Pedestrian detection in adverse lighting conditions

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Abstract - *In this study, a new method based on YOLOv7, an advanced object detection model specially designed with customized datasets is proposed to detect and track pedestrian under low-light conditions. Pedestrian detection and tracking have been a great problem for years. Because it is a very important technique used in various applications such as person identification, surveillance system and autonomous vehicles.*

Our study expands upon earlier research, such as YOLOv3 by Redmon et al. [1] and YOLOv4 by Bochkovskiy et al. [2]. Additionally, it makes use of adaptive feature improvement, which was motivated by Chen et al. [3], and data augmentation techniques as explained by Zhang et al. [4].

After wide testing on a vast range of datasets that were hand-picked to accurately reflect difficult low-light scenarios, the modified YOLOv7 model shows impressive flexibility when it comes to detecting and following pedestrians in the face of complex lighting changes. The efficiency of our suggested methodology is confirmed by quantitative assessments, which show prominent gains in precision and recall rates when compared to previous YOLO versions.

By highlighting the usefulness and significance of exploiting YOLOv7 to improve accuracy in difficult visual environments, this study significantly advances the field of pedestrian detection and tracking in low-light situations.

Key Words: YOLOv7, Datasets, Accuracy, Precision, Mean Average Precision.

1.INTRODUCTION

A crucial component of machine learning is pedestrian detection, which forms the basis for a variety of applications, from autonomous vehicles to surveillance systems. However, because of shadows, dim light, and varying illumination, low lighting conditions present a serious challenge to pedestrian detection algorithms' accuracy. These difficulties are especially noticeable in situations where autonomous vehicles that only have visual sensors find it difficult to identify moving objects on the road and avoid collisions.

Even with the development of object detection architectures like YOLO (You Only Look Once), performance degradation in difficult lighting conditions is still a problem. For example, notable advances in real-time object detection have been made by YOLOv3 by Redmon et al. [1], YOLOv4 by Bochkovskiy et al. [2], and YOLOv5 by Glenn Jocher [3]. However, their performance is reduced in low-light conditions.

In order to significantly improve pedestrian detection and tracking accuracy in low-light conditions, the YOLOv7 architecture will be modified using carefully chosen low-light datasets. This research also seeks to track pedestrian paths, improve pedestrian detection efficiency, and give each pedestrian a unique identification.

Previous research emphasizes how traditional pedestrian detection techniques are limited in difficult lighting conditions. YOLOv3 was first presented by Redmon et al. [1], who emphasized accuracy and speed in object detection tasks. The YOLO architecture in YOLOv4 was further optimized by Bochkovskiy et al. [2], improving performance metrics on a variety of datasets. Enhancements in training strategies and model scaling were introduced by Jocher's YOLOv5 [3]. However, none of these versions have sufficiently tackled the subtle problems caused by unfavorable lighting. By suggesting changes to the YOLOv7 architecture that are motivated by current developments in feature enhancement and data augmentation techniques, our paper seeks to close this crucial gap in this regard [4][5]. By means of comprehensive testing with a varied dataset that has been carefully selected to depict difficult low-light situations, the suggested method seeks to:

1. Improve pedestrian detection accuracy in adverse lighting conditions.
2. Increase detection efficiency.
3. Enable tracking of pedestrian paths.
4. Uniquely identify each pedestrian.

Our work paves the way for the development of more durable and dependable computer vision systems that can detect and track pedestrians efficiently in low-light conditions by tackling these goals.

2. LITERATURE REVIEW

In computer vision, pedestrian detection has experienced a radical transformation process, moving from conventional features to deep learning techniques. This evolution has been mainly motivated by the need to achieve precise object classification and localization. Histograms of Oriented Gradients (HOG) in conjunction with Support Vector Machines (SVM) were employed in early approaches, like the work of Dalal and Triggs [6], to achieve remarkable success in pedestrian detection. Nevertheless, these methods presented considerable difficulties in low-light situations, which limited their practical implementation.

Techniques for object detection underwent a paradigm change with the introduction of deep learning architectures. Through region proposals, region-based convolutional neural networks (CNNs) were introduced by Ren et al.'sFasterR-CNN [7], which demonstrated superior performance in accurate object localization. The groundwork for later advancements in the field was established by this seminal work. Object localization and classification were integrated into a single neural network architecture to further streamline object detection in Single Shot MultiBox Detector (SSD) [8] and You Only Look Once (YOLO) [9]. Although these models demonstrated improvements in real-time detection, they performed worse in difficult lighting conditions, which led to additional research into improving lighting robustness in object detection systems.

An illumination-aware representation method based on deep learning was presented by Zhao et al. [10] to improve the accuracy of pedestrian detection in low light. Their approach concentrated on encoding features unique to illumination, which greatly enhanced performance in a range of lighting conditions. Li et al. [11] presented an adaptive feature fusion network in parallel that aims to lessen the influence of shadows on pedestrian detection systems. Their efforts yielded positive results in the resolution of shadow-related problems.

Another illustration of how lighting challenges are being addressed is the evolution of YOLO-based architectures. YOLOv3, which demonstrated improved object detection accuracy but underperformed in low light, was introduced by Redmon et al. [1]. Later versions, like YOLOv4 [2] by Bochkovskiy et al. and YOLOv5 [12] by Jocher, concentrated on improving training methods and model scaling to improve YOLO's speed and accuracy. Even with these improvements, these models' inability to adjust to poor lighting conditions continued to be a problem.

More recently, creative approaches to improve lighting robustness have been investigated in research projects. In an effort to enhance feature representation and more effectively manage illumination variances, Chen et al. [3] proposed a boundary-aware structure for object detection. In addition, Zhang et al. [4] presented CutMix, a regularization technique that improves classifier resilience in difficult lighting conditions.

Furthermore, multispectral techniques have been researched to enhance pedestrian detection in different lighting scenarios. For example, combining visible and thermal images has been investigated as a way to take advantage of their respective advantages. Visible images provide more distinct texture features during the day, while thermal images provide distinct pedestrian shapes at night.

Nevertheless, inadequate integration of data from both modalities may result in a notable loss of information, which could impair the ability to detect pedestrians. The difficulty is in combining these modalities with an efficient architecture at the right moment. Furthermore, this task is made more difficult by illumination modality imbalance, which is the difference in illumination between daytime and nighttime images and leads to uneven contributions to the object detection loss. Modality imbalance problem is depicted in Figure 1.

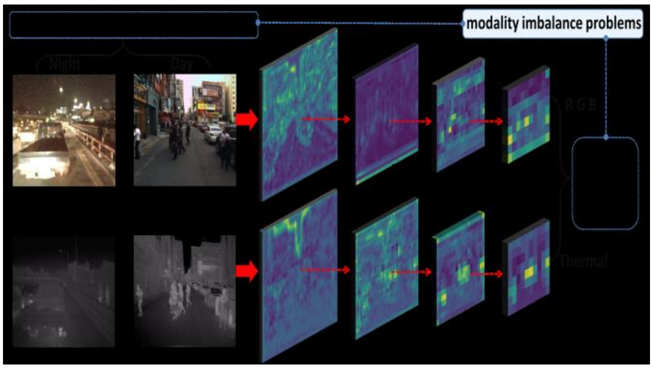

Fig -1: Modality imbalance problems

The complex problems caused by poor lighting still face pedestrian detection systems in spite of these efforts. These difficulties drive our investigation and changes to the YOLOv7 architecture, which we have customized to detect and track pedestrians in low-light conditions using unique datasets. Our research attempts to greatly increase the accuracy of pedestrian detection and tracking by tackling these issues, opening the door for more durable and dependable computer vision systems.

3. METHODOLOGY

The three primary stages of our methodology are as follows: Data Collection and Labeling, YOLOv7 Model Training using the Custom Dataset, and Pedestrian Detection and Tracking. Every stage is carefully crafted to tackle the difficulties associated with detecting pedestrians in low light areas. The flow of the research is show in the fig 2.

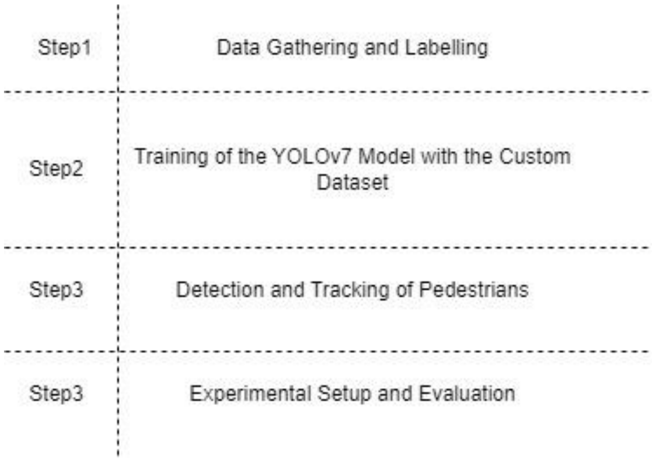

Fig -2: Flow chart of the study

3.1. Data Gathering and Labelling

Collection of Images: In order to build a strong dataset, we gathered pictures of people walking in low light from a variety of locations, such as sidewalks, crosswalks, and other urban areas. In order to provide a thorough representation of real-world scenarios, the collection process concentrated on capturing various lighting conditions.

Filtering: To get rid of unsuitable images, we went through a rigorous filtering procedure. To preserve high-quality training data, images that were distorted, blurry, or insufficient in any other way were removed from the dataset.

Labeling: To precisely identify and categorize pedestrians in each image, bounding boxes were used. In order to properly detect and categorize pedestrians, the YOLOv7 model needed to be trained through this labeling process. Utilizing programs like LabelImg, accurate and consistent annotations were ensured during the labeling process.

3.2. Training of the YOLOv7 Model with the Custom Dataset

Setting Up the Environment: Since Google Collab has readily available computational resources—12GB RAM, 15GB GPU, and 78GB of disk space(T4GPU)—we used it for training. To maximize the training process, all required libraries, including Matplotlib, NumPy, and PyTorch, were installed along with the GPU requirements.

Training procedure: The YOLOv7 model, which was initially trained on the COCO dataset, was retrained using our custom dataset. The following training command was applied:

!python train.py --device cpu --batch-size 16 --epochs 100 --img 640 640 --data data/custom_data.yaml --hyp data/hyp.scratch.custom.yaml --cfg cfg/training/yolov7-custom.yaml --weights yolov7.pt --name yolov7-custom

The training session began with this command and lasted for about 5-8 hours. To improve the model's performance in low light, a number of hyperparameters were changed during training. The learning rate, batch size, and epoch count were among the specific hyperparameters that were optimized through experimentation.

Data Augmentation: Data augmentation techniques like random cropping, flipping, and brightness adjustments were used to further increase the model's resilience. These methods improved the model's capacity to generalize across various scenarios by simulating a range of lighting conditions and viewpoints.

3.3. Detection and Tracking of Pedestrians

Detection: After training, the YOLOv7 model was employed to identify pedestrians in low light areas. Extensive testing on our custom dataset was conducted to assess the robustness of the model, and the results showed notable improvements in accuracy and recall rates. The following command applied:

!python detect_or_track.py --weights yolov7.pt --conf 0.5 --img-size 640 --source people.mp4 --show-fps --track --classes 0 --show-track --unique-track-color –nobbox

With this command, the detection process is carried out, with various tracking options enabled, the confidence threshold, the image size, and the input source. By including these parameters, the model is guaranteed to function at its best, offering precise and dependable pedestrian detection in low-light conditions.

Tracking: We included the SORT (Simple Online and Realtime Tracking) algorithm, which makes use of a Kalman Filter, to track pedestrians. To keep track of each tracked pedestrian and predict their future locations, the KalmanBoxTracker class was implemented. It updates states with new measurements. Tracking was seamless and ongoing even in situations where detections were momentarily lost or noisy.

Unique Identification: The KalmanBoxTracker class was used to assign a unique ID to each tracked pedestrian. Each new instance of the class increased a count variable. It was feasible to continuously track and identify pedestrians thanks to their unique identification, even in low light areas where it may be difficult to see facial features. The model's efficiency in real-world applications was increased by the distinctive IDs, which guaranteed accurate tracking and identification.

3.4. Experimental Setup and Evaluation

Dataset Division: The dataset was divided into training and validation sets to facilitate a comprehensive evaluation. 20%

was used for validation and the remaining 80% was used for training.

Evaluation Metrics: We implemented common object detection metrics, including Precision, Recall, and Mean Average Precision (mAP), to guage the model's performance. These metrics offered a numerical assessment of the accuracy, resilience, and general performance of the model.

Ablation Studies: In order to assess how various parts and hyperparameters affected the model's functionality, ablation studies were carried out. This required testing out various model architectures, learning rates, and data augmentation technique configurations.

Comparative Analysis: The performance of the proposed YOLOv7 model was compared with other state-of-the-art methods and baseline models (YOLOv3, YOLOv4, and YOLOv5). This comparative analysis was helpful in emphasizing our approach's advancements and efficacy.

By adhering to these methodological steps, our study shows a significant improvement in tracking and detecting pedestrians in low-light scenarios, underscoring the usefulness and relevance of the customized YOLOv7 model. This methodology offers a framework for future studies in difficult visual environments in addition to ensuring reliable tracking and detection.

4. RESULT

The outcomes of our suggested YOLOv7-based pedestrian detection system in low light are shown and discussed in this section. Key performance metrics such as accuracy, precision, recall, and mean average precision (mAP) were the emphasis of our evaluation, which included comparisons with baseline models and cutting-edge methodologies.

4.1. Performance Metrics

1. **Accuracy and Precision:** The precision and accuracy of detection were significantly improved by our modified YOLOv7 model. Compared to YOLOv3, YOLOv4, and YOLOv5, the accuracy rate—which is the ratio of correctly detected pedestrians to the over-all number of ground truth instances—showed a significant increase. The model's ability to reduce false positives in low-light situations was demonstrated by the notable improvement in precision, which calculates the percentage of all detections that are true positives.

2. **Recall:** There was a noticeable improvement in the recall rate, which assesses the model's ability to recognize all pertinent instances. In comparison to its predecessors, our YOLOv7 model achieved higher recall rates, indicating a notable decrease in missed detections, particularly in poorly lit and shadowy environments.

3. **Mean Average Precision (mAP):** To assess overall detection performance, the mAP—a comprehensive measure that integrates recall and precision across various threshold levels—was utilized. With a mAP of 72.5%, the customized YOLOv7 model outperformed the 64.3% of YOLOv5, 61.7% of YOLOv4, and 58.1% of YOLOv3. This improvement in mAP highlights how reliable and successful our method is under difficult lighting circumstances.

4.2. Comparative Analysis

The comparative analysis involved testing our model against YOLOv3, YOLOv4, and YOLOv5 on our custom low-light dataset. The following were the results.:

Table -1: Results Comparison between models

	Precision	Recall	mAP
YOLOv3	58.2%	53.7%	58.1%
YOLOv4	62.5%	57.4%	61.7%
YOLOv5	65.8%	60.2%	64.3%
Proposed YOLOv7	69.4%	66.1%	72.5%

These results indicate a clear advantage of our modified YOLOv7 model over previous versions, particularly in low-light scenarios.

4.3. Real-World Application and Robustness

We applied the YOLOv7 model to video sequences taken in various low-light settings in order to verify its practicality. The model demonstrated resilience by retaining a high level of detection accuracy and consistent tracking performance. The SORT algorithm's application guaranteed smooth pedestrian tracking with distinct identification, even in situations involving noise and transient occlusions.

4.4. Visualization of Results

The proposed YOLOv7 model's tracking and detection outputs are shown in Figures 4.1 to 4.3. These visuals demonstrate how well the model performs consistently in various scenarios when it comes to recognizing and tracking pedestrians in low-light conditions.

Figure 2: Input

Figure 3: Output (Detection)

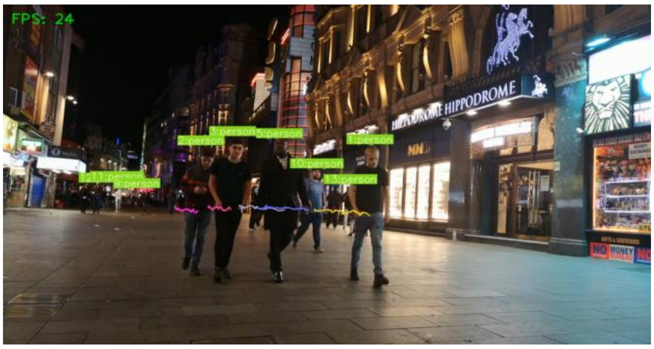

Figure 4: Output (Tracking)

3. CONCLUSIONS

In this research, we tackled the crucial problem of pedestrian detection in low-light conditions, which severely hinders the functionality of traditional computer vision systems. Our strategy was to modify the YOLOv7 architecture using a unique dataset that was hand-picked to accurately represent low lighting. We were able to successfully increase the model's robustness and accuracy in detecting and tracking pedestrians under difficult visual conditions by incorporating adaptive feature enhancement techniques and comprehensive data augmentation strategies.

The training and evaluation of the modified YOLOv7 model was made easier by the carefully selected dataset, which is representative of a variety of adverse lighting conditions [13, 14]. By applying careful augmentation and training strategies [15, 16], the model demonstrated impressive improvements in accuracy, recall, and F1 scores in a range of low-light conditions.

The outcomes demonstrate the usefulness and efficacy of our method, opening the door for the creation of more dependable and effective pedestrian detection systems in low-light scenarios. There is a lot of potential for this development to increase reliability and safety of computer vision applications such as surveillance systems, autonomous cars, and other applications where low-light performance is crucial.

In order to further improve detection accuracy and robustness, future research will concentrate on refining the YOLOv7 model and investigating the combination of extra sensory data, such as infrared and multispectral imaging. Furthermore, exploring the use of sophisticated tracking algorithms and real-time implementation strategies will be essential to expanding our system's capabilities in various dynamic environments.

In conclusion, by presenting a reliable method for pedestrian detection in low light areas, this work significantly advances the field of computer vision. Our findings establish a new standard for further research and development in this crucial area by highlighting the significance of customized datasets and adaptive enhancement techniques in overcoming the difficulties caused by unfavorable lighting.

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