**Full version of article: https://ieeexplore.ieee.org/document/10591528**

# Approach Based on YOLOv9 for High-Resolution Remote Sensing

1st Ivan Saetchnikov
*Radiophysics Department*
*Belarusian State University*
Minsk, Belarus
saetchnikovivan@gmail.com

2nd Victor Skakun
*Radiophysics Department*
*Belarusian State University*
Minsk, Belarus
skakun@gmail.by

3rd Elina Tcherniavskaia
*Physics Department*
*Belarusian State University*
Minsk, Belarus
tcherniavskaia@gmail.by

***Abstract*— the rapid advancements in Cube and Nano satellites have made high-quality remote sensing images easily accessible, leading to crucial object recognition tasks with extensive applications range. The particular task of aircraft detection is placed as one of the most promising applications of computer vision systems for aerospace data processing, primarily due to its broad application prospects starting from aircraft traffic planning and controlling for potential threats detection, environmental monitoring to managing CO2 emissions all the way to logistics supply chain optimization based on spatial finance insights. However, analyzing high-quality remote sensing data presents a significant challenge, particularly in the detection tasks of densely located aircrafts, aircrafts with various size ranges, etc. In this regard, this article focuses on addressing these challenges through a deep learning-based approach based on an optimized version of YOLOv9 for aircraft detection on high-resolution remote sensing data. The proposed approach has been trained and evaluated based on the images from Airbus dataset and demonstrates 3% increase in accuracy detection compared to existing state-of-the-art approaches, achieving 0.987 in average precision (AP) and 0.746 in mean average precision (mAP).**

***Keywords—neural network, deep learning, aircraft detection, object detection, YOLO (you only looks once), remote sensing, aerospace image analysis.***

## I. Introduction

The decreasing cost of launching Cube and Nano satellites, along with rapid advancements in their development [1], has made high-quality remote sensing images easily accessible [2], particularly in earth observation satellites. As a result, object detection and recognition in these images have become crucial tasks [3], enabling the development of a new generation of object recognition and classification systems.

The application of preprocessed remote sensing data and detected objects is extensive, ranging from intelligent transportation systems [4] and urban traffic management [5 - 6] to environmental monitoring, mining, forest, and water resource optimization [7]. Even in side domains, such as financial markets, remote sensing data processing finds application in fast-growing spatial finance [8], e.g., risk management assessment for airline industry. All the aforementioned examples demonstrate the proven demand for high-quality satellite image analysis and processing. However, the analysis of high-quality remote sensing data presents a significant challenge due to the extensive spatial coverage and complex image backgrounds. Deep learning-based approaches have proven to be effective in capturing complex recognition patterns of objects in cluttered urban scenes, even in scenarios with a limited angle of view, such as satellite imagery [9] or footage from unmanned aerial vehicles. [10] The recognition of aircrafts in aerospace imagery presents a distinct and unique challenge due to their complex shapes, varied sizes, and diverse appearances.

Up to now, numerous detectors have been developed for identifying aircrafts in remote sensing images. For example, in [11] the authors successfully implement multi-scale object detection by incorporation multi-scale feature fusion techniques on optical images. Despite the significant advancements in remote sensing image object detection, they still exhibit weaknesses in accurately detecting small grouped objects and objects of the same class with similar contrast. In [12], the Single-Shot Detector (SSD) feature fusion coupled with dilated convolutional has been proposed to partly mitigate the issue. Additionally, in [13] the authors introduced the similar multi-scale feature fusion boosted with adaptive sample filtering technique to improve the detection accuracy and performance of nearby located objects in aerospace images. However, the Single-Shot Detector (SSD) - based networks struggle with low-contrast object detection tasks, as well as the low likelihood of separating individual objects in high-density images.

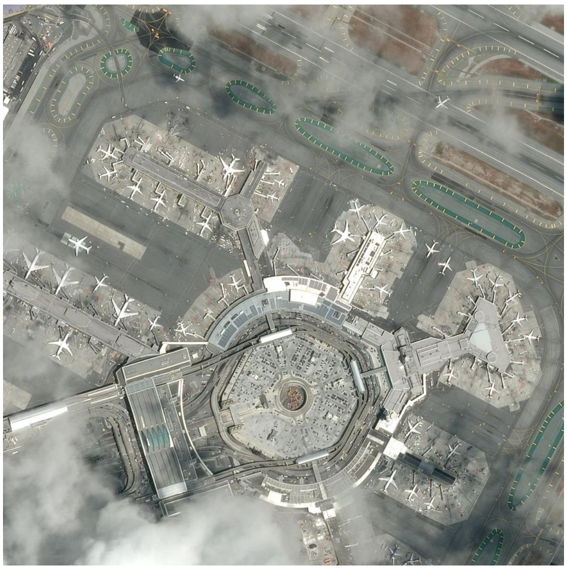

Fig. 1. Observed aicrafts on high-resolution remote sensing data.

The mentioned issues have been partially addressed by authors in [14] through the proposal of a spatially oriented technique, and in [15] via multi-scale feature pyramids and Faster-Region-Based Convolutional Neural Networks (Faster-RCNN) as a backbone. However, these approaches struggled with detecting aircrafts of varying sizes. In contrast, in [16] the Multi-scale Visual Transformer as well as in [17] the Eff-Matching-Oriented Transformer effectively handle aircrafts of different scales, achieving high robustness on object detection applied to remote sensing data. Nonetheless, transformer-based approaches exhibit both substantial amount of training data and high computational complexity, which can be a critical consideration in the field of remote sensing images. In contemporary object detection technology, you look only once (YOLO)-based networks stand out for their exceptional accuracy and robustness. In [18], the authors introduced an enhanced version of YOLOv4 incorporating a feature extraction process utilizing residual modules in conjunction with a Feature Pyramid Network (FPN), and exhibits strong performance even when operating with limited training datasets.

To summarize, despite the significant progress in remote sensing data analysis, the following challenges in the realm of aircraft detection still need to be studied further:

- There is a possibility of inaccurate detection of nearby small aircrafts or business jets, leading to gaps or misgrouping, potentially resulting in misclassification into another class.
- The extraction of airplane features is restricted to the satellite's top view. Consequently, the complex shape of airplanes can lead to semantic confusion with other object classes, e.g., as transportation tunnels (Fig. 1).
- Registered and transmitting equipment, along with climatic conditions, may obscure objects of interest with clouds (Fig. 1), smog, or blurring, ultimately resulting in a reduced signal-to-noise ratio.

Thus, the following research article will focus on addressing the aforementioned challenges by researching and developing a deep learning-based approach for aircraft detection in high-resolution remote sensing data.

## II. Acknowledgments

This is a shortened version of the article. The full article is available on the website: https://ieeexplore.ieee.org/document/10591528.

## References

[1] J. Kopacz, R. Herschitz and J. Roney, “Small satellites an overview and assessment”, Acta Astronautica, vol. 170, pp. 93-105, Mai 2020.

[2] G. Cheng, X. Xie, etc., "Remote Sensing Image Scene Classification Meets Deep Learning: Challenges, Methods, Benchmarks, and Opportunities", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 3735-3756, June 2020.

[3] L. Zhang and L. Zhang, "Artificial Intelligence for Remote Sensing Data Analysis: A review of challenges and opportunities", IEEE Geoscience and Remote Sensing Magazine, vol. 10, no. 2, pp. 270-294, June 2022.

[4] L. Zhang, F. Yang, Y. Daniel Zhang and Y. J. Zhu, "Road crack detection using deep convolutional neural network," 2016 IEEE International Conference on Image Processing (ICIP), Phoenix, AZ, USA, pp. 3708-3712, August 2016.

[5] I. Saetchnikov, V. Skakun and E. Tcherniavskaia, "Robust S-Y-biLSTM object tracking method for on-road objects shoot from an unmanned aerial vehicle," 2022 IEEE 9th International Workshop on Metrology for AeroSpace, 2022, pp. 270-274.

[6] I. Saetchnikov, V. Skakun and E. Tcherniavskaia, "Pattern recognition on aerospace images using deep neural networks," 2020 IEEE 7th International Workshop on Metrology for AeroSpace, Pisa, Italy, 2020, pp. 336-340.

[7] W. Tang, F. He, etc., “A remote sensing image rotation object detection approach for real-time environmental monitoring”, Sustainable Energy Technologies and Assessments, Vol. 57, pp. 103270, Mai 2023.

[8] B. Caldecott, M. McCarten, C. Christiaen, C. Hickey, “Spatial finance: practical and theoretical contributions to financial analysis”, Journal of Sustainable Finance & Investment, 2022.

[9] I. Saetchnikov, V. Skakun and E. Tcherniavskaia, "Pattern recognition on aerospace images using deep neural networks," 2020 IEEE 7th International Workshop on Metrology for AeroSpace, Pisa, Italy, 2020, pp. 336-340.

[10] I. V. Saetchnikov, E. A. Tcherniavskaia and V. V. Skakun, "Object Detection for Unmanned Aerial Vehicle Camera via Convolutional Neural Networks," in IEEE Journal on Miniaturization for Air and Space Systems, vol. 2, no. 2, pp. 98-103, June 2021.

[11] Z. Hong et al., "Multi-Scale Ship Detection From SAR and Optical Imagery Via A More Accurate YOLOv3," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 6083-6101, 2021,

[12] J. Qu, C. Su, Z. Zhang and A. Razi, "Dilated Convolution and Feature Fusion SSD Network for Small Object Detection in Remote Sensing Images," in IEEE Access, vol. 8, pp. 82832-82843, 2020.

[13] L. Suidong, Z. Lei and W. Wenwu, "Improving SSD for detecting small target in Remote Sensing Image," 2020 Chinese Automation Congress (CAC), Shanghai, China, 2020, pp. 567-571.

[14] D. Yu and S. Ji, "A New Spatial-Oriented Object Detection Framework for Remote Sensing Images," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-16, 2022.

[15] W. Miao, Z. Luo, “Aircraft detection based on multiple scale faster-RCNN”, International Conference on Virtual Reality and Visualization (ICVRV), Qingdao, China, pp. 90-93, 22–24 October 2018.

[16] C. Zhang, T. Liu and K. -M. Lam, "Angle Tokenization Guided Multi-Scale Vision Transformer for Oriented Object Detection in Remote Sensing Imagery," IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, Kuala Lumpur, Malaysia, 2022, pp. 3063-3066.

[17] Z. Hu et al., "EMO2-DETR: Efficient-Matching Oriented Object Detection With Transformers," in IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1-14, 2023.

[18] Intelligence.airbus.com. (n.d.). Explore OneAtlas Satellites Imagery and Data Services. [online] Available at: https://intelligence.airbus.com/imagery/how-to-order-imagery-and-data/services/ [Accessed 2 Feb. 2024].

[19] J. Redmon, S. Divvala, R. Girshick and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 779-788.

[20] G. -S. Xia et al., "DOTA: A Large-Scale Dataset for Object Detection in Aerial Images," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA, 2018, pp. 3974-3983.

[21] Ma, L.; He, T.; Sun, Y.; Hu, B.B, “Lightweight YOLOv4 Algorithm for Remote Sensing Image Detection”, 14th International Conference on Signal Processing Systems (ICSPS), NJ, USA, 2022, pp. 793–797.

[22] Y. Li, Q. Fan, H. Huang, Z. Han, and Q. Gu, ‘‘A modified YOLOv8 detection network for UAV aerial image recognition,’’ Drones, vol. 7, no. 5, p. 304, May 2023.

[23] Wang, Chien-Yao et al. “YOLOv9: Learning What You Want to Learn Using Programmable Gradient Information.” ArXiv abs/2402.13616 (2024): n. pag.

[24] S. Ren, K. He, R. Girshick and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137-1149, 1 June 2017.

[25] F. Ji et al., “Aircraft detection in high spatial resolution remote sensing images combining multi-angle features driven and majority voting CNN,” Remote Sens., vol. 13, no. 11, 2021.

[26] I. Saetchnikov, V. Skakun and E. Tcherniavskaia, "Efficient objects tracking from an unmanned aerial vehicle," 2021 IEEE 8th International Workshop on Metrology for AeroSpace (MetroAeroSpace), Naples, Italy, 2021, pp. 221-225.

[27] I. Saetchnikov, V. Skakun and E. Tcherniavskaia, "Robust S-Y-biLSTM object tracking method for on-road objects shoot from an unmanned aerial vehicle," 2022 IEEE 9th International Workshop on Metrology for AeroSpace, Pisa, Italy, 2022, pp. 270-274.

[28] I. V. Saetchnikov, V. V. Skakun and E. A. Tcherniavskaia, "Deep Neural Network-Based Dynamical Object Recognition and Robust Multiobject Tracking Technique for Onboard Unmanned Aerial Vehicle’s Computer Vision-Based Systems," in IEEE Journal on Miniaturization for Air and Space Systems, vol. 4, no. 3, pp. 250-256, Sept. 2023.

[29] I. Saetchnikov, V. Skakun and E. Tcherniavskaia, "biLSCCS: modular dynamical on-road objects trajectory prediction approach," 2023 IEEE 10th International Workshop on Metrology for AeroSpace, Milan, Italy, 2023, pp. 131-135.