

# Low-Light Image Enhancement Framework for Improved Object Detection in Fisheye Lens Datasets

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## Abstract

*This study addresses the evolving challenges in urban traffic monitoring detection systems based on fisheye lens cameras by proposing a framework that improves the efficacy and accuracy of these systems. In the context of urban infrastructure and transportation management, advanced traffic monitoring systems have become critical for managing the complexities of urbanization and increasing vehicle density. Traditional monitoring methods, which rely on static cameras with narrow fields of view, are ineffective in dynamic urban environments, necessitating the installation of multiple cameras, which raises costs. Fisheye lenses, which were recently introduced, provide wide and omnidirectional coverage in a single frame, making them a transformative solution. However, issues such as distorted views and blurriness arise, preventing accurate object detection on these images. Motivated by these challenges, this study proposes a novel approach that combines a **transformer-based image enhancement framework** and **ensemble learning technique** to address these challenges and improve traffic monitoring accuracy, making significant contributions to the future of intelligent traffic management systems. Our proposed methodological framework won **5th place** in the 2024 AI City Challenge, Track 4, with an F1 score of **0.5965** on experimental validation data. The ex-*

*perimental results demonstrate the effectiveness, efficiency, and robustness of the proposed system. Our code is publicly available at <https://github.com/daitranskku/AIC2024-TRACK4-TEAM15>.*

## 1. Introduction

In the field of urban infrastructure and transportation management, the development of advanced traffic monitoring systems has become a crucial solution to the growing challenges posed by urbanization and increasing vehicular density[6, 10, 19, 31]. These systems, utilizing state-of-the-art technologies such as computer vision, machine learning, and data analytics, are tasked with ensuring not only the smooth flow of traffic but also enhancing safety[2, 15, 38, 39] and efficiency on busy roadways[25]. As cities grow in size and population, there is an increasing need for advanced traffic monitoring and management solutions that surpass traditional strategies.

Traditional traffic monitoring methods, which rely on static cameras with limited fields of view (FoV) [11, 18, 46], have proven insufficient in dealing with the dynamic and complex nature of modern urban environments. These cameras typically provide narrow perspectives of roadways and intersections, requiring the deployment of multiple cameras to achieve comprehensive coverage[13]. This not only raises the cost and complexity of surveillance infrastructure but also creates blind spots and gaps in monitoring, particu-

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larly in areas with complex road layouts or high traffic volumes. The need for real-time insights, comprehensive coverage, and adaptive response mechanisms has highlighted the importance of more advanced and versatile surveillance techniques.

In recent years, the introduction of fisheye lenses has revolutionized surveillance and traffic monitoring systems due to their ability to provide natural, wide, and omnidirectional coverage [13]. This unique feature addresses a significant limitation of traditional cameras with narrow fields of view (FoV), allowing for the capture of large scenes in a single frame—an accomplishment not possible with conventional counterparts. Fisheye lenses in traffic monitoring systems have proven particularly advantageous in reducing the number of required cameras, offering a cost-effective solution to cover broader views of streets and intersections [7]. *However, this innovation comes with its own set of challenges, as fisheye cameras inherently present distorted views, which require sophisticated design approaches for image undistortion and unwarping [13]. Additionally, objects at the edges or far ends of the captured scenes appear small and blurry. This makes it difficult for object detection systems to accurately identify important elements such as cars, pedestrians, and road signs during traffic monitoring [13].* These challenges underscore the need for dedicated strategies to address distortions and blurriness during image processing, and that is what this study seeks to do.

Inspired by these challenges, the overarching goal of this study is to develop a robust framework for traffic monitoring using data from fisheye lens cameras. To achieve this goal, we propose a **Low-Light Image Enhancement Framework** to enhance image quality, resulting in improved object detection accuracy for fisheye images. The proposed image enhancement framework aims to *improve image clarity and accuracy in object detection by addressing poor visibility at night and blurriness in video-generated images.* To achieve a robust object detection model, the study incorporates the principle of **ensemble learning**, drawing upon diverse state-of-the-art object detection models for this task. By using the ensemble learning technique, we mitigate the limitations associated with using individual models for object detection tasks. The models utilized in this study include collaborative detection transformer (Co-DETR), You Only Look Once (YOLOv8x), and YOLOv9.

To this end, the study's main contributions can be summarized as follows:

1. We propose a unique data preprocessing framework called the **Low-Light Image Enhancement Framework**. This framework utilizes a transformer-based image enhancement technique, NAFNET [10], to improve image clarity by removing blurriness, and GSAD [14] to convert nighttime images (low illumination) to daytime images (high illumination) to improve object detection

accuracy in fisheye images during model training. To enhance object detection accuracy during inference, the study used a super-resolution postprocessing technique to increase image pixels, as well as an **ensemble model technique** for robust detection.

2. We performed a detailed comparative analysis of our proposed ensemble model to other state-of-the-art object detection models (Co-DETR, YOLOv8x, and YOLOv9e). By evaluating their performance in detecting objects from fisheye lens-captured images, we aimed to demonstrate the superiority of our proposed model over the current state-of-the-art models. In addition, we demonstrate that our pre- and post-processing techniques are effective in leading to improved object detection.
3. Our proposed approach showed its robustness in AICity Challenge Track 4, placing **5th out of 52 teams**.

The experimental results of this study hold paramount importance in shaping the future of intelligent traffic monitoring systems, particularly those utilizing fisheye lens cameras. The proposed robust framework, anchored by the transformer-based image enhancement technique and enriched by ensemble learning, represents a significant stride towards overcoming the challenges posed by fisheye distortions in urban environments. These results offer valuable insights into the feasibility and real-world applicability of our approach, providing a tangible foundation for the advancement of traffic monitoring technology.

The remainder of the paper is structured as follows: In section 2, we present a discussion of related works. Section 3 discusses our methodological framework. In section 4, we present our data and experimental findings, which demonstrate the efficacy of our proposed method in detecting objects in fisheye lens cameras. In section 5, we discuss the implications of our findings and make suggestions for future research in this field.

## 2. Related Work

Traffic surveillance has advanced significantly in recent years as a result of the convergence of computer vision, machine learning, and data analytics. Our ability to accurately detect and track vehicles, pedestrians, and motorists in surveillance videos is critical for ensuring road safety, optimizing traffic flow, and improving overall transportation efficiency. Object detection, a critical task in traffic surveillance systems, has advanced dramatically as new algorithms and techniques emerge. This literature review focuses on three techniques or algorithms of object detection: multiple/two-stage detectors, single-stage detectors, and transformer-based models.

## 2.1. Multiple/Two-stage detectors

A variety of studies have investigated the utilization of two-stage detection algorithms in transportation systems[27, 32, 43]. Shirpour et al. developed a real-time traffic object detection system, achieving 91% accuracy by employing a combination of multi-scale HOG-SVM and Faster R-CNN models[27]. Also, Nizar et al. utilized HOG and SVM for feature extraction and KLT for object counting, achieving an average accuracy of 95.15% [18]. Wang & Zhang proposed a hybrid method for vehicle detection, integrating shadow area search with ROI, HOG, and SVM algorithms, along with K-means clustering[43]. Gavrilu introduced a two-step approach for pedestrian detection, leveraging contour features and hierarchical template matching in the first step, and intensity features and pattern classification in the second step[12]. Additionally, Zhang proposed a vision-based method for vehicle detection, featuring an improved common region algorithm for background subtraction and a threshold segmentation method for object extraction, achieving enhanced accuracy and stability compared to existing algorithms[44]. Collectively, these studies underscore the potential of two-stage detection algorithms in enhancing the accuracy and robustness of object detection in transportation systems.

## 2.2. Single-stage detectors

Recent advancements in object detection have witnessed the emergence of single-stage detection algorithms, offering simpler and faster alternatives to traditional two-stage methods. Ye et al introduced the feature-enhanced single-shot detector (FE-SSD) for railway traffic, significantly improving feature discrimination and robustness[47]. Alvarez et al proposed a monocular target detection system for transport infrastructures, incorporating vanishing point extraction for automatic camera calibration and a background subtraction method for object segmentation [7]. Stuparu et al presented a one-stage object detection model for vehicle detection in overhead satellite images, achieving high accuracy and low detection time[37]. Qiu et al., further enhanced vehicle detection in intelligent transportation systems with a deep learning-based algorithm, achieving a 99.82% recognition rate in real traffic scenes[23]. Redmon et al. introduced YOLO, a novel approach to object detection that significantly revolutionizes single-stage object detection frameworks[3–5, 24, 30, 35]. YOLO utilizes a single neural network to directly forecast bounding boxes and class probabilities from complete images in one assessment, enabling end-to-end optimization for detection efficacy.

## 2.3. Transformer-based detectors

Transformers have recently emerged as a significant advancement in computer vision, particularly in the realm of object detection. These models have introduced end-to-end

learning systems and have been integrated into various architectures to enhance detection performance. Recent advancements in object detection have witnessed the emergence of transformer-based algorithms, which have demonstrated promising results in enhancing both accuracy and convergence time[40]. A comprehensive review of object detection algorithms, encompassing transformer-based detectors, has highlighted substantial progress in the field, particularly in the era of deep learning [36]. The integration of Vision and Detection Transformers (ViDT) has further enhanced the efficiency and effectiveness of object detection, with ViDT+ achieving high scalability for large models[24]. Carion et al present a novel approach named DETection TRansformer (DETR), which conceptualizes object detection as a direct set prediction problem. DETR simplifies the detection pipeline by eliminating the necessity for hand-designed components such as non-maximum suppression or anchor generation[22]. Shou et al used the MS Transformer model to enhance object detection in medical images by addressing challenges such as low resolution, high noise, and small object size[33]. It surpasses existing methods on benchmark datasets like DeepLesion and BCDD, demonstrating superior performance in medical image analysis. extend ViDT to ViDT+ to facilitate joint-task learning for object detection and instance segmentation [33].

## 3. Methodology

Figure 1 and Algorithm 1 illustrated our proposed approach. Our approach consists of three major stages: 1) an effective data pre-processing step, 2) model training, and 3) a robust post-processing strategy.

### 3.1. Effective Data Pre-processing Strategy

In order to address the data challenges such as blurriness, small object detection at image edges, and low illumination in nighttime images, we proposed an effective pre-processing strategy called *Low-Light Image Enhancement Framework*. The proposed framework consists of 3 key steps, namely image enhancement, clustering by illumination, and night-to-day image conversion.

**NAFNet-based Image Enhancement.** The initial phase involves enhancing the raw fisheye images ( $\mathcal{I}_{raw}$ ) to rectify issues related to low light and noise, common in such datasets. Utilizing the NAFNet image enhancement model, each raw image  $i$  is processed to yield an enhanced version  $E(i)$ , forming a set of enhanced images,  $\mathcal{I}_{enh}$ . This step not only improves the visual quality of the images but also prepares them for more accurate object detection by reducing noise and enhancing details. As shown in Figure 2, by using NAFNet[8], objects are enhanced and show clearer quality compared to the original image.

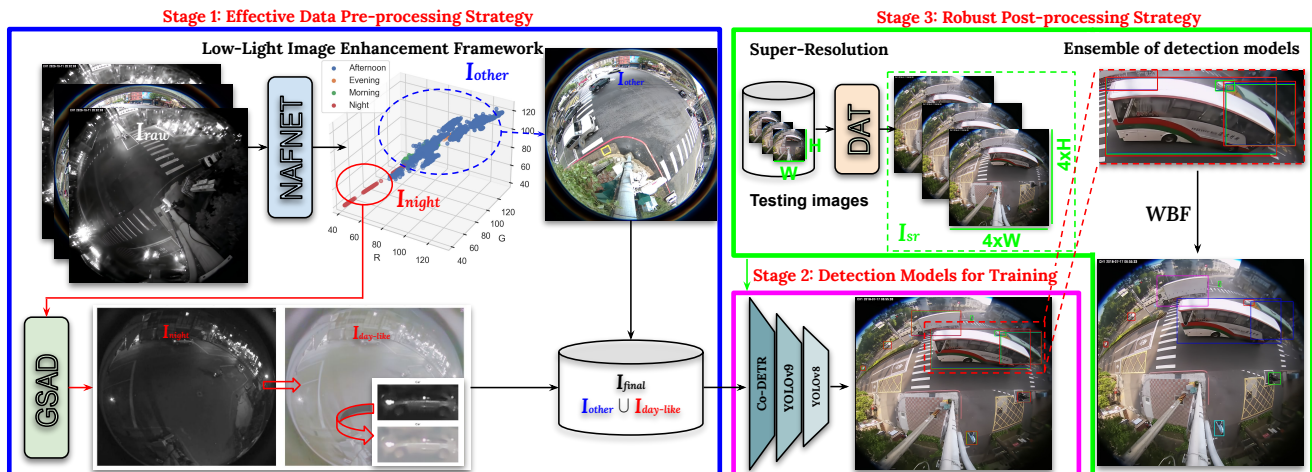


Figure 1. The proposed approach has three stages. 1) effective data preprocessing strategy (NAFNET [8]; GSAD [14]), 2) detection models for training ( Co-DETR [49];YOLOv8[4];YOLOv9[42] ), and 3) robust post-processing strategy (DAT [9]; WBF [34])

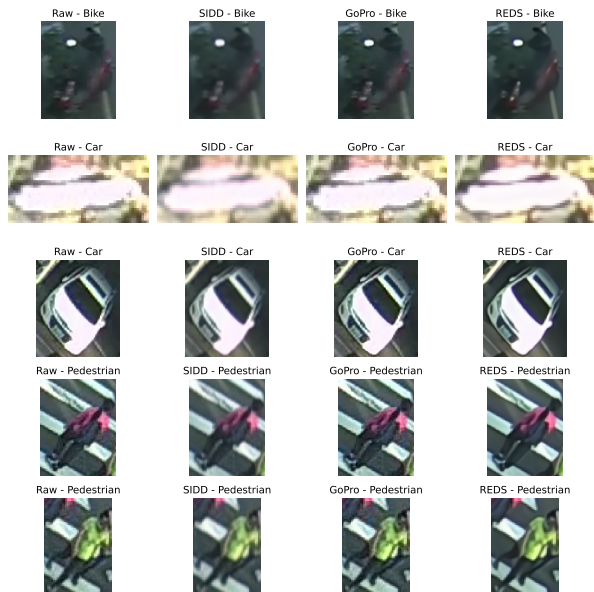


Figure 2. Compare NAFNet [8] image enhancement algorithm with different trained dataset.

To achieve the best image enhancement on our training images, three pre-trained NAFNet models were considered, as illustrated in Figure 2. They are NAFNet trained on SIDD[1], GoPro[20], and REDS[21]. Each pre-train model demonstrated the capacity of the NAFNet algorithm to improve image clarity, sharpness, and overall visibility of details. For example, the Bike images in Figure 2 show less noise and clearer contours after enhancement. The Car images also show more defined shapes and textures, while the Pedestrian images show more details and contrast, making their features easier to see. In this research, NAFNet network that

was pre-trained on REDS was utilized for improving image quality.

**Clustering by illumination condition.** Post-enhancement, the images are clustered into two subsets based on their mean values, distinguishing between night-time and other time-of-the-day images. This step is crucial for tailoring subsequent processing to the specific challenges associated with low-light conditions. Night-time images,  $\mathcal{I}_{night}$ , are identified through a predefined threshold,  $\mathcal{T}_{night}$ , whereas the remaining images are categorized as  $\mathcal{I}_{other}$ . Figure 3 provided 3D scatter plot of the mean color values in RGB color space under four different illumination conditions of the FishEye8K dataset: Morning, Afternoon, Evening, and Night. Clearly, there is a distinct shift towards the lower end of the RGB value spectrum from Night condition.

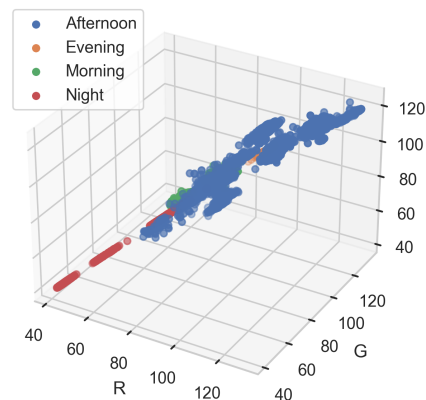


Figure 3. Compare mean value from all scenario images.

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**Algorithm 1** Object Detection in Fisheye Datasets

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1: Input:  $\mathcal{I}_{raw}$  - Set of raw fisheye images.
2: Output:  $\mathcal{O}$  - Object detection results.

3: procedure ENHANCEIMAGES( $\mathcal{I}_{raw}$ )
4:   Initialize  $\mathcal{I}_{enh}$  as an empty set
5:   for each image  $i$  in  $\mathcal{I}_{raw}$  do
6:      $E(i) \leftarrow$  Apply enhancement model  $E$  to  $i$ 
7:     Add  $E(i)$  to  $\mathcal{I}_{enh}$ 
8:   end for
9: end procedure

10: procedure CLUSTERINGBYILLUMINATIONCONDITION( $\mathcal{I}_{enh}$ )
11:   Initialize  $\mathcal{I}_{night}$ ,  $\mathcal{I}_{other}$  as empty sets
12:   for each image  $i$  in  $\mathcal{I}_{enh}$  do
13:     if  $L(i) < T_{night}$  then
14:       Add  $i$  to  $\mathcal{I}_{night}$ 
15:     else
16:       Add  $i$  to  $\mathcal{I}_{other}$ 
17:     end if
18:   end for
19: end procedure

20: procedure CONVERTNIGHTTODAY( $\mathcal{I}_{night}$ )
21:   Initialize  $\mathcal{I}_{day-like}$  as an empty set
22:   for each image  $i$  in  $\mathcal{I}_{night}$  do
23:      $G(i) \leftarrow$  Apply GSAD model  $G$  to  $i$ 
24:     Add  $G(i)$  to  $\mathcal{I}_{day-like}$ 
25:   end for
26: end procedure

27: procedure PREPAREDATASETFORTRAINING
28:    $\mathcal{I}_{final} \leftarrow \mathcal{I}_{other} \cup \mathcal{I}_{day-like}$ 
29: end procedure

30: procedure TRAINANDENSSEMBLEMODELS( $\mathcal{I}_{final}$ )
31:   Train multiple object detection models on  $\mathcal{I}_{final}$ 
32:   Apply ensemble method to integrate models into  $F$ 
33: end procedure

34: procedure APPLYSUPERRESOLUTION( $\mathcal{I}_{final}$ )
35:   Initialize  $\mathcal{I}_{sr}$  as an empty set
36:   for each image  $i$  in  $\mathcal{I}_{final}$  do
37:      $SR(i) \leftarrow$  Apply DAT model to  $i$ 
38:     Add  $SR(i)$  to  $\mathcal{I}_{sr}$ 
39:   end for
40: end procedure

41: procedure GENERATEDETECTIONRESULTS( $\mathcal{I}_{sr}$ )
42:   for each image  $i$  in  $\mathcal{I}_{sr}$  do
43:      $F(i) \leftarrow$  Apply unified model  $F$  to  $i$ 
44:     Add  $F(i)$  to  $\mathcal{O}$ 
45:   end for
46:   return  $\mathcal{O}$ 
47: end procedure
```

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**Night-to-day conversion.** The night-time images undergo a transformation process using a GSAD model,  $G$ , designed to convert night scenes into day-like scenes. This step, producing  $\mathcal{I}_{day-like}$ , aims to normalize the lighting conditions across the dataset, thereby reducing the variability in illumination that can negatively impact object detection performance. In this study, we utilized the GSAD model pre-trained on the LOLv2 Synthetic dataset for the experiment. Mainly because this pre-trained model demonstrates superior performance with significant improvements in brightness, contrast, and color saturation, as shown in Figure 4.

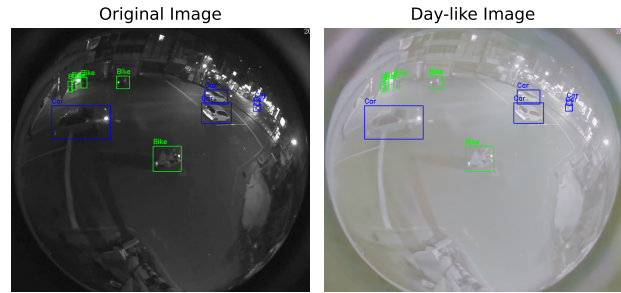


Figure 4. Converting night time image to day-like image using GSAD model.

### 3.2. Detection Models for Training

After the data preprocessing step, a unified dataset,  $\mathcal{I}_{final}$ , is prepared by combining the other time-of-the-day images,  $\mathcal{I}_{other}$ , with the day-like images,  $\mathcal{I}_{day-like}$ . This process ensures that the training dataset exhibits a consistent lighting condition, mimicking daytime scenes and thus facilitating more effective learning by the object detection models. The models used in this study are YOLOv8x, YOLOv9e, and Co-DETR.

**YOLOv8.** YOLOv8 [4], like YOLOv5 [2, 28, 30], consists of the backbone, head, and neck. Significant advancements have been made to the YOLOv8 architecture, including a complete redesign of the architecture, improved convolutional layers in the backbone, and a more advanced detection head. Because of these updates, it is now the preferred method for real-time object detection. The model uses the Darknet-53 backbone network, which is known for its faster and more accurate performance compared to its predecessor, the YOLOv7 network [3, 29, 41]. The YOLOv8 model uses an anchor-free detection head to predict bounding boxes. This approach is remarkably effective due to its improved feature map and convolutional network, which result in increased precision and speed.

**YOLOv9** [42] represents a significant advancement in real-time object detection, introducing innovative tech-

niques such as Programmable Gradient Information (PGI) and the Generalized Efficient Layer Aggregation Network (GELAN). The architecture was designed in a manner to fundamentally overcome the challenges of information loss in deep neural networks. The YOLOv9 uses innovative Reversible Functions that are central to its architecture, ensuring its high efficiency and accuracy. Furthermore, the introduction of PGI aimed at alleviating the information bottleneck problem and preserving critical data across deep network layers. This preservation allows for the generation of dependable gradients, which facilitates precise model updates and improves overall model performance.

**Co-DETR.** Co-DETR[49] stands out in its structure with a unique collaborative training scheme that tackles limitations in the DETR architecture. It achieves this by introducing auxiliary heads alongside the main decoder. These auxiliary heads train with a one-to-many object assignment approach, unlike the decoder’s attention mechanism. This strengthens the encoder’s ability to learn discriminative features for objects. Furthermore, Co-DETR leverages these auxiliary heads to create more high-quality training data specifically for the decoder, improving its focus and performance.

### 3.3. Robust Post-processing Strategy

The postprocessing technique employed in this stage includes super-resolution of test images and our proposed ensemble model for detection.

**Super-resolution.** Before performing inference on our validation dataset or on the experimental test data, the images are processed through a Dual Aggregation Transformer (DAT) [9] model. This model upscales the images by a factor of four, as shown in Figure 5, significantly enhancing the resolution and detail available for object detection.

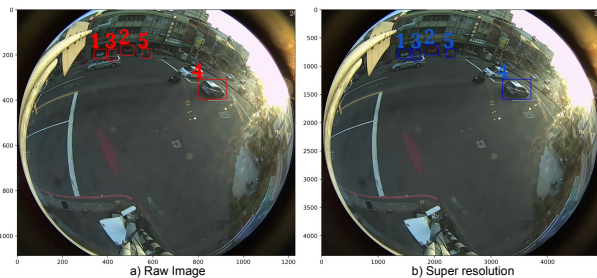


Figure 5. Using super-resolution to increase image size by a factor of four. a) raw image, b) super-resolution image

Additionally, Figure 6 compares the raw image with the super-resolution image at the object level. From the Figure, we observed an enhanced image quality, allowing better detection by the object detection model during inference.

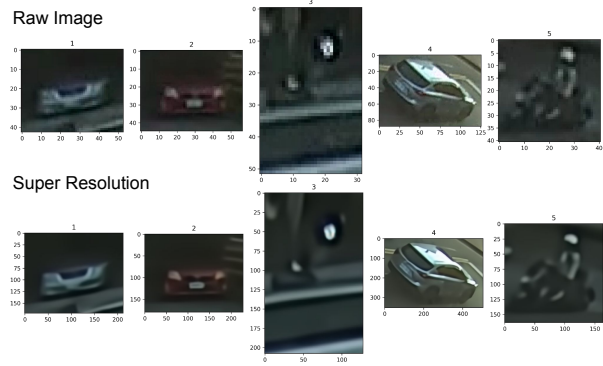


Figure 6. Using super-resolution to increase image size by a factor of four. a) raw image, b) super-resolution image

**Ensemble of detection models.** The trained detection models were ensembled into one model, leveraging their respective strengths to detect various objects from the fisheye lens camera images. To achieve this, an ensemble method, weighted box fusion (WBF) [34], is then applied to integrate these models into a single, comprehensive detection model,  $F$ , enhancing the overall detection accuracy and robustness.

## 4. Experiments

### 4.1. Dataset

**Challenge of the given dataset.** As shown in Figure 7, the labeled objects are: *Bus, Bike, Car, Pedestrian, and Truck*. The majority of the objects are labeled with small area pixels less than  $64 \times 64$ . Additionally, the quality of the dataset is affected by noise and blur due to the extraction process from recorded videos. Furthermore, fisheye lenses cause significant distortion, especially at the edges of the images, which can alter the appearance of objects, making it harder for detection algorithms to accurately identify and classify them. Some objects may be partially obscured by others or overlap, particularly in crowded urban scenes, making it difficult to distinguish one object from another. That is, differentiating between similar-shaped objects, such as cars and trucks or bikes and motorcycles, can be difficult, especially in low-resolution images.

**Implementation detailed.** The proposed approach is inferred on Intel Core i9, and NVIDIA 4090 24GB and 64GB RAM. Models are trained on Intel Xeon Silver 4210R, and 2 NVIDIA RTX A6000 48GB and 126GB RAM. Here is the list of models that are utilized for training:

- YOLOv8: YOLOv8x are used for training models for comparison, multiple image scales such as 640, and 1280 are trained and validated. Other hyperparameters remained the same in the original model.

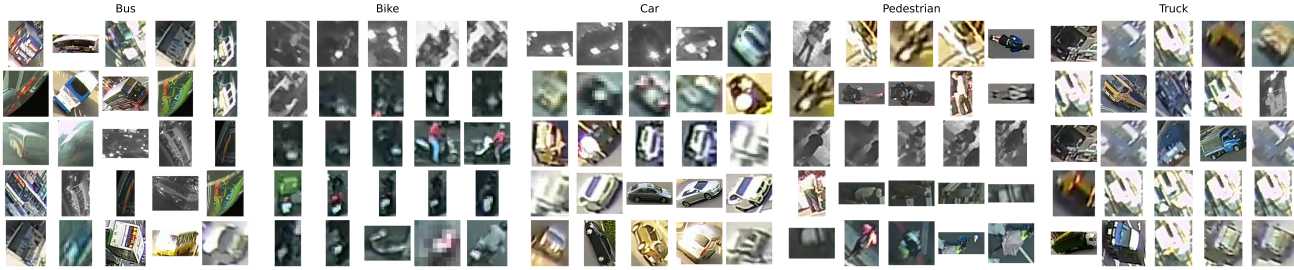


Figure 7. Sample cropped objects from the FishEye8K dataset.

- YOLOv9: At the time of writing this paper, YOLOv9e is claimed that achieved better performance compared to other YOLO variants. Therefore, the strongest YOLOv9-E with image size 1280 is used for the training model.
- Co-DETR: For the large detection model like Co-DETR. The pre-trained model on foundation datasets such as COCO[17] or Objects365[26] is important for improving fine-tuning model accuracy. In this research, the model is trained with image size 1024 and a fine-tuned model trained on Objects365 pre-trained + COCO dataset (Co-DETR-O365). Other hyperparameters and augmentation processes are utilized from the default model[48].

## 4.2. Evaluation Metrics

In the challenge, the evaluation of object detection models was anchored on two main metrics: the mean Average Precision (mAP) and the F1 Score. The mAP can be expressed as the mean of the AP values across all classes, where AP is calculated using the area under the precision-recall curve. The mAP can be expressed as the mean of the AP values across all classes, where AP is calculated using the area under the precision-recall curve. In a setting with  $C$  classes, the mAP is defined as:

$$mAP = \frac{1}{C} \sum_{c=1}^C AP_c \quad (1)$$

The F1 Score is defined as the balance mean of precision (P) and recall (R):

$$F1 = 2 \times \frac{P \times R}{P + R} \quad (2)$$

## 5. Results and Discussion

### 5.1. Comparative analysis on validation set

Table 1 provides a comparative analysis of object detection models trained and tested on the raw FishEye8K dataset. The models are evaluated based on their Average Precision (AP) from a threshold of 0.5 to 0.95, offering a rigorous metric for detection accuracy across different levels of intersection over union (IoU).

**In detailed.** A baseline model referenced as [13], which sets the initial benchmark with an AP of 0.4029. Two iterations of the YOLOv8X model with different input resolutions (640 and 1280), show APs of 0.33 and 0.36 respectively. The Co-DETR model demonstrates a competitive AP of 0.39. This comparison establishes the performance standards before the application of our proposed image enhancement techniques.

ID	Method	$AP_{0.5-0.95}$
1	Baseline [13]	0.4029
2	Yolov8X-640 [16]	0.33
3	Yolov8X-1280 [16]	0.36
4	Co-DETR [48]	0.39

Table 1. Model comparison, training, and testing on raw FishEye8K dataset.

In Table 2, we extend our comparison to models trained on the image-enhanced FishEye8K dataset. The enhancements are presumed to improve model training by providing clearer and more accurate representations of objects. The models in this table include YOLOv9e-1280, achieving an AP of 0.399. The Co-DETR model, this time reaching an AP of 0.409. The Co-DETR-O365, shows a marked improvement with an AP of 0.485. Our proposed approaches, referred to as Our-1 and Our-2, surpass the others with APs of 0.486 and 0.489, respectively. The advancement of our models is indicated by the higher precision rates, demonstrating the effectiveness of our methods in handling the unique challenges of fisheye lens distortions and low-light conditions.

Figure 8 illustrates the trend in model performance as measured by mAP across the range of 0.5 to 0.95 IoU. The baseline AP is indicated by a dashed green line, against which subsequent model performances are measured. The red line denotes the mAP trend, clearly showing a significant improvement in AP values with the introduction of image enhancement, marked by a dashed vertical line. Models 1 through 4, which are trained on raw images, show lower mAP values. Beginning with model 5 and extending

ID	Method	$AP_{0.5-0.95}$
5	YOLOv9e-1280 [42]	0.399
6	Co-DETR [48]	0.409
7	Co-DETR-O365 [48]	0.485
8	Our-1	0.486
<b>9</b>	<b>Our-2</b>	<b>0.489</b>

Table 2. Model comparison, training, and testing on image enhancement FishEye8K dataset. Our-1: Co-DETR-O365 test on validation set contains day-like images. Our-2: Co-DETR-O365 train on training set contains day-like images and tests on high-resolution images.

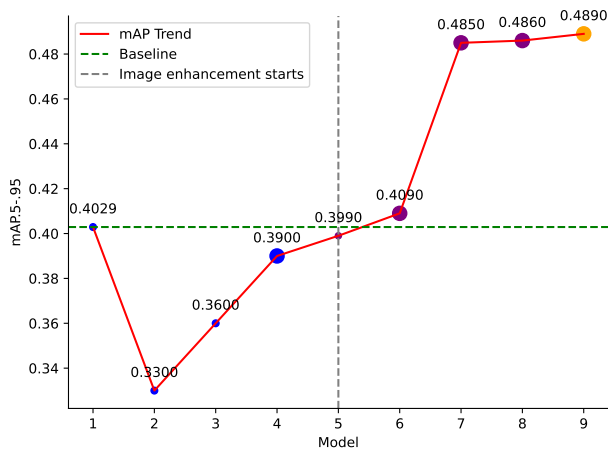


Figure 8. Model performance comparison.

to model 9, there is a notable uptick in mAP, underscoring the beneficial impact of image enhancement on model accuracy. Our proposed methods (Our-1 and Our-2) stand out with the highest AP values, affirming the superiority of the advancements we have implemented over existing models.

## 5.2. Model performance on CVPR challenge set

Table 3 presents the standings from the public leaderboard of AIC24 Track 4[45], evaluating the performance of various teams on the full test set as measured by the F1 Score. In the competition, our team achieved a ranking of **5th out of 52 teams** with an F1 Score of **0.5965**. Figure 9 presents a qualitative comparison between ground truth annotations and the results achieved using our image enhancement and detection framework. Our approach not only matches the ground truth but also reveals additional objects, highlighting the potential of our method to improve resolution and detection capabilities beyond the limitations of original low-resolution annotations.

Table 3. Public leaderboard of AIC24 Track 4 on the full test set.

Rank	Team ID	Team Name	F1 Score
1	9	VNPT AI	0.6406
2	40	NetsPresso	0.6196
3	5	SKKU-AutoLab	0.6194
4	63	UIT-AICLUB	0.6077
<b>5</b>	<b>15</b>	<b>SKKU-NDSU (Our)</b>	<b>0.5965</b>
6	33	MCPRL	0.5883
7	156	zzl	0.5828
8	52	DeepDrivePL	0.5825
9	86	NCKU-ACVLAB	0.5764
10	13	FRDC-SH	0.5637

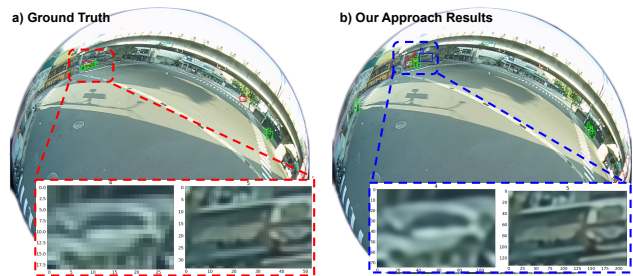


Figure 9. Qualitative Result

## 6. Conclusion

We developed an efficient object detection system that is robust to varying lighting conditions and times of the day. To achieve this goal, we proposed a unique data processing strategy referred to as the *“low-light image enhancement framework”* and utilized an ensemble of YOLOv8, YOLOv9, and Co-DETR as our objection detection model. Our experimental results demonstrated the effectiveness and robustness of the proposed system in detecting objects from fisheye lens camera images.

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