Acta Infologica
acin 2023, 7 (2), 308–316
DOI: 10.26650/acin.1273088

Research Article / Araştırma Makalesi

Vision-Based Amateur Drone Detection: Performance Analysis of New Approaches in Deep Learning

Görüntü Tabanlı Amatör Drone Tespiti: Derin Öğrenmede Yeni Yaklaşımların Performans Analizi

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ABSTRACT

Interest in unmanned aerial vehicles (UAVs) has increased significantly. UAVs capable of autonomous operations have expanded their application areas as they can be easily deployed in various fields. The expansion of UAVs' areas of operation also brings safety issues. Although legally prohibited places for UAV flights are defined, measures should be taken to detect violations. This study tested recently proposed methods that are used to detect objects from images on UV images, and their performances were discussed. We tested the models on a new dataset named GDrone that we created by collecting various images of drones. Two tested models, YOLOv6 and YOLOv7, have never been tested with a drone dataset. According to the experimental tests, the most successful model was YOLOv7 architecture, and its mAP (mean Average Precision) was 95.8% on GDrone dataset.

Keywords: Unmanned aerial vehicles, amateur drone detection, convolutional neural networks, UAW dataset

ÖZ

İnsansız hava araçlarına (İHA) olan ilgi önemli ölçüde artmıştır. Otonom çalışabilen İHA'lar, çeşitli alanlara kolaylıkla konuşlandırılabilmeleri nedeniyle uygulama alanlarını genişletmiştir. İHA'ların faaliyet alanlarının genişlemesi, aynı zamanda güvenlik sorunlarını da beraberinde getirmektedir. İHA uçuşları için yasaklanmış olan yerler yasal olarak tanımlanmış olsa da ihlallerin tespitine yönelik tedbirlerin alınması gerekmektedir. Bu çalışmada, ultraviyole görüntüler üzerinde nesnelerin tespit edilmesi için kullanılan ve son zamanlarda önerilen yöntemler test edilmiş ve performansları tartışılmıştır. Modelleri, çeşitli drone görüntülerini toplayarak oluşturduğumuz GDrone isimli yeni bir veri seti üzerinde test ettik. Test edilen YOLOv6 ve YOLOv7 modelleri daha önce bir drone veri seti ile test edilmemiştir. Deneysel testlere göre en başarılı model YOLOv7 mimarisi oldu ve GDrone veri kümesindeki mAP (ortalama hassasiyet) değeri %95,8 olarak belirlendi.

Anahtar Kelimeler: İnsansız hava araçları, amatör drone tespiti, evrişimli sinir ağları, İHA veri seti

Submitted	: 29.03.2023
Revision Requested	: 17.08.2023
Last Revision Received	: 14.09.2023
Accepted	: 22.09.2023
Published Online	: 21.11.2023

1. INTRODUCTION

Unmanned aerial vehicles (UAVs) are small, hard-to-track vehicles that pose a security risk and expose experts and authorities working in this field to various security risks (Vattapparamban et al. 2016). UAVs, which were first used in the entertainment industry or for filming purposes, are used in traffic monitoring, photography, communication (Khan, Park, and Gonzalez 2017; Tang et al. 2017)), disaster relief (Al-Hourani, Kandeepan, and Jamalipour 2015) and autonomous driving. Thanks to their capabilities and programmability, they are also used in vegetation monitoring (Onishi and Ise 2021). On the contrary, the UAV can also be used for maliciously damaging purposes. These purposes include military espionage activities intelligence gathering, physical attacks on public facilities, infrastructure networks, or people in crowded environments. In addition, terrorist elements can use drones to transport weapons, ammunition, explosives, and even radioactive material. This shows that even the physical presence of drones can have dire consequences. The use of UAVs for espionage purposes can also pose a serious threat to the security of states, as they provide images from areas that may be considered sensitive points of a country (military and police units) (Al-Emadi et al. 2019). Because these security threats are not negligible or acceptable risks, detecting the presence and identity of a drone in the air is an unavoidable problem that must be addressed in terms of public safety. For this reason, the importance of UAV detection systems is increasing day by day. The development of malicious drone detection systems, anti-drone systems, addresses the problems of detecting drones, determining the type of drone, and locating the drone. Anti-drone systems can also ensure that the drone conducting a malicious flight is neutralized by force of arms or by disrupting its signal (Carter and Schwartz 2010).

Drones leave three different traces when hovering. These traces are: the sounds they make, the radio frequencies, and the physical images they emit to find their flight path or to receive commands. Sounds (Liu et al. 2017), images (Pham and Nguyen 2020) or radio frequencies (Al-Sa'd et al. 2019) can be used for drone detection. Sound-based drone detection is an altitude-dependent process that may not be detected if the drone is flying at a high altitude. However, ambient noise (birds, wind noise, etc.) may suppress the sound of the drone and prevent it from being detected. Radio frequency detection systems, on the other hand, are a method that uses signals between the drone's control unit and the drone. However, since autonomous drones do not have a separate control unit, such detection is impossible. In addition, many communication devices use radio frequencies. This can make the detection of a drone using radio frequencies very complicated. Drone detection systems on images have convincing elements. Another difficulty in detecting drones on images is distinguishing them from other objects that may be in the air, such as kites or birds. Because they may be various backgrounds that make the drones detection more difficult.

In this study, new methods for UAV detection on captured images were tested and their performances were discussed. Since images contain various backgrounds, in this way, the success of existing and new models in detection a drone under challenging conditions was measured. To sum up, the contributions of this study to the literature are listed below:

- A new dataset containing 600 drone images was proposed.
- The performance of the latest architectures such as YOLOv7, YOLOv6 was measured for the first time on a drone dataset and compared with other methods.
- An object detector with the fewest parameters, the lowest computational cost, the highest efficiency and performance was proposed.

2. LITERATURE REVIEW

Object detection is one of the most important tasks that occupies a wide space in the field of computer vision. Despite advances in deep learning, localizing an object is a very challenging process. While existing solutions use machine learning methods based on manual feature extraction, feature maps are autonomously extracted using convolutional neural networks in conjunction with deep learning studies (Aydin, Salur, and Aydin 2021). With the advent of modern object detectors, studies in the field of object detection have come into focus. These object detectors are divided into two classes: single-stage object detectors and two-stage object detectors. Object detectors such as R-CNN and Fast R-CNN (Girshick 2015), fall into the two-stage class, while object detectors such as YOLO (Redmon et al. 2016) and SSD (Liu et al. 2016), are single-stage object detectors. Two-stage object detectors make a site proposal in the first step and perform object inspection in those regions in the second step. However, object detectors such as YOLO and SSD operate less expensively, faster, because the region recommendation step is eliminated. Real-time drone detection systems are needed because drones are small and difficult to detect and must be detected quickly to prevent violations. Using single-stage object detectors for these real-time systems is more advantageous because of their speed.

Because drones are valuable tools, they can serve practical purposes in many professions, but this does not prevent the malicious use of drones. To prevent these malicious purposes, drone detection is of great importance. There are various studies on drone detection using combination of sound, audio and video, radio frequency, audio, and thermal imaging. However, these studies require some pre-processing. Studies on image data have focused on real-time systems. In this way, detection operations can be performed without preprocessing. For this reason, this section focuses on literature studies on image data.

With their modification of the YOLOv4 (Wang, Bochkovskiy, and Liao 2023) algorithm, (Liu et al. 2021) have developed a highly successful detection detector suitable for real-time use. For the data collected in their study, their model achieved the highest mean average precision (mAP) of 93.6%. The researchers claimed that the model runs at 43 FPS (frames per second). In another study, (Zheng et al. 2021) trained with different architectures for the dataset they created. By using the Grid R-CNN architecture, the researchers achieved a success rate of 90.1%. Similarly, (Sahin and Ozer 2021) performed a detection model on a dataset with 10 classes. In the model, they used the YOLOv3 architecture. In the study by (Behera and Raj 2020) the drone data set was analyzed using the YOLOv3 model. As the best result over 150 epochs, the researchers achieved 74% success in their studies. Another study was conducted by (Lee, La, and Kim 2018), achieved an 89% success rate in drone detection using the Haar Feature-based Cascade Classifier, which they adapted to their object detection model. In the another study, (Nalamati et al. 2019) used both Single Shot Detector (SSD) models and various CNN-based architectures such as ResNet-101 and Inception with Faster-RCNN to detect drones in long-range surveillance video. Due to sparse data, the best success rate of researchers using transfer learning was 0.49 mAP in experiments with Faster-RCNN. Müller (2017) investigated the suitability of image differentiation and background subtraction techniques for extracting and examining candidate regions in video data obtained from static and moving cameras (Müller 2017).

3. METHOD

3.1. Data Collection

The proposed GDrone dataset contains 600 images with different backgrounds obtained from various sources. Since these images are from the areas where drones are used in daily life, it is expected to reflect realistic results. The images in the dataset are sampled from various videos. Each image has a size of 416x416. All images in the dataset were carefully manually labeled by a research group specifically set up for this task. The drone dataset has a more difficult structure than other datasets, as it contains images of different daylight levels taken in different environments and drone images located at different distances. Emphasis is placed on the widely influential DJI phantom 4. Some sample images can be seen in Fig 1. The dataset created in the study can be accessed by other researchers using the link https://github.com/ahmetmericaydin/GDrone-Dataset

Figure 1. Some sample of images from the GDrone dataset

The GDrone dataset contains drone images at different distances and under different lighting conditions. In addition, the GDrone dataset contains different backgrounds such as sea and sky. The proposed dataset contains different types of drone images. Since the structures or sizes of drones may be different, this is one of the challenges in drone detection. One of the main purposes of creating a dataset is to evaluate different datasets. Considering these aspects, the GDrone dataset can be classified as a suitable dataset for evaluating the performance of drone detection methods.

In the study, 70% of the data was used for training, 20% for validation, and 10% for testing. The algorithms were run on a remote server with a Tesla T4 graphics card and 16 GB RAM.

3.2. Data Augmentation

Data augmentation is one of the common methods to improve accuracy variance in training data. Applying translation and rotation operations to the data set ensures that the existing data set is tripled. Various methods can be applied in data augmentation and the size of the dataset can be further increased. However, since the goal of the study was to achieve effective and efficient results with a short training time, the data augmentation method was used less frequently. It can be observed that the data augmentation applied to the GDrone dataset leads to an increase in the mean average precession (mAP) value. By applying the augmentation procedure to the training dataset, a total of 1200 images were obtained in the training dataset. No augmentation is applied to the test data.

3.3. YOLO

The YOLO (You Only Look Once) architecture, developed with the rapid developments in deep learning in recent years, is one of the effective methods used and developed for object detection. YOLO, developed for real-time object detection, continues to be further developed in different variants. There are versions developed by many scientists due to the various changes in the architecture and improvements in the number of parameters, high performance and performance. The fast operation of the YOLO algorithm is due to the fact that it can estimate the class and weight of the objects on the image by scanning the image once. The YOLO algorithm creates bounding boxes to identify objects on the image. While doing this, the midpoint where the object intersects in the image is used. In this way, bounding boxes are obtained.

Height, width, class and frame centers are created to define a bounding frame (box). Each bounding box consists of certain parameters. Each box also creates its own prediction score.

$$y = (pc, bx, by, bh, bw, c) \tag{1}$$

The bx given in Equation 1 represents the center of the by-frame. C indicates the desired classes. bh and bw indicate the height and width of the frame. As specified in Equation 1, the object belonging to the class is included in the frame, and the object is determined according to the class to which it belongs. If the number of overlapping boxes is more than one, the correct boundaries are drawn based on the maximum number of overlaps IoU (Intersection over Union) and inserted into the boxes. If the prediction score is one, the boundaries of the object were predicted correctly. However, depending on the overflow rate at the borders, the percentage overflow rate is subtracted as an error margin and the success rate is determined accordingly.

3.4. Overview of YOLOv7

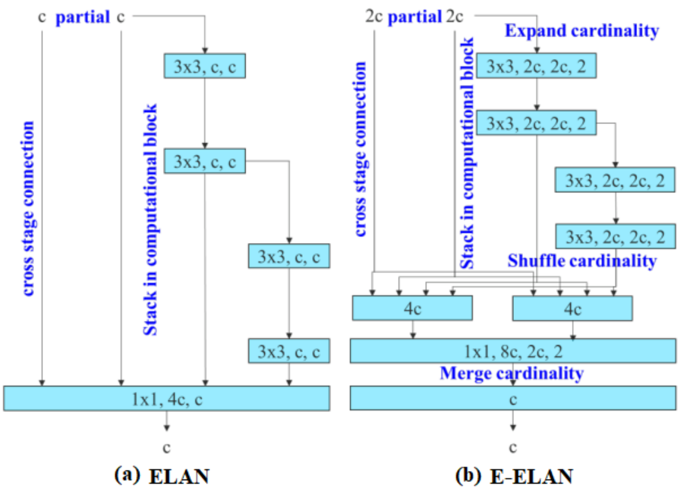

Figure 2. ELAN and E-ELAN architectures ((Wang et al. 2022))

The latest object detector, YOLOv7 (Wang et al. 2023), outperforms other known object detection models in both speed and accuracy with the dataset COCO. The YOLOv7 architecture is based on the extended (E- ELAN) architecture based on ELAN (Wang, Liao, and Yeh 2022). Figure 2 shows the architectures ELAN and E- ELAN.

Figure 2 shows the improvements made to the architecture of ELAN. The researchers in (Wang et al. 2022) extended the architecture of ELAN and applied it to the YOLOv7 model. In this way, they have improved the performance. In contrast, the E-ELAN architecture proposed in YOLOv7 architecture uses the cardinality of extend, shuffle and combine to improve the learning capability of the network. ELAN, on the other hand, provides performance by simply changing the architecture in the computational block. It uses RepConv (Ding et al. 2021) for merging and scaling. The YOLOv7 architecture is an architecture in which different architectures are developed and adapted. Comparisons of the YOLOv7 architecture with other object detectors are presented in (Wang et al. 2022).

4. METRICS

To measure the performance of the proposed model mAP is used. Since all images in the dataset contain drones, we used mAP, which is commonly used to evaluate whether any searched object is detected. Object detection models also make classification; classification metrics are also included. mAP is a widely used performance metric in the field of computer vision and information retrieval, particularly for tasks such as object detection and image retrieval. mAP is calculated by Equation (3).

$$Precision(P) = \frac{TP}{(FP + TP)} \tag{2}$$

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k \tag{3}$$

where TP stands for true positive, TN for true negative, FP for false positive, FN for false negative, n is the number of classes and APk is the average precision of class k.

5. EXPERIMENTS RESULTS

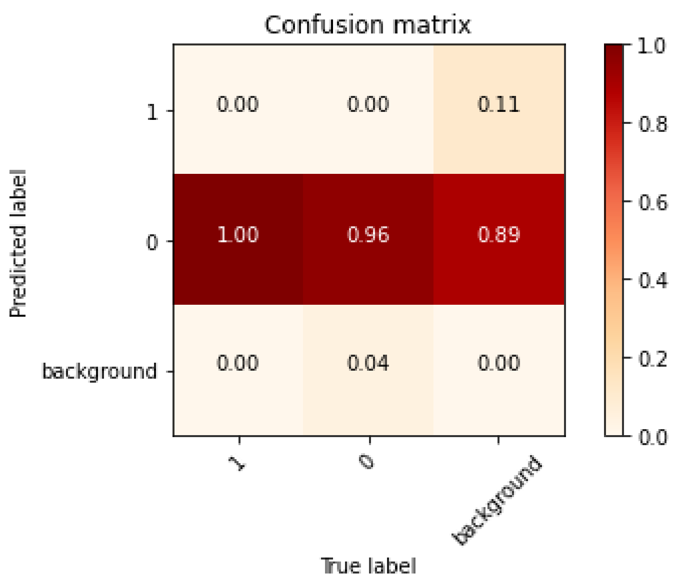

Figure 3. Dataset showing the performance of the YOLOv7 model on the GDrone dataset

This section shows how successful the YOLOv7 architecture is in using image data from the GDrone dataset. The YOLOv7 model has 415 layers. In the experimental tests, images of size 640x640 were applied to the model as input. As parameters, the model was run with 8 batch sizes and 100 cycles. The experimental results showed that the YOLOv7 model achieved a mAP accuracy of 95.8% for the GDrone dataset. The actual complexity values shown in Figure 3 illustrate the performance on a known test data set.

When Figure 3 is examined, it can be observed that approximately 96% of the estimated data is correct, but there is an almost 4% margin of error due to the dataset having various backgrounds and consisting of different drones. The findings show that the dataset is an effective dataset in measuring the effect of a model. In Figure 4, other performance measures obtained from the study of the model are given.

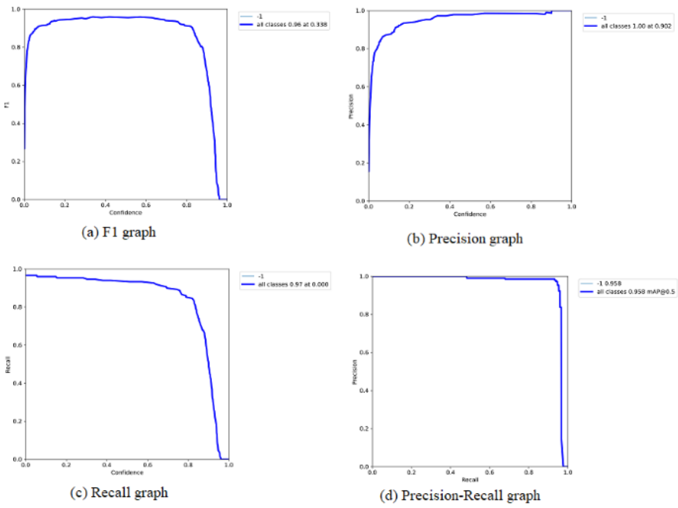

Figure 4. a) Represents the model's F1 graph b) Represents the model's precision graph c) Represents the model's recall graph d) Represents the model's precision-recall graph

Figure 4 (a) shows the F1 success plot of the YOLOv7 model. The F1 success rate of the YOLOv7 model is 96%. The F1 plot shown represents the harmonic mean of the precision value of the model and the recall value, and is a value used when comparing models. The recall value is the value that indicates how many data were positively predicted based on how many of the data were defined as positive. The precision value in Figure 5 (b) produced results greater than 90%. The precision value indicates how many of the positively predicted values are actually positive. Figure 5 (c) shows a recall value of 97%. The recall value is the value that indicates how many of the data presented as positive were actually predicted to be positive. In Figure 5 (d), the YOLOv7 model provides a result with an accuracy of 95.8% mAP. This result shows the average sensitivity. The YOLOv7 model has shown that it can be applied to an embedded real-time system and perform with 95.8% mAP and 52 FPS.

In different model studies with the same parameter values on the same data set, the success rate (mAP) for the YOLOS (Fang et al. 2021) model is 90.1%, for the YOLOv6 model 91.8%, and for the YOLOv5 model 89.1%. Table I shows the performance of the models in comparison.

Table 1. Performance Plot of the Latest Object Detectors Implemented On Gdrone

Model	Image Size	GFlops	Parameter (M)	mAP(%)
YOLOv5	416x416	7.3	16.8	94.1
YOLOS	416x416	-	6.5	90.1
YOLOv6	416x416	18.62	17.19	91.8
YOLOv7	640x640	103.2	36.48	95,8

Table 1 shows that the YOLOv5 model achieves the least success, while the YOLOS model achieves more successful results than the YOLOv5 model, even though it has the fewest parameters. Although the YOLOv6 model is more successful than the YOLOv5 and YOLOS models, it appears to be less powerful compared to the real-time performance of the other models. However, it was found and shown that the YOLOv7 model performs better than the other models tested in terms of both performance and success. Table II compares the success of the different models in similar studies.

When the results in Table 2 are examined, the successes of the architectures tested on different datasets are shared. In (Zheng et al. 2021), the YOLOv3 model gave the worst result when tested on the Det-Fly dataset. Immediately after, in

Table 2. Performance of the Models on Different Datasets

Model	Image Size	GFlops	Parameter (M)	mAP(%)
YOLOv5	416x416	7.3	16.8	94.1
YOLOS	416x416	-	6.5	90.1
YOLOv6	416x416	18.62	17.19	91.8
YOLOv7	640x640	103.2	36.48	95,8

source (Behera and Raj 2020), the success of the YOLOv3 model is reported to be 74%. Source (Liu et al. 2021) states that the Pruned YOLOv4 model works effectively and the author obtained results of over 94% when experimenting with his own dataset. The YOLOv5 model used in the study numbered (Zhao et al. 2021) can be considered the most effective study in the literature to date. However, considering different improvements and studies with different datasets, it is observed that the YOLOv7 architecture achieves the best result with a mAP success rate of 95.8%. Since the YOLOv7 architecture has not yet been used on a similar dataset in the literature, it is not possible to compare YOLOv7. However, the dataset we have is open source and is made available to researchers for study and comparison. Figure 5 shows the test results of YOLOv7.

Figure 5. Some examples of test results of the YOLOv7 model

As can be seen from Figure 5, factors such as different backgrounds and the distance of the drone from the camera were considered in terms of suitability for real-world conditions. Since drones are expected to be a threat in any region, the diversity of the dataset is one of the most important elements for the study. The fact that the proposed model works with 95.8% success and 52 FPS shows that it can work in a real-time system.

6. CONCLUSION

Artificial intelligence technology, which is widely used today, is used as a driving force for revolutionary changes in many fields such as production, education, health and defense industry (Talan 2021). With this technology, it is not only limited to increasing computerized computing capacity, but also used to develop human-like thought and behavior processes. Analyzing people's emotions (Korkmaz, Aktürk, and Talan 2023), detecting perceived objects, facial recognition and acting like a human are among these processes. Especially applications such as object recognition, face recognition, biometric recognition (Aktürk, Aydemir, and Rashid 2023) and classification are frequently used in the health and security sectors. In this study, performance analysis of image processing algorithms was carried out by focusing on the detection of UAVs. Because it is possible to say that the increasing prevalence of UAVs in parallel with the development of technology brings with it some security threats. In other words,

It is an unavoidable fact that the development of UAVs and such vehicles carries risks and may pose serious risks to states such as various irregularities, illegal activities and ultimately public safety. Examples of serious security problems are the transport of prohibited substances, the transfer of explosives to target areas, or espionage activities. Therefore, UAVs or drones must be detected effectively. In this study, the performance of new object detectors is evaluated and a high-sensitivity model is proposed for real-time applications. Various models were created with the data obtained from different sources and the success of these models were compared. The YOLOv7 model has an improvement rate of 1.7% compared to the YOLOv5 model. The proposed method appears to be an effective and accurate tool. In this study, a drone dataset was added as a contribution to the iteration. In addition, the YOLOv7 and YOLOv6 models were tested on a drone dataset for the first time, the performances of these methods were compared and the results were presented. It has been shown that the YOLOv7 model can be used to defend against incoming threats, especially in organizations with high security needs and in regions exposed to threats.

Peer Review: Externally peer-reviewed.

Author Contributions: Conception/Design of Study- A.A., T.T., C.A.; Data Acquisition- A.A., T.T., C.A.; Data Analysis/Interpretation- A.A., T.T., C.A.; Drafting Manuscript- A.A., T.T., C.A.; Critical Revision of Manuscript- A.A., T.T., C.A.; Final Approval and Accountability- A.A., T.T., C.A.; Material and Technical Support- A.A., T.T., C.A.; Supervision- A.A., T.T., C.A.

Conflict of Interest: : The authors have no conflict of interest to declare.

Grant Support: This study was supported by the BAP (The Scientific Research Projects) under Grant No: 2021-FM-02.

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How cite this article

Aydin, A., Talan, T., Akturk, C. (2023). Vision-based amateur drone detection: performance analysis of new approaches in deep learning. *Acta Infologica, 7*(2), 308-316. https://doi.org/10.26650/acin.1273088