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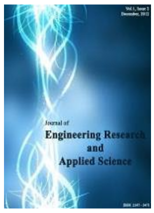

Runway Intrusion Detection with YOLOv10: A Deep-Learning Based Approach

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Abstract

A large number of people use airports intensively for travel and transportation. However, the excess number and the traffic density can cause potential crimes at airports. With the development of technology and security management strategies, the possibility of accidents and attacks is reduced by increasing safety measures. For such reason, security systems are used to monitor the terminal and passengers and reveal any vulnerabilities. The incidents that develop or are likely to develop at airports are detected by these systems. Applications such as border violations and tracking, and prevention attempting to enter the runway during takeoff or landing are carried out around the airport. In this study, early warning systems, which are a critical issue for airport security, were examined. Focusing on object detection, image processing methods by the YOLOv10 model are introduced to prevent threats around the airport. Imaginary border violation scenarios determined by object detection and classification were evaluated. As a result, the classification success rates for tree, human, and animal (cat) were determined as 99%, 94%, and 100% for the testing dataset.

Keywords: *Airport security, Early warning systems, Image processing, Camera system, Artificial intelligence*

1. Introduction

The airports are very important places to provide security services as they contribute to the economic life of the country [1]. They have been the center of attraction from an aspect of security for a long time since a small mistake can increase the consequences of their actions [2]. The importance of security in the aviation sector was observed more clearly with more than 364 hijackings occurred between 1968-1972 [3].

Since the late 1960s, airports and civil aviation have been the target of politically motivated crimes [4]. However, the type of illegal acts that pose a threat to civil aviation all over the world has changed over time. While the hijacking of planes in the 1970s and the bombing of airplanes in the 1980s and 1990s were the most important threats, the aviation information systems were connected to computers and targeted in the 2000s [5]. Since illegal acts have posed a danger for years, it is necessary to protect international civil aviation against illegal acts by action [6].

The loss of life in the aviation sector, as well as the negative economic effects caused by the obstruction of air transportation, have become critical. The ability to prevent actions depends on increasing security measures in the entire system [7]. In addition to ensuring the safety of employees and passengers, airport management is also required to ensure or take measures to ensure the best protection of buildings, aircraft, and other equipment. However, rapid security measures have to be taken into account since it is critical [8].

The illegal acts took place in airports, so it requires security measures to be taken in international standards. For instance, the passenger terminal building is one of the most critical places where security measures can be applied. Indeed, full execution of airport security is required by the cooperation and determination of the central and local administration, including airport authorities, police, security personnel, as well as the community [9].

There are various acts of sabotage against airports. For example, the attacker can easily move away from the scene [10]. Alternatively, acts may include placing explosives in places such as handbags and suitcases, shooting with guns, using other objects, smuggling explosives along with weapons into the aircraft [5].

Security units should be attentive and careful to avoid disruptions in the security system to ensure peace and functioning [11]. Since airports actively serve many

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people throughout the day, security systems must be operational 24 hours a day. In addition, controlling the airport perimeter is very critical for the protection of aircraft, airport facilities, and buildings against external attacks on the airport [5]. This control includes patrolling the area around the airport by guards and monitoring it by closed-circuit TV systems and having observation points [11]. In addition, special attention should be paid to places where saboteurs can easily hide, such as around the approach and departure routes of the aircraft, forest areas, and car parking areas [12]. Airport security starts from 3.04 m away from the fence on each side, so that safety barriers should be illuminated and warning devices should be used to reveal when these obstacles are observed [8]. In addition, airport perimeter security should be ensured by increasing the number of security personnel at checkpoints and positioning the camera system along the border line to detect people entering the airside [13].

The most important elements that can be used in airport security management are technology and people. However, technology can handle the requirements when it is complemented by humans [14]. Therefore, all the resources used in the security management of the airport must be actively and harmoniously operated [15].

Modern technology allows airport security to manage both terminal and perimeter security [16]. For instance, passengers boarding, disembarking from the plane, and taking their luggage are delivered at the terminal section. The security section covers the areas outside the airport terminal on the border line. The efforts are performed to ensure the safety of the runway, to detect any kind of threat to prevent them [17]. Stopping anyone from crossing the border, supervising aircraft landings and take-offs, and tracking animals approaching the runway are among the possible security violations. There are also security cameras along the airport to monitor any violations [18-19].

Researchers have not conducted many studies on security measures at airports. For this reason, the YOLOv10 deep learning approach was applied in this study to detect the objects, First of all, the image processing and object detection approaches in the literature used for security were examined. The possible use of the YOLOv10 algorithm in airport security was explored. These studies were introduced and compared to others, while the advantages and disadvantages of them were presented. In this regard, research on using artificial intelligence for image perception was reviewed. The sample studies showed what the YOLO algorithm is capable of performing in various classification processes.

Sharma et al. [20] applied the normalized cross-correlation method to identify animals (dogs). The mechanism performed pattern matching on 5000 images and managed to achieve a consistency of 86.25%.

Eldem et al. [21] developed a study on spotting people’s faces in photos. Development of OpenCVSharp in C# relied on the OpenCV (Open Source Computer Vision Library), and the comparison process provided a 79% accuracy rate in face recognition.

For the wild animal image research, Yabanova and Kaya [22] compared several types of classification algorithms. They found that Artificial Neural Network (ANN) outperformed support vector machines (SVM) in terms of accuracy. The evaluation results indicate that the proposed method is 100% accurate in spotting and counting wild animals [22].

Algur et al. [23] introduced a hybrid system that classifies human actions in pictures outdoors, where YOLO was used to identify the people. Google Street View was used while the identified objects were predicted by using the Convolutional Neural Network (CNN). The class validation result was reported to be 85.71%, considering four types of subclasses.

Şimşek et al. [24] used the YOLO method to detect humans in image traps. They used 2880 images with the dimensions of 2048x1536. The results showed that 94.6% of the images containing humans were identified [24] successfully.

Adopting the YOLO algorithm in deep learning makes the security issue more efficient since it allows to perform rapid performance. Since it is capable of detecting threats and objects, it creates a more organized and effective security system. For instance, Choubisa et al. [25] performed an intrusion classification study using an optical camera. The researchers focused on interpreting images of people with guns, sitting in cars, and creeps, as well as movements by animals. The results indicated a 95.65% match between human and animal classes, while the other class reached 89.57%. Furthermore, the algorithm developed in Saudi Arabia was used outdoors in real time, and it achieved an accuracy of 92% [25].

YOLOv4 was performed by Önal and Dandıl [26] to see how workers in industrial areas use equipment designed for personal protection. The research indicated that the model recognized helmets, vests, masks, gloves, and goggles with an accuracy of 91.18%. In addition, Nayak et al. [28] implemented an intrusion detection system for immediate applications in smart cities. The study relied on YOLO to identify intruders and used the SORT algorithm to follow the attacker in real time. The 97% accuracy was obtained by YOLOv2 on the dataset [28]. In another paper, Sevi and Aydın [29] developed a YOLOv8 approach using RailSem19 images to identify foreign objects near railroads. Using Google Colab, the training led to an accuracy of 88.8% for several models during experiments with mAP 50 [29].

Lately, deep learning models are being used widely, especially in managing traffic systems. For his study, Alemdar [30] cooperated using YOLOv8 for the object identification application of double-row parking. The training for the model was handled by the Google Colab engine. All 891 images were taken on the streets with much traffic activity in İzmit and Erzurum. The results lead to the top-1 (F1 score) value of 0.83, the double row section’s value of 0.87, the normal row’s value of 0.92, while the mAP 50 was 0.89. The accuracy of double-row parking detection was determined to be 89% [30]. Real-time analysis and spotting of vehicles as well as pedestrians was studied by Sadik et al. [31]. For extreme scenes in urban areas, YOLOv8 and RT-DETR provided results with a mAP accuracy of 80.9% and 81.7%, respectively [31].

2. Materials and Methods

In the study, the prevention of possible threats around the airport and the control of runway safety were carried out. Within the scope of Airport Security Warning Systems, the YOLOv10 algorithm was used for the detection and classification of images violating the airport border line.

An image database, specifically obtained from airports, is required for the study, however it was difficult to get any since it would cause a security vulnerability due to the strategic structure and importance of the airports. For this reason, a personal database was created consisting 1000 color images with a resolution of 30 frames per second (fps) and size of 720x1280 (width * height). Among them, 80% was used for training, while 20% was for testing (Table 1).

The labeling of the images in the dataset was performed with *Roboflow*, a software tool used in image labeling for object detection, classification, and segmentation and compatible with Yolo. The images in the dataset were labeled with the bounding box technique, labeling with human, animal, and tree [32].

The YOLOv10 model was used in this study. It has a CNN structure that uses a single neural network to make classification. It was developed in 2024 and offers models optimized for high-performance object detection [33]. It meets different computational requests and accuracy requirements for a variety of applications. The study was conducted using Google Colab for 60 epochs. The flow diagram of the study is provided in Figure 1. The learning and loss curves corresponding to the training process are presented in Figure 2.

Table 1. The partition of the dataset concerning sub-classes.

	Education	Test
Human being	450	110
Cat	50	10
Tree	300	80
Sum	800	200

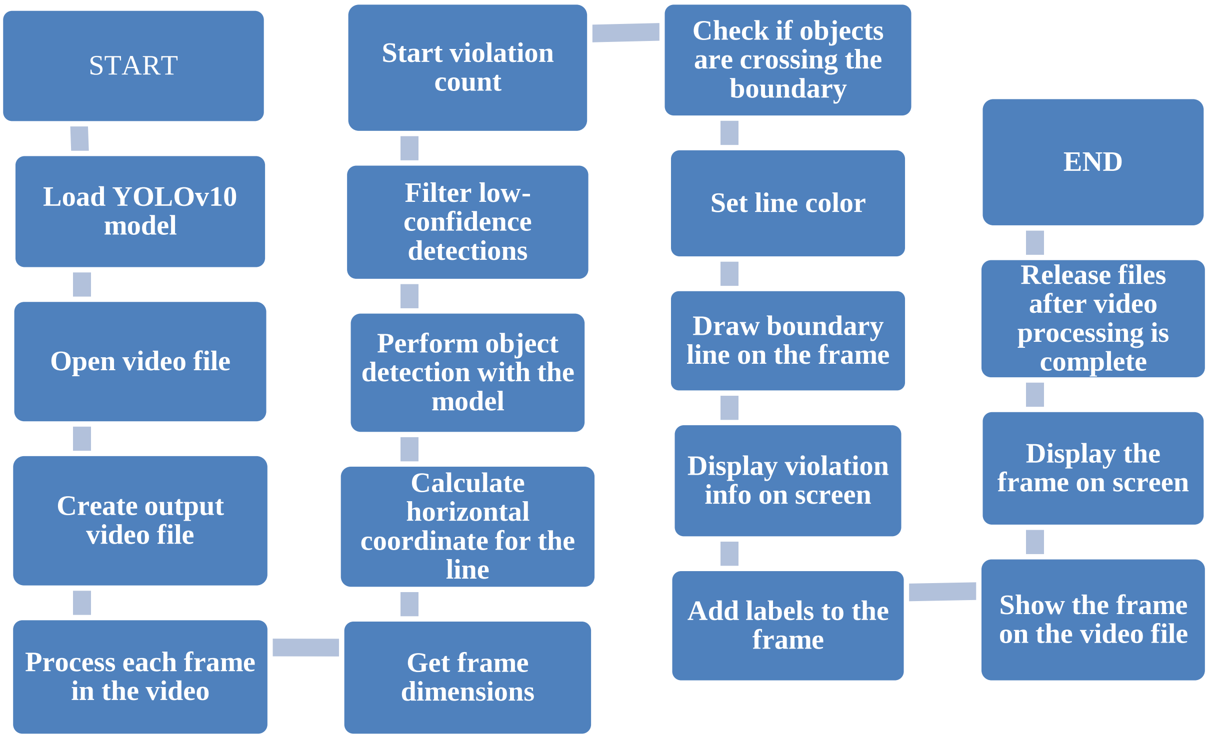

Figure 1. Workflow diagram of the proposed work

3. Results and Discussion

The study consists of classifying an image as a human, tree, or animal (cat). During the evaluation, the intersection (IoU) parameter on the union is forced to be greater than 0.5 for the trained model. There is also intersection and performance parameters. Of these, *accuracy* refers to the accuracy of the model, *precision* indicates how much of the actual data set of input images is predicted positively by the model, and *recall* provides information about how much of the input images that should be positively predicted by the model [34-35]. The *F1 score* is obtained by the mean of the precision and sensitivity amounts. Mathematical expressions of performance parameters are provided in Equations 1,2,3, and 4. [34-35-36].

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

$$F1\ \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

The YOLOv10 model is trained with a total of 800 images (Table 1). The *accuracy* parameter is used to determine the accuracy and sensitivity of the model by measuring the performance with the mAP parameter. The results of the *F1 score*, *sensitivity* and *precision* graphs were obtained in Figure 3.

Apart from classification *accuracy*, *F1 score*, *precision*, and *sensitivity*, the confusion matrix is used to summarize the performance of the classification algorithm. It provides information about the match between the model classification and the true values so that the type of error can be estimated. The model is applied to the test dataset, and the normalized confusion matrix is presented in Figure 4, while samples are provided in Figure 5.

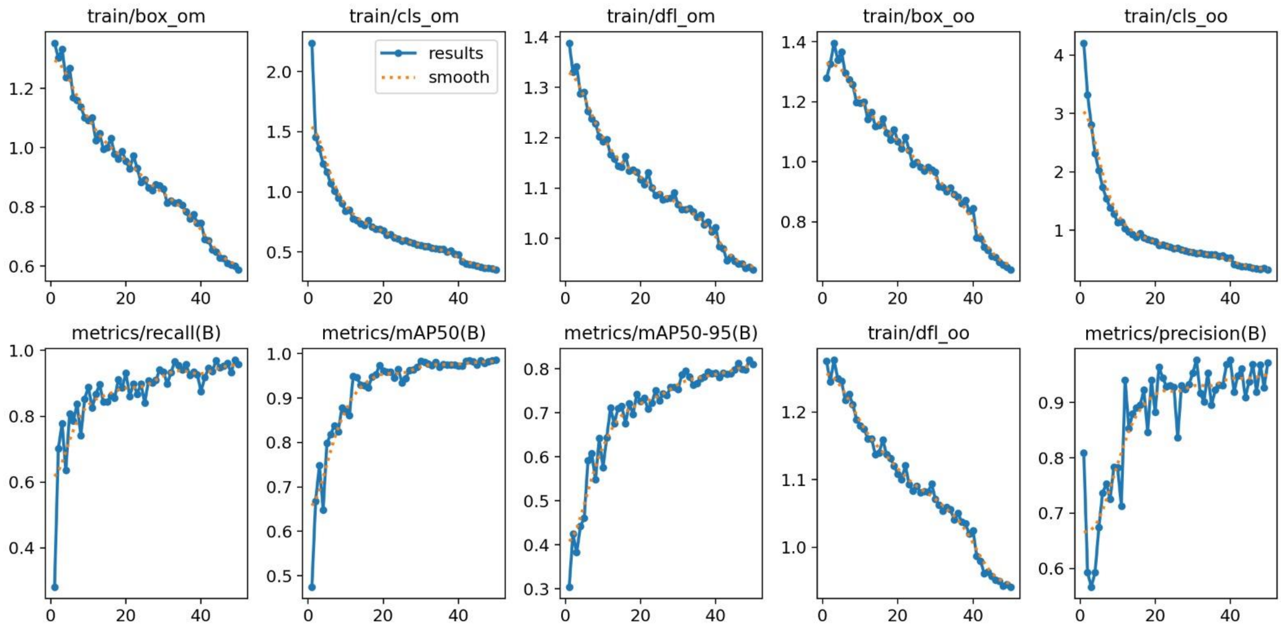

Figure 2. The learning rate and train parameters

The trained model was also re-run on the 5-minute Oxford Street video recording used in Reid's work, and the results obtained in this study were confirmed. The accuracy rate on randomly selected frames was estimated as 91% [37]. A sample image section of the analysis results is presented in Figure 6.

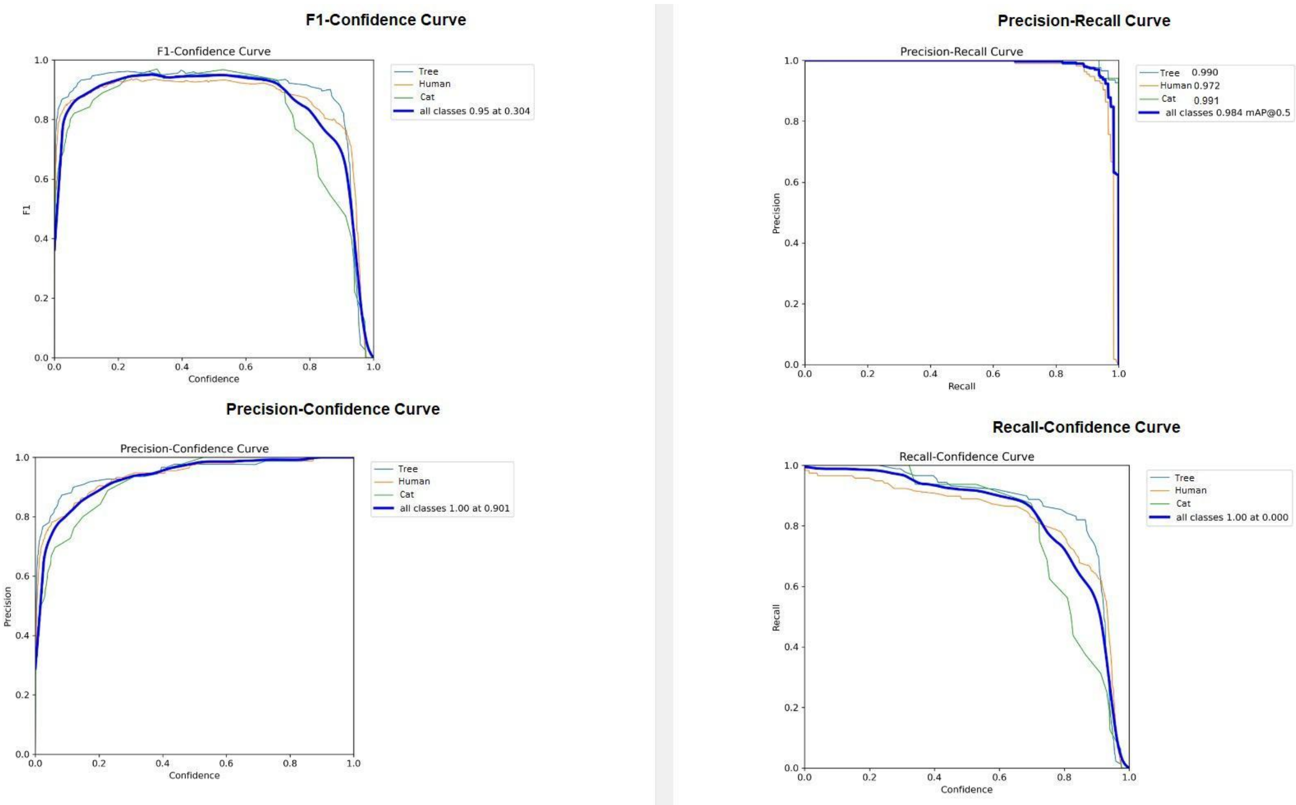

Figure 3. The F1 score, sensitivity, and precision variation for the training dataset

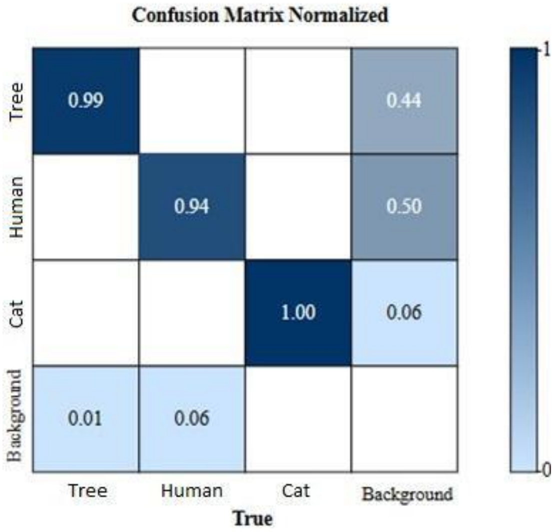

Figure 4. Confusion matrix of the YOLOv10 model for the test dataset

Figure 5. Samples of the prediction and layer images for the test dataset

Figure 6. A sample example of the snapshot of Oxford Street

4. Conclusions

The YOLOv10 model's overall accuracy for the mAP 50 value was obtained as 0.984. However, the images at the endpoints at mAP 50 are not evaluated, so that it will allow the F1 score to be higher. The average F1 score was obtained as 0.95 in this study. The result shows that the model was created successfully and gave considerable results.

The classification results for the human, tree, and animal were obtained at 94%, 99%, and 100%, respectively (Figure 4). The results showed that the model has a very high *accuracy*. These values are better than the results of Sadik et al. [31] study, where they performed real-time detection of vehicles and pedestrians with mAP values of 80.9% and 81.7%, respectively. On the other hand, Algur et al. [23] obtained a mAP value of 85.71%, on the classification of people's movements in outdoor while Sharma et al. [20] performed a study on various dog images and identification with a mAP value of 86.25%.

Considering the results of this study, security is very important, as the strategic location of airports is a leading area of the service sector. Airport perimeter security is provided by cameras positioned along the border line to report violations. With the model obtained in the study, it can detect and classify even if a human or an animal pass through the imaginary boundary line. A different boundary can also be determined concerning the image. Trees are also included in the classification group as a constant object so that they do not provide false alarms in case of violation. The model also detects the number of people or animals violating the determined area. This feature distinguishes it from other studies in literature.

There are also limitations in this study. First of all, a certain number of classifications were taken into account. A new study may consider increasing the number of classes. Secondly, the image numbers considered for training should be increased since it will provide better results. Finally, the alarm scenarios can also be modified and applied specifically to the airports for reporting any type of violation.

Conflict of Interest

The authors have collaborated jointly on this study, and there is no conflict of interest to declare. This research is partially derived from the Master's thesis of Ümit Yeşilyurt conducted under the supervision of Dr. Ayşe Aydın Yurdusev.

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