Efficient Object Detection from Fused RGB and IR Aerial Images Enhanced by Token Selection

***Abstract*—Object detection is a fundamental task in computer vision, with critical applications in autonomous driving, surveillance, and robotics. Traditional object detection models primarily rely on RGB images, which perform well under favorable lighting but degrade in low-visibility environments such as nighttime or adverse weather. Infrared (IR) imagery, which captures thermal information, offers improved performance in such conditions but lacks structural and color details. Combining RGB and IR modalities has the potential to enhance detection accuracy by leveraging their complementary strengths. However, RGB-IR fusion for aerial imagery remains underexplored, and the scarcity of publicly available paired datasets further limits research in this area. Additionally, implementing onboard fusion models for aerial applications, such as on drones, poses significant challenges, including feature-level fusion complexity and high computational overhead. In this work, we propose an efficient RGB-IR fusion framework specifically designed for aerial image datasets. Our framework integrates pixel-level fusion and transformer-based feature-level fusion to capture both low-level and high-level cross-modal interactions. To address computational constraints, we introduce a token selection mechanism that dynamically selects the most informative tokens, reducing inference time while maintaining high detection performance. Extensive experiments conducted on an RGB-IR aerial image dataset demonstrate that our proposed framework significantly improves detection accuracy and computational efficiency.**

I. Introduction

Object detection is a key task in computer vision, with critical applications in autonomous driving, surveillance [1]–[3], and robotics [4], [5]. Traditional object detection models predominantly rely on RGB images, which capture rich visual information under favorable lighting conditions. However, their performance declines considerably in low-visibility scenarios, such as nighttime or adverse weather, where RGB data alone proves insufficient. Infrared (IR) imagery, which records thermal signatures, provides an advantage in such conditions by enhancing visibility. Despite this benefit, IR imagery lacks the structural and color details inherent in RGB images, leading to reduced performance when used independently. The fusion of RGB and IR modalities offers the potential to overcome these individual limitations by leveraging their complementary strengths, resulting in improved detection performance across diverse environmental conditions [6]–[9].

Although multimodal fusion methods have been widely studied, most existing works focus on fusing point cloud data from LiDAR with RGB images or combining RGB images from different viewpoints. Few studies have specifically explored RGB-IR fusion in robotics or real-time systems, and even fewer have addressed its application in aerial imagery [10], [11]. This is especially significant given the growing demand for accurate aerial monitoring in fields such as environmental surveillance, agriculture, and search-and-rescue operations. Additionally, publicly available RGB-IR paired datasets for aerial imagery are scarce, which hampers progress in developing advanced fusion techniques for such applications. Compared to LiDAR, IR sensors offer distinct advantages for short-range sensing, including lower cost and reliable performance in low-light environments, making RGB-IR fusion a promising direction for efficient, cost-effective object detection solutions.

Despite its promise, RGB-IR fusion presents significant challenges when applied to IoT devices, particularly drones. Beyond the scarcity of datasets, several technical hurdles must be addressed. First, the inherent differences between RGB and IR modalities complicate effective feature-level fusion, especially in aerial imagery where objects are often small and exhibit significant variability [12], [13]. Second, deploying large-scale fusion models in resource-constrained IoT environments requires careful optimization to balance detection accuracy with computational efficiency, ensuring low latency and minimal energy consumption for real-time operations [14], [15].

To address these challenges, we propose an efficient RGB-IR fusion framework tailored specifically for aerial image datasets. The framework is composed of two core components, including fusion strategies and a token selection mechanism. In the first step, we explore both pixel-level fusion, which directly combines RGB and IR images, and transformer-based feature-level fusion, which captures complex cross-modal interactions for enhanced detection [16], [17]. To reduce inference time and computational overhead, we then introduce a token selection mechanism that dynamically selects the most informative tokens for feature representation, enabling faster detection while maintaining accuracy [18], [19].

Our primary contributions can be summarized as follows:

- An RGB-IR fusion framework tailored for aerial imagery, combining pixel-level and transformer-based feature-level fusion to enhance detection in low-visibility environments.
- Development of a token selection mechanism integrated with a detection transformer (DETR) model to improve computational efficiency.
- Comprehensive evaluation of the proposed approach on a paired RGB-IR aerial image dataset, highlighting significant improvements in detection accuracy and efficiency.

II. Related Work

A. Traditional Methods

Traditional image fusion methods that do not involve neural networks have been widely studied in the literature. These methods primarily focus on pixel-level fusion techniques that

directly combine information from multiple modalities, such as RGB and IR images, using mathematical transformations. Some of the most commonly used traditional methods include:

- **Discrete Cosine Transform (DCT)**: This method transforms an image into the frequency domain, allowing the selection of significant frequency components for fusion [20], [21].
- **Sparse Representation (SR)**: SR methods represent images as a linear combination of sparse basis functions, enabling efficient fusion by retaining only the most critical features [22], [23].
- **Principal Component Analysis (PCA)**: PCA is a statistical method that reduces dimensionality by projecting data onto principal components. It is often used in image fusion to extract important features from both RGB and IR images [24], [25].

While these methods are computationally efficient and straightforward to implement, they fail to capture complex interactions between different modalities. Additionally, traditional pixel-level fusion techniques are often unable to adapt to varying environmental conditions, such as changes in lighting or weather.

B. AI-Related Methods

With the rise of deep learning, various AI-based methods have been proposed to enhance image fusion for object detection. These methods can be categorized into three main approaches:

- **Early Fusion**: In early fusion, RGB and IR images are combined at the input level before feature extraction. This approach is simple but often results in suboptimal performance due to the loss of modality-specific information [6], [26].
- **Mid Fusion**: Mid fusion involves extracting features separately from RGB and IR images and then combining them at an intermediate layer within the neural network. This approach allows for more complex interactions between modalities and generally achieves better performance than early fusion [13], [27].
- **Late Fusion**: In late fusion, RGB and IR images are processed independently, and their outputs are combined at the decision-making stage using ensemble methods such as non-maximum suppression (NMS) [28], [29].

Transformer-based models have also gained traction in the field of object detection. Models like DETR (DEtection TRansformer) [30], [31] reformulate object detection as a set prediction problem, eliminating the need for traditional anchor boxes and non-maximum suppression. However, these models come with a significant computational cost, which limits their applicability in real-time systems.

To address this issue, token selection mechanisms have been proposed to reduce the number of input tokens processed by the transformer, thereby improving efficiency without compromising accuracy [18], [32], [33].

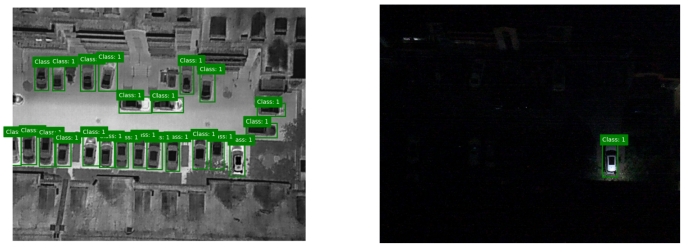
C. Efficient AI

Efficiency is a critical requirement for deploying AI models in real-time applications, particularly on resource-constrained devices such as drones and IoT systems. Several techniques have been explored to improve the efficiency of transformer-based models and multimodal fusion frameworks:

- **Pruning and Quantization**: These techniques involve reducing the size of neural networks by removing redundant weights (pruning) or using lower-precision data types (quantization) to reduce memory usage and improve inference speed [34]–[36].
- **Token Selection Mechanisms**: Token selection methods dynamically select a subset of the most relevant input tokens from the fused image, significantly reducing the computational load of transformer-based models while maintaining accuracy [18], [32], [33] .
- **Knowledge Distillation**: This technique involves training a smaller, more efficient model (the student) to mimic the behavior of a larger, more complex model (the teacher), resulting in faster and more efficient inference [**?**].

Despite these advancements, there are still gaps in the existing literature, particularly in the context of RGB-IR fusion for real-time object detection in aerial imagery. Most existing works focus on LiDAR-based fusion or multimodal fusion for ground-based applications. This work addresses these gaps by combining transformer-based feature-level fusion with token selection to develop an efficient object detection framework tailored for aerial RGB-IR datasets.

III. Motivation Analysis



(a) (b)

Fig. 1: Examples of RGB and IR Images for a Single Scenario with Ground Truth Bounding Boxes: (a) RGB, and (b) IR.

Traditional object detection models primarily rely on RGB images, which perform well under favorable lighting but degrade significantly in low-visibility environments such as nighttime, fog, or adverse weather conditions. These limitations arise because RGB sensors depend heavily on ambient light, making it challenging to detect objects in dark or occluded scenes [37], [38]. Conversely, infrared (IR) sensors capture thermal radiation, providing consistent visibility regardless of lighting conditions [39], [40].

Fig. 1 illustrates this limitation by showing RGB and IR images captured for a single scenario (same time and same location). In the RGB image, only one object is faintly visible due to poor lighting, whereas the IR image clearly reveals

24 densely packed objects, highlighting the superiority of IR imaging in low-visibility environments [41], [42].

TABLE I: Annotation Details for Vehicle Categories

Category	RGB Annotations	IR Annotations
Car	389,779	428,086
Truck	22,123	25,960
Bus	15,333	16,590
Van	11,935	12,708
Freight Car	13,400	17,173

Furthermore, in the DroneVehicle dataset [43], which includes paired RGB and IR images, the RGB images contain 452,570 annotation bounding boxes, while the IR images have 500,517 annotation boxes, as shown in Table I. This disparity emphasizes the complementary nature of these modalities, as IR images often detect objects that RGB images miss and vice versa. Therefore, retrieving comprehensive information from both IR and RGB images plays a crucial role in enhancing the robustness of object detection systems in diverse environmental conditions [7], [21].

Despite the clear advantages of combining IR and RGB data, there are relatively few works focusing on IR and RGB fusion for object detection. Most existing research targets LIDAR and RGB image fusion[13], [44] . Developing effective IR and RGB fusion methods could significantly improve performance in scenarios such as autonomous driving, search and rescue operations, and surveillance, where reliable detection in all lighting conditions is essential.

IV. Problem Definition

Let $\mathcal{D} = \{(X_i^{\text{RGB}}, X_i^{\text{IR}}, Y_i^{\text{RGB}}, Y_i^{\text{IR}})\}_{i=1}^{N}$ represent an aerial dataset consisting of N paired samples, where each $X_i^{\text{RGB}} \in \mathbb{R}^{H\times W\times 3}$ denotes an RGB image, $X_i^{\text{IR}} \in \mathbb{R}^{H\times W\times 1}$ represents the corresponding infrared image, and $Y_i^{\text{RGB}}, Y_i^{\text{IR}}$ contain the ground truth bounding box annotations for objects in the RGB and IR images, respectively [45], [46]. The unified ground truth bounding boxes Y_i are defined as the union of Y_i^{RGB} and Y_i^{IR}:

$$Y_i = Y_i^{\text{RGB}} \cup Y_i^{\text{IR}}. \tag{1}$$

The goal is to develop an object detection model f_θ parameterized by θ, capable of predicting bounding boxes and class labels by leveraging fused information from both RGB and IR modalities [47], [48].

To address the fusion of RGB and IR images, we define a fusion function $F : \mathbb{R}^{H\times W\times 3} \times \mathbb{R}^{H\times W\times 1} \to \mathbb{R}^{H\times W\times d}$, where d denotes the number of feature channels in the fused representation. The fused feature map Z_i for a given pair $(X_i^{\text{RGB}}, X_i^{\text{IR}})$ can be expressed as:

$$Z_i = F(X_i^{\text{RGB}}, X_i^{\text{IR}}), \tag{2}$$

where F may involve pixel-level concatenation, attention-based feature fusion, or a transformer-based fusion mechanism [49], [50].

The object detection model f_θ operates on the fused representation Z_i and outputs a set of predicted bounding boxes $\hat{Y}_i = \{(\hat{b}_{ij}, \hat{c}_{ij})\}_{j=1}^{M_i}$, where $\hat{b}_{ij} \in \mathbb{R}^4$ represents the j-th bounding box coordinates, and $\hat{c}_{ij} \in \{1, \ldots, K\}$ denotes the corresponding class label among K possible classes. Formally, the object detection process can be expressed as:

$$\hat{Y}_i = f_\theta(Z_i) = f_\theta(F(X_i^{\text{RGB}}, X_i^{\text{IR}})). \tag{3}$$

To train the model, we minimize a multi-task loss function $\mathcal{L}(\theta)$ that combines the bounding box regression loss $\mathcal{L}_{\text{bbox}}$ and the classification loss $\mathcal{L}_{\text{cls}}$ for all training samples:

$$\mathcal{L}(\theta) = \frac{1}{N}\sum_{i=1}^{N}\left(\mathcal{L}_{\text{cls}}(Y_i, \hat{Y}_i) + \lambda\mathcal{L}_{\text{bbox}}(Y_i, \hat{Y}_i)\right), \tag{4}$$

where λ is a hyperparameter that controls the balance between the two loss components.

Given the computational constraints in IoT devices, such as drones [51], [52], we introduce a token selection mechanism $T : \mathbb{R}^{H\times W\times d} \to \mathbb{R}^{m\times d}$ that selects the top m most informative tokens from the fused feature map Z_i. The final token-reduced representation $\tilde{Z}_i$ is then given by:

$$\tilde{Z}_i = T(Z_i), \tag{5}$$

where $m \ll H\times W$ to reduce the computational complexity and inference latency. The object detection model is subsequently applied to $\tilde{Z}_i$ to produce the final predictions.

V. Algorithm Design

A. Overview of the Proposed Framework

As shown in Fig. 2, the proposed framework integrates three main components: RGB and IR image fusion, token selection, and object detection [53], [54]. In the image fusion step, two distinct paths are employed, pixel-level fusion and transformer-based fusion [55], [56]. The pixel-level fusion path adjusts a weighting parameter α to combine the RGB and IR images, preserving low-level features such as edges and textures from both modalities. In the transformer-based fusion path, RGB image queries are used to extract relevant information from the IR image, resulting in fused high-level feature representations. The outputs from both paths are concatenated to form the final fused feature map. Once the fused feature map is obtained, token selection is applied to identify and retain the most informative tokens, reducing the computational overhead of subsequent transformer operations. The selected tokens are then fed into a detection decoder to produce object bounding boxes and class labels.

B. RGB and IR Image Fusion

Given an RGB image $I_{\text{RGB}} \in \mathbb{R}^{H\times W\times 3}$ and an IR image $I_{\text{IR}} \in \mathbb{R}^{H\times W\times 1}$, we define the pixel-level fused image F_{pixel} as:

$$F_{\text{pixel}} = \alpha I_{\text{RGB}} + (1-\alpha) I_{\text{IR}}, \tag{6}$$

where $\alpha \in [0, 1]$ is a tunable parameter controlling the contribution of each modality. This approach ensures that low-level features from both modalities are preserved.

For the transformer-based fusion, let $Q_{\text{RGB}} \in \mathbb{R}^{h_q\times d}$ denote the query embeddings obtained from the RGB image, and $K_{\text{IR}}, V_{\text{IR}} \in \mathbb{R}^{h_k\times d}$ denote the key and value embeddings

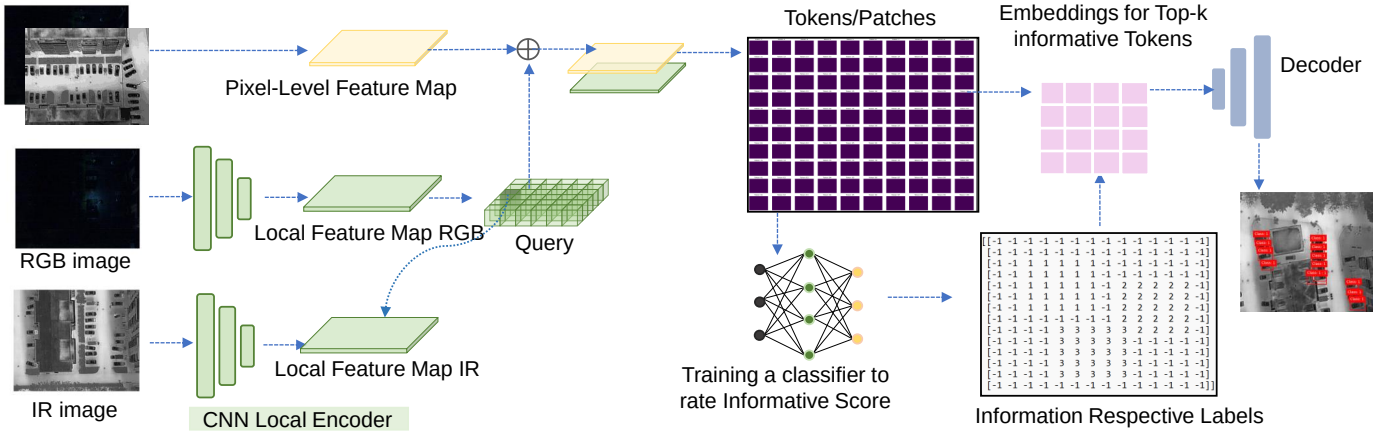


Fig. 2: An overview of our proposed framework for object detection through the fusion of RGB and IR images.

obtained from the IR image [57], [58]. The fused feature map F_{trans} is computed using multi-head attention:

$$\text{Attention}(Q_{\text{RGB}}, K_{\text{IR}}, V_{\text{IR}}) = \text{softmax}\left(\frac{Q_{\text{RGB}} K_{\text{IR}}^{\top}}{\sqrt{d}}\right) V_{\text{IR}}, \quad (7)$$

$$F_{\text{trans}} = \text{Concat}(\text{head}_1, \ldots, \text{head}_h) W^O, \quad (8)$$

where h denotes the number of attention heads, and W^O is a learnable projection matrix. The final fused feature map F is obtained by concatenating the outputs of the pixel-level and transformer-based fusion paths:

$$F = \text{Concat}(F_{\text{pixel}}, F_{\text{trans}}). \quad (9)$$

To ensure consistency in the fused feature map, we minimize a reconstruction loss $\mathcal{L}_{\text{recon}}$:

$$\mathcal{L}_{\text{recon}} = \frac{1}{N} \sum_{i=1}^{N} \left(\|F_i - I_{\text{RGB},i}\|_2^2 + \|F_i - I_{\text{IR},i}\|_2^2 \right), \quad (10)$$

where N is the total number of training samples.

C. Token Selection for Lightweight Feature Representation Learning

To reduce the computational complexity of the downstream object detection task, we introduce a token selection mechanism that retains only the most informative tokens from the fused feature map [59], [60]. Let $T \in \mathbb{R}^{HW \times d}$ denote the tokenized representation of the fused image F. The informativeness score for each token $t_i \in T$ is computed using a learnable scoring function $\phi : \mathbb{R}^d \to \mathbb{R}$:

$$s_i = \phi(t_i) = \text{MLP}(t_i), \quad (11)$$

where MLP denotes a multi-layer perceptron. The top m tokens with the highest scores are selected, where m is a hyperparameter controlling the number of retained tokens. The selected tokens $\tilde{T} \in \mathbb{R}^{m \times d}$ are given by:

$$\tilde{T} = \text{Top-}m(T, s). \quad (12)$$

After applying the token selection mechanism to obtain the reduced token set $\tilde{T} \in \mathbb{R}^{m \times d}$, the selected tokens are integrated into the feature representation map F and subsequently passed through the object detection pipeline [61], [62].

VI. Experimental Results

This section evaluates the performance of the proposed framework on the RGB-IR paired image dataset, DroneVehicle [43], [63], [64]. We first introduce the experimental setup, detailing the dataset, evaluation metrics, and implementation specifics. Next, a comprehensive performance overview is presented through quantitative evaluation, analyzing the detection accuracy and computational efficiency of various fusion techniques [65], [66]. We then conduct a qualitative evaluation using three visualized examples, highlighting the strengths and weaknesses of each method under different lighting and noise conditions. Finally, the limitations of the proposed approach are discussed

A. Experimental Settings

Dataset. DroneVehicle dataset comprises a total of 28,439 groups of paired RGB and IR images, capturing five distinct vehicle categories: car, truck, bus, van, and freight car. The annotation statistics for these categories are summarized in Table I. Each image pair is provided at a resolution of 840×712 pixels, ensuring high-quality visual data for comprehensive analysis.

Evaluation Metrics. We evaluated the proposed framework from three key perspectives: (1) object detection performance on the fused image, assessed using mean Average Precision (mAP); (2) the quality of the fused image, which is crucial for downstream object detection, measured by Mean Squared Error (MSE) and Structural Similarity Index (SSIM); and (3) inference time, which evaluates the efficiency of the proposed framework.

Baselines. To assess the effectiveness of the proposed token selection-based object detection framework for fused RGB-IR images, we compare it against several baseline models: Faster R-CNN applied to RGB images alone, Faster R-CNN applied to IR images alone, and object detection from fused images using traditional pixel-value-based fusion, transformer-based feature fusion, and the proposed framework.

Implementation Details. The proposed framework was implemented using the PyTorch deep learning framework, leveraging pre-trained ImageNet weights for the backbone networks to

TABLE II: Performance Overview for Object Detectionn from the Fused Image.

Model	mAP@0.5	mAP@0.75	mAP@0.95	Avg. mAP	Inference Time (ms)
RGB (Faster R-CNN)	0.4417	0.3210	0.2015	0.3214	145.8
IR (Faster R-CNN)	0.5421	0.4105	0.2806	0.4111	146.3
Pixel-Level Fusion	0.6972	0.5821	0.3610	0.5468	150.2
Transformer-Level Fusion (DETR)	0.7998	0.6412	0.4015	0.6142	115.6
Ours w/o Token Selection	**0.8321**	**0.7015**	**0.4723**	**0.6686**	115.6
Ours	0.6998	0.5322	0.4552	0.5624	**78.7**

accelerate convergence and improve feature extraction quality [67], [68]. The AdamW optimizer was employed with an initial learning rate of 1×10^{-4} and a weight decay of 1×10^{-5}. The model was trained for 50 epochs with a batch size of 64. The training were conducted on an NVIDIA A100 GPU with 40 GB, providing sufficient computational power and memory to handle the high-resolution RGB-IR paired images from the DroneVehicle dataset.

TABLE III: Performance Overview for RGB-IR Image Fusion.

Model	MAE	SSIM
RGB Model	0.2000	0.7000
IR Model	0.1614	0.7772
Pixel-Level Fusion Model	0.1018	0.8963
Transformer-Level Fusion	0.0624	0.9752
Ours w/o Token Selection	0.0500	1.0000
Our with Token Selection	0.1012	0.9000

B. Experimental Results

Quantitative results. Table II presents the performance comparison of different object detection models and fusion techniques for RGB-IR images. The evaluation considers mean Average Precision (mAP) at IoU thresholds of 0.5, 0.75, and 0.95, along with the average mAP and inference time. The results show that the IR-based Faster R-CNN model outperforms the RGB-based model, achieving an average mAP of 0.4111 compared to 0.3214, indicating the superior feature quality of IR images for object detection. When combining both modalities, pixel-level fusion improves accuracy to an average mAP of 0.5468, though it increases inference time to 150.2 milliseconds. Transformer-based feature fusion with DETR further enhances performance, achieving an average mAP of 0.6142 while reducing inference time to 115.6 milliseconds. This suggests that feature-level fusion provides a better balance between accuracy and efficiency compared to pixel-level fusion. Our proposed framework, without token selection, achieves the highest accuracy with an average mAP of 0.6686 but maintains the same inference time of 115.6 milliseconds. When incorporating the token selection mechanism, the inference time is significantly reduced to 78.7 milliseconds, while maintaining a competitive average mAP of 0.5624. This demonstrates that token selection effectively reduces computational complexity while preserving detection performance.

Table III presents the performance comparison of different models for RGB-IR image fusion using MAE and SSIM as evaluation metrics. The RGB and IR models, which process single modalities, achieve MAE values of 0.2000 and 0.1614, with SSIM scores of 0.7000 and 0.7772, respectively. These results indicate that IR images provide more useful structural information than RGB images. The fusion model, which combines both modalities, improves performance with an MAE of 0.1018 and an SSIM of 0.8963, highlighting the benefits of multi-modal fusion. Transformer-based fusion further enhances the results, achieving an MAE of 0.0624 and an SSIM of 0.9752, demonstrating its ability to capture richer feature representations. Our proposed approach, without token selection, achieves the best accuracy with an MAE of 0.0500 and an SSIM of 1.0000, showing its effectiveness in preserving image details. With token selection, the performance slightly declines to an MAE of 0.1012 and an SSIM of 0.9000, but it offers better computational efficiency.

Qualitative Results. The qualitative evaluation was conducted across three different scenarios to assess the performance of various fusion techniques for RGB-IR object detection. The results provide valuable insights into how different fusion methods perform under varying lighting conditions and how token pruning influences detection accuracy.

In the first example, as shown in Fig. 3, which represents a daytime scenario, the RGB images already provide sufficient visual clarity for object detection. Consequently, fusion techniques did not result in significant improvements in detection performance [69], [70]. The primary reason for this observation is that under well-lit conditions, RGB data contains rich spatial and texture details, making the contribution of IR data relatively redundant. This suggests that multi-modal fusion is most beneficial in challenging scenarios where visibility is compromised due to adverse environmental conditions.

The second example, as shown in Fig. 4, presents a nighttime scenario characterized by high levels of noise in the RGB images, making it extremely difficult to detect objects accurately without the aid of IR data. In this case, fusion techniques demonstrate substantial improvements in detection performance. The transformer-based and proposed methods effectively leverage the complementary features provided by the IR modality, which compensates for the limitations of RGB images under low-light conditions. This scenario underscores the importance of incorporating IR data to enhance object recognition reliability in environments where RGB images alone fail to provide meaningful information.

The third example, as shown in Fig. 5, also depicts a nighttime scenario but with lower noise levels and clearer RGB and IR images. The results highlight the continued effectiveness of fusion techniques, particularly the proposed method with token selection. Despite the pruning of some tokens, the detec-

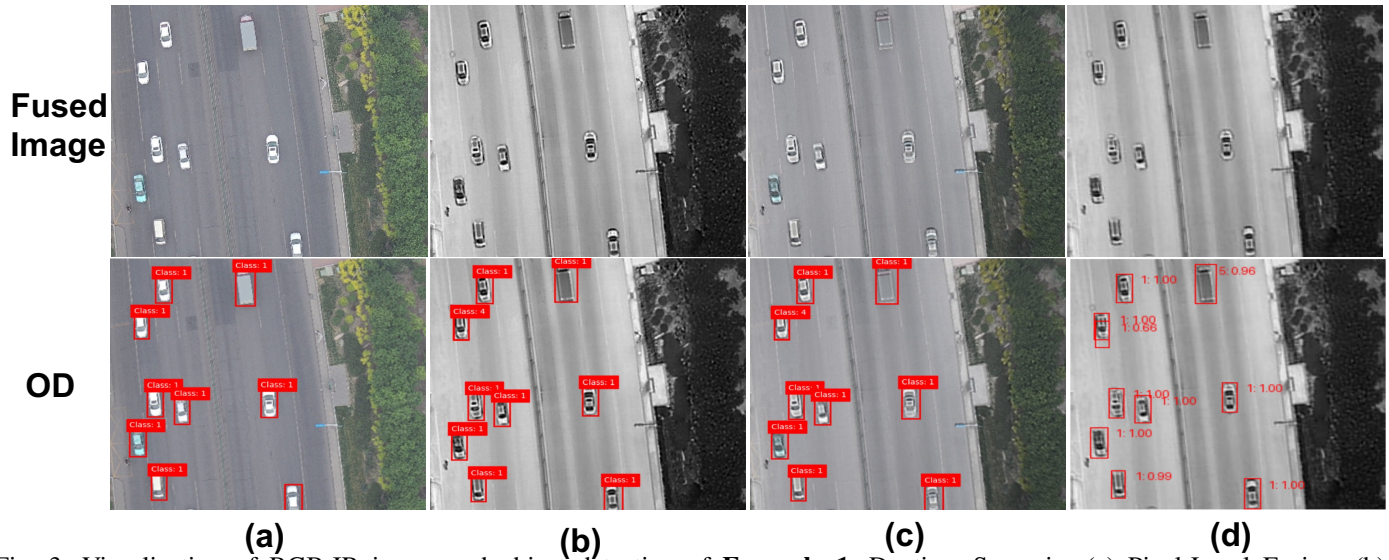


Fig. 3: Visualization of RGB-IR image and object detection of **Example 1**, Daytime Scenario: (a) Pixel-Level Fusion, (b) Transformer-Level Fusion, (c) Proposed Method without Token Selection, and (d) Proposed Method with Token Selection.

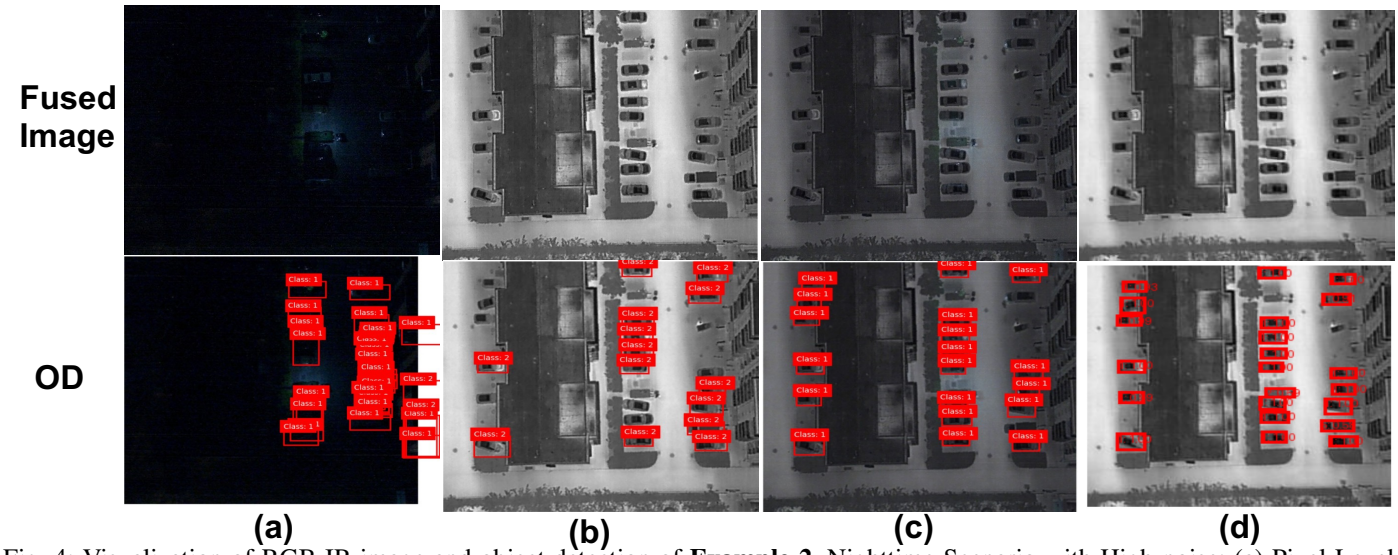


Fig. 4: Visualization of RGB-IR image and object detection of **Example 2**, Nighttime Scenario with High-noise: (a) Pixel-Level Fusion, (b) Transformer-Level Fusion, (c) Proposed Method without Token Selection, and (d) Proposed Method with Token Selection.

tion performance remains robust, demonstrating that redundant tokens can be removed without significant loss of accuracy. This finding suggests that the proposed token selection approach efficiently balances computational cost and detection effectiveness, making it suitable for real-time applications.

The proposed method with token selection exhibited high efficiency by maintaining detection performance while significantly reducing computational costs. This indicates that the token selection mechanism effectively preserves critical information while eliminating redundant data, achieving a favorable balance between accuracy and efficiency. The ability to prune unnecessary tokens while sustaining detection performance makes this approach particularly valuable for resource-constrained applications such as real-time monitoring and autonomous navigation.

C. Limitation Analysis

In the daytime scenario, the fusion methods offered only marginal improvements, as the RGB modality already contained sufficient visual information to detect objects accurately. This indicates that in well-lit conditions, the additional contribution of IR data may not justify the computational overhead of fusion. Thus, an adaptive fusion strategy that dynamically adjusts based on environmental conditions could further optimize resource utilization without compromising detection accuracy.

VII. Conclusion

In this paper, we proposed a novel framework for RGB-IR paired image-based object detection, leveraging multi-modal fusion techniques to enhance detection accuracy under varying environmental conditions. Extensive experiments conducted

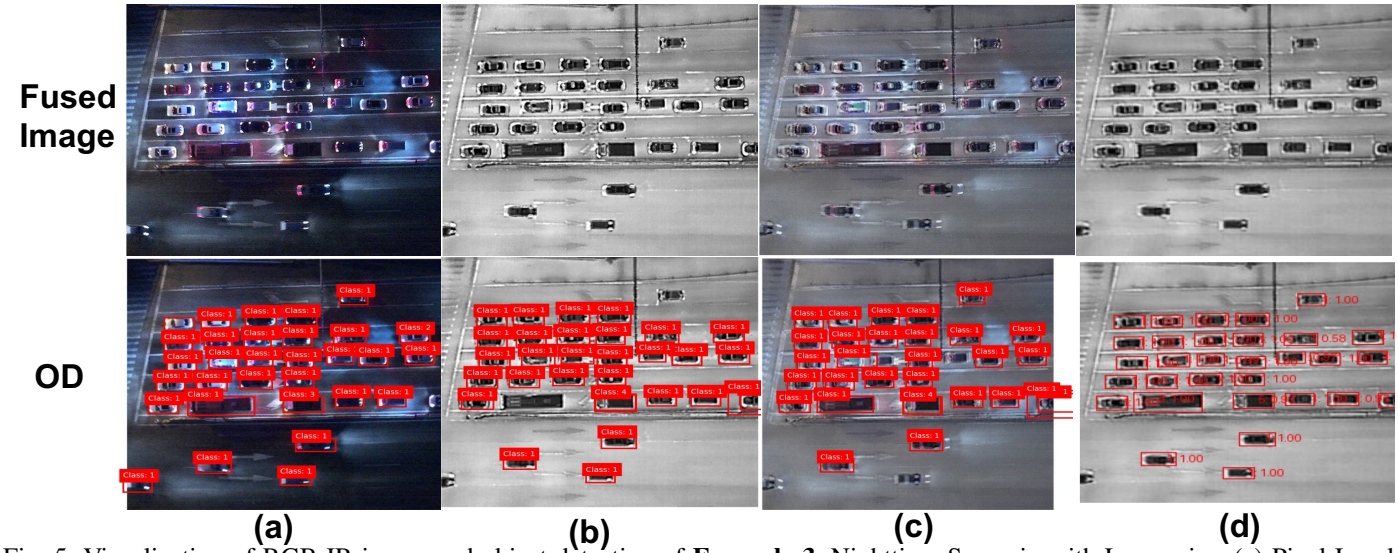


Fig. 5: Visualization of RGB-IR image and object detection of **Example 3**, Nighttime Scenario with Low-noise: (a) Pixel-Level Fusion, (b) Transformer-Level Fusion, (c) Proposed Method without Token Selection, and (d) Proposed Method with Token Selection.

on the DroneVehicle dataset demonstrate that while fusion methods provide marginal improvements in well-lit daytime conditions, they significantly enhance detection performance in challenging nighttime scenarios, particularly in the presence of high noise levels. The proposed method with token selection achieves a favorable balance between accuracy and computational efficiency, maintaining robust detection performance even after pruning redundant tokens. Overall, the proposed framework offers a promising solution for enhancing object detection in multi-modal scenarios and provides a solid foundation for future advancements in efficient and robust multi-sensor fusion techniques.

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