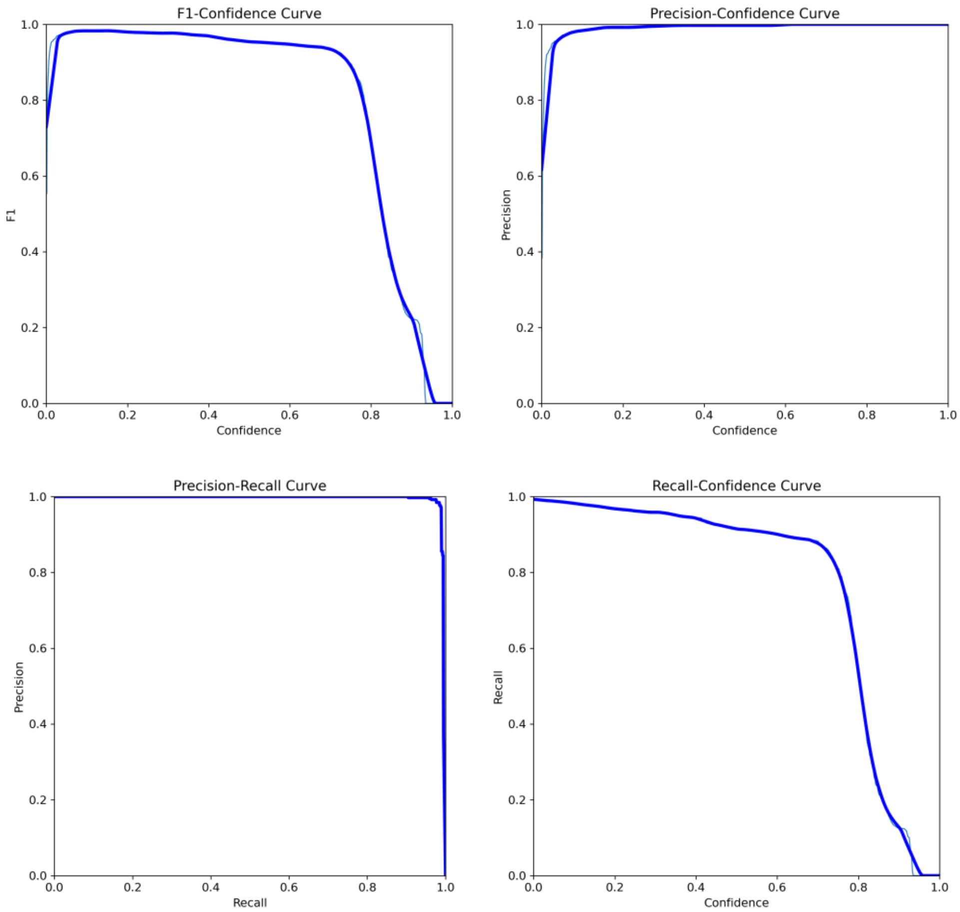


**Figure 3.** modelling evaluation.
(Photo credit : Original)

From the confusion matrix, F1 confidence, precision confidence, accuracy, recall and recall confidence curve of the model, it can be seen that the YOLOv8 algorithm, which dynamically adjusts the learning rate through the learning rate decay strategy, can detect and recognise the car in the image very accurately, and all the parameters have reached the optimum.

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The labels of the test set are shown in Fig. 4, and the target detection outputs of the test set are shown in Fig. 5. By comparing the target detection results of the test set with the LABEL it can be seen that YOLOv8 optimised for learning rate achieves 100% prediction accuracy and is able to identify and label the cars in the image very well.

**Figure 4.** The labels of the test set.
(Photo credit : Original)

**Figure 5.** Target detection outputs.
(Photo credit : Original)

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## 5. Conclusion

In this study, the YOLOv8 algorithm is used to dynamically adjust the learning rate based on the requirements of target detection in vehicle images, and the learning rate decay strategy is introduced to dynamically adjust the learning rate. By observing the confusion matrix, F1 confidence, precision confidence, accuracy, recall, and recall confidence curves of the model, the results show that the YOLOv8 algorithm optimised by the learning rate decay strategy performs well in the vehicle detection and recognition task, and all the parameters have reached the optimal state. Further comparison of the target detection results with the labelled data in the test set reveals that YOLOv8 optimised by the learning rate achieves 100% prediction accuracy and shows excellent performance in recognising and labelling cars in images. Therefore, this study verifies that the YOLOv8 algorithm optimised by learning rate tuning has an efficient and accurate capability in the task of target detection in vehicle images, which provides reliable technical support in the application areas of traffic safety, intelligent traffic management and autonomous driving.

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