10.48047/jocaaa.2023.31.04.61

RESEARCH ON THE KEY TECHNOLOGIES OF PEDESTRIAN DETECTION BASED ON DEEP LEARNING

CHEN HUIHONG 1, VIVEKANANDAM BALASUBRAMANIAM 2

ABSTRACT

The fast advancement of autonomous vehicles, intelligent intelligence, and smart city services has made pedestrian detection one of the most important study topics in computer vision as well as intelligent systems. Robust feature extraction, great flexibility, and better detection accuracy under complicated circumstances are just a few ways in which deep learning has recently transformed pedestrian detection. This study delves into the essentials of deep learning-based pedestrian detection systems, with an emphasis on training methods, optimisation approaches, and model architectures. Many sophisticated frameworks, including You Only Look Once (YOLO) and Faster Region-based Convolutional Neural Network (Faster R-CNN), as well as Convolutional Neural Networks (CNNs) and Region-based Convolutional Neural Networks (R-CNNs), have shown better performance in real-time pedestrian detection. Problems with occlusion, multi-scale variations, backdrop clutter, and low-light conditions still exist, however. This work aims to solve these challenges by integrating many techniques to improve detection robustness and generalisation. These techniques include attention mechanisms, multi-scale feature fusion, transfer learning, and statistical augmentation. For real-world applications like embedded systems and mobile devices, it is essential that they accomplish rapid performance with limited computing resources. To that end, researcher investigated lightweight models and periphery deployment methodologies. Recent benchmark experimental study confirms that, when compared to conventional methods, deep learning-based pedestrian identification is noticeably more accurate, faster, and more adaptable This study contributes to smarter and safer intelligent transportation while urban management systems by providing a thorough examination of the existing state-of-the-art approaches, highlighting present limits, and proposing interesting areas for future work.

10.48047/jocaaa.2023.31.04.61

Keywords: Deep learning, Convolutional Neural Networks, Attention-Based Deep Learning, Pedestrian detection.

1. INTRODUCTION

Due to its extensive use in smart cities, autonomous driving, surveillance footage, and intelligent transportation systems, pedestrian detection has become an important field of study in computer vision while artificial intelligence. To guarantee public safety, reduce traffic accidents, and enable human-computer interaction, it is crucial to be able to correctly detect and locate people in varied contexts. The adaptability of traditional pedestrian recognition techniques was found to be lacking in real-world scenarios with occlusions, background clutter, lighting changes, along with multi-scale variations (Carrasco et al., 2021). These methods relied heavily on customised characteristics and classifiers using machine learning like Histogram of Orientated Gradients (HOG) and Support Vector Machines (SVM). With the development of deep learning, models can now build strong feature representations with hierarchies from massive amounts of data, which has completely changed the game for pedestrian detection (Choi & Kim, 2023). Detection accuracy and efficiency greatly enhanced by CNNs, R-CNNs, along with real-time detection frameworks like YOLO and Single Shot MultiBox Detector (SSD) (Wang et al., 2023). Dealing with pedestrians in crowded areas, identifying people with partial obstructions, and attaining accurate identification in challenging environmental situations like nightfall or bad weather are all ongoing issues. Attention-grabbing modules, multi-scale feature amalgamation, transfer learning, including generative data augmentation are some of the advanced mechanisms that have recently been the focus of significant technology research (Garg et al., 2024). These mechanisms aim to overcome these issues. Furthermore, there has been a recent uptick in interest in lightweight models that are optimised for edge devices; these models guarantee real-time processing while using limited

10.48047/jocaaa.2023.31.04.61

computing resources. These developments show how crucial it is to strike a balance between precision, efficiency, as well as scalability for actual use in the real world. The key objectives of this study are to (1) identify the relevant deep learning technologies for pedestrian detection, (2) assess the efficacy of these technologies, and (3) suggest ways to circumvent current constraints. Intelligent systems that prioritise efficiency, flexibility, and safety in dynamic urban contexts may benefit from the study's investigation of state-of-the-art technique (Gen et al., 2021).

2. BACKGROUND OF THE STUDY

Autonomous vehicles, smart surveillance, as well as public safety management are just a few of the important areas that are directly affected by pedestrian identification, a basic problem in computer vision. The need for reliable pedestrian detection systems has increased significantly due to the rising popularity of smart transport and urban security systems (Gong et al., 2024). Once upon a time, pedestrian detection relied on more conventional methods. These methods included neural networks related SVM as well as handmade attributes like Haar-like descriptors and HOG. These approaches had some success, but they had a hard time adjusting to the intricacies of real life, such as different pedestrian stances, occlusions, illumination variations, and congested situations (Hua et al., 2023). Deep learning's revolutionary feature learning capabilities made possible by neural network architectures, the field of pedestrian detection research has undergone a sea change (Hussain, 2023). By eliminating the need for human feature engineers and instead learning discriminative features automatically CNNs as well as variants have shown to outperform their predecessors. Models like R-CNN, Faster R-CNN, SSD, and YOLO have contributed to excellent practical implementation possible by enabling real-time and very accurate pedestrian identification. Particularly in difficult situations like night sceneries, heavy traffic, or complicated metropolitan landscapes, these

10.48047/jocaaa.2023.31.04.61

deep learning-based algorithms surpass conventional methods (Jain et al., 2023). A number of obstacles persist, even with these improvements. Problems with processing limits on embedded devices, multi-scale variations, small-scale pedestrian recognition, and partial occlusion continue to prevent wider adoption. So, to make detection more efficient and robust, researchers are now working on merging attention mechanisms, generative data augmentation, multi-scale feature fusion, and lightweight architectures. Improving intelligent systems requires knowledge of the history and major technologies of pedestrian detection. Within this framework, this article analyses the advances made by deep learning and proposes avenues for future research that can improve pedestrian detection systems for practical use (Kumar et al., 2023).

3. PURPOSE OF THE STUDY

The primary objective of this research is to enhance the accuracy, efficiency, and resilience of deep learning-based pedestrian detection systems by studying and analysing the underlying technologies. Exploring methodologies that may overcome the constraints of old methods and fulfil the rising need for intelligent, dynamic systems is critical, since detection of pedestrians plays a significant role in areas such as autonomous vehicle operation, intelligent surveillance, as well as smart city development. The goal of this study is to compare and contrast several deep learning-based designs, such as CNNs, R-CNNs, SSDs, and YOLO structures (Li et al., 2023). Through this approach, the research seeks to provide a thorough comprehension of how these models aid in tackling issues including occlusion, multi-scale detection, backdrop clutter, and low-light settings. Emerging approaches including multi-scale feature fusion, mechanism of attention, augmenting data, along with transfer learning are also the subject of the research. These have great promise for making detection systems more resilient and flexible (Peng & Huang, 2023). Lightweight and optimised models for deployment on constrained by resources

10.48047/jocaaa.2023.31.04.61

devices, including mobile platforms and edge computing systems, are another goal of this work. For situations with limited processing resources, this is of paramount importance for real-time pedestrian identification (Qian et al., 2022). Additionally, the study aims to pinpoint areas where existing research is lacking and provide ways forward for creating solutions that are more practical, efficient, and scalable. By delving into current best practices, identifying obstacles, and suggesting solutions, this study hopes to add to what is already known about pedestrian detection technologies, with the ultimate goal of making intelligent systems in ever-changing urban settings more trustworthy and safer for everyone (Schulz & Perez, 2023).

4. LITERATURE REVIEW

In applications like intelligent transportation systems, video surveillance, and autonomous driving, pedestrian detection has been the subject of substantial research as a part of computer vision. Feature extraction by hand and traditional machine learning were the backbone of the early approaches. For example, in conjunction with SVMs as well as AdaBoost classifiers, Haar-like features and the HOG were extensively used for pedestrian detection. In complicated contexts, these methods failed, especially when confronted with changes in stance, size, lighting, or backdrop clutter, yet they worked well in controlled conditions. With the advent of deep learning, neural networks proved they could learn hierarchical as well as discriminative features from data, greatly improving pedestrian detection (Song et al., 2020). The current pedestrian identification relies heavily on CNNs. By combining region proposal processes with end-to-end learning, region-based CNNs like Fast R-CNN and Faster R-CNN brought about a paradigm shift in detection, resulting in improved accuracy. Unfortunately, the high computing costs of these models made them unsuitable for use in real-time applications (Sun et al., 2020). Speed and efficiency were addressed with the introduction of one-stage detectors like YOLO and SSD. These designs were well-suited for autonomous driving systems because they put an

10.48047/jocaaa.2023.31.04.61

emphasis on real-time detection without drastically lowering accuracy. But occlusions, small-scale pedestrians, especially scenarios with large crowds were still difficult to handle. The focus of recent studies has changed to finding better ways to make detections more resilient. In order to improve identification under occlusion, attention techniques have been extensively used to enable models to concentrate on important areas. Feature Pyramid Networks (FPNs) are a common way to create multi-scale feature fusion algorithms, which have improved pedestrian detection at different sizes. To tackle the problem of inadequately annotated datasets, data augmentation using transfer algorithms and generative adversarial networks, or GANs for short, has also been implemented. Lightweight architectures tailored to edge computing as well as mobile devices are another area of increasing interest in the literature. Models like EfficientDet and MobileNet show how important it is to balance accuracy and processing efficiency for real-world deployment. Research shows that pedestrian identification has progressed from manual techniques to methods powered by deep learning, leading to considerable improvements in efficiency and accuracy. However, there must be ongoing innovation to overcome obstacles including occlusion, low-light settings, and real-time processing in contexts with limited resources. Attention integration, multi-scale fusion, and lightweight models have been the focus of current research aimed at improving pedestrian recognition in real-world applications. (Wang et al., 2023).

5. RESEARCH QUESTION

- What are the impact of key technologies on deep learning?

6. RESEARCH METHODOLOGY

6.1 Research Design

The SPSS version 25 was used for the quantitative data analysis. A 95% confidence interval and odds ratio were used by the researchers to assess the direction and strength of the statistical

10.48047/jocaaa.2023.31.04.61

association. A statistically significant criteria was established by the researchers at $p < 0.05$. The data's basic features were revealed via a thorough investigation. Data examined using computer tools for statistical assessment and data gathered via surveys, questionnaires, and other methods are often subject to quantitative techniques of evaluation.

6.2 Sampling

A sample of 1455 individuals was determined using the Rao-soft algorithm. A grand total of 1600 surveys were distribute to a carefully stratified populace, comprising students, educators, guardians, and administrators within the urban realms of China. A total of 1539 surveys were duly returned, yielding a commendable raw response rate. 39 surveys were cast aside on account of lacking completeness or pertinent information. The ultimate sample deemed fit for use comprised 1500 valid respondents.

6.3 Data and Measurement

The study mostly utilised data acquired from a questionnaire survey. The participant's essential demographic information was requested first. Participants were subsequently given a 5-point Likert scale to evaluate the online and offline channels. The researchers rigorously analysed several resources, especially internet databases, for this secondary data acquisition.

6.4 Statistical Software

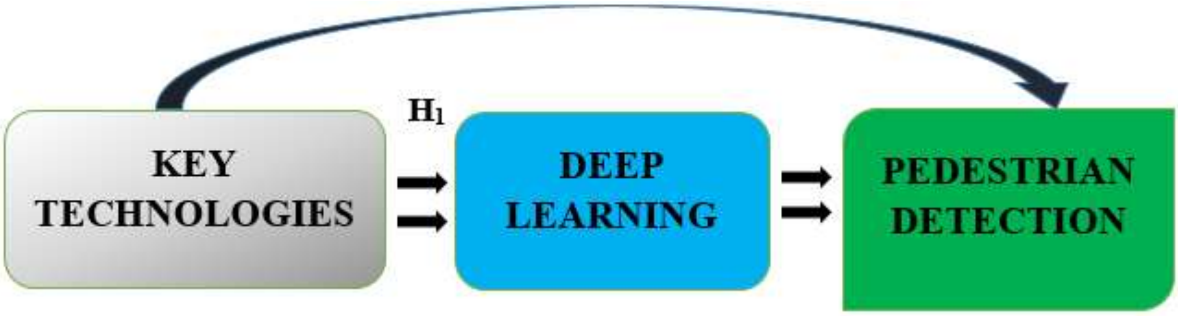
Statistical analysis was conducted using Excel and SPSS 25.

6.5 Statistical Tools

The primary characteristics of the data were understood via the use of descriptive analysis. Using ANOVA, the researcher must examine the data.

7. CONCEPTUAL FRAMEOWRK

10.48047/jocaaa.2023.31.04.61



8. RESULTS

- **Factor Analysis**

Factor Analysis (FA) is often used to find hidden variables in observable data. Regression coefficients are often used to provide evaluations in the absence of discernible visual or diagnostic indicators. Success in financial analysis is significantly reliant on models. The goals of modelling are to identify errors, intrusions, and apparent linkages. The Kaiser-Meyer-Olkin (KMO) Test is one tool for evaluating datasets that have been generated by numerous regression analyses. The representativeness of the model and the variables in the sample are checked by them. There seems to be data duplication based on the numbers. Data is more easily comprehensible when proportions are smaller. The output of KMO is an integer from 0 to 1. A sufficient sample size is defined as a KMO value between 0.8 and 1. According to Kaiser, these are the acceptable limits: According to Kaiser, the following are the requirements for admission:

The usual range is 0.60 to 0.69, however this range is much lower at 0.050 to 0.059.

A range of 0.70 to 0.79 is considered average for middle grades.

Ranging from an 80 to an 89 on the quality point scale.

They discover awe between 0.90 and 1.00.

10.48047/jocaaa.2023.31.04.61

Testing for Bartlett's Sampling Adequacy and KMO (Table1) The Kaiser-Meyer-Olkin .918 scale

The findings of Bartlett's sphericity test are as follows: Chi-square, significance = .000, about 190 degrees of freedom this substantiates the legitimacy of the assertions made on sampling. The researchers used Bartlett's Test of Sphericity to ascertain the relevance of the correlation matrices. A Kaiser-Meyer-Olkin value of 0.918 indicates that the sample is deemed adequate. Bartlett's sphericity test yields a p-value of 0.00. A researcher may ascertain that the correlation matrix is not an identity matrix if Bartlett's sphericity test yields a significant result.

Table 1: KMO and Bartlett's Test

KMO and Bartlett's Test[a]		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.918
Bartlett's Test of Sphericity	**Approx. Chi-Square**	4350.175
	df	190
	Sig.	.000
a. Based on correlations		

Moreover, the Bartlett Test of Sphericity confirmed the broad applicability of correlation matrices. The Kaiser-Meyer-Olkin metric of sample adequacy is 0.918. The researchers obtained a p-value of 0.00 via Bartlett's sphericity test. The correlation matrix did not pass Bartlett's sphericity test, indicating a significant outcome.

❖ INDEPENDENT VARIABLE

- **Key Technologies**

Improvements in accuracy, robustness, along with real-time performance are the primary goals of key deep learning technologies in pedestrian detection. The backbone, which allows for

10.48047/jocaaa.2023.31.04.61

automated feature extraction from raw photos to detect pedestrians in different environments, are CNNs. To successfully localise pedestrian candidates, RPNs and anchor-based approaches are used. To tackle the problem of recognising people in complicated settings who are varied in size and shape, multi-scale combination of features is an additional important technique. Researcher looked for a model that can balance speed and accuracy in detection, try Faster R-CNN, SSD, or YOLO. By including attention processes and context-aware learning, the model becomes more adept at handling occlusion and cluttered environments, ultimately improving its capacity to discern fine details. To enhance generalisation with small datasets, data augmentation and transfer learning are equally important. Devices with limited resources may nevertheless perform real-time pedestrian detection with the help of optimisation methods like pruning and lightweight designs (Wang et al., 2023).

❖ MEDIATING VARIABLE

- **Deep Learning**

A branch of AI and machine learning, deep learning is concerned with the autonomous learning and feature extraction from massive datasets via the use of artificial neural networks. Deep learning allows models to detect hierarchical representations and complicated patterns in input data like pictures, music, or text without the need for manually created features, in contrast to conventional machine learning approaches. The word "deep" comes from the fact that neural networks with several layers are the building blocks of deep learning. The input data is abstracted and made more relevant with each successive layer. For example, CNNs are very effective at recognising spatial elements like textures, forms, and edges; as a result, they find extensive use in computer vision applications like pedestrian identification. With its ability to automatically detect changes in size, position, and light, these networks excel in practical applications. When it comes to pedestrian identification, deep learning is head and shoulders

10.48047/jocaaa.2023.31.04.61

above the competition because to its enhanced accuracy, flexibility, and resilience under harsh conditions. This enables models to identify pedestrians in challenging illumination, crowded areas, or when partially obscured. Intelligent and dependable pedestrian detection systems are still in their infancy, but deep learning is at the forefront of this industry because to improvements in architectures and optimisation methods (Yuping & Yi, 2021).

- **Relationship Between Key Technologies And Deep Learning**

Deep learning is the cornerstone that propels improvements in detection efficiency and accuracy, it is clear that there is a close link between deep learning and key technologies. Deep learning is a key component of several important technologies, including multi-scale feature fusion CNNs, and Region Proposal Networks (RPNs). These technologies allow models to autonomously recognise hierarchical characteristics from pictures. In order for this technology to learn complicated visual patterns, deep learning supplies the computational framework, and these technologies improve deep learning's capacity to deal with real-world obstacles such as occlusion, size variation, and crowded surroundings. By honing down on crucial areas, attention mechanisms as well as context-aware modules—both with their origins in deep learning—increase the flexibility of pedestrian detection systems. How important technologies modify deep learning models for real-time application is further shown by lightweight architectures and optimisation methodologies. Therefore, solutions for scalable, accurate, and reliable pedestrian identification are born from the combination of deep learning with these technologies (Zhang et al., 2020).

On the basis of the above discussion, the researcher formulated the following hypothesis, which was analyse the relationship between Key Technologies and Deep Learning.

"H_{01}: There is no significant relationship between Key Technologies and Deep Learning."

10.48047/jocaaa.2023.31.04.61

"H_1: There is a significant relationship between Key Technologies and Deep Learning."

Table 2: H_1 ANOVA

ANOVA					
Sum					
	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	67943.158	519	5942.354	2269.806	.000
Within Groups	587.294	980	2.618		
Total	68530.452	1499			

The outcome is substantial in this research. Statistical significance is achieved with a p-value of .000 (below the .05 alpha level), and the F value is 2269.806. This suggests that researchers might support the alternative view, ***"H_1: There is a significant relationship between Key Technologies and Deep Learning"*** is accepted and the null hypothesis is rejected.

9. DISCUSSION

There have been tremendous strides in pedestrian detection studies utilising deep learning technology, but there are still many unanswered questions about how to use these findings in the actual world. In terms of detection accuracy and flexibility, deep learning-based models—specifically CNNs, Faster R-CNN, SSD, as well as YOLO—have substantially surpassed conventional feature-engineering methods, according to a number of recent research. Instead of relying on manually created features that struggled with size, position, and backdrop fluctuations, these models can learn high-level representations from data. These models work well in simple settings, but they struggle in more complicated metropolitan settings. Reliable detection is still challenged by issues including partial occlusion, overcrowded pedestrian scenarios, and poor illumination. Researchers have developed focused attention and multi-scale feature fusion techniques to mitigate the effects of these challenges. Against enhance the model's robustness against occlusion as well as clutter, multi-scale combination of features along with focus modules collaborate to integrate information across feature maps, enabling

10.48047/jocaaa.2023.31.04.61

the model to recognise pedestrians of varying sizes. Achieving a balance between both precision and effectiveness is a contentious issue. The processing demands of two-stage detectors like Faster R-CNN render them unsuitable for real-time applications, despite the fact that they attain better accuracy. On the other hand, one-stage detectors such as YOLO and SSD could be quicker, but they might miss tiny or partly concealed pedestrians due to their lack of accuracy. This trade-off shows how important it is to choose the right model for the job; for example, autonomous driving can put an emphasis on speed, whereas surveillance systems might put an emphasis on accuracy. Lightweight architectures are now the focus of study due to the increasing need for real-time surveillance of pedestrians on embedded and mobile systems. By decreasing computing complexity while preserving satisfactory accuracy, models like EfficientDet and MobileNet provide a hopeful path. This development highlights the need of developing detection frameworks that are both scalable and capable of adapting to various hardware configurations. As a whole, the conversation shows that improving pedestrian recognition algorithms while also taking hardware into consideration is the way to go. The significance of methods like edge computing integration, generative augmentation, and transfer learning is anticipated to grow. Smart city surveillance, safety-critical applications, and intelligent transportation may all benefit from pedestrian detection systems that are more robust and overcome current constraints.

10. CONCLUSION

A look at the most important deep learning-based pedestrian detection systems reveals how revolutionary sophisticated neural network designs are for improving efficiency, resilience, and accuracy. CNNs, Faster R-CNN, SSD, and YOLO are examples of deep learning techniques that automatically learn hierarchical feature representations, outperforming traditional methods that depend on handcrafted features in dynamic situations. These models have greatly improved

10.48047/jocaaa.2023.31.04.61

pedestrian detection in challenging environments with occlusion, size variation, crowds, and low light. The flexibility of pedestrians detection systems has also been improved by new approaches such as mechanisms of attention, transfer learning, generative data augmentation, multi-scale feature fusion, and so on. Deploying these models in resource-constrained situations, such as autonomous cars and mobile devices, becomes viable with the development of thinner designs optimised for edge computing, which also guarantees real-time processing. Finally, deep learning allows for novel opportunities in intelligent, scalable pedestrian detection systems while simultaneously resolving issues with conventional approaches. To overcome present problems, it is vital to continue researching algorithmic innovation as well as hardware optimisation. In the long run, these innovations can help make intelligent transportation, inspection, and urban management solutions safer, smarter, and more dependable.

10.48047/jocaaa.2023.31.04.61

REFERENCES

Carrasco, D.P.; Rashwan, H.A.; García, M.Á.; Puig, D. T-YOLO: Tiny vehicle detection based on YOLO and multi-scale convolutional neural networks. IEEE Access 2021, 11, 22430–22440.

Choi, Y.; Kim, H. Convex hull obstacle-aware pedestrian tracking and target detection in theme park applications. Drones 2023, 7, 279

Garg, S.; Sharma, S.; Dhariwal, S.; Priya, W.D.; Singh, M.; Ramesh, S. Human crowd behaviour analysis based on video segmentation and classification using expectation–maximization with deep learning architectures. Multimed. Tools Appl. 2024, 1–23.

Gen, Q.; Li, W.; Kai, C. Research on high pressure vessel detection technology based on infrared image fusion algorithms. Chin. Meas. Test 2021, 47, 7.

Gong, L.; Huang, X.; Chen, J.; Xiao, M.; Chao, Y. Reparameterized dilated architecture: A wider field of view for pedestrian detection. Appl. Intell. 2024, 54, 1525–1544.

Hua, J.; Li, L.; Ning, P.; Schwebel, D.C.; He, J.; Rao, Z.; Cheng, P.; Li, R.; Fu, Y.; Li, J.; et al. Road traffic death coding quality in the WHO Mortality Database. Bull. World Health Organ. 2023, 101, 637.

Hussain, M. YOLO-v1 to YOLO-v8, the Rise of YOLO and Its Complementary Nature toward Digital Manufacturing and Industrial Defect Detection. Machines 2023, 11, 677.

10.48047/jocaaa.2023.31.04.61

Jain, D.K.; Zhao, X.; González-Almagro, G.; Gan, C.; Kotecha, K. Multimodal pedestrian detection using metaheuristics with deep convolutional neural network in crowded scenes. *Inf. Fusion* 2023, *95*, 401–414.

Kumar, S.; Sharma, S.; Kumar, R. Wireless Sensor Network Based Real-Time Pedestrian Detection and Classification for Intelligent Transportation System. Int. J. Math. Eng. Manag. Sci. 2023, 8, 194.

Li, J.; Xu, Z.; Xu, L. Vehicle and pedestrian detection method based on improved YOLOv4-tiny. Optoelectron. Lett. 2023, 19, 623–628.

Li, Z.; An, Z.; Cheng, W.; Zhou, J.; Zheng, F.; Hu, B. MHA: A multimodal hierarchical attention model for depression detection in social media. Health Inf. Sci. Syst. 2023, 11, 6.

Peng, X.; Huang, C. An Improved Real-Time Multiple Object Tracking Algorithm Based on YOLOv8. In Proceedings of the 2nd International Conference on Signal Processing, Computer Networks and Communications, Xiamen, China, 8–10 December 2023; pp. 180–184.

Qian, X.; Wang, X.; Yang, S. A YOLO Algorithm with Lightweight Feature Fusion Network for Multi-Scale Defect Detection. IEEE Access 2022, 10, 130339–130349.

Schulz, D.; Perez, C.A. Two-Stage Pedestrian Detection Model Using a New Classification Head for Domain Generalization. Sensors 2023, 23, 9380.

Song, X.; Zhao, K.; Chu, W.S.; Zhang, H.; Guo, J. Progressive refinement network for occluded pedestrian detection. In Computer Vision—ECCV 2020: 16th European Conference, Glasgow, UK, 23–28 August 2020, Proceedings, Part XXIII 16; Springer: Cham, Switzerland, 2020; pp. 32–48.

10.48047/jocaaa.2023.31.04.61

Sun, Z.; Chen, J.; Chao, L.; Ruan, W.; Mukherjee, M. A survey of multiple pedestrian tracking based on tracking-by-detection framework. IEEE Trans. Circuits Syst. Video Technol. 2020, 31, 1819–1833.

Wang, G.; Chen, Y.; An, P.; Hong, H.; Hu, J.; Huang, T. UAV-YOLOv8: A small-object-detection model based on improved YOLOv8 for UAV aerial photography scenarios. Sensors 2023, 23, 7190

Wang, N.; Shang, L.; Song, X. A Transformer-Optimized Deep Learning Network for Road Damage Detection and Tracking. Sensors 2023, 23, 7395.

Yuping, W.; Yi, Z. Pedestrian detection in infrared images using ROI fusion and human visual mechanism. Chin. Meas. Test 2021, 47, 87–93.

Zhang, J.; Lin, L.; Zhu, J.; Li, Y.; Chen, Y.C.; Hu, Y.; Hoi, S.C. Attribute-aware pedestrian detection in a crowd. IEEE Trans. Multimed. 2020, 23, 3085–3097.