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A Research on Pedestrian-Vehicle Detection Algorithm based on YOLO

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Abstract:- With the continuous advancement of urbanization, the importance of pedestrian and vehicle detection is becoming more and more prominent in many fields such as intelligent transportation, autonomous driving, and public safety. Traditional methods of pedestrian-vehicle detection often suffer from slow speed and inaccuracy. In this paper, we systematically review and deeply analyze target detection algorithms, with a focus on the progression from YOLOv1 to YOLOv10 in pedestrian-vehicle detection, and summarize the various network enhancement strategies reported in the literature. Despite progress in feature extraction, network structure, algorithm optimization, lightweight design, and multimodal exploration, pedestrian-vehicle detection algorithms still confront significant challenges, particularly in detecting extremely small targets and adapting to various environments. This paper offers a thorough perspective and serves as a valuable reference for research in pedestrian-vehicle detection, significantly advancing the development of more precise and resilient detection technology.

Keywords: *Pedestrian Detection1, Pedestrian-Vehicle2, Vehicle Detection3, YOLO4.*

1. Introduction

With the advancement of urbanization, pedestrians and vehicles have become essential components of urban transportation systems, making their detection and recognition extremely crucial for intelligent transportation systems, autonomous driving, and public

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safety monitoring. The traditional object detection methods, relying on filtering and feature extraction, have been proven effective in some cases but are restricted by slow speeds and low accuracy. The YOLO algorithm has emerged as a remarkable research area due to its rapid and precise target detection capabilities.

This review conducts an in-depth analysis of pedestrian-vehicle detection algorithms, providing researchers with an overall perspective on the potential and future direction of this technology. A comprehensive examination of the current literature indicates that the YOLO-based algorithms are expected to play a more significant role in pedestrian-vehicle detection as technological development and innovation continues. Additionally, this review clarifies the challenges and issues in the current research and proposes possible optimization approaches to inform future studies.

Overview of pedestrian-vehicle detection

Importance of pedestrian-vehicle detection

Pedestrian-vehicle detection utilizes computer vision to automatically identify and locate pedestrians and vehicles in images or videos. The process entails feature extraction and differentiation from complex backgrounds, facilitating precise recognition and tracking of targets[1]. The significance of pedestrian-vehicle detection extends across various fields:

In the domain of urban planning and the development of intelligent transportation systems, precise detection of pedestrians and vehicles is indispensable for traffic management and road safety, facilitating the timely detection of pedestrians and vehicles and providing data for traffic signal management and autonomous driving. assisting decision-makers in understanding traffic flows and patterns across various regions, and providing a scientific basis for the rational planning of road infrastructure and traffic facilities. assisting decision-makers in understanding traffic flows and patterns across various regions, and providing a scientific basis for the rational planning of road infrastructure and traffic facilities.

In the safety assistance systems of autonomous driving, pedestrian-vehicle detection assists drivers in perceiving their surroundings, a critical technology for ensuring vehicle safety by enabling environmental recognition and decision-making, ND facilitates warnings or emergency braking when danger is detected, thereby enhancing driving safety and minimizing collision risks.

In the field of public safety, pedestrian-vehicle detection can identify suspicious activities,

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and prevent incidents by continuously monitoring and analyzing traffic conditions, additionally, it can oversee critical locations and intersections, providing real-time insights into the movements of people and vehicles, which is vital for crime prevention and safeguarding public security.

Furthermore, pedestrian-vehicle detection offers foundational support for applications such as intelligent video surveillance and drone identification and fosters the advancement and innovation within related sectors[2].

In summary, pedestrian-vehicle detection plays a crucial role in guaranteeing traffic safety, strengthening urban management, and promoting scientific and technological advancement, and it represents a research focus in the field of object detection and tracking.

Key technologies for pedestrian-vehicle detection:

Pedestrian-vehicle detection, a crucial application within the field of target tracking and detection, is classified into two principal types: traditional detection algorithms and those founded on deep learning, distinguished by the employment of deep learning techniques.

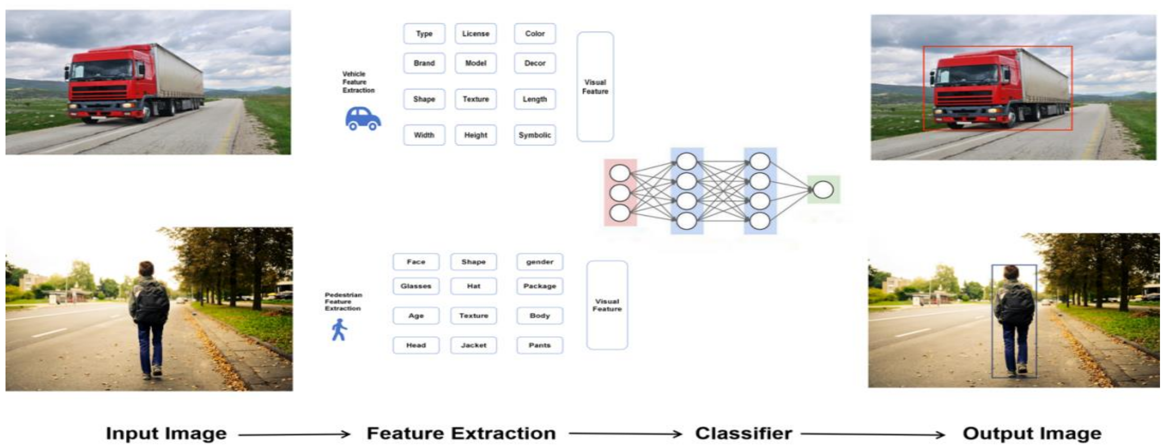

Figure 1. Traditional pedestrian-vehicle detection technique

The traditional pedestrian-vehicle detection algorithm is mainly composed of the following stages: region selection, feature extraction, and classification through a classifier. Initially, the image is scanned by a sliding window to determine the regions of interest based on the location and size characteristics of the vehicle. Subsequently, features are extracted from these regions, and then classification is carried out using methods such as artificial neural networks (ANN)[3], support vector machines (SVM), and Adaboost to finalize vehicle detection[4]. As shown in Figure 1.

Power System Technology
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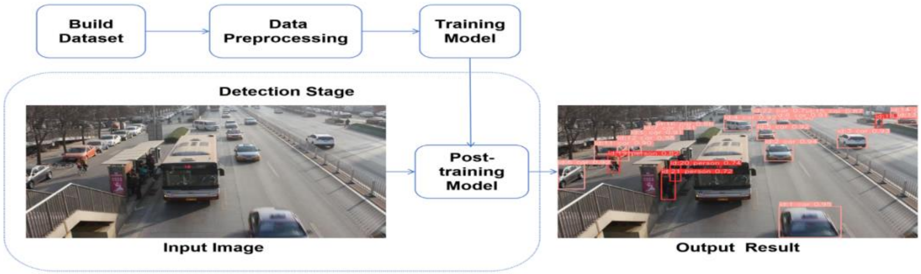

Figure 2. Pedestrian-vehicle detection technique based on deep learning

In traditional pedestrian-vehicle detection algorithms, the region selection based on the sliding window is non-specific, resulting in numerous redundant windows and an increased time complexity. Moreover, the variability in lighting and backgrounds during pedestrian-vehicle movement complicates the manual design of robust vehicle features, with the feature extraction's effectiveness directly impacting classification accuracy. These shortcomings make it challenging for traditional detection models to achieve accurate and timely detection. With the progress of deep learning, convolutional neural networks (CNNs) for feature extraction have substituted manual feature design, significantly improving the accuracy of real-time vehicle detection. Concurrently, single-stage detection networks based on deep learning bypass the acquisition of candidate regions, directly predicting the bounding box and category from the input image, thereby accelerating the detection speed. The model's simplicity makes it well-suited for use in embedded devices with constrained computing and storage capabilities, enhancing its practical application value. As depicted in Figure 2.

Pedestrian-vehicle detection algorithm

Overview of Pedestrian-Vehicle Detection Algorithms

Deep learning-based detection algorithms are classified into two major types in light of their procedural attributes[5]: Two-Stage and One-Stage object detection algorithms.

Two-stage detection algorithms, represented by the R-CNN family, provide higher accuracy in detection yet are slower, rendering them less appropriate for real-time applications such as pedestrian-vehicle detection where timeliness is crucial.

One-stage detection algorithms, characterized by the YOLO, SSD, and Anchor-Free series, are renowned for their equilibrium of accuracy and speed and are widely employed in pedestrian-vehicle detection. The evolution of these algorithms for pedestrian-vehicle detection is depicted in Figure 3.

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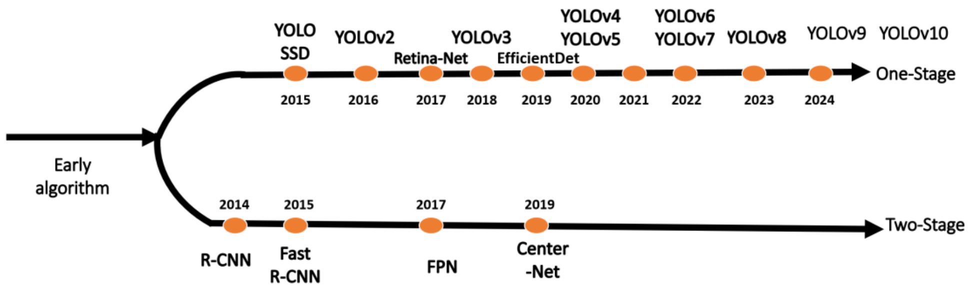

Figure 3. Timeline for the development of Pedestrian vehicle detection algorithm.

The R-CNN algorithm, standing for Region-based Convolutional Neural Networks, marked a milestone in 2014 by integrating deep learning into target detection[6]. It leverages deep learning to automatically extract features from input images, enhancing sample classification and prediction accuracy. The subsequent Faster R-CNN algorithm, which incorporates a Region Proposal Network (RPN)[7], has notably increased detection speed and demonstrated high precision in the detection of pedestrians and vehicles.

1. YOLO (You Only Look Once) series algorithms: The YOLO algorithm initiated the deep learning-based one-stage target detection algorithm and is renowned for its rapid detection speed. The evolution of the YOLO algorithm in the domain of pedestrian-vehicle detection is elaborated in detail in Section 3.2.
2. The SSD (Single Shot Multi Box Detector) algorithm, introduced by Wei et al.[8],merges the strengths of Faster-RCNN and YOLO. It achieves multi-scale target detection by simultaneously predicting bounding box locations and category probabilities within a unified framework across various feature map scales. Despite its robustness, SSD struggles with the detection of small targets. Additionally, its parameter-tuning process is experience-dependent and demands considerable computational resources.
3. The Retina Net algorithm performs end-to-end target detection within a unified network framework[9]. It integrates the Focal Loss function to tackle class imbalance, thereby improving the accuracy of detecting small and hard-to-detect targets.
4. The Efficient Det algorithm, introduced by Tan et al., achieves a balance between detection velocity and precision[10]. It optimizes the network architecture through the combination of scale, depth, and width factors, and achieves high-precision detection with minimal computational cost. This methodology offers new insights for dealing with the trade-off between detection efficiency and accuracy. However, the model structure may sometimes hinder the accurate detection of small objects. The small object detection has

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been removed for brevity.

5. The Center Net algorithm[11] redefines the challenge of object detection by focusing on pinpointing the center points of object frames. As an anchor-free detection method, it avoids the complexities associated with anchor-based detectors and maintains high detection speeds. However, it may have difficulties in differentiating objects with overlapping center points, which may limit its detection accuracy.

In summary, the field of pedestrian-vehicle detection has made remarkable progress through the improvement of detection algorithms. These developments have promoted the evolution of object detection technology and provided a clear way for future research. Notably, the YOLO algorithm has risen to prominence in the research area, because of its fast detection speed and improved accuracy.

Evolution of the YOLO algorithm in the field of pedestrian-vehicle detection

The YOLO algorithm, introduced by Joseph Redmon et al. in 2015[12], represents a milestone innovative in the field of object detection. This method not only accelerates the detection process for pedestrians and vehicles but also sustains a high level of accuracy.

The YOLO family has evolved through multiple versions, from YOLOv1 to YOLOv10, with each version enhancing the network's architecture and performance. Table 1 presents a comparative analysis of the key advancements in each YOLO iteration, specifically from the standpoint of pedestrian-vehicle detection.

YOLO, put forward by Joseph Redmon in 2015, revolutionized the field with its one-stage detection model. Its core notion is to transform the detection task into a regression problem, using a single convolutional neural network (CNN) to concurrently extract features and predict the bounding box confidence for each grid cell. The final stage involves applying the non-maximum suppression (NMS) algorithm to filter and refine the bounding boxes, generating the optimal detection outcomes. On the PASCAL VOC2007 dataset, YOLO achieved a remarkable 155 FPS detection speed with an average accuracy of 52.7%, effectively pioneering a new era for one-stage detection algorithms. The repetition of the performance metrics has been removed for conciseness and clarity.

YOLOv2: also known as YOLO9000,[13] builds upon the foundation of YOLOv1 by refining the network architecture. It incorporates Anchor Boxes to enhance target localization and modifies the loss function to better handle positional regression. Additionally, it adopts a multi-scale training strategy. These enhancements have rendered YOLOv2 particularly

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effective for real-time pedestrian-vehicle detection applications.

YOLOv3 enriches feature representation by incorporating a Feature Pyramid Network (FPN), which enables the extraction of multi-scale features. It also introduces a novel loss calculation method that fine-tunes the loss function, enhancing the model's training stability and detection precision. [14] The bounding box prediction process has been refined to boost the accuracy of small target and complex scene localization.

In 2020, Alexey unveiled the YOLOv4 algorithm,[15] integrating the Mish activation function[16] and Mosaic data augmentation techniques[17] to enhance both training and inference efficiency.

Table 1. Evolution of YOLO versions from the field of pedestrian-vehicle detection

	Framework	Advantageous	Defective
YOLO	Goog Le Net	Considering target detection as a regression problem, the detection speed is greatly improved over traditional vehicle detection algorithms	Inaccurate localization of the bounding box leads to poor detection of small target pedestrians and vehicles, and each grid can only predict a single category, with the problem of missed detection
YOLOv2	Darknet-19	Introducing anchor frames to predict bounding boxes, accelerating model training using batch normalization, and improving detection of small targets through multiscale prediction	Using only 2 dimensional feature maps, the detection of smaller vehicle targets still suffers from omission and misdetection, the
YOLOv3	Darknet-53	Multi-scale prediction and feature pyramid networks are brought in to notably enhance the detection of	There are still omissions and errors for vehicle detection in traffic congestion environments as well as small target vehicle detection. There is an increase in

Power System Technology
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		targets of different sizes.	model complexity and computational resource consumption
YOLOv4	CSPDarknet-53	Improved Overlapping Vehicle Detection Performance with Increased Speed and Accuracy for Autonomous Driving	The model is large in size, the detection speed is slow on small mobile devices, and the accuracy of small object detection needs to be enhanced
YOLOv5	PY Torch	Fast detection speed; there are various network structures for more flexible use. Lightweight and easy to deploy	Accuracy can be further improved in complex scenes such as in changing light, heavy occlusion, etc.
YOLOv6	PY Torch	Good balance between speed and accuracy	Target detection can be enhanced for extremely small or heavily occluded targets
YOLOv7	PY Torch	Has high detection accuracy and speed. Can provide more accurate results while meeting real-time requirements	Adaptability can be further improved under different weather conditions, different road types, etc.
YOLOv8	PY Torch	Extremely high speed, appropriate for dynamic environments	May have difficulties with very small or fast-moving objects
YOLOv9	PY Torch	High accuracy and recall	Demands an extensive dataset for training
YOLOv10	PY Torch	Improved accuracy-efficiency balance, model without	Complicated configuration for multi-source integration

Power System Technology
ISSN:1000-3673
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		NMS	

YOLOv5 has emerged as a pivotal method in target detection [17], striking an effective balance between accuracy and speed. The method is categorized into four variants—YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x—with no change in the network architecture but differences in model depth and width.

In 2022, Mission introduced YOLOv6 [18], employ label assignment to enhance model prediction accuracy, training strategies, and quantization techniques. It demonstrated strong performance in industrial applications. Also in 2022, Alexey unveiled YOLOv7[19], introducing a reparametrized convolutional module devoid of constant mapping.

YOLOv8, released by Ultralights in 2023[20], takes advantage of the advancements of its predecessors and offers a series of model variants customized for various performance and computational requirements: YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x. The variety of models ensures that users can select the most appropriate model type in accordance with their specific needs.

YOLOv9 is designed with an emphasis on retaining critical information within the network [21], ensuring a strong gradient flow and preventing the degradation of data quality. This makes it a viable option for pedestrian-vehicle detection within specialized contexts. However, the scarcity of research to date has limited a thorough evaluation of its various applications. Additional studies and a larger dataset are necessary to fully realize its potential.

YOLOv10 [22], the advanced iteration by Tsinghua University, has made remarkable progress in the field of real-time object detection. This version introduces a dual-head architecture, eliminating the need for Non-Maximum Suppression (NMS) during training and decreasing latency. Furthermore, it reduces information loss during feature recovery. YOLOv10 also incorporates a rank bootstrap block design to optimize efficiency. On the MS-COCO dataset, the various iterations of YOLOv10 show mean Average Precision (MAP) scores that span from 38.5% to 54.4%. The YOLOv10-N and YOLOv10-S models perform well in low-latency contexts, with latencies as minimal as 1.84 MS and 2.49 MS. The YOLOv10-X variant leads with an m AP of 54.4% and a latency of 10.70 MS, with enhancements in both accuracy and speed. The progression and implementation of YOLOv10 are likely to mark a new period of object detection technology.

In summary, since the birth of YOLOv1, the YOLO family has gradually occupied a position in the field of pedestrian-vehicle detection. With each version, the applications of these

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algorithms have become more complex, particularly with YOLOv8 and YOLOv10. The application scope of these versions in the detection field has significantly expanded. The refinements in these algorithms offer valuable insights for the next generation of detection algorithm design. It is evident that innovations in backbone network architecture and efficient feature fusion are pivotal for enhancing detection performance.

2. Results and Discussion

Building upon the YOLO algorithms for pedestrian-vehicle detection, researchers have delved deeper into the field. A systematic review of the literature has been conducted, with Table 2 summarizing key arguments, the merits and demerits of various studies, and other pertinent information.

Table 2. Improvement of Pedestrian Vehicle Detection Algorithm

Author (year)	Thematic specific topic	major arguments gaps	strengths and weaknesses
Jin Du et al(2023)	Fast Pedestrian-vehicle Detection based on YOLO-FPN	lack of detailed analysis of limitations	Strength: Fast detection. Weakness: Unclear how it fares in complex environments.
Ke-Lin Du et al (2024)	Research on a Lightweight Pedestrian Detection Method Based on YOLO	May not address scalability issues	Strength: Lightweight. Weakness: This may have reduced accuracy for certain scenarios.
Jianhua Cao et al(2021)	Pedestrian Detection Algorithm Relying on Vi Be and YOLO	May not handle diverse lighting conditions well	Strength: Hybrid approach. Weakness: Dependency on ViBe may introduce additional complexity.
Guimin Zou et al (2023)	Pedestrian object detection algorithm based on improved YOLO	Unclear improvement limitations	Strength: Improved version. Weakness: May have compatibility issues with older systems.

Power System Technology
ISSN:1000-3673
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	v5		
Lisang Liu et al (2022)	Research on Pedestrian Detection Algorithm Based on Mobile Net-Yo Lo	Performance issues with limited resources	Strength: Mobile-friendly. Weakness: May have lower accuracy compared to more powerful models.
Xinwei Zhang et al(2023)	Pedestrian-vehicle Detection Using the YOLO Framework and Multi-Model Approaches	Complexity and resource consumption	Strength: Multiple models may improve accuracy. Weakness: Increased complexity and potential for overfitting.
Daniel et al (2023)	T-YOLO: Tiny Vehicle Detection Based on YOLO and Multi-Scale Convolutional Neural Networks	May not be suitable for large vehicles	Strength: Tiny vehicle focus. Weakness: Limited to specific vehicle sizes.
Zhe Chen, et al(2021)	A Shape Transformation-Based Dataset Augmentation Framework for Pedestrian Detection	May not generalize well to different datasets	Strength: Augmentation approach. Weakness: Dependency on specific transformation may limit applicability.
Azzedine Boukerche et al (2021)	Design Guidelines on Deep Learning-based Pedestrian Detection Methods for Supporting	Lack of practical implementation examples	Strength: Guidelines provide direction. Weakness: Abstract nature may make it difficult to implement directly.

Power System Technology
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	Autonomous Vehicles		

The analysis highlights that innovations in pedestrian-vehicle detection algorithms are primarily centered around several pivotal areas.

1. Enhanced feature extraction

Fernandez et al. (2021) proposed vehicle recognition based on integrated deep learning features, which recognize specific vehicles with high recognition accuracy[20] by synthesizing training datasets, orientation and background features, and camera feature extraction. Cao et al. (2021)[24] proposed a pedestrian detection algorithm based on Vi Be and YOLO, which combines background subtraction technique with YOLO to improve the detection ability in complex backgrounds.

2. Improvement for network structure:

Yuan (2021) enhanced YOLOv3 to address its shortcomings in detecting small and medium-sized targets, introducing an improved algorithm named DX-YOLO.[25] This modification enhances the detection capabilities by refining the network's structure and feature extraction techniques.

In 2015, Kaiming He[26] presented the Spatial Pyramid Pooling Layer (SPP), enabling the network to process input image features with multiple pooling operations and classify them within a variable-sized pooling layer. This design allows the network to produce fixed-size feature maps from varied input sizes in a single computation, eliminating the need for redundant convolutions.

In 2017, Lin [27] introduced the Feature Pyramid Network (FPN), a new network structure that abandons the sole use of top-layer feature maps. FPN integrates the feature outputs from various network layers, realizing an in-depth use of feature information, and thereby achieving more accurate object detection.

Du Jin [28] introduced a rapid pedestrian-vehicle detection method by employing a YOLO-FPN hybrid model, which combines the advantages of YOLO and FPN to enhance the detection speed and efficacy feature utilization. However, this approach may lead to an increase in complexity and computational demands.

In 2021, Liu [29] introduced a new attention mechanism based on the Transformer architecture. This model uses a hierarchical attention mechanism to manage larger input

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images, enriching the feature expression by integrating local details and cross-layer connectivity. It also adopts separable convolution to reduce the computational load, ensuring that the object detection task maintains both accuracy and speed.

3. Targeting algorithm improvement

Basar [30] proposed a set of methods for truck recognition. They relied on the Gaussian Mixture Model (GMM) based on vehicle attribute data, the Naive Bayesian (NB) approach, the Bayesian Model (BM), and the Mathematical Assignment Algorithm (AA). These methods were evaluated by using various metrics to determine the accuracy of vehicle matching. The study concluded that the BM, which is based on a mixture of distributions, performed better than the NB model.

Aharon [31] addressed the challenges arising from inadequate Kalman filter estimation and camera motion, proposing new tracking solutions. Used to balance and enhance the model's performance across different performance indicators.

4. Lightweight design of the model

To solve the problem of high algorithmic complexity and computational resource consumption, researchers have introduced lightweight methods for object detection. Sah [32] proposed a pedestrian re-identification (Re-ID) study using ResNet-50 and Google networks. Evaluate and compare a number of lightweight networks that have proven

effective in object recognition tasks to reduce the computational power requirement we compare their accuracy and complexity. The evaluation is performed on the commonly used Market-1501 dataset. Ke-Lin [33] propose a lightweight YOLO-based pedestrian detection method to develop pedestrian detection models suitable for deployment on devices with limited.

5. Development explorations for multimodality

Boukerche [34] proposed a vision-based approach for automatic vehicle recognition that relies on deep learning with powerful feature extraction and pattern learning capabilities. In vehicle detection, by using a high-resolution camera and advanced image processing algorithms, the position and silhouette of a vehicle can be recognized more accurately. In vehicle make and model recognition, a deep learning model is used to train a large number of images of different vehicle models, thus improving the recognition accuracy. For vehicle re-identification, multimodal data, such as the color, decoration, and other features of the vehicle, can be combined to enhance the reliability of the recognition. Khorramshahi [35]

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proposed a deep representation learning model for multi-camera vehicle recognition at the urban scale, optimizing the results and eliminating the specific bias through a series of post-processing steps, while using the multi-observable information of the vehicle for fine-grained retrieval of the Results. Xiangfeng [36] proposed real-time infrared vehicle and pedestrian detection using IR-YOLO. to detect vehicles and pedestrians in infrared images in applications that require real-time processing. Potential limitations of YOLO performance in IR data or complex environments are analyzed.

3. Conclusions

This review, after an extensive literature review and analysis of key technologies, concludes the following:

Pedestrian vehicle detection is crucial for intelligent transportation, autonomous driving, and public safety. The YOLO algorithm's strengths in detection speed and versatility have made it a focal point of research. This paper traces the evolution from YOLOv1 to YOLOv10 in pedestrian-vehicle detection, noting how each iteration has refined the network architecture and performance. Innovations such as the anchor box mechanism, multi-scale prediction, and feature pyramid networks have been highlighted. The paper also examines current research trends in pedestrian-vehicle detection algorithms, including enhanced feature extraction, network structure improvements, algorithm optimization, lightweight design, and multimodal exploration.

Furthermore, the paper acknowledges that despite the YOLO algorithm's significant progress in pedestrian-vehicle detection, challenges remain in detecting extremely small targets and in adapting to various environments. Future research is encouraged to delve into efficient network architectures, loss functions, data enhancement techniques, and multi-source data fusion strategies to achieve more precise and robust detection capabilities.

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