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ARTIFICIAL INTELLIGENCE BASED HELIPAD DETECTION WITH CONVOLUTIONAL NEURAL NETWORK

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A B S T R A C T

When a malfunction occurs in the helicopter or the pilot faints during a flight or performing a duty, and in order to ensure the safety of the pilot and the helicopter, a system must be available to detect the helicopter landing pads, so that the helicopter can land at the airport. Closest safe place immediately. This study focuses on helicopter landing pad detection using YOLOv8 and YOLOv5 models. A dataset of 1877 images collected from the Internet was used to evaluate the performance of the models. YOLOv8 showed good performance in helipad detection with 96.7% accuracy and 95.8% recall, resulting in an average accuracy (mAP@0.5) of 98.8%. As for YOLOv5, it reached 95.1% precision, 95.8% recall, and 97.5% mAP@0.5. Both models showed good results, but YOLOv8 outperformed it by a small percent.

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Introduction

The helipad, serving as a designated zone for helicopter take-offs and landings, constitutes a critical element in aviation infrastructure. This predetermined area, known as the Touchdown and Lift-Off Area (TLOF), requires meticulous planning and adherence to specific criteria, including unobstructed surroundings and the presence of a wind cone for safe operations. Consequently, diverse configurations of helipad placements have emerged. Notably, most landing sites incorporate distinctive markings, often featuring a prominent white "H" at the center of the landing surface boundary, as depicted in Figure-1 It's worth mentioning that hospital helipads further emphasize their significance by incorporating a cross adjacent to the "H" or replacing the "H" with a recognizable logo

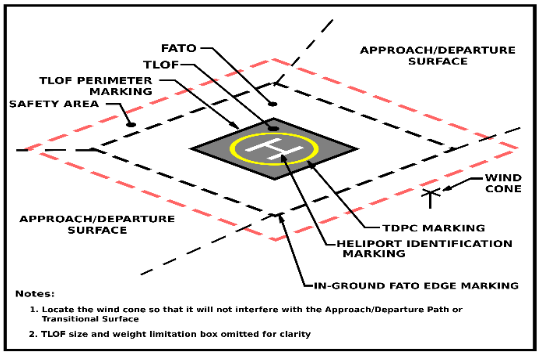


Figure 1. Structure of a Helipad.

Helipad

Helicopter landing platform, which is a flat area created to facilitate the safe take-off and landing of helicopters without human or mechanical losses, as helipads vary in size, design, and location according to need and use, and there are some types of helipads for common helicopters:

- Helipads on the surface of the earth, which are built on the surface of the earth in a flat and safe place, as they are intended for take-off and landing, and they have a mark such as the letter (H) [1].
- Helipads existing on the roofs of buildings designated for take-off and landing, such as those in hotels, hospitals, and government buildings.
- A helipad for helicopters above the sea surfaces, where the platform is established above shipso facilitate take-off and landing, especially in military operations [2].

For the safety of the aircraft and the pilot, there are some factors for helicopter landing that need to be taken into consideration:

- Reducing the speed: the plane's speed must be reduced upon landing if the pilot is present working to reduce it, but if something happens to the pilot, the plane's automatic system works to reduce the plane's speed[3].
- Monitor and determine the height: To maintain the aircraft, the appropriate height must be determined to land safely without losses.
- Determine the helipad: In the event that the pilot is present, he performs the process of determining the runway, or in the event that something happens to the pilot, there are several ways to determine the helipad via the Global Positioning System (GPS) or through the camera.
- Final landing:When the aircraft heads to its designated helipad, it should be slow and steady toward the helipad deck [4].

Among the factors dependent on the success of landing are:

The situation suitable for landing in terms of air or the location of the airstrip, is it safe or not .Due to its capabilities to take off, maneuver and land, helicopters have achieved significant improvement and due to their complex system, they require a certain mechanism to ensure the success of their mission in take-off and landing . One of the wrong methods used in landing is the use of an infrared camera in the plane because it will lead to a disaster in the landing process due to delays Because it takes a smaller amount of images using the fractionation method, it misses one image . Contrary to the convention, the airstrip can detect aircraft instead of the plane detecting the airstrip, and this has been proven to be possible even in low light conditions using deep learning[5].

METHODOLOGY

History of yolo

In the year 2015, YOLO, an acronym for "You Only Look Once," was conceived by Joseph Redmon and his dedicated team. The initial iteration, YOLOv1,In the year 2015 quickly proved its mettle by exhibiting both efficiency and rapid interception, leading to a swift rise in popularity within the realm of advanced object detection models, including the likes of R-CNN, MobileNet, and AlexNet, among others. With its mounting acclaim, YOLO began to draw the attention of numerous researchers who embarked on a journey to refine and enhance YOLO across diverse domains.Joseph Redmon, the ingenious original author and developer of YOLO, persisted in its evolution, birthing subsequent versions - YOLOv2,In the year 2016 and In the year 2018 appearedYOLOv3,. These newer iterations introduced improvements and supplementary features to their predecessors, bolstering YOLO's prowess. However, following the introduction of YOLOv3, Joseph Redmon made a momentous decision to halt further YOLO development. This decision stemmed from his principled concern that the technology he had birthed might be employed for nefarious purposes, particularly in contexts involving military and unethical applications.Yet, the torch was passed to innovators. In the year 2020 YOLOv4 emerged through the collaborative endeavors of Alexey Bochkovskiy, Chien Yao Wang, and Hong-Yuan Mark Liao, reinvigorating YOLO's momentum. Thereafter, the Ultralytics team, under the adept leadership of Glenn Jocher, unfurled YOLOv5, which indisputably stood as the zenith among all YOLO iterations.The global impact was profound, birthing variants and adaptations such as YOLOv6, YOLOvx, PP-YOLO, and YOLOv7, originating from diverse corners of the world. These iterations embodied alterations and refinements of the foundational YOLOv5 model, reflecting the dynamic and collaborative nature of object detection research.The narrative progressed to its zenith with the unveiling of YOLOv8 in January 2023 by the Ultralytics team. This iteration exemplified an ongoing dedication to advancing object detection technology and exploring its potential applications. As the timeline continues to unfurl, YOLO retains its status as a pivotal player in the ever-evolving landscape of computer vision and artificial intelligence[6].

Yolov5

The YOLO (You Only Look Once) framework is the foundation of the object detection model known as YOLOv5. The Ultralytics team first launched it, and it quickly garnered popularity for its quickness, precision, and effectiveness in real-time object identification jobs[7]. The architecture of YOLOv5 is depicted in Figure-2

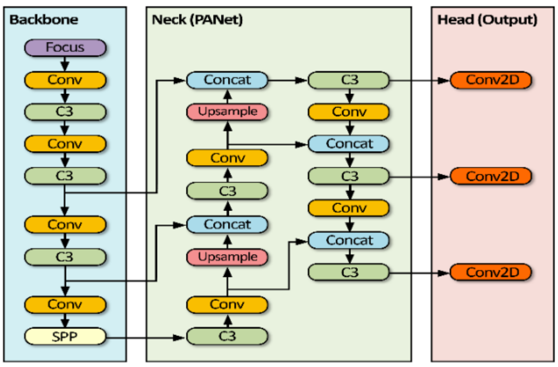


Figure. 2 . yolov5 Structures.

YOLOv5 model Architecture :

- Backbon Network: To extract information from the input image, YOLOv5 employs a backbone convolutional neural network (CNN).The backbone network's architecture can vary, and YOLOv5 offers choices like CSPDarknet53 and CSPResNeXt50. These backbones are made to represent multiple sizes of hierarchical structures[8].
- Neck Network: To improve the model's capacity to recognize objects of various sizes, YOLOv5 contains a "neck" network that combines data from various scales. To perform feature fusion across many layers, YOLOv5 uses the PANet (Path Aggregation Network) module[9].
- Detection Head: The YOLOv5 detection head forecasts bounding boxes, object classifications, and confidences for object detection. To enhance its capability to find items of various sizes, YOLOv5 uses anchor boxes of various scales[10].

Yolov8

YOLOv8 is released by Ultralytics in January 2023, the same team had released YOLOv5 in 2020[6].

The architecture of YOLOv8 is depicted in Figure-3 and can be deconstructed into several key components, which are elucidated as follows:

- Backbone network: The foundational framework for feature extraction from the input image resides in the backbone network. Within the context of YOLOv8, this network is structured on the foundation of the cross-stage partial.
- Neck: Serving as the bridge between the backbone and the detection head, the neck encompasses a Spatial Pyramid Pooling (SPP) module in YOLOv8. This module employs various pooling sizes to capture features across multiple scales.
- Detection head: Charged with forecasting bounding boxes and class probabilities for each object within the input image, the detection head comprises an assembly of convolutional layers. These are subsequently followed by anchor boxes, instrumental in forecasting bounding boxes and class probabilities for each object category.
- Loss function: The loss function in YOLOv8 integrates multiple components, encompassing the objectness loss, classification loss, and bounding box regression loss. The objectness loss penalizes instances of mispredicted objectness, a determinant of object presence within a given location.
- Post-processing: Subsequent to the detection head's projections of bounding boxes and class probabilities, YOLOv8 employs non-maximum suppression to curtail superfluous bounding boxes and isolate the most probable ones. Furthermore, the utilization of anchor boxes refines the predicted bounding boxes, thereby

elevating the precision of the ultimate detections[11].

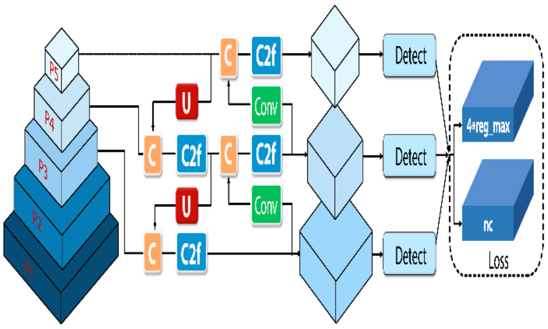


Figure. 3. yolov8 Structures

Comparison between yolov5 and yolov8 algorithm

YOLOv5

YOLOv5 is an evolution in the YOLO model family designed for object detection, image classification, and instance segmentation. It was developed by Glenn Jocher, the same developer behind YOLOv8. YOLOv5 follows the working principle of the Feature Network Pyramid (FNP), which includes the backbone, neck, and head components

YOLOv8

YOLOv8 is the latest addition to the YOLO model family, serving the purposes of object detection, image classification, and instance segmentation. It is also developed by Glenn Jocher, who was responsible for YOLOv5. YOLOv8 shares the same fundamental working principle with YOLOv5, featuring the FNP with backbone, neck, and head components

Key Changes Between YOLOv5 and YOLOv8

Changes in the kernel size for the first convolutional layer in both backbone and neck modules.

Replacement of C3 modules with C2f in YOLOv8.

Transformation of the head module structure from coupling to decoupling.

YOLOv8 is an anchor-free model, directly predicting the center of an object instead of an offset from predefined anchor boxes [12] .

Evaluation Metrics of Model Performance

Precision

Precision is the fraction of true positive samples accurately detected
by the model out of all positive samples predicted.

P=TP/((TP+FP)) %100 (1)

P= Precision.
TP=True Positives (properly anticipated positive samples).
FP=False Positives (incorrectly projected positive samples).[13]

Recall

The capacity of a classification model to accurately identify all positive instances out of all actual positive examples is measured by recall. It is calculated using the following formula:

Recall =TP/((TP+FN)) (2)

Recall measures a model's capacity to avoid missing positive cases, making it a crucial metric in circumstances where false negatives are expensive or undesired, such as medical diagnosis or anomaly detection. A greater recall value shows that the model captures more positive instances.[14]

Mean average precision (MAP)

Mean Average Precision is a popular metric for evaluating model performance in object detection and information retrieval tasks, particularly when working with several classes . Average Precision (AP): AP for each class represents the area under the Precision-Recall curve for that class. It quantifies how well a model can separate and rank instances of that class.To calculate mAP, you first compute the AP for each class using the Precision-Recall curve for that class. Then, you take the mean of these individual AP values. The formula for AP is:

$AP=\int_0^1 (precision)d(Recall)$ (3)[15].

Materials and Procedures

Dataset Curation

A comprehensive dataset was meticulously curated, encompassing a collection of 1877 images depicting helicopter landing pads. Sourced from a variety of online platforms as well as the Kaggle repository, these images were thoughtfully selected. Each image boasted dimensions of 640x640 pixels, ensuring consistency throughout the dataset. Employing the Roboflow platform,the annotation process was executed with remarkable seamlessness. The images were seamlessly uploaded to the platform, where essential annotations were added.

Data Splitting

The images were divided into three distinct subsets. These subsets were created with the intention of forming a well-balanced dataset that fulfills the model's training needs while allowing for comprehensive testing of its capabilities. Figure-4 shows the division of images into training, validation, and testing. the training set, which encompasses 70% of the original 1,877 images, totaling 1,503 images. Next, the validation set was established, consisting of 20% of the images, which amounts to 375 images. Finally, the test set was composed, including only 10% of the total 1,877 images, which equates to 188 images.

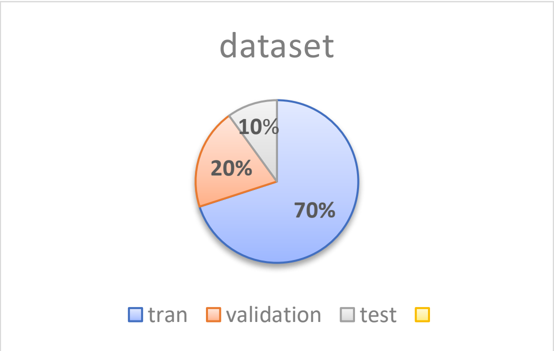
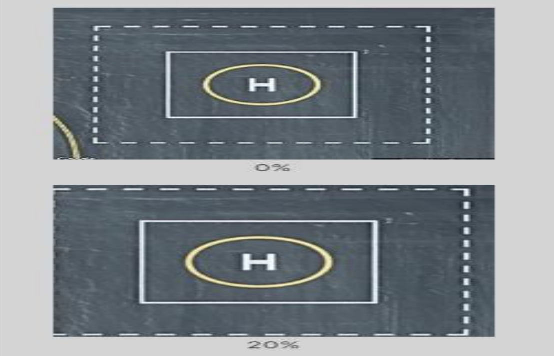


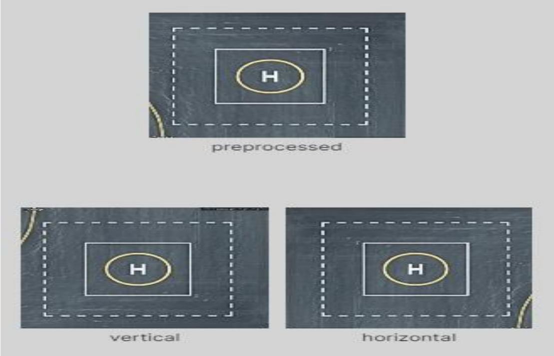
Figure. 4 . Split dataset.

Data Augmentation

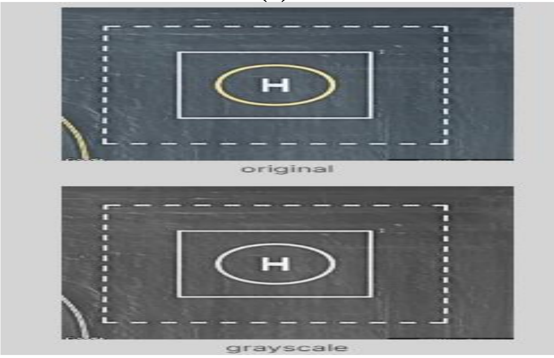
Following the division of data, a series of preprocessing operations were meticulously applied to the images. Notably, the resizing of images to a standardized 640x640 pixel resolution enhanced processing efficiency while also mitigating resource usage. Further enhancing the dataset's diversity, augmentation techniques were skillfully introduced. Horizontal and vertical flipping, cropping for varied levels of zoom (ranging from 0% to 20%), grayscale transformation for about 25% of the images, and the introduction of controlled noise to a maximum of 5% of a given image's pixels constituted this multifaceted approach. This concerted strategy aimed to amplify the dataset's versatility, ultimately culminating in an uplifted performance of the final model. This augmentation process, as illustrated in Figure-5. Upon the culmination of these intricate steps, the dataset stood adorned with a noteworthy count of 4505 images. This augmented dataset is positioned to serve as a potent catalyst, substantially elevating the efficacy of the upcoming model's accuracy in pinpointing helicopter landing pads.



(a)



(b)



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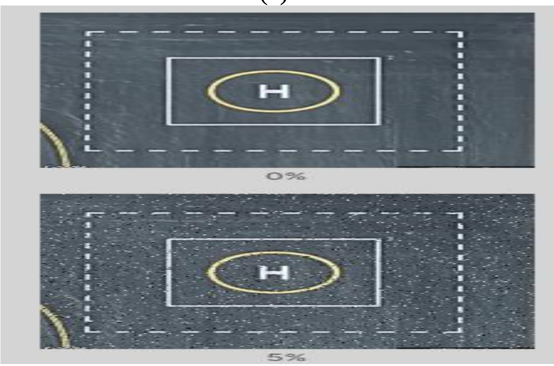


(d)

Figure. 5.Augmenting the dataset :crop (a) filp Horizontal ,vertical (b) grayscale(c) noise (d).

Modles train and implementation

The curated image dataset, prepared via the Roboflow platform, is processed and ready for training. Then, the processed dataset was downloaded and stored on Google Drive. Google Colab was then used to train two models, YOLOv5 and YOLOv8, on the same dataset. Both models were trained for a total of 100 epochs, using a batch size of 32 for comparison purposes. The specific model versions used are YOLOv5s, YOLOv5n, YOLOv8s, and YOLOv8n., as shown in Figure-6.

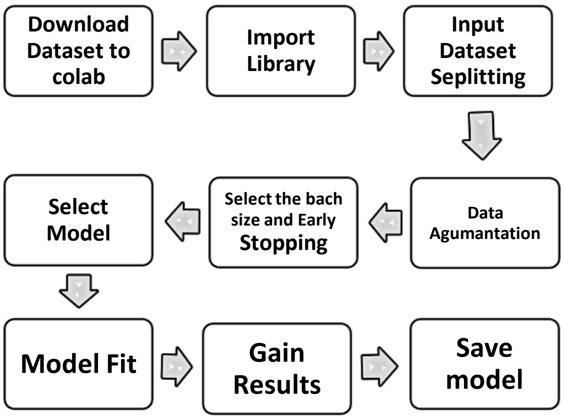


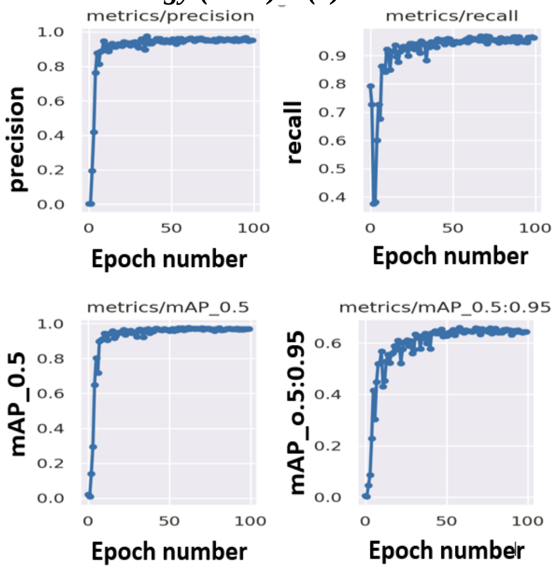
Figure. 6. blockdigram about the algorithems training using colab program.

In this study, the dataset was acquired, processed, and prepared for training using Roboflow. The trained models, YOLOv5 and YOLOv8, were subjected to identical conditions in terms of training durations and batch size. Differences in model structure are represented by the use of YOLOv5s, YOLOv5n, YOLOv8s, and YOLOv8n. This structured approach is designed to facilitate comprehensive comparison between YOLOv5 and YOLOv8 models, providing insights into their performance under consistent training conditions

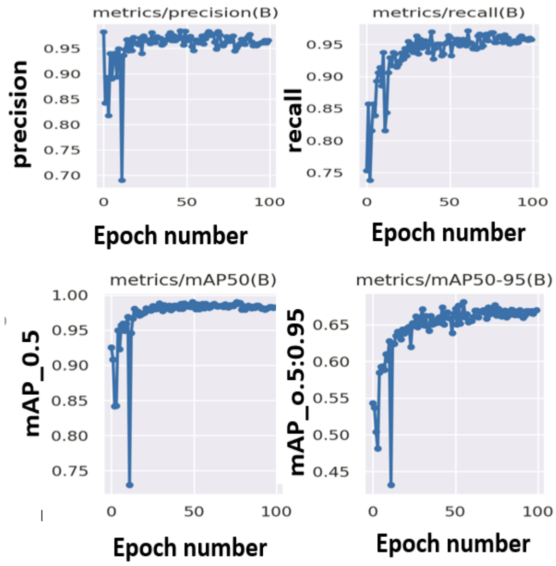
Results of the models their comparion and discussion

Results of models

The YOLOv8 and YOLOv5 models were employed for the purpose of detecting helicopter landing pads. The results were showcased for four distinct model variations, which are yolov5n, yolov5s, yolov8n, and yolov8s, as depicted in Figure-7 . This utilization aimed at enhancing the system's capability to recognize helicopter landing areas.



(a)



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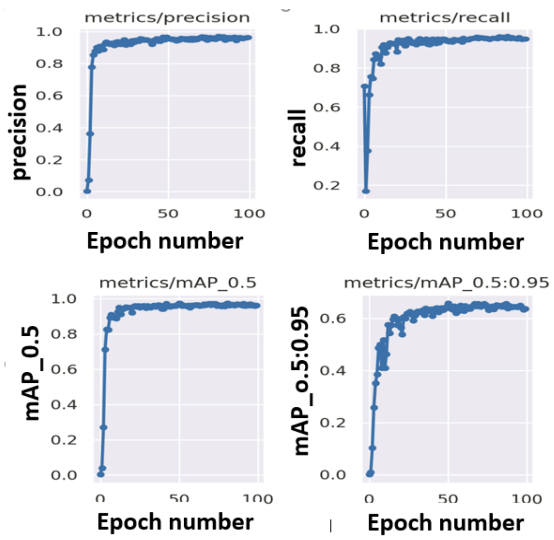

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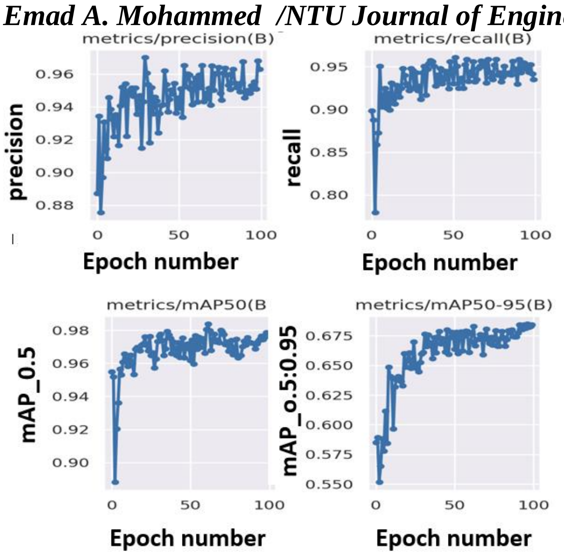

(d)

Figure. 7 two models results :yolov5n (a) yolov8n (b) yolov5s (c) yolov8s (d) **.**

Evaluating the performance of YOLOv8n, YOLOv5n, YOLOv5s, and YOLOv8s models in detecting helicopter landing pads yielded valuable insights YOLOv8n demonstrated a high accuracy of 96.7%, indicating that a significant portion of detected cases were precise positive predictions. Furthermore, its recall rate of 95.8% demonstrates its efficiency in identifying a large portion of actual helicopter landing pads within the dataset. This impressive combination of high precision and recall resulted in a remarkable average precision (mAP@0.5) score of 98.8%, further confirming the exceptional detection capabilities of the model.YOLOv5n showed a slightly lower accuracy of 95.1%, indicating a minor margin of error. This represents a trade-off between accurate positive predictions and the possibility of false positives. However, the recall rate remained steady at 95.8%, in line with its counterpart. The model achieved a commendable average accuracy (mAP@0.5) of 97.5%, demonstrating its strong overall performance in detecting helicopter landing pads.The YOLOv5 also delivered promising results: Accuracy - 95.7%, Recall - 94.5%, and Average Precision (mAP@0.5) 97.4%.YOLOv5s also performed well, boasting high accuracy and recall, resulting in a good average precision score.On the other hand, the results of the YOLOv8 model showed an accuracy of 95.5%, a recall of 94.3%, and an average precision of 97.5%. YOLOv8s displayed similar performance to YOLOv5s in terms of accuracy and recall, achieving a good average precision as well.When comparing the models, YOLOv8n showed marginally higher accuracy and a slightly improved mAP@0.5 score compared to YOLOv5n, YOLOv5s, and YOLOv8s. The choice between models should consider factors such as the desired balance between precision and recall, as well as the computational complexity of the models.the evaluation results underscore the outstanding detection capabilities of the YOLOv8n, YOLOv5n, YOLOv5s, and YOLOv8s models in identifying helicopter landing pads.

Comparing the results and discussing them

Two versions of the YOLOv8 model, YOLOv8n and YOLOv8s, were trained, alongside two versions of the YOLOv5 model, YOLOv5n and YOLOv5s, for the purpose of comparison to determine their respective performance levels. The results obtained from these models are presented in the table1. Notably, when it comes to the detection of helicopter landing pads, the YOLOv8n model exhibited superior performance compared to the other models.

Table 1. Comparison Between Two Models (YOLOv8, YOLOv5) and Their Versions (YOLOv8n, YOLOv8s, YOLOv5n, YOLOv5s)

Models	Versions	Precision	Recall	MAP @50
Yolov8	Yolov8n	96.7%	95.8%	98.5%
	Yolov8s	95.5%	94.3%	97.5%
Yolov5	Yolov5n	95.1%	95.8%	97.5%
	Yolov5s	95.7%	94.5%	97.4%

The table provides a concise overview of the performance metrics achieved by each model, enabling a comprehensive comparison. Based on these results, it was concluded that for the specific task of detecting helicopter landing pads, the YOLOv8n model outperformed the other options.

Conclusion

This study investigated the YOLOv8 and YOLOv5 models for helicopter landing pad detection. Both models showed strong performance in accurately identifying landing zones. Notably, YOLOv8n showed slightly higher accuracy and average accuracy (mAP@0.5) compared to YOLOv5n. These evaluation results confirm the potential of both models to significantly enhance the safety and efficiency of helicopter operations.

The choice between YOLOv8 and YOLOv5 should be conditional on the specific application requirements, taking into account factors such as precision, recall and computational complexity. As the field of object detection technology continues to evolve, innovations such as YOLOv8 and YOLOv5 are paving the way for increased safety in helicopter landing scenarios. Model parameters can be tuned and new techniques explored aimed at further improving the accuracy and reliability of helicopter landing pad detection systems.

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