Vehicle Detection and Tracking Based on YOLOv11

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Abstract: Since its initial proposal in 2015, the You Only Look Once (YOLO) series of object detection algorithms has rapidly become a popular research direction in real-time object detection due to its efficient single-inference mechanism. YOLO divides the image into grids and simultaneously predicts bounding boxes and class probabilities in a single forward pass, achieving rapid detection. The series has continuously optimized from YOLOv1 to the latest YOLOv11, enhancing feature extraction capabilities, multi-scale perception abilities, and detection accuracy. This paper explores the application of the YOLOv11 algorithm and advanced tracking models (ByteTrack and BoTSORT) in traffic monitoring systems. Ultimately, YOLOv11 achieved a mAP50 of 0.806 and a mAP50-95 of 0.501; precision reached 1.0 under a confidence level of 0.988 and a recall rate of 68.8% when the confidence threshold was 0, with a final frame rate of 63fps. The ByteTrack and BoTSORT tracking algorithms ensured stability and accuracy in tracking through multi-stage data association and trajectory management.

1 INTRODUCTION

Traffic monitoring systems play a crucial role in modern urban management and traffic planning, with accurate and real-time vehicle detection and tracking key to efficient traffic management. In recent years, the rapid development of deep learning technology, especially breakthroughs in object detection and tracking, has brought greater convenience to traffic systems. With its efficient single-stage detection framework, the You Only Look Once (YOLO) series algorithm has become essential in computer vision.

This study is dedicated to the application of YOLOv11 in vehicle detection for traffic monitoring systems (Khanam & Hussain, 2024). As the latest version of the YOLO series, YOLOv11 has significantly improved detection speed and accuracy compared to its predecessors through improved network structures and training strategies. Its introduction of attention mechanisms and fine-grained feature extraction capabilities make it perform well in dynamic traffic environments, especially in terms of robustness to small object detection and complex backgrounds (Wang et al., 2022).

To further improve the stability and reliability of vehicle tracking, this study integrates advanced tracking algorithms ByteTrack(Wang & Mariano, 2024) and BoTSORT (Aharon et al., 2022). ByteTrack is a tracking-by-detection algorithm that predicts bounding boxes and uses Intersection over Union (IoU) and confidence scores for target matching. It is particularly good at handling occlusion issues. BoTSORT combines ReID technology and uses a two-stage data association strategy to effectively reduce the problem of target loss and false matches, especially in dense target scenarios (Yang et al., 2024).

The main objective of this study is to evaluate the performance of YOLOv11 in detecting vehicles under different road conditions and compare the effectiveness of ByteTrack and BoTSORT in maintaining accurate and stable tracking.

The experimental results indicate that YOLOv11 is superior to its predecessors in terms of detection speed and accuracy and can process traffic monitoring video streams in real-time. ByteTrack and BoTSORT each have advantages in tracking performance: ByteTrack excels in handling low-score frames and occlusion scenarios, while BoTSORT

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significantly reduces ID switching through its ReID module, enhancing tracking accuracy.

This study's findings provide crucial insights for the development of more efficient traffic monitoring systems. By leveraging YOLOv11's powerful detection capabilities and advanced tracking algorithms, traffic monitoring systems can better achieve traffic flow analysis, accident prevention, and intelligent traffic management.

2 DATASET AND MODELS

2.1 Page Setup

To assess the performance of YOLOv11 and tracking algorithms, this paper collects data from various highway and urban roads. The dataset used in this paper includes 10,870 images of the target objects. There are four categories of objects: "car," "bus," "van," and "others." Each image includes at least two categories, which can increase the model's accuracy.

This paper sets 80% of all images as the training set and 20% as the test set. The model training parameters set the batch value to 4, the total number of training rounds to 100, the image size to 640, disabled multi-thread loading, and enabled image caching.

2.2 Model

The network architecture of YOLO11 (as shown in Figure 1) fully reflects the balance of efficiency and accuracy. Its core components include the basic leading trunk network (Backbone), the connection layer network (Neck), and the detection module (Head). First, the input image is processed by the Backbone (leading trunk network) through a series of convolutional layers (Conv) and C3k2 modules to extract image features (Alif, 2024). The C3k2 module, as an efficient convolutional block, can effectively extract multi-scale features while reducing computational redundancy. This is different from the main trunk network design of YOLOv5 (Zhang et al., 2022) and YOLOv8(Talaat & ZainEldin, 2023): YOLOv5 uses CSPDarknet53 (Mahasin & Dewi, 2022) as the leading trunk network, and the core module is the C3 module, while YOLOv8 introduces the C2f module to further lightweight the network structure. YOLO11 optimizes on this basis, using the C3k2 module instead of C2f to further improve computational efficiency.

Next, the feature map enters the Convolutional Block with the Spatial Attention (CBSA) module, which integrates the spatial attention mechanism and can dynamically adjust the importance of different regions in the feature map, thereby enhancing the feature representation capability. This design does not explicitly appear in YOLOv5 and YOLOv8; YOLOv5 mainly relies on the Focus module for feature extraction, while YOLOv8 introduces depthwise separable convolution and dilated convolution to optimize feature extraction efficiency. YOLO11 further strengthens feature representation capabilities through the CBSA module, giving it an advantage in complex scenarios.

Then, the feature map enters the Neck, whose main task is to process further and fuse the features extracted by the Backbone to detect targets of different scales better. In the Neck stage, the feature map is processed through multiple C3k2 modules and convolutional layers, and the resolution is increased through Upsample operations to restore detailed information. In addition, the feature maps are fused between different levels through Concat operations, which can effectively combine low-level detail information and high-level semantic information. Compared with YOLOv5 and YOLOv8, YOLOv5 uses PANET (Hussain, 2024) for feature fusion. At the same time, YOLOv8 optimizes the PANet structure, removes the convolutional structure in the upsampling stage, and introduces the SPPF module for multi-scale feature fusion. YOLO11 adds the C2PSA module behind the SPPF module to further enhance feature extraction capabilities, making it perform better in multi-scale target detection (Jooshin et al., 2024).

Finally, the feature map processed by the Neck is sent to the Head (detection module), responsible for outputting the final detection results. The detection module includes multiple parallel detection layers, each responsible for detecting targets of different scales to adapt to diverse targets in complex scenarios. Each detection layer contains a C3k2 module to process the feature map further and then outputs the detection results through the Detect layer, including the category and location of the target. Compared with YOLOv5 and YOLOv8, YOLOv5 adopts an Anchor-Based design, while YOLOv8 introduces an Anchor-Free design and uses a Decoupled Head to handle classification and regression tasks separately. YOLO11 further optimizes the detection head, introduces depthwise separable convolution to reduce redundant calculations, and significantly improves accuracy.

The entire network architecture is designed to extract rich features through the Backbone, fuse multi-scale features through the Neck, and perform accurate target detection through the Head, thereby achieving efficient and accurate target detection. This layered design improves detection efficiency and enhances the model's adaptability to complex scenarios, enabling it to meet better the dual requirements of real-time and accuracy in practical applications. Compared with YOLOv5 and YOLOv8, YOLO11 has reached new heights in detection accuracy, computational efficiency, and multi-task support capabilities, providing a more powerful tool for real-time target detection tasks.

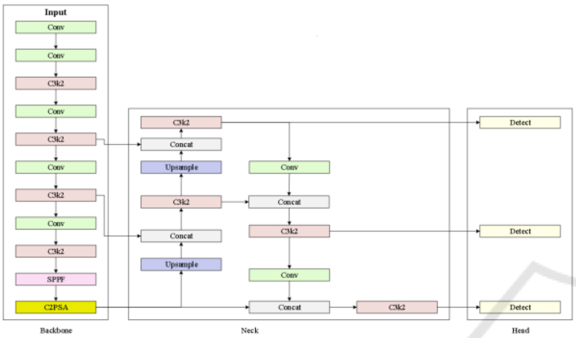


Figure 1: Model structure. (Picture credit: Original)

3 EXPERIMENTAL RESULTS

The experiments were conducted on the Win11 system, using Pytorch: 1.10.0 and Python 3.8.5 as environments. While testing the effectiveness of YOLO11 detection, the tracking function was also evaluated

3.1 Evaluation indicators

The evaluation indicators used in this experiment include precision, recall, and F1 score mean average precision(MAP). The calculation formulas for accuracy, recall, and F1 indicators are shown in formulas (1), (2), (3), and (4).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

$$\text{MAP} = \frac{1}{\text{n}} \sum_{\text{i}=1}^{\text{n}} \text{AP}_{\text{i}} \tag{4}$$

TP represents a correct detection: the number of correctly classified bounding box coordinates in the predicted result box. FP stands for error detection, which refers to the number of classification errors or incorrect bounding box coordinates in the predicted bounding box, that is, the number of incorrectly predicted bounding boxes. The recall rate is the ability of a model to find all relevant targets, that is, how many real targets can be covered by the predicted results. When the F1 score is imbalanced between accuracy and recall, it can be used as a comprehensive evaluation indicator. When it is between 0 and 1, the closer the value is to 1, the better the model performance. MAP refers to the mean of the highest accuracy at different recall rates, where n is the number of categories and is the average accuracy of the i-th category.

$$\text{MAP} = \frac{1}{\text{n}} \sum_{\text{i}=1}^{\text{n}} AP_i \tag{5}$$

3.2 Data Enhancement

Figure 2 illustrates how the dataset undergoes data augmentation. For example, in the image demonstrated below, mosaic data stitching was performed, which significantly increased the diversity of the dataset by stitching four different pictures into a new image. This method enables the model to learn features of multiple scenes and targets from a single training sample, thereby improving the model's understanding of complex scenes. Along with color changes and random image flipping, the model's adaptability to directional changes and robustness to color changes have been improved, thereby achieving data augmentation.

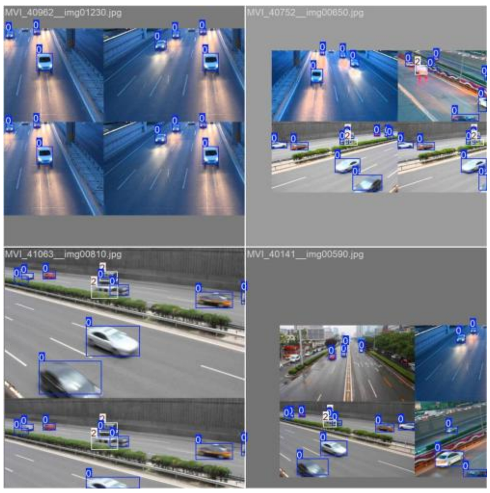


Figure 2: Data enhancement. (Picture credit: Original)

3.3 Tracking Algorithms

Regarding vehicle target tracking, ByteTrack and BoTSORT have characteristics and advantages (as shown in Figures 3 and 4). The ByteTrack algorithm is favored for its fast processing speed, which enables it to run in near real-time, which is crucial for vehicle tracking applications that require rapid response. However, BoTSORT performs better in accuracy, especially in scenarios involving REID (Re-identification) and new tracker associations, where BoTSORT's effectiveness is higher. In addition, BoTSORT adopts the selection of appearance feature extractors in its feature fusion strategy, using the ResNeSt50 backbone model, which makes it more effective in capturing subtle differences between vehicles in multi-target tracking (MOT) tasks.

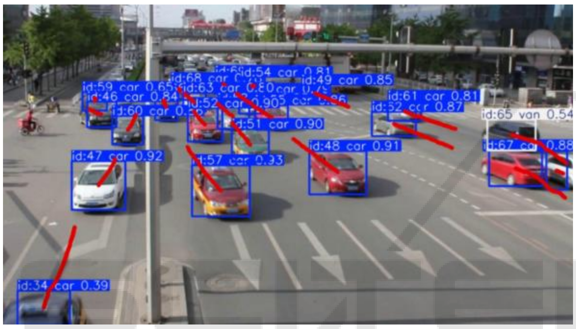


Figure 3: Bytetrack tracking configuration. (Picture credit: Original)

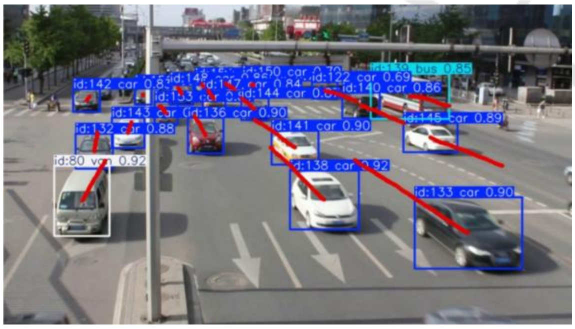


Figure 4: Bot-Sort tracking configuration. (Picture credit: Original)

3.4 Results

Figures 5, 6, and 7 show several key indicators of the YOLO training process that can be used to evaluate the model's performance during the training period.

In the analysis of loss functions and performance metrics for YOLOv5, YOLOv8, and YOLOv11 models, it can be observed that each version has been optimized and improved during the training process. In terms of training loss, all models showed a gradual decrease in bounding box loss (box-loss) with increasing training epochs, indicating that the models are learning more accurate bounding box predictions. YOLOv11 has a smoother downward trend, making its optimization algorithm more stable. In classification loss (cls_loss), all three versions have reduced losses, but YOLOv8 has a faster decline rate than YOLOv5, while YOLOv11 further improves this metric. In addition, the unique distributed aggregation loss (dfl_loss) of YOLOv11 suggests that it may have better optimization in bounding box localization, which YOLOv5 and YOLOv8 do not possess.

In terms of Validation Loss, although all models have some fluctuations, YOLOv11 has more minor fluctuations, which may indicate an improvement in its generalization ability. Performance metric analysis shows that the precision and recall of all models improve with training, but YOLOv11 shows a more significant improvement with more minor fluctuations, indicating better performance in detection accuracy and coverage. Regarding average accuracy (MAP), whether MAP@0.5 or MAP@0.5-0.95, YOLOv11 shows a better improvement trend, indicating better adaptability under different IoU thresholds.

From the perspective of model optimization and improvement, YOLOv11, as the latest version, has innovated in the design of the loss function by introducing dfl_loss to optimize bounding box localization. At the same time, it has shown better performance in accuracy, recall, and average accuracy, indicating that YOLOv11 has effectively optimized the model structure and training strategy. In contrast, although YOLOv8 has been optimized in some aspects, such as improving the speed of reducing classification loss, there is still room for improvement in verifying the loss volatility, and further adjustments may be needed to enhance stability. As an earlier version, YOLOv5 has relatively weak performance in various indicators, especially in terms of the fluctuation of validation loss and the improvement of average accuracy, reflecting the model's limitations in generalization ability and detection accuracy. YOLOv11 has demonstrated significant advantages in model performance thanks to its continuous improvement and innovation in model design and training strategies.

By analyzing the chart, it can also be inferred that the current model may be overfitting, as the validation loss no longer decreases after a certain number of rounds, possibly due to the uneven distribution of vehicle types in the dataset.

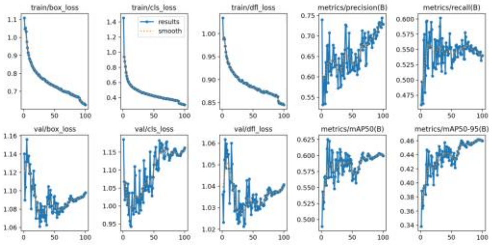
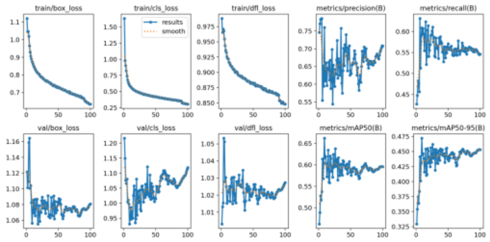


Figure 5: YOLO11 Model performance evaluation. (Picture credit: Original)



Fugure 6: YOLOv8 Model performance evaluation. (Picture credit: Original)

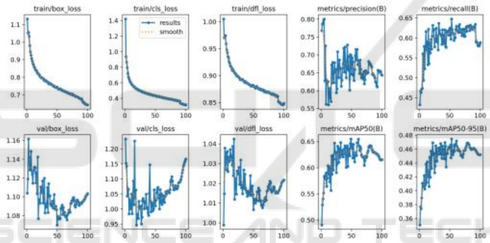


Figure 7: YOLOv5 Model performance evaluation. (Picture credit: Original)

By comparing the F1 Confidence curves of YOLOv5, YOLOv8, and YOLOv11 (as shown in Figures 8, 9, and 10), the following conclusion can be drawn: in terms of overall performance, YOLOv8 leads with an average F1 score of 0.67, YOLOv5 closely follows with 0.64, and YOLOv11 ranks third with a score of 0.59. The comparison of various categories shows that the bus category performs well in all models, with YOLOv8 particularly outstanding. In contrast, the truck category performs well in the medium confidence range but decreases slightly at high confidence levels. For the "other" category, all models have higher F1 scores at low confidence but rapidly decrease as confidence increases, indicating poor recognition performance of the models for these categories at high confidence. Regarding confidence threshold selection, YOLOv8 achieves the best average F1 score at higher confidence thresholds, while YOLOv5 and YOLOv11 achieve the best scores at lower confidence thresholds. Future improvement directions can focus on improving the model's generalization ability, reducing performance differences between categories, and optimizing the selection of confidence thresholds further to enhance the practical application effectiveness of the model. Although YOLOv8 performs the best in overall average F1 scores, YOLOv11 still performs well in specific categories, while YOLOv5 performs slightly better than the other two models. These analysis results provide valuable references for further optimization of the model.

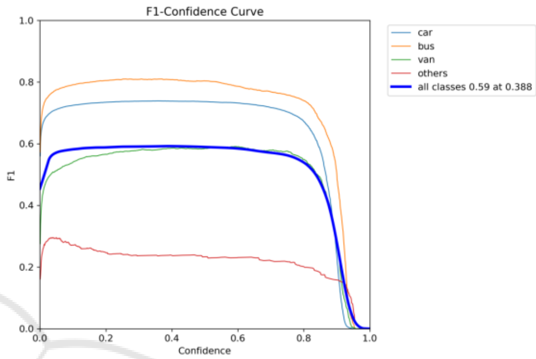


Figure 8: YOLO11 F1score. (Picture credit: Original)

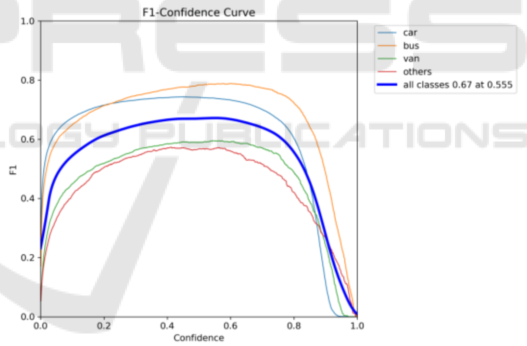


Figure 9: YOLOv8 F1score. (Picture credit: Original)

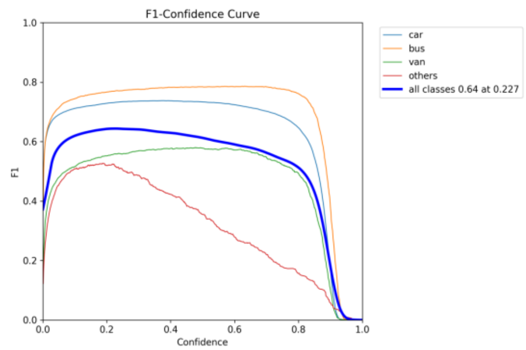


Figure10: YOLOv5 F1score. (Picture credit: Original)

4 CONCLUSIONS

We hope you find the information in this template useful in the preparation of your submission.This article delves into applying the YOLOv11 algorithm and advanced tracking models ByteTrack and BoTSORT in traffic monitoring systems, focusing on vehicle detection and tracking performance. Through experimental comparison, we evaluated the performance of YOLOv11 in detecting vehicles under different road conditions and compared the effectiveness of ByteTrack and BoTSORT in maintaining accurate and stable tracking.

The experimental results show that YOLOv11 is superior to its predecessor in terms of detection speed and accuracy and can process traffic monitoring video streams in real time. Regarding tracking performance, ByteTrack and BoTSORT each have advantages: ByteTrack performs well in low frame processing and occlusion scenes, while BoTSORT significantly reduces ID switching and improves tracking accuracy through the ReID module. This indicates that by combining YOLOv11's powerful detection capabilities and advanced tracking algorithms, traffic monitoring systems can better achieve traffic flow analysis, accident prevention, and intelligent traffic management.

In addition, by analyzing the F1 Confidence curves of YOLOv5, YOLOv8, and YOLOv11, we can conclude that YOLOv8 performs the best overall, followed by YOLOv5, while YOLOv11 performs better in certain categories. These analysis results provide valuable references for further optimization of the model, pointing out the importance of improving the model's generalization ability, reducing performance differences between categories, and optimizing the selection of confidence thresholds.

This study not only demonstrates the potential application of YOLOv11 and its tracking algorithm in traffic monitoring but also provides important technical support for the development of future intelligent transportation systems. Through continuous model optimization and algorithm innovation, we can expect further improvements in the accuracy, real-time performance, and stability of traffic monitoring systems, making greater contributions to modern urban management and traffic planning.

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