# A Real-Time DETR Approach to Bangladesh Road Object Detection for Autonomous Vehicles

Irfan Nafiz Shahan

Department of Electrical and Electronic Engineering Shahjalal University of Science and Technology Sylhet, Bangladesh irfannafizislive@gmail.com

Saadman Sakib

Department of Robotics and Mechatronics Engineering Dhaka University Dhaka, Bangladesh saadman.sakib2020@gmail.com Arban Hossain

Department of Robotics and Mechatronics Engineering Dhaka University Dhaka, Bangladesh arbanhossain@gmail.com

Al-Mubin Nabil

Department of Computer Science and Engineering Shahjalal University of Science and Technology Sylhet, Bangladesh almubinnabil@gmail.com

Abstract—In the recent years, we have witnessed a paradigm shift in the field of Computer Vision, with the forthcoming of the transformer architecture. Detection Transformers has become a state of the art solution to object detection and is a potential candidate for Road Object Detection in Autonomous Vehicles. Despite the abundance of object detection schemes, real-time DETR models are shown to perform significantly better on inference times, with minimal loss of accuracy and performance. In our work, we used Real-Time DETR (RTDETR) object detection on the BadODD Road Object Detection dataset based in Bangladesh, and performed necessary experimentation and testing. Our results gave a mAP50 score of 0.41518 in the public 60% test set, and 0.28194 in the private 40% test set.

*Index Terms*—vehicle detection, DETR, transformer model, BadODD, computer vision

#### I. INTRODUCTION

Computer vision (CV) plays a critical role in the modern day, and used commonly in some security cameras. Beyond security, the scope of computer vision extends into the realm of autonomous vehicles, where it plays a pivotal role in vehicle detection and tracking within the sensor fusion framework.

For autonomous vehicles, accurate and swift object detection can be a matter of life and death - for proper decisionmaking depends solely upon the inference of the machine learning model involved that analyses data to provide powerful conclusions to a complex road scenario. Therefore, advances in road vehicle detection is paramount for the future safety and capabilities of autonomous vehicles.

The forthcoming of major developments in machine learning, such as transformer models, [1] paved the way towards improved object detection models, namely Detection Transformers (DETRs) [2]. DETRs took the spotlite in 2020, becoming a cornerstone to faster, lower memory and lower power methods of object detection. Traditionally before the emergence of DETR, Region-based Convolutional Neural Networks (R-CNN) were - and still are - actively being used for making complex computation models. A very popular such architecture is You-Only-Look-Once (YOLO) [4]that utilizes Fast R-CNNs to enable incredible inference times, with it's pretrained model capable of being fine-tuned to significantly commendable accuracy in most scenarios.

In a paper by Lv et al [3], it is shown that Real-Time DETR (RTDETR), outperforms classical YOLO [4] variants and Fast R-CNN models significantly due to it's lower end-toend latency and customizability. Furthermore does not suffer from any major reduction in accuracy and performances. RTDETR (Real-Time DETR) represents a fusion of the speed and efficiency of YOLO-style architectures with the expressive power of transformers. Unlike traditional convolutional neural networks (CNNs) used in YOLO [4] and R-CNN variants, transformers rely on self-attention mechanisms to capture global dependencies in the input data, enabling more effective object detection.

Hence, beyond using conventional YOLOv8 [4] based finetuned models, we aimed at using RTDETR on the BadODD - Bangladeshi Autonomous Driving Object Detection Dataset [5].

#### II. METHODOLOGY

## A. Understanding BadODD

BadODD dataset consists of a total of 13 classes, including auto-rickshaw, bicycle, bus, car, cart-vehicle, constructionvehicle, motorbike, person, priority-vehicle, three-wheeler, train, truck, and wheelchair.

The distribution of classes within the dataset is disproportionate,1 with some classes having significantly more instances than others. This class imbalance poses a challenge for training and evaluating object detection models, as it can affect the model's ability to accurately detect and classify objects across all classes.

In the dataset, there are a total of 5896 images available for training and 1964 images for testing. The disparity in class frequencies within these images further exacerbates the

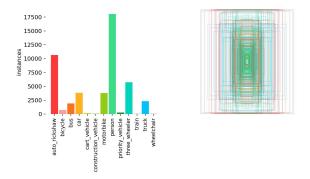


Fig. 1. Dataset Analysis of BadODD, showcasing the disparity in model class occurrences and the uneven distribution of bounding box sizes,



Fig. 2. Original picture with flare (left), flare-reduced picture (right)

challenge of developing a robust object detection model that performs well across all classes.

Beyond these issues, there are some potential concerns in the dataset that pose challenges in training the model.

- Flares: Flares pose a challenge as they may obscure objects in images, potentially reducing detection accuracy. While their removal could improve accuracy, it requires additional resources. 2 We used the Flare7k model to conduct tests. [7] [8]
- Night Images: Night images are challenging due to low visibility and sensor artifacts. They often lack clarity, making feature detection difficult. 3. Tested using Dai's Night to Day nighttime model. [9]
- Windshield Stains: Stains on windshields can hinder accurate labeling and bounding box detection, affecting model performance. 4 Blur removal conducted using Wei's reflection model. [6]
- 4) **Motion Blur:** Motion blur distorts object features, complicating detection. While deblurring techniques exist, they're computationally intensive.
- Double Inference Pass: Running inference twice on an image can refine detections but increases computational cost. Optimizing this process is crucial for real-time



Fig. 3. Original night picture (left), night to day converted picture (right)



Fig. 4. Original picture with windshield stain (left), corresponding stain-reduced image (right)

# applications.

We conducted experiments to address these challenges, however, due to constraints in resources and time, these preprocessing methods were not ultimately integrated into our RTDETR model. Nevertheless, our experimentation highlights their relevance and potential for future work. In subsequent iterations, addressing these challenges could enhance the robustness and accuracy of object detection systems, warranting further investigation.

#### B. Model Selection

We opted for a Real-Time Detection Transformer (RT-DETR) instead of the regular YOLOv8 pre-trained model. YOLO [4] is reputed for its fast inference time, which often comes with the cost of reduced accuracy. DEtection TRansformers (DETR), first introduced in 2020, leverages vision transformers and their encoder-decoder architecture to predict all objects at once. This approach is simpler, more efficient than regular object detectors, and performs better on state-ofthe-art baseline datasets like COCO. But it is also very slow, making it unusable for real-time inference.

RT-DETR mitigates this challenge by adapting and supporting flexible adjustment of inference speed using different decoder layers, removing the need for retraining. This allows us to take advantage of the strength of Vision Transformers while also retaining a very high inference speed. Transformers also enable parallel processing and capture long-range dependencies better.

#### C. Data Preprocessing

Our workflow includes several layers of significant preprocessing to ensure valid and consistent input to our model. The RT-DETR architecture expects  $416 \times 416$  pixel images. We resized the images and adjusted the labels accordingly. We applied augmentation such as blur, median blur, and grayscale conversion. These allow the model to generalize better over different types of inputs. We also tested other augmentations such as perspective transform, random scaling, random translation, and mosaic augmentation.

#### D. Model Configuration and Hyperparameter Tuning

We considered multiple configurations for our RT-DETR model. These configurations are listed in Table. For optimal tuning, we considered whether the model was pre-trained or not, the learning rate, warmup iterations, weight decay, momentum, and image batch size.

3
937
50
16

TABLE I TUNED HYPERPARAMETERS

## E. Training

After selecting the model and performing preprocessing, we proceeded with the training process to develop the deep learning model for object detection. Optimization was achieved using the AdamW optimizer, and the hyperparameters listed in table I. We used a slow learning rate and a moderate number of epoch to reach a appreciable mAP score.

#### **III. RESULTS AND DISCUSSION**

The performance metrics for the model are illustrated in table III. The model achieves a mean Average Precision (mAP) score of 0.4151 on the public 60% of the dataset. Accordingly, it scores 0.2891 on the remaining 40%. Table III shows that the model achieves high precision and recall values. The final loss of the model settles at 0.000808. The loss curves are also presented in the figure below (Figure 7). The model also achieves an average inference time of 22.44ms (Table II). These results underscore the model's ability to generalize well across diverse data distributions.

Table III further highlights the model's impressive precision and recall values, indicating its capacity to achieve high accuracy while minimizing false positives and negatives. This balanced performance is crucial for real-world applications where reliable object detection is paramount.

preprocess	0.2 ms
inference	22.4ms
loss	0.0ms
postprocess	0.7ms

TABLE II Time Taken Per Image

The model's average inference time of 22.44 milliseconds, as depicted in Table II, is noteworthy. Low inference times are critical for real-time applications such as autonomous driving and surveillance systems, where rapid decision-making is essential for ensuring safety and efficiency. The model's efficient inference time enables timely processing of input data, facilitating swift responses to dynamic environmental changes.

Despite its notable achievements, the model may encounter certain challenges and limitations. For instance, while it excels in detecting objects of various sizes, it may struggle with accurately identifying extremely small or occluded objects.





Fig. 5. Ground Truth Labels showing congested persons

Fig. 6. Predicted Labels Trying to Identify the congested labels

Addressing such challenges requires ongoing research and development efforts aimed at enhancing the model's robustness and adaptability across diverse scenarios.

## IV. CONCLUSION AND FUTURE WORK

In this work, we propose a real-time object detection approach using a fine-tuned RT-DETR architecture to detect road objects in Bangladesh. While our method addresses key challenges in the domain, further improvements are needed. We explored several augmentation techniques, which show promise, and suggest that enhancing preprocessing to handle blurs, flares, glass stains, and night images could lead to significant improvements, along with new challenges. Additionally, the dataset is imbalanced, with only a few images of classes like *wheelchair* and *train*, which affects model performance. Lastly, the model struggles with congested areas, where it erroneously predicts multiple objects in a single space, an issue worth further investigation.

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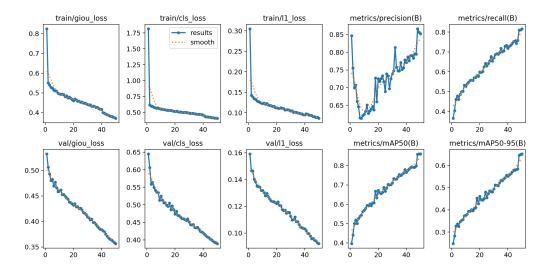
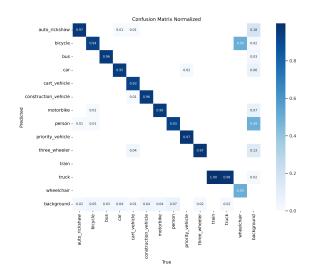


Fig. 7. Performance Metrics for the RTDETR-X model

Class	Images	Instances	Box(P)	Box(R)	Box(mAP50)	Box(mAP50-95)
all	5896	47118	0.852	0.815	0.861	0.652
auto rickshaw	5896	10614	0.931	0.939	0.968	0.759
bicycle	5896	673	0.9	0.892	0.933	0.592
bus	5896	1885	0.954	0.936	0.966	0.74
car	5896	3785	0.95	0.914	0.953	0.724
construction vehicle	5896	141	0.885	0.879	0.916	0.685
motorbike	5896	3749	0.916	0.92	0.944	0.613
person	5896	18010	0.9	0.858	0.915	0.599
priority vehicle	5896	229	0.936	0.953	0.973	0.792
three wheeler	5896	5710	0.927	0.946	0.971	0.762
train	5896	1	0	0.916	0.923	0.705
truck	5896	2296	0.971	0.948	0.98	0.752
wheelchair	5896	2	1	0.5	0.75	0.75

TABLE III Results tabulated for each class.



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Fig. 8. Confusion Matrix for each of the categories