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Research Article

Developments in Deep Learning for Low Light Object Detection: A Comprehensive Review of YOLO and YOLOv8

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ABSTRACT

Object Detection (OD) is one among the challenging tasks in the Computer Vision (CV) field. Significant challenges, especially in Low-Light (LL) environments, are owing to the minimized visibility, increased noise, and poor contrast that often accompanies such conditions. Deep learning (DL)-centric techniques have taken over this field because of its rapid development. DL applications for LL object identification are numerous and include robotic activities at night, drone attacks, and reconnaissance and surveillance. Techniques still faced problems when used directly in LL, including missing detections and false positives although conventional OD techniques showed good results on datasets with typical illumination. Moreover, by the presence of small, dense, and obstructed objects, the models' Detection Accuracy (DA) in LL is further reduced. Nevertheless, You Only Look Once (YOLO), which is also a DL algorithm, plays a crucial role in accurate Low-light Object Detection (LOD), and the updated version YOLOv8 enhances this capability even further. YOLOv8's advanced neural network architecture allows for better Feature Extraction (FE), improved image quality, and higher DA in challenging Low-Light conditions (LLC). Thus, knowing the objective of the review paper helps to explore the DL growth and significance of YOLO and YOLOv8 for LOD.

Keywords: Low light, Object detection, Deep learning, You Only Look Once, Detection rate, Precision, and Accuracy

INTRODUCTION

There has been a lot of research and an increasing interest in CVs recently. CV aims to build machines that can automate tasks requiring visual cognition by modeling the human visual system [1]. OD has become an important issue in the CV field. Video surveillance, face detection, autonomous driving, and other fields have made extensive use of OD, which aims to locate and identify a given object in images or videos [2]. Systems frequently fail to detect extreme LL levels, where the fine details in collected images are not perceptible, even though current OD systems can produce accurate findings in daylight conditions with adequate illumination. Computational tasks like OD become much more challenging because of the noise, glare, and shadow present in LL [3]. Also, due to a lack of illuminated datasets designed for LL scenarios, it is challenging to train and assess detection models efficiently. Advanced algorithms and methods are needed, including improved FE, brightness adjustment, and specific training datasets to overcome these challenges and increase DA and dependability in LLC. Advanced methods, such as DL, a branch of Artificial Intelligence (AI), have improved FE, brightness control, and the development of particular training datasets, greatly enhancing OD in LLC [4]. These algorithms are capable of extracting complex information from LL images that conventional techniques might manage by utilizing advanced neural networks. Also, DL techniques make it easier to modify the contrast and brightness of images, improving the overall quality of images taken in dim environments. These models are now more reliable and accurate in difficult situations and help to develop customized training datasets for LLCs.

DL, mainly Convolutional Neural Networks (CNNs), has revolutionized the OD field, providing state-of-the-art performance across various domains [5]. CNNs tend to lose their

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robustness in such conditions although they achieve better performance in LOD and are designed using bright and quality images. Nevertheless, the modern DL technology YOLO comes to explain and cope with the problem of low illumination environments, as it provides accurate detection of objects in LL [6]. Successive versions of YOLO have introduced improvements in accuracy, speed, and the handling of diverse image conditions over the years. YOLOv8, the latest iteration in the YOLO family, has added several architectural innovations and optimizations that make it more suitable to detect objects in LL and other challenging conditions [7]. The common object-detection algorithms for detecting conditions in low-illumination environments using the YOLO approach are depicted in Figure 1, and the remaining section headings to be focused on the literature review paper, which is depicted in Figure 2.

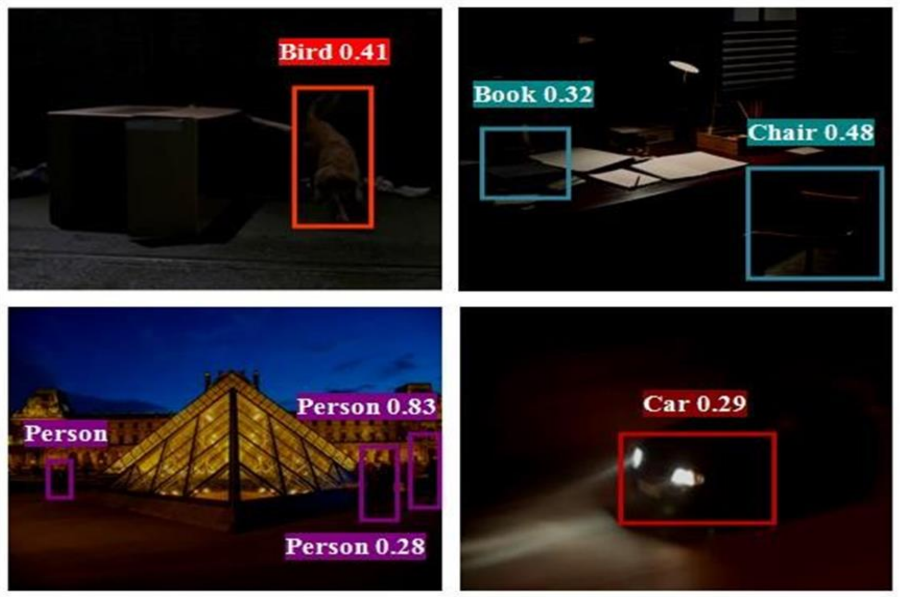

Figure 1: Common object-detection algorithms for detecting conditions in low-illumination environments using YOLO approach

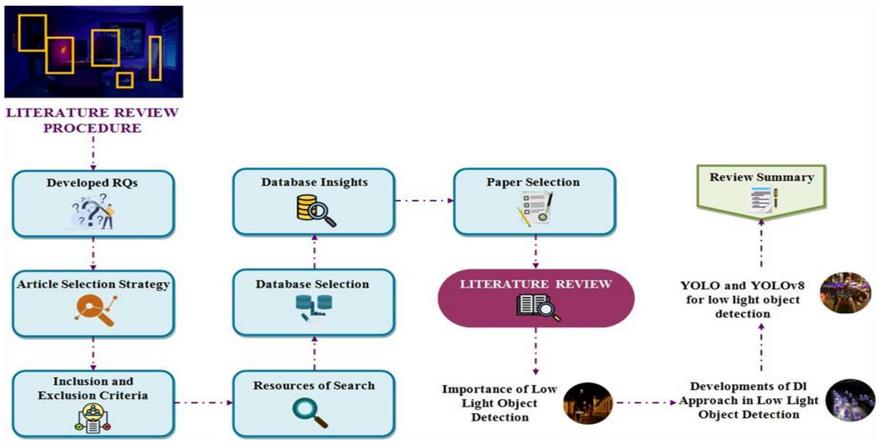

Figure 2: Remaining section headings to be focused in the literature review paper

RESEARCH QUESTION AND ARTICLE SELECTION STRATEGY

Research questions

The basis of a successful literature review is the Research Questions (RQs). As an orientation, RQ confirms the relevance, depth, and focus of the review process by directing it. Authors can identify the exact knowledge gaps that need to be filled by making concise and accurate RQs. Additionally, it helps individuals to concentrate and direct their literature search.

Development of RQs

Peer review RQs are meant to objectively evaluate the developments and performance of the DL models under dim lighting. These inquiries seek to determine the advantages and disadvantages of YOLO and YOLOv8, evaluate how well they function in comparison to earlier versions, and investigate possible opportunities for further development. The peer review can offer important perceptions and suggestions for improving the precision and dependability of OD in difficult LLCs by revealing these RQs. The following are some of the significant RQs

RQ1: What are the research articles covering LOD?

RQ2: What are the developments of DL in LOD?

RQ3: What are the research articles covering the YOLO and YOLOv8 for LOD?

Article selection strategy

A clear selection process helps to narrow down the vast amount of available content by only including the most important and relevant articles in the review. This helps to keep the review focused and prevents it from being overly broad. The article selection approach for the

objective is developed to guarantee a comprehensive and objective analysis of the most pertinent and superior research works.

The review attempts to give a thorough summary of the developments, advantages, and disadvantages of YOLO and YOLOv8 in LL object identification by carefully choosing papers. The DL approach facilitates the identification of significant contributions, patterns, and gaps in the existing literature, allowing for a comprehensive analysis and providing information for the next advancements in the subject.

a. Inclusion and Exclusion Criteria

To ensure a thorough and unbiased examination of relevant research studies, the inclusion criteria and exclusion criteria are explained.

Inclusion criteria: The English language is thought to be unique and understandable to a broad spectrum of people. Research papers written entirely in English were included in the study. Articles about LOD were included in the literature review. Research studies published between 2014 and 2024 were included in the literature review.

Exclusion criteria: Articles that only discussed the issues associated with LOD using the DL algorithm were left out.

b. Resources of search and selection strategy

Here, an explanation of the resources used for the literature search and review process is provided in this section.

Resources: A number of academic search engines were identified, including Google Scholar, Springer, Elsevier, and IEEE Xplore based on the early inquiry. Data regarding the matched target was kept in the architecture of the aforementioned academic search engines.

Database selection: Important databases used to find and choose articles for the literature review were Scopus, Web of Science (WOS), and Science Citation Index Expanded (SCIE).

Database Insights: The journal-based database was distinguished from the others by its extensive abstract and citation databases of peer-reviewed material published in scientific journals. The selected databases provided significant benefits when it came to assessing appearance and content.

c. Paper Selection

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A total of 25 publications were selected for examination after the precise number of journals relevant to the primary keywords was examined. The papers were chosen according to predetermined standards. A visual representation of the search results for this review-based study is depicted in Figure 3.

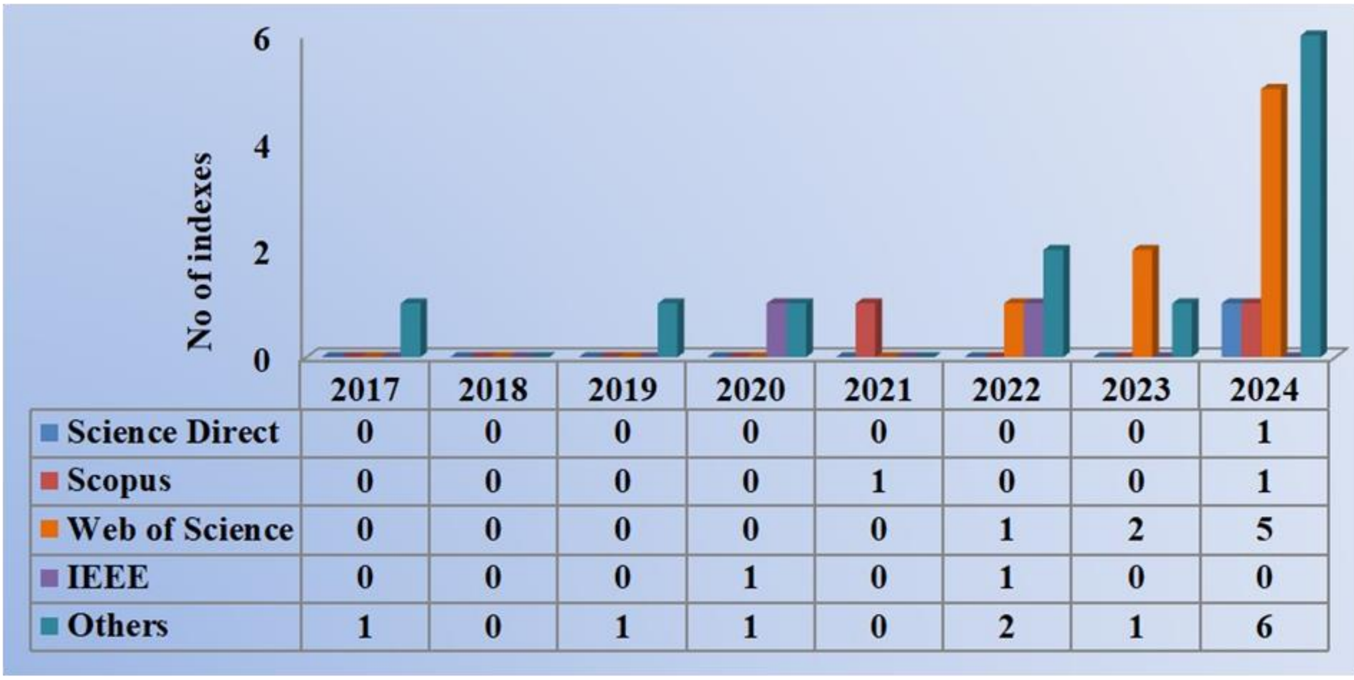

Figure 3: Search results of the article

LITERATURE REVIEW

For a variety of applications, including autonomous driving, nighttime monitoring, and search and rescue operations, LOD is important because it makes it possible to accurately identify and recognize objects in dimly illuminated environments. LL object recognition has greatly progressed as a result of DL advancements with algorithms, such as YOLO, and its most recent iteration, namely YOLOv8, set the standard. YOLO and YOLOv8 are extremely effective and efficient at processing images and recognizing objects, especially in difficult LLCs because of their well-known real-time detection capabilities. These models use complicated neural networks to improve image quality, brightness control, and FE and enable more accurate OD.

Thus, the advancements in DL have significantly improved the ability to detect objects in LLC, enhancing the safety and efficiency of critical applications and contributing to the overall progress in the field of AI. These developments highlight the importance of continued research and innovation in DL to further advance OD.

Importance of Low Light Object Detection

LOD is essential because it improves the capacity to recognize and follow effects in dimly illuminated environments in several domains, including security, autonomous cars, and surveillance [8]. This feature is essential for maintaining efficiency and safety at night. For example, by identifying pedestrians in poor light, autonomous driving can enhance navigation and reduce accidents. Comparably, in security applications, it makes it possible for surveillance systems to continue monitoring effectively even in the absence of sufficient lighting, preventing possible dangers from going undetected [9]. Besides, the overall performance and dependability of automated systems in difficult environments are greatly enhanced by developments in LL detection technologies, such as infrared and night vision [10].

Roman, *et al* [11] elucidated OD in images with LLC. The bilateral filtering and wavelet thresholding-based picture denoising technique was introduced. The boosting technique for OD was utilized, which combined symmetrical local binary patterns with modified Haar-like characteristics. As per the results, an improved OD rate is depicted by integrating the applied boosting method of object recognition with the prior processing stage, which included the bilateral filter and wavelet thresholding method of image denoising.

Pengpeng, *et al* [12] defined LOD. The CO-DETR model, which served as the basis for the method, was trained on two sets of data, namely photographs taken in LL and images taken in complete darkness. By applying different augmentation strategies to the test data, multiple sets of prediction results were generated. Results from experiments showed how well the implemented strategy worked to increase item DA in difficult situations.

Khurram, *et al* [13] examined the featEnHancer with the enhancement of hierarchical features for OD along with beyond under LL vision. A module called FeatEnHancer was used in order to generate appropriate representations. The effectiveness of improving hierarchical features under LL vision was demonstrated by the results, which showed improvements in a number of lowlight vision tasks, including video OD (+1.8 mAP on DarkVision), nighttime semantic segmentation (+5.1 mIoU on ACDC), face detection (+1.5 mAP on DARK FACE), and dark OD (+5.7 mAP on ExDark).

Xiaohan, *et al* [14] elucidated the trash to treasure for LOD through decomposition along with aggregation. A semantic aggregation module was developed to integrate multi-scale scene-connected semantic information in the context space. As per the results, the information extracted from illumination was reasonable. Then, the FPN network dramatically improved mAP by 8.6% and 0.74 for LL pictures (L) and reflection (R) inputs, respectively.

Developments of DL Approach in Low-Light Object Detection

Recently, the development of DL approaches in LOD has seen significant advancements. Traditional CV techniques face difficulties in detecting and identifying objects effectively as LL environments pose challenges, such as noise, poor contrast, and reduced visibility [15]. Nevertheless, the adaptability and learning capabilities of DL algorithms confirm continuous improvement, paving the way for more effective along with dependable solutions in LLC [16].

a. YOLO and YOLOv8 for low-light object detection

The YOLO algorithm plays a major role in this field even though there are numerous DL algorithms designed for LOD. YOLO stands out due to its ability to perform real-time detection with high accuracy and efficiency, making it an essential tool for applications, where timely along with reliable OD is important. YOLO, which is capable of processing images and identifying objects in challenging LL environments, is a DL algorithm known for its speed and precision. This makes it particularly valuable for applications, such as nighttime surveillance, autonomous driving, and search and rescue missions, where traditional algorithms may face problems in maintaining performance. YOLO enhances FE and image quality by using advanced neural network architecture, explaining the unique challenges posed by LLC, and ensuring that critical objects are detected accurately. The research articles associated with the YOLO and YOLO8 for low OD with their objectives, findings, and limitations are elucidated in Table 1. In Table 1, the mAP is found to be the mean average precision, P is the precision, R is the Recall, and M is the map.

Table 1: Research articles associated with the YOLO and YOLO8 for low object detection with its objectives, findings, and limitations

Author s' name	Approaches	Objectives	Dataset s	Findings	Limitations
Zhenqi, et al [17]	YOLO and YOLOv 8	3L-YOLO was applied for augmenting the FE capability for LL objects while sustaining a	ExDark , ExDark +, along with DARK FACE	Across the three datasets, 3L-YOLO improved mAP@0.5 by 2.7%, 4.3%, and 1.4%, outperforming YOLOv8n in LOD.	Dependence on synthetic LL datasets for evaluation might not fully capture the variability faced in real- world scenarios.

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		lightweight network.			
Jifeng, et al [18]	YOLOv 8	To explore the Lightweight boosted YOLOv8n underwater OD network for LL environments.	RUOD underwater dataset and Pascal VOC2012 dataset	The PDSC-YOLOv8n's mAP@0.5 along with mAP@0.5:0.95 might achieve 86.1% and 60.8%, respectively. The original Yolov8n algorithm's mAP@0.5 and mAP@0.5:0.95 on the RUOD dataset were 79.6% and 58.2%, correspondingly.	The algorithm's performance might be impacted by dynamic lighting changes and the presence of noise in LL images.
Songwen, et al [19]	YOLO	To explain the LI-YOLO as an OD for UAV Aerial Images in Lower-Illumination Scenes.	Drone Vehicle dataset and LLVIP dataset	The mAP 50 was enhanced using LI-YOLO by 6.9% on the LLVIP dataset and 3.1% on the DroneVehicle dataset.	LI-YOLO required large amounts of high-quality annotated data to achieve optimal performance.
Haitong, *et al* [20]	YOL O v 8	To analyze the DC- YOLOv8: small-size OD centered on a camera sensor for LL environments.	Visdron dataset, Tinyperson dataset, together with PASCAL VOC2007 dataset	For the Visdron dataset, M, P, and R ratios of DC- YOLOv8 were 2.5%, 1.9%, and 2.1% > YOLOv8s, respectively. For the Tinyperson dataset, M, P, and R ratios of DC-YOLOv8 were 1%, 0.2%, and 1.2% > YOLOv8s, correspondingly. For the PASCAL VOC2007 dataset, M, P, and R ratios of DC- YOLOv8 were 0.5%, 0.3%, and 0.4% > YOLOv8s, respectively.	Since DC-YOLOv8 was based on specific camera sensors, it might require calibration and optimization for different sensor types.

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Yun, *et al* [21]	YOLO	To analyze the LIDA-YOLO as an unsupervised lower-illumination OD centered on domain adaptation.	ExDark dataset and PASCAL VOC	LIDA-YOLO achieved 2.7% (performance improvement) when weighed against the supervised baseline YOLOv3.	LIDA-YOLO was trained on a particular set of LL data; so, overfit risk might occur in those specific scenarios, thus reducing its ability.

Zhiqiang, et al [22] elucidated the low illumination Target Detection (TD) technique centered on a dynamic gradient gain allocation strategy. The incoming DimNet model improved by 4.28% and 3.77% when weighed against the base model YOLOv8 and by 4.15% and 2.25% when weighed against the ideal model YOLOv9 according to experiments conducted on the ExDark dataset. It also obtained 79.09% and 75.60% on precession and mAP50, respectively. As per several experimental comparisons, DimNet performed better regarding DA along with performance than both earlier and existing approaches.

Wenyu, et al [23] defined the image-adaptive YOLO for OD in adverse weather conditions and for LL scenarios. By using the IA-YOLO technique, images might be adaptively processed in both favorable and unfavorable weather circumstances. IA-YOLO significantly outperformed all test datasets with similar running times despite only adding 165K trainable parameters. As per the experimental findings, the usage of the IAYOLO approach was effective in both LL and foggy conditions, which was highly encouraging.

Mengqing, et al [24] elucidated the GOI-YOLOv8 grouping offset as well as isolated giraffedet LL-TD. A modified model called Grouping Offset and Isolated GiraffeDet TD- YOLO was used centered on the YOLOv8. As per the experimental data, the GOI-YOLO decreased the number of parameters by 11% while lowering the computing requirements by 28% when compared to YOLOv8. On the ExDark dataset, this solution produced a competitive surge of 2.1% in Map50 along with 0.6% in Map95 while improving real-time performance.

Sikkandar, et al [25] defined the real-time OD in LL environments employing YOLOv8 as a case study with a custom dataset. This study included an evaluation of the model's real-time performance employing a custom video feed. The YOLOv8 model proved its great accuracy and speed by successfully learning to detect a wide variety of objects in difficult nighttime situations. Also, in real-time, including bicycles, cars, vans, people, and cycles, the model recognized and categorized every object, thereby demonstrating its potential for useful applications in traffic monitoring along with nocturnal surveillance.

SUMMARY OF THE STUDY

In LL environments, the detection of objects is a key challenge in CV, particularly for applications in autonomous systems, surveillance, and robotics. Owing to issues like reduced visibility, image noise, together with poor contrast, traditional OD methods often experience problems in LLC. To address these challenges, DL approaches have become increasingly prominent, with YOLO emerging as a leading framework for real-time OD. YOLO has trouble correctly identifying and categorizing objects because of the damage to the image quality. Several changes have been made to improve YOLO's performance in these situations. The most recent version, YOLOv8, has made a number of improvements that increase its performance for applications involving the detection of objects in LL. The model can more easily recognize objects from noisy backgrounds and also identify YOLOv8's notable integration of improved image preprocessing techniques that aid in clarifying low- illumination images. Also, the

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RQs have been categorized into RQ1, RQ2, and RQ3 to make the present review paper more innovative. The following table 2 explains the questions and answers.

Table 2: Questions and Responses

Numbers	Questions	Responses
01	What are the research articles covering LOD?	The research articles from the 11th to 14th references covered LOD.
02	What are the developments of DL in LOD?	The growth of DL in LOD was explained in Section 3.2.
03	What are the research articles covering the YOLO and YOLOv8 for LOD?	The references from 17 to 25 were the research articles covering the YOLO and YOLOv8 for LOD.

Thus, in the field of LOD, YOLO and YOLOv8 represent significant progress, offering a promising solution for real-time applications. The advancements in YOLOv8, including image enhancement, multi-task learning, and attention mechanisms, make it better suitable for handling the challenges of low-illumination environments.

CONCLUSION

Lastly, substantial progress in LOD is demonstrated by DL approaches, particularly YOLO and YOLOv8. In YOLOv8, the combination of advanced techniques like image enhancement, noise reduction, and improved architecture contributed to better DA and efficiency in low-illumination environments. These advancements had significant implications for various applications like autonomous vehicles, surveillance systems, along with robotics, where real-time OD was important for challenging lighting conditions. YOLOv8 depicted improvements in its architecture, allowing it to process LL images more effectively while maintaining the speed and real-time detection capabilities that were characteristic of the YOLO framework. The limitation was identified from the analyzed research articles other than benefits. However, YOLOv8's architecture, while optimized for speed, could still be computationally demanding, especially when applied to LL images that required additional processing steps like enhancement and noise reduction. This limitation will be noted by future researchers to explore the need for enhancement as well as reduction of the noise. Thus, ongoing research and development in these areas will continue to enhance the applicability and performance of DL models in real-world LOD tasks.

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