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Examining The Effect of Different Networks on Foreign Object Debris Detection

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Abstract

Foreign Object Debris (FOD) at airports poses a risk to aircraft and passenger safety. FOD can seriously harm aircraft engines and injure personnel. Accurate and careful FOD detection is of great importance for a safe flight. According to the FAA's report, FOD types are aircraft fasteners such as nut, safety; aircraft parts such as fuel blast, landing gear parts, rubber parts; construction materials such as wooden pieces, stones; plastic materials, natural plant and animal parts. For this purpose, in this study, the effect of different networks and optimizer on object detection and accuracy analysis were examined by using a data set of possible materials at the airport. AlexNet, Resnet18 and Squeezenet networks were used. Application is applied two stages. The first one, 3000 data were divided into two parts, 70% to 30%, training and test data, and the results were obtained. The second one, 3000 data were used for training, except for the training data, 440 data were used for validation. Also, for each application, both SGDM and ADAM optimizer are used. The best result is obtained from ADAM optimizer with Resnet18, accuracy rate is %99,56.

1. Introduction

FOD is defined as a living or inanimate object that is not in a suitable location that can damage employees, equipment or aircraft within the airport [1]. Objects such as tools left on the runway, fragments from the ground, animal remains, and pebbles carried by the wind, plastic, metal and tin components threaten flight safety and may even cause fatal accidents. Since FOD is critical safety hazard and effect the economic hazard, FOD recognition system is useful for reducing its damages. Aviation organizations around the world have detailed various FOD detection technologies in order to prevent debris hazard on runways, maintain clean and safe aircraft maneuvering areas, and prevent FOD damage to aircraft [2]. Some countries have a FOD detection system. FODRAD, the first and only FOD detection radar developed in Turkey, was established at Antalya Airport in 2018. FODRAD is a mm-wave radar system that is designed to meet the recommendation criteria of Federal Aviation Administration (FAA) AC150/5220-24 and performs 24/7 surveillance [3]. Considering this application, some studies have been carried out in the literature. Han et al. [4] created a FOD dataset at runways of Shanghai Hongqiao International Airport and campus of their research institute and created a FOD recognition system based on both Transfer Learning and D-CNN. In [5], the authors used the Yolo3 algorithm for FOD detection. They used deep residual network to extract features from the data and multi-scale feature fusion for small-scale FOD detection. In [6], a dataset named FOD-A was created. They used machine learning models for object detection. In [7] for initial dataset unmanned aerial system (UAS) and portable cameras are used to collect the data at the airport. Later these FOD video were split into frames and using You Only Look Once algorithm efficiency detection was done. In [8], YOLOv4 which is one of the YOLO model, is used with transfer learning and obtained fast results for FOD detection. In [9], the authors present a spatial

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transformer network (STN), region recommendation network (RPN) and convolutional neural network (CNN)-based method for detecting FOD. In [10], DenseNet and Faster R-CNN are used for small scale FOD detection. In [11], the authors proposed to collect images with drones and detect any FODs with an artificial intelligence-based specific trained algorithm. In [12], the authors propose a new random forest-based FOD detection framework that uses representative PVF to accurately segment FOD regions and effectively suppress background interference in airport images. In [13], to classify FOD images, an ensemble learning algorithm, namely KNN, Adaboost, and Random Forest Tree, is used. As feature extraction methods, Linear Discriminant Analysis (LDA) and Gray-level co-occurrence matrix(GLCM) are used.

FOD is materials that can harm the airport, airport personnel and aircraft. Taking measures to detect and remove these materials with a smart system before it is too late will provide security and contribute to the prevention of serious economic losses. In the literature, efficient results have been obtained with the Yolo algorithm for deep learning-based object recognition. In this study, the pros and cons of different optimization algorithms are examined and a performance comparison is made between the selected ADAM and SGDM algorithms. Also, AlexNet, Resnet18 and Squeezenet pre-trained networks are used and the success rate of the current method is compared with the literature.

2. Material and Method

2.1. Dataset

Created by the researchers using the runway and its surroundings, the dataset has three labels: metal, concrete, and plastic [4], [14]. The dataset consists of a total of 3440 images, of which 3000 are training and 440 tests. In the training set, each class has 1000 images, and in the validation set, concrete has 100, metal 105, and plastic 235 images. In this study, two applications are applied. The first one, 70% of the 3000 data was used for training and 30% for testing. The second one, 3000 data used for training and test, except for this data, 440 data were used for validation and performance analysis was examined. Some images of the dataset are available in Figure 1. The numbers of the FOD dataset are given in Table 1. Also, bar graph of data distribution is in Figure 2.

Figure 1. Samples of dataset

Table 1. Dataset distribution

Dataset	Training	Validation
Concrete	1000	100
Metal	1000	105
Plastic	1000	235
Total	**3000**	**440**

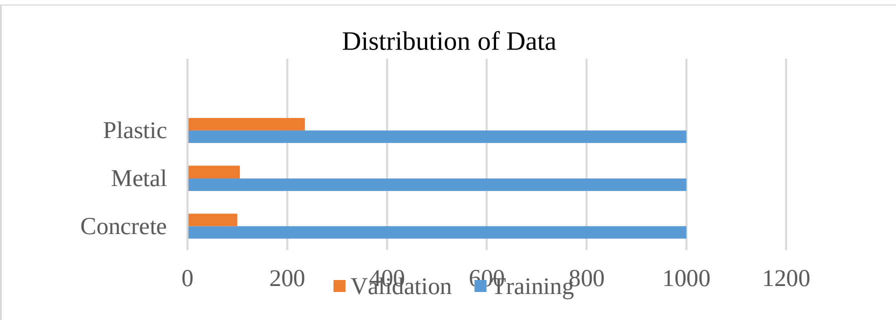

Figure 2. Bar graph of data distribution

2.2 Methods

Machine learning has long been a very popular field for detecting and evaluating any situation [15]-[17]. Machine learning requires feature extraction from raw data with a feature extraction method. However, with the use of deep learning approach recently, this feature extraction process is done with its own layers without the need for a separate feature extraction method has made this area the center of attention. Deep learning has the advantage of learning information by creating deep architectures. Also, with deep learning, the model automatically provides fast learning [18].

In this study, the features of the FOD dataset with different networks, such as AlexNet, Resnet18 and Squeezenet, were extracted and the classification results were compared. For each application, SGDM and ADAM (Adaptive Moment Estimation) optimizers are used. The block diagram of the study is given in Figure 3.

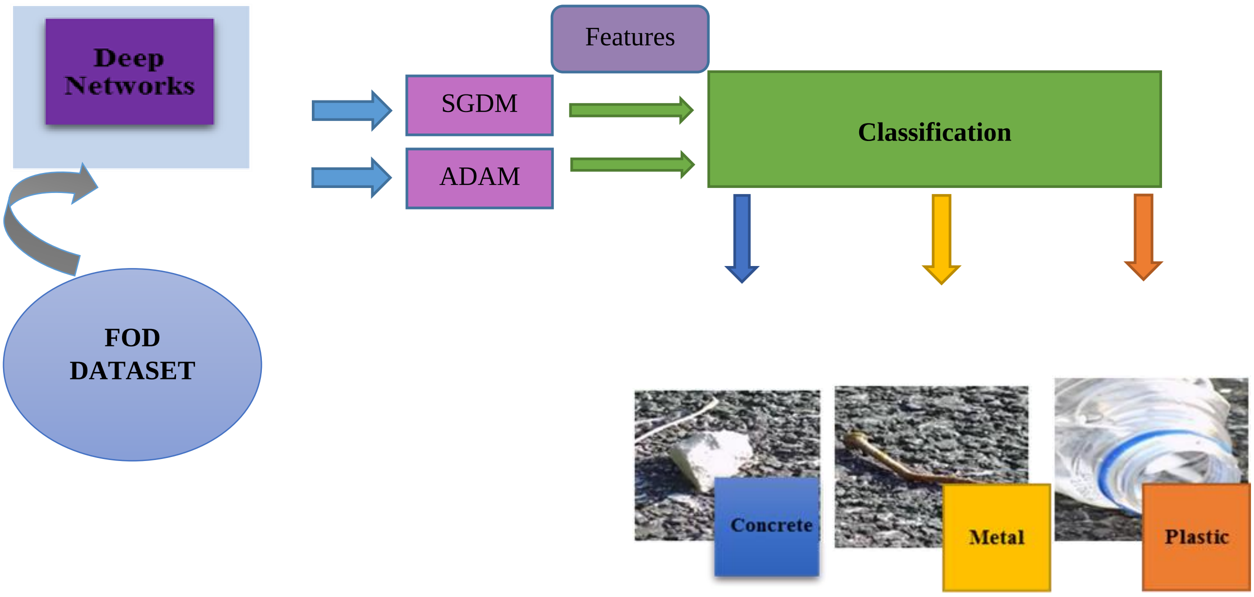

Figure 3. The block diagram of the used method

2.2.1. Pre-Trained Networks

The architectures used in the deep network are shown in Figure 4. AlexNet model proposed by Alex Krishevskyi et al. [19] is an important step in the field of deep learning [20], showing high performance in object recognition and image classification, which includes 1000 class labels. In this architecture, a total of seven layers are used, 5 of which are convolutional and two are fully connected, named FC6 and FC7. The first of the convolutional layers uses 11 * 11, the second 5 * 5, and the rest use 3 * 3 filters. ReLU activation function and maximum pooling are used in the architecture. ResNet-18 is a convolutional neural network that is 18 layers deep. The pre-trained network can classify images into 1000 object categories. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224 [21]. The feature vector is obtained from the fully connected layer called “fc1000” in the ResNet network. SqueezeNet is an architecture was developed by Iandola et al [22] and that is 18 layers deep. The network has an image input size of 227-by-227. This architecture aims to achieve fast and efficient accuracy rates with the architecture they create with few parameters [22].

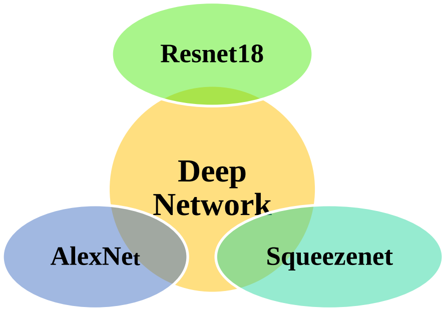

Figure 4. The used deep networks

2.2.2. Optimization Algorithms

Optimization is used to min the difference between the output generated by the network and the actual value. SGD (Stochastic gradient descent), Momentum, Adagrad, RMSProp, Adadelta and ADAM algorithms are frequently used in Machine Learning. In SGD, the gradient weights of the randomly received training data are updated instead of the gradients in the whole data. Draws a zigzag path to the global minimum point. In case using SGD alone, the initial cost value may oscillate to the smallest point at different derivative values calculated at each step. This will take time to reach the minimum value. Therefore, by using SGD together with momentum, oscillations will decrease and these oscillations will be large horizontally and small vertically. Thus, it will be possible to reach a quick result [23].

Adagrad makes frequent updates for infrequent parameters and smaller updates for frequent parameters. Here, each parameter has its own learning rate, and according to the characteristics of the algorithm, this learning rate gradually decreases and stops learning at some point in time. Adadelta uses momentum summary of square difference between existing weights and updated weights. RMSprop squares momentum gradients and prevents rapid decline. the learning rates of each of the parameters. That is, it combines the positive aspects of RmsProb and momentum. [24]

The ADAM algorithm is known as adaptive estimation. ADAM's algorithm, unlike Adadelta, stores learning rate and momentum changes in memory; that is, it combines the positive aspects of RMSprop and momentum. It also performs better than SGD in terms of speed [25].

3. Results and Discussion

The application was made in two stages and the results are given in tables. In the first application, 70% of the 3000 data was reserved for training and 30% for testing. The program was run as it is and the results were obtained. In the other application, 3000 data were used for training-testing at a rate of 70% to 30%, and 440 data was used for validation.

As seen in Tables 2 and Table 3 some parameter values are given. The mini-batch size means how many data the model will process simultaneously. While the model is being trained, the data is included in the training in parts. In deep learning, the first piece is trained, the performance of the model is tested, and the weights are updated according to the performance. Then the model is retrained with the new training set and the weights are updated again. Each of these training steps is called “epoch”. Before training the data, shuffling is done with Shuffle. Here, data shuffling is done in each epoch. Optimization methods are used to solve the optimum value in solving nonlinear problems.‘initial learn’ represents the learning rate. The ‘Validation Frequency’ value is the number of iterations between evaluations of validation metrics.

In this work, Verbose, max epoch, Mini Batch size, validation frequency, initial learn are 50,10,64,50,0.001, respectively. Shuffle is done every epoch.

For application 1, only 3000 data used both training and test. Also Table 2 presents experimental results for this application. As seen in Table 2, the best result is obtained with ‘ADAM’ optimizer for Resnet18. But, the other results are close to each other. Figure 5 shows accuracy comparisons both optimizers for application 1.

For application 2, 3000 data were used for training-testing at a rate of 70% to 30%, and 440 data was used for validation. As seen in Table 3, the best result is obtained with ‘ADAM’ optimizer.

Table 2. Experimental Results for Application 1

Models	Max Epoch	MiniBatch Size	Shuffle	Algorithm	Initial Learn	Validation Frequency	Accuracy Rate
AlexNET	10	64	Everyepoch	SGDM	0.0001	50	% 97.22
Resnet18	10	64	Everyepoch	SGDM	0.0001	50	% 98.22
Squeezenet	10	64	Everyepoch	SGDM	0.0001	50	% 97.56
AlexNET	10	64	Everyepoch	ADAM	0.0001	50	% 98.44
Resnet18	10	64	Everyepoch	ADAM	0.0001	50	% 99.56
Squeezenet	10	64	Everyepoch	ADAM	0.0001	50	% 98.89

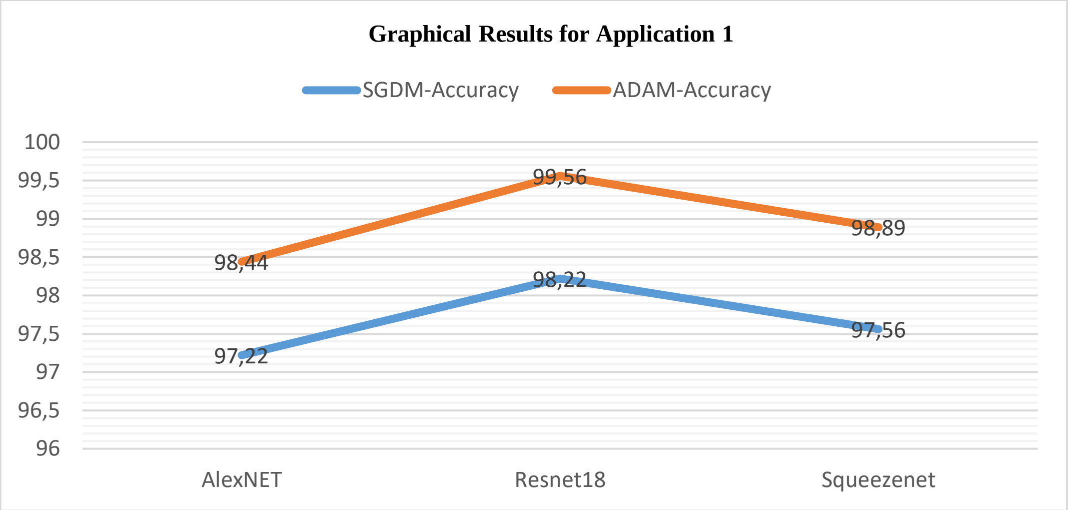

Figure 5. Graphical Comparison for Application 1

In second application, the performance is low due to the fact that the validation data source. Therefore, the obtained results were lower than the first application. But, the best result is obtained with ADAM optimizer.

Table 3. Experimental Results for Application 2

Models	Max Epoch	MiniBatch Size	Shuffle	Algorithm	Initial Learn	Validation Frequency	Accuracy Rate
AlexNET	10	64	Everyepoch	SGDM	0.0001	50	% 75.91
Resnet18	10	64	Everyepoch	SGDM	0.0001	50	% 71.36
Squeezenet	10	64	Everyepoch	SGDM	0.0001	50	% 75.91
AlexNET	10	64	Everyepoch	ADAM	0.0001	50	% 79.32
Resnet18	10	64	Everyepoch	ADAM	0.0001	50	% 71.36
Squeezenet	10	64	Everyepoch	ADAM	0.0001	50	% 73.86

Table 4 presents literature comparisons of different FOD datasets in terms of method and success parameters, such as accuracy, precision, recall, True Positive(TP), False Negative(FN), Average Precision (AP). As seen in Table 4, artificial intelligence-based methods have yielded important results.

Table 4. Literature Comparisons

<table>
<tr><th>Author</th><th>Dataset</th><th>Method</th><th colspan="6">Performance</th></tr>
<tr><td>[4]</td><td>create a FOD dataset consisting of images from the runways of Shanghai Hongqiao International Airport and the campus of research institute.</td><td>deep convolutional neural network (D-CNN) model.</td><td colspan="6">Accuracy=%78</td></tr>
<tr><td>[5]</td><td>established a picture dataset for airport runways</td><td>YOLOv3</td><td colspan="6">mAP=%92.2
Recall=0.931
FPS=32</td></tr>
<tr><td>[6]</td><td>FOD-A dataset created</td><td>SSD</td><td colspan="6">SSD loss=0.651</td></tr>
<tr><td>[8]</td><td>collected using a drone on the runways of an air force range.</td><td>YOLOv4-csp</td><td colspan="6">AP=%92.13
TP=2099
FN=210
Precision=0.83
Recall=0.91</td></tr>
<tr><td rowspan="2">[9]</td><td rowspan="2">sampled by a vehicular imaging system in Tianjin Binhai International Airport</td><td>CNN (RPN + FOD Detector)</td><td colspan="6">mAP=98.41%</td></tr>
<tr><td>CNN(STN+FODclassification+fine-tune)</td><td colspan="6">Recall=97.67%</td></tr>
<tr><td>[10]</td><td>collected on the airport runway by a HIKVISION camera</td><td>Faster R-CNN with DenseNet</td><td colspan="6">Accuracy=%95.6</td></tr>
<tr><td rowspan="4">[11]</td><td rowspan="4">Collected by Drone at an airport runway.</td><td rowspan="2">the online general model and the local compact model.</td><td colspan="2">Precision %</td><td colspan="2">Recall %</td><td colspan="2">mAP %</td></tr>
<tr><td>G</td><td>C</td><td>G</td><td>C</td><td>G</td><td>C</td></tr>
<tr><td>Multi</td><td>77</td><td>96.3</td><td>72.7</td><td>5.6</td><td>77.5</td><td>40.7</td></tr>
<tr><td>Single</td><td>85.7</td><td>88.8</td><td>90.5</td><td>37.2</td><td>94</td><td>55.4</td></tr>
<tr><td>[12]</td><td>collected by research group at Shahe Airport in Beijing, China.</td><td>random forest-based FOD detection framework that uses representative PVF</td><td colspan="6">Precision=%94.88
Recall=%95.43
mAP= %93.47</td></tr>
</table>

4. Conclusion and Suggestions

Apart from preventing damage to the airport, airport personnel and aircraft, FOD shortens the delay time of the aircraft, and with a more advanced application, it can make an effective detection even in adverse weather conditions day and night. In this paper, to detect foreign object debris detection with different networks and optimizers are compared with two stages. In the first stage of this study, the data reserved for training in the data set were separated as training and test at certain rates and results were obtained. In the second step, an external dataset is used for validation. One of the important advantages of deep learning is that it has gradient descent based optimization algorithms that minimize the error. SGD, Momentum, Adagarad, RMSprop, Adadelta and Adam algorithms are the most well-known optimization algorithms. Some weights are updated with the frequently used SGD.

Since momentum gradients are used to reduce the excess oscillation that occurs while searching for the optimum point in SGD, a controlled descent takes place and the oscillation decreases. In terms of the smoothness of the data used in the first application, the success of the first application was higher, and it was seen that Adam optimizer was also an efficient algorithm.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

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