Object Detection In Low-Light Environment Using YOLOv7

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ABSTRACT

Object detection in low-light conditions is very essential in many applications such as autonomous driving, surveillance and security systems. Deep learning and neural networks are widely used in object detection applications, many algorithms were modified to improve the detection in low-light environments. You Only Look Once (YOLO) is one of the latest computer vision algorithms that provides accurate object detection and optimized algorithm run-time. In this work, the latest YOLO algorithm (version 7) is trained and validated using Exclusively Dark Image Dataset (ExDark) to detect twelve classes in dark environments. Results are displayed and compared with the latest related research work in this field. The detection precision and recall are 0.7153 and 0.6556 respectively. YOLOv7 showed a major improvement in the mean average precision (mAP) over a previous recent work who used the same dataset.

Introduction

Object detection using Convolutional Neural Network (CNN) is a commonly used approach in computer vision systems, especially in complex detection problems, due to their ability to learn from training data and build very accurate detection models. Many CNN computer vision algorithms were introduced in the past few years for object detection. These approaches were developed and improved to achieve high detection accuracy and to reduce algorithms run-time.

Ross Girshick et al. introduced region based CNN (R-CNN) for object detection[1]. R-CNN method generates approximately 2000 regions and pass it to CNN for classification. CNN works as feature extractor, the features are passed to Support Vector Machine (SVM) classifier for classification. The main drawback of this method is the huge amount of time it requires for training and classification, which makes it difficult for real time implementation. The same author introduced a fast version of the R-CNN, he called it fast R-CNN[2]. This algorithm feeds the image to CNN to construct feature map, region proposals are made from the produced feature map using selective search approach. The fast R-CNN is much faster than the original R-CNN as it doesn't pass fixed amount of candidates. Shaoqing et al. introduced faster R-CNN that uses a new approach for region generation[3]. Instead of using the selective search in R-CNN and fast R-CNN, faster R-CNN uses a network called Region Proposal Network (PRN) to generate region candidates. Faster R-CNN showed significant improvement in the algorithm run-time and accuracy.

Liu et al. intorduced the Single Shot Detection (SSD) approach for object detection[4]. SSD has two networks; a backbone model and SSD head. The backbone is a pre-trained CNN, and it is used for objects feature extraction. SSD head is more convolutional layers to the backbone feature map to enable detecting objects at different scales.

All the previous approaches use selective search to find region with high probability of having objects. You Only Look Once or YOLO is a new approach for object detection where the whole image is passed to a CNN to predict the bounding boxes and the object probabilities for each box. The first release of YOLO algorithm was in 2016, it was released under the name of YOLOv1 by Redmon et al[5]. a more accurate and faster version of YOLO was introduced in the same year by the same author, it was called YOLOv2[6]. In this algorithm, the author used batch normalization for all the layers, he also dropped some Max pooling layers to increase features resolution. In 2018, Redmon et al. introduced YOLOv3[7]. In this version more improvements in accuracy and run-time were made. In this version, the author used more bounding boxes at different scales for each grid, he also used deeper backbone networks to extract more accurate features. For ethical concerns, Redmon stopped the development of YOLO algorithm. YOLOv4 was introduced by Bochkovskiy et al. in 2020[8]. In this approach, the author included new improvements to the training process under the name of bag of freebies. YOLOv4 was also introduced the cross mini-Batch Normalization[9], a new normalization method designed to increase the stability of the training process.

A newer version of YOLO was introduced in 2020 and it was called YOLOv5, there is no official scientific paper about this algorithm, but the source code can be found on github[10]. YOLOv5 uses a new backbone network called EfficientNet[11]. The new architecture allows it to achieve better accuracy and generalization to a wider range of object categories. YOLOv5 used spatial pyramid pooling (SPP) to reduce the spatial resolution of the features to improve the detection of small objects. YOLOv6 was introduced in 2022 by Li et al.[12]. YOLOv6 used an improved version of EfficientNet architecture, it is called EfficientNet-L2[13]. L2 network has less parameters than the original EfficientNet, which improved the run-time of the algorithm.

YOLOv7, the algorithm used in this paper, was released in 2022 by Wang et al.[14]. The algorithm uses Extended efficient layer aggregation networks (E-ELAN) as a backbone network. YOLOv7 uses the Focal Loss[15], it is a new training technique designed to address the class imbalance problem that often arises in object detection tasks. More details about YOLOv7 architecture and training techniques will be addressed in another section of this paper. YOLOv8 release was confirmed by ultralytics[16], but still no official scientific paper is published about this algorithm. Until writing this paper, YOLOv7 is the latest official published release of YOLO series.

The different approaches of CNN and deep learning techniques such as YOLO family, SSD and RCNN were implemented in many computer vision applications. For example, road object detection using SSD was implemented by Barba et al.[17]. Road object detection using Kitti dataset for several road objects such as cars, trucks and pedestrian using YOLOv3 was implemented by Al-refai et al.[18]. Biswas et al. implemented Single Shot Detection (SSD) and MobileNet-SSD to estimate traffic density by detecting vehicles in the road[19]. Alsanad et al. used YOLOv3 for human detection using drones images[20].

This research focuses on object detection in low-light environments due to the importance of this detection scenario in many applications, such as security and autonomous driving applications. This work covers detection situations for indoor and outdoor low-light environments. YOLOv7 algorithm will be used as the computer vision model, because it is the latest official YOLO release and the algorithm is equipped with new techniques that allows the model to learn from low level features , which will improve object detection in dark environments. ExDark dataset is used to train and test the model. The results of this research is compared to the latest low-light object detection approaches. The paper is designed to include the following sections: Section two introduces to related work for object detection in dark environment using deep learning approaches. Section three includes more details about YOLOv7 backbone architecture and improved training techniques. Section four explains the deadset that used for algorithm training and validation, it also explains the training and validation process. Section five shows the detection results of the algorithm, it also compares the results with other related work that used the same dataset. Finally, the discussion section highlights the main takeaways from this research and suggests future work to improve the results.

Related Work

Many researches have been conducted on object detection in low-light environment such as dark indoor areas, night detection, and adverse weather conditions such as foggy weather. Wang et al. proposed a new approach for night object detection by using DCGAN (Deep Convolution Generative Adversarial Networks) combined with a very advanced Faster R-CNN (Region-based Convolution Neural Networks) target detection system, through deep convolution feature fusion and multi-scale ROI (Region Of Interest) pooling[21]. Image-Adaptive YOLO (IA-YOLO) framework was proposed by Liuwenyu et al.[22]. In this approach, images are enhanced for better detection performance, they trained CNN-PP and YOLOv3 jointly in an end-to-end fashion. This work used ExDark image dataset for testing. A multiScale Domain Adaptive YOLO (MS-DAYOLO)[23] is also another work that used YOLOv3 for low-light object detection. Joint semantic learning for object detection in inclement weather conditions were validated using ExDark dataset for low-light object detection by Huang et al.[24].

Lai et al. proposed a new technique for pedestrian detection in low-light road conditions using optimized mask RCNN[25]. They proposed fusion algorithm that adjusts Region Proposal Network (RPN) and delete instance mask branch to achieve better pedestrian detection performance of algorithm in low-light environment. A low-light foggy weather detection for road objects using YOLOv7 and defogging algorithms is proposed by Qiu et al.[26]. In his proposed framework, a CNN network is used for image defogging, and YOLOV7 is used for object detection. An improved low light object detection using YOLOv5 is proposed by Wang et al.[27]. He used low-light image enhancement algorithm to generate enhanced images that achieve relatively better visual effects, then YOLOv5 is used to detect objects in images. A multitask auto encoding transformation (MEAT) with orthogonal tangent regularity network is proposed for Dark Object Detection[28]. The proposed model combines human vision and machine vision tasks to enhance object detection in a dark environment.

YOLOv4 is used for object detection in on a belt conveyor in a low-Illumination environment[29]. The KinD++ low-light image enhancement algorithm is used to improve the quality of the captured low-quality images through feature processing[30], and then YOLOv4 is used for object classification. A survey that summarizes the latest approaches for object detection in challenging weather conditions using deep learning was conducted by Ahmed et al.[31].

YOLOv7 Overview

In this research project, YOLOv7 is used for low-light object detection. The main reason to choose this approach is that YOLOv7 surpasses all other YOLO releases in both accuracy and speed, and it is the latest official release of YOLO series with a published scientific paper[14]. In addition to that, YOLOv7 uses training techniques called 'bag of freebies', these techniques helps the model to learn from low level features, this should improve low-light object detection. This work implements YOLOv7 on ExDark dataset to study how efficient YOLOv7 works in low-light environment and compares the results with the latest low-light detection approaches. The following subsections highlights the main features and techniques that is introduced in YOLOv7:

E-ELAN (Extended Efficient Layer Aggregation Network)

E-ELAN is the backbone network for YOLOv7 approach. the authors of YOLOv7 designed the backbone network by taking into consideration the amount of memory it takes to keep layers in memory along with the distance that it takes a gradient to back-propagate through the layers. The shorter the gradient, the more powerfully their network will be able to learn. With these design considerations, they chose E-ELAN, an extended version of the ELAN computational block. According to the authors, E-ELAN uses expand, shuffle and merge cardinality to achieve the ability to continuously enhance the learning ability of the network without destroying the original gradient path. Figure 1 shows the architecture of the E-ELAN as proposed in the official YOLOv7 paper[14].

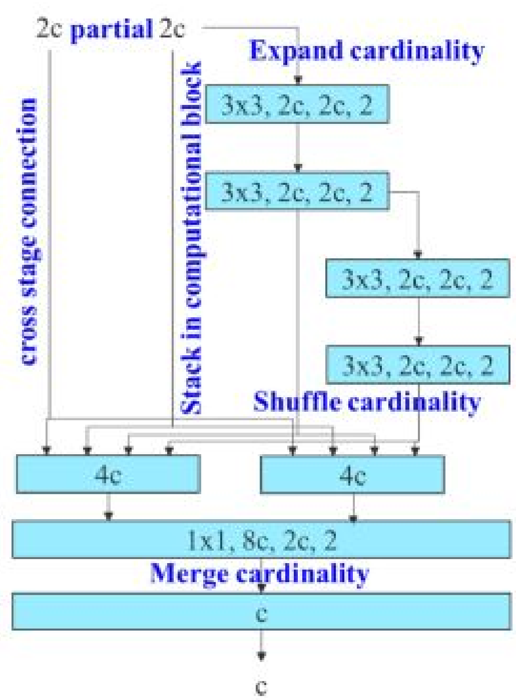

Figure 1. The architecture of E-ELAN[14]

Model Scaling for Concatenation-Based Models

Model scaling is used to adjust some attributes of the model to generate models at different scales. The previous used scaling models were causing the the size of the output features to increase or decrease. In the proposed scaling model of YOLOv7, only the depth in a computational block needs to be scaled, and the remaining of transmission layer is performed with corresponding width scaling. According to authors, the proposed compound scaling method can maintain the properties that the model had at the initial design and maintains the optimal structure. Figure 2 shows the difference between the traditional depth scaling up that causes the output width of a computational block to increases, while the concatenation based models, only the depth in a computational block needs to be scaled, and the remaining of transmission layer is performed with corresponding width scaling

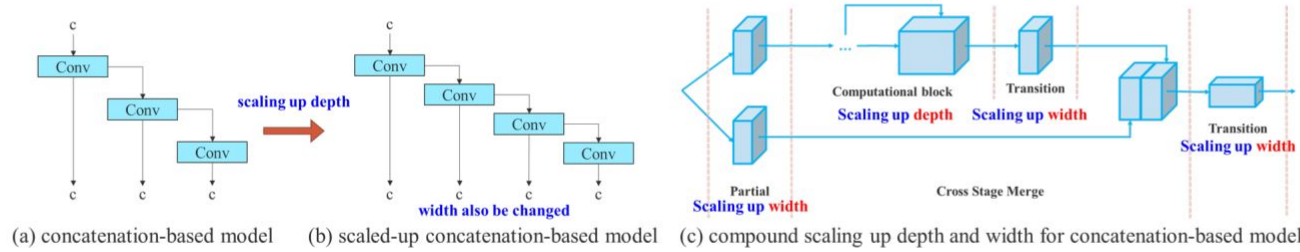

Figure 2. Model Scaling for Concatenation-Based Models[14]

Trainable Bag-of-Freebies

Re-Parameterized Convolution

Re-parameterized Convolution[32] showed enhanced results in some network architectures such as VGG[33], and significant drop in accuracy on other architectures like ResNet[34] . In YOLOv7 development, authors uses gradient flow propagation paths to analyze how re-parameterized convolution should be combined with different network.Therefore, they designed planned re-parameterized convolution accordingly.

Coarse for Auxiliary and Fine for Lead Loss

A YOLO architecture, the head contains the predicted model outputs. YOLOv7 has two heads. The lead head which is responsible for the final output , and the auxiliary head which is used to assist training in the middle layers. Figure 3 shows the architecture of auxiliary head and lead head in YOLOv7.

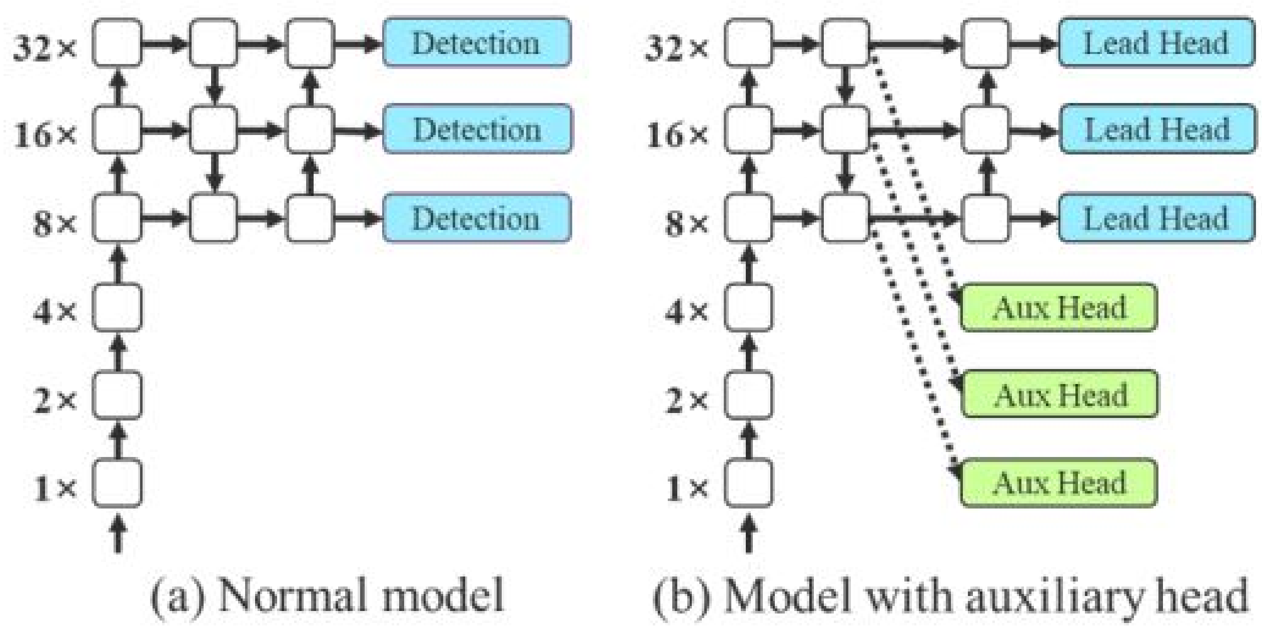

Figure 3. Auxiliary and lead heads in YOLOv7 compared to normal models with single head[14]

Batch normalization and EMA model

The batch normalization and Ensemble Mean Teacher (EMA) are two training techniques were carried over from YOLOv4 architecture and used in YOLOv7. The batch normalization integrate the mean and variance of batch into the bias and weight of convolutional layer at the inference stage. Mean Teacher improves test accuracy and enables training with fewer labels[35].

Dataset, training and validation process

Due to the importance of low-light object detection in computer vision applications, there are several low-light datasets were developed to enable the research in this field. NightOwls dataset is developed to focus on pedestrian detection at night[36]. The Dark Face dataset provides 6,000 real-world low light images captured during the nighttime, at teaching buildings, streets, bridges, overpasses, parks, etc., all labeled with bounding boxes for of human face[37]. However, Exclusively Dark Image Dataset (ExDark dataset) is known to be the largest available low light images dataset. The dataset was developed and maintained by Loh et al.[38]. The latest update on the dataset was made on September 02, 2022 as of writing this paper. The official dataset is available on github[39].

ExDark dataset is a collection of 7363 low-light images from very low-light environments, the dataset includes 12 labeled object classes on both image class level and local object bounding boxes. The classes included in the dataset is as following:

- Bicycle - 652 images
- Boat - 679 images
- Bottle - 547 images
- Bus - 527 images
- Car - 638 images
- Cat - 735 images
- Chair - 648 images
- Cup - 519 images
- Dog - 801 images
- Motorbike - 503 images
- People - 609 images
- Table - 505 images

In order to train and validate the YOLOv7 model, each class is divided to 80% for model training and 20% for model validation. This is 5704 images for training and 1659 images for validation. A special code was developed to convert the original dataset annotations format to fit YOLOv7 annotation format. YOLOv7 annotation shall include the class, x center, y center, width, and height of the bounding box.

The official YOLOv7 is implemented using PyTorch library. The pre-trained YOLOv7 weights of COCO dataset were used as initial wights before training using Ex Dark dataset[40]. The training of the model using ExDark dataset is done with Batch size of 4 and input image of 640 x 640 (YOLOv7 default size). The training is stopped at 50 epochs as the Precision and the recall values reached to their peaks. The best precision and recall values achieved during the training are 0.7153 and 0.6556 respectively. Figure 4 shows the training precision and recall curves with the epoch value.

Results

The detection results of the algorithm is represented as confusion matrix that shows the detection result per class and the mean average precision (mAP) at classification threshold of 0.5. The mAP is very popular metric in object detection measurement, it also helps us to compare our work to other related work. Figure 5 shows the confusion matrix for the ExDark classes.

Detection results show that bicycles class has the highest detection accuracy, while table class has the lowest detection accuracy. This is due to the false detection of background objects as tables (high background false negatives). The highest wrong classification for an object was for cats detected as dogs. The highest background false positive detection was for

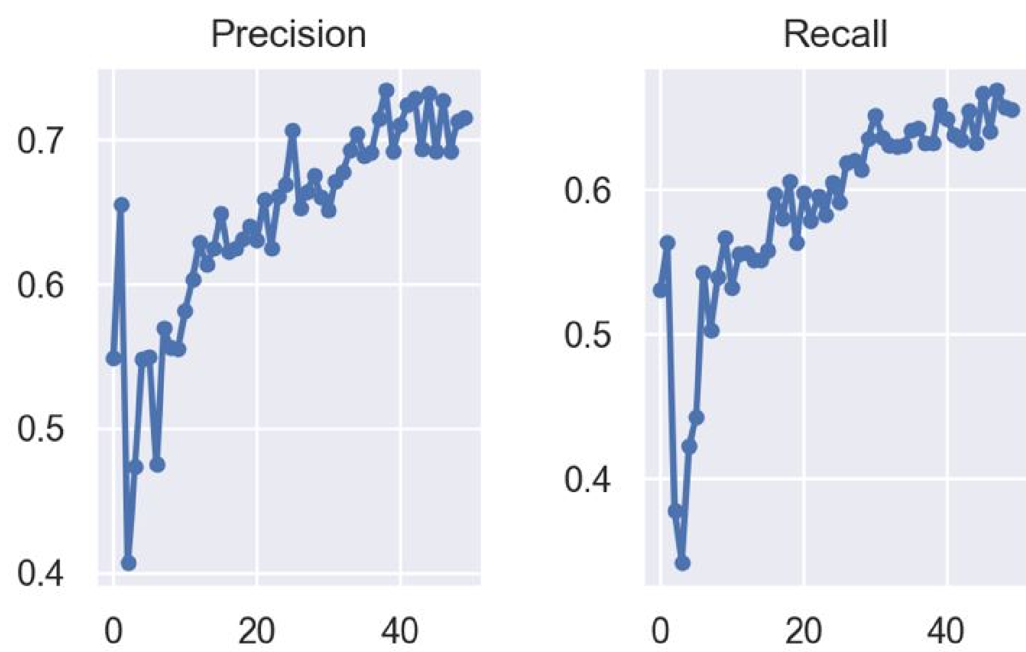

Figure 4. The precision and recall values with Epoch during YOLOv7 training using ExDark dataset

pedestrians, they were miss-detected and classified as background. Figure 6 shows some of the detection results for ExDark images.

In order to judge the performance of YOLOv7 with latest low-light detection algorithms, we picked three of the latest low-light detection algorithms that uses deep learning as backbone and they were tested in the same dataset we used in this work (ExDark). The first algorithm is Image Adaptive YOLO (IAYOLO)[22], in this approach an image processing module is added before feeding the data to YOLOv3. The module will enhance the input image by implementing Defogging, White Balance(WB) and Sharpening filter. The second approach is YOLOv5 which was implemented as a baseline to compare it to in Wangs et al. research approach[27]. The third approach is an improved YOLOv5 for low-light detection[27]. In this approach, an additional feature learning module is introduced to the training allowing for the acquisition of more informative low-level features. It also used coupled head for detection, where the weight parameters are shared between the classification and regression tasks in the object detection task.

YOLOv7 showed better precision, recall and mAP than IAYOLO and YOLOv5. Improved YOLOv5 showed slightly higher mAP and precision values than YOLOv7, while YOLOv7 showed better recall results. That means YOLOv7 has more false positives while improved YOLOv5 shows more false negatives. Table 1 summarizes the performance of YOLOv7 compared to the baseline algorithms.

Method	mAP@ 0.5	Precision	Recall
Image Adaptive YOLOv3[22]	0.403	-	-
YOLOv5[27]	0.642	0.672	0.573
Improved Low-Light YOLOv5[27]	0.698	0.715	0.629
YOLOv7 (Our work)	0.675	0.715	0.656

Table 1. Performance Comparison of YOLOv7 in low-light detection using ExDark dataset

Discussion

YOLOv7, the latest official release of YOLO series, is tested for low-light environment object detection. ExDark, which is one of the largest low-light environment datasets, is used to train and validate YOLOv7. The results of the algorithm is compared to

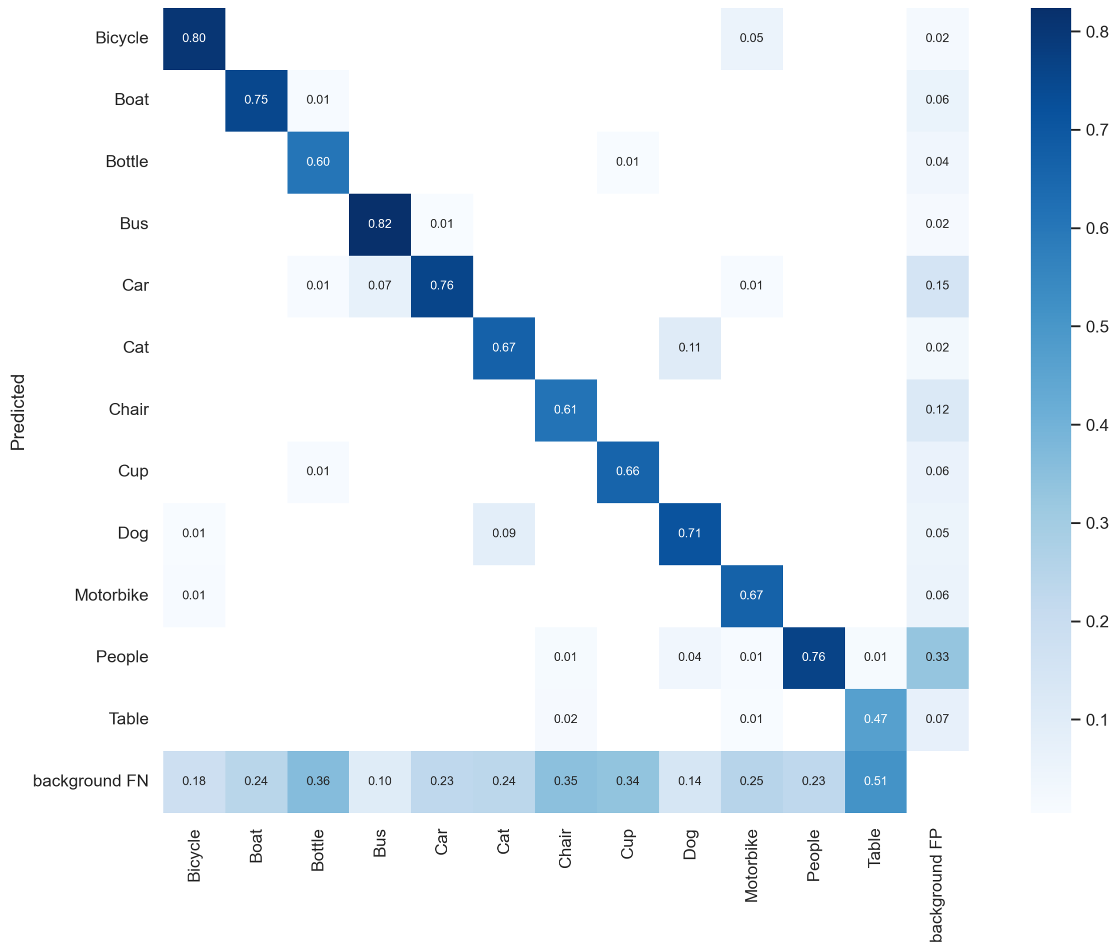

Figure 5. The confusion matrix for ExDark dataset classes using YOLOv7

the latest related work for low-light detection using deep learning.

YOLOv7 shows very excellent detection results compared to the previous YOLO release YOLOv5. That means the improvements introduced to YOLOv7 such as the backbone network (E-ELAN), compound scaling methods, re-parameterized convolution and auxiliary head approach have caused essential improvement in low-light object detection. Even though these techniques weren't developed in the purpose of enhancing low-light detection, they improved low-light detection as these techniques enabled the model to learn from low level features.

High false negative detection were seen in tables class as background, and high false positives in pedestrian class. More enhancements of edges feature can reduce this false detection. The improved YOLOv5 approach[27] is compared to YOLOv7 and it showed higher precision than YOLOv7, which means YOLOv7 can be improved to reduce false positive detection.

YOLOv7 detection results can be significantly improved by applying image enhancement algorithms to highlight the low light features. Image enhancement can be done using the traditional approaches such is histogram equalization techniques like gamma transformation. A survey for histogram equalization techniques for image enhancement is done by Kaur et al.[41]. Retinex is another technique for low-light image enhancement. The theory of Retinex is based on the idea that the color of an object is determined by its ability to reflect light waves. An Empirical Study on Retinex Methods for Low-Light Image Enhancement is conducted by Rasheed et al.[42]. Machine learning and deep learning techniques such CNN can also be used to enhance images for night vision. Ren et al. proposed an approach for low light image enhancement using a trainable hybrid network[43]. A Convolutional Neural Network(MSR-net) that directly learns an end-to-end mapping between dark and bright

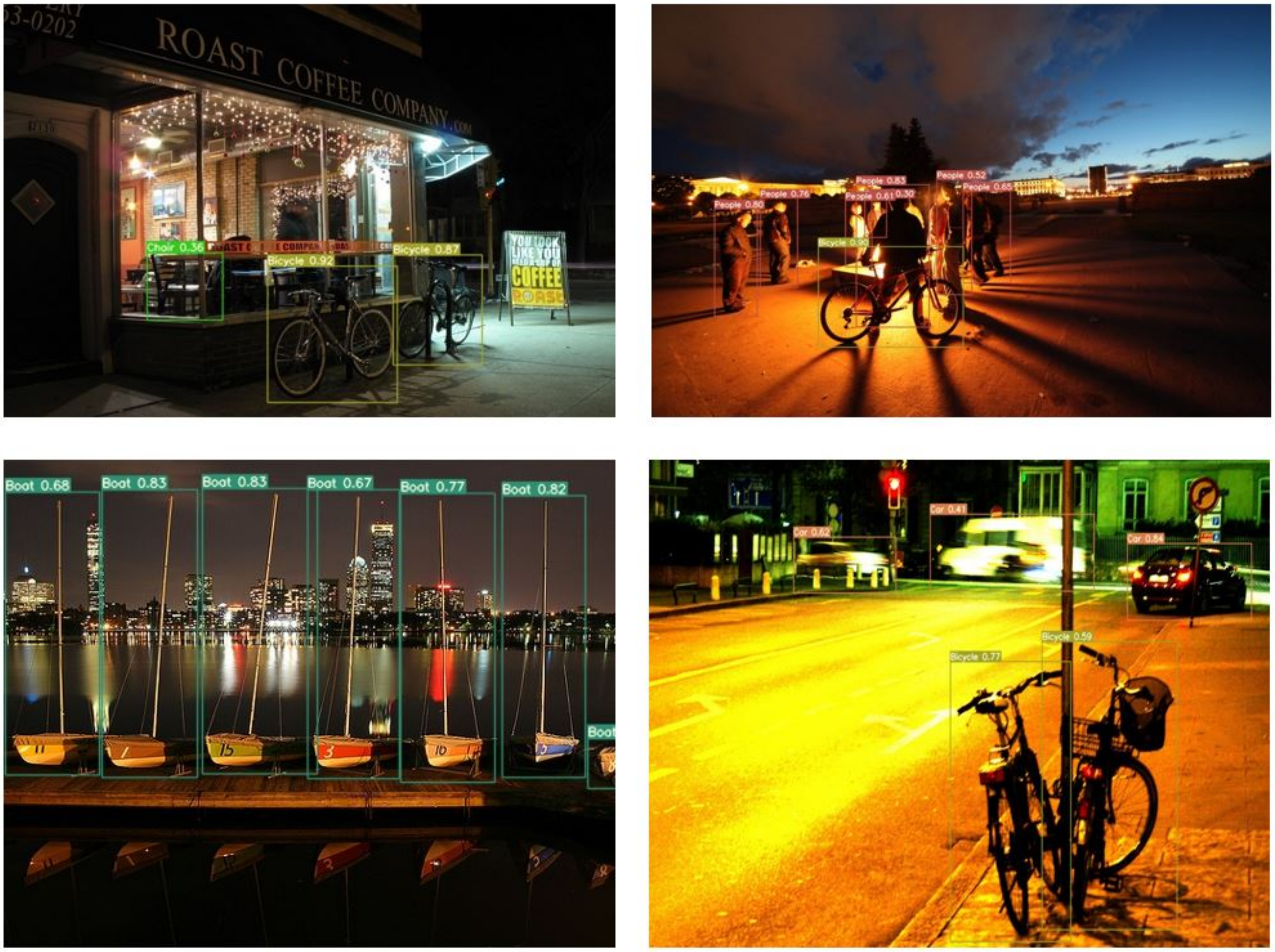

Figure 6. Detection examples from ExDark dataset using YOLOv7

images were proposed by Shen et al.[44]. A survey for the latest approaches in image enhancement using deep learning is done by Li etl al.[45]. Fusing deep learning approach for image enhancement with YOLOv7 can be a future work to be done to improve YOLOv7 detection results.

Data Availability

The datasets analysed during the current study are available in the [Exclusively-Dark-Image-Dataset] repository, [https://github.com/cs-chan/Exclusively-Dark-Image-Dataset/tree/master]

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Author contributions statement

G.A. structured the paper, implemented the algorithm in Python, analyzed the results and wrote the results and discussion section, H.E. contributed in YOLOv7 explanation section and the dataset, training and validation process, M.R and M.A contribute to the introduction and relarted work sections. All authors reviewed the manuscript.

Additional information

I declare that the authors have no competing interests as defined by Nature Research, or other interests that might be perceived to influence the results and/or discussion reported in this paper.

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