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METHOD FOR IDENTIFYING MOTOR VEHICLE TRAFFIC VIOLATIONS BASED ON IMPROVED YOLOV NETWORK

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Abstract. The use of traditional manual supervision means to deal with motor vehicle traffic safety violations can result in a large amount of wasted manpower and oversight problems. To assist road managers in better directing traffic order and managing traffic situations, the study proposes an improved target tracking network model. Simple online real-time tracking, deep correlation metrics, and cascading open-source computer vision libraries are combined to create a tracking model for motor vehicle traffic infraction recognition. Pursuant to the experimental findings, the Institute's upgraded target recognition network model had accuracy and recall rates of 95.7% and 99.7%, respectively, with an accuracy rate of 16.6% higher than the model's historical counterpart. The recognition accuracy of the constructed motor vehicle traffic violation recognition and tracking model regarding the three basic traffic violations was 98.2%, 98.7%, and 97.9%, respectively; the missed detection rate was 2.0%, 0.31%, and 2.1%, respectively; and the false detection rate was 0.17%, 0.31%, and 0%, respectively. It shows that the improved network model of the study is advanced and the motor vehicle traffic offence model has a good recognition rate and stable performance, which can assist traffic managers in their operations to a certain extent.

Key words: YOLOV; motor vehicles; SE; CBAM; traffic offences; OpenCV

1. Introduction. Motor vehicles have brought great convenience to the travel of human life, but the corresponding number of motor vehicle traffic accidents is also rising year by year. The use of artificial intelligence technology to build an intelligent traffic management system nowadays has become a hot spot for research [1, 2]. Intelligent traffic systems mainly cover traffic monitoring systems, vehicle management systems and advanced traffic management systems, etc. Among them, traffic monitoring systems can assist traffic managers to deal with various traffic accidents effectively and quickly. Traditional traffic video surveillance systems generally use a large number of human assistances, the workload involved is large, but also more prone to errors [3]. First, motor vehicles have various behaviors on the road, and the complexity of the traffic scene makes the task of traffic violation identification extremely challenging. Secondly, the traditional traffic violation identification methods will encounter some limitations when dealing with large-scale data. For large-scale traffic video data, traditional methods based on manually design features face the difficulty of feature extraction and high computational complexity. Therefore, a more optimized and efficient approach to address these challenges needs to be sought. Finally, the existing traffic violation identification methods still have some limitations in terms of accuracy and robustness. Due to the complexity of traffic scenarios and changes in video data, existing methods may in some cases misjudgment or fail to accurately distinguish between illegal and non-illegal behaviors. Therefore, the improved methods need to better solve these problems and improve the accuracy and stability of the identification methods. By optimizing the network structure and feature extraction methods, we hope to address the challenges faced by existing methods in terms of traffic scene complexity, large-scale data processing, and accuracy. The main objective of this study is to provide a more efficient, accurate, and robust method for identifying traffic violations, thereby helping to improve traffic supervision and road safety levels, improve the smoothness of road traffic, and thus save people's time and resources. And then formulate more reasonable Transportation planning and route optimization strategies to improve the efficiency of the overall transportation system. Reduce accident risk and provide important support for decision-making. The study is divided into four parts. The first part discusses the results of relevant research in recent years, the second part focuses on the construction of an improved motor vehicle model, the third part validates the performance of the constructed model and the fourth part draws conclusions from the study.

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2. Related Works. Many scholars have conducted in-depth research in intelligent systems put into intelligent management of motor vehicles. Motor vehicle traffic violations may lead to traffic accidents, road congestion and unequal traffic distribution. Therefore, accurate identifying and monitoring of motor vehicle traffic violations is critical to improving road safety and traffic efficiency. This paper improves the YOLOV network to perform better in identifying motor vehicle traffic violations. Through this study, computer vision and deep learning techniques can be better understood and applied to solve traffic safety problems. This study is of great significance for traffic management departments, traffic safety researchers, and technical personnel in related fields. By developing accurate and efficient methods for identifying motor vehicle traffic violations, the efficiency of traffic enforcement can be improved and provide more data support for traffic management, so as to help decision makers to develop more reasonable traffic policies and planning. Sungan et al. in order to propose a CNN-based object detection model that incorporates a TDM-trained multimodal YOLO framework of models to manage the road pothole problem [4]. This method can be used for the analysis of motor vehicle traffic violation recognition, such as the recall and accuracy of the recognition model. Using wireless sensor networks and RFID technologies, Changhong et al. created a framework for an intelligent logistics supply chain management system to increase location accuracy and coverage [5], This framework can be used to establish an identification framework for this study. Fraser et al. artificially analyzed the factors that trigger motor vehicle unsafe events, used cross-case studies to compare potential hazard triggers, and experimentally validated the effectiveness of the proposed study [7]. Zhang et al. created a four-scale detection structure for the purpose to increase the recognition accuracy of long-range tiny target detection [8]. To further enhance the accuracy of YOLO vehicle categorization, Azimjonov et al. suggested a bounding box-based vehicle tracking method and validated the effectiveness of its experimental algorithm [9]]. Ahmed et al. presented a fusion transfer learning technique in a deep learning tracking framework to boost the detection model's precision, and they empirically demonstrated its efficacy [10]. In an effort to reduce tracking losses caused by processing occlusion and to achieve more stable tracking, Duan C et al. used a depth-ordered multi-target tracking algorithm to filter multi-target tracking of pedestrians and vehicles in traffic scenes [11]. An experimental study showed that the proposed algorithm can reduce ID switching in real-time traffic. Huiyuan et al. used asymmetric convolution with depth-separable convolution to reduce model parameters to speed up model recognition tracking by gathering vehicle position, trajectory, and other important driving parameters to meet the demands of autonomous driving in a timely manner, and they validated the efficacy of the proposed multi-vehicle tracking framework through in-depth experiments [12]. To address the issues of unsatisfactory detection rate in the YOLOv5 structure, Dong et al. suggested a kind of algorithm that introduces C3Ghost in the YOLOv5 neck structure [13]. Comparison experiments with the YOLOv5 structure were used to demonstrate the effectiveness of their improved algorithm. Wei et al. used the improved YOLOv5 detection to identify riders and helmets and validate their algorithm performance in subsequent experiments [14]. An enhanced YOLO fusion joint-non-maximum suppression model was put forth by Tan et al. to increase the precision of small target identification. The performance of their model was verified through comparison experiments with four existing detection methods [15].

In summary, when conducting further comparative analysis on the use of multi-objective recognition network models in the transportation field, the first thing to consider is the achievements and potential they have achieved. This network model has shown its ability to efficiently handle complex traffic scenarios, such as identifying oncoming vehicles, pedestrians, and even determining the color of traffic lights. By adding appropriate algorithms, such as deep learning or neural network algorithms, the recognition and prediction efficiency can be further improved. However, there are few relevant research materials in the field of motor vehicle Moving violation identification. On this basis, a method for developing a basic model for identifying and tracking automobile traffic safety violations is proposed, which combines deep correlation measurement, open-source computer vision library, and simple online real-time tracking algorithms.

3. Model Construction for Identification and Detection of Motor Vehicle Traffic Violations. The multi-objective tracking model is enhanced in this study. The improved model is further fused within open-source computer vision library to construct a motor vehicle traffic violation recognition pursuit model.

3.1. Construction of a Motor Vehicle Tracking Recognition Model based on YOLOv5s. YOLOv5 It has a faster reasoning speed while maintaining its accuracy. This is achieved by employing some optimiza-

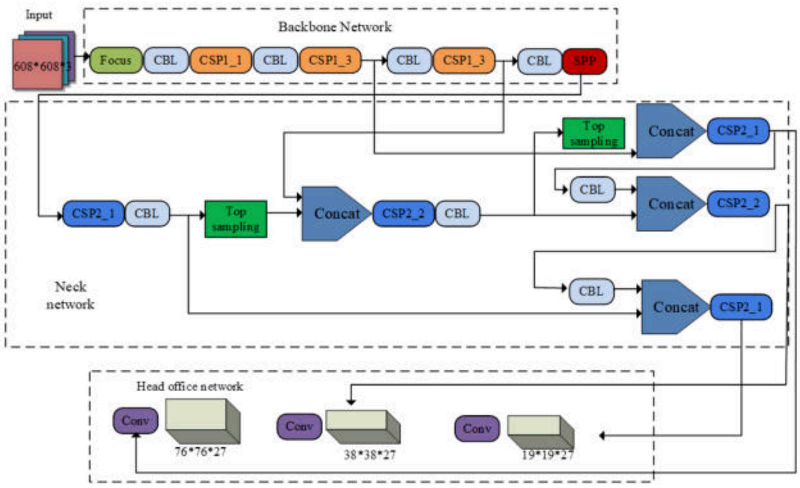


Fig. 3.1: YOLOv5s network structure schematic

tion techniques, such as feature pyramid networks, adaptive receptive fields, and cross-stage feature fusion. YOLOv5 Some improvements in the network architecture, using CSPDarknet53 as the backbone network to improve the accuracy of detection, through techniques such as feature aggregation and attention mechanism. Compared to other target detection models, YOLOv5 has smaller models and occupies less hard disk memory and video memory resources, which allows it to operate in more resource-constrained environments. YOLOv5 provides a complete set of code base and pre-trained models that can be easily used and deployed. In addition, it supports multiple platforms and frameworks, including PyTorch, TensorFlow, etc., and therefore is therefore more flexible and scalable. You Only Look Once (YOLO) is primarily used for the detection of multiple target categories and locations. YOLO does not only manage to identify the type of these objects, but also to mark their location. Because it only needs to look once, YOLO is known as a Region Free (RF) method, and in contrast to region-based (RB) methods, YOLO does not need to find the area where the target is likely to be in advance. As the network model of the YOLO family of algorithms has fewer parameters and runs faster, making it more convenient for experiments on embedded platforms, the study builds a corresponding target detection model. YOLOv5 is the OneStage family of algorithms, and its confidence level is given in equation 3.1.

$$Confidence = Pr(Object) \times IOU_{pred}^{truth} \tag{3.1}$$

In equation 3.1, P represents the likelihood of containing objects within the bounding box and indicates the degree of accuracy of the prediction using the loss function IOU. YOLOv5 will provide different detection models for different object size detection, such as YOLOv5s, YOLOv5m, YOLOv51, YOLOv5x. The YOLOv5s network structure is demonstrated in Figure 3.1 [15].

In Figure 3.1, the model is divided into four structures. The input rated data is sliced and processed, and the image pixel values are extracted and then cut to enhance the perceptual field and reduce image information loss. The above data undergoes a convolution operation and then enters the CSP layer, The research introduces the Attention Mechanism, which weights and aggregates all historical information to reduce important information loss. The additive model is used to calculate attention scores, as shown in equation 3.2.

$$s(v_i^{'}, v_t^{'}) = \tilde{v_T} tanh(W_1 v_i^{'} + W_2 v_t^{'}) \tag{3.2}$$

In equation 3.2, $v_i^{'}$ represents the encoding of historical sequence information after dimensionality reduction, $v_t^{'}$ show t encoding of input information after time dimensionality reduction. W, v, these are the network parameters of the Department of Science. Focus state $s_t$expressed as H, the weighted sum of is expressed in

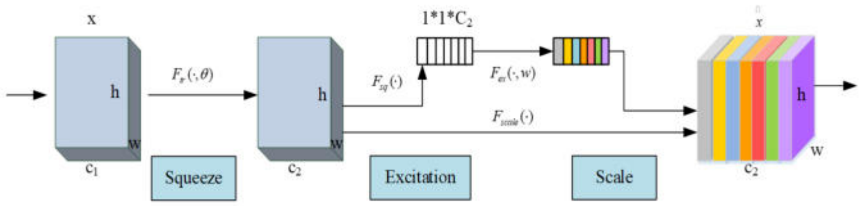


Fig. 3.2: SE schematic diagram

equation 3.3.

$$s_t = \sum_{j=1}^{t} \alpha_j h_j \tag{3.3}$$

In equation 3.3, combine s_t and h_t, the probability calculation expression for motor vehicle identification and monitoring is shown in equation 3.4.

$$y_t = \sigma\left(W\left(s_t \oplus h_t\right) + b\right) \tag{3.4}$$

Cross entropy can be used to measure the difference between the probability distribution of the real tag and the predicted result in machine learning. Therefore, it is used as the Loss function of the model, as shown in equation 3.5.

$$L = -\sum_t \left(a_{t+1} \log y_t^T \delta\left(q_{t+1}\right) + \left(1 - a_{t+1}\right) \log\left(1 - y_t^T \delta\left(q_{t+1}\right)\right)\right) \tag{3.5}$$

In equation 3.5, a_{t+1} represents the true probability distribution, $y_t^T \delta\left(q_{t+1}\right)$ is the probability distribution for prediction. For the GloU_Loss loss function, let there exist rectangles P and P, and the area where the two rectangles intersect is I, the expression of the function is 3.6.

$$GIoU = A^p + A^g - I - \frac{A^c - U}{A^c} \tag{3.6}$$

In equation 3.6, A^p, A^g denotes the areas of rectangles p and g respectively, U denotes the area of disjoint rectangles and A^c is the area of the smallest external rectangle. To build an algorithm better suited for motor vehicle detection, the study improves the TOLOv5 network structure: the convolutional operation template in the TOLOv5 backbone network model is replaced with a Ghost template to reduce parameter redundancy during training. The related function expression is shown in Equation 3.7.

$$y_{ij} =_{i,j} (y_i'), \forall i = 1, 2, ..., m; j = 1, 2, ..., s \tag{3.7}$$

In equation 3.7, i, j is the linear transformation function that generates the j^{th} ghost feature map of $y_i^{'}$. After reducing the amount of computational data in the model, the accuracy of the backbone network lightweight YOLOv5 model is considered to be further improved so that it can focus more on the key information to solve the task at hand amidst the large amount of input information. The study introduces Squeeze-and-Excitation (SE) and Convolutional Block Attention Module (CBAM) to improve the accuracy and efficiency of target detection. the SE schematic is shown in Figure 3.2.

As can be seen in Figure 3.2, the squeeze layer architecture of the SE is used to show the relevance of the modeled feature channels by turning the two-dimensional feature channel into a scalar with a global receptive field, and by making the shallow layer also acquire a global receptive field. In addition, the stimulus layer of

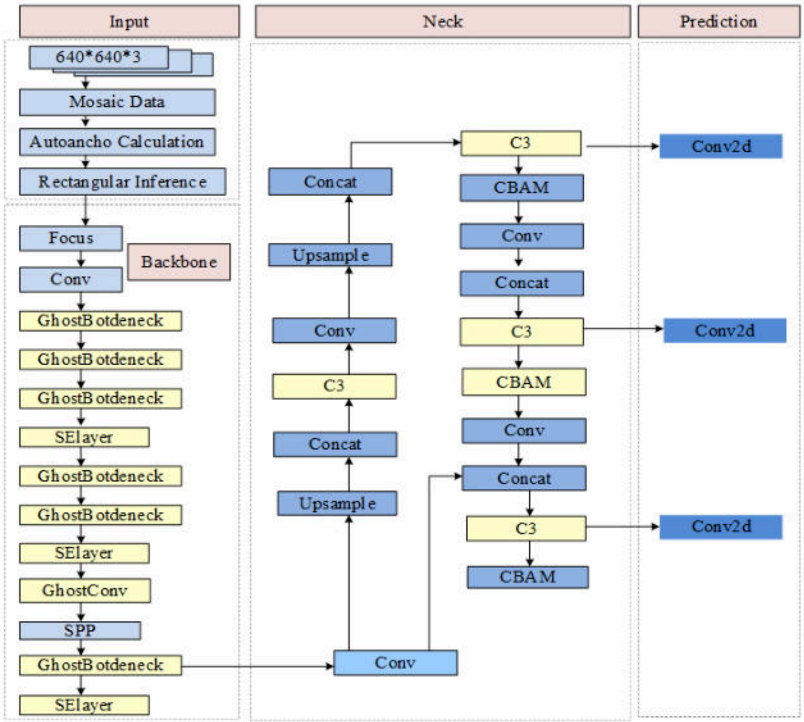


Fig. 3.3: YOLOv5-Ghost network structure diagram

SE is primarily used to generate weights for a particular channel at full connectivity to show the relevance of the modelled feature channels. The equation is shown in equation 3.8.

$$A(x) = \alpha(MLP(AvgPool(x)) + MLP(MaxPool(x)) \tag{3.8}$$

In equation 3.8 x is the input feature map, $AvgPool$ is the average pooling operation, $MaxPool$ is the maximum pooling operation, MLP is the fully connected layer and denotes the sigmoid function. sigmoid function as a weighted multiplication method with normalized weights achieves the attention threshold highlighted by the algorithm by assigning attention weights to the input features. sigmoid equation is shown in 3.9.

$$f(x) = \frac{1}{1+e^{-x}} \tag{3.9}$$

The corresponding replacement templates are Ghost Bottleneck module and Ghost Conv module. One of the Ghost Bottleneck modules consists of two Ghost modules stacked twice. The backbone network is then given the feature map convolution operation. The CABM template is added into the lower adoptive layer of the neck to patch the deficiency of uneven weight distribution of the SE module, thus enhancing the feature representation capability. Figure 3 depicts the YOLOv5-Ghost network's organizational structure [15].

In Figure 3.3, the constructed YOLOv5-Ghost replaces the original BottleneckCSP in the neck with a C3 structure, thus making the constructed YOLOv5-Ghost model structure more efficient and concise, the network structure is also more simplified, and the resulting parameter operations involved are reduced accordingly.

3.2. Model Construction of Multi-objective Motor Vehicle Tracking and Violation Recognition Algorithm. Simple online Realtime tracking with a deep association metric (DeepSort) is a multi-target tracking algorithm based on target detection and is suitable for multi-target portrait tracking. DeepSort uses

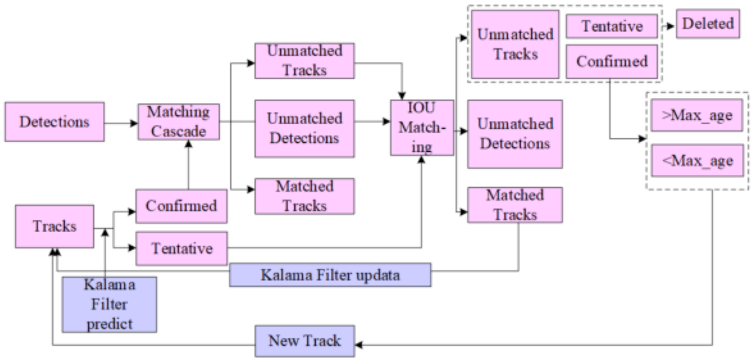


Fig. 3.4: Flowchart of Deep Sort

cascade matching to reduce the number of target ID jumps and retains the simple online Realtime tracking (SORT) algorithm for the transport characteristics of a matched target. Similarity. The covariance calculation equation is shown in Equation 3.10.

$$d_{i,j} = (d_j - y_i)^T \frac{1}{S_i} (d_j - y_i) \tag{3.10}$$

In equation 3.10, d_j is the position of the detection frame of the j^{th} target, y_i, S_i denotes the tracking position of the i^{th} Kalman filter on the target, and S_i denotes the covariance matrix. The standard deviation between the mean value of the target's tracking position by the Kalman filter and the detection frame is used to estimate the uncertainty between the measured and true values of the target. Additionally, a specific covariance distance value is set to filter out targets that are not correlated. This operation will also involve the calculation of the cosine distance, and the relevant equation is shown in equation 3.11.

$$h_{(i,j)} = \min\{1 - {r_j}^T r_k^{(i)} | r_k^{(i)} \in R_i\} \tag{3.11}$$

In equation 3.11, $r_j^T r_k^(i)$ is the cosine similarity and $h_{i,j}$ is the minimum cosine distance between the set of vectors closest to the location tracked by the i^{th} Kalman filter and the feature vector of the j^{th} detection result. As $d_{i,j}$ and $h_{i,j}$ can only provide the possible positions of moving objects and cannot be applied to position prediction after the target has been obscured for a long period of time, this leads to the introduction of the correlation degree characterising the degree of combination of motion features and apparent features, which is expressed in the equation shown in equation 3.12.

$$c_{i,j} = \lambda d_{i,j} + (1 - \lambda) h_{i,j} \tag{3.12}$$

In equation 3.12, is the weighting factor. Rectification leads to the flow chart of DeepSort shown in Figure 3.4.

In Figure 3.4, the Deep Sort uses mainly recursive Kalman filtering to correlate frame-by-frame data, with a single hypothesis tracking algorithm at its core. while Deep Sort has good performance in multi-target portrait tracking processing, it is not directly applicable to multi-target tracking of motor vehicles. Therefore, some training of the Deep Sort algorithm with the dataset is needed to make it applicable to the deep appearance training model for motor vehicles. As the Veri-776 dataset contains a large amount of highly reproducible and multi-attribute motor vehicle data, and the captured images are realistic and unconstrained, and also annotated with information about different attributes, the study uses the Veri-776 dataset to train the Deep Sort algorithm for a deep appearance model applicable to motor vehicles. The constructed model is to a certain extent able to recognize multi-objective motor vehicle detection and tracking, but it cannot be better implemented for whether a motor vehicle has an illegal behavior. Open-Source Computer Vision Library (OpenCV) to identify basic

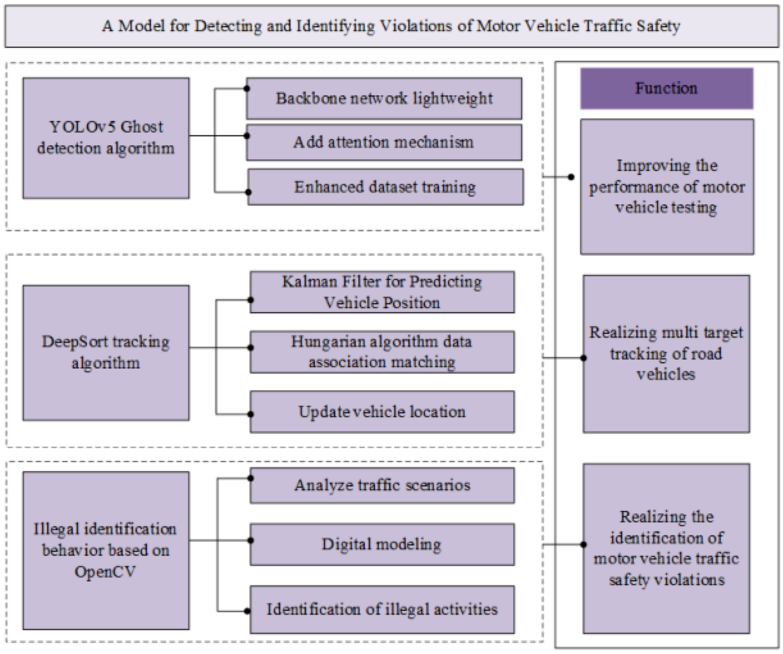


Fig. 3.5: Cascade OpenCV after YOLOv5-DeepSort algorithm model

traffic safety violations. The YOLOv5-DeepSort algorithm model by cascading OpenCV is shown in Figure 3.5.

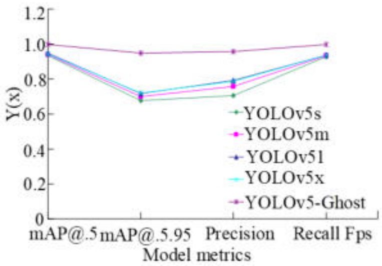
The structure diagram for the motor vehicle traffic safety violation detection and recognition model is separated into three sections as shown in Figure 3.5. The main purpose of the YOLOv5-Ghost detection method is to enhance the performance of motor vehicle detection. This algorithm is primarily used to track multiple objectives while updating the position of road motor vehicles. And OpenCV is mainly used to analyses traffic scenes, realize digital modelling and the recognition of violations to ensure the effective recognition of motor vehicle safety violations.

4. Analysis of the Results of the Motor Vehicle Violation Recognition Model.

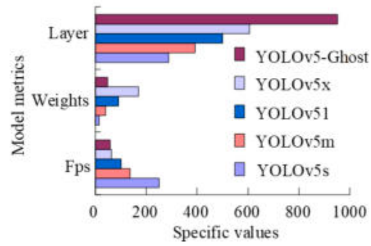
4.1. Detection and training analysis of optimized models and other models. The pre-processed KITTI dataset and the UA-DETRAC dataset were utilized in the study to train the motor vehicle detection algorithm in order to account for the issues with dataset format and detection target. The 89,566 total images in the two pre-processed datasets are randomly split into training and test sets in the ratio of 8:2, resulting in a total of 70,635 training images and 18,931 test images. The training environment for the YOLOv5 network was built when the dataset conversion was finished, and the specific server setup parameters for the trial run are presented in Table 4.1. To compare the experimental results of YOLOv5s, YOLOv5m, YOLOv51, YOLOv5x, and YOLOv5-Ghost regarding accuracy, recall, weight assignment, and detection speed, tests were created to assess the performance of the YOLOv5 network structure. The dataset used for the experiments was 1565 images from the pre-processed KITTI. The results of the five network models regarding target detection are shown in Figure 4.1. As can be seen in Figure 4.1, YOLOv5Ghost has the highest accuracy and recall of 0.957 and 0.997 respectively. The number of network model layers, 91, ranks highest among the five algorithms, and the parameters required for the model calculation are 25092769.It can be said that the enhanced YOLOv5Ghost model has raised the network structure depth in comparison to the original YOLOv5, and on the basis of this, reduces the computational parameters. In terms of detection speed, the YOLOv5Ghost model has the lowest Fps value and is not as fast as the YOLOv5 model, but has improved the accuracy and recall by up to 25.1%

Table 4.1: Detailed Parameters of the Server Configuration for the Experimental Run

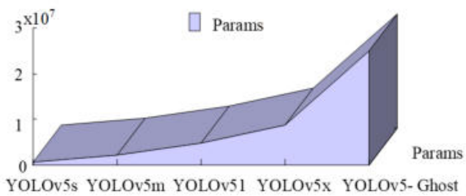
Experimental Equipment	Experimental Parameters
System	Windows Server 2016 Standard
Memory	512GB
CPU	Intel(R) Xeon(R) CPU E7-8890v4 @ 2.20GHz
GPU	NVIDIA Quadro P6000



(a) Partial Results of Motor Vehicle Model Testing



(b) Partial Results of Motor Vehicle Model Testing

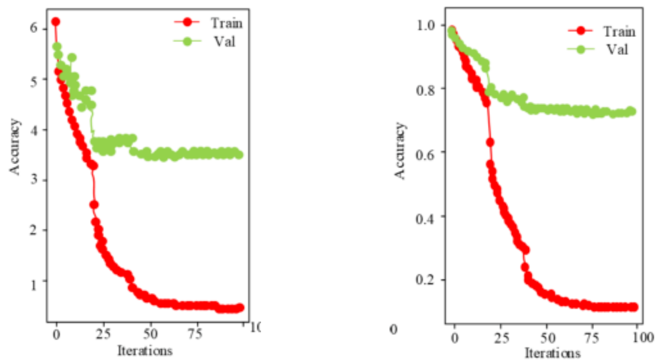


(c) Partial Results of Motor Vehicle Model Testing

Fig. 4.1: Target detection results for five network models

and 6.9%. The weight value of the improved YOLOv5Ghost model is 48.4MB, which is 42.4MB and 120MB lower than the YOLOv51 and YOLOv5x models, respectively. the reduced weight file size allows the model to run stably on embedded devices and the increased number of network detection layers reduces the operating parameters. According to the experimental findings, the Institute's modified YOLOv5Ghost model performs better in terms of motor vehicle identification than the original YOLOv5. The Deep Sort tracking algorithm was trained using the same experimental environment as the motor vehicle tracking algorithm. The experimental outcomes are depicted in Figure 4.2. The probability and loss rate of both the training and test sets with regard to the inaccurately predicted target drop as the number of iterations rises, as shown in Figure 4.2. The decreasing trend of the LOSS curve for the training set is stable at the beginning of the iterations and increases after the number of iterations is 25. The decreasing trend of the probability of incorrect prediction curve before the number of iterations is 25 is greater than the decreasing trend after the number of iterations is 25, and the decreasing trend is again obvious when the number of iterations is 40. At around 60 iterations, the Loss curve and the probability of error prediction curve do not change significantly, indicating that the training is saturated at this point. Experiments were designed to validate the performance of the constructed YOLOv5-DeepSort motor vehicle detection and tracking algorithm.

4.2. Analysis of weekly peak recognition efficiency test for motor vehicles. The road surface monitoring of Highway 648 and the 900m western half of the G4 Beijing-Hong Kong-Macao Expressway in Henan Province were selected as the experimental objects. The number of motor vehicles on the western half of the road section was counted manually against the number of vehicles required to be counted travelling from north to south. Table 4.2 displays the outcomes of the tracking experiment. As shown in Table 2, the Institute's proposed locomotive detection method is able to find the corresponding number of locomotives in a predetermined period of time. The best tracking experimental results are those obtained when the video duration is 50 s. The actual number of vehicles and the number of detected vehicles are the same, both being 72. The rest of the time period has a maximum error rate of 1.10% in diagnosis, corresponding to a time period of 120 s. The few cases of missed detection of vehicles that occur may be due to the fact that



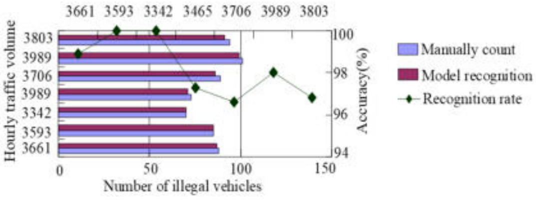
(a) Loss (b) Toplerr

Fig. 4.2: Deep Sort training results schematic

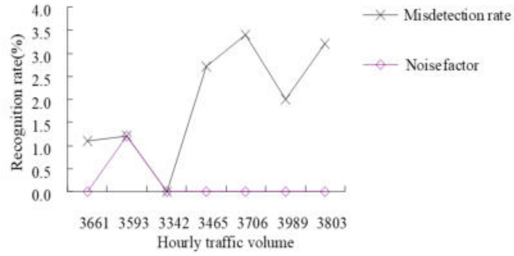
Table 4.2: The Results of Motor Vehicle Detection and Tracking Algorithms in Practical Work

Video Duration (s)	Actual No. of Vehicles	No. of Vehicles Tested	No of Missed Inspections	Misinspection Quantity
120	188	186	3	1
70	88	87	1	0
60	112	111	2	1
50	72	72	0	0

some of the motor vehicles have similar colors to the environment and the detection targets are small and the algorithm identifies them as pseudo-targets. False detections can arise due to interference from other dynamic objects in the surveillance vision, such as small vehicles obscuring large vehicles, thus allowing large vehicles to be identified as multiple detection targets and not being successfully merged together. After verifying the recognition and tracking effectiveness of the motor vehicle detection model, the performance of the cascaded OpenCV algorithm for determining motor vehicle traffic violations needs to be verified. The basic traffic safety violations can be categorized into three types of motor vehicle pressure realization lane change, pressure in the form of guiding lanes and intersection section vehicle turnaround violations. For the three different basic traffic safety violations, different field data are selected for the experiments. For the detection of motor vehicle lane changing violations by pressing the solid line, the real-time surveillance video of the urban section of Xiuxiang Avenue in Nanning City, Guangxi Province, from June 27, 2021 to July 3, 2021, during the period from 16:30 to 17:30 p.m. was selected for the experiment to compare the manual statistics of the weekly peak hour motor vehicle lane changing results by pressing the solid line, and Figure 4.3 displays the outcomes of the experiment. In Figure 4.3, the experimental set of statistics traffic flow can reach 3651 vehicles per hour, the total number of vehicles that change lanes by pressing the solid line is 600, and the model identifies a total of 589 vehicles, with an average recognition rate of 98.2%. Compared to traditional manual recognition statistics, the accuracy rate of the vehicle violation recognition model constructed by the Institute ranged from 96.6% to 100%. There was no significant relationship between the recognition accuracy and peak hour traffic flow, with an average miss rate of 2.0%, a maximum miss rate of 3.4% and a minimum miss rate of 1.1%. Only one of the seven statistics included a false detection rate of 1.2%, while the false detection rate was zero in the remaining six cases. A roundabout on Chunguang Street in Fengmin District, Handan City, Hebei Province, with good weather conditions and suitable sightline conditions was selected as the subject of the experiments.

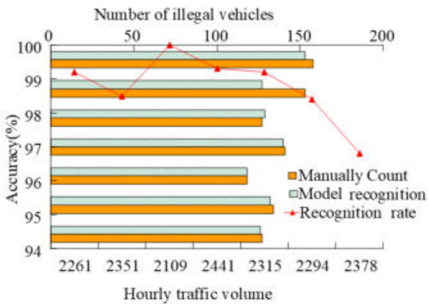


(a) Identification Results 1 of Lane Change of Motor Vehicle Compaction Line During Peak Hours of the Weak

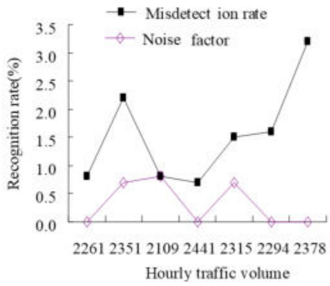


(b) Identification Results 2 of Lane Change of Motor Vehicle

Fig. 4.3: Week Peak Hour Vehicle Compaction Line Change Results



(a) Driving Results 1 of Motor Vehicle Pressure Guide Line



(b) Driving Results 1 of Motor Vehicle Pressure Guide Line

Fig. 4.4: Week Peak Hour Motor Vehicle Pressure Flow Line Driving Results

The data set was selected as vehicle movement statistics from 14:30 to 15:30 in the afternoon of each day from 23 January 2022 to 29 January 2022. A UAV was used to count the relevant traffic volumes and upload the data photos to the backend. The vehicle identification tracking offence system constructed by the study was then used to compare the traditional manual statistics to produce the relevant experimental results, as shown in Figure 4.4. In figure 4.4, the average traffic flow at the roundabout was 2307 vehicles per hour. The total number of motor vehicles manually counted driving against the guideway was 937, and the model identified 925, with an average recognition accuracy of 98.7%. Again there was no significant relationship between peak hour traffic and recognition accuracy, with the highest model recognition accuracy of 100% and the lowest of 96.8% for the seven time periods. Each time period is subject to a miss detection rate, with the minimum being 0.7%. The relatively high false detection rate may be due to some vehicles driving along the edge of the guide line and the model deciding that they are pressing the line, while the high false detection rate is due to two vehicles driving along the guide line at the same time and the vehicle behind them not being effectively identified due to obscuration. The same weather conditions and good view conditions were selected, and the intersection of Bei Er Wei Yi Road in Siping City, Jilin Province was used as the experimental object. The traffic flow from 16:30 to 17:30 in the afternoon of each day from 2021.3.22 to 3.28 was selected as the data set, and experiments were designed to verify the performance of the model regarding motor vehicle illegal U-turn recognition, again comparing the traditional manual statistical results, and Figure 10 displays the outcomes of the experiments. In Figure 4.5, the traffic flow at the intersection averaged 637 vehicles/hour after manual counting, with a total of 96 vehicles in violation, and the model identified a total of 94 vehicles in violation,

(a) Recognition Results 1 of Illegal Turning of Motor Vehicles

(b) Recognition Results 1 of Illegal Turning of Motor Vehicles

Fig. 4.5: Week peak hour motor vehicle turnaround violation identification results

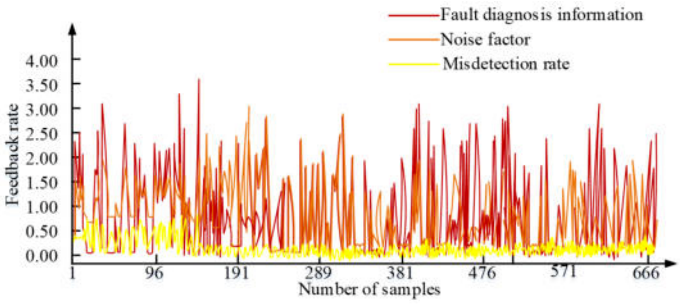


Fig. 4.6: On board system feedback information on motor vehicle violations

with an average recognition accuracy of 97.9%. Compared to the other two basic traffic violations, the model's violation recognition accuracy is higher. The recognition accuracy was 100% in five of the seven time periods. The average rate of missed detection was 2.1%, and the average rate of erroneous detection was 0%. The reason for the missed detection was that the detector was unable to precisely identify the motor vehicle in issue since some vehicles were severely veiled. We selected Chenghua Avenue in Chengdu, Sichuan Province as the experimental object, and selected daily traffic from 18:30 to 21:00 on March 11, 2023 to March 16, 2022 as the dataset. We designed an experimental validation model and provided feedback information on the vehicle system for motor vehicle violations, as shown in Figure 4.6.

In Figure 4.6, when the number of samples on Chenghua Avenue exceeds 190, there is a significant decrease in the false alarm rate; When the sample size is 381 or above, there is a significant decrease in the number of noise points, but there is still rebound. When the sample size is between 230 and 360, the prediction accuracy of fault diagnosis information will significantly decrease.

5. Conclusion. In order to solve the problem that manual supervision means are time-consuming and laborious in dealing with motor vehicle violations and prone to oversight omissions, the research designs a motor vehicle traffic violation identification and tracking model with an improved YOLOv5Ghost model fused with OpenCV modules. The results of the experimental performance test reveal that the modified YOLOv5Ghost model has an accuracy and recall rate of 95.7% and 99.7%, respectively, with a maximum improvement of 25.1% and 6.9% when compared to the YOLOv5 model. Comparing the performance of manual statistics and the YOLOv5-DeepSort algorithm regarding motor vehicle detection and tracking, YOLOv5-DeepSort has an accurate recognition rate of 98.7%, a missed detection rate of 1.55% and a false detection rate of 0.67%. The performance of the motor vehicle recognition model incorporating the OpenCV module is verified by comparing manual statistics in a real-world environment. The experimental results show that in the experiments of changing lanes by pressing the solid line, there are 600 vehicles in total in the manual solvent and 589 vehicles in total are identified by the model, with an average recognition rate of 98.2%, an average miss detection rate of 2.0% and an average false detection rate of 0.17% by the model. The average recognition accuracy of the model was 98.7% and the average false detection rate was 0.31% in the experiment of driving on the pressure guide line. In the experiments on illegal motor vehicle U-turn identification, a total of 96 vehicles were counted manually and 94 vehicles were identified by the model, with an average recognition accuracy rate of 97.9%. The research results indicate that the modified YOLOv5Ghost model of Deepsort performs better than the original YOLOv5 model in motor vehicle recognition. The constructed motor vehicle violation recognition model has good recognition rate and stable performance, which can save a certain amount of manpower and financial resources compared to traditional manual statistics. The YOLOv5 Ghost model structure constructed is more efficient and concise, and the network structure is also more simplified, resulting in a corresponding reduction in parameter operations.

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