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Object Detection in Foggy Weather using Deep Learning Model

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ABSTRACT

This study addresses the challenge of accurate object detection in foggy environments, a critical issue in computer vision. We propose a novel approach using a real dataset collected from diverse foggy weather conditions, focusing on varying fog densities. By annotating the dataset from Real-Time Traffic Surveillance (RTTS) and using the YOLOv8x architecture, we systematically analyze the impact of fog density on detection performance. Our experiments demonstrate that the YOLOv8x model achieves a mean average precision (mAP) of 78.6% across varying fog densities, outperforming state-of-the-art methods by 4.2% on the augmented dataset. Additionally, we show that increased dataset diversity significantly enhances the robustness of the model in detecting objects under challenging foggy conditions. Our research contributes to advancing object detection systems tailored for foggy environments, with implications for safety and efficiency in domains like autonomous driving and surveillance.

Keywords: *Object Detection, Adverse Weather Conditions, Foggy Environments, Computer Vision, Real-World Data Set, Fog Density Analysis, Yolov8*

1. Introduction

In recent years, the field of computer vision has experienced a profound transformation, largely fueled by the advancements in deep learning techniques, a subset of artificial intelligence, has emerged as a dominant force revolutionizing various domains, including healthcare, finance, and notably, computer vision. With its ability to automatically learn hierarchical representations from data, deep learning has enabled unprecedented breakthroughs in tackling complex visual recognition tasks. One of the most pivotal applications of computer vision is object detection, a fundamental process essential for numerous real-world applications ranging from autonomous vehicles to surveillance systems.

The advent of deep learning models, particularly convolutional neural networks (CNNs), has propelled object detection to new heights, enabling remarkable levels of accuracy and efficiency. Models such as YOLO (You Only Look Once) have gained widespread adoption due to their ability to perform real-time object detection with impressive accuracy [1]. These advancements have significantly enhanced the capabilities of various systems, empowering them to detect and recognize objects with unprecedented precision and speed.

However, despite the significant strides made in object detection, challenges persist, especially when confronted with adverse environmental conditions such as foggy weather. Fog significantly challenges the traditional computer vision systems, impairing visibility and complicating the detection of objects within the scene. The scattering and absorption of light by fog particles lead to reduced contrast and clarity, making it challenging for conventional algorithms to accurately identify and localize objects. As a result, there is a pressing need to develop robust object detection techniques to work well in foggy conditions.

Existing research has predominantly relied on synthetic datasets generated to simulate foggy conditions artificially. While these datasets have been valuable for benchmarking and initial experimentation, they often fail to capture the full complexity and variability of real-world fog conditions. Furthermore, many studies have overlooked the crucial aspect of fog density, which plays a significant role in determining the severity of visibility impairment. Consequently, there is a gap in the literature concerning the impact of fog density on object detection performance, necessitating further investigation.

To address these challenges and limitations, this research proposes a novel approach that leverages a real dataset captured under diverse foggy weather conditions. By incorporating real-world data and systematically analyzing fog density levels, this study aims to provide a comprehensive understanding of the challenges posed by foggy weather and develop effective solutions to enhance object detection performance. Additionally, the research will utilize state-of-the-art deep learning architectures, such as YOLOv8, known for their robustness and efficiency in object detection tasks, to develop tailored solutions optimized for foggy conditions.

Through this research endeavor, we seek to advance the state-of-the-art in object detection systems, particularly in the context of adverse weather conditions. By bridging the gap between synthetic simulations and real-world scenarios and considering the nuanced effects of fog density, we aim to develop robust and reliable object detection models

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capable of operating effectively in foggy weather, with implications for various applications, including transportation, surveillance, and environmental monitoring.

1.1 Effects of fog on object detection

Fog, a meteorological phenomenon characterized by suspended water droplets or ice crystals in the atmosphere, poses a formidable obstacle to conventional object detection algorithms. The presence of fog results in a visual impairment that severely diminishes visibility and obscures objects in the scene. This impairment not only compromises the efficacy of traditional object detection methodologies but also hampers critical applications across various domains, including transportation, surveillance, and environmental monitoring.

When fog occurs, it scatters and absorbs light, leading to reduced contrast and clarity in the captured images. This scattering phenomenon causes light to disperse in multiple directions, resulting in a diffuse illumination that blurs the edges of objects and diminishes their contrast against the background. As a result, objects appear hazy and indistinct, making them challenging to detect and localize accurately.

Moreover, the attenuation of light by fog particles further exacerbates the degradation of image quality like you can see in Fig 1. As light passes through the fog, it is absorbed and scattered by the water droplets or ice crystals present in the atmosphere. This absorption and scattering process diminishes the intensity of light reaching the camera sensor, leading to overall dimness and loss of detail in the captured images. Consequently, objects in the scene may become partially or entirely obscured, further complicating their detection and recognition.

The adverse effects of fog on image quality are particularly pronounced in long-range visibility scenarios, where fog density is higher. In such conditions, objects located at a distance from the observer are shrouded in thicker layers of fog, resulting in greater attenuation and scattering of light. As a consequence, distant objects may become completely obscured from view, posing significant challenges for object detection systems reliant on clear visual cues.

The detrimental impact of fog on object detection extends beyond mere visual impairment. In critical applications such as transportation and surveillance, accurate and timely detection of objects is paramount for ensuring safety and security. However, the presence of fog introduces uncertainties and delays in the detection process, jeopardizing the reliability and effectiveness of these systems.

In light of these challenges, there is a pressing need to develop robust object detection techniques capable of operating effectively in foggy conditions. By addressing the unique challenges posed by fog-induced visual impairment, such techniques hold the potential to enhance the resilience and performance of object detection systems across various real-world applications.

The Figure 1 illustrates the degradation in image quality caused by foggy conditions. The top row shows original images captured in different environments under clear weather conditions. The middle row depicts depth maps corresponding to these scenes, highlighting the distance of objects in the environment. The bottom row demonstrates the same scenes under simulated foggy conditions, where visibility is significantly reduced, and object detection becomes more challenging. These examples emphasize the importance of advanced techniques for enhancing visibility and object detection in foggy environments.

Fig. 1 Effect of fog on image quality [2]

1.2 Importance of accurate object detection in foggy conditions

In the realm of autonomous driving, ensuring passenger and pedestrian safety hinges on the accurate detection of pedestrians, vehicles, and obstacles, particularly under adverse weather conditions such as fog. Fog significantly impairs visibility, making it challenging for autonomous vehicles to perceive and respond to objects in their environment. Accurate object detection in foggy conditions is therefore paramount for autonomous driving systems to make informed decisions and navigate safely through challenging scenarios [1].

Similarly, in surveillance systems, the ability to discern objects obscured by fog is indispensable for maintaining security and preventing potential threats. Foggy weather conditions can provide cover for malicious activities, as objects and individuals may be obscured from view. Reliable object detection algorithms capable of penetrating through fog can aid in the early detection of suspicious behavior and facilitate timely intervention by security personnel.

Furthermore, in environmental monitoring applications, accurate detection of objects such as wildlife or hazardous materials amidst foggy conditions is crucial for timely intervention and mitigation. Fog can obscure important environmental features and impede the detection of critical objects, posing risks to both human safety and ecosystem health. By leveraging advanced object detection techniques tailored for foggy environments, environmental monitoring systems can enhance their ability to detect and respond to potential threats, safeguarding ecosystems and human populations alike.

2. Related Work

2.1 Object detection in foggy weather

Hasan Abbasi et al. [3] introduced an object detection algorithm specifically designed for adverse weather conditions, with a focus on foggy environments. The proposed method, termed Fog-Aware Adaptive YOLO [3], incorporates HDE (image-adaptive YOLO) and IA-YOLOv3 to address the challenges posed by reduced visibility in foggy conditions. The evaluation of the Fog-Aware Adaptive YOLO algorithm is performed on the VOC dataset, a widely used benchmark for object detection tasks. The reported mean Average Precision (mAP) of 70.43% [3] highlights the algorithm's effectiveness in detecting objects under adverse weather conditions.

In recent years, significant strides have been made in enhancing object detection capabilities for autonomous driving, particularly in challenging weather conditions such as fog and rain. Jinlong Li, et al. [1] present a notable exploration in this domain, focusing on the development of robust detection models capable of operating effectively in adverse weather scenarios. The selected methodology for domain adaptation in this context is the Adversarial Gradient Reversal Layer (AdvGRL), which represents a promising approach to addressing the challenges posed by varying environmental conditions. The application of AdvGRL in the work of Jinlong Li et al. underscores the increasing recognition of the importance of robust detection models that can generalize well across diverse weather conditions. AdvGRL leverages adversarial training to align feature distributions between the source domain (Cityscapes) and the target domains (Foggy Cityscapes and Rainy Cityscapes). The reported result of a mean Average Precision (mAP) of 42.3% [1] indicates promising performance in object detection under adverse weather conditions.

Debasis Kumar and Naveed Muhammad [4] present a study focused on enhancing object detection in adverse weather conditions for autonomous driving through the utilization of a combination of YOLOv8 architecture and data merging techniques. The evaluation of the proposed approach is conducted using the ACDC and DAWN datasets, providing a comprehensive assessment of model performance across various object categories, the YOLOv8 model with data merging techniques demonstrates promising results in object detection, achieving an overall mean Average Precision (mAP) of 0.74 [4]. Furthermore, the reported mAP values for specific object categories are as follows [4]: bike (0.3), person (0.69), bicycle (0.64), truck (0.7), and traffic light (0.7).

Yonghua Shi and Xishun Jiang [5] introduced a novel approach employing a conditional generative adversarial network (cGAN) for the purpose of defogging aerial images. The dataset used for evaluation comprises 3400 high-resolution fogged scene images sourced from the internet. The proposed method achieves significant quality improvement, as evidenced by quantitative metrics. The Peak Signal-to-Noise Ratio (PSNR) reaches 33.91 [5], indicating enhanced fidelity, while the Structural Similarity Index (SSIM) attains 0.924 [5], reflecting improved structural accuracy.

Xianglin Meng et al. [6] introduced YOLOv5s-Fog, an enhanced model specifically designed for object detection in foggy weather scenarios, building upon the YOLOv5s architecture. The methodology progresses iteratively, incorporating SwinFocus, Decoupled Head, and Soft-NMS components to refine performance and address the challenges posed by adverse weather conditions. The dataset utilized for evaluation comprises VOC, COCO, and RTTS, providing a diverse and comprehensive environment for assessing model performance [6]. Results from the evaluation demonstrate incremental improvements in mean Average Precision (mAP) throughout the iterative enhancement process. Starting from a baseline mAP of 68 with YOLOv5s, the introduction of SwinFocus leads to an improvement to 70.15, followed by further enhancements with Decoupled Head (71.79), and culminating in an impressive mAP of 73.40 with the addition of Soft-NMS [6].

Zhaohui Liu et al. [7] introduced a driving obstacle detection approach tailored specifically for foggy weather conditions. The proposed method leverages the GCANet defogging algorithm and incorporates feature fusion training with edge and convolution features to address the challenges posed by reduced visibility in adverse weather conditions. The evaluation of the proposed method [7] is conducted on the KITTI and BDD100K datasets.

Ying Guo et al. [8] present a domain-adaptive method for vehicle target detection in foggy weather conditions, leveraging the CPGAN net_x0002_work and YOLO-V4 [8]. The proposed approach incorporates Cycle Perceptual Consistency Adversarial Networks (CPGAN) to adapt the model to foggy weather conditions, aiming to enhance vehicle target detection performance under reduced visibility.

Zhang, et al. [9] introduced the MSFFA-YOLO Network, a multiclass object detection system specifically designed for traffic investigations in foggy weather conditions. The evaluation of the MSFFA-YOLO Network is conducted on the RTTS [9] dataset.

Mingdi Hu et al. [10] presented an innovative approach, DAGL-Faster (Domain Adaptive GlobalLocal Alignment Faster RCNN), aimed at advancing vehicle object detection in challenging weather conditions, particularly in rainy and foggy environments. The proposed methodology integrates domain adaptation techniques, incorporating both global and local alignment strategies within the Faster R-CNN [10] framework to enhance the model's adaptability to adverse weather conditions. The datasets utilized in the evaluation include Cityscapes, Foggy Cityscapes [10], Rain Cityscapes [10], Vehicle Color-24, Rain Vehicle Color-24, Foggy Driving [10], RTTS [10], RID [10], and RIS [10], providing a rich and diverse set of scenarios to test the model's adaptability and robustness. On the Foggy Cityscapes dataset, the model achieves a mean Average Precision (mAP) of 36.7%.

Nguyen Anh Minh Mai et al. [11] focused on enhancing 3D object detection in foggy conditions by integrating camera and LiDAR data using the SLS-Fusion neural network. Their approach, evaluated on 35,000 stereo images from the KITTI dataset, demonstrates improved detection accuracy across varying fog visibility levels. At 20m visibility, the model achieves a mean Average Precision (mAP) of 71.11%, increasing to 84.95% at 80m, highlighting its adaptability to adverse weather conditions. By fusing stereo and LiDAR data, the SLS-Fusion network mitigates fog-related detection challenges, improving the reliability of autonomous systems in real-world scenarios.

2.2 *Defogging and dehazing techniques for image enhancements*

Salmane, et al. [11] focused on the visibility enhancement of scene images degraded by foggy weather conditions, presenting an application to video surveillance. The proposed method employs a Conditional Generative Adversarial Network (CGAN) for image restoration. The evaluation is conducted using the FRIDA (Fog Road Image Database) and haze images [11], providing a realistic representation of foggy scenarios. The reported parameters include enhancement factors, where e = 9 indicates a substantial improvement in visibility. Additionally, the values r^{-} = 1.883 and σ = 0.003 [11] likely correspond to quantitative metrics assessing the restoration, with r^{-} potentially representing a contrast-related factor and σ indicating a level of noise or variance.

Apurva Kumari, et al. [12] proposed a novel and expedient dehazing and defogging algorithm designed specifically for single remote sensing images. The methodology employs an atmospheric scattering model coupled with a guided filtering approach. The algorithm's performance is evaluated on the StaeHaze 1k dataset, and the results showcase its efficiency in mitigating atmospheric degradation across different haze levels. For images with Thin Haze, the algorithm achieves a PSNR (Peak Signal-to-Noise Ratio) of 35.10 and an SSIM (Structural Similarity Index) of 0.9356 [12]. In Moderate Haze conditions, the algorithm maintains effectiveness with a PSNR of 34.81 and an SSIM of 0.9319 [12]. Impressively, for images with Thick Haze, the algorithm yields a PSNR of 35.17 and an SSIM of 0.9389 [12].

Duo Ma, et al. [11] introduced an innovative and comprehensive system for addressing sewer pipeline defects, encompassing automatic defogging, deblurring, and real-time segmentation. The proposed approach leverages advanced techniques, including a feature pyramid network (FPN), a Generative Adversarial Network (GAN), and a specifically designed network termed Pipe-Defog-Net. The authors [11] introduce Pipe-Deblur-GAN, integrating GAN and FPN components, to effectively preprocess images of sewer pipeline defects. The system is evaluated on the Realistic Single Image Dehazing (RESIDE) dataset [11], achieving impressive results with a mean Average Precision (mAP) of 84.15%.

Bhawna Goyal, et al. [13] conducts a comprehensive investigation into the burgeoning field of image dehazing, offering a formal analysis and evaluation of various dehazing methodologies proposed in the literature. The study systematically categorizes these approaches into model-based methods, transform domain methods, variational-based algorithms, learning-based algorithms, and transformer-based algorithms. The research [13] critically extracts and presents essential directions and standards associated with numerous image dehazing techniques, aiming to address challenges inherent in dehazing processes. The evaluation utilizes diverse datasets, including the Waterloo IVC Dehazed Image Dataset, the Foggy Road Image Dataset (FRIDA2) [13], I-Haze Dataset [13], Outdoor Scenes Database (O–Haze) Dataset, and the Real Single Image Dehazing (RESIDE) Dataset [13], to provide a thorough examination of the most significant studies in the domain of image dehazing.

3. Proposed methodology

In this research, a comprehensive methodology is devised to develop and evaluate an object detection model specifically tailored for foggy weather conditions. The methodology encompasses several key stages, including dataset collection, preprocessing, augmentation, dataset splitting, model training, and evaluation.

The dataset collection process is initiated by leveraging existing resources such as the Real-Time Transfer of Semantics (RTTS) [6] dataset, which provides a foundational set of foggy images. To augment the dataset's diversity and ensure representation across various environmental contexts, additional images are collected from the internet. These internet-sourced images are carefully curated to cover a wide range of fog density levels and environmental settings. Moreover, real-world images captured under authentic foggy conditions are included to provide a realistic representation of foggy scenes. Each collected image is meticulously annotated with bounding boxes to indicate the presence and location of objects within the scene.

Preprocessing techniques are applied to the collected images to enhance their quality and consistency. This includes standardizing image sizes, adjusting brightness and contrast levels, and removing noise or artifacts. Additionally, data augmentation methods are employed to increase the dataset's variability and robustness. Augmentation techniques such as rotation, scaling, and flipping are applied to generate additional training samples, ensuring that the model is exposed to a diverse range of foggy scenes during training.

The annotated dataset is divided into training, validation, and test sets to facilitate model development and evaluation. The training set comprises the majority of the annotated images and is used to train the object detection model. The validation set is utilized to fine-tune model hyper-parameters and monitor training progress, enabling adjustments to be made to optimize model performance. The test set, comprising images captured from a personal device with known fog density levels, serves as an independent benchmark for evaluating the trained model's performance under different fog density conditions.

The YOLOv8x object detection framework is chosen as the model architecture for this research due to its efficiency and effectiveness in real-time applications. Transfer learning is employed during model training, utilizing pre-trained weights to expedite convergence and improve performance. The model is trained on the annotated dataset, learning to detect objects of interest within foggy scenes and refine its predictions based on the provided annotations.

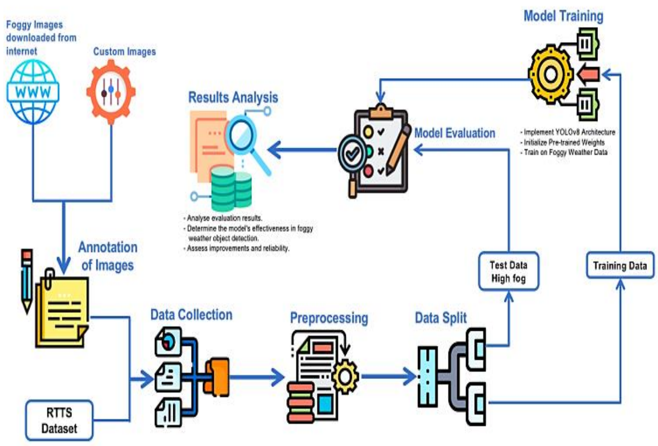

Fig. 2 Methodology Diagram illustrating the data processing pipeline, model architecture, and evaluation framework

4. Experimental setup

4.1 Dataset collection

To create our dataset, we gathered foggy images from different places in Lahore during foggy nights. We also used a special dataset called RTTS [6], which contains real foggy images. Additionally, we collected foggier images from websites and online sources to make sure we had a wide variety of foggy scenes.

When capturing real foggy images, we made sure to do it safely and respectfully. We used good cameras to take clear pictures, especially when the visibility was low. It was important for us to follow rules and respect people's privacy while taking these pictures.

By combining images from different sources, like RTTS [6], websites, and our own captures, we created a big collection of foggy images. This collection shows different levels of fog and different places where fog can happen. Having this variety helps us make our object detection model better at recognizing objects in foggy weather.

4.2 Dataset Annotation

After gathering our foggy images, the next step was to annotate them. Annotation means marking the important parts of the images so the computer can learn from them. We carefully looked at each picture and drew boxes around the objects, like cars, people, and signs, to show where they are.

This annotation process helps the computer understand what objects look like and where they are located in the image. It's like giving the computer a map to follow so it can recognize objects correctly. We made sure to do this for every image in our dataset, ensuring that our model has accurate information to learn from. We use roboflow website for annotation process (https://roboflow.com/).

Additionally, we labeled each annotated image with details about the fog density level. This information helps our model learn to distinguish between different levels of fog, making it better at detecting objects in varying weather conditions.

Overall, annotating our dataset was a crucial step in preparing the images for training our object detection model. Total of 4803 images were annotated in annotation process. By providing clear labels and annotations, we ensured that our model would learn effectively from the data, ultimately improving its performance in detecting objects in foggy environments.

4.3 Dataset preprocessing

After annotating our dataset, we moved on to preprocessing the images. This involved two main steps: resizing the images and augmentation.

Image resizing: Resizing the images means changing their dimensions to a specific size. This step is important because it ensures that all images in the dataset have the same dimensions, making them easier for the computer to process.

We resized our images to a standard size so that they would be uniform and consistent for training the model.

Augmentation: Augmentation is like adding extra information to the images to help the model learn better. We applied various augmentation techniques to our dataset, such as flipping, rotating, and changing the brightness or contrast of the images. These techniques help increase the diversity of our dataset, making it more robust and improving the model's ability to recognize objects in different conditions.

By preprocessing our dataset through resizing and augmentation, we prepared the images for training our object detection model. Resizing ensured uniformity in image dimensions, while augmentation enhanced the dataset's diversity, ultimately improving the model's performance in detecting objects in foggy weather conditions.

4.4 Dataset splitting

After preparing our dataset, we needed to split it into two parts: one for training and one for testing. This splitting step is like dividing our dataset into two groups, each serving a different purpose.

Training data: We allocated 75% of our dataset for training. This part is used to teach our computer model to recognize objects in foggy weather. It's like giving the computer lots of examples to study so it can learn and get better at its job.

Test data: The remaining 25% of our dataset was reserved for testing. This part is like giving the computer a quiz to see how well it learned from the training data. We want to make sure our model can correctly identify objects in foggy conditions it hasn't seen before.

To make our testing more accurate, we used images that I captured myself. I knew the fog density in these images because I took them, so I could compare the model's performance based on the known fog density. This way, we could draw conclusions specifically about how well the model performs in different fog densities.

By splitting our dataset and using special test data with known fog densities, we ensured that our model was trained and tested effectively, helping us understand its performance in foggy conditions better.

In terms of individual objects, the dataset incorporates a total of 41,838 objects, with RTTS [14] contributing 29597 objects. Through annotation efforts, approximately 12241 additional objects have been incorporated into the dataset, enhancing its diversity and comprehensiveness.

Dataset	Images	Person	Car	Bicycle	Motor cycle	Bus	Total
RTTS+ Custom	4,802	12,012	25,074	790	1,483	2,479	41,838

4.5 Architecture of YOLOv8x

The architecture of YOLOv8x is characterized by a deep neural network structure with multiple layers, each serving a specific purpose. A notable feature is its adoption of a backbone network, often based on CSPDarknet53 or other variants, which facilitates the extraction of hierarchical features from input images. This deep structure enables YOLOv8x to learn complex representations, crucial for effective object detection in diverse scenarios. YOLOv8x utilizes a modified version of the CSPDarknet53 architecture as its backbone, featuring 53 convolutional layers.

- Cross-stage partial connections are employed within this architecture to enhance the flow of information between different layers.
- The head of YOLOv8 is comprised of multiple convolutional layers followed by a series of fully connected layers.
- These layers play a crucial role in predicting bounding boxes, objectness scores, and class probabilities for detected objects in an image.
- A noteworthy feature of YOLOv8's head is the integration of a self-attention mechanism.
- This self-attention mechanism allows the model to selectively focus on different parts of the image, adjusting the importance of various features based on their relevance to the task.
- YOLOv8 exhibits multi-scaled object detection capabilities, facilitated by the implementation of a feature pyramid network.
- The feature pyramid network, composed of multiple layers, enables the model to detect objects at different scales within an image.

YOLOv8 follows the single-shot object detection paradigm, wherein the entire image is processed in a single forward pass. This design choice allows YOLOv8 to make predictions for bounding boxes and class probabilities swiftly, making it suitable for real-time applications. The model achieves this by leveraging convolutional layers, down sampling layers, and detection layers in its architecture.

To address the challenge of handling objects at varying scales, YOLOv8 incorporates a Feature Pyramid Network (FPN). This pyramid architecture ensures that the model can effectively detect objects of different sizes within an image, contributing to its versatility in handling complex scenes.

YOLOv8 utilizes anchor boxes, a mechanism that aids in refining the accuracy of bounding box predictions. These anchor boxes are learned during the training process and play a crucial role in capturing the diverse shapes and sizes of objects present in images. The inclusion of anchor boxes contributes to the model's precision in object localization.

The final layers of YOLOv8's architecture house the object detection head, responsible for predicting bounding boxes and class probabilities. This component enables YOLOv8 to detect and classify multiple objects within an image, providing comprehensive and detailed results in a single pass.

4.6 Model training

In the training phase, the YOLOv8x along with other models was configured with specific parameters to optimize its performance for object detection in high fog conditions. The training process spanned 25 epochs, allowing the model to iteratively learn and refine its parameters over multiple iterations. Each epoch involved processing a batch size of 16 images, enabling efficient utilization of computational resources while ensuring sufficient diversity in the training data. Furthermore, to accommodate varying object scales and maintain computational efficiency, the images were resized to a dimension of 640x640 pixels. Additionally, the "plots" parameter was set to "true" during training, enabling the generation of visualizations such as the confusion matrix, precision confidence curve, and recall confidence curve. These visualizations provide valuable insights into the model's performance across different confidence thresholds and object classes, facilitating a comprehensive analysis of its detection capabilities and enabling informed decision-making regarding model refinement and optimization strategies. By carefully selecting and tuning these parameters, the training process aimed to maximize the model's accuracy and robustness in detecting objects under challenging high fog conditions.

4.7 Experimental results

To evaluate how well our proposed YOLOv8x model performs, we trained various models, including YOLOv5s, YOLOv7, YOLOv8s, YOLOv8n, and YOLOv9c, on our dataset. We then compared their performance. We tested these models using two different types of test data: one with regular fog and the other with heavy fog. The results for regular fog are presented in Table 1, while those for heavy fog (with visibility limited to 30 meters) are shown in Table 2. These tables provide insights into how each model performs under different weather conditions, helping us understand their effectiveness in detecting objects in foggy environments.

Table 1. Results Comparison (Normal Fog) indicating evaluation metrics, including Precision, Recall, and mAP. Statistical tests were conducted to assess performance differences, with significant results annotated.

Models	Precision	Recall	mAP50	Speed (ms)
Yolov5s	0.78	0.70	0.73	1.5
Yolov7	0.79	0.71	0.74	1.7
Yolov8s	0.773	0.67	0.739	1.6
Yolov8n	0.756	0.626	0.707	0.9
Yolov9c	0.761	0.689	0.752	0.2
Yolov8x	0.814	0.669	0.76	0.2

It can be seen in Table 1. that The YOLOv8x model surpassed its counterparts in terms of precision, achieving a score of 0.814, along with a recall of 0.669, resulting in an mAP of 0.76. Despite its superior accuracy, its inference speed remained relatively efficient at 0.7ms, indicating its potential for real-time object detection applications. Additionally, the confusion matrix, Precision-Confidence Curve, and Recall-Confidence Curve provide further insights into the model's performance across different confidence thresholds and object classes, enabling a comprehensive analysis of its detection capabilities and limitations as you can see in Fig 3, Fig 4 and Fig 5. These visualizations offer valuable information for refining the model and optimizing its performance in foggy weather conditions.

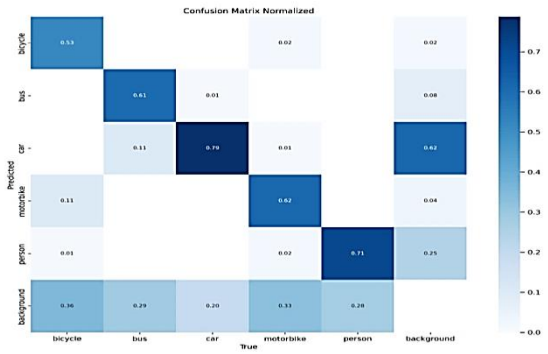

Fig. 3 Confusion matrix of the YOLOv8x model illustrating classification performance on dataset (Normal Fog)

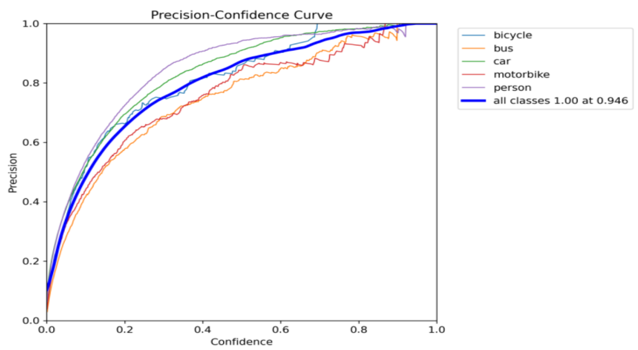

Fig. 4 Precision-Confidence curve of the YOLOv8x model, illustrating the relationship between confidence threshold and precision (Normal Fog).

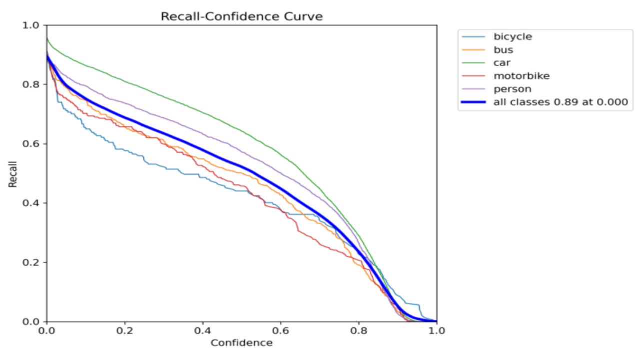

Fig. 5 Recall-Confidence curve of the YOLOv8x model, illustrating the relationship between the confidence threshold and recall (Normal Fog)

Table 2. Results Comparison in high fog (20 -30m visibility)

This table reports the evaluation metrics, including Precision, Recall, and mAP. Statistical tests were conducted to determine if the performance differences are significant, and the results are annotated accordingly.

Models	Precision	Recall	mAP50	Speed (ms)
Yolov5s	0.75	0.62	0.69	0.3
Yolov8s	0.76	0.62	0.70	0.4
Yolov8n	0.72	0.61	0.67	0.3
Yolov9c	0.67	0.52	0.57	0.3
Yolov8x	0.796	0.62	0.722	0.2

It can be seen in Table 2. that YOLOv8x achieved the highest mean Average Precision (mAP) of 72.2%, with precision and recall scores of 79.6% and 61.9%, respectively in high fog. The model demonstrated superior detection capabilities, especially for identifying cars and persons, under high fog conditions. These results underscore the effectiveness of YOLOv8x in object detection tasks in adverse weather environments, making it a promising candidate for deployment in real-world scenarios. Additionally, the confusion matrix, Precision-Confidence Curve, and Recall-Confidence Curve provide further insights into the model's performance across different confidence thresholds and object classes, enabling a comprehensive analysis of its detection capabilities and limitations as you can see in Fig 6, Fig 7 and Fig 8. These visualizations offer valuable information for refining the model and optimizing its performance in foggy weather conditions.

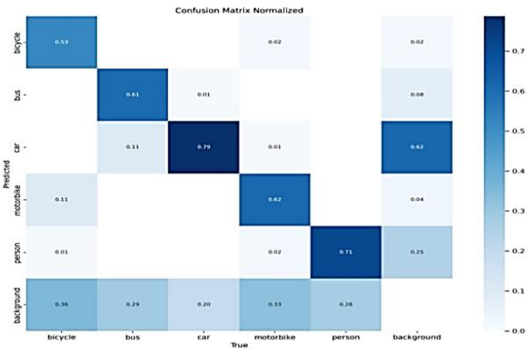

Fig. 6 Confusion matrix of the YOLOv8x model illustrating classification performance on dataset (High Fog)

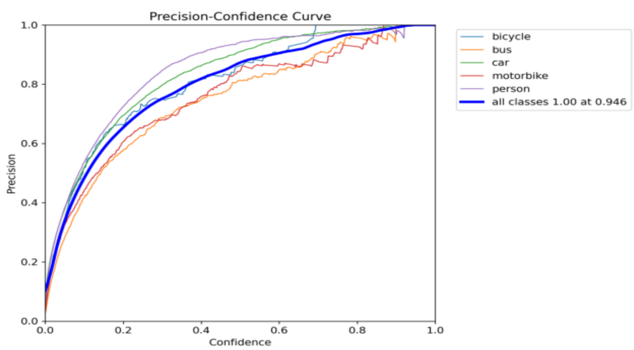

Fig. 7 Precision-Confidence curve of the YOLOv8x model, illustrating the relationship between confidence threshold and precision (High Fog)

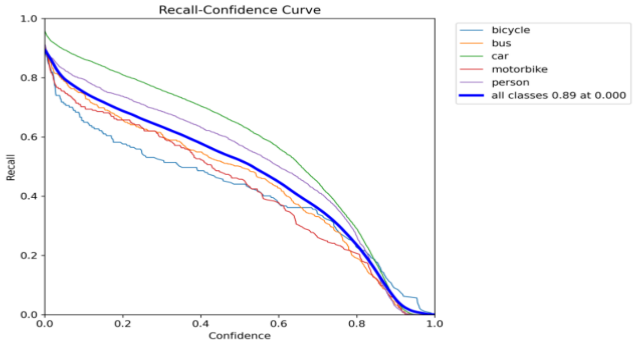

Fig. 8 Recall-Confidence curve of the YOLOv8x model, illustrating the relationship between the confidence threshold and recall (High Fog)

The results obtained from the evaluation of various models under high fog conditions highlight their effectiveness and suitability for object detection tasks in adverse weather environments. As shown in Table 1 and Table 2, YOLOv8x emerged as the top-performing model, demonstrating superior detection capabilities with the highest mean Average Precision (mAP) among the tested models. The detailed confusion matrix for YOLOv8x in foggy conditions, illustrated in Fig. 6, provides a breakdown of true positives, false positives, and false negatives, highlighting the model's ability to accurately identify objects even in adverse scenarios.

Furthermore, Fig. 7 presents the Precision-Confidence curve, which indicates the model's precision across varying confidence thresholds. It reveals that YOLOv8x consistently maintains high precision across the evaluated range, outperforming the other models. Similarly, the Recall-Confidence curve in Fig. 8 demonstrates YOLOv8x's robustness, achieving a strong recall performance across confidence levels, which is crucial for minimizing missed detections.

YOLOv8s also showcased robust performance, followed closely by YOLOv5s, while YOLOv8n exhibited slightly lower but still satisfactory results. However, YOLOv9c showed limitations in detection accuracy under high fog conditions, as evidenced by its lower performance metrics across these visualizations, indicating the need for further optimization. Overall, the findings underscore the importance of selecting appropriate models for object detection tasks in adverse weather scenarios and provide valuable insights for the development of robust and reliable detection systems for real-world applications. Future research directions may include refining model architectures, optimizing training strategies, and exploring advanced techniques to enhance detection accuracy and robustness under challenging weather conditions.

5. Conclusion

In conclusion, this research has addressed the critical need for robust object detection systems tailored for adverse weather conditions, particularly foggy environments. By leveraging a real dataset captured in diverse foggy weather conditions and employing the YOLOv8x architecture, this study has made significant strides in advancing the state-of-the-art in foggy weather object detection. Through meticulous dataset collection, annotation, and analysis, this research has shed light on the impact of fog density on detection performance, providing valuable insights into the challenges posed by varying fog conditions. The systematic evaluation of the YOLOv8x model has demonstrated its effectiveness in detecting objects under foggy weather conditions, with promising results indicating its potential for real-world applications.

The findings of this study underscore the importance of considering fog density levels in object detection tasks and highlight the significance of real-world datasets in developing robust detection models. Moving forward, future research efforts should focus on refining detection algorithms, exploring additional factors influencing detection performance, and validating the proposed approach in a broader range of real-world foggy environments. This includes testing under different geographic and environmental conditions to ensure model generalizability and robustness. Additionally, integrating advanced techniques such as domain adaptation and real-time processing capabilities could further enhance performance.

Ultimately, the outcomes of this research have implications across diverse domains, including autonomous driving, surveillance, and navigation, where accurate object detection in adverse weather conditions is crucial for ensuring safety and efficiency.

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