UDC 004.8

AIRCRAFT DETECTION WITH DEEP NEURAL NETWORKS AND CONTOUR-BASED METHODS

Radionov Y. D. – Postgraduate student of Department of Information Technology and Computer Engineering, Dnipro University of Technology, Dnipro, Ukraine.

Kashtan V. Yu. – PhD, Associate Professor, Associate Professor of Department of Information Technology and Computer Engineering, Dnipro University of Technology, Dnipro, Ukraine.

Hnatushenko V. V. – Dr. Sc., Professor, Head of Department of Information Technology and Computer Engineering, Dnipro University of Technology, Dnipro, Ukraine.

Kazymyrenko O.V. – Postgraduate student of Department of Information Technology and Computer Engineering, Dnipro University of Technology, Dnipro, Ukraine.

ABSTRACT

Context. Aircraft detection is an essential task in the military, as fast and accurate aircraft identification allows for timely response to potential threats, effective airspace control, and national security. The use of deep neural networks improves the accuracy of aircraft recognition, which is essential for modern defense and airspace monitoring needs.

Objective. The work aims to improve the accuracy of aircraft recognition in high-resolution optical satellite imagery by using deep neural networks and a method of sequential boundary traversal to detect object contours.

Method. A method for improving the accuracy of aircraft detection on high-resolution satellite images is proposed. The first stage involves collecting data from the HRPlanesv2 dataset containing high-precision satellite images with aircraft annotations. The second stage consists of preprocessing the images using a sequential boundary detection method to detect object contours. In the third stage, training data is created by integrating the obtained contours with the original HRPlanesv2 images. In the fourth stage, the YOLOv8m object detection model is trained separately on the original HRPlanesv2 dataset and the dataset with the applied preprocessing, which allows the evaluation of the impact of additional processed features on the model performance.

Results. Software that implements the proposed method was developed. Testing was conducted on the primary data before preprocessing and the data after its application. The results confirmed the superiority of the proposed method over classical approaches, providing higher aircraft recognition accuracy. The mAP50 index reached 0.994, and the mAP50-95 index reached 0.864, 1% and 4.8% higher than the standard approach.

Conclusions. The experiments confirm the effectiveness of the proposed method of aircraft detection using deep neural networks and the process of sequential boundary traversal to detect object contours. The results indicate this approach's high accuracy and efficiency, which allows us to recommend it for use in research related to aircraft recognition in high-resolution images. Further research could focus on improving image preprocessing methods and developing object recognition technologies in machine learning.

KEYWORDS: machine learning, image and contour recognition, optical image preprocessing, high-resolution imagery, aircraft detection.

ABBREVIATIONS

AI is an Artificial Intelligence;
CNN is a Convolutional Neural Network;
FP is a False Positive;
FN is a False Negative;
FPS is a Frames Per Second;
IoU is an Intersection Over Union;
ML is Machine Learning;
SAR is a Synthetic-Aperture Radar;
TN is a True Negative;
TP is True Positive;
UAV is Unmanned Aerial Vehicle.

NOMENCLATURE

AP is an average precision for a single class;

mAP Is a mean average precision;

Precision is a is the fraction of TP detections among all detections made at a particular IoU threshold;

Recall is the fraction of TP detections found among all possible detections made at a particular threshold.

INTRODUCTION

In the contemporary information landscape, characterized by an exponential growth in data, object recognition tasks have gained immense prominence. Artificial intelligence and machine learning have emerged as pivotal technologies for addressing these challenges. Beyond their widespread application in socioeconomic spheres, these technologies hold immense significance in the military domain. The proliferation of satellite imagery, coupled with the surge in the utilization of unmanned aerial vehicles (UAVs) of varying scales in military operations, has generated a deluge of visual information far exceeding the processing capabilities of human analysts.

Object recognition in the information age is a critical task with far-reaching implications for both civilian and military applications. AI and ML technologies offer a promising approach to address the challenges posed by the massive volume, complexity, and variability of visual data.

The object of study is aircraft detection on high-resolution satellite images using machine learning methods.

DOI 10.15588/1607-3274-2024-4-12

The subject of study is the method for aircraft detection on high-resolution satellite images using machine learning methods.

The purpose of the work is to increase the accuracy of aircraft detection on high-resolution satellite images using machine learning methods.

1 PROBLEM STATEMENT

The burgeoning availability of high-resolution satellite imagery has opened a new frontier for automated aircraft detection in diverse applications, from surveillance to environmental monitoring. However, achieving high recognition accuracy remains a formidable challenge. This challenge stems from the inherent complexities of satellite imagery, including variable backgrounds, fluctuating illumination conditions, and indistinct object edges in raw images. These factors significantly impede the feature extraction capabilities of deep learning models, often resulting in the misidentification of aircraft. Consequently, a critical need exists for novel methodologies that enhance the effectiveness of deep learning models for aircraft detection in high-resolution satellite imagery. This research addresses this gap by proposing a novel preprocessing approach that leverages the power of contour detection techniques. This method aims to improve the performance of deep learning models in aircraft recognition tasks by strategically accentuating the boundaries of aircraft objects and suppressing background clutter.

2 REVIEW OF THE LITERATURE

Deep learning techniques, especially convolutional neural networks (CNNs), have proven highly effective in object recognition and classification tasks in recent years. Researchers actively apply these approaches to analyze aerospace imagery obtained from uncrewed aerial vehicles, satellites, and other remote sensing platforms. These tasks have gained significant importance in a wide range of applications, including object detection in autonomous vehicles [1], facial recognition [2], medical image analysis [3], and remote sensing [4].

Machine learning techniques have notably advanced remote sensing applications, particularly in automatically extracting water bodies from satellite imagery. In work [5], machine learning methods for water body detection using Sentinel-2 imagery were investigated, showing significant improvements in the accuracy and efficiency of remote sensing techniques. Specifically, the paper [6] proposed an enhancement to the YOLOv5 architecture, resulting in a 3.5% improvement in model accuracy.

Also, in another paper [7], authors proposed a framework that tackles small object detection in high-resolution remote sensing images. It utilizes a deconvolutional module to refine feature maps and recover spatial information lost during pooling layers. Additionally, a squeeze-and-excitation attention mechanism focuses on informative features crucial for small object detection. This combination achieves high accuracy in detecting small aircraft within complex backgrounds.

RefineContourNet is a ResNet-based multi-path refinement CNN specifically designed for object contour detection [8] could be explored for refining aircraft object boundaries after initial detection by deep learning models.

In another study [9], authors developed an algorithmic technique for aircraft segmentation based on fuzzy logic that achieves an accuracy of 92.5%.

YOLO-extract algorithm [10] shows faster convergence speed and reduces the calculation amount by 45.3GFLOPs and a number of parameters by 10.526 million. At the same time, the algorithm increases mAP by 8.1% and detection speed by 3 times in aircraft detection compared to YOLOv5.

The YOLO-class model [11] represents an enhanced version of the YOLO-extract model, incorporating modifications to the network architecture. These changes significantly improved detection accuracy, increasing from 0.608 to 0.704, and in FPS, rising from 36.16 to 39.598, when compared to the original YOLO-extract.

YOLO architecture can be used and improved for aircraft detection using SAR data [12]. By adding Attention-Efficient Layer Aggregation Network-Head (A-ELAN-H) module that prioritizes essential features for improved accuracy authors increased *mAP50* by 2.1% and *mAP50-95* by 1.9%.

The current body of research has predominantly concentrated on one of two approaches: object detection or contour detection. While these methods have achieved notable success individually, their integration remains an underexplored area of research.

3 MATERIALS AND METHODS

The aircraft detection technology proposed in the paper consists of four stages, as shown in Fig. 2.

The first stage consists of downloading the HRPlanesv2 [13] dataset the second iteration of HRPlanes dataset. It contains 2120 very high-resolution Google Earth images, with a total of 14335 aircraft labeled. The dataset has been divided into three parts: 70% for training, 20% for validation, and 10% for testing.

The second stage is retrieving contours using OpenCV contour detection. A technique, based on the border following algorithm [14], for identifying and analyzing connected regions within an image that exhibit similar intensity or color characteristics. It analyzes the binary image to identify connected components, where all pixels share the same intensity (white in our case) and are adjacent to each other. These connected components represent the object boundaries or contours. These regions often correspond to distinct shapes or objects present in the image.

The four boundaries of an image are referred to as its frame. An image with width w and height h can be represented as a matrix of order $h \times w$, composed of individual pixels. The rows 1 and h, and the columns 1 and w, form the image frame. A pixel with a gray value of zero is defined as a zero pixel, while a pixel with a gray value of one is termed a one pixel. In this algorithm, the frames of the binarized image are treated as zero pixels. If the frame

DOI 10.15588/1607-3274-2024-4-12

of the input image contains any one pixel, they are converted to zero pixels.

An example of Suzuki's algorithm is shown in Fig. 1, where pixels with the same absolute value are associated with the same boundary. The relationships between each boundary are illustrated on the right side of the figure. In this context, *ob* refers to the outer border, *hb* denotes the hole border, and the parent border indicates that the outer layer acts as the parent of the inner layer.

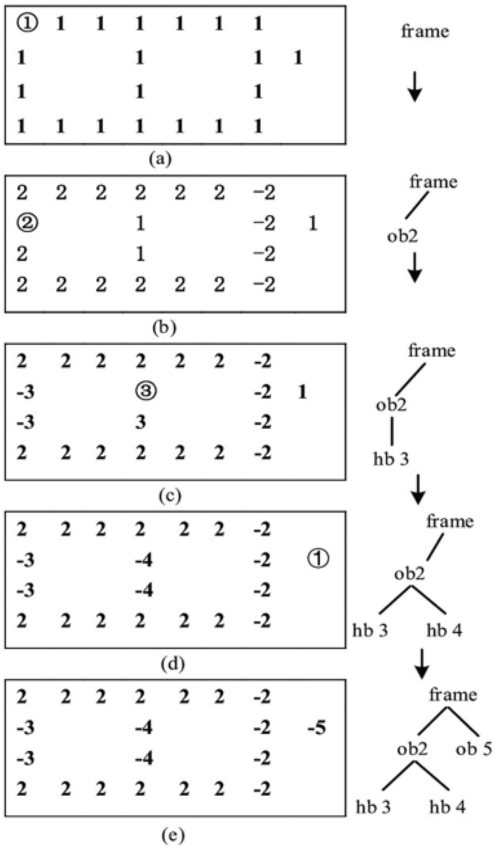


Figure 1 – Example diagram of border-following algorithm [15]

The circled pixel points in (a–e) correspond to the border descriptions for each link on the right.

The circled pixel points in (a–e) correspond to the border descriptions for each link on the right.

The third stage is data pre-processing by combining contours with the original image. During the fourth stage, we opted to train the YOLOv8m object detection model. The architecture of the model is shown in Fig. 3.

Model selection was motivated by its favorable balance between model complexity (295 layers and 25.9 million parameters) and reported performance. This characteristic allowed us to balance object detection accuracy and computational efficiency.

The YOLOv8 architecture adheres to a modular design principle and can be divided into two primary components: the backbone and the head.

The backbone network serves as the foundation for feature extraction. It consists of 53 convolutional layers enhanced with cross-stage partial connections. YOLOv8 offers flexibility by employing a variety of backbone options, including CSPDarknet53 and EfficientDet. This selection allows for a trade-off between the capability to extract informative features and the associated computational complexity.

The head generates predictions based on the features extracted by the backbone network and the neck architecture. It predicts bounding box coordinates, objectness scores, and class probabilities for each anchor box associated with a grid cell. The architecture uses anchor boxes to predict objects of different shapes and sizes efficiently.

4 EXPERIMENTS

In the paper, we tested the proposed method on the HRPlanesv2 dataset and compared different contour detection techniques:

1. Canny edge detection. A multi-stage algorithm designed for robust edge extraction in images. It achieves a balance between high edge detection rates, accurate localization of edges, and minimal false positives. The algorithm employs a series of steps, including noise reduction through Gaussian filtering, calculation of image gradients, non-maximum suppression for thinning edges, and hysteresis thresholding for robust edge selection.

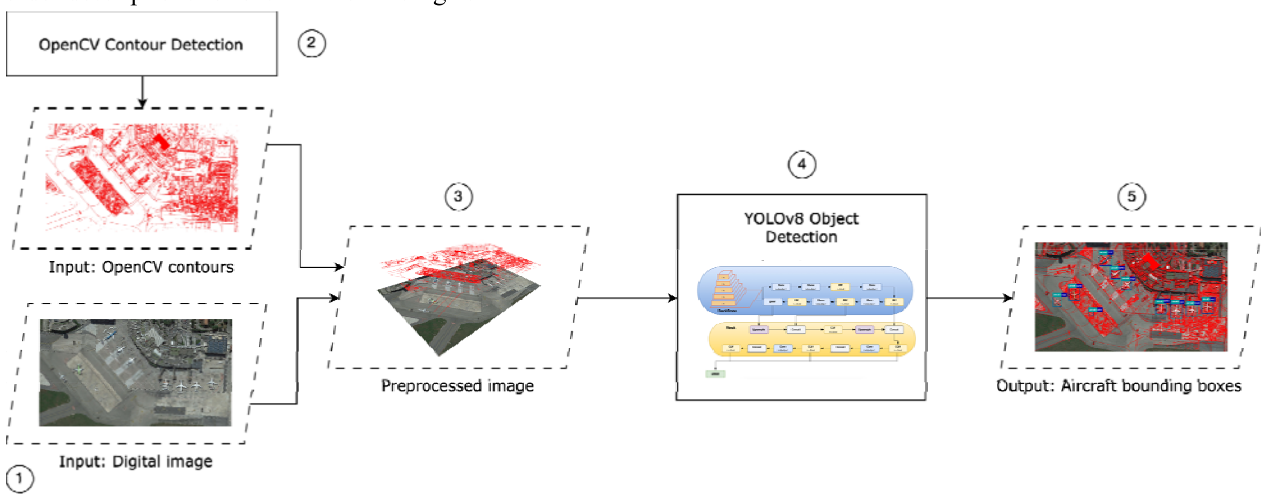


Figure 2 – Diagram of the proposed method

DOI 10.15588/1607-3274-2024-4-12

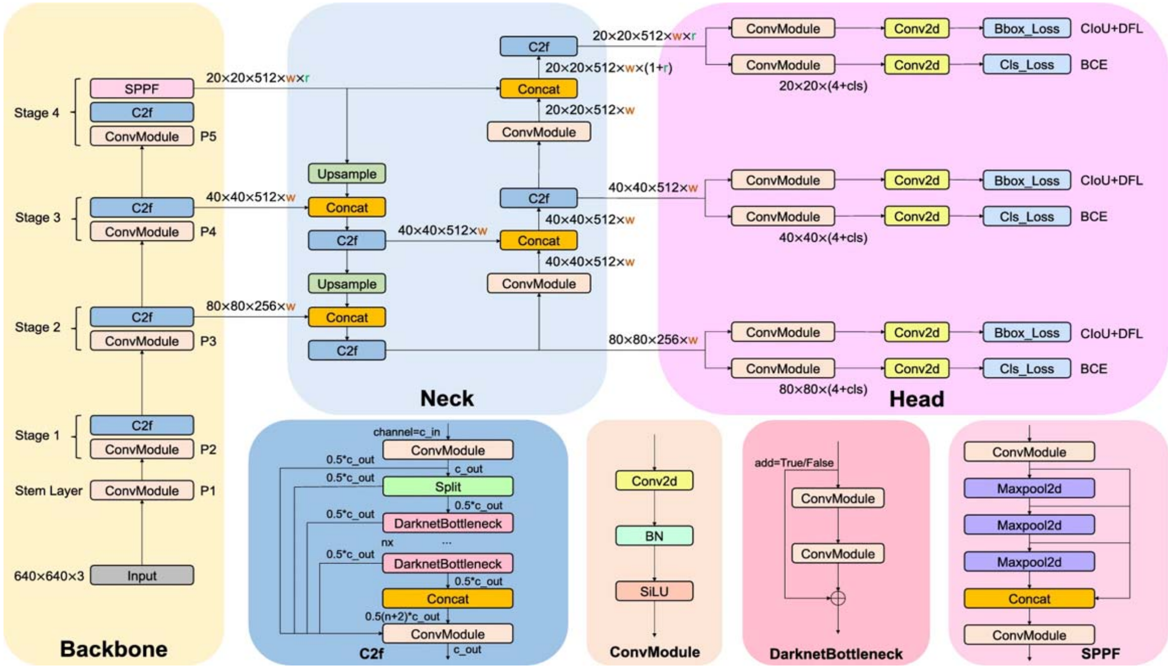


Figure 3 – YOLOv8 architecture [16]

2. Border following algorithm for contour detection.

3. The Laplacian. A mathematical operator is employed in image processing for edge detection and image sharpening. It calculates the second derivative of the image intensity, highlighting regions with rapid intensity changes, which frequently correspond to edges. Positive Laplacian values signify regions where intensity brightens towards the center (convex regions), while negative values indicate regions where intensity darkens (concave regions). A zero value indicates flat areas or edges where the direction of intensity changes flips.

4. The Sobel filter. A fundamental tool used for edge detection in image processing. It approximates the image gradient, representing the direction and magnitude of intensity change within the image. The filter utilizes two small kernels, one designed to detect horizontal edges and another for vertical edges, to estimate these gradients. The Sobel filter plays a crucial role in edge detection and feature extraction and serves as a building block for the Canny edge detection algorithm.

5. Canny and Laplacian operators applied sequentially.

Since YOLO measures the model's accuracy in terms of its ability to identify and locate objects of interest in an image accurately, the *mAP* was used. *mAP* is a combination of precision and recall values calculated over multiple confidence thresholds, also called the Intersection over Union threshold. Varying the IoU threshold will result in different True Positives and False Positives.

Precision is the fraction of TP detections among all detections made at a particular IoU threshold by the formula (1):

$$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}} \tag{1}$$

Recall by the formula (2) is the fraction of TP detections found among all possible detections made at a particular threshold:

$$\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}} \tag{2}$$

The general formula for calculating *mAP* is shown in formula (3):

$$\text{mAP} = \frac{1}{\text{N}}\sum_{n=1}^{N} AP_i, \tag{3}$$

where N is the number of object classes, and AP_i is the average precision for the *i*-th class. It's common to denote what IoU thresholds are used with digits following the *mAP*, e.g. *mAP50-95* uses a range of IoU thresholds from 0.5 to 0.95 with a 0.05 step size while *mAP95* uses a IoU threshold of 0.95.

The average precision for a given class is determined by first sorting all detected objects in descending order based on their confidence scores, then calculating the precision and recall at each threshold, and finally finding the area under the precision-recall curve by integrating it across all possible thresholds, as outlined in formula (4):

$$\text{Average Precision (AP)} = \int_{r=0}^{1} p(r)\text{dr} \tag{4}$$

In machine learning and computer vision, a confusion matrix is an essential tool for evaluating the performance of classification models. This matrix provides a clear

DOI 10.15588/1607-3274-2024-4-12

visualization of classification results, helping to assess the model's accuracy. It records the number of correct and incorrect classifications for each category. Specifically, TP refers to correctly classified positive instances, while TN denotes correctly classified negative cases. FP represents instances incorrectly classified as positive, and FN refers to instances mistakenly classified as negative.

5 RESULTS

Table 1 summarizes the accuracy metrics the object detection model achieved on datasets that underwent various pre-processing techniques. The presented metrics provide insights into the effectiveness of different pre-processing methods in enhancing the model's ability to detect objects within the datasets.

The original, unprocessed dataset achieved the highest *Recall* value and the second-highest *mAP50-95*. This suggests that the raw images already contain sufficient information for the model to identify a significant portion of aircraft present.

Its superior performance in Precision, *mAP50,* and *mAP50-95* demonstrates this. The results suggest that the extracted contours significantly improve the model's ability to accurately detect and distinguish aircraft from background elements. Consequently, this technique was chosen for the proposed method.

The Laplacian operator and Sobel filter pre-processing techniques demonstrated descent performance, but significantly lower than the original dataset and border-following contour detection. However, these methods led to a considerable loss of information compared to the original images. This indicates that, although they may emphasize potential edges, they could introduce artifacts or eliminate essential details needed for accurate object detection.

The Canny edge detection algorithm produced the lowest performance across all metrics. This could be attributed to the presence of noise or inconsistencies in the high-resolution satellite imagery.

The combined Canny-Laplacian approach yielded average results, falling between the single Canny and Laplacian pre-processing performance. While it outperformed Canny alone, it remained less effective than Laplacian pre-processing. This suggests that the combined approach might not have effectively leveraged the strengths of both techniques, potentially introducing redundant or conflicting information for the model.

These findings highlight the importance of selecting appropriate pre-processing techniques for specific image datasets and tasks. While edge detection can enhance feature extraction, the choice of method needs to balance edge delineation with information preservation to achieve optimal performance in deep learning models for object recognition.

The confusion matrix, presented in Fig. 4, illustrates the performance of the classification models by displaying the number of correctly and incorrectly classified objects across each category.

Table 1 – Aircraft detection accuracy metrics

Pre-processing type	Precision	Recall	mAP50	mAP50-95
None	0.990522	**0.981679**	0.991079	0.831246
Canny	0.902949	0.782908	0.859798	0.592251
Border-following	**0.996403**	0.975793	**0.994272**	**0.863925**
Laplacian	0.951500	0.885149	0.958168	0.713322
Sobel	0.965968	0.958904	0.982615	0.809901
Canny + Laplacian	0.948966	0.827006	0.897425	0.654177

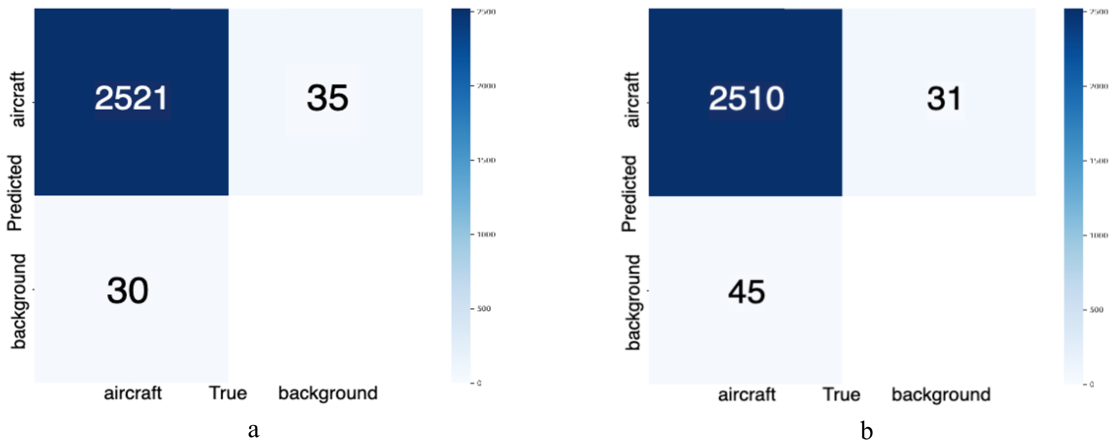


Figure 4 – Confusion matrix for: a – original dataset; b – a dataset with the proposed technology

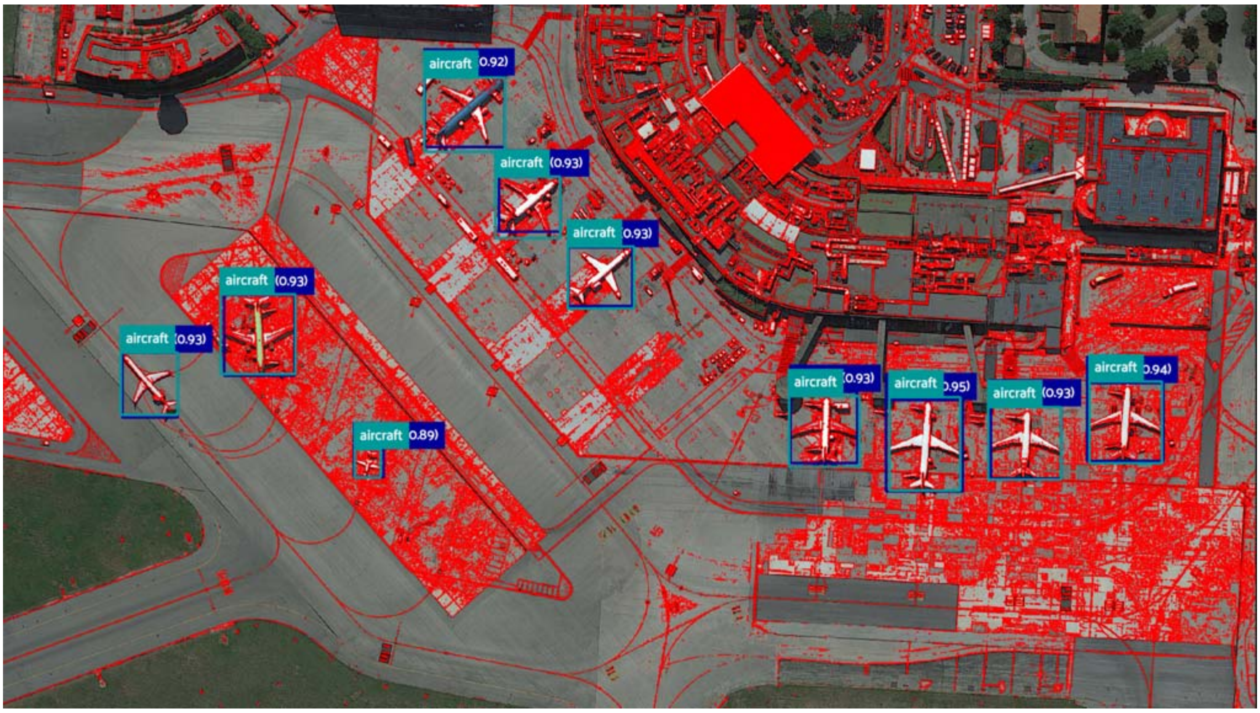
The results shown in Fig. 4 demonstrate the comparison of confusion matrices for two approaches: using the original dataset (Fig. 4a) and the modified dataset using the proposed technology (Fig. 4b). In the original dataset, the number of correctly classified objects in the "airplane" class was 2,521, with 71 false positives and 34 false nega-

DOI 10.15588/1607-3274-2024-4-12

tives. After implementing the proposed method, the number of false positives dropped to 31, reflecting an improvement in accuracy. However, the false negatives increased to 45, which means a specific decrease in completeness. Thus, the proposed technology improves the accuracy of classifying objects of the "airplane" class, but this is achieved at the expense of a slight decrease in the completeness index.

Fig. 5 illustrates the detection outcomes for the original dataset without pre-processing (a) and the dataset after applying the border-following contour detection method (b). In both images, cyan bounding boxes indicate ground truth annotations, while blue bounding boxes show the detections made by the respective model.

a



b

Figure 5 – Results of proposed technology: a – original dataset [14]; b – dataset with proposed technology

DOI 10.15588/1607-3274-2024-4-12

6 DISCUSSION

The proposed aircraft detection technology, leveraging edge detection pre-processing in a four-stage pipeline (Fig. 2), improved recognition accuracy compared to a baseline model trained on raw images. By incorporating pre-processed images with accentuated aircraft boundaries, the model is better equipped to distinguish aircraft from background clutter, improving recognition performance.

Our investigation into various edge detection techniques yielded valuable insights. The border-following algorithm, implemented in OpenCV, emerged as the most effective. Intriguingly, the combined Canny-Laplacian approach showed promise, suggesting potential for further optimization in future research to explore potential synergies between different techniques. While the proposed method demonstrates a clear advancement in aircraft detection using high-resolution satellite imagery, there are limitations to consider. The evaluation was conducted using a single dataset (HRPlanesV2). Future work should expand upon these findings by incorporating a broader range of datasets encompassing diverse image characteristics and backgrounds. This will provide a more comprehensive understanding of the generalizability and robustness of the proposed approach across different scenarios. Additionally, exploring alternative deep learning models with architectures specifically designed for high-resolution image recognition tasks could potentially yield further improvements. Furthermore, investigating even more advanced edge detection techniques, leveraging recent advancements in deep learning for image processing, could be a fruitful avenue for future research.

In conclusion, this research effectively demonstrates the value of incorporating edge detection pre-processing into the aircraft detection pipeline. The proposed method achieved superior performance in recognizing aircraft within high-resolution satellite imagery. The findings pave the way for further exploration and refinement, ultimately contributing to developing increasingly accurate and robust automated aircraft detection systems.

CONCLUSIONS

This study investigated the impact of pre-processing techniques on the performance of a deep-learning model for aircraft detection in high-resolution imagery.

Our results show that pre-processing techniques can significantly improve a model's precision in object detection tasks. The findings emphasize how pre-processing enhances the model's ability to extract critical features from the data, leading to greater detection accuracy. Additionally, the study highlights the importance of understanding the interaction between pre-processing methods and the selected deep-learning model architecture.

The scientific novelty o of the obtained results is that, for the first time, a method is proposed to improve the accuracy of aircraft recognition on high-resolution satellite images, combining deep neural networks with the technique of sequential boundary traversal to detect object contours. The developed approach allows automating the process of aircraft detection and provides high recognition accuracy, which is a significant improvement over the existing classical method. The implementation of this method allows for efficient image processing, increasing the accuracy of object detection by optimizing the use of preprocessing and modern machine-learning algorithms.

The practical significance lies in developing software that implements the proposed method. The experiments have confirmed the effectiveness of the new approach for recognizing aircraft on satellite images. The research results suggest using this method for practical airspace monitoring and aviation security tasks. Further improvement of image preprocessing methods and object recognition technologies can increase the efficiency of these systems in various practical applications.

Prospects for further research are to improve image preprocessing methods. In addition, it is advisable to explore the possibilities of expanding the functionality of the developed software by integrating new neural network architectures and advanced machine learning algorithms to improve the accuracy and speed of real-time object recognition. It also promises to apply the proposed approach to other objects and images, which can expand its practical application and increase its versatility in various fields.

REFERENCES

1. Tarmizi I. A., Aziz A. A.Vehicle Detection Using Convolutional Neural Network for Autonomous Vehicles, *International Conference on Intelligent and Advanced System, ICIAS 2018.* Kuala Lumpur, Malaysia, 2018, pp. 1–5. – DOI: 10.1109/ICIAS.2018.8540563.
2. Li L., Mu X., Li S., Peng H. A Review of Face Recognition Technology, *IEEE Access,* 2020, Vol. 8, pp. 139110–139120. DOI: 10.1109/ACCESS.2020.3011028.
3. Galić I., Habijan M., Leventić H., Romić K. Machine Learning Empowering Personalized Medicine: A Comprehensive Review of Medical Image Analysis Methods, *Electronics,* 2023, Vol. 12, № 21, P. 4411. DOI: 10.3390/electronics12214411.
4. Hnatushenko V., Kashtan V. Automated pansharpening information technology of satellite images, *Radio Electronics, Computer Science, Control*, 2021, № 2, pp. 123–132. DOI 10.15588/1607-3274-2021-2-13.
5. Kashtan V., Hnatushenko V. Machine learning for automatic extraction of water bodies using Sentinel-2 imagery, *Radio Electronics, Computer Science, Control*, 2024, № 1, pp. 118–127. DOI: 10.15588/1607-3274-2024-1-11
6. Zhou F., Deng H., Xu Q., Lan X. CNTR-YOLO: Improved YOLOv5 Based on ConvNext and Transformer for Aircraft Detection in Remote Sensing Images, *Electronics,* 2023, Vol. 12, № 12, P. 267. DOI: 10.3390/electronics12122671.
7. Zhou L., Yan H., Shan Y., Zheng Ch., Liu Y., Zuo X., Qiao B. Aircraft Detection for Remote Sensing Images Based on Deep Convolutional Neural Networks, *Journal of Electrical and Computer Engineering*, 2021, Vol. 2021, pp. 1–16. DOI: 10.1155/2021/4685644.
8. Kelm. A. P., Rao V. S., Zoelzer U. Object Contour and Edge Detection with RefineContourNet, *Computer Analysis of Images and Patterns. CAIP 2019, Salerno, 2–6 September, 2019*. Springer, Cham, 2019, pp. 246–258. DOI: 10.1007/978-3-030-29888-3_20.

DOI 10.15588/1607-3274-2024-4-12

9. Berezina S., Solonets O., Lee K., Bortsova M. An information technique for segmentation of military assets in conditions of uncertainty of initial data, *Information Processing Systems,* 2021, №4(167), pp. 6–18. DOI: 10.30748/soi.2021.167.01.
10. Liu Z., Gao Y., Du Q., Chen M., Lv W. YOLO-Extract: Improved YOLOv5 for Aircraft Object Detection in Remote Sensing Images, *IEEE Access*, 2023, Vol. 11, pp. 1742–1751. DOI: 0.1109/ACCESS.2023.3233964.
11. Liu Z., Gao Y., Du Q. YOLO-Class: Detection and Classification of Aircraft Targets in Satellite Remote Sensing Images Based on YOLO-Extract, *IEEE Access,* 2023, Vol. 11. pp. 109179–109188. DOI: 10.1109/ACCESS.2023.3321828.
12. Chen J., Shen Y., Liang Y., Wang Z., Zhang Q. YOLO-SAD: An Efficient SAR Aircraft Detection Network, *Applied Sciences,* 2023, Vol. 14, № 7, P. 3025. DOI: 10.3390/app14073025.
13. Unsal D. HRPlanesv2 – High Resolution Satellite Imagery for Aircraft Detection, *Zenodo,* 2022. DOI: 10.5281/ZENODO.7331974.
14. Suzuki S., Be K.Topological structural analysis of digitized binary images by border following, *Computer Vision, Graphics, and Image Processing,* 1985, Vol. 30, № 1, pp. 32–46. DOI: 10.1016/0734-189X(85)90016-7.
15. Song X., Zhang S., Yang J., Zhang J. Research on Luggage Package Extraction of X-ray Images Based on Edge Sensitive Multi-Channel Background Difference Algorithm, *Applied Sciences,* 2023, Vol. 13, № 21, P. 11981. DOI: 10.3390/app132111981.
16. Ju R-Y,. Cai W. Fracture detection in pediatric wrist trauma X-ray images using YOLOv8 algorithm, *Scientific Reports*, 2023, Vol. 13, №1, P. 20077. DOI: 10.1038/s41598-023-47460-7.

Received 02.07.2024.
Accepted 17.09.2024.

УДК 004.8

РОЗПІЗНАВАННЯ ЛІТАКІВ ЗА ДОПОМОГОЮ ГЛИБОКИХ НЕЙРОННИХ МЕРЕЖ ТА ВИЯВЛЕННЯ КОНТУРІВ

Радіонов Є. Д. – аспірант кафедри інформаційних технологій та комп’ютерної інженерії Національного технічного університету «Дніпровська політехніка», Дніпро, Україна.

Каштан В. Ю. – канд. техн. наук, доцент, доцент кафедри інформаційних технологій та комп’ютерної інженерії Національного технічного університету «Дніпровська політехніка», Дніпро, Україна.

Гнатушенко В. В. – д-р техн. наук, професор, завідувач кафедри інформаційних технологій та комп’ютерної інженерії, Національний технічний університет «Дніпровська політехніка», Дніпро, Україна.

Казимиренко О. В. – аспірант кафедри інформаційних технологій та комп’ютерної інженерії Національного технічного університету «Дніпровська політехніка», Дніпро, Україна.

АНОТАЦІЯ

Актуальність. Розпізнавання літаків є важливою задачею у військовій сфері, оскільки швидка та точна ідентифікація літальних апаратів дозволяє своєчасно реагувати на потенційні загрози, ефективно контролювати повітряний простір і підтримувати національну безпеку. Використання глибоких нейронних мереж підвищує точність розпізнавання літаків, що є важливим для сучасних потреб оборони та моніторингу повітряного простору.

Мета роботи – підвищення точності розпізнавання літаків на оптичних космічних знімках високої роздільної здатності за допомогою глибоких нейронних мереж та методу послідовного обходу меж для виявлення контурів об’єктів.

Метод. Запропоновано метод для підвищення точності розпізнавання літаків на супутникових знімках високої роздільної здатності. На першому етапі здійснюється збір даних із набору HRPlanesv2, що містить високоточні супутникові зображення з анотаціями літаків. Другий етап передбачає попередню обробку зображень за допомогою методу послідовного обходу меж для виявлення контурів об’єктів. На третьому етапі створюються навчальні дані шляхом інтеграції отриманих контурів з оригінальними зображеннями HRPlanesv2. На четвертому етапі модель виявлення об’єктів YOLOv8m тренується окремо на оригінальному наборі даних HRPlanesv2 та на наборі даних із застосованою попередньою обробкою, що дозволяє оцінити вплив додаткових оброблених характеристик на продуктивність моделі.

Результати. Розроблено програмне забезпечення, яке реалізує запропонований метод. Тестування проводилося як на первинних даних до попередньої обробки, так і на даних після її застосування. Результати підтвердили перевагу запропонованого методу над класичними підходами, забезпечуючи вищу точність розпізнавання літаків. Показник mAP50 досяг 0.994, а mAP50-95 – 0.864, що на 1% і 4,8% відповідно, вище, ніж у стандартного підходу.

Висновки. Проведені експерименти підтверджують ефективність запропонованого методу розпізнавання літаків за допомогою глибоких нейронних мереж та методу послідовного обходу меж для виявлення контурів об’єктів. Результати вказують на високу точність і ефективність цього підходу, що дозволяє рекомендувати його для використання в задачах, пов’язаних із розпізнаванням літаків на зображеннях високої роздільної здатності. Подальші дослідження можуть зосередитися на вдосконаленні методів попередньої обробки зображень і розвитку технологій розпізнавання об’єктів у машинному навчанні.

КЛЮЧОВІ СЛОВА: машинне навчання, розпізнавання образів та контурів, попередня обробка оптичних зображень, знімки високої роздільної здатності, розпізнавання літаків.

ЛІТЕРАТУРА

1. Tarmizi I. A. Vehicle Detection Using Convolutional Neural Network for Autonomous Vehicles / I. A. Tarmizi, A. A. Aziz // International Conference on Intelligent and Advanced System, ICIAS 2018, Kuala Lumpur, Malaysia. – 2018. – P. 1–5. – DOI: 10.1109/ICIAS.2018.8540563.
2. A Review of Face Recognition Technology / [L. Li, X. Mu, S. Li, H. Peng] // IEEE Access. – 2020. – Vol. 8. – P. 139110–139120. DOI: 10.1109/ACCESS.2020.3011028.

DOI 10.15588/1607-3274-2024-4-12

3. Machine Learning Empowering Personalized Medicine: A Comprehensive Review of Medical Image Analysis Methods / [I. Galić, M. Habijan, H. Leventić, K. Romić] // Electronics. – 2023. – Vol. 12 № 21. – P. 4411. DOI: 10.3390/electronics12214411.
4. Hnatushenko V. Automated pansharpening information technology of satellite images / V. Hnatushenko, V. Kashtan // Radio Electronics, Computer Science, Control. – 2021. – № 2. – P. 123–132. DOI:10.15588/1607-3274-2021-2-13.
5. Kashtan V. Machine learning for automatic extraction of water bodies using Sentinel-2 imagery / V. Kashtan, V. Hnatushenko // Radio Electronics, Computer Science, Control. – 2024. – № 1. – P. 118–127. DOI: 10.15588/1607-3274-2024-1-11
6. CNTR-YOLO: Improved YOLOv5 Based on ConvNext and Transformer for Aircraft Detection in Remote Sensing Images / [F. Zhou, H. Deng, Q. Xu, X. Lan] // Electronics. – 2023. – Vol. 12, № 12. – P. 267. DOI: 10.3390/electronics12122671.
7. Aircraft Detection for Remote Sensing Images Based on Deep Convolutional Neural Networks / [L. Zhou, H. Yan, Y. Shan, Ch. Zheng et al.] // Journal of Electrical and Computer Engineering. – 2021. – Vol. 2021. – P. 1–16. DOI: 10.1155/2021/4685644.
8. Kelm. A. P. Object Contour and Edge Detection with RefineContourNet / A. P. Kelm, V. S. Rao, U. Zoelzer // Computer Analysis of Images and Patterns. CAIP 2019, Salerno, 2–6 September, 2019. – Springer, Cham, 2019. – P. 246–258. DOI: 10.1007/978-3-030-29888-3_20.
9. An information technique for segmentation of military assets in conditions of uncertainty of initial data / [S. Berezina, O. Solonets, K. Lee, M. Bortsova] // Information Processing Systems. – 2021. – №4(167). – P. 6–18. DOI: 10.30748/soi.2021.167.01.
10. YOLO-Extract: Improved YOLOv5 for Aircraft Object Detection in Remote Sensing Images / [Z. Liu, Y. Gao, Q. Du et al.] // IEEE Access. – 2023. – Vol. 11. – P. 1742–1751. DOI: 0.1109/ACCESS.2023.3233964.
11. Liu Z. YOLO-Class: Detection and Classification of Aircraft Targets in Satellite Remote Sensing Images Based on YOLO-Extract / Z. Liu, Y. Gao, Q. Du // IEEE Access. – 2023. – Vol. 11. – P. 109179–109188. DOI: 10.1109/ACCESS.2023.3321828.
12. Chen J. YOLO-SAD: An Efficient SAR Aircraft Detection Network / [J. Chen, Y. Shen, Y. Liang et al.] // Applied Sciences. – 2023. – Vol. 14, № 7. – P. 3025. DOI: 10.3390/app14073025.
13. Unsal D. HRPlanesv2 – High Resolution Satellite Imagery for Aircraft Detection / D. Unsal // Zenodo. – 2022. DOI: 10.5281/ZENODO.7331974.
14. Suzuki S. Topological structural analysis of digitized binary images by border following / S. Suzuki and K. Be // Computer Vision, Graphics, and Image Processing. – 1985. – Vol. 30, № 1. – P. 32–46. DOI: 10.1016/0734-189X(85)90016-7.
15. Research on Luggage Package Extraction of X-ray Images Based on Edge Sensitive Multi-Channel Background Difference Algorithm. / [X. Song, S. Zhang, J. Yang, J. Zhang] // Applied Sciences. – 2023. – Vol. 13, № 21. – P. 11981. DOI: 10.3390/app132111981.
16. Ju R-Y. Fracture detection in pediatric wrist trauma X-ray images using YOLOv8 algorithm / R.-Y. Ju, W. Cai // Scientific Reports. – 2023. – Vol. 13, № 1. – P. 20077. DOI: 10.1038/s41598-023-47460-7.

DOI 10.15588/1607-3274-2024-4-12