ISSN 2616-5775 Vol. 7, Issue 3: 91-96, DOI: 10.25236/AJCIS.2024.070313

Road Safety Monitoring Model Based on YOLOV8

Ding Yushen

Tiangong University, Tianjin, China, 300387
Computer Science, Tiangong University, Tianjin, China
yushending1014@gmail.com

Abstract: *In urban traffic, pedestrians frequently break into the road has become an important cause of traffic accidents. To solve this problem, a road safety monitoring model based on YOLOv8 object detection algorithm is constructed in this study. The model is designed to monitor vehicles, pedestrians, bicycles and other elements on the road in real time and record pedestrian violations, with a special focus on trespassing in prohibited areas. Through advanced computer vision technology and Streamlit, an efficient traffic monitoring system is realized, which improves the level of urban traffic safety and reduces the potential risk of traffic accidents. This innovative project will play an important role in the field of urban safety management.*

Keywords: *Computer vision, Machine learning, Deep learning, Yolov8, Object detection, Traffic safety*

1. Introduction

Road traffic safety has always been an important issue in urban management. Traffic accidents and traffic violations may lead to loss of life and property, so effective traffic monitoring and safety measures are required. [1][2]This study aims to develop a traffic safety monitoring model based on YOLOv8 object detection algorithm to detect and prevent violations in urban traffic, especially violations of pedestrians entering prohibited areas, and issue alerts. The purpose of this study is to improve the accuracy and real-time of traffic monitoring through deep learning technology.

2. Methods and techniques

YOLOv8 object detection algorithm is selected as the technical pillar in this study. YOLOv8 is famous for its efficient real-time performance and excellent multi-category target processing ability[4][5], which is consistent with the requirements of simultaneous identification of vehicles, pedestrians, bicycles and other traffic elements in urban traffic monitoring [6]. The design of the algorithm pays attention to real-time, which is of key significance for timely detecting and recording pedestrian violations and improving the overall traffic safety level.

In this study, in addition to choosing YOLOv8 object detection algorithm as the technical pillar, OpenCV is also used as an image processing tool. OpenCV is a powerful computer vision library that is widely used for image processing, object detection, and other visual tasks. Specifically, OpenCV is used to design a pedestrian detection algorithm based on the midpoint, which is used to determine whether the pedestrian has entered the restricted area. By combining YOLOv8 and OpenCV, real-time monitoring of various elements in road traffic and detection of violations can be achieved, thus improving the level of traffic safety.

For system visualization, use Streamlit, which is a unique choice for web side GUI[3]. This system can not only run smoothly on the local computer, but also has the ability to easily deploy the application to the server. This flexibility provides great convenience for teamwork, remote monitoring, and wider user access, enabling traffic monitoring results to be accessed and shared anytime, anywhere, further enhancing the practicality and usability of the system.

3. Data set selection and training process

The Traffic Detection Project data set publicly available on the Kaggle[7]platform was used in this study. The dataset contains traffic camera images from different countries with global geographic coverage. The dataset covers images taken in different weather and lighting conditions, providing a

ISSN 2616-5775 Vol. 7, Issue 3: 91-96, DOI: 10.25236/AJCIS.2024.070313

diversity of training data for the model. The training set contains 5805 images and 549 test images. The folder to save the image and the label folder must be saved in the same directory, and the txt file of each label must correspond to the image. Each label information includes class, x_center, y_center, width, and height. In addition, images have been automatically oriented and resized (640x640), generating three versions, including horizontal flipping, random brightness adjustment, and the addition of 2% salt and pepper noise, improving training data diversity and helping deep learning models better adapt to various image variants.

In the process of project training, the required data was first obtained from the Kaggle platform, and then the Conda virtual environment of Yolov8 was established. Ultralytics package was adopted to ensure the consistency of environment configuration, and torch environment was configured to invoke RTX A4000 graphics card for training acceleration. The Traffic data set was trained by selecting the official COCO data set pre-training model yolov8n.pt and the detailed configuration YAML file. Training 300 rounds, the best results are saved in the best-pt file. After the training is completed, we focus on the design of pedestrian detection algorithm based on OpenCV. The location of pedestrian is set by the middle point of the bottom edge. When the target selection box is set, whether the pedestrian enters the prohibited area is judged by whether the middle point of the bottom edge enters the drawn electronic fence. Finally, through the web version of the GUI, intuitive operation experience and results display is provided.

Figure 1 Two batches output the result graph

The two batches output result graph [Figure 1] shows the output results of the two batches, which are saved in the runs folder generated after yolov8 training. It can be clearly and intuitively seen that the targets to be detected in the test set have been accurately predicted and marked by the algorithm.

4. Model effect evaluation

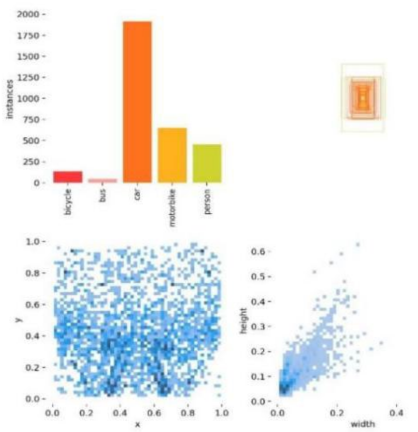

Figure 2 Label drawing

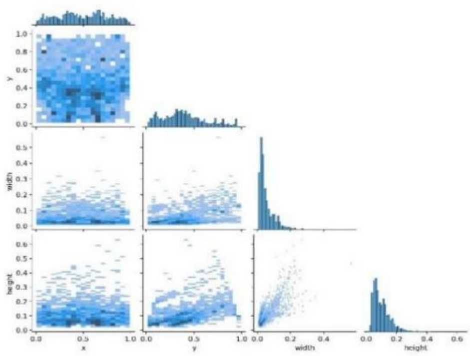

Figure 3 Color matrix diagram

ISSN 2616-5775 Vol. 7, Issue 3: 91-96, DOI: 10.25236/AJCIS.2024.070313

The label drawing [Figure 2] shows the data amount of the training set, which contains a total of 5 categories, including 'bicycle', 'bus', 'car', 'motorbike' and 'person', among which car has the largest number. The scatterplot in the lower left corner of Figure 2 shows the position of the center point relative to the entire figure, indicating that the center point of the label is dispersed. The color matrix diagram [Figure 3] shows the correlation between labels predicted by the object detection algorithm during training. The rows of the matrix represent the classes used in the model training, and each cell represents the correlation between the predictions of the corresponding labels. The darker the color in the matrix, the stronger the correlation between the corresponding labels; The lighter the color, the weaker the correlation. The colors on the diagonal represent each label's own relevance and are usually the deepest. Through this graph, it can be seen that some labels have strong correlation, which helps to optimize the training and prediction effect of the model.

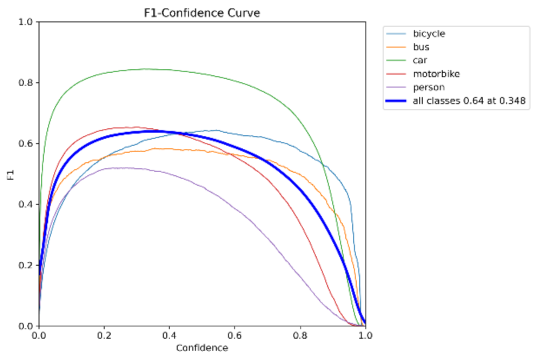

Figure 4 F1-confidence Curve

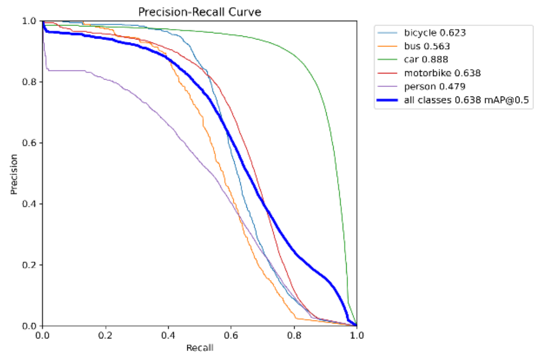

Figure5 Precision-Recall Curve

When evaluating the classification model based on YOLOv8, the output evaluation index result graph analysis reveals that the vehicle category performs particularly well in the balance of accuracy rate and recall rate, as shown in the F1-Confidence curve [Figure 4] and Precision-Recall curve [Figure 5]. Especially for the car category, the Precision of 0.888 is achieved on the precise-recall curve, which highlights the accuracy of the model in identifying the positive category. Although the performance of the automobile category is the most significant, other categories such as bicycles, buses, motorcycles and pedestrians also show satisfactory performance, which collectively reflects the reliability and efficiency of the model in multi-class object detection. These charts provide a valuable perspective for research to help select the optimal threshold to achieve the best predictive balance in real-time road safety monitoring.

5. Experimental results

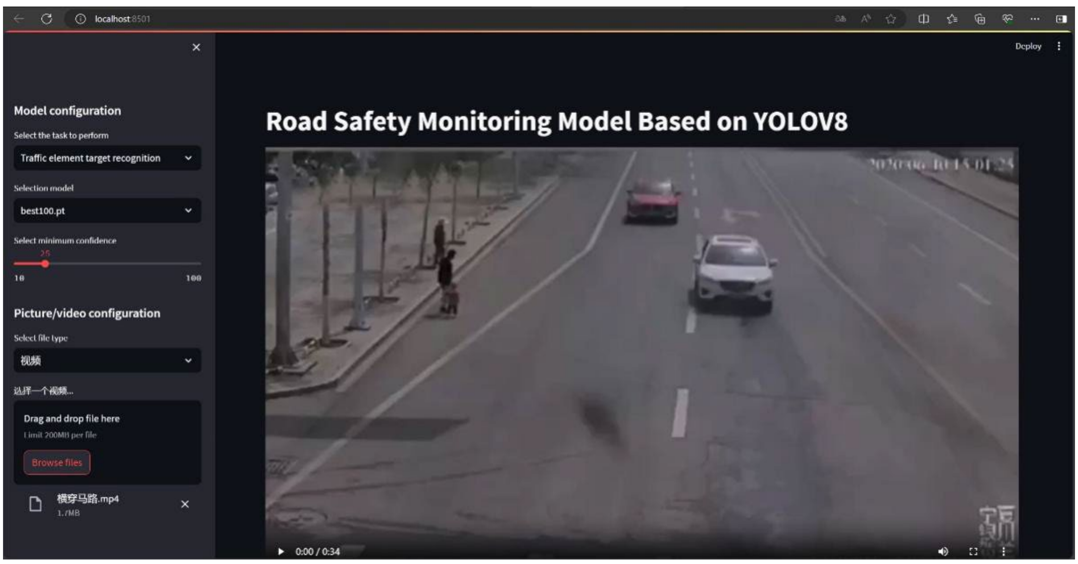

Figure 6 Visualization GUI page

ISSN 2616-5775 Vol. 7, Issue 3: 91-96, DOI: 10.25236/AJCIS.2024.070313

Figure 7 Model prediction result map

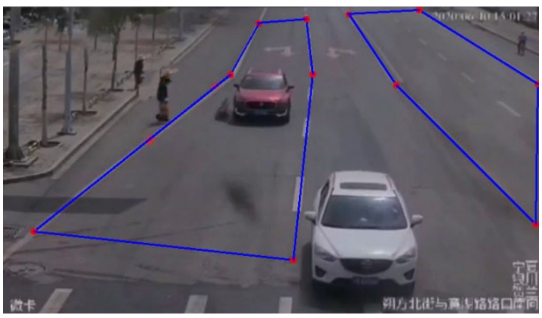

Figure 8 Electronic fence drawing

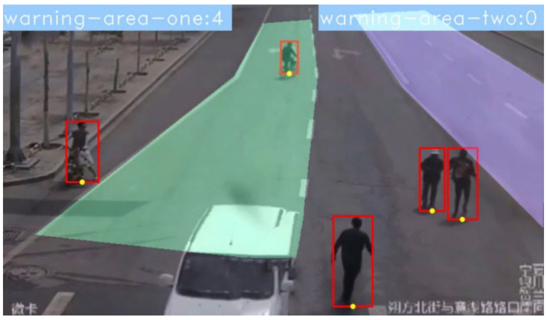

Figure 9 Pedestrian warning map

The resulting images [Figure 7] show the visual interface of the model and the model prediction results, using the original video footage taken from the Internet. The results show that the system successfully identifies and labels pedestrians and motorcycles on the road. The border around each identified object clearly marks the category and the confidence level, which indicates the level of certainty of the model's prediction. The image 8 [Figure 8] shows the creation of an electronic fence and a pedestrian warning system. The blue lines in the figure form the preset electronic fence areas, while the red and green boxes identify different warning areas. When a pedestrian is detected entering these areas, the system will generate warnings. The light blue part of the figure indicates how many times the pedestrian has entered the dangerous area and how many alarms have been output. From the experimental results, these images [Figure 9] clearly demonstrate the effectiveness and accuracy of the YOLOv8 model in a real-time environment. The above figure [Figure 6] shows the results of running and testing on the experimental equipment. If put into the actual application scenario, the alarm can be output to the terminal of the traffic management personnel, so as to send the nearest duty personnel to deal with it, to ensure the safety of people's lives and property, and reduce the probability of safety accidents caused by pedestrians breaking into the highway or the road.

6. Improvement direction and expansion scenarios

6.1. Improvement direction

Optimize the number of training rounds: Since it was observed that the accuracy did not rise above 90% on the test set, consider increasing the number of training rounds for the model to improve performance. More iterations may help overcome the underfitting problem, especially for pedestrian recognition performance.

Improving the GUI: Research is needed to further improve the GUI to ensure that button slot functions with new features are successfully connected, thus improving the user experience and making the GUI more user-friendly.

System function enhancement: The research should further increase and improve the system functions, consider introducing more advanced computer vision techniques or optimizing existing algorithms to cope with complex traffic monitoring scenarios.

dataset expansion: Follow-up studies consider expanding the datasets, especially adding pedestrian samples in different scenarios, to improve the performance of pedestrian recognition. More diverse data sources may be used to improve the generalization ability of the model.

6.2. Extended Application Scenarios

This traffic safety monitoring model can be applied to many other different scenarios in the future. Here are some possible extensions and application scenarios:

Intelligent Traffic Management: Models are applied to places such as intersections, road networks and parking lots in cities to monitor traffic flow, violations and vehicle parking in real time.

Campus safety: The model is applied to the school campus to monitor the behavior of students and vehicles, and timely detect possible safety hazards, such as crossing walking and vehicle speed exceeding the limit.

Commercial area security: In the commercial area, it can be used to monitor pedestrians and vehicles, prevent criminal activity, and improve the overall level of safety in the commercial area.

7. Conclusion

Through in-depth technology selection and clever method flow, this study successfully established a road safety monitoring model based on YOLOv8 object detection algorithm, aiming to effectively solve the safety hazards caused by pedestrian violations in urban traffic.

7.1. Main findings of the study

The wise choice of technical pillar: the YOLOv8 algorithm has successfully met the demand of multi-class target processing in traffic monitoring. Its high real-time performance and excellent multi-class processing capability provide a solid technical foundation for the success of the project.

Full use of diverse datasets: The Traffic Detection Project dataset on the Kaggle platform was selected, which covers traffic scenarios in different weather and lighting conditions worldwide. This provides rich and diverse data sources for model training and enhances its generalization performance.

Detailed model training process: Through the in-depth and detailed model training and evaluation process, the performance of YOLOv8 on traffic monitoring tasks was comprehensively understood. Multiple adjustments and iterations make the model training more precise and reliable.

7.2. Main research achievements

Successfully trained traffic safety monitoring model based on YOLOv8: By training on a large amount of traffic data, this study successfully fine-tuned the YOLOv8 model, so that it can detect vehicles, pedestrians and other traffic elements more accurately in the actual scene.

Problem finding and direction of improvement: In the observation of the model on the test set, the problem of insufficient pedestrian recognition is found, and clear direction of improvement is proposed. This lays the foundation for future work, allowing the model to perform better in more complex scenarios.

In this study, the traffic safety monitoring model based on YOLOv8 was successfully implemented, and after several rounds of iterative fine-tuning, the performance was improved. The experimental results show that the model can effectively detect multiple traffic elements and has the potential to be widely used in the field of urban traffic safety. Future work will focus on further optimizing the model for more complex scenarios and increasing its performance levels.

References

[1] Zhuang Xiangling. "Study on the Factors and Safety Auxiliary Design Strategies in Pedestrian Crossing Safety." 2015.
[2] Qian Tianzi. "Research on Factors Influencing Unsafe Behaviors of Pedestrians at Road Intersections." Ph.D. diss., Beijing Jiaotong University, 2015.
[3] Cheng Jie, Chen Jianhua, and Xu Shuhan. "Intelligent Glove and Translation System for Sign Language Collection and Input." Electronic Products World, vol. 30, no. 8, 2023, pp. 61-65.
[4] Solawetz J., & Francesco. "What is YOLOv8? The Ultimate Guide." 2023.
[5] Feng Jing, Fu Dandan, Liu Qiang, and Zhu Kejia. "Research on Aerial Vehicle Detection Technology Based on YOLOv8." Computer Science and Applications, vol. 13, no. 12, 2023, pp. 2399-2407.

ISSN 2616-5775 Vol. 7, Issue 3: 91-96, DOI: 10.25236/AJCIS.2024.070313

[6] Zhao Enxing, & Wang Chao. "Traffic Signal Recognition Based on YOLOv8." Artificial Intelligence and Robotics Research, vol. 12, no. 3, 2023, pp. 246-254.
[7] Narayanan Arvind, Shi Elaine, & Rubinstein, Benjamin I. P. "Link Prediction by De-anonymization: How We Won the Kaggle Social Network Challenge." 2011.