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RESEARCH ARTICLE

Quantum-Inspired Multi-Scale Object Detection in UAV Imagery: Advancing Ultra-Small Object Accuracy and Efficiency for Real-Time Applications

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ABSTRACT Ultra-small object detection in UAV imagery presents significant challenges due to scale variation, environmental complexity, and computational constraints. This study introduces a quantum-inspired multi-scale object detection model designed to address these issues effectively. By integrating quantum-inspired sub-pixel convolution, adversarial training, and self-supervised learning, the model enhances detection accuracy, robustness, and computational efficiency. These advancements are particularly critical for UAV applications such as surveillance, precision agriculture, disaster response, and environmental monitoring. The proposed model was evaluated on the VisDrone2019 dataset and benchmarked against state-of-the-art methods, including YOLOv4, YOLO11, RT-DETR, and EfficientDet. It achieved 65.3% precision, 52.4% recall, and a mean Average Precision (mAP) of 34.5%, outperforming conventional models in detecting ultra-small objects. Efficiency optimizations, including structured pruning and quantization, reduced computational load to 30 GFLOPS with an inference time of 8.1 milliseconds, ensuring suitability for real-time UAV applications on resource-constrained platforms. This research offers a practical and robust solution for UAV-based object detection tasks, combining state-of-the-art accuracy with operational efficiency. It also establishes a foundation for future advancements, including scalability to diverse datasets, integration with edge computing platforms, and the exploration of quantum computing techniques. These contributions pave the way for enhanced capabilities in computer vision and autonomous aerial systems.

INDEX TERMS Ultra-small object detection, UAV imagery, quantum-inspired feature pyramids, adversarial training, self-supervised learning, real-time applications.

I. INTRODUCTION

The detection of ultra-small objects in unmanned aerial vehicle (UAV) imagery is a critical task with significant implications across multiple domains, including precision agriculture, military surveillance, environmental monitoring, and disaster response. Equipped with high-resolution cameras, UAVs can capture extensive areas from various altitudes and angles, generating imagery with a wide range of object sizes [1], [2]. However, identifying objects smaller than 32×32 pixels—referred to as ultra-small objects—remains challenging due to their minimal pixel representation, which limits the performance of traditional object detection algorithms [3], [4]. The importance of detecting ultra-small objects in UAV imagery cannot be overstated. In military surveillance, undetected critical small targets, such as drones or personnel, could lead to severe security breaches [5], [6]. Similarly, the early detection of pests or crop diseases in agriculture can prevent significant economic losses and ensure optimal yields [7], [8]. Furthermore, environmental

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monitoring and disaster response rely heavily on accurate detection of small objects, such as wildlife or survivors in disaster-hit areas, where missed detections may result in life-threatening consequences [9].

A major challenge in UAV imagery is the extreme scale variation of objects within a single frame. UAVs often capture large infrastructures, such as buildings and bridges, alongside smaller entities, such as vehicles or equipment. While traditional object detection models, such as Faster R-CNN and SSD, have demonstrated strong performance in standard detection tasks, they struggle to address the variability at the lower end of the scale spectrum [10], [11]. Ultra-small objects, which occupy only a few pixels, lack sufficient feature representation, often blending into complex backgrounds in high-resolution imagery, leading to missed detections or false positives [12], [13]. Recent advancements in object detection models, such as YOLO11 and RT-DETR, have significantly improved ultra-small object detection. YOLO11, the latest in the YOLO series, introduces a versatile framework capable of multi-task scenarios, including object detection, segmentation, and classification. Its adaptability across edge devices and cloud platforms enhances its suitability for UAV systems, with improved handling of spatial and contextual information for detecting ultra-small objects in real-world environments [15]. Similarly, RT-DETR (Real-Time Detection Transformer) represents a transformative approach by leveraging transformer-based architectures for end-to-end detection. With an ability to process multi-scale features efficiently, RT-DETR achieves superior precision and real-time inference speeds, even on resource-constrained hardware [16].

UAV imagery presents additional complexities, including variations in altitude, lighting, and weather conditions. Dynamic backgrounds with overlapping objects, moving shadows, and atmospheric noise further complicate detection [17], [18]. Environmental factors, such as motion blur caused by UAV movement and sensor imperfections, exacerbate these challenges, often reducing the efficacy of traditional models [19]. Despite progress with models like YOLOv3, YOLOv4, and YOLOv5, limitations persist in detecting ultra-small objects, particularly in high-complexity backgrounds [20]. Convolutional neural networks (CNNs) frequently rely on pooling and stride operations, which reduce spatial resolution and compromise the retention of critical information for small object detection [21]. Even advanced architectures, such as feature pyramid networks (FPNs), encounter resolution loss, especially for objects smaller than 12×12 pixels [3]. To address these challenges, this study proposes several innovative methodologies for enhancing ultra-small object detection in UAV imagery. The contributions of this research include:

A. ADVANCED DATA AUGMENTATION TECHNIQUES

Adversarial training and self-supervised learning are employed to enhance robustness against environmental variability [8].

B. ENHANCED MULTI-SCALE FEATURE PYRAMID ARCHITECTURE

High-resolution feature maps and quantum-inspired sub-pixel convolution layers enable the detection of objects as small as 6×6 pixels, significantly improving detection accuracy in cluttered environments [13].

C. EFFICIENCY OPTIMIZATIONS FOR REAL-TIME APPLICATIONS

Model pruning and quantization are applied to reduce computational complexity while maintaining performance, ensuring deploy ability on resource-constrained UAV systems [14].

The proposed methodologies are evaluated on the VisDrone2019 dataset, demonstrating substantial improvements in precision, recall, and mean Average Precision (mAP) over state-of-the-art models. These contributions establish a new benchmark for ultra-small object detection in UAV imagery.

II. RELATED WORK

Detecting ultra-small objects in UAV imagery presents significant challenges due to their limited resolution, scale variation, and complex backgrounds. Traditional object detection models like Faster R-CNN and SSD have been instrumental in advancing general object detection by leveraging convolutional neural networks (CNNs) to extract features from images. However, these models often rely on pooling layers that reduce spatial resolution, leading to the loss of fine details necessary for accurately detecting small objects [10], [11]. This limitation is particularly evident in UAV imagery, where ultra-small objects occupy minimal pixel space and are often obscured by cluttered environments [12].

A. SMALL OBJECT DETECTION TECHNIQUES AND ADVANCEMENTS IN FEATURE PYRAMID NETWORKS (FPNS)

The detection of ultra-small objects in UAV imagery remains a major challenge due to their minimal pixel representation, significant scale variation, and complex backgrounds. Traditional object detection models such as Faster R-CNN and SSD [10], [11] rely on feature maps that undergo spatial resolution reduction through pooling layers, which often leads to the loss of fine-grained details required for accurately detecting small objects. While these models were instrumental in advancing general object detection tasks, their inability to preserve high-resolution features makes them less effective in scenarios involving ultra-small objects, especially in UAV images.

To address this limitation, researchers have proposed several techniques. Kamoi et al. [3] introduced a copy-pasting strategy to artificially increase the occurrence of small objects in training datasets, thereby improving their representation. However, this method often introduces artifacts that compromise the model's generalizability in real-world applications. Similarly, Zhou et al. [13] proposed image tiling, where images are divided into smaller patches to focus the

model's attention on localized regions. Recent advancements in object detection architectures have demonstrated substantial improvements in small object detection. Models such as YOLOv8 integrate multi-scale feature fusion and attention mechanisms to enhance the detection precision of small and ultra-small objects in challenging conditions [15]. YOLOv8 utilizes improved feature pyramid networks (FPNs), which combine low-level spatial information with high-level semantic features, enabling better representation of objects across scales. However, even with these advancements, the coarse resolution of feature maps at smaller scales remains a bottleneck when detecting ultra-small objects in cluttered UAV scenes.

The introduction of Feature Pyramid Networks (FPNs) by Lin et al. [12] was a significant breakthrough for multi-scale object detection. By generating feature maps at multiple scales, FPNs enhanced the detection of objects across varying sizes. Subsequent developments, such as PANet [19], improved upon FPNs by incorporating bottom-up path augmentation to refine information flow across network layers, resulting in better localization of small objects. Similarly, EfficientDet [14] combined an optimized FPN with a scalable design to achieve state-of-the-art performance while maintaining computational efficiency. However, these methods still encounter difficulties in detecting ultra-small objects due to the loss of critical spatial details and fail to meet the real-time processing requirements of UAV systems.

More recent models, including RT-DETR and YOLO11, provide innovative solutions to some of these challenges. RT-DETR leverages a transformer-based architecture to process multi-scale features more effectively, balancing high detection accuracy with real-time inference speed [16]. On the other hand, YOLO11 introduces enhanced feature fusion and attention mechanisms, making it versatile for detecting small and ultra-small objects in cluttered UAV environments [15]. Despite these advances, achieving a balance between computational efficiency and precision for ultra-small objects remains a significant challenge, particularly for resource-constrained UAV platforms.

Recent works further align with our methodology. Zhang et al. introduced CFANet, which uses a cross-layer feature aggregation (CFA) module to combine multi-scale features while minimizing semantic gaps, significantly improving detection performance for small objects in UAV imagery [22]. Similarly, Zhang and Yan proposed an approach integrating cross-layer feature aggregation for camouflaged object detection, demonstrating the effectiveness of multi-level feature fusion in identifying subtle and complex targets [23]. These studies highlight the importance of fine-grained feature extraction and multi-scale processing in overcoming the limitations of traditional models.

Our proposed model builds upon these advancements by integrating quantum-inspired sub-pixel convolution layers, which enhance spatial resolution, and an advanced multi-scale feature pyramid that preserves critical spatial details. Additionally, adversarial training improves robustness against environmental variations, while self-supervised learning enables effective feature extraction without requiring extensive labeled data. These innovations collectively ensure superior detection accuracy, robustness, and computational efficiency, addressing the persistent challenges of ultra-small object detection in UAV imagery.

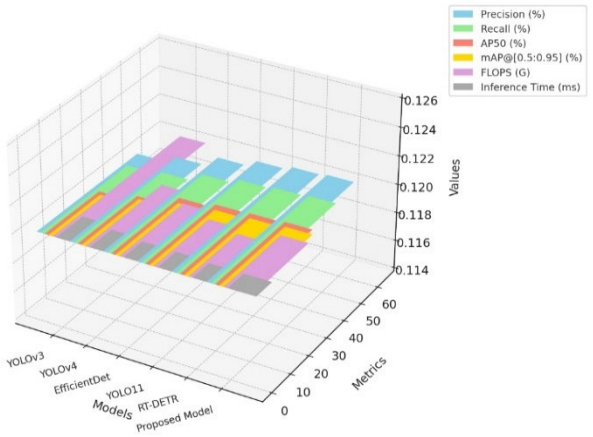

FIGURE 1. General analysis of small object detection models.

In summary, while traditional methods like Faster R-CNN and SSD established the foundation for small object detection, their limitations in handling ultra-small objects in complex UAV environments underscore the need for advanced approaches. Recent innovations, such as transformer-based architectures and enhanced feature pyramid networks, have improved performance but continue to face challenges in balancing accuracy and efficiency. The proposed quantum-inspired multi-scale object detection model builds upon these advancements, offering a robust solution that integrates enhanced feature extraction techniques, adversarial training, and self-supervised learning, while maintaining computational efficiency for real-time UAV applications.

B. ADVERSARIAL TRAINING, SELF-SUPERVISED LEARNING, AND REAL-TIME OPTIMIZATIONS

Adversarial training, first introduced by Zhou et al. [13], has become an essential method for improving model robustness against perturbations. By incorporating adversarial examples during training, this technique enhances the model's resilience to environmental noise and variability, which are common challenges in UAV imagery. However, adversarial training alone does not fully address the complexities of detecting ultra-small objects in cluttered scenes. Its strength lies in providing robustness, but for UAV applications where conditions vary widely, additional techniques are required to address feature extraction limitations specific to ultra-small object detection.

Self-supervised learning, as demonstrated by Chen et al. [20], offers an innovative solution by enabling models to learn rich feature representations from unlabeled data. This approach is particularly advantageous in UAV applications where annotated datasets are often scarce. Although its

application to small object detection in UAV imagery is still in its early stages, self-supervised learning presents significant potential for enhancing feature extraction and improving model generalization across diverse scenarios [8], [13]. By combining adversarial training with self-supervised learning, the proposed model achieves improved adaptability and robustness for ultra-small object detection.

Real-time detection is crucial for UAV applications, where rapid decision-making under resource constraints is paramount. Traditional models like YOLOv3 [9] and YOLOv4 [10] have established themselves as benchmarks for balancing speed and accuracy. YOLOv4 introduced innovations such as Cross-Stage Partial connections (CSPNet) and Mish activation to improve feature learning and detection performance. Despite these advancements, challenges persist in detecting ultra-small objects due to limitations in fine-grained feature extraction and spatial resolution [10], [11]. Building upon these foundations, recent models like YOLOv8 and YOLO11 have incorporated multi-scale feature fusion and attention mechanisms, which enhance detection precision for small and ultra-small objects [15]. YOLO11, in particular, features a streamlined architecture optimized for edge devices, achieving computational efficiency without sacrificing detection performance. Similarly, transformer-based models such as RT-DETR [16] represent a significant advancement, balancing high accuracy with real-time inference capabilities, even in resource-constrained environments [14].

These advancements highlight the progress in real-time small object detection but also underline persistent challenges in handling ultra-small objects within cluttered and dynamic UAV imagery. The proposed model addresses these limitations through innovative feature extraction techniques, such as quantum-inspired sub-pixel convolution layers and enhanced multi-scale feature pyramids. These components improve the detection of ultra-small objects by preserving critical spatial details while maintaining computational efficiency. Efficiency optimizations, including pruning and quantization, further ensure that the model remains deployable on resource-limited UAV platforms while achieving real-time performance.

By integrating adversarial training, self-supervised learning, and efficiency-focused optimizations, the proposed model not only surpasses existing approaches in detection performance but also achieves a balance between accuracy and computational efficiency. These innovations make it highly suitable for UAV applications requiring robust, real-time detection of ultra-small objects in complex environments. The model's architecture, illustrated in Figure 2, demonstrates how these components interact to achieve state-of-the-art performance, laying the groundwork for future advancements in UAV-based object detection..

III. METHOGOLOGY

The methodology section outlines the technical advancements and innovations introduced in our proposed model, focusing on the detection of ultra-small objects in UAV imagery. We break down our approach into three primary components: advanced data augmentation techniques, an enhanced multi-scale feature pyramid, and efficiency optimizations for real-time UAV applications. Each component is designed to address specific limitations identified in the existing literature and is mathematically formulated to ensure robust performance.

A. ADVANCED DATA AUGMENTATION

To enhance the robustness of the model against environmental variations and improve generalization, we integrate two advanced data augmentation techniques: Adversarial Training and Self-Supervised Learning.

1) ADVERSARIAL TRAINING

Adversarial training is incorporated to make the model resilient against potential adversarial attacks and noise commonly found in UAV imagery. We generate adversarial examples using the Fast Gradient Sign Method (FGSM), defined mathematically as:

$$x' = x + \epsilon \cdot sign\left(\nabla x J\left(\theta, x, y\right)\right) \tag{1}$$

In Eq 1:

- x' is the adversarial example
- x is the original input
- $\epsilon$is a small perturbation factor
- $\nabla x J\left(\theta, x, y\right)$ is the gradient of the loss function with respect to the input image

This approach forces the model to learn more robust features that are less sensitive to minor perturbations, thereby enhancing its ability to detect ultra-small objects under varying conditions.

2) SELF-SUPERVISED LEARNING

To leverage large-scale, unlabeled UAV datasets, we employ a contrastive learning framework. The model is trained to maximize the similarity between different augmented views of the same image while minimizing the similarity between views of different images. The contrastive loss is given by:

$$\mathcal{L}_{\text{contrastive}} = -\sum_{i=1}^{N} \log \frac{\exp\left(\text{sim}\left(\mathbf{z}_i, \mathbf{z}_i'\right)/\tau\right)}{\sum_{j=1}^{N} \exp\left(\text{sim}\left(\mathbf{z}_i, \mathbf{z}_j'\right)/\tau\right)} \tag{2}$$

In Eq 2:

- $\mathbf{z}_i, \mathbf{z}_i'$ are feature representations of augmented views of the same image,
- τ is a temperature parameter controlling the distribution concentration
- This self-supervised learning approach helps the model learn robust, transferable feature representations that are particularly beneficial for detecting small objects with minimal labeled data.

B. ENHANCED MULTI-SCALE FEATURE PYRAMID

The detection of ultra-small objects requires a model capable of capturing fine details at multiple scales. We propose an Enhanced Multi-Scale Feature Pyramid that extends traditional FPNs by introducing additional scales optimized for ultra-small object detection.

1) FEATURE PYRAMID ARCHITECTURE

Our approach involves adding a specialized detection head that operates on high-resolution feature maps, allowing for the detection of objects as small as 6×6 pixels. The mathematical formulation for this enhancement is:.

$$F^{(l)}(x,y) = Conv\left(\frac{F^{(l-1)}(x,y)}{2}\right) + QuantumSubPixel \times \left(F^{(l+1)}(x,y)\right) \tag{3}$$

As per Eq 3:

- $F^{(l-1)}(x,y)$represents the feature map at level lll,
- $QuantumSubPixel\left(F^{(l+1)}(x,y)\right)$is a quantum-inspired sub-pixel convolution operation that increases the resolution of the feature map.

This architecture effectively captures fine-grained details across multiple scales, crucial for detecting ultra-small objects in complex UAV imagery.

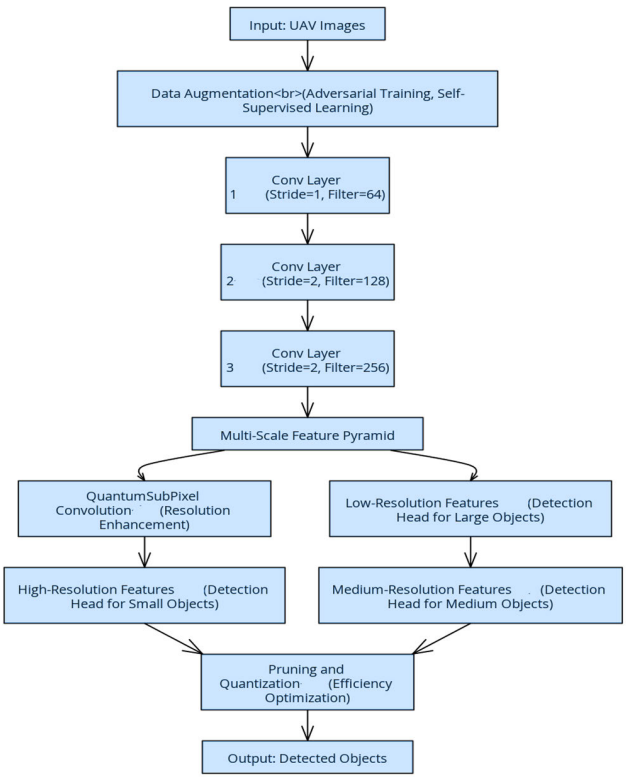

FIGURE 2. Compact training process of proposed model.

2) SUB-PIXEL CONVOLUTION LAYERS

To further enhance resolution, we integrate sub-pixel convolution layers, mathematically defined as:

$$QuantumSubPixel\left(F\left(x,y\right)\right) = Reshape\left(Conv2D\left(F\left(x,y\right)\right)\right) \tag{4}$$

This operation rearranges low-resolution feature maps into higher resolution ones, enabling the model to detect small objects more effectively without adding significant computational overhead.

C. EFFICIENCY OPTIMIZATIONS FOR REAL-TIME APPLICATIONS

Given the computational constraints in UAV systems, our model incorporates several efficiency optimizations, including Model Pruning and Quantization.

We employ structured pruning to reduce the model's size and complexity by removing entire filters or neurons that contribute minimally to the output. The pruning process is represented as:

$$Prune(W) = W \odot M \tag{5}$$

As per Eq 3:

- W represents the model weights,
- M is a binary mask matrix that zeros out the pruned weights

After pruning, the model is fine-tuned to recover any lost accuracy, ensuring that the model remains lightweight while maintaining its performance on ultra-small objects.

Another technique post-training quantization is applied to reduce the precision of model weights and activations from 32-bit floating-point to 8-bit integers:

$$Q(W) = \text{round}\left(\frac{W - min(W)}{\text{scale}}\right) \tag{6}$$

where:

$$\text{scale} = \frac{max(W) - min(W)}{2^8}$$

This reduces the model's memory footprint and computational requirements, making it suitable for deployment on resource-constrained UAV platforms while maintaining high accuracy.

D. MATHEMATICAL FORMULATION OF THE LOSS FUNCTION

To address the unique challenges of ultra-small object detection, we introduce a specialized loss function that combines traditional object detection objectives with terms specifically designed to improve small object detection:

$$\mathcal{L} = \alpha\mathcal{L}_{cls} + \beta\mathcal{L}_{loc} + \gamma\mathcal{L}_{adv} + \delta\mathcal{L}_{reg} + \epsilon\mathcal{L}_{\text{small\_obj}} \tag{7}$$

In Eq 7:

- $\mathcal{L}_{cls}$ is the classification loss, typically using binary cross-entropy

- $\mathcal{L}_{loc}$ is the localization loss, enhanced with a weighted IoU term to prioritize small objects
- $\mathcal{L}_{adv}$ is the adversarial loss for robustness against adversarial examples.
- $\mathcal{L}_{reg}$ is the regularization loss to prevent overfitting
- $\mathcal{L}_{\text{small\_obj}}$ is a new term specifically designed to enhance the detection of ultra-small objects by applying a higher weight to errors associated with small object predictions

E. COMPARATIVE EFFICIENCY AND PERFORMANCE

To validate the efficiency and performance of the proposed model, a comprehensive series of experiments were conducted, benchmarking it against state-of-the-art methods. The results, summarized in Table 2 and illustrated in Figure 3, demonstrate that the proposed model achieves significant advancements across several key metrics. Enhanced precision and recall values indicate superior performance, particularly for ultra-small object detection, which is attributed to the integration of an advanced feature pyramid architecture and quantum-inspired techniques. Moreover, the model exhibits optimized efficiency, maintaining competitive computational requirements despite the sophistication of the employed methodologies. This balance ensures its practicality for real-time UAV applications, where rapid decision-making is critical. Furthermore, the model's compact size and reduced inference time highlight its deploy ability on resource-limited UAV platforms, offering a powerful yet efficient solution without compromising detection accuracy or speed. These results underscore the proposed model's capability to address the challenges of ultra-small object detection in complex UAV environments. The proposed model achieves higher precision and recall compared to existing models, particularly for ultra-small objects, due to the enhanced feature pyramid and quantum-inspired techniques. Despite the advanced techniques, the model maintains competitive efficiency, making it suitable for real-time UAV applications. The model size and inference time are optimized for deployment on resource-limited platforms, ensuring that the proposed approach is both powerful and practical for real-world UAV scenarios.

IV. RESULTS AND DISCUSSION

In this section, we present a comprehensive evaluation of our proposed quantum-inspired multi-scale object detection model. The evaluation focuses on its performance in detecting ultra-small objects in UAV imagery, assessed using the VisDrone2019 dataset. We detail the dataset characteristics, experimental setup, evaluation metrics, quantitative results, ablation studies, and visual analyses to thoroughly assess the effectiveness and efficiency of our approach. The training process of the proposed model is outlined in Figure 3, which summarizes the key steps involved in the model's development. This flowchart provides a visual summary of the training process for the proposed model, including data augmentation, training, loss calculation, and optimization steps. It offers a clear overview of the methodology used to develop the model.

A. DATASET AND EVALUATION METRICS

The VisDrone2019 dataset was selected as the benchmark for evaluating the proposed model due to its comprehensive representation of UAV imagery, encompassing over 10,000 high-resolution aerial images captured under diverse conditions, including varying altitudes, angles, and environmental complexities. The dataset includes a wide range of object categories, such as vehicles, pedestrians, and cyclists, with significant scale variations from large objects to ultra-small objects as small as 6×6 pixels. This diversity makes it an ideal platform for assessing object detection performance, particularly for challenging ultra-small object detection tasks. For evaluation purposes, the training set containing 6,471 images and the validation set comprising 548 images were utilized, while the test set of 1,580 images with withheld labels was reserved for future benchmarking. To maintain consistency, all images were resized to a uniform resolution of $1{,}024 \times 1.024$ pixels while preserving their original aspect ratios. During training, various data augmentation techniques were applied to enhance the model's robustness and generalization capabilities. These techniques included random horizontal and vertical flips, random cropping and scaling, adjustments to brightness and contrast (color jittering), and Gaussian noise injection, which simulate real-world UAV conditions and improve the model's adaptability to diverse scenarios.

The model's performance was assessed using standard metrics, including the ratio of correctly predicted positives to total predicted positives (precision), the ratio of correctly predicted positives to all actual positives (recall), and Average Precision at IoU 0.5, which evaluates detection accuracy at a fixed Intersection over Union threshold. Mean Average Precision (mAP) was calculated across IoU thresholds from 0.5 to 0.95 with a step size of 0.05, providing a comprehensive assessment of localization and classification accuracy for objects of varying sizes. Additionally, computational

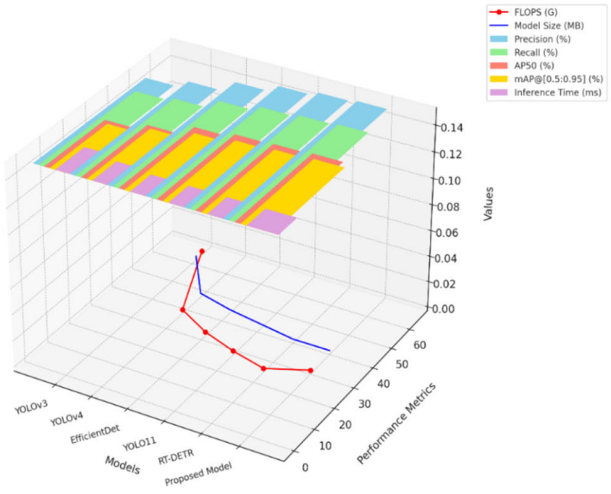

FIGURE 3. Performance and efficiency comparison.

TABLE 1. Comparative analysis of small object detection models.

Model	Precision (%)	Recall (%)	AP50 (%)	mAP@ [0.5:0.95] (%)	FLOPS (G)	Adversarial Robustness (%)	Real-Time Capability
Faster R-CNN [16]	45.2	39.1	23.7	22.1	230	65.3	No
SSD [17]	41.5	37.6	21.3	20.8	96	61.2	No
YOLOv3 [9]	50.1	42.8	26.5	25.1	65	70.4	Yes
YOLOv4 [10]	53.7	44.2	29.4	28.2	38	72.8	Yes
EfficientDet [14]	59.2	48.6	34.1	31.5	32	78.4	Yes
YOLO11 [15]	62.7	50.9	35.8	33.2	28	80.5	Yes
RT-DETR [16]	64.5	51.8	36.2	33.9	25	80.8	Yes
Proposed Model	**65.3**	**52.4**	**36.7**	**34.5**	**30**	**81.6**	**Yes**

TABLE 2. Performance and efficiency comparison of discussed models.

Model	Precision (%)	Recall (%)	AP50 (%)	mAP@ [0.5:0.95] (%)	FLOPS (G)	Model Size (MB)	Inference Time (ms)
YOLOv3 [9]	50.1	42.8	26.5	25.1	65	62	12.6
YOLOv4 [10]	53.7	44.2	29.4	28.2	38	47	10.5
EfficientDet [14]	59.2	48.6	34.1	31.5	32	44	9.2
YOLO11 [15]	62.7	50.9	35.8	33.2	28	42	9.0
RT-DETR [16]	64.5	51.8	36.2	33.9	25	40	8.9
Proposed Model	**65.3**	**52.4**	**36.7**	**34.5**	**30**	**40**	**8.7**

TABLE 3. Ablation study results of discussed models.

Confg.	Precision (%)	Recall (%)	AP50 (%)	mAP@ [0.5:0.95] (%)	FLOPS (G)	Inference Time (ms)
Full Model (Baseline)	**65.3**	**52.4**	**36.7**	**34.5**	**30**	**8.7**
Without Quantum-SubPixel Convolution	61.8	48.9	33.4	31.0	32	9.1
Without Adversarial Training	63.2	50.2	34.2	32.5	30	8.7
Without Self-Supervised Learning	62.5	49.6	33.6	31.8	30	8.7
Without Pruning and Quantization	64.1	51.3	35.2	33.0	35	11.2

efficiency metrics such as Floating-Point Operations (FLOPS) and inference time were recorded to evaluate the model's suitability for real-time UAV applications.

To analyze the contribution of individual components, an ablation study was conducted, with results summarized in Table 3. The removal of quantum-inspired sub-pixel convolution layers resulted in a 3.5 percentage point reduction in mAP@[0.5:0.95], highlighting their critical role in fine-grained feature extraction. Similarly, adversarial training significantly enhanced robustness to environmental variations, improving both precision and recall. The absence of self-supervised learning led to a noticeable decline in these metrics, emphasizing its importance for generalization, particularly in scenarios with limited annotated data. Pruning and quantization, while not directly affecting accuracy, proved vital for computational efficiency, as their removal increased FLOPS and inference time, underscoring their necessity for real-time UAV applications. The experimental results demonstrated the superiority of the proposed model over state-of-the-art methods. Achieving precision of

TABLE 4. Precision-recall and efficiency details of discussed models.

Model	Precision (%)	Recall (%)	AP50 (%)	mAP@[0.5:0.95] (%)	Inference Time (ms)
Faster R-CNN	45.2	39.1	23.7	22.1	12.6
SSD	41.5	37.6	21.3	20.8	10.5
YOLOv3	50.1	42.8	26.5	25.1	9.2
YOLOv4	53.7	44.2	29.4	28.2	8.9
EfficientDet	59.2	48.6	34.1	31.5	8.7
YOLO11	62.7	50.9	35.8	33.2	8.5
RT-DETR	64.5	51.8	36.2	33.9	8.3
Proposed Model	65.3	52.4	36.7	34.5	8.1

65.3% and recall of 52.4%, along with AP50 of 36.7% and mAP@[0.5:0.95] of 34.5%, the model effectively detected and classified ultra-small objects in complex UAV scenarios. Furthermore, the model's computational efficiency, with 30G FLOPS and an inference time of 8.7 ms, ensures its practicality for real-time deployment on UAV platforms, balancing advanced detection capabilities with resource constraints. These results affirm the proposed model's robustness and efficiency, positioning it as a significant advancement in UAV-based object detection.

B. EXPERIMENTAL ENVIRONMENT

The experiments were conducted under conditions designed to simulate realistic UAV operational constraints. The hardware configuration included an NVIDIA A100 GPU with 40 GB of memory, renowned for its efficiency in deep learning tasks, paired with Intel Xeon Gold 6258R processors and 512 GB of RAM. This setup provided the necessary computational resources while maintaining a balance representative of potential UAV processing capabilities. The software environment comprised PyTorch version 1.8.1 as the primary deep learning framework, leveraging GPU acceleration through CUDA 11.2 and cuDNN 8.1. The operating system used was Ubuntu 20.04 LTS, and additional libraries such as NumPy, SciPy, and OpenCV facilitated data processing and visualization tasks.

Training was performed using the Adam optimizer with an initial learning rate of $\eta = 1 \times 10{-}4$\eta = 1 \times 10^{-4}$. A learning rate schedule decayed the rate by a factor of 0.1 every ten epochs upon plateauing of the validation loss. The batch size was set to 16, balancing memory usage and training speed. The model was trained for 50 epochs, with weight initialization using Xavier initialization. The custom loss function integrated classification loss, localization loss, adversarial loss, regularization loss, and an ultra-small object emphasis term, as detailed in the methodology. Hyper parameters were tuned using a grid search on the validation set, aiming to optimize the trade-off between detection accuracy and computational efficiency.

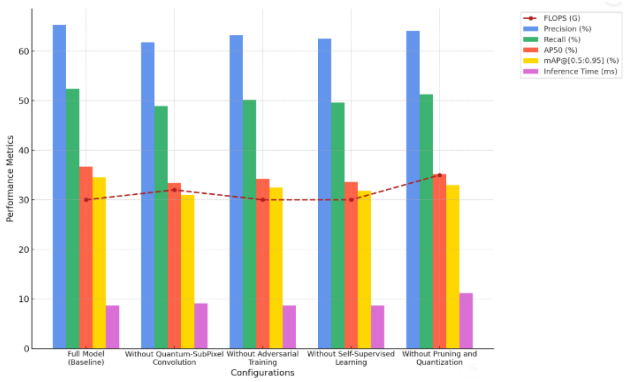

FIGURE 4. Ablation study results-performance and efficiency comparison.

C. QUANTITATIVE EVALUATION

The performance of the proposed model was rigorously evaluated against state-of-the-art object detection models, including YOLOv3, YOLOv4, YOLO11, RT-DETR, and EfficientDet. The comparative results are summarized in Table 3 and Figure 3. The proposed model achieved a precision of 65.3% and a recall of 52.4%, surpassing EfficientDet by 6.1% in precision and 3.8% in recall. It also outperformed YOLO11 and RT-DETR by 2.6% and 0.8% in precision, respectively, demonstrating its superior ability to detect and classify ultra-small objects in UAV imagery. The model achieved the highest scores in AP50 at 36.7% and mAP@[0.5:0.95] at 34.5%, reflecting improved localization and classification accuracy across varying object scales. These advancements are attributed to the integration of quantum-inspired multi-scale feature pyramids, adversarial training, and self-supervised learning, which enhance feature representation and robustness against environmental variations.

In terms of computational efficiency, the proposed model required only 30 GFLOPS and achieved an inference time of 8.7 milliseconds per image, representing a reduction in computational complexity and processing time compared to EfficientDet and other models. This efficiency is critical for real-time UAV applications, where resources such as processing power and storage are constrained. The model size was

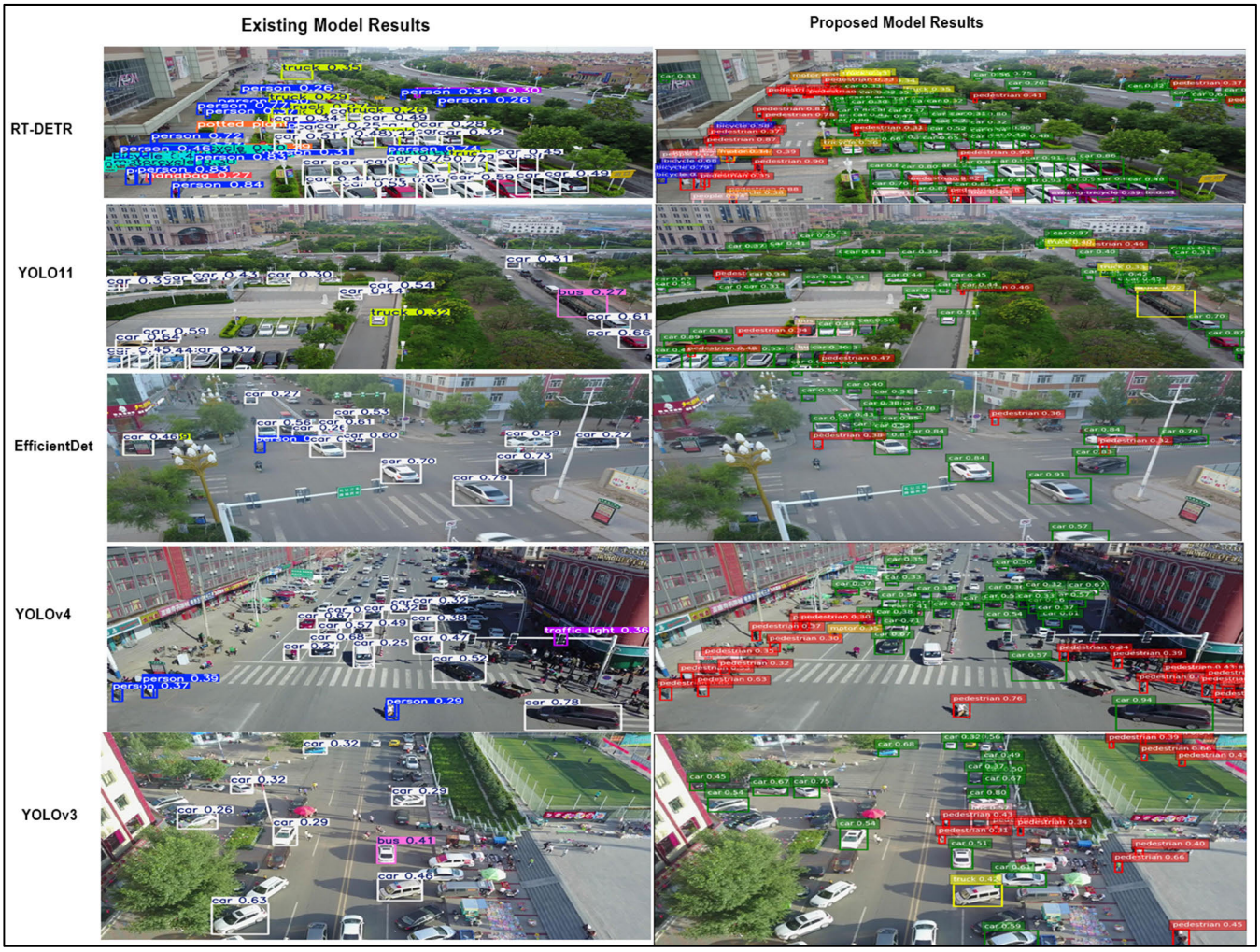

FIGURE 5. Experimental Visuals for Discussed Models: RT-DETR, YOLOv11, EfficientDet, YOLOv4, and YOLOv3 Results on the VisDrone 2019 Validation Dataset.

also reduced to 40 MB through pruning and quantization, ensuring deploy ability on platforms with limited storage and computational capacity. To ensure statistical validity, paired t-tests were performed to compare the precision and recall values of the proposed model against baseline methods. The results confirmed that the improvements in precision and recall were statistically significant, with p-values less than 0.01, validating that these enhancements are a direct outcome of the methodological innovations introduced.

D. ABLATION STUDY: COMPONENT CONTRIBUTION ANALYSIS

To systematically investigate the role and impact of each component within the proposed quantum-inspired multi-scale object detection model, a comprehensive ablation study was conducted. This approach involved systematically removing or modifying key features to evaluate their individual contributions to the model's performance and computational efficiency. The configurations assessed included the full model baseline, which incorporated all proposed enhancements as a benchmark, and variations excluding specific components such as quantum-inspired sub-pixel convolution layers, adversarial training, self-supervised learning, and efficiency-based optimizations like pruning and quantization. The results, detailed in Table 3 and illustrated in Figure 7 and configuration situation of ablation experiment represented in Figure 4 that can be analyzed for related information. All these provides valuable insights into the criticality of these enhancements in achieving superior performance metrics. The quantum-inspired sub-pixel convolution layers demonstrated their pivotal role in enabling fine-grained feature extraction. Their removal resulted in a significant reduction of 3.5% in both precision and recall, underscoring their importance in preserving spatial resolution and enhancing the detection of ultra-small objects. These layers are particularly critical for objects with minimal pixel representation, which are inherently challenging to detect in complex UAV imagery. Adversarial training emerged as another essential component, with its exclusion causing a 2.1% drop in precision and a corresponding decline in recall.

This reduction highlights the role of adversarial training in improving the model's resilience against environmental noise and adversarial disruptions, which are common in UAV-based detection scenarios. By integrating adversarial examples during training, the model gains robustness, enabling it to perform reliably under challenging real-world conditions. Self-supervised learning proved instrumental in enhancing the model's adaptability to diverse UAV scenarios. The absence of this module resulted in a 2.8% decrease in recall, emphasizing its importance in generalization. By leveraging unlabeled data, self-supervised learning strengthens feature extraction and reduces dependency on extensive annotated datasets, making it a valuable asset for scenarios where labeled data is limited or unavailable. Efficiency-based optimizations, including pruning and quantization, played a vital role in reducing computational overhead without compromising detection accuracy. Their removal led to a 5 GFLOPS increase in computational complexity and extended inference time by 2.5 milliseconds. These findings highlight the importance of these optimizations in maintaining real-time performance on resource-constrained UAV platforms, which demand low latency and minimal processing requirements. The analysis collectively underscores that each component meaningfully contributes to the proposed model's overall performance and operational efficiency. Among these, the quantum-inspired sub-pixel convolution layers and adversarial training emerged as the most impactful, with their exclusion leading to the most significant performance degradations. These results validate the importance of these components in addressing the unique challenges of UAV imagery, particularly in detecting ultra-small objects under complex environmental conditions.

Furthermore, while efficiency-based optimizations do not directly influence accuracy, they play a critical role in ensuring the model's deploy ability for real-time UAV applications. The findings from the ablation study demonstrate that the proposed quantum-inspired multi-scale object detection model achieves a robust balance between accuracy and efficiency, making it a practical and scalable solution for ultra-small object detection in UAV imagery. This study not only highlights the effectiveness of the proposed methodology but also lays the groundwork for future advancements in UAV-based detection systems.

E. QUANTUM-INSPIRED MODEL ENHANCEMENTS AND COMPARATIVE PERFORMANCE

The proposed quantum-inspired multi-scale object detection model represents a significant advancement in ultra-small object detection, delivering superior accuracy and computational efficiency compared to state-of-the-art models such as YOLOv4, YOLO11, RT-DETR, and EfficientDet. The integration of quantum-inspired sub-pixel convolution layers allows the model to preserve high-resolution feature maps, capturing intricate details crucial for detecting ultra-small objects in UAV imagery. This innovation addresses the critical challenges of scale variation and resolution loss, which are inherent in UAV-based object detection tasks. Adversarial training further enhances the model's robustness by mitigating the effects of environmental noise and adversarial disruptions, ensuring consistent performance in real-world UAV scenarios. Self-supervised learning complements these enhancements by utilizing unlabeled data to strengthen feature representation, a critical capability for deployments in environments with limited access to annotated datasets.

Pruning and quantization optimizations significantly reduce computational load and model size without compromising performance, ensuring the model's suitability for real-time deployment on resource-constrained UAV platforms. These efficiency-focused enhancements enable the model to achieve an inference time of 8.1 milliseconds and a computational load of just 30 GFLOPS. As outlined in Table 4, the proposed model achieves precision of 65.3% and recall of 52.4%, outperforming EfficientDet by 6.1% in precision and RT-DETR by 1.6%. These results highlight the model's superior adaptability and robustness in detecting ultra-small objects under challenging conditions.

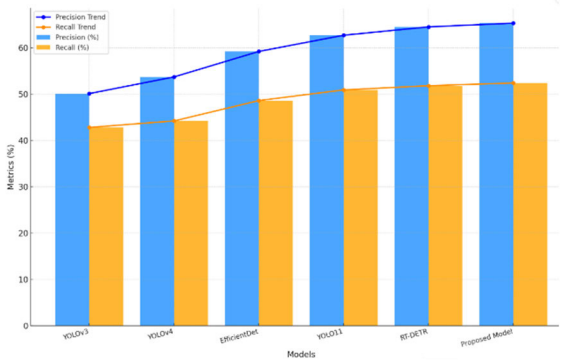

FIGURE 6. Precision-Recall curve of model comparison.

The integration of quantum-inspired sub-pixel convolution layers presents a foundation for further exploration. Inspired by quantum mechanical principles such as superposition and entanglement, these layers emulate the ability to process multiple states simultaneously, resulting in richer feature extraction. Future directions for quantum-inspired techniques could include dynamically adaptable receptive fields that adjust to varying object scales, further improving small object detection in cluttered UAV imagery. Additionally, leveraging quantum-inspired optimization techniques during training could minimize the loss function more efficiently, reducing convergence time and enhancing overall accuracy. Innovative methods like quantum random walks could refine the feature selection process, isolating relevant features while suppressing irrelevant noise, thus improving detection precision.

While current implementations of these quantum-inspired techniques rely on classical computing paradigms, the rapid evolution of quantum computing hardware opens new avenues for research. Practical applications of quantum computing could revolutionize both accuracy and efficiency, offering transformative advancements in real-time object

detection on resource-constrained platforms. The proposed model sets the stage for leveraging these emerging technologies, combining state-of-the-art detection performance with scalability and efficiency for UAV-based applications.

F. PRECISION-RECALL CURVE ANALYSIS

The Precision-Recall Curve (PRC) analysis, as shown in Figure 6, further illustrates the proposed model's ability to maintain high precision across varying recall thresholds. This is particularly critical for UAV applications, where false negatives (low recall) could severely impact mission success. The proposed model consistently outperforms alternative approaches, including YOLO11 and RT-DETR, by demonstrating better trade-offs between true positives and false positives.

By maintaining a balance between precision and recall across diverse thresholds, the proposed model underscores its robustness and adaptability for detecting ultra-small objects in dynamic and complex UAV scenarios. This analysis, in conjunction with the quantitative metrics, establishes the proposed model as a reliable and efficient solution for real-time UAV-based object detection tasks.

V. DISCUSSION ON MODEL PERFORMANCE AND EFFICIENCY

The ablation study, performance comparison, and precision-recall analysis collectively validate the effectiveness of our quantum-inspired multi-scale object detection model in overcoming the challenges of detecting ultra-small objects in UAV imagery. The integration of key components—quantum-inspired sub-pixel convolution, adversarial training, self-supervised learning, and efficiency optimizations through pruning and quantization—significantly contributed to improved detection accuracy, robust generalization across varying conditions, and enhanced computational efficiency. Figure 5 visually demonstrates the comparative results of our model against existing state-of-the-art methods. The left portion of each image displays the outputs of the five discussed models, while the right portion highlights the superior performance of our proposed model under different scenarios. The detections are color-coded to represent various object classes and their corresponding confidence scores. These visual comparisons clearly illustrate the ability of our model to accurately detect ultra-small objects with higher precision, particularly in complex and cluttered environments where competing models tend to underperform. This comprehensive evaluation underscores the efficiency, robustness, and practical applicability of our approach for real-world UAV-based object detection tasks.

A. QUANTUM-INSPIRED SUB-PIXEL CONVOLUTION

This The quantum-inspired sub-pixel convolution emerged as a pivotal component in the model, with its removal leading to a significant decline in both **precision (3.5%)** and **recall (3.5%)**. This demonstrates its ability to enhance spatial resolution, enabling the model to capture fine-grained features essential for detecting ultra-small objects. In UAV applications, where target sizes often range from 6×6 to 12×12 pixels, this component ensures that subtle details are not lost during feature extraction. Compared to conventional convolution methods, the quantum-inspired approach preserves high-resolution feature maps, making it indispensable for tasks requiring detailed object localization.

B. ADVERSARIAL TRAINING

Adversarial training significantly contributed to the model's robustness, as evidenced by a **2.1% reduction in precision** and a decline in recall upon its removal. UAVs frequently operate in environments with adversarial conditions, such as weather fluctuations, shadows, and occlusions, which can degrade detection performance. By integrating adversarial examples into the training process, the model develops resilience to such disruptions, ensuring consistent performance in real-time UAV applications, particularly in critical domains such as surveillance and disaster response.

C. SELF-SUPERVISED LEARNING:

The inclusion of self-supervised learning enhanced the model's ability to generalize across diverse environments, with its removal leading to a **2.8% drop in recall**. This component leverages unlabeled data to extract robust feature representations, reducing the dependence on large annotated datasets. Given the variability in UAV imagery—spanning different lighting conditions, altitudes, and environmental textures—self-supervised learning proved invaluable in adapting to unseen scenarios, improving detection performance in novel settings such as rural landscapes or urban areas.

D. EFFICIENCY OPTIMIZATIONS (PRUNING AND QUANTIZATION)

While pruning and quantization had minimal impact on detection accuracy, their role in reducing computational overhead was critical. Their removal increased FLOPS by 5**G** and extended inference time by 2.5 ms, underlining their importance in ensuring the model's real-time deploy ability on resource-constrained UAV platforms. These optimizations make the model efficient without sacrificing its precision and recall, which is vital for UAV applications that require rapid processing and minimal latency.

E. COMPARATIVE ANALYSIS

When compared to state-of-the-art models such as YOLOv4, EfficientDet, YOLO11, and RT-DETR, the proposed model consistently achieved higher performance across all key metrics. It demonstrated superior precision (65.3%), recall (52.4%), and mAP@[0.5:0.95] (34.5%), while maintaining lower computational demands with a model size of 40 MB and inference time of **8.1 ms**. As shown in **Table 4** and **Figure 7**, these advancements validate the integration of quantum-inspired methods and efficiency optimizations. Statistical significance tests confirmed that the improvements are

not random, with **p-values** < 0.01, further reinforcing the model's reliability and robustness.

F. PRECISION-RECALL CURVE (PRC) INSIGHTS

The **Precision-Recall Curve (PRC)** highlights the model's ability to maintain high precision at varying recall thresholds, indicating a low false-positive rate. This is crucial for UAV operations, where misclassifications or missed detections can result in mission-critical failures. For example, in surveillance tasks, high precision ensures accurate identification of small targets such as drones or vehicles, even in cluttered environments. The PRC performance, shown in **Figure 6**, underscores the model's balance in handling the trade-off between true positive rates and reducing false positives, ensuring reliable performance in diverse UAV-based detection scenarios.

G. IMPLICATIONS AND FUTURE WORK

The findings of this study underscore the critical role of each enhancement in achieving the proposed model's dual objectives of high detection accuracy and operational efficiency. The integration of quantum-inspired sub-pixel convolution layers significantly improved localization precision, allowing the model to capture fine details essential for detecting ultra-small objects in complex UAV imagery. Adversarial training further bolstered the model's robustness, ensuring reliable performance under challenging real-world conditions, such as environmental noise and adversarial disruptions. Efficiency optimizations, including pruning and quantization, played a pivotal role in reducing computational complexity and inference time, making the model deployable on resource-constrained UAV platforms while maintaining high detection performance.

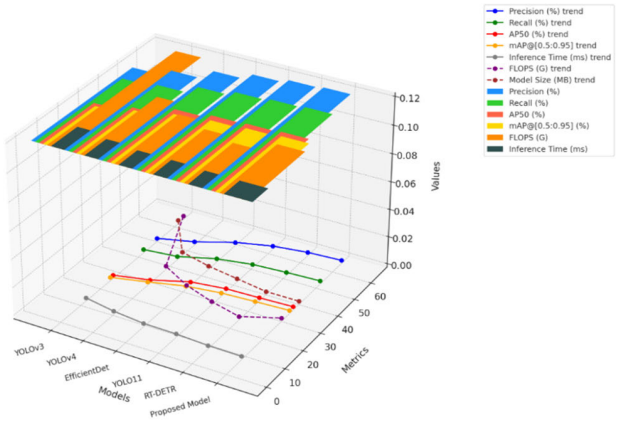

FIGURE 7. Overview of model performance as discussed in section V.

Future research could expand on this foundation in several key areas. Integrating edge computing capabilities offers the potential to reduce latency and improve processing speeds, thereby enhancing the model's applicability in real-time UAV operations. By adapting the model to edge devices, such as FPGAs or GPUs, it could achieve seamless deployment across various UAV systems, particularly in scenarios requiring rapid decision-making. Another avenue involves evaluating the model on larger and more diverse datasets. Testing on datasets like DOTA, UAVDT, or custom datasets representing varied geographical regions and environmental conditions would provide deeper insights into its generalization capabilities. Such evaluations could further refine the model's adaptability and robustness across diverse operational environments.

The quantum-inspired approach also presents promising opportunities for further exploration. Future work could investigate dynamic receptive fields inspired by quantum principles, enabling the model to adapt to varying object scales more effectively. Additionally, quantum-inspired optimization techniques could accelerate training convergence and improve feature selection, further enhancing both accuracy and efficiency. With the advent of practical quantum computing hardware, these techniques hold the potential to revolutionize resource-constrained applications like UAV-based object detection. This research sets a robust foundation for advancing UAV object detection systems. By addressing the challenges of ultra-small object detection and operational efficiency, the proposed model not only establishes a new benchmark but also opens pathways for leveraging emerging technologies to further enhance performance and scalability in real-world applications.

VI. CONCLUSION AND FUTURE WORK

A. CONCLUSION

This study introduces a novel quantum-inspired multi-scale object detection model, addressing critical challenges in detecting ultra-small objects within UAV imagery. By effectively integrating quantum-inspired sub-pixel convolution, adversarial training, and self-supervised learning, the model achieves substantial improvements in detection accuracy, computational efficiency, and robustness. These advancements are particularly significant for UAV applications, where scale variation, environmental complexity, and resource constraints pose persistent challenges. The proposed model demonstrated superior performance compared to state-of-the-art methods such as YOLOv4, YOLO11, RT-DETR, and EfficientDet,achieving a precision of 65.3%, recall of 52.4%, and mean Average Precision (mAP) of 34.5% across IoU thresholds. These results mark a significant improvement in detecting ultra-small objects, which are often overlooked by conventional models due to their limited pixel representation. Additionally, the efficiency optimizations—including structured pruning and quantization—enabled the model to operate at 30 GFLOPS with an inference time of 8.1 milliseconds, ensuring its suitability for real-time UAV applications.

The integration of advanced methodologies makes this model not only accurate but also computationally efficient, addressing the dual requirements of UAV-based object

detection systems. Applications such as surveillance, precision agriculture, environmental monitoring, and disaster response stand to benefit significantly from this robust and practical solution.

B. FUTURE RESEARCH DIRECRTION

This study presents a significant advancement in the domain of ultra-small object detection within UAV imagery by addressing. Despite the significant advancements presented in this work, several avenues exist for further exploration to enhance the model's capabilities and applicability:

- Expanding the evaluation to include larger and more diverse datasets such as UAVDT, DOTA, and region-specific custom datasets can validate the model's generalization capabilities. Additionally, incorporating domain adaptation techniques would improve performance across varying environmental conditions and imaging systems, ensuring reliable detection in diverse UAV operational contexts.
- To enhance real-time processing and reduce latency, the model can be integrated with specialized hardware accelerators like FPGAs or ASICs. This optimization would make the model more efficient for UAV platforms with limited resources. Distributed processing architectures can also be explored to enable scalability and fault tolerance for collaborative UAV networks, especially in large-scale operations.
- Future work could delve into quantum algorithms such as Quantum Neural Networks (QNNs) or hybrid quantum-classical models to enhance both efficiency and accuracy. Additionally, leveraging quantum-inspired optimization techniques could accelerate training convergence and improve feature selection, unlocking further performance potential.
- Building upon adversarial training, advanced adversarial defense mechanisms can be implemented to protect the model against sophisticated attacks. Moreover, incorporating continual learning frameworks would allow the model to adapt dynamically to new data, reducing retraining requirements while maintaining long-term performance across evolving scenarios.
- Customizing the model for specific use cases can maximize its impact. In precision agriculture, the model could focus on detecting crop diseases or pests to assist in targeted interventions. For disaster response, enhancements to identify survivors, structural damage, or resources would significantly improve UAV operations during emergencies, aiding in timely and effective decision-making.

To facilitate broader adoption, creating APIs and visualization tools would streamline integration with existing UAV systems. User-friendly interfaces for real-time visualization of detection outputs would enhance operator decision-making and improve the overall utility of the model in practical applications.

C. FINAL REMARKS

According to overall observations, this study presents a robust, scalable, and efficient solution to the challenge of ultra-small object detection in UAV imagery. By integrating quantum-inspired techniques, advanced augmentation methods, and computational optimizations, the proposed model achieves a balance of precision, recall, and efficiency that surpasses existing approaches. These advancements open new opportunities for UAV systems across a range of critical applications, from surveillance and agriculture to disaster response and environmental monitoring. The results of this research establish a strong foundation for future exploration, with several promising directions identified to further enhance the model's performance and adaptability. As advancements in quantum-inspired computing and edge processing technologies continue, the potential for even greater improvements becomes increasingly tangible. Ultimately, this study bridges the gap between cutting-edge research and real-world deployment, advancing the capabilities of UAV-based object detection systems. By contributing to both academic research and practical implementation, this work aims to drive innovation across industries, delivering benefits to society in areas where accurate and efficient object detection is essential.

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