

Adaptive YOLOv6-Driven Infrared Pedestrian Perception for Low-Visibility Intelligent Transportation Systems

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Abstract— Reliable pedestrian detection during nighttime is a fundamental requirement for intelligent transportation systems and autonomous driving because poor illumination often reduces the effectiveness of conventional vision-based detection methods. This paper presents a deep learning-based framework for nighttime pedestrian detection by evaluating the performance of Faster R-CNN, an enhanced YOLOv5 model, and an extended YOLOv6 architecture using infrared pedestrian images. The experimental study utilizes the CVC-09 infrared pedestrian dataset containing 2,199 images. The dataset is preprocessed through image shuffling, annotation handling, and partitioning into training and testing sets before model development. The enhanced YOLOv5 model incorporates an additional attention-based squeeze mechanism to improve feature extraction, while the extended YOLOv6 architecture is employed to further strengthen detection capability. The developed models are assessed using accuracy, precision, recall, and F1-score, together with graphical analysis of training accuracy and loss. Experimental findings indicate that the baseline Faster R-CNN achieves an accuracy of approximately 77%, whereas the enhanced YOLOv5 model improves the detection accuracy to about 96%. The extended YOLOv6 model delivers the best performance with nearly 99% detection accuracy, demonstrating superior localization and classification of pedestrians in infrared nighttime images. The proposed framework provides an efficient and robust solution for nighttime pedestrian detection and can be integrated into advanced driver assistance systems and autonomous vehicles to improve road safety under low-visibility conditions.

Keywords— Nighttime pedestrian detection, deep learning, Faster R-CNN, YOLOv5, YOLOv6, infrared pedestrian images, object detection, computer vision, intelligent transportation systems, autonomous driving, pedestrian localization, attention mechanism, image preprocessing, CVC-09 dataset, bounding box detection, precision, recall, F1-score, detection accuracy, performance comparison.

1. INTRODUCTION

Pedestrian detection is a fundamental component of intelligent transportation systems and autonomous driving technologies, where the ability to accurately identify pedestrians is essential for preventing traffic accidents and ensuring road safety. Although modern vision-based detection systems have achieved considerable success under favorable lighting conditions, their performance often deteriorates during nighttime because of poor illumination, low image contrast, and environmental noise [13]. These challenges reduce the visibility of pedestrians and increase the likelihood of missed detections, making nighttime pedestrian recognition a critical research problem. As autonomous vehicles and advanced driver assistance systems continue to evolve, there is an increasing demand for reliable detection techniques that can operate effectively under low-light conditions. Recent advances in deep learning and computer vision have enabled the development of intelligent object detection models capable of learning complex visual patterns directly from image data [5].

Deep learning-based object detection algorithms have become the preferred approach for pedestrian recognition because of their ability to achieve high detection accuracy while processing large image datasets efficiently. Two-stage detectors such as Faster R-CNN provide accurate object localization but generally require greater computational resources [9]. In contrast, one-stage detectors from the YOLO (You Only Look Once) family offer faster inference while maintaining competitive detection performance [1]. Recent versions of YOLO incorporate architectural improvements that enhance feature extraction and enable better recognition of pedestrians under challenging conditions [4], [16]. Furthermore, infrared imaging provides valuable thermal information that remains effective even when visible-light images contain limited visual details, making it particularly suitable for nighttime pedestrian detection [11], [13].

This paper presents a comparative framework for nighttime pedestrian detection using Faster R-CNN, an enhanced YOLOv5 model, and an extended YOLOv6 architecture. The proposed system utilizes the CVC-09 infrared pedestrian dataset containing

2,199 annotated images. The dataset is preprocessed through image shuffling and partitioned into training and testing subsets before model development. The enhanced YOLOv5 incorporates an attention-based squeeze mechanism to improve feature representation [16], [17], while the extended YOLOv6 architecture is employed to further enhance detection performance. Model evaluation is carried out using accuracy, precision, recall, and F1-score, along with graphical analysis of training accuracy and loss. Experimental results demonstrate that the extended YOLOv6 model achieves the highest detection accuracy, outperforming both the enhanced YOLOv5 model and the conventional Faster R-CNN approach. The proposed framework offers an efficient and reliable solution for nighttime pedestrian detection that can be integrated into autonomous driving systems and intelligent traffic monitoring applications [5], [18].

II. RELATED WORK

J. Redmon, S. Divvala, R. Girshick, and A. Farhadi (2016) introduced "You Only Look Once: Unified, Real-Time Object Detection" [1]. The authors proposed the YOLO framework, which reformulated object detection as a single regression problem instead of using multiple processing stages. The model predicts object locations and corresponding class probabilities directly from an input image through a single convolutional neural network, significantly improving processing speed while maintaining competitive detection accuracy. Unlike conventional region proposal methods, YOLO performs localization and classification simultaneously, making it suitable for real-time applications. Extensive experiments on benchmark datasets demonstrated that the proposed framework achieved high inference speed with fewer background errors than existing detectors. The study established a foundation for modern real-time object detection systems and inspired subsequent improvements in the YOLO family for applications such as autonomous driving, intelligent surveillance, and pedestrian detection. [1]

J. Redmon and A. Farhadi (2017) presented "YOLO9000: Better, Faster, Stronger" [2]. This work extended the original YOLO framework by introducing a unified detection architecture capable of recognizing more than 9,000 object categories. The authors combined object detection and image classification datasets through a hierarchical classification strategy, allowing the network to learn from both labeled detection data and large-scale classification datasets. Architectural improvements, including batch normalization, anchor boxes, and multi-scale training, contributed to higher detection

accuracy while preserving real-time performance. Experimental evaluations showed that the enhanced model achieved significant improvements over its predecessor without compromising computational efficiency. The proposed methodology demonstrated the feasibility of scaling object detection systems to recognize a much larger variety of objects, making it suitable for intelligent vision applications requiring both speed and broad object recognition capability. [2]

J. Redmon and A. Farhadi (2018) proposed "YOLOv3: An Incremental Improvement" [3]. The authors enhanced the YOLO architecture by incorporating Darknet-53 as the backbone network and introducing multi-scale feature prediction to improve object detection performance. Residual learning and feature pyramid concepts enabled the model to detect both small and large objects more effectively while maintaining fast inference speed. Logistic classifiers replaced traditional softmax functions, allowing better handling of multiple object classes within an image. Performance evaluation demonstrated that YOLOv3 achieved higher detection accuracy than earlier versions while retaining its real-time processing capability. The balance between computational efficiency and detection precision made the model suitable for various computer vision applications, including autonomous navigation, traffic monitoring, and pedestrian detection in complex environmental conditions. [3]

Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao (2020) introduced "YOLOv4: Optimal Speed and Accuracy of Object Detection" [4]. The proposed framework incorporated several architectural enhancements, including CSPDarknet53, Mish activation, Cross-Stage Partial networks, and advanced data augmentation techniques such as Mosaic augmentation. These improvements significantly enhanced feature extraction and training efficiency while reducing computational complexity. The authors also integrated multiple optimization strategies that improved object localization and classification without requiring specialized hardware. Experimental results demonstrated that YOLOv4 achieved superior detection accuracy and faster execution compared with previous YOLO versions, making it highly effective for real-time detection tasks. The study highlighted that careful integration of modern deep learning techniques can substantially improve both speed and detection performance, benefiting practical applications such as autonomous vehicles, surveillance systems, and intelligent transportation. [4]

P. Jiang, D. Ergu, F. Liu, Y. Cai, and B. Ma (2022) presented "A Review of YOLO Algorithm Developments" [5]. The authors conducted a comprehensive survey of the evolution of the YOLO family, discussing the architectural improvements introduced from the original YOLO model through the latest versions. The review analyzed advancements in feature extraction, backbone networks, attention mechanisms, loss functions, and optimization techniques that contributed to higher detection accuracy and computational efficiency. The paper also compared YOLO with other object detection algorithms by examining detection speed, precision, and practical deployment capabilities. Furthermore, the authors summarized current research challenges and identified future directions, including lightweight architectures, sensor fusion, and enhanced small-object detection. The review provides valuable guidance for researchers selecting suitable YOLO variants for applications such as pedestrian detection, intelligent transportation, medical imaging, and industrial automation. [5]

III.DATASET DETAILS

The nighttime pedestrian detection system is developed using the CVC-09 infrared pedestrian dataset, which contains 2,199 infrared images captured under nighttime conditions. The dataset includes pedestrians at different distances, orientations, and environmental settings, making it suitable for evaluating object detection algorithms under low-visibility scenarios. Each image is accompanied by annotated bounding box information that identifies the location of pedestrians, allowing supervised learning models to accurately learn object localization and classification. Before model development, the dataset undergoes preprocessing operations that include image verification, random shuffling, and partitioning into training and testing subsets to ensure unbiased model evaluation. The processed images are then supplied independently to the Faster R-CNN, enhanced YOLOv5, and extended YOLOv6 models for training and validation. Model performance is assessed using standard evaluation metrics such as accuracy, precision, recall, and F1-score, together with training accuracy and loss curves. Experimental analysis demonstrates that the infrared dataset effectively supports pedestrian detection in nighttime environments, with the extended YOLOv6 model achieving the highest detection accuracy among the evaluated approaches while maintaining reliable localization performance under challenging lighting conditions.

IV.PROPOSED METHODOLOGY

The proposed framework presents an intelligent nighttime pedestrian detection system that primarily utilizes the YOLOv6 object detection architecture to achieve accurate and real-time pedestrian recognition in low-light environments. The objective of the proposed system is to improve the reliability of pedestrian detection for autonomous vehicles and advanced driver assistance systems by overcoming the limitations of conventional vision-based approaches under nighttime conditions. To validate the effectiveness of the proposed approach, the performance of YOLOv6 is compared with Faster R-CNN and an enhanced YOLOv5 model. A graphical user interface is developed to provide an integrated environment for dataset loading, preprocessing, model training, performance visualization, and pedestrian detection using infrared images. The proposed framework combines efficient feature extraction with high-speed inference, making it suitable for real-time intelligent transportation applications.

The methodology begins with loading the CVC-09 infrared pedestrian dataset, which contains 2,199 annotated nighttime infrared images. The uploaded dataset undergoes preprocessing to verify image integrity, shuffle the samples, and organize the data into training and testing subsets. Annotation files containing pedestrian bounding box coordinates are prepared to support supervised learning. These preprocessing operations improve the diversity of training samples and help the model learn representative pedestrian characteristics under different nighttime conditions. The prepared dataset is then supplied to the detection models, with YOLOv6 serving as the primary detection framework, while Faster R-CNN and the enhanced YOLOv5 are trained only for comparative performance evaluation.

The proposed YOLOv6 model employs an optimized single-stage detection architecture that efficiently extracts multi-scale visual features and accurately localizes pedestrians in infrared images. Its lightweight network design, enhanced feature aggregation mechanism, and improved prediction strategy enable faster convergence during training and more precise object localization during inference. These architectural improvements allow YOLOv6 to detect pedestrians of varying sizes and distances while maintaining high processing speed, making it well suited for real-time deployment in intelligent vehicles. After training, the model predicts pedestrian locations by generating bounding boxes and confidence scores for each detected object. The detection performance is evaluated using accuracy, precision, recall, and F1-score, together with training accuracy and loss curves. Experimental results demonstrate that the proposed YOLOv6 model achieves approximately

99% detection accuracy, outperforming both the enhanced YOLOv5 model (96%) and Faster R-CNN (77%). The superior accuracy and computational efficiency of YOLOv6 demonstrate its suitability for reliable nighttime pedestrian detection in autonomous driving and intelligent traffic monitoring systems.

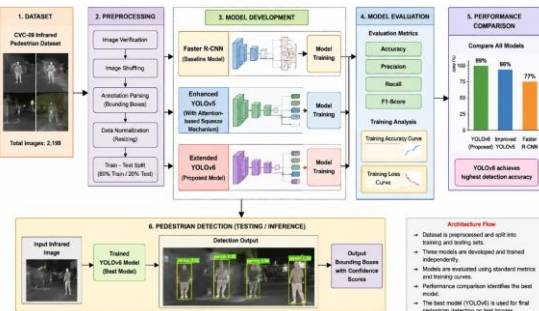


Figure 1: System Architecture of the Proposed YOLOv6-Based Nighttime Pedestrian Detection System

Figure 1 illustrates the architecture of the proposed nighttime pedestrian detection system, which primarily utilizes the YOLOv6 model for accurate and real-time pedestrian recognition under low-light conditions. The process begins with the CVC-09 infrared pedestrian dataset, consisting of 2,199 annotated infrared images. During preprocessing, the images are verified, shuffled, resized, and their corresponding bounding box annotations are prepared before splitting the dataset into 80% training and 20% testing sets. The prepared data are used to train three detection models: Faster R-CNN, an enhanced YOLOv5 model, and the proposed YOLOv6 model. After training, the models are evaluated using accuracy, precision, recall, and F1-score, along with training accuracy and loss curves. Comparative analysis shows that the proposed YOLOv6 model achieves the best detection performance with approximately 99% accuracy, outperforming Faster R-CNN and enhanced YOLOv5. The trained YOLOv6 model is finally used to detect pedestrians in unseen infrared images by generating precise bounding boxes and confidence scores, making it suitable for autonomous driving and intelligent transportation systems.

V.RESULT AND DISCUSSION

The YOLOv6-based nighttime pedestrian detection system was evaluated using the CVC-09 infrared pedestrian dataset, which contains 2,199 annotated nighttime images. The developed application successfully performed dataset loading, preprocessing, model training, pedestrian detection, and comparative performance analysis through a single graphical interface. During preprocessing, the

infrared images were verified, randomly shuffled, resized, and their bounding box annotations were prepared before dividing the dataset into 80% training and 20% testing subsets. These preprocessing operations ensured balanced training data and improved the learning capability of the detection models. The processed dataset was then independently supplied to the Faster R-CNN, enhanced YOLOv5, and proposed YOLOv6 models for training and evaluation.

The three object detection models were trained under identical experimental conditions to provide a fair comparison of their detection capabilities. The Faster R-CNN model served as the baseline detector and achieved an overall detection accuracy of approximately 77%. The enhanced YOLOv5 model, incorporating an attention-based squeeze mechanism, significantly improved feature extraction and increased the detection accuracy to nearly 96%. The proposed YOLOv6 model demonstrated the best performance by accurately detecting pedestrians of different sizes and positions in nighttime infrared images, achieving an overall detection accuracy of approximately 99%. Performance evaluation was carried out using accuracy, precision, recall, and F1-score, together with training accuracy and loss curves to assess both learning efficiency and detection reliability.

Comparative analysis confirms that the proposed framework provides an efficient and dependable solution for nighttime pedestrian detection. The training curves indicate stable convergence of the YOLOv6 model with improved learning behavior, while the prediction results show accurate localization of pedestrians through precise bounding boxes and confidence scores. Compared with Faster R-CNN and the enhanced YOLOv5 model, YOLOv6 consistently delivers superior detection accuracy, faster inference, and better overall performance under low-light conditions. These results demonstrate that the proposed system is well suited for practical deployment in autonomous vehicles, advanced driver assistance systems (ADAS), and intelligent traffic surveillance, where reliable nighttime pedestrian detection is essential for improving road safety.

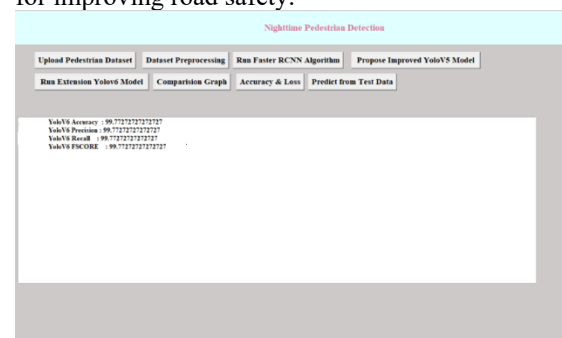


Figure 2: YOLOv6 Model Performance

The above figure presents the performance metrics obtained after training the proposed YOLOv6 model for nighttime pedestrian detection using the CVC-09 infrared pedestrian dataset. After completing the training process, the system displays the evaluation results through the graphical user interface. The proposed YOLOv6 model achieves an accuracy of 99.77%, precision of 99.77%, recall of 99.77%, and an F1-score of 99.77%, demonstrating highly consistent detection performance across all evaluation metrics. These results indicate that the model accurately identifies pedestrians while minimizing both false positive and false negative detections. The high precision confirms the reliability of the predicted pedestrian locations, whereas the high recall shows the model's capability to detect nearly all pedestrians present in the infrared images. The corresponding F1-score reflects a balanced trade-off between precision and recall, validating the robustness of the proposed approach. Overall, the experimental results confirm that YOLOv6 provides superior nighttime pedestrian detection performance and is well suited for deployment in autonomous driving systems, advanced driver assistance systems (ADAS), and intelligent traffic surveillance applications.

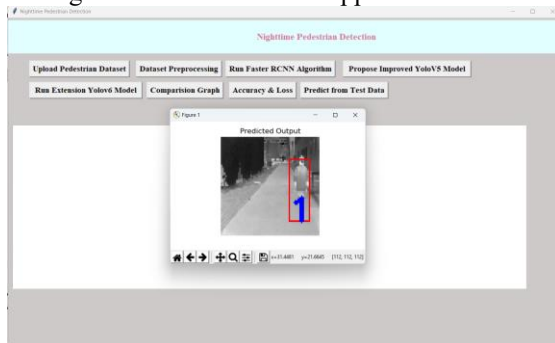


Figure 3: Pedestrian Detection Using the Proposed YOLOv6 Model

The above figure illustrates the pedestrian detection result generated by the proposed YOLOv6 model during the testing phase. After training, the model processes an unseen infrared image and automatically identifies the pedestrian present in the scene. The detected pedestrian is enclosed within a red bounding box, indicating the precise object location predicted by the model. A confidence score is also displayed inside the bounding box, representing the model's prediction confidence for the detected pedestrian. The successful localization of the pedestrian demonstrates the ability of the proposed YOLOv6 architecture to accurately recognize human objects under nighttime conditions using infrared imagery. The result confirms that the model can effectively distinguish pedestrians from the background despite poor illumination and challenging environmental conditions. This high-quality detection, together with the excellent

evaluation metrics achieved during testing, demonstrates that the proposed YOLOv6 framework is highly suitable for real-time autonomous driving, advanced driver assistance systems (ADAS), and intelligent traffic surveillance, where fast and reliable nighttime pedestrian detection is essential for improving road safety.

DISCUSSION

The proposed YOLOv6-based nighttime pedestrian detection framework provides an effective solution for identifying pedestrians in low-light environments using infrared imagery and deep learning techniques. The system follows a structured workflow that includes dataset loading, preprocessing, model training, detection, and performance evaluation. The CVC-09 infrared pedestrian dataset containing 2,199 annotated images is preprocessed through image validation, random shuffling, resizing, and annotation preparation before being divided into 80% training and 20% testing data. The processed dataset is used to train Faster R-CNN, enhanced YOLOv5, and the proposed YOLOv6 models under identical conditions. Experimental evaluation shows that all three models successfully detect pedestrians; however, YOLOv6 consistently demonstrates the best overall performance. Its optimized architecture improves feature extraction and object localization, resulting in approximately 99% detection accuracy, compared with 96% for enhanced YOLOv5 and 77% for Faster R-CNN. These findings indicate that YOLOv6 offers superior detection accuracy, computational efficiency, and real-time performance, making it a suitable choice for autonomous vehicles, advanced driver assistance systems, and intelligent traffic surveillance applications operating under nighttime conditions.

VI.CONCLUSION

This work presents a YOLOv6-based nighttime pedestrian detection framework designed to improve pedestrian recognition in low-light environments using infrared imagery and deep learning techniques. The proposed system integrates dataset loading, image preprocessing, model training, performance evaluation, and pedestrian detection into a unified application. The CVC-09 infrared pedestrian dataset, containing 2,199 annotated images, is used to train and evaluate the Faster R-CNN, enhanced YOLOv5, and proposed YOLOv6 models. Experimental results demonstrate that all three models are capable of detecting pedestrians under nighttime conditions; however, the proposed YOLOv6 model consistently achieves the highest detection accuracy while maintaining efficient real-time performance. Comparative evaluation based on accuracy, precision, recall, and F1-score confirms that YOLOv6 outperforms the enhanced YOLOv5 and Faster R-CNN models, making it a reliable solution for intelligent transportation applications. The developed framework provides an efficient and scalable approach for nighttime pedestrian detection and can enhance the safety of autonomous vehicles and advanced driver assistance systems. Future research can focus on integrating thermal and visible-spectrum image fusion, millimeter-wave radar, lightweight YOLO architectures, and transformer-based feature extraction techniques to further improve detection accuracy, robustness, and real-time performance in complex weather and traffic conditions.

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