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Railway Security System Design Using Unmanned Aerial Vehicle Image Processing and Deep Learning Methods

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Abstract: With the developing technology, technological blessings make human life easier and help them every day. Unmanned aerial vehicles (UAV), which is one of the technological blessings, have shown themselves in many fields, especially in fields such as the military, defence industry, photography, and hobby. With the development of defence systems with UAVs, the security of railways has also been left to UAVs. In this study, while the foreign matter separation is made on the railway by using the deep learning model in real-time, the image taken on the UAV is simultaneously controlled by using the image processing method. The fact that the deep learning model has a 0.99 mAP rate increases the reliability of the model.

İnsansız Hava Aracı ile Görüntü İşleme ve Derin Öğrenme Yöntemleri Kullanılarak Demiryolu Güvenlik Sistemi Tasarımı

Anahtar Kelimeler
Derin Öğrenme, Görüntü İşeleme, İnsansız Hava Aracı

Öz: Gelişen teknoloji ile her geçen gün teknolojik nimetler insan hayatını kolaylaştırmakta ve onlara yardım etmektedir. Teknolojik nimetlerden olan insansız hava araçları (İHA) askeri, savunma sanayi, fotoğrafçılık ve hobi gibi alanlar başta olmak üzere birçok alanda kendisini göstermiştir. İHA ile savunma sistemlerinin gelişmesiyle birlikte demiryollarının güvenliği de İHA'lara bırakılmaya başlanılmıştır. Bu çalışmada İHA üzerinden alınan görüntü gerçek zamanlı olarak derin öğrenme modeli kullanılarak demiryolu üzerinde yabancı madde ayrımı yapılırken eş zamanlı olarak görüntü işleme metodu kullanılarak demiryolunun sağlamlığı kontrol edilmektedir. Derin öğrenme modelinin 0.99 mAP oranına sahip olması modelin güvenirliliğini artırmaktadır.

1. INTRODUCTION

Today, the use of public transportation vehicles is increasing with the decrease in energy resources and the increase in costs [1]. Among the public transport vehicles, rail transport is the most efficient, cost-effective, and convenient means of transportation. It has lower fuel costs, can carry large loads, is environmentally friendly, and is safer because it is not affected by weather conditions as in air transportation [2]. Therefore, rail transport has become the backbone of every developing country. One of the most important components that make rail transport safe is its infrastructure. The railway infrastructure usually consists of sleepers installed at regular intervals between them and steel rails supported by the ballast structure. Steel rails in train transportation directly affect passenger safety and comfort as transportation infrastructure. The deterioration of the railway line, the wear of the materials on the lines over time, foreign materials falling on the railway, and deliberate sabotage on the railway put the safety of railway passengers at risk. Considering all these factors, a fast and efficient inspection system is required to ensure the safety of railways [3-5].

Railway inspection is of critical importance to ensure the safety of railway traffic and protect human health [6]. Most of the inspection processes in use today are done visually. In this method, which is traditionally called, the detection of any damage to the railway components or a foreign substance is carried out by the assigned people walking along the rail [7]. However, performing this process manually with an auditor is slow, costly, dangerous, and labour-intensive. As a result of the increase in the number of railway networks, the frequency of inspection studies with traditional methods is decreasing [2]. This situation creates a risk in transportation by causing the defects in the railway not to be detected in a timely manner. Therefore, to eliminate these risks, the disadvantages of traditional methods should be overcome. Compared to traditional methods, ultrasonic, acoustic, emission, and eddy current-based techniques are also used. However, such techniques can be applied with train movement and cannot provide information about the size of the defect [8,9].

Recently, rail companies around the world have been working on autonomous inspection systems that can more efficiently inspect railroad defects. With the development of autonomous control systems, more advanced control techniques have been designed to overcome the shortcomings of traditional methods [10, 11]. Among these techniques is the use of UAVs. Unmanned aerial vehicles are systems that can fly controlled or autonomously without the need for a pilot. Today, it is frequently preferred in military, health, commercial, scientific studies, and civil aviation studies. In addition, more efficient systems can be designed by integrating deep learning and image processing techniques into unmanned aerial vehicles [12]. Deep learning is based on the principle that a set of pictures, video, or audio data is analyzed with certain algorithms to give an estimated value as output. Applications such as product classification, object counting, and face recognition can be given as examples of deep learning study areas [10,13].

In line with this study, an autonomous system has been developed with the UAV by using deep learning and image processing techniques. The system is flying along a railway and collecting images via the camera on it. While the collected images are checked for the integrity of the railway bypassing through histogram equalization and gaussian filtering processes, the same images are simultaneously analyzed with YOLO v5, one of the deep learning algorithms, to check whether there is a foreign substance on the railway. As a result of the deep learning output, it can be determined whether there are defects in the railway and whether there is any sabotage situation [14].

2. MATERIAL AND METHOD

The methods used in the study, the creation of the data set, the deep learning algorithm, and performance evaluation metrics were examined as three sub-titles and discussed in detail below. The method part of the study was carried out as shown in the workflow diagram given in Figure 4.

2.1. Material

In the study, a system proposal developed by using image processing methods based on an artificial intelligence system was made in order to detect foreign materials on the train tracks and to control the integrity of the rails. In the study, it was trained with the data set obtained using the YOLOv5 deep learning network. The accuracy of the deep learning network, whose training was completed, was evaluated according to the mAP, precision, and recall metrics.

2.1.1. Create datasets

The data set was carried out by taking pictures of foreign materials placed on the railways in different locations in Isparta province with a drone. The photographs were collected in different time periods at different angles and at different distances. Figure 1 shows some photos of the data set. The data set includes a total of 785 photographs of foreign substances. At the same time, there is a video of 3 minutes and 23 seconds in which the drone flies on the railway to check the image processing methods and the stability of the train tracks in the dataset.

Figure 1. Datasets

2.1.2. Yolo v5

YOLO v5 network is the latest version among YOLO architectures as of 2022. It gives fast and high accuracy compared to other versions [15]. YOLO networks are algorithms used for object recognition using convolutional neural networks developed by Joseph Redmon in 2016 [16]. There is no official article for YOLO v5 at the time of preparation of this article, as the YOLO v5 network is published by different developers and not by the official publisher [17]. The YOLO v5 network uses the spine, neck, and head structure that we frequently encounter in object recognition processes. While the objects trained on ImageNet are used as backbones, the bounding boxes of the objects are called heads, and the YOLO, which is used for object detection, is called the spine [18]. The YOLOv5 network is presented in 4 different models. These are YOLOv5s, YOLOv5l, YOLOv5m, and YOLOv5x [19]. Figure 2 shows the YOLOv5 architecture.

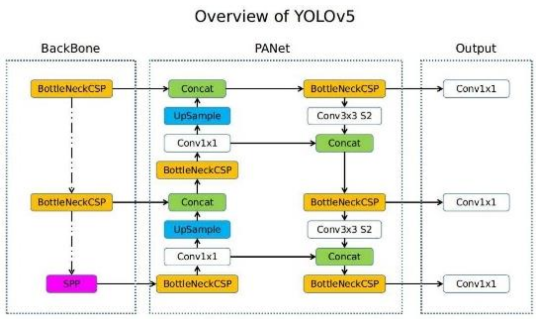
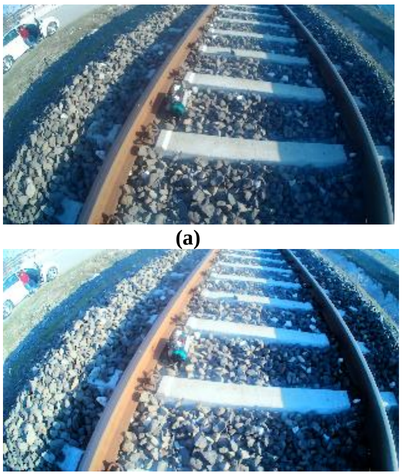


Figure 2. Yolo v5 Architecture

2.1.1. Histogram equalization

Images taken from the camera have RGB color space. The pixel values of an image in the RGB color space have three elements, so the images are converted to gray format, that is, the pixel values between 0-255, to perform the operations quickly in computer vision processes [20]. Histogram equalization is used to provide color distribution by distributing the clustered pixels in the images equally to all sides [21]. With histogram equalization method, it is a method that is frequently used to reveal the shapes that are not clear on the image, with low brightness or in the dark region [20]. In Figure 3, the original image is shown with the histogram equalization method applied on an image.



(a)

(b)

Figure 3. Histogram Equalization (a) Original Image b) Histogram Equalized Image

2.1.1. Gussian filter

It is the method used for blurring the picture. The blurring process is used to reduce the noise on the picture and to determine the edges. It is obtained by multiplying the two-dimensional convolution matrix with the image pixels [22]. With the Gussian filter, it is aimed to equalize the frequency on the image and increase the view on the image [23]. It is the method used for blurring the picture. The blurring process is used to reduce the noise in the picture and to determine the edges. It is obtained by multiplying the two-dimensional convolution matrix with the image pixels. The formula for the Gaussian filter is given in equation 1.

$$G(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{2\sigma}} \tag{1}$$

2.1.1. Performance evaluation metrics

Deep learning results are evaluated according to certain metric values. Details about mAP, precision, and recall being used in this study are given below. The mAP value is the value that measures the accuracy of the location of the bounding boxes to evaluate the object recognition algorithms between 0-1 [24,25]. It means the average of the AP value. The closer the mAP value is to 1, the more accurate the model is found to make predictions. The equation of the mAP metric is given in equation 2 [24].

$$mAP = \frac{1}{N}\sum_i AP_i \tag{2}$$

Precision is the metric that gives us how many of the values we consider positive in the confusion matrix. Precision value is used to evaluate the closeness between the measured value and the actual value. In Equation 3, the equation of the precision metric is given.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

The recall is the value that gives how many of the images we evaluate positive are positive. It represents the ratio between the samples taken and the samples detected. In Equation 4, the equation of the recall metric is given.

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

2.2. Methods

The workflow diagram of the study is given in Figure 4. First, the dataset was created to feed and train the YOLO v5 network. Labelling was performed on the dataset on the roboflow framework. The data set, which was prepared for the training phase, was put into training on Google Collab, and the weights trained in the YOLO v5 network were downloaded to the computer. At the same time, an image processing system to control the integrity of the railway was prepared, and the two methods were combined. The real-time image is simultaneously inserted into both the image processing method and the deep learning network, and the results are displayed in an interface.

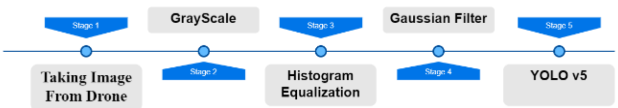


Figure 4. Workflow diagram

3. RESULTS

The findings obtained as a result of the study are given below. YOLO v5 network training results are based on mAP, precision, and recall values. 785 images were used in the data set. The images were separated as test and training data after labelling. While 628 images were used in the training dataset, 157 images were used in the test dataset. Figure 5 shows the mAP graph of the YOLO v5 network. A precision graph of YOLO v5 network is given in Figure 6. Figure 7 shows the recall graph of the YOLO v5 network.

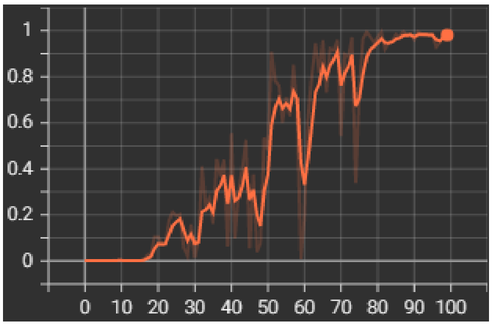


Figure 5. mAP graph

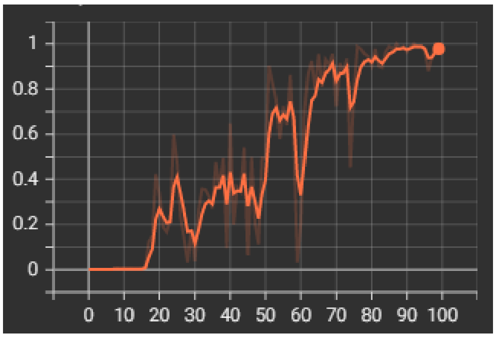


Figure 6. Precision graph

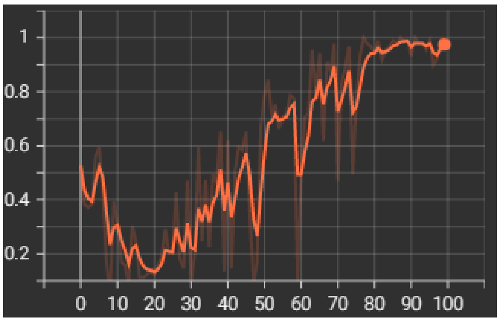


Figure 7. Recall graph

The table where the graphic values are given is shown in Table 1 below.

Table 1. Performance Evaluation Metrics

Metrics	Value
MAP	0.995
PRECISION	0.978
RECALL	1

When the training result values of the YOLO v5 network are examined, it is observed that the trained model performs the prediction process with high accuracy.

4. DISCUSSION AND CONCLUSION

As a result of the work done, it is a tiring and time-consuming process to determine the soundness of the railway and the detection of foreign matter by walking thousands of kilometres. In our proposed system, a UAV has been developed to detect foreign materials on the railway by flying along the railway and to warn the officials by checking the soundness of the railway. Future studies it is aimed to train on new models by increasing and diversifying the number of images in the data set. At the same time, it is aimed to carry out new studies on the integrity of the railway by using deep learning methods.

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