Signals Intelligence Based Drone Detection Using YOLOv8 Models

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Abstract. The reduced costs associated with deploying and utilizing Unmanned Aerial Vehicles (UAVs) have spurred their widespread adoption across various industries, including aerial photography, information gathering, and search and rescue operations. However, this rapid uptake has also raised concerns regarding safety and privacy, particularly due to instances of misuse and potential hazards posed by convertible drone technology. Addressing these concerns, this study investigates the application of emerging Artificial Intelligence (AI) techniques in computer vision for the detection and classification of ISM band transmissions, distinguishing between conventional Bluetooth signals and those used for drone control. Several YOLOv8 architectures, optimized for lighter hardware, are evaluated using a publicly available ISM band visual dataset. Results demonstrate that even lighter models, such as nano and small architectures, can achieve significant precision rates, with the best-performing models reaching a peak precision of 90%. However, medium-sized architectures are recommended for optimal performance.

Keywords: Unmanned Aerial Vehicles · Signals Intelligence · YOLOv8 · Computer vision · Radio frequency spectrum

1 Introduction

The last decade has brought us an increasing use of drones, from filming for film and television, commercial and artistic photography. Agriculture in the form of crop monitoring, object surveillance and even in rescues due to their ability to access any point and visualize it with cameras, of all types of delivery, their use is constantly increasing [19]. This opens up the other side, the availability and ease of handling, allows the drone to be used by anyone and anywhere, which brings with it various risks for security and privacy.

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In the past, it was necessary to hire a helicopter or an airplane to take pictures and photographs from the sky [21], today these small devices do it, with perhaps even better results [25]. Monitoring and control of hard-to-reach areas with drones is also facilitated, as well as rescuing people, searching large territories and even delivery in all locations, possibilities and needs are increasing daily. Although there are a large number of benefits, on the other hand, the issue of safety is raised.

Institutions and places with high new security are primarily under attack there, so detection and control is one of the areas that is necessary [27]. Licensing is one of the types of control that should be present, but an automated system for detecting drones is also necessary. One of the possible ways, which is offered as a drone detection system, is the monitoring of the Industrial, Scientific, and Medical (ISM) radio frequency spectrum [18], which can be used to detect the presence of drones. They have the ability to identify the control units that make the drones fly. And with the technique itself like goniometry, it is easy to locate the very position from where the drone is controlled. This ISM spectrum monitoring system works on a specialized and expensive technique, which is an obstacle to any wider application.

Looking for cheaper solutions, computer vision with its trained recognition models could certainly take the stage. The idea is to apply these models for the analysis of spectrum visualization [8, **?**], this would aim to detect drones in approximately real time, and the price would certainly be more affordable for wider use. With low training costs, it opens the door to this concept, which would aim to have easier and more effective control in protecting privacy and security in times where drones play an increasingly prominent role.

The latest version of the object detection algorithm You Only Look Once (YOLOv8) [10] was used in this paper. YOLO is already known for its speed and efficiency, but also very easy to use, a few lines of code are enough to start training a model. This work is based on three YOLOv8 architectures - nano, small and medium.

The contributions of this work may be summarized as:

- A proposal for a computer vision system based approach for ISM band monitoring
- The use of transfer learning models for drone control signal detection in spectrograms
- The exploration of several YOLOv8 model architectures for this increasingly pressing security issue.

The remainder of this work is structured as per the following: Section 2 demonstrates preceding works that helped inspired and support this research. In Section 3 the concepts behind the methodology are introduced. Section 4 and Section 5 define experimental parameters and showcase the attained outcomes respectively. Section 6 provides a conclusion to the work.

2 Related Works

The constant increase in the use of unmanned aerial vehicles (UAVs), better known as drones, the wide range of their capabilities and uses have also opened numerous security challenges. Scientists all over the world are searching for the best solutions for their detection. First of all, we should refer to radio goniometry and doppler radio goniometry. By combining these techniques, enviable results were achieved in the detection of drones.

The scientific paper [3], presents a method for drone identification using identification marks in radio frequency (RF) signals. In order to estimate the position of the drone, this technique is based on the extraction of telemetry data through the decoding of ID packets in real time. All this results in detecting the position, height and speed of the drone. This system with an error ranging from 15 to 35 meters at a distance of up to 1.3 - 3.7 km for the detection of certain models of drones accurately estimates the position and speed in a 2D view.

This study [4], used the technique "You Only Look Once" (YOLOv5) [31] algorithm, for drone detection. Leightweight models have shown impressive object detection results [12]. The study was based on drone and bird photos from different angles and heights, achieved good results in recognition FPS of 20.5 and 19.0, and the mAP was 74.36 percent. I another work [30], a wide range of technology for the detection, classification and tracking of drones is covered, the emphasis is on machine learning (ML). ML is said to be able to perform pattern recognition using modalities, which humans cannot fully perceive.

Theorem "no free lunch" (NFL) [34], i.e. there is no special algorithm that can be universal for all types of problems. One algorithm may be good for one type of problem while for another concept it may give less good results. It is important to understand the nature of the problem, i.e. the type of data, optimization objectives and constraints, before choosing a particular algorithm.

Metaheuristic algorithms in the optimization of drone detection, in addition to genetic algorithm [20], simulated annealing [1], or some others. It is possible to additionally optimize detector parameters and improve detection precision. Some of the metaheuristic algorithms, it is possible is to automatically adjust detection thresholds or filtering parameters, which would result in a lower number of false negatives and false positives. Because of all this, metaheuristics will play a key role in improving algorithm performance [15, 11, 14].

Hybridization is a popular approach for modifying and improving the performance of metastatic optimizes. Hybrid optimizers have seen several implementations in recent works with some notable examples include financial and cyptocurrency forecasting [28, 24, 29]. Additional implementations include maritime safety [23], medical [13] and other applications [16, 14].

The gap in current scientific research indicates a space in research with currently the latest model of computer vision YOLOv8. Furthermore, leightweight architectures have the potential to improve drone detection capabilities, primarily for future research in this rapidly developing field.

3 Methods

3.1 Yolo Models

YOLO object detection models (you only look once), have a wide application in various industries and everyday situations, areas where it is already present are agriculture, health, security, surveillance, vehicle autonomy, but in some areas YOLO has yet to take its place and it is up to the scientific community to open the door to these changes. YOLO stands out with its ability to quickly and accurately detect objects in the image and is the best in the field where time plays a major role.

YOLO differs from traditional methods because it looks at the image as a whole, then predicts bounding boxes and class probabilities for all objects at once. This process takes place by dividing the image into a grid of cells, in which each cell predicts the bounding boxes, but also the probabilities of each object within it [26].

The evolution of the YOLO model went through several iterations from YOLOv1 to YOLOv8, each of which brought some improvements. YOLOv8 is the last of the series of learned models and stands out for its speed and accuracy compared to the others. Innovations are present in the field of network architecture, optimization and advanced learning techniques, all with the aim of better accuracy and efficiency of object detection [5].

Advanced techniques used to improve object detection such as non-maximum suppression (NMS), eliminate overlapping box boundaries, then anchor boxes are used to improve the prediction of bounding boxes, but also multi-scale training, detection of objects of different sizes, by training on images that differ in scale [17].

The application of the YOLO model due to its efficiency and speed is ubiquitous, but where it could have its limitations is in the detection of very small or densely grouped objects, but also in the detection of objects outside the data set on which they were trained [26].

3.2 Transfer learning

The concept of transfer learning is a learning process that can be transferred from one task to another, this approach is called transfer learning [32], it gives the opportunity to learn faster, more efficiently and easier, using knowledge that is already acquired in some fields [9]. For years, the scientific community has worked on various open source projects, refining complex models, gigantic amounts of data for generic randoms. The application is wide ranging from object detection in video, object detection in images, transcription of audio recordings, sentiment analysis for text. The training of data from scratch is sometimes expensive and unnecessary, that's why transfer learning made it easier to start training the model. Also by using a well-tested and well-established model the overall model will be improved. But even if we do not have enough data for the problem we are working on, the use of a pre-trained model can benefit us. [2] Transfer learning problems can be divided into three groups, i.e., transductive, inductive, and unsupervised transfer learning [22]. Learning in which the data is labeled, and it is used when it is necessary that the task it was solving in the target domain is different from the task in the source domain is called Inductive transfer learning, often the tasks can be similar if the model was trained to recognize cars, and now it needs to recognize trucks. Transductive learning is based on the fact that the source and target tasks are the same, but the domains themselves are different. This indicates that there is a lot of data in the source domain, but not in the target domain. While learning in which neither the source nor the target domains have labeled data is called unsupervised transfer learning. This is definitely more demanding learning, because the model has to use knowledge without clear instructions.

Transfer learning settings themselves are divided into two categories, namely homogeneous and heterogeneous based on different characteristics. Homogeneous transfer learning [33], the source and target domains share the same feature and label space, however the distribution itself differs. This indicates that the image of the car may be the same but may differ in the lighting of the image, the task is identical but the context has changed. Heterogeneous transfer learning when feature or label spaces differ from the target domain. If in one task we analyzed pictures, and in another we want to analyze text or if the categories themselves are different. [7].

4 Experiemntal Setup

This work explores the feasibility of applying three different YOLOv8 architectures to signals intelligence in the ISM band. The focus on this research is on lighter architectures that allow for real time use with minimal investments after model training. A publicly available dataset [6] is utilized last accessed on the 20.03.2024 [1]. The dataset consists of images of ISM band spectrograms with two classes labeling Bluetooth transmissions and drone control signals. Samples of inputs can be seen in Figure 1.

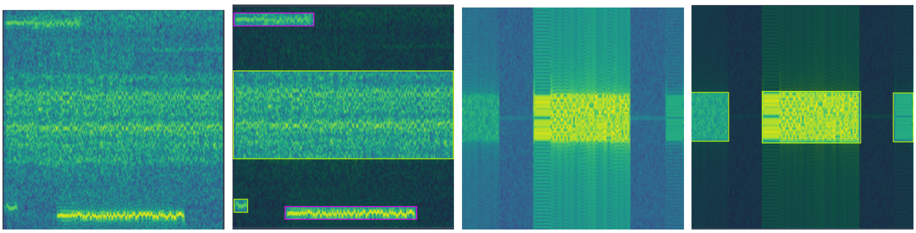

Fig. 1. Image samples containing drone control and Bluetooth signals.

[1] https://universe.roboflow.com/intelligent-digital-communications/ism-band-packet-detection

Nano, small and medium models are trained and evaluated using standard metrics for classification including precision, recall, mAP50 and mAP50-95 providedd in the following equations:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{1}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{2}$$

$$\text{mAP@50} = \frac{1}{n}\sum_{i=1}^{n} \text{AP}_i^{(50)} \tag{3}$$

$$\text{mAP@50-95} = \frac{1}{n}\sum_{i=1}^{n} \text{AP}_i^{(50-95)} \tag{4}$$

where n denotes the number of classes, mAP@50 is the Average Precision for class i at a threshold of 0.5, and mAP@50-95 is the average precision for class i averaged over thresholds from 0.5 to 0.95. Additional details are provided on model performance in the form of confusion matricides and precision-recall (PR) curves.

5 Simulation Outcomes

The following section presents and discusses outcomes of three simulations carried out in this work. Simulations with nano, small and medium models are provided alongside discussions of the results. Finally samples of the best preforming models classifications are presented.

5.1 Nano architecture outcomes

Table 1 displays the performance of the YOLOv8 nano model across training epochs. After completing 15 epochs, the model achieved a precision of 0.78010, a recall of 0.68754, a mAP50 of 0.76277, and a mAP50-95 of 0.50337. These results indicate that while the model has shown respectable performance, it appears to face challenges in further enhancement with improvements slowly stagnating after the 13-th iteration. Expanding the architecture might yield more favorable outcomes. However, architecture expansion can increase computational demands for both training and deployment.

A confusion matrix for the nano model is provided alongside the PR curve in Figure 2. The model has a decent rate of detection of drone signals however it strucles with Bluetooth classfications. Several bluetooth signals fade in to the background. This is less pronounced with drone control signals with only 19% being missed as background images.

The limited image resolution used for the pre-trained model reduces detection. This can further be tackled by introducing additional empty background images into the training dataset to improve differentiation objects form the background.

Table 1. Nano architecture training outcomes.

Epoch	precision	recall	mAP:50	mAP:50-95
1	.00000	.00000	.00000	.00000
2	.00008	.00588	.00004	.00000
3	.00008	.00588	.00004	.00000
4	.61114	.13529	.09682	.03730
5	.33796	.37286	.28145	.10642
6	.24796	.34960	.22849	.06983
7	.34304	.38750	.30296	.12652
8	.57537	.57861	.58786	.28208
9	.66859	.62865	.65499	.34239
10	.68475	.61278	.64927	.33806
11	.69965	.61176	.63782	.36585
12	.64585	.63824	.64497	.38231
13	.75679	.71898	.75508	.45075
14	.78603	.68937	.75866	.49284
15	.78010	.68754	.76277	.50337

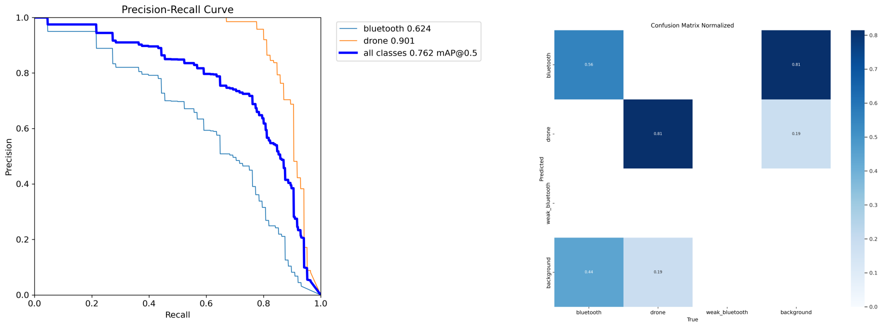

Fig. 2. Nano model PR curve and confusion matrix.

5.2 Small architecture outcomes

Table 2 displays the performance of the YOLOv8 small model across training epochs. After completing 15 epochs, the model achieved a precision of 0.77935, a recall of 0.78717, a mAP50 of 0.81828, and a mAP50-95 of 0.61030. While a small drop in percussion can be seen in comparison to the nano model peak precision during training is 0.86641, while recall maP50 and mAp50-95 scores show a clear improvement using the small model. The expanded architecture showcases improved outcomes. However, the longer training times should be noted due to the larger number of parameters that need to be adjusted to facilitate model training.

Table 2. Small architecture training outcomes.

Epoch	precision	recall	mAP:50	mAP:50-95
1	.65854	.51732	.55754	.31696
2	.49968	.50260	.38507	.20677
3	.69921	.57253	.61679	.41097
4	.39534	.53621	.42343	.22106
5	.58687	.44960	.40474	.22121
6	.62514	.72364	.65028	.40157
7	.78430	.71170	.75559	.49192
8	.64943	.70742	.76834	.50319
9	.72814	.75423	.79483	.54489
10	.86641	.72326	.82267	.58346
11	.66184	.73095	.73726	.52853
12	.81709	.72874	.79995	.57388
13	.82942	.75570	.80526	.57693
14	.80028	.75289	.80490	.58795
15	.77935	.78717	.81828	.61030

A confusion matrix for the small model is provided alongside the PR curve in Figure 3. A reduced precision for drone detection is observed with an 82% correct classifications, however, Bluetooth detection has improved.

5.3 Medium architecture outcomes

Table 2 displays the performance of the YOLOv8 medium model across training epochs. After completing 15 epochs, the model achieved a precision of 0.90404, a recall of 0.71210, a mAP50 of 0.83716 , and a mAP50-95 of 0.61398. The medium model attained overall the best outcomes compared to the other models. This suggest that larger architectures are better suited to addressing this issue. it is also worth noting that further training might yield additional improvements as the training outcomes do not suggest stagnation in performance. The PR curves and confusion matrix for the medium model are provided in Figure 4.

Classification examples of the best performing architecture (medium) are provided in Figure |reffig:MediumBest

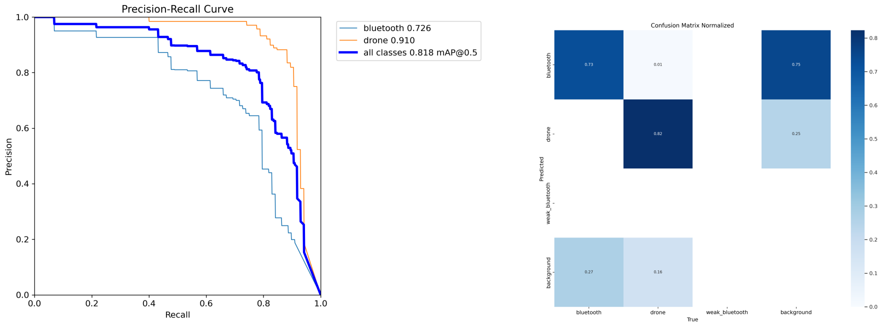

Fig. 3. Small model PR curve and confusion matrix.

Table 3. Medium architecture training outcomes.

Epoch	precision	recall	mAP:50	mAP:50-95
1	.58348	.33576	.38691	.26323
2	.00301	.18443	.00180	,00066
3	.35063	.45281	.33018	.17783
4	.39750	.59505	.44531	.25132
5	.44546	.43749	.27127	.15062
6	.46376	.56005	.49434	.25231
7	.31193	.35020	.27625	.10748
8	.63279	.61611	.63470	.40239
9	.78555	.67921	.72866	.52628
10	.77791	.69545	.76697	.54995
11	.73074	.71726	.75974	.52656
12	.87946	.69409	.80563	.58535
13	.82336	.76455	.83939	.58598
14	.85876	.70747	.81666	.58408
15	.90404	.71210	.83716	.61398

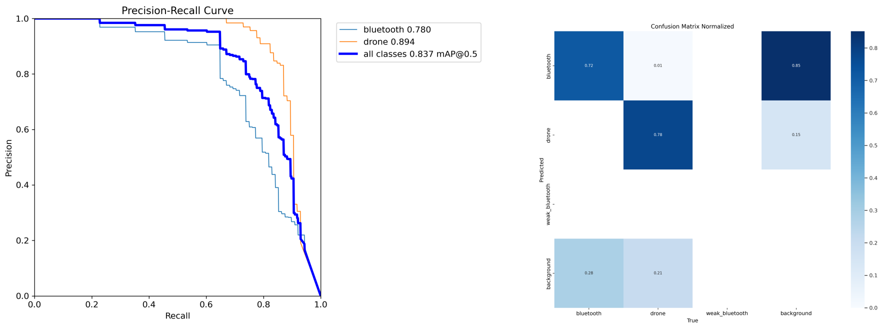

Fig. 4. Medium architecture PR curve and confusion matrix.

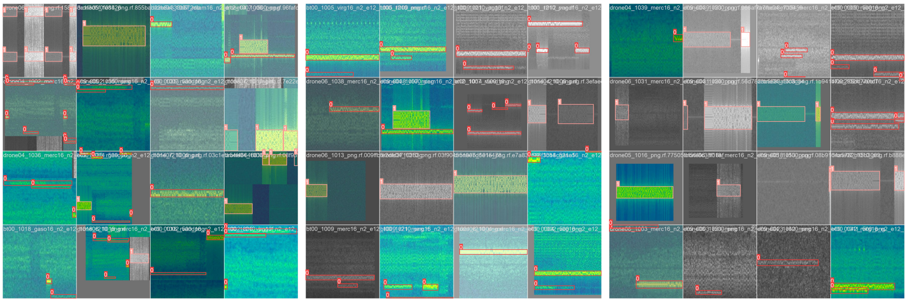

Fig. 5. Sample classifications made by the best performing model (mdeium).

6 Conclusion

The decreasing costs of deployment and use of UAVs have led to increased adoption in many sectors. Aerial photography, information gathering, and search and rescue have seen numerous benefits from the proliferation of this technology. However, several concerns have arisen from the rapid adaptation of drones. Convertible drones have been misused in various situations, demonstrating that they can be a dangerous asset. Efficient detection and tracking have become priorities for those concerned with safety and privacy. This work explores the application of emerging AI technologies for computer vision to identify and classify ISM band transmissions between ordinary Bluetooth and drone control signals. To facilitate the classification, several YOLOv8 architectures are considered, with a focus on lighter weight (nano, small, and medium) models to enable larger scale implementations on more moderate hardware. Models are trained and evaluated on a publicly available ISM band visual dataset under identical conditions. The best-performing models reached a peak precision of 90%, suggesting that application in this form is a viable method for drone control signal detection in the ISM band. However, at least a medium architecture is required to attain these results.

Future work will focus on further refining the proposed methodology. Optimization metaheuristics will be utilized to overcome some of the inadequacies of the default model and further refine outcomes.

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