Journal of Engineering Science and Technology Review 17 (4) (2024) 119 - 127

Research Article

JOURNAL OF
Engineering Science and Technology Review

www.jestr.org

Lateral Offset Detection Method Based on Deep Learning for Mixed Traffic

Likai Wang[1], Ping Cui[2,*], Weiwei Liu[1] and Nan Zhou[1]

[1]*Traffic Police Detachment, Xuzhou Police Bureau, Xuzhou 221002, China*
[2]*School of Information Engineering, Xuzhou University of Technology, Xuzhou 221018, China*

Received 24 June 2024; Accepted 28 August 2024

Abstract

Traffic accidents are prone to occur in mixed-traffic flows of nonmotorized and motorized vehicles. Particularly, electric two-wheeled vehicles face risks when they move laterally to the motor vehicle lane to avoid obstacles. To decrease accident risks caused by lateral offset in mixed-traffic flows, this study proposed a lateral offset detection method based on deep learning technology. A vehicle lateral offset risk recognition model of You Only Look Once Version 8 (YOLOv8) was established using actual traffic scenes in Xuzhou as a dataset. The model was trained by loading the pre-processed and labelled dataset, selecting the model architecture suitable for target detection in traffic scenes, setting training parameters, and executing. Then, the training results were analyzed based on images, such as labelled images, training result plots, and model curves, and the accuracy and reliability of the model were evaluated using standard metrics, such as precision, recall, and average precision. Results demonstrate that the offset model of YOLOv8 can detect the lateral offset risk of vehicles from traffic surveillance videos. The proposed model has robustness in category judgment. The detection precision of lateral offset in the model is 0.638, the recall rate is 0.626, the mean average precision calculated at an intersection over union (IoU) threshold of 0.50 (mAP50) is 0.679, and the mean average precision calculated at an IoU threshold of 50%-95% (mAP50-95) is 0.358. The study provides an important reference for the construction and performance evaluation of lateral movement models of vehicles in mixed-traffic flows.

Keywords: Mixed-traffic flows, Lateral offset detection, YOLOv8, Traffic accident prevention

1. Introduction

As a convenient means of transportation for short-distance commuting, electric two-wheelers are lightweight, low-carbon, and environmentally friendly, and their usage cost is low. Constrained by economic or engineering conditions, different types of vehicles share a road surface in China [1], resulting in mixed-traffic flows composed of motorized and nonmotorized vehicles, such as electric two-wheelers that have been existing in China's urban road network for a long time and have become a remarkable feature of urban road traffic in China.

However, with the increase in the number of electric two-wheelers and motorized vehicle travel in recent years, the high acceleration and speed of electric two-wheelers have resulted in numerous traffic accidents. About 78% of injuries and fatalities involving electric two-wheelers occur in mixed-traffic sections of motorized and nonmotorized vehicles [2]. Evidently, mixed traffic poses potential safety hazards.

To ensure the efficiency of driving and the safety of nonmotorized drivers, scholars have conducted numerous studies from the perspectives of active safety system optimization [3, 4], methodology application [5], and collision data feedback [6]; these perspectives involve active safety systems, precrash scenarios, and post-accident data summarization of electric two-wheelers and motorized vehicles. The safety of the mixed-traffic flow of electric two-wheelers and motorized vehicles has been effectively improved. However, many factors, such as traversing motorized two-wheelers, influence the safety of mixed-traffic flow and increase the instability of traffic flow and collision risks. Therefore, how to observe and measure the offset of electric two-wheelers relative to motor vehicles and how to use the results for the assessment of traversal risks in traffic monitoring systems are urgent problems that need to be solved. This study proposed a deep learning-based detection model that aims to improve the safety and efficiency of electric vehicle avoidance behavior. A vehicle lateral offset volume model for mixed traffic of electric two-wheelers and motor vehicles in on-street parking environments was established by focusing on lateral offset behavior. Through deep learning technology, electric two-wheeler and motor vehicle streams were distinguished from traffic monitoring videos and a risk assessment was conducted based on the degree of traffic mixing and the density of traverse intrusion into motor vehicle lanes. Automatic warnings were issued by the model on the basis of real-time traffic conditions. These warnings can effectively reduce casualties caused by traffic accidents and improve urban traffic safety.

2. State of the art

Existing studies on vehicle lateral offset behaviors have examined autonomous driving technologies [7], early warning strategies [8], and detection methods [9]. However, imperfect technologies and growing demands bring considerable challenges to the modeling and control of vehicles that have lateral offset behaviors.

With the development of autonomous driving technology, vehicle offset has gradually attracted the attention of

*E-mail address: cp2580@163.com
ISSN: 1791-2377
doi:10.25103/jestr.174.14

scholars. Tork et al. [10] used an adaptive improved neural transverse–longitudinal control system to control vehicle lateral offset and improve driving safety, but the system is only suitable for self-driving vehicles. Narayanan et al. [11] proposed an offset-based collision detection and avoidance system in curvilinear motion to avoid possible collisions of both-end vehicles; the system focuses on avoiding collisions in dense traffic. Hu et al. [12] established a lateral safety distance model by using the relative velocity and position of moving targets crossing roads and developed an obstacle avoidance algorithm on the basis of the lateral safety distance model. In their study, the influence of road conditions on the experiment was fully considered. However, the developed model is only applicable to active vehicle safety obstacle avoidance. Lyu et al. [13] established a trajectory prediction model based on long short-term memory by analyzing the feasibility of lane change and the change rate of lateral offset. After comparing the warning confusion matrix and warning time, they found that the proposed cut-through collision warning model is superior to the traditional collision warning model, but it is only applicable to active driver assistance systems that warn about the surrounding vehicles and traffic environment. Although the aforementioned autonomous driving technologies can actively avoid accidents, they are inapplicable to vehicles that do not have autonomous driving functions.

At present, the effects of vehicle lateral deviation are still being explored, and warning strategies need to be further improved. Liu et al. [14] modeled and stimulated overtaking events of different types of nonmotorized vehicles on a mixed roadway and assessed the performance of different types of nonmotorized vehicles in terms of their lateral position. However, the model is only suitable for validation purposes. Kotagi et al. [15] analyzed the effects of vehicle lateral movement by modeling the lateral offset of vehicles in mixed traffic on an undivided urban roadway, but they focused only on real-world scenarios in India. Luan et al. [16] proposed a method that combines driver intent prediction and vehicle behavior recognition to predict vehicle lateral motion; the method achieves predictive results but relies heavily on driver information, such as age and personality. Kumar et al. [17] developed an Internet of Things-based sensor fusion vehicle accident detection and classification system that aims to reduce casualties and promote the progress of smart cities. However, the proposed model focuses on after-the-fact statistics. How to efficiently accomplish the recognition and detection of target vehicle crossing in real time has become the focus of current study.

Improving the efficiency of identification and detection and identifying suitable detection methods for target vehicle traversal is the core of solving the current safety problem of lateral movement in mixed traffic. By conducting a survey of collision avoidance driving safety on the basis of sensing, vehicular communication, and artificial intelligence (AI), Fu et al. [18] compared the most common AI algorithms with different functions in a collision avoidance system, but the scalability and reliability of the algorithms were not assessed. Tavanti et al. [19] proposed a novel microwave radar-based technology for short-range detection and classification of multiple vehicle targets traversing a surveillance area. Guo et al. [20] predicted the lateral deviation trajectories of vehicles in a mixed human–motor vehicle driving environment by using millimeter-wave radar and sensors, such as Global Positioning System. However, other targets, such as nonmotorized vehicles, were not studied. Lin et al. [21] used millimeter-wave radar to collect continuous motion trajectories of targets, and their approach has superior tracking performance under lateral traffic interference. However, the sensor or radar is inferior to vision solutions in recognizing the type and characteristics of moving objects.

In terms of vision schemes, Pawar et al. [22] proposed a deep learning-based road traffic accident detection and localization system for traffic surveillance videos; the system helps promote the development of traverse detection technology, but its real-time situational awareness is insufficient. Barbu [23] investigated deep learning-based multiscale video target detection and tracking, which can detect and track multiple vehicles automatically, but their focus on vehicle traversal in mixed-traffic flows was insufficient. On the basis of the improved You Only Look Once Version 5s (YOLOv5s) + DeepSort neural network, Deng [24] established a prediction model for vehicle detection and tracking. The model can detect violations of turning vehicles on the basis of speed, direction, and lateral displacement, and it focuses on reducing vehicle violations. Duman et al. [25] fine-tuned the YOLOv5 model by using unmanned aerial vehicle (UAV) images to realize real-time vehicle detection. The use of these images improves the architecture and performance of the model. However, the model depends on UAV aerial photography and is affected by extreme weather. Yi et al. [26] developed a collision warning system based on YOLOv5 that includes the judgment of dangerous areas caused by vehicle offset. The ability of the collision warning system was improved to perceive the surrounding environment, but the system was not compared with the subsequent model.

The studies above focused on vehicle lateral offset in different models or systems. The new generation of vision programs with high real-time performance was not investigated, and only a few studies used You Only Look Once Version 8 (YOLOv8) model programs in vehicle lateral offset detection. In this study, the YOLOv8 algorithm was employed to establish a model for lateral offset risk recognition of two-wheelers and motor vehicles in mixed traffic, and the training results were analyzed using images such as labeled images, training result images, and model curves. The application effect of the model in actual traffic monitoring scenarios was evaluated based on standard indices, such as precision, recall, and average precision. The results provide a basis for the optimization and experimentation of deep learning-based lateral offset risk recognition in mixed-traffic flows.

The remainder of this study is organized as follows. Section 3 describes the data acquisition process and image labeling method and shows the operating environment of the model and the training method of the dataset. A model of lateral offset risk recognition in mixed traffic is established by analyzing the characteristics of motor vehicle lateral offset avoidance behavior. Section 4 shows the training results of the model obtained by analyzing images, such as labeled images, training result graphs, and model curves. The model is evaluated with standard indices, such as precision, recall, and average precision, and the accuracy and reliability of the model are verified. Section 5 summarizes the study and presents relevant conclusions.

3. Methodology

3.1 Dataset preparation

In the development and optimization of a traffic safety monitoring and warning system for two-wheelers and motor vehicles in a mixed-traffic flow, representative and sufficient training-set samples can effectively improve the prediction accuracy and stability.

Given the complex operating environment, this study constructed a dataset of two-wheelers and motorized vehicles in a mixed-traffic flow. In the experiment, with the specific road traffic system in Xuzhou City as the research object, existing traffic equipment and surveillance cameras were used to obtain actual traffic images in a mixed-traffic flow. The images were collected in mid-April 2023. After the sample data were collected and analyzed, necessary adjustments were made to the image samples. The collected images were screened to remove blurred or duplicate images. This process ensures stability during model training and avoids overfitting. A total of 738 high-quality images were retained. The images were randomly divided into training and validation sets at a ratio of 8:2. When motorized two-wheelers and motorized vehicles were close to each other and had obvious angles, they were considered to be transverse, and the vehicles in this area were annotated. If no obvious angle was observed between close motorized two-wheelers and motorized vehicles, traffic was considered normal, and the vehicles were annotated accordingly. The open-source visual annotation tool LabelImg [27] was utilized, and a maximum horizontal rectangular box was used to frame the image area at multiple angles. The data were saved in PASCAL VOC format. By using the training-set samples, this study trained machine learning models that could accurately recognize and predict warning scenes.

3.2 Dataset training

The environment configuration provided the study with stable, efficient computational resources to support the complex computational requirements of model training and evaluation. The experimental environment was based on the Ubuntu 18.04.5 long-term support operating system with the kernel version of GNU/Linux (5.4.0-42-generic) and the Python programming language (version 3.8.19). The deep learning framework was PyTorch 2.0.0, which operates on a Tesla T4 GPU hardware-accelerated platform, and the CUDA version was 12.0.

The You Only Look Once Version 8n (YOLOv8n) model was applied to perform the target detection task by using a customized dataset. A pretrained YOLOv8n.pt model was adopted as a starting point, and the key parameters during the training process included the number of samples per batch (i.e., 4). The input image size was set to 640 × 640 pixels. The initial learning rate was set to 0.01, and the learning rate scheduling strategy based on a cosine function was adopted to optimize the convergence speed and performance of the model. The optimizer used an adaptive configuration, and the training process lasted for 300 epochs. For data enhancement, various techniques, such as random transformation, color warping, and blending, were employed to enhance the scene diversion generalization ability of the model. Mixed precision training was applied to enhance the computation speed while reducing the memory footprint to further enhance the training effect. In addition, a nonmaximal suppression (NMS) algorithm was implemented to improve the accuracy and stability of the detection results and ensure that the output bounding box and category predictions meet the expected requirements. Detailed log records and performance graphs were obtained during the training process for subsequent result analysis and presentation.

During the training process, a validation set and corresponding evaluation metrics, such as an intersection-over-union (IoU) threshold of 0.7 and maximum number of detections equals to 300, were set to verify the generalization ability of the model. These steps helped in the comprehensive performance evaluation and result analysis at the end of the training. The training goal was to enable the YOLOv8n model to achieve excellent results in vehicle traverse detection through effective hyperparameter tuning and data processing techniques.

3.3 Modeling of lateral offset in mixed-traffic flow

In restricted road spaces, such as streets with on-street parking, drivers of two-wheelers illegally occupy other lanes because of the need for lateral safety space, resulting in lateral friction interference that affects the speed of motorized vehicles. Therefore, the effects of different traffic factors on motorized and nonmotorized vehicle behaviors were studied prior to modeling. The causes of nonmotorized lane encroachment were observed in surveillance videos and categorized into natural and human factors, and appropriate remedial strategies were developed. Presupposing such problems helps in the micro modeling and simulation of vehicle behaviors in mixed-traffic flows.

Model reliability depends on the accuracy of traffic simulation, so samples need to be obtained from the field. Various traffic data acquired from the Xuzhou Transportation Department were the basis for calibrating and validating the model parameters in this study. A model study was performed on a real system to realize real-system modeling. The results of the actual system were observed, collected, analyzed, and used to calibrate and validate the model. The mixed-traffic lateral-offset-behavior model employed the YOLOv8n algorithm to model the lateral offset behavior between motorized and nonmotorized vehicles and was implemented in the system. The core objective of the model was to reduce accidents caused by vehicle lateral offset. First, traffic surveillance videos of the corresponding road section were collected through cameras or drones at the intersection, and from them, the picture frames containing the traveling status of motorized and nonmotorized vehicles were obtained. Second, the image frames that had undergone data cleaning and processing were labeled to generate a dataset unique to the road section. Third, the system environment and training dataset were configured to improve the ability of the model to recognize the risk of lateral offset or normal traffic flow. Last, in combination with the trained model data, the model was deployed and operated on edge-computing servers and processed based on the feedback. The model provides real-time alerts so that relevant personnel can deal with the risks of vehicle lateral offset in a timely manner, thereby reducing the complexity and danger of urban roadway conditions, shortening the vehicle passing time, alleviating congestion, and safeguarding the safety of citizens. The mixed traffic lateral offset model is shown in Fig. 1.

This design utilized the YOLOv8n algorithm to perform vehicle detection and tracking. The algorithm divides the input image into multiple grids, each of which is responsible for recognizing and predicting the type of object inside it. The NMS technique is used to minimize repetition and excessive overlap between bounding boxes. The network architecture of YOLOv8n consists of a convolution module, a cross-stage partial bottleneck with two convolutions (C2f) module, and a spatial pyramid pooling fast (SPPF) module. The main role of the SPPF module is to integrate the multiscale features and effectively extract local and global features of the target. Although the C2f module can effectively improve the overall accuracy, its effectiveness in detecting small or partially occluded targets still needs to be enhanced. The network model of YOLOv8n is shown in Fig. 2.

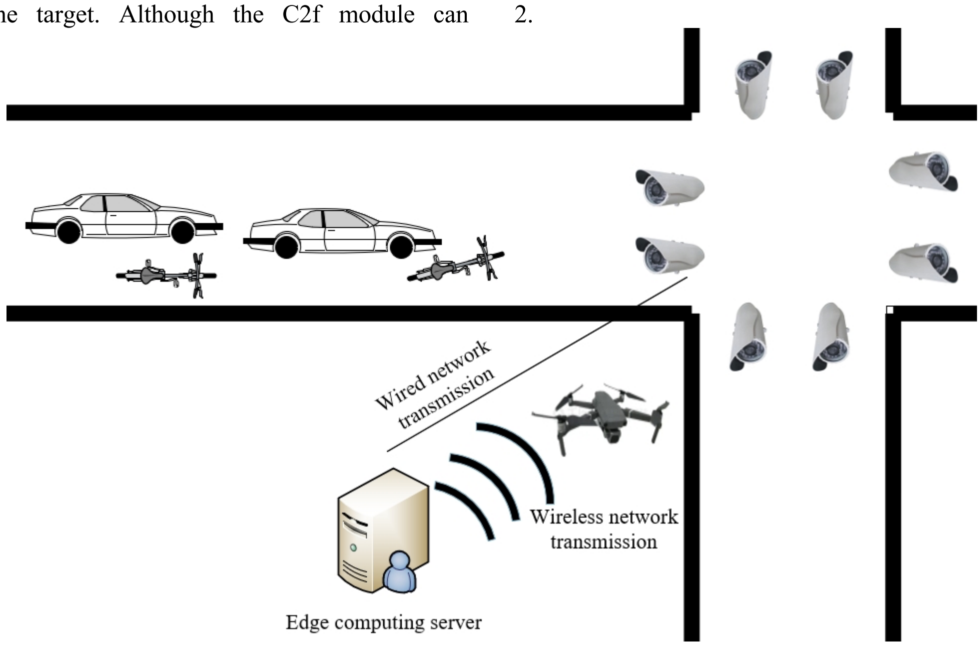

Fig. 1. Mixed traffic lateral offset model

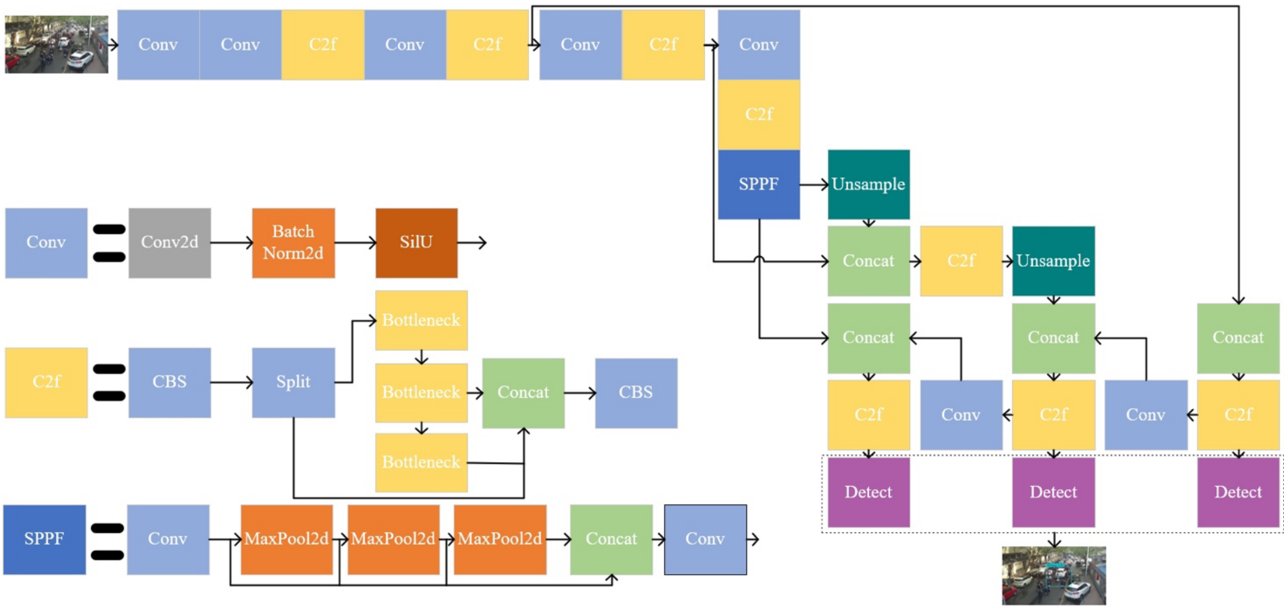

Fig. 2. Mixed traffic lateral offset model

The vehicle lateral offset problem can be investigated thoroughly by pre-studying different traffic factors and analyzing detailed surveillance data. In this study, the dataset was trained to obtain training charts for adjusting the training parameters of the model. The traffic risks of lateral offset can be assessed in real time by using the advanced YOLOv8n algorithm to detect and track vehicles. With the help of timely warning and treatment solutions, traffic accidents can be effectively decreased to improve the overall efficiency and safety of urban transportation.

The lateral relationship between vehicles can be understood accurately by studying lateral no-deviation behavior, and the change trend of traffic flow can be further analyzed. This method can improve the accuracy and response speed of traffic monitoring systems and provide strong support for urban traffic management to ensure traffic safety and smooth flow. System monitoring accuracy is improved, and potential safety hazards caused by lateral offset can be detected and resolved in a timely manner. The lateral-offset-free behavior model is a powerful tool for traffic managers to formulate effective traffic planning and management strategies. The data output of this model not only considerably improves the monitoring and warning of traffic flows, but also supports the intelligent development of urban transportation planning.

4. Result Analysis and Discussion

4.1 Dataset labeling analysis

On the basis of the dataset constructed in Section 3.1, this section presents the object instance distribution in the dataset and a location analysis. The dataset has normal and shifting instance distributions. Given that the percentage of normal-traveling electric two-wheelers and motorized vehicles is high, the number of object instances in the normal category is much higher than that in the shifting category, indicating that the dataset is captured frequently at regular locations of the objects. An uneven distribution may affect model training, making the model demonstrate improved object recognition performance in the normal category. The upper-right part of the labeling image shows the variation in the density and location of the bounding boxes and the spatial consistency and trend of the objects in the dataset. Most of the bounding boxes are concentrated in a particular region, showing high spatial concentration, because of the fixed location of the objects in a particular position in the scene. The following scatter plots present the normalized position (x and y coordinates) and size (width and height) of the objects. These plots also show the generalized position and size distribution of the objects in the images and provide data support for adjusting the sense field and anchor frame size in the target detection algorithm. In this way, the algorithm can be optimized effectively for target objects of different sizes and locations, which in turn improves detection accuracy and robustness. The labeling images are shown in Fig. 3.

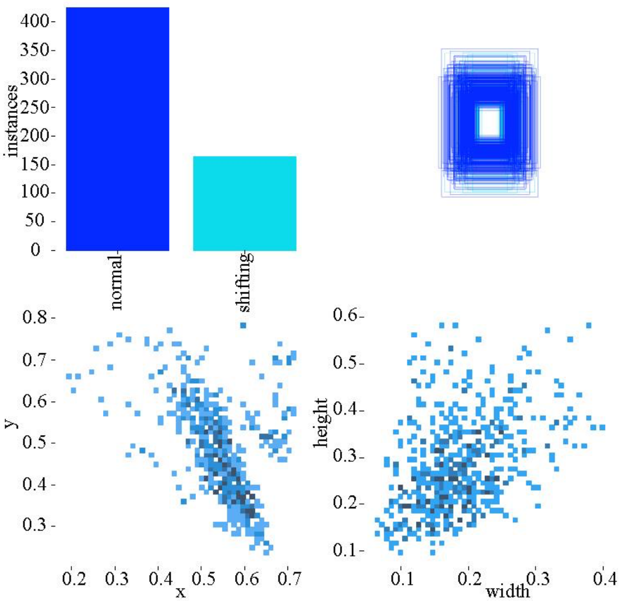

Fig. 3. Labels

As indicated in Fig. 4, the label correlation map provides complex data visualization of the multivariate distribution and a univariate histogram, which can be used to analyze the spatial distribution and dimensional characteristics of targets in a target detection dataset. The combined analysis of the scatter plots and histograms for each dimension provides insights into the statistical characteristics of the target position (x and y coordinates) and size (width and height) in the image. The histogram of the y coordinates shows that the targets are mainly concentrated in the middle region vertically, indicating that most of the targets are in the center of the image. The distribution of the x coordinate shows a similar concentration tendency but is slightly more dispersed than the distribution of the y coordinate, which may be related to the image shooting angle or target movement. Meanwhile, the histograms of width and height show a skewed distribution and the distribution of width is concentrated, whereas the distribution of height is dispersed. These distribution characteristics may be related to the target vehicle and shooting distance. The results of the analysis of the distribution plots can be used to adjust the size and proportion of the anchor frame in the target detection algorithm to effectively adapt to the actual distribution of targets in the dataset. In addition, the target detection model can be further optimized to improve its detection accuracy and robustness for targets of different sizes and locations by comprehensively analyzing the joint distribution of x and y coordinates and the aspect ratio.

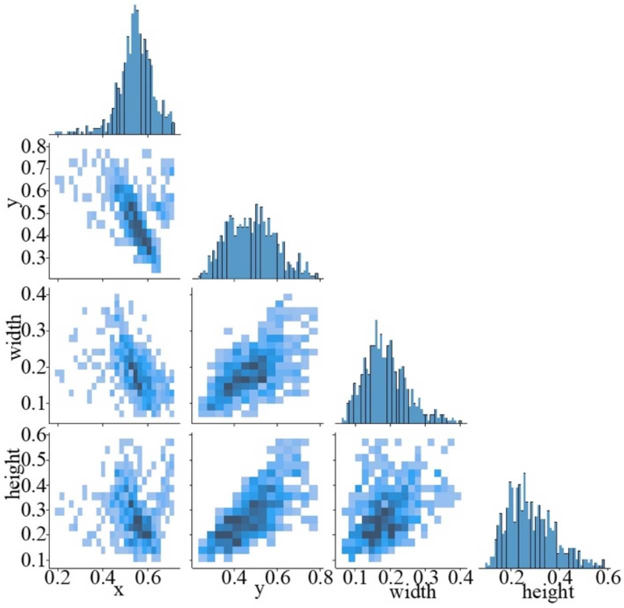

Fig. 4. Labels' correlogram

4.2 Model graphical analysis

On the basis of the experimental environment and training method in Section 3.2, the YOLOv8n model was used for training and validation. During the training process, the bounding box loss (box_loss), category loss (cls_loss), and direction loss (dfl_loss) decreased considerably with the increase in the training period, indicating that the model was stable and that its effectiveness gradually improved during the continuous learning process. With regard to the direction loss, the loss of the training set decreased from nearly 1.8 to about 0.4, indicating an excellent learning effect. However, the decrement trend of the bounding box and direction losses at the validation phase was not as stable as that at the training phase, and both of them fluctuated at the late training stage. Meanwhile, the category loss on the validation set stabilized and gradually decreased after the initial fluctuation, indicating that the model was robust in category judgment. In terms of the performance indices, the model had good performance in precision and recall. The mean average precision calculated at an IoU threshold of 0.50 (mAP@0.5) was about 68%, and the mean average precision averaged over an IoU threshold of 50%–95% (mAP@0.5-0.95) exceeded 30%, reflecting the model's detection ability under different IoU thresholds. These results confirm that the model has a strong generalization ability and reliable performance, and it is applicable to practical target detection scenarios. The variation of each loss and performance index is shown in Fig. 5.

The precision–confidence curve (P_curve) shows the change in the accuracy of a model under different confidence thresholds. The accuracy and usefulness of detection can be balanced by choosing an appropriate confidence threshold. In the curve, the horizontal axis represents the confidence threshold, and the vertical axis represents the corresponding accuracy value. The curves indicate that the accuracy of both categories gradually increased with the increase in the confidence threshold, showing that the model could recognize the target with high confidence. In addition, the accuracy of all categories reached 1 at a confidence level of about 0.916, indicating that the model could recognize targets in all categories with high accuracy above this threshold. The P_curve plot is shown in Fig. 6.

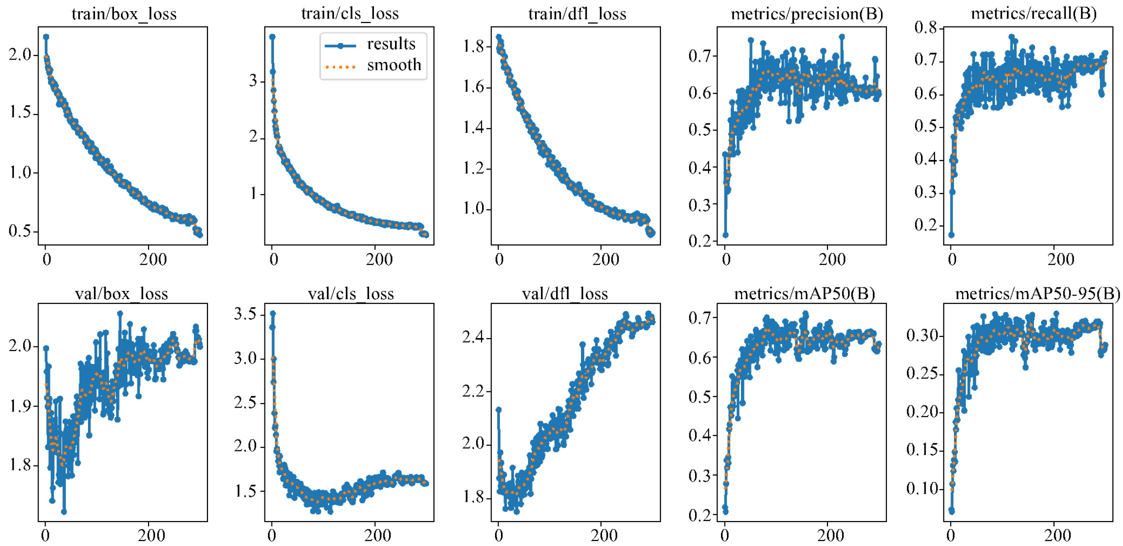

Fig. 5. Result graph

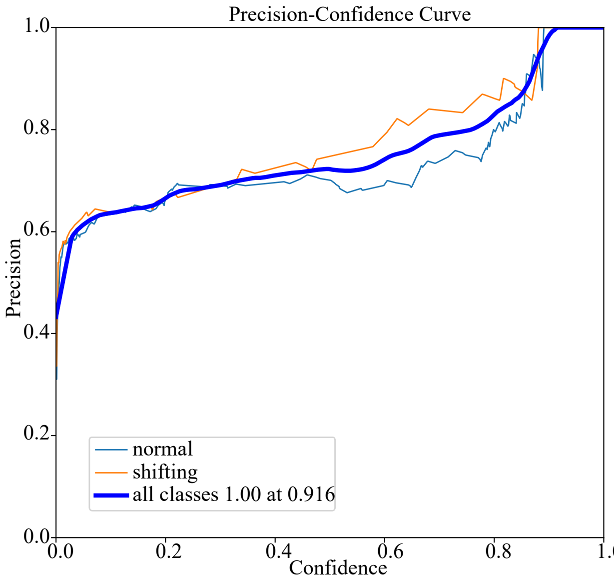

Fig. 6. P_curve graph

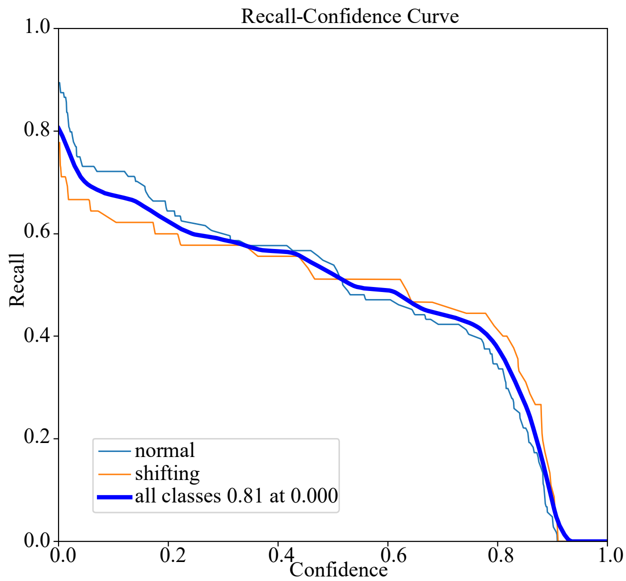

Fig. 7. R_curve graph

The recall–confidence curve (R_curve) reflects the detection recall of a target by a target detection model at different confidence thresholds. Recall measures the model's ability to identify all positive samples, and the confidence threshold affects the choice of model predictions. As shown in the figure, recall decreased as the confidence threshold increased because a high confidence threshold allows a model to make predictions only when it is confident, thus reducing the number of predictions but increasing the precision of the predictions. Furthermore, recall decreased dramatically to 0 at a confidence level of 0.81 for all categories. This phenomenon indicates that an appropriate confidence threshold must be selected in applications to ensure that the system does not miss too many real targets nor make too much false detection. Therefore, in traffic safety monitoring scenarios, careful analysis of the recall–confidence curve and fine-tuning and optimization of the target detection model are crucial to achieving an efficient detection system. The R_curve plot is shown in Fig. 7.

The F1-confidence curve (F1_curve plot) is used to evaluate the comprehensive performance of a target detection model at different confidence thresholds. The F1 score is a standard measure of categorization. It is a function of the harmonic mean of precision and recall between 0 and 1. As shown by the curves, the F1 scores for all categories increased rapidly to a peak at low confidence levels then gradually declined with increasing confidence. This trend suggests that although low confidence leads to high recall, accuracy is low. Although accuracy increased as confidence increased, the decrease in recall led to an overall decrease in the F1 scores. In addition, the F1 scores for all categories reached a maximum of 0.65 at a confidence level of about 0.076, indicating that performance reached a balanced optimum at this threshold. The F1_curve plot is shown in Fig. 8.

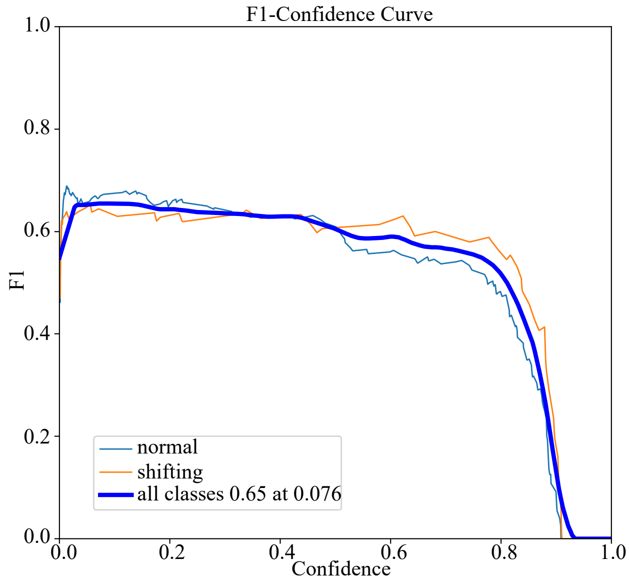

Fig. 8. F1_curve graph

The precision–recall curve (PR_curve) reflects a model's ability to recognize positive samples by showing the precision that the model can achieve at different recall levels. As shown in the figure, the precision of the two categories gradually decreased as recall increased. Specifically, the maximum mAP@0.5 of the normal and shifting categories was 0.693 and 0.681, respectively, indicating that the detection performance of the normal category was slightly better than that of the shifting category at the standard IoU threshold of 0.5. The difference in performance may be related to the sample distribution, sample quality, or variability of the two categories in the training data. The normal category made model learning easy because of its large number of samples and low variability, so it performed well in the detection task. The shifting category posed challenges to model learning because of the high variability in location or morphology. Overall, the average accuracy (mAP@0.5) of all the categories was 0.687, showing the high robustness of the model in the recognition of multicategory targets under the current configuration. These results provide important references for further optimizing the model parameters, improving the training strategy, and adjusting the category balance to achieve good detection performance and application results. The PR_curve plot is given in Fig. 9.

4.3 Detection results

On the basis of the lateral offset model for mixed-traffic flow constructed in Section 3.3, this study evaluated the detection performance of the vehicle lateral movement model in mixed-traffic flow. The performance evaluation indices of the model included detection precision, recall, and average precision (AP). The definitions of the three indices are shown in Eqs. (1), (2), and (3), where TP denotes the number of targets detected by the model and recognized correctly, false positive (FP) is the number of incorrectly detected samples, and false negative (FN) refers to the number of the targets not detected by the model.

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

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

$$\text{AP} = \sum \int_0^1 P(R)dR \tag{3}$$

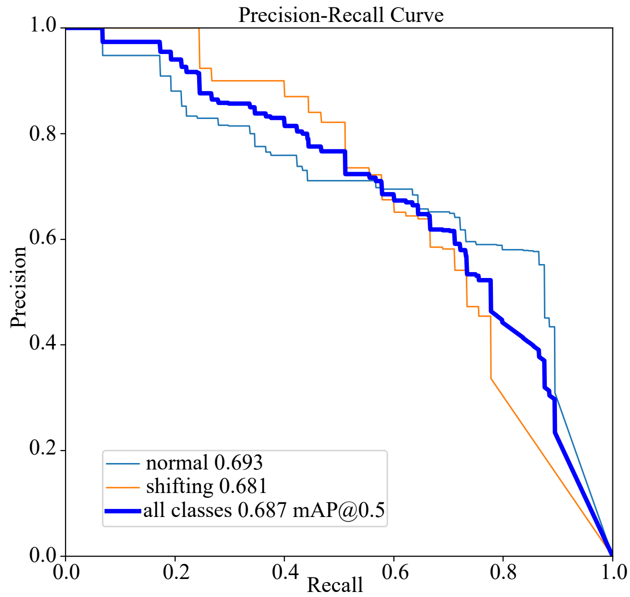

Fig. 9. PR_curve graph

Detection precision can measure the ratio of correctly detected targets to all detected targets in the detection results. The higher the precision rate is, the lower the proportion of false alarms is among the objects detected by the model. Recall can measure the ratio of targets correctly detected by the model to all true targets. A high recall value means that the model misses a few detected targets only. mAP50 represents the average precision when the IoU ratio is 0.5. The IoU ratio is a metric used to measure the overlap between the predicted bounding box and the true bounding box. mAP50-95 is a comprehensive metric that is typically used to calculate the average mAP for all IoU thresholds from 0.5 to 0.95. The index considers not only loose IoUs, but also tight IoUs, thus allowing for a comprehensive assessment of model performance under overlap conditions of varying stringency. The test results are shown in Table 1.

Table 1. Test results

Class	Precision	Recall	mAP50	mAP50-95
All	0.636	0.674	0.688	0.331
Normal	0.634	0.721	0.696	0.304
Shifting	0.638	0.626	0.679	0.358

The detection results showed that the detection accuracy for electric two-wheelers and nonmotorized vehicles approaching but passing normally in the mixed-traffic flow was 0.634, the recall value was 0.721, mAP50 was 0.696, and mAP50-95 was 0.304. The detection accuracy, recall, mAP50, and mAP50-95 for shifting were 0.638, 0.626, 0.679, and 0.358, respectively. Although the model can provide accuracy and coverage when detecting the lateral offset of electric two-wheelers and nonmotorized vehicles, it needs to be further optimized.

Lateral offset detection in mixed-traffic flow can effectively identify the transverse movements of motorized and nonmotorized vehicles in mixed traffic on a motorway. The detection effect is shown in Fig. 10.

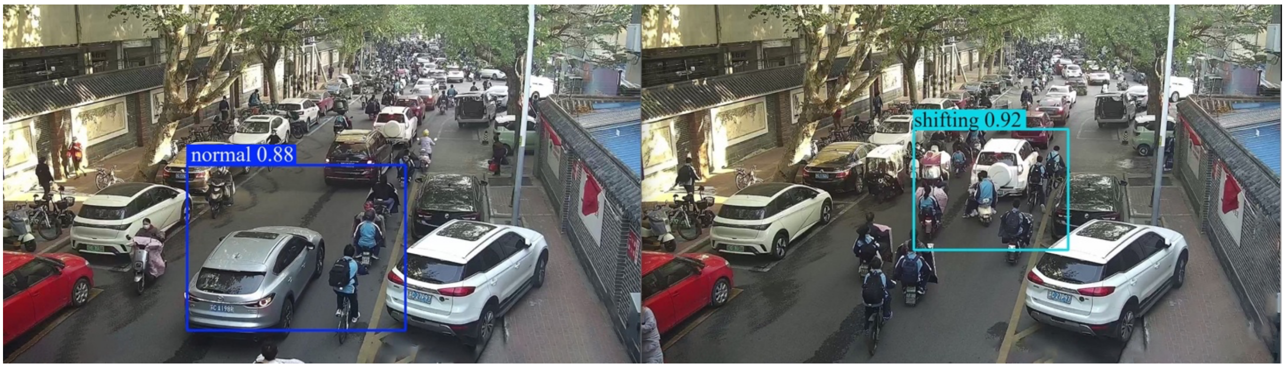

Fig. 10. Detection effect

5. Conclusions

To explore the lateral offset characteristics of vehicles and reduce the traffic congestion and safety risks caused by lateral offset, this study trained a model of vehicle lateral offset in mixed-traffic flow via the collection and processing of traffic data from specific road sections. The dataset labels and the charts involved were analyzed to study the detection effect. The following conclusions could be drawn:

(1) YOLOv8n can effectively provide real-time warning on the basis of the data from traffic surveillance cameras, and it can be used to study vehicle lateral offset models in mixed-traffic flows.

(2) The category loss on the validation set stabilizes and gradually decreases after initial fluctuations, indicating that the vehicle lateral offset model is suitable for category judgment.

(3) The performance index of mAP@0.5 of the vehicle lateral offset model is about 68%, and the performance index of mAP@0.5-0.95 is above 30%. These values show the model's detection ability under different IoU thresholds. The model has a strong generalization ability and reliable performance.

By combining deep learning algorithms and practical applications of traffic monitoring, this study proposed a new method for vehicle lateral offset detection. The model can be used for traffic traverse detection. However, the trained model has some deficiencies. When the target detection image contains targets of different sizes, small targets are not detected because of the fixed sensing field and the low resolution of the extracted feature maps. Vehicle tracking suffers from tracking target loss under occlusion. In the future, the model must be further optimized and tested with additional real data to improve its applicability and enhance its detection capability.

Acknowledgements
This work was financially supported by Xu Zhou Science and Technology Plan Project (Grant No. KC21309), and the Natural Science Foundation of the Jiangsu Higher Education Institutions of China (22KJA520011).

References

[1] X. Kuang, Y. Wu, P. Liu, J. Zhang, and Y. Chen, "Mixed traffic flow model considering lateral expansion effect in speed-space," *J. Highway Transp. Res. Dev.*, vol. 38, no. 7, pp. 114-123, Jul. 2021.
[2] X. Zhu, Z. Chu, J. Zhu, and S. Dai, "Analysis and countermeasures of causes of electric bicycle traffic accidents in China," *Urban Transp. China*, vol. 19, no. 6, pp. 64-70, Nov. 2021.
[3] L. Hu, H. Li, P. Yi, J. Huang, M. Lin, and H. Wang, "Investigation on AEB key parameters for improving car to two-wheeler collision safety using in-depth traffic accident data," *IEEE Trans. Veh. Technol.*, vol. 72, no. 1, pp. 113-124, Jan. 2023.
[4] G. Savino *et al.*, "Active safety systems for powered two-wheelers: A systematic review," *Traffic Inj. Prev.*, vol. 21, no. 1, pp. 78-86, Jan. 2020.
[5] D. Pan, Y. Han, Q. Jin, H. Wu, and H. Huang, "Study of typical electric two-wheelers pre-crash scenarios using K-medoids clustering methodology based on video recordings in China," *Accid. Anal. Prev.*, vol. 160, Sep. 2021, Art. no. 106320.
[6] X. Wang, Y. Peng, S. Yi, H. Wang, and W. Yu, "Risky behaviors, psychological failures and kinematics in vehicle-to-powered two-wheeler accidents: results from in-depth Chinese crash data," *Accid. Anal. Prev.*, vol. 156, Jun. 2021, Art. no. 106150.
[7] A. E. Sharkawy, M. Yacoub, and M. Asfoor, "Comprehensive evaluation of emerging technologies of advanced driver assistance systems: An overview," *J. Eng. Sci. Mil. Technol.*, vol. 6, no. 1, pp. 41-51, Mar. 2022.
[8] Y. Liu, R. Alsaleh, and T. Sayed, "Modeling lateral interactions between motorized vehicles and non-motorized vehicles in mixed traffic using accelerated failure duration model," *Transportmetr. A Transp. Sci.*, vol. 18, no. 3, pp. 910-933, Dec. 2022.
[9] A. Boukerche and Z. Hou, "Object detection using deep learning methods in traffic scenarios," *ACM Comput. Surv.*, vol. 54, no. 2, pp. 1-35, Apr. 2021.
[10] N. Tork, A. Amirkhani, and S. B. Shokouhi, "An adaptive modified neural lateral-longitudinal control system for path following of autonomous vehicles," *Eng. Sci. Technol. Int. J.*, vol. 24, no. 1, pp. 126-137, Feb. 2021.
[11] P. Narayanan, S. Sengan, B. P. Marimuthu, and R. K. Paulra, "Novel collision detection and avoidance system for midvehicle using offset-based curvilinear motion," *Wireless Pers. Commun.*, vol. 119, no. 3, pp. 2323-2344, Aug. 2021.
[12] Z. Hu, S. Huang, Z. Du, X. Guo, and H. Gao, "Active obstacle avoidance algorithm based on lateral safety distance model," *Automot. Eng.*, vol. 42, no. 5, pp. 581-587, May 2020.
[13] N. Lyu, J. Wen, Z. Duan, and C. Wu, "Vehicle trajectory prediction and cut-in collision warning model in a connected vehicle environment," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 2, pp. 966-981, Feb. 2022.
[14] Q. Liu, J. Sun, Y. Tian, and L. Xiong, "Modeling and simulation of overtaking events by heterogeneous non-motorized vehicles on shared roadway segments," *Simul. Model. Pract. Theory*, vol. 103, Sep. 2020, Art. no. 102072.

[15] P. B. Kotagi, P. Raj, and G. Asaithambi, "Modeling lateral placement and movement of vehicles on urban undivided roads in mixed traffic: a case study of India," *J. Traffic Transp. Eng. Engl. Ed.*, vol. 7, no. 6, pp. 860-873, Dec. 2020.
[16] Z. Luan, Y. Huang, W. Zhao, S. Zou, and C. Xu, "A comprehensive lateral motion prediction method of surrounding vehicles integrating driver intention prediction and vehicle behavior recognition," *Proc. Inst. Mech. Eng., Part D: J. Automob. Eng.*, vol. 237, no. 1, pp. 61-74, Jan. 2023.
[17] N. Kumar, D. Acharya, and D. Lohani, "An IoT-based vehicle accident detection and classification system using sensor fusion," *IEEE Internet Things J.*, vol. 8, no. 2, pp. 869-880, Jan. 2021.
[18] Y. Fu, C. Li, F. R. Yu, T. H. Luan, and Y. Zhang, "A survey of driving safety with sensing, vehicular communications, and artificial intelligence-based collision avoidance," *IEEE Trans. Intell. Transp. Syst.*, vol. 27, no. 3, pp. 6142-6143, Jul. 2022.
[19] E. Tavanti, A. Rizik, A. Fedeli, D. D. Caviglia, and A. Randazzo, "A short-range FMCW radar-based approach for multi-target human-vehicle detection," *IEEE Trans. Biomed. Eng.*, vol. 60, pp. 1-16, Mar. 2022, doi:10.1109/TGRS.2021.3138687.
[20] J. Guo, Z. He, Y. Luo, and K. Li, "Vehicle cutting-in trajectory prediction based on deep learning in human-machine mixed driving environment," *Automot. Eng.*, vol. 44, no. 02, pp. 153-160, Feb. 2022.
[21] Y. Lin, N. Chen, and K. Lu, "Intersection vehicle trajectory tracking method based on millimeter-wave radar point cloud," *J. South China Univ. Technol. Nat. Sci. Ed.*, vol. 51, no. 10, pp. 110-125, Oct. 2023.
[22] K. Pawar and V. Attar, "Deep learning based detection and localization of road accidents from traffic surveillance videos," *ICT Express*, vol. 8, no. 3, pp. 379-387, Sep. 2022.
[23] T. Barbu, "Deep learning-based multiple moving vehicle detection and tracking using a nonlinear fourth-order reaction-diffusion based multi-scale video object analysis," *Discrete Contin. Dyn. Syst. Ser. S*, vol. 16, no. 1, pp. 16-32, Jan. 2023.
[24] Z. Deng, "Design and implementation of intelligent electronic police system," *Softw. Eng. Appl.*, vol. 11, no. 4, pp. 667-678, Aug. 2022.
[25] Z. N. Duman, M. B. Çulcu, and O. Katar, "YOLOv5-based vehicle objects detection using UAV images," *Turk. J. Forecast.*, vol. 6, no. 1, pp. 40-45, Aug. 2022.
[26] Z. Yi, Z. Zhan, Q. Mao, B. Sun, and J. Wang, "Research on collision warning system based on improved YOLOv5 and dangerous area judgment," *Automob. Technol.*, vol. 2024, no. 04, pp. 1-6, Apr. 2024.
[27] C. Sager, C. Janiesch, and P. Zschech, "A survey of image labelling for computer vision applications," *J. Bus. Anal.*, vol. 4, no. 2, pp. 91-110, Apr. 2021.