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Application of AI-Driven Multi-Scale Feature Fusion in Small Target Detection in Aerial Photography

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Abstract: Healthcare, banking, manufacturing, and education are just a few of the areas that artificial intelligence (AI) is transforming. In healthcare, AI-powered diagnostic tools enhance early disease detection through automated analysis of medical imaging, while in finance, machine learning algorithms optimize fraud detection and algorithmic trading strategies. Rapid developments in computer vision, Natural language processing (NLP), and deep learning have greatly improved AI's capacity for data analysis, automated decision-making, and intelligent human-machine interaction. For instance, computer vision enables autonomous vehicles to navigate complex environments, and NLP-driven chatbots streamline customer service interactions across sectors. AI-driven innovations are improving efficiency, accuracy, and productivity, but they also introduce challenges related to data privacy, ethical concerns, and technological limitations. This paper examines AI's key applications across multiple sectors, analyzing both its transformative potential and the obstacles hindering its widespread adoption. Additionally, it explores emerging trends, such as explainable AI, AI-driven automation, and regulatory developments, highlighting their implications for future research and policy-making. By conducting a comprehensive review of current advancements and challenges, this study provides insights into AI's evolving role and proposes strategic recommendations for its responsible and sustainable integration across industries.

Keywords: Artificial Intelligence (AI), Deep Learning, Computer Vision, Aerial Target Detection.

1. Introduction

Aerial photography has greatly improved due to the quick development of artificial intelligence (AI), especially in the area of small target recognition.

Small object detection plays a crucial role in various applications such as environmental monitoring [1] disaster management [2], urban planning [3], and military surveillance [4]. However, despite technological progress, detecting small objects in aerial imagery remains a major challenge due to factors such as low resolution, high background noise, and variations in object scale and illumination conditions [5]. Traditional object detection methods often struggle with these challenges, leading to low accuracy and high false detection rates, which hinder their practical application in real-world scenarios [6].

To address these issues, deep learning-based object detection models, particularly the You Only Look Once (YOLO) series, have been widely applied due to their real-time processing capabilities and high detection accuracy [7]. In a variety of object identification tasks, YOLO-based techniques

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have shown impressive performance [8], however, their effectiveness in small target detection is often limited by insufficient feature extraction and the inability to capture fine-grained details in high-resolution aerial imagery [9]. Small objects tend to lose critical features when passed through multiple convolutional layers, reducing detection accuracy and increasing false positives [10].

Researchers have put forth sophisticated methods including multi-scale feature fusion and attention processes to get beyond these restrictions.Multi-scale feature fusion strategies enhance small object detection by integrating features from different layers of deep neural networks, enabling models to retain more detailed information from smaller objects [11]. Additionally, attention mechanisms, such as transformer-based designs [12] and the Convolutional Block Attention Module (CBAM) [13], refine feature selection by focusing on the most informative regions within an image, leading to improved detection precision and robustness in aerial imagery applications [14]. These methods have been instrumental in mitigating scale-related issues and improving the efficiency of small target detection models [15].

Additionally, choosing the right assessment measures and datasets is essential for evaluating how well small target identification models work. Datasets such as the VisDrone dataset [16] and the DOTA dataset [17] provide diverse aerial images with varying levels of complexity, which are essential for training robust models. The efficacy of various detection algorithms is assessed with the use of performance indicators including Mean Average Precision (mAP) [18], F1-score [19], and Intersection over Union (IoU) [20].

This paper explores the application of AI-driven multi-scale feature fusion strategies in small target detection for aerial photography. Analyze the principles and advantages of YOLO-based approaches, evaluate their limitations, and investigate fusion and attention-based techniques for enhanced performance. Furthermore, it assesses different datasets and performance metrics to provide a comprehensive evaluation of these methods. Finally, this study systematically analyzes the principles and limitations of YOLO-based methods,examines attention processes and multi-scale feature fusion to improve performance, and assesses datasets and metrics to offer a thorough framework for improving small target recognition in aerial images.

2. Aerial object detection based on YOLO

YOLO excels in aerial object detection due to its real-time efficiency. Unlike two-stage models (e.g., Faster R-CNN), YOLO predicts object locations and categories simultaneously in a single step, drastically reducing inference time. This makes it ideal for UAV-based surveillance, disaster monitoring, and environmental assessments. To improve small object recognition, iterations such as YOLOv5, v7, and v8 include improvements including multi-scale feature fusion, attention modules, and improved anchor mechanisms.

However, standard YOLO struggles with small targets due to detail loss from downsampling, scale imbalance in aerial datasets, and background noise in complex environments. Current research focuses on optimizing YOLO for these challenges.

Recent studies have introduced effective modifications to YOLO for small object detection in aerial scenarios. Li et al. proposed Infrared-YOLO, a model tailored for infrared aerial imagery, which incorporates adaptive feature extraction layers and a noise suppression module to mitigate occlusion effects. Their approach demonstrated 10.5% higher precision in detecting small aircraft under low-visibility conditions [21]. Wang et al. designed EdgeLight-YOLO, a lightweight variant of YOLOv4-Tiny optimized for UAV edge devices. By pruning redundant channels and introducing spatial-aware feature selection, their method maintained real-time inference at 35 FPS while improving small object detection accuracy by 8.3% on the VisDrone dataset [22].

While YOLO-based models demonstrate remarkable real-time efficiency in aerial object detection, their inherent feature extraction mechanisms struggle to preserve fine-grained details critical for small

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targets. Traditional YOLO architectures rely on progressive downsampling, which dilutes shallow-layer spatial information (e.g., edges, textures) and fails to effectively integrate multi-scale contextual cues. This limitation leads to reduced sensitivity to small objects, particularly under challenges such as occlusions, scale variations, and dynamic lighting conditions in aerial environments.

To address these gaps, enhanced YOLO variants leverage multi-scale feature fusion to aggregate hierarchical information, yet this often introduces computational overhead incompatible with UAV hardware constraints. Future research must therefore balance accuracy and efficiency by embedding lightweight attention mechanisms to prioritize salient features, adopting self-supervised learning to reduce dependency on annotated data, and designing adaptive feature selection frameworks that dynamically optimize computational pathways. These strategies aim to retain the benefits of multi-scale fusion while ensuring real-time performance on resource-limited platforms.

3. Aerial object detection based on YOLO and multi-scale feature fusion

Feature fusion enhances small object detection in aerial imagery by preserving spatial details lost during downsampling. Techniques like FPNs and PANs improve YOLO's multi-scale detection by integrating fine-grained and semantic features, reducing false negatives. Recent advances leverage multiple backbones and recursive enhancements for greater accuracy.

Several studies have explored multi-scale feature fusion to enhance YOLO's performance in aerial small object detection. Zhou et al. introduced SMA-YOLO, which integrates multi-scale feature aggregation and positional attention, achieving a 15.6% mAP increase on the VisDrone dataset, surpassing baseline YOLO models in aerial surveillance [23]. Li et al. proposed MFA-YOLO, combining multi-scale fusion with CBAM to improve detection under extreme weather, yielding a 12.3% mAP gain in challenging conditions [24]. Wang et al. developed Edge-YOLO, a lightweight model optimized for UAV-based industrial inspection. By incorporating multi-scale feature propagation and spatial enhancement modules, it improved detection accuracy while maintaining real-time processing at 30+ FPS, making it suitable for resource-limited UAVs [25]. Huang et al. developed RSP-YOLO, a recursive scale-aware pyramid network that enhances multi-scale feature fusion by integrating cross-layer attention mechanisms, achieving a 12.8% mAP improvement on the DOTA dataset compared to baseline YOLOv5 models [26].

Despite advancements, challenges persist in implementing multi-scale feature fusion for aerial object detection. High computational overhead and feature redundancy can hinder efficiency. Future research may focus on adaptive fusion mechanisms to selectively integrate relevant features and incorporate self-supervised learning to enhance small object detection and model generalization.

4. Other methods

Several deep learning models have been investigated for small item recognition in aerial photography in addition to YOLO-based methods. Region-based methods such as Faster R-CNN have demonstrated high accuracy by leveraging region proposal networks (RPNs) to refine object localization. However, these methods often suffer from slower inference speeds, making them less suitable for real-time UAV applications. Additionally, Single Shot MultiBox Detector (SSD) models provide a balance between accuracy and speed by predicting multiple bounding boxes per grid cell. However, SSD struggles with detecting extremely small objects due to feature loss in deep convolutional layers [16].

Recent hybrid systems have included multi-scale feature and focus approaches to enhance small object identification performance. For instance, studies incorporating FPNs with Faster R-CNN have improved detection accuracy by preserving fine details across different scales. Lin et al. proposed FPN to merge multi-level features via top-down pathways, enhancing scale robustness in object

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detection [27]. Wang et al. integrated FPN with Faster R-CNN, achieving a15.6% mAP gain on the VisDrone dataset through cross-layer feature aggregation [22]. Similarly, Zhou et al. combined FPN with attention mechanisms, boosting recall by 12.3% in occlusion-prone aerial scenes [23].

Additionally, lightweight transformer-based architectures, such as Swin Transformer, have been combined with convolutional models to improve small object recognition in cluttered aerial environments. Liu et al. proposed a hybrid framework integrating Swin Transformer's shifted window attention with convolutional layers, enhancing multi-scale feature fusion for aerial imagery [28]. Their approach leverages Swin Transformer's hierarchical structure to capture long-range dependencies, while convolutional layers preserve local details. This combination achieved a 12.8% mAP improvement on the DOTA dataset compared to pure CNN-based methods, particularly excelling in detecting sub-1m objects under occlusion and complex backgrounds.

These alternative methods provide valuable insights into enhancing aerial object detection beyond YOLO-based frameworks.

5. Data sets and assessment indicators

A number of datasets representing a range of settings, including metropolitan landscapes, rural areas, and military surveillance, have been created to evaluate small object detection models in aerial images.

VisDrone, for instance, contains UAV-captured images of pedestrians, vehicles, and bicycles in dynamic urban settings, making it a key benchmark for real-world aerial detection tasks [18]. xView provides satellite imagery with large-scale annotations for military and disaster monitoring, offering high-resolution scenes with complex object distributions [29]. Table 1 summarizes the key characteristics of these widely used aerial datasets.

Table 1: Overview of aerial object detection datasets

Dataset	Key Features
VisDrone	UAV-captured images, dynamic urban environments, pedestrian/vehicle detection
DOTA	High-resolution imagery, multi-oriented object annotations
xView	Satellite images, large-scale military and disaster monitoring applications
AU-AIR	UAV-based dataset, diverse environments, includes video sequences.

Several performance criteria are employed to assess small object identification models' efficacy.

These metrics help quantify a model's precision, recall, and overall accuracy in detecting small objects within aerial imagery.

The mean Average Precision (mAP), which assesses the precision-recall tradeoff across numerous intersections over union (IoU) thresholds, is one of the most popular metrics:

$$\mathrm{mAP} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{AP_i} \tag{1}$$

where $\mathrm{AP_i}$ is the total number of classes and A is the average precision for each object class [20].

Another crucial metric is the F1-score, which balances precision and recall:

$$\mathrm{F1} = 2 \times \frac{\mathrm{Precision} \times \mathrm{Recal}}{\mathrm{Precision} + \mathrm{Recall}} \tag{2}$$

Other measures include IoU, which computes the overlap between predicted and ground truth bounding boxes, and FPS, which assesses a model's real-time efficiency [30].

The overlap between the predicted and ground truth bounding boxes is computed by IoU.

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$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \tag{3}$$

FPS Quantifies real-time efficiency by measuring the amount of frames are processed in a second.

$$\text{FPS} = \frac{1}{\text{Inference Time per Frame (seconds)}} \tag{4}$$

6. Conclusions

The limitations of YOLO in managing small-scale targets in complicated contexts were examined in this study, along with developments in airborne small object recognition.

While YOLO's real-time efficiency and adaptability make it well-suited for aerial applications, its performance is often hindered by issues such as scale imbalance, loss of fine details, and high background noise. To address these challenges, recent developments have incorporated multi-scale feature fusion strategies, such as FPNs and PANs, along with attention mechanisms like the Convolutional Block Attention Module. These enhancements refine feature extraction, reduce false positives, and improve detection accuracy, leading to more robust performance in complex aerial scenarios.

Empirical results demonstrate that these improvements significantly enhance small object detection precision and increase processing efficiency,

making AI-driven aerial surveillance more reliable. Moving forward, the integration of lightweight Transformer-based models and computational optimization techniques will be crucial in improving real-time performance. Additionally, addressing computational constraints, designing more effective loss functions for small objects, and developing self-adaptive models capable of learning from diverse aerial conditions will be essential for future research.

Beyond UAV-based surveillance, these advancements hold significant potential for applications in disaster response, precision agriculture, environmental monitoring, and military reconnaissance. As aerial remote sensing technologies evolve, AI-driven intelligent detection systems will become more scalable, accurate, and efficient, paving the way for next-generation autonomous aerial analytics.

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