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Object Detection for Mixed Traffic under Degraded Hazy Vision Condition

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Abstract

Vehicle detection in degraded hazy conditions poses significant challenges in computer vision. It is difficult to detect objects accurately under hazy conditions because vision is reduced, and color and texture information is distorted. This research paper presents a comparative analysis of different YOLO (You Only Look Once) methodologies, including YOLOv5, YOLOv6, and YOLOv7, for object detection in mixed traffic under degraded hazy conditions. The accuracy of object detection algorithms can be significantly impacted by hazy weather, so creating reliable models is critical. An open-source dataset of footage obtained from security cameras installed on traffic signals is used for this study to evaluate the performance of these algorithms. The dataset includes various traffic objects under varying haze levels, providing a diverse range of atmospheric conditions encountered in real-world scenarios. The experiments illustrate that the YOLO-based techniques are effective at detecting objects in degraded hazy conditions and give information about how well they perform in comparison. The findings help object detection models operate more accurately and consistently under adverse weather conditions.

Keywords: Object detection, Degraded hazy conditions, YOLO, Vehicle detection.

1. Introduction

Object detection plays a vital role in the field of computer vision by encompassing the recognition and precise positioning of objects within an image or video. Various sensors are engaged in object detection to capture the images of the object that are to be detected. Due to unfavorable weather conditions such as fog, rain, snowstorms, dusty blasts, and dim light, the

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quality of images captured by the sensors are substantially degraded [1]. Researchers and developers have demonstrated a rising interest in actively developing object detection algorithms that accurately perform in various environmental conditions, including degraded hazy conditions. Mixed traffic is one such environment that presents unique challenges for object detection due to the presence of multiple types of vehicles and pedestrians. Object detection is essential for a variety of applications, including autonomous driving, traffic monitoring, smart surveillance, and public safety. However, hazy conditions can significantly impact the accuracy of object detection algorithms.

Haze is a common weather condition that can significantly affect object detection in computer vision. Haze refers to the presence of small particles, such as dust or smoke, in the air that can scatter and absorb light, leading to a reduction in visibility as shown in Figure 1. Firstly, it can reduce visibility, making it difficult to distinguish objects from their background. Secondly, it can increase contrast by scattering light, resulting in a loss of color and texture information in the objects. This loss of information can make it difficult to differentiate between objects with similar colors or textures. For example, large vehicles like trucks or buses may appear closer than they actually are, while smaller vehicles like bicycles or motorcycles may completely be obscured. Pedestrians may also face difficultly in detecting due to the loss of color and texture information.

Figure 1. Hazy Weather Conditions.

Over the past few decades, the demand for creating new algorithms for object detection in poor atmospheric situations has increased. To meet this demand, large datasets have been designed [2], [3]. But still, current datasets do not fully represent the diverse range of atmospheric conditions that moving object detectors are likely to encounter in real-world scenarios, making it difficult to develop accurate and robust detection models. Therefore, there is a need for the development of new video datasets that can capture the variety of atmospheric conditions encountered in outdoor scenes, to enhance the precision and reliability of object detection models, particularly at night. Several approaches have been proposed to address object detection under adverse weather conditions, including the use of image dehazing techniques [4] and the integration of visual and depth information. However, most of these methods have been evaluated under adverse weather conditions like rainy, snowy, foggy, and dusty or on a limited dataset.

In this paper, the research presents a comparative analysis for object detection in mixed traffic under degraded hazy conditions by comparing different YOLO methodologies like YOLO v5, v6, and v7. The YOLO model is a popular object detection algorithm that can identify objects in an image or video with high accuracy and speed. The YOLO algorithm converts an input picture into a grid of cells. Each cell forecasts a given number of bounding boxes and the objectness scores related to them. The objectness score measures the confidence that an object exists within a given bounding box. In addition to the objectness score, each bounding box also predicts the class probabilities for the objects contained within it. YOLO uses a convolutional neural network to perform all of these predictions simultaneously, which results in a faster processing time compared to other object detection algorithms that use separate networks for different tasks. This approach is to find the best YOLO model and deep learning-based object detection to enhance the accuracy of detecting objects under hazy circumstances. YOLO versions is evaluated on an open-source dataset of video collected from surveillance cameras mounted on traffic signals of different vehicles (like cars, buses, trucks, motorcycles, and persons) captured under hazy conditions and demonstrate significant improvements over state-of-the-art approaches.

The rest of the paper is divided into the following sections. The related research is presented in Section 2 of this work. the methodology is given in Section 3 that includes information on dataset collecting, the algorithms employed, and evaluation metrics. The experimental and comparison results are visually demonstrated in Section 4. Section 5 provides the conclusion and recommendations for future work.

2. Related Work

Object detection in degraded hazy conditions is a challenging problem in computer vision, and there has been significant research in this area over the past few years. To solve this issue, a number of deep learning-based techniques have been presented, with YOLO being one of the most popular object detection algorithms used for this task. In these years, YOLO has evolved into various versions, including YOLOv4, YOLOv5, YOLOv6, and YOLOv7. These versions of YOLO have incorporated various improvements over their predecessors, including changes to network architecture, improvements to the training process, and enhancements to the object detection algorithm. This section discusses prior work related to recognizing weather conditions from images or videos.

The researchers [5] present a modified version of the YOLOv3 object detection model that is designed to perform well in foggy conditions on the publicly available RTTS dataset. The model incorporates elements of DenseNet architecture to reduce feature loss, as well as an attention module to enhance the detection of low-quality images. Additionally, the loss function has been optimized to improve performance on imbalanced datasets. The model is too big to run on edge devices as it requires a large amount of computational power and memory; thus, it is not suitable for the deployment of edge devices.

In this study [6], the researchers made an effort to locate automobiles in a variety of meteorological situations, including fog, dust, sandstorms, snow, and rain, as well as during the day and at night. The architecture proposed is based on YOLO v4 CSPDarknet53, with modifications that include the addition of a spatial pyramid pooling (SPP-NET) layer and the removal of some Batch Normalization layers. The researchers made the DAWN dataset more challenging by adjusting the color, saturation, brightness, and darkness, as well as by adding other kinds of noise and blur.

In this study [7], researchers created and annotated a new video dataset called the Tripura University Video Dataset at Nighttime (TU-VDN), which contains around 60 outdoor videos that depict four various weather conditions: fog, rain, dust, and low light. This dataset was designed to be used for evaluating the performance of moving object segmentation methods in adverse weather conditions. They compared the outcomes of 10 different state-of-the-art moving object segmentation techniques using the TU-VDN dataset namely- Vibe, Subsense, LOBSTER, PAWCS, PBAS, Multicue, KDE, MoG_V2, Eigen-background, Codebook. The evaluation metrics suggest that MoG_V2, Codebook, and Eigen background have remained the poorest for nearly all conditions, while Vibe, Subsense, PBAS, and Multicue techniques are doing better.

A YOLO v3-based nighttime vehicle detection system is proposed in [8] on real-time night scenes. An ideal MSR (Multi Scale Retinex) algorithm was used to improve all photos to reduce uneven brightness and increase sharpness and detail. From these enhanced images they

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fine-tuned YOLO v3 network and extracted features from images. The testing dataset was used to evaluate the proposed approach, which was found to detect more cars and obtain higher AP and FPS values.

A novel IA-YOLO [9] method enhances input images adaptively to improve object detection in bad weather. A tiny convolutional neural network predicts hyper-parameters, while a fully differentiable image processing (DIP) module restores latent content. To learn a suitable DIP module, the framework is trained from beginning to end using a hybrid training and parameter prediction network. This method outperforms earlier methods in both foggy and low-light situations, handling both normal and adverse weather conditions.

Without the need for model retraining, the study [10] presented a vehicle detection system with a visibility complementation module that can precisely recognize and detect cars in a variety of challenging weather situations. For the majority of extreme weather circumstances, considerable increases in detection and recognition were seen through testing. In low-contrast settings, the suggested method improved accuracy by about 5%, while in rainy conditions, it increased accuracy by an outstanding 50%, satisfying real-time requirements. However, there is a need to develop a more efficient method for handling haze conditions.

While existing methods perform adequately in normal situations, their performance is sub-optimal when faced with unfavorable weather conditions. In this research the performance of YOLOv5, YOLOv6, and YOLOv7 for object detection in mixed traffic under degraded hazy conditions is compared. The experiments carried out demonstrate the effectiveness of these algorithms in object detection under degraded hazy conditions and provide insights into the relative performance for this task.

3. Methodology

3.1 Data Collection

The open-source dataset containing videos collected from surveillance cameras mounted on traffic signals to evaluate the performance of the YOLO-based methodologies is used . The dataset contains videos of traffic data captured in various conditions, including hazy conditions. It contains various traffic objects, including cars, buses, trucks, motorcycles, bicycles, persons, and traffic lights. To ensure the diversity and representativeness of the dataset, the video includes both daytime and nighttime scenes, with varying levels of haze. this kind of dataset was selected with the aim of considering the significant impact that real-world traffic scenarios in degraded hazy conditions can have on object detection accuracy on a large scale. The dataset served as a benchmark to assess the accuracy, robustness, and reliability of the YOLO-based methodologies in challenging weather conditions, providing valuable insights into the performance of these models in real-world scenarios.

3.2 Algorithms Used

. A real-time processing method for object detection is called YOLO. Since the prediction is made using 1x1 convolutions, the acronym YOLO stands for "you only look once". The feature map and the prediction map both have the same size. One neural network is used by the YOLO method to process the entire full image. After that, the network divides the image into areas, providing bounding boxes and predicted probabilities for each region. These generated bounding boxes are weighted using the predicted probabilities.

3.2.1 YOLOv5

Three basic structural components make up the YOLO family of models: the backbone, the neck, and the head are shown in Figure 2.

- The YOLOv5 backbone uses CSPDarknet to extract features from photos made up of cross-stage partial networks(CSPNet) [11].
- The YOLOv5 neck uses a feature pyramid network (FPN) which has the base of a path aggregation network (PANet) [12] for collecting the features and sending the results to the head for prediction.
- YOLOv5 Head layers are those that generate predictions for object identification from the anchor boxes. These layers generate feature maps of three different sizes (18 × 18, 36 × 36, 72 × 72), which gives the multi-scale [13] predication.

Training of the YOLOv5 uses ADAM, Leaky ReLU, SGD, and sigmoid activation as the optimizers. For the loss function, logits loss is used along with binary cross-entropy.

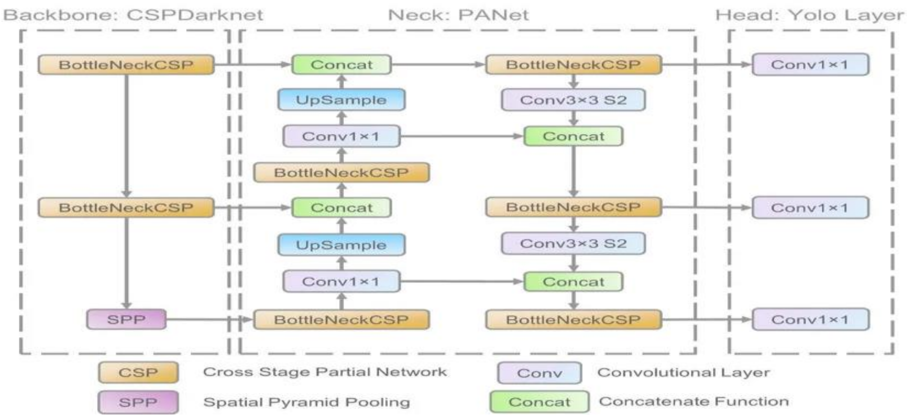


Figure 2. Yolov5's Network Architecture [14].

3.2.2 YOLOv6

All the earlier YOLO versions use anchor-based methods in their architecture but YOLOv6 [15] uses anchor-free method, which makes it 51% faster than others. It performs better than YOLOv5 in terms of detection, accuracy, and inference speed. In comparison to all previous YOLOv5 versions, YOLOv6s offers a better mean Average Precision (mAP) and approximately 2 times faster inference time.

It is also based on the three components backbone, neck, and head. Architecture is shown in Figure 3. YOLOv6 uses a reparametrized backbone, which changes the network structure between training and inference. For the small models, YOLO v6 use reparametrized VGG networks and for medium and large models it employs reparametrized variants of the CSP backbone known as the CSPStackRep. The whole backbone of the YOLOv6 design is known as EfficientRep. The multi-scale features accumulate by the neck of YOLOv6 by utilizing modified Path Aggregation Networks known as reparametrized PAN (Rep-PANet). Efficient Decoupled Head was utilized in YOLOv6 architecture this improves the accuracy of the algorithm.

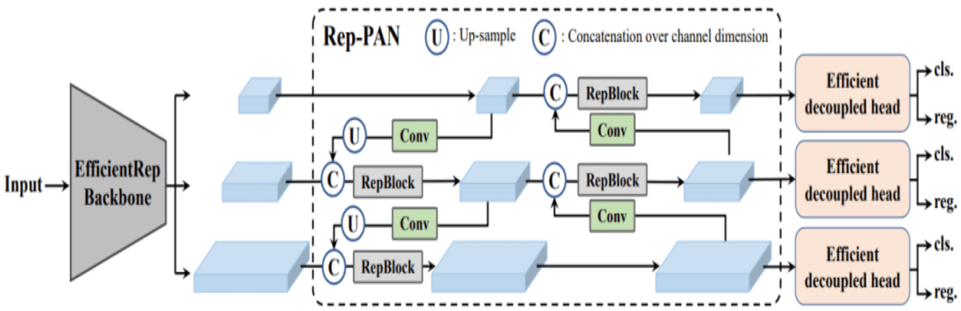


Figure 3. The Architecture of the YOLOv6 Model [15].

3.2.3 YOLOv7

YOLOv7 [16] trained on the COCO dataset. There are some modifications in the architecture of YOLOv7, which increases its accuracy and speed among all the previous versions of the YOLO family. The responsible network for this is the E-ELAN (Extended Efficient Layer Aggregation Network) addition with a compound model scaling strategy, which increases YOLOv7 learning potential.

Here without breaking the initial gradient route the learning capabilities of the YOLOv7 algorithm are improved by the E-ELAN which employs expand, shuffle, and merge cardinality. The transition layer is unaltered in the architecture of E-ELAN but there is a modification in the design of the computational block as shown in Figure 4.

Generally, for parameter-specific scaling, NAS (Network Architecture Search) is utilized however here YOLOv7 model is optimized and scaled with the help of the compound model scaling technique as shown in Figure 5.

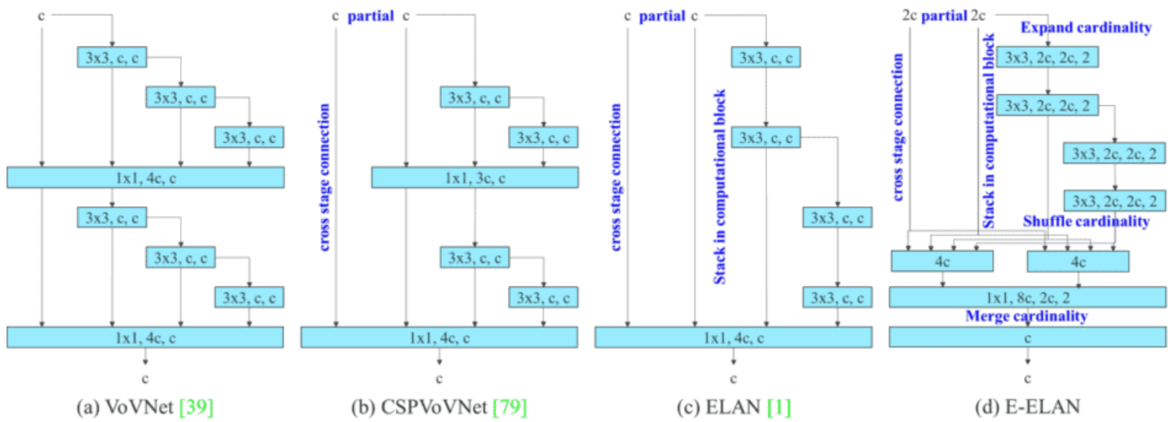


Figure 4. For Improved Network Learning, Compare VoVNET [17], CSPVoVNET [18], LAN, and ELAN.

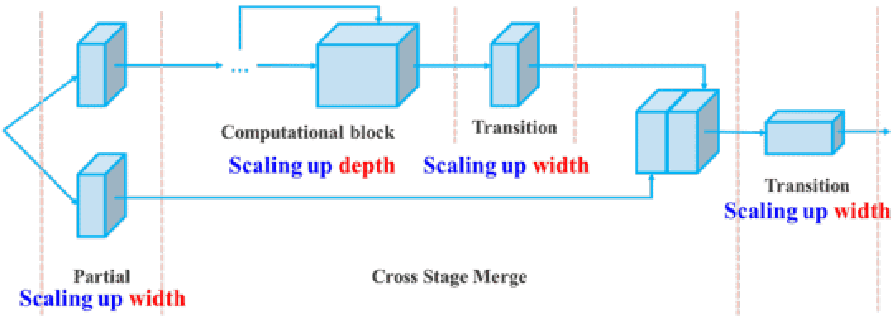


Figure 5. Compound Model Scaling.

Apart from the traditional architecture of the YOLO family which is a neck, a head, and a backbone with outputs obtained in the head, YOLO v7 has several heads to accomplish anything it desires. The comparison of the average precision (AP) of YOLOv7 to other YOLO Family models.

3.3 Evaluation Metrics

In this research, to evaluate the effectiveness of object detection algorithms in degraded hazy environments, number of widely used evaluation metrics were employed . The metrics used in the experiments include True Positives (TP), False Positives (FP), False Negatives (FN), Recall, and Precision.

1. Recall, also referred to as True Positive Rate (TPR) or Sensitivity, is a metric for how well a model detects objects. It is calculated as the ratio of TP to the sum of TP and FN and represents the proportion of objects that are correctly detected by the model out of the total number of objects in the ground truth.

$$\text{Recall} = TP / (TP + FN) \quad (1)$$

2. Precision, also referred to as Positive Predictive Value (PPV), is a measure of the model's ability to provide accurate predictions. It is calculated as the ratio of TP to the sum of TP and FP and represents the proportion of objects that are correctly detected by the model out of the total number of objects predicted by the model.

$$\text{Precision} = TP / (TP + FP) \quad (2)$$

4. Results and Discussion

In this research, the performance of three different versions of the YOLO object detection models, namely YOLO v5, YOLO v6, and YOLO v7, for detecting objects in mixed traffic under degraded hazy conditions were evaluated . The pre-trained YOLO models on an open-source video dataset was used and the performance was tested on our own dataset, which consists of surveillance videos captured during hazy weather conditions. Additionally, we drew a line in the middle of the video to separate the video frames into two regions: above the line and below the line. The line in the middle of the video frames served as a reference point for our analysis. This was done for the purpose of analysis and visualization, as it allowed us to easily distinguish and compare the object detection results in these two regions. By considering the object detection below the line, the research focused on evaluating the performance of the YOLO models in detecting objects in the lower part of the video frames, which may represent objects closer to the ground or objects that are partially obstructed due to the hazy conditions. This allowed us to specifically assess the robustness of the YOLO models in detecting objects under degraded hazy conditions, which can pose challenges for computer vision models due to reduced visibility.

The ability of the YOLO models was analyzed to detect small, medium, and heavy-sized vehicle objects in videos. For each class, distinct colors were allocated to the bounding boxes that were painted around the items that were detected. For example, YOLOv5 used red for people, orange for cars, and green for buses or trucks. Classification scores of the detected objects were also displayed with the bounding boxes, with scores ranging from 0 to 1. Figure 6 showcases some images of object detection using the YOLOv5 model from the videos of hazy conditions, demonstrating that the models were able to correctly identify objects in hazy scenarios.

Figure 6. Images Extracted at the Time of Testing from the Output Video of YOLOv5.

4.1 Comparison of Performance

Figure 7 depicts detection for YOLOv5, YOLOv6, and YOLOv7 it can be observed that YOLOv5 and YOLOv6 models missed some objects and made misclassifications, whereas the YOLOv7 model correctly classified those objects. This indicates that the YOLOv7 model has performed effectively in reducing misclassifications between different categories compared to YOLOv5 and YOLOv6. The performance of YOLOv7 out-shined YOLOv5 and YOLOv6 in terms of detection. YOLOv7 showcased exceptional capabilities in detecting objects, even in cases where haze obscured them and they were situated at a considerable distance. Additionally, YOLOv7 demonstrated a higher object detection rate per frame compared to both YOLOv5 and YOLOv6.

(a) (b)

(c)

Figure 7. Detection Results. (a) YOLOv5. (b) YOLOv6. (c) YOLOv7.

4.2 Results

In this subsection, experimental results for YOLOv5, YOLOv6, and YOLOv7 models are analyzed . To begin, Table 1 represents the experimental result which compares the performance for Mixed Traffic under Degraded Hazy Conditions. The results of our comparative analysis are summarized in Table 1 below.

Table 1. Experimental Results: (a), (b), and (c).

(a) Medium Object Detection: Cars.

Metrics	**YOLO v5**	**YOLO v6**	**YOLO v7**
Average Precision(AP)	0.72	0.75	0.83
Average Recall(AR)	0.68	0.39	0.70
Frames per Second(FPS)	30	30	30
Robustness to Hazy Conditions	Good	Moderate	Excellent
Object size detection	Accurate	Accurate	Accurate

(b) Big Object Detection: Buses and Trucks.

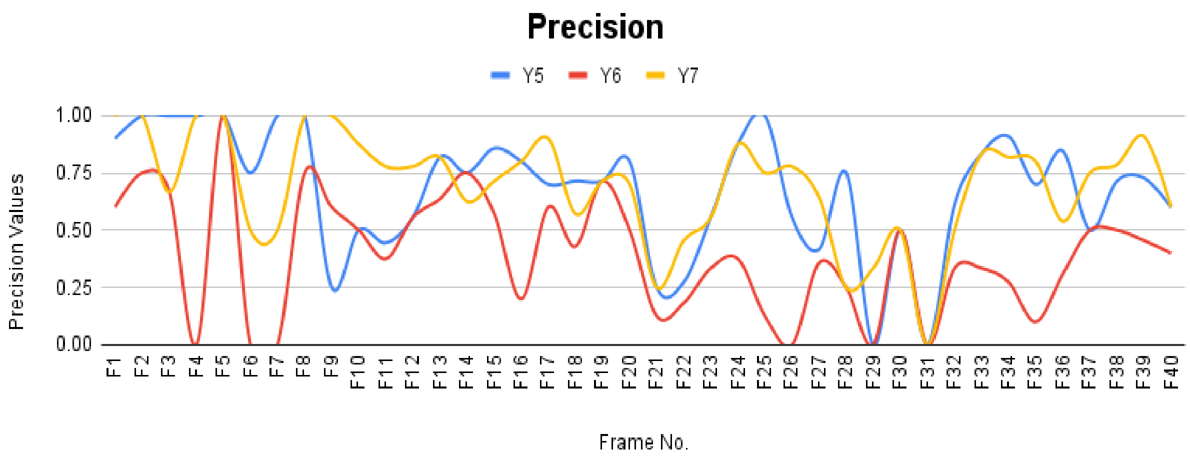
Metrics	**YOLO v5**	**YOLO v6**	**YOLO v7**
Average Precision(AP)	0.15	0.12	0.33
Average Recall(AR)	0.07	0.08	0.26
Frames per Second(FPS)	30	30	30
Robustness to Hazy Conditions	Moderate	Moderate	Good
Object size detection	Accurate	Accurate	Accurate

(c) Small-Object Detection: Motorcycles and Pedestrians.

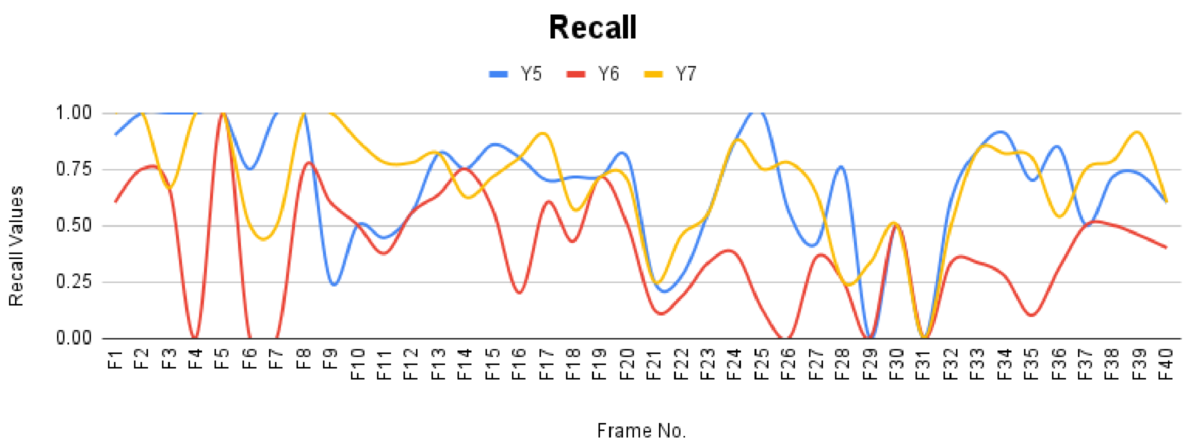
Metrics	**YOLO v5**	**YOLO v6**	**YOLO v7**
Average Precision(AP)	0.03	0.05	0.19
Average Recall(AR)	0.00	0.01	0.06
Frames per Second(FPS)	30	30	30
Robustness to Hazy Conditions	Poor	Poor	Poor
Object size detection	Accurate	Accurate	Accurate

The output's Precision and Recall, were determined and then the average Precision and Average Recall was also observed . Table 1 shows the comparison of the average precision, average recall, frames per Second (fps), Robustness to Hazy Conditions, and object size detection between models YOLOv5, YOLOv6, and YOLOv7. This is due to the low visibility of small objects.

It can be seen that object size detection varies for small, medium, and big objects category when affected by hazy weather. Detection of big objects (like buses and trucks) and medium objects(cars) are better than the detection of small objects (like motorcycles and pedestrians). The experimental details are shown in Figures 8, 9, and 10, including the Precision curve and Recall curve.

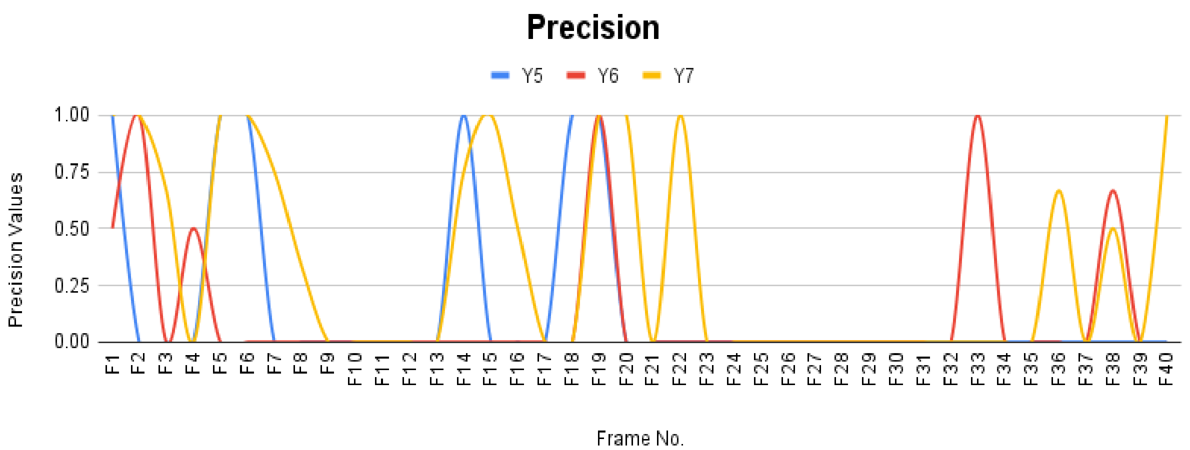


(a)

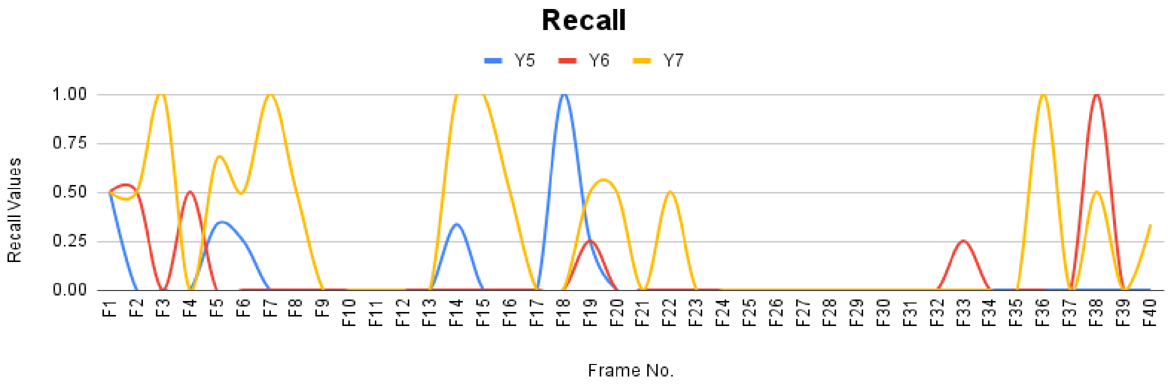


(b)

Figure 8. (a) Precision and (b) Recall Graph for Medium-Sized Objects Like Cars.

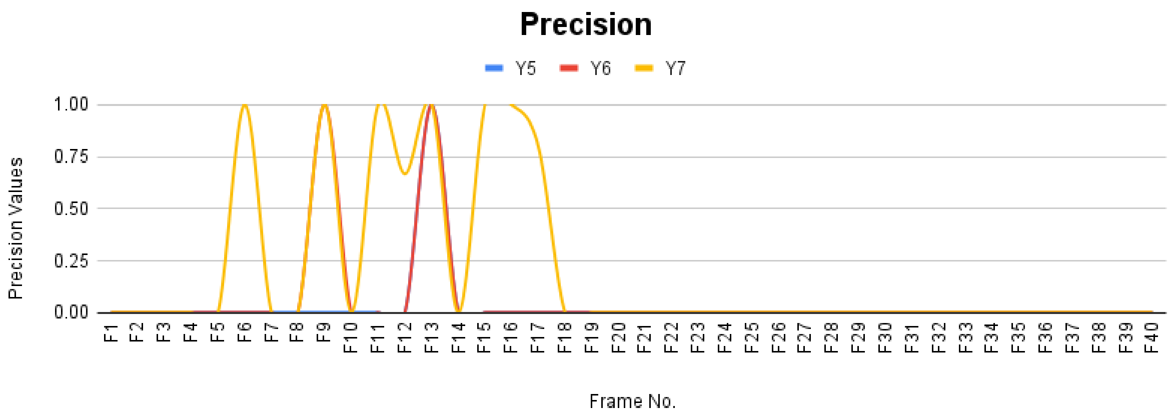


(a)

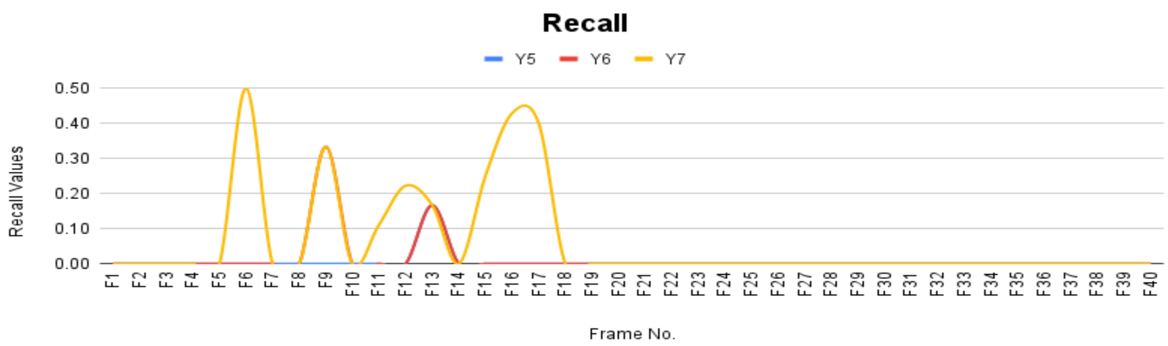


(b)

Figure 9. (a) Precision and (b) Recall Graph for Big-Sized Objects Like Buses and Trucks



(a)



(b)

Figure 10. (a) Precision and (b) Recall Graph for Small-Sized Objects Like Motorcycles and Pedestrians.

The results demonstrate the improved accuracy and robustness of the YOLOv7 model in object detection under degraded hazy conditions, potentially making it a more suitable choice for such scenarios. Therefore, we may draw a conclusion by saying that the YOLOv7 deep learning-based model can successfully detect objects in videos that have been distorted by hazy weather.

5. Conclusion

The challenging problem of object detection is addressed for mixed traffic under degraded hazy conditions. Through this comparative analysis, the performance of three versions of the YOLO algorithm: YOLOv5, YOLOv6, and YOLOv7 was evaluated. Leveraging an open-source dataset consisting of videos captured in hazy weather conditions, the models' ability to detect and classify objects accurately was examined. The findings revealed that all three YOLO versions demonstrated promising results in object detection and classification under hazy scenarios. However, YOLOv7 exhibited superior performance, outperforming the other models in terms of accuracy and precision.

The implications of the research extend to a wide range of real-world applications, including automated driving, traffic monitoring, and advanced security systems. Accurate object detection and classification in hazy conditions are pivotal for ensuring public safety and enabling efficient operations in these domains. By adopting YOLOv7, practitioners can enhance the reliability and effectiveness of such applications, empowering better decision-making based on accurate object detection.

Future research should focus on object detection algorithms for degraded hazy conditions, considering factors like haze levels, object types, and environmental challenges. Larger datasets and thorough evaluations under realistic scenarios will enhance robust models.

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