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Research Article

Drone Detection with Deep Learning and Image Processing: CNN- Based Feature Extraction and Machine Learning Classification

Begum OZYER [a,*], ***Ali YASAR*** [b], ***Yavuz Selim TASPINAR*** [b]

[a] *Department of Mechatronics Engineering, Institute of Science and Technology, Selcuk University, Konya, Türkiye*
[b] *Department of Mechatronics Engineering, Faculty of Technology, Selcuk University, Konya, Türkiye*

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ABSTRACT

Drones are now widely used in the entertainment industry, cargo and transportation, security and logistics. However, drones can be confused with many objects and creatures that are similar to them or that they are in the same environment. Due to their widespread use and the fact that they have similar characteristics with other objects and living things, they pose some problems. These problems become problems that concern and sometimes disturb the society. For this reason, image processing methods have been used to classify drone and non-drone objects. Thanks to image processing, drones can be classified without any contact. Thanks to deep learning, data sets containing a large number of images can be classified quickly and accurately. In this study, it is aimed to classify drone and non-drone objects. In this study, a total of 1081 data sets consisting of 597 drone images, 484 non-drone objects and live images were used. 20% of the dataset was used for testing and 80% for training. Convolutional Neural Network (CNN) method was used to determine the features of these images. For each image, 4608 image features obtained from the CNN model were classified with Artificial Neural Network (ANN), K Nearest Neighbor (KNN) and Random Forest (RF) machine learning models. Precision, recall, F1 Score and accuracy metrics were used to evaluate the performance of the CNN model. Classification of the features obtained from the CNN model with ANN, KNN and RF models resulted in 89.9, 85 and 85 classification successes, respectively. The highest classification success was obtained from the ANN model in the classifications made with the features of the CNN model. With the results obtained, it is seen that the proposed classification and feature extraction models can be used to distinguish between drone and non-drone objects.

1. Introduction

In recent years, drone technology has advanced rapidly in different sectors and has been used in various fields such as agriculture, security, media and logistics. Drones play an important role in modern life due to their low cost and ease of use in many areas of daily life, from official state affairs such as border security and forest fires to civilian private sector affairs such as first aid and disaster management [1]. However, the widespread use of this technology has also brought some problems. And these problems have become issues of great public concern and public concern [2]. Examples of these problems include airspace security, privacy and detection of unauthorized flights. In this context, accurately classifying and distinguishing drone and non-drone objects has become an important requirement, especially for security systems and air traffic management. When classifying drones based on visual data, challenges such as environmental factors (light, weather, background) and the diversity of drone types should be taken into account. In order to solve this problem, deep learning bases have attracted attention in recent years with their high accuracy rates and fast processing capacity. Especially convolutional neural networks (CNN) provide highly effective results in the field of object detection and classification [3]. In this study, an effective deep learning model is developed for drone and non-drone classification. The model was trained on a dataset containing various drone images and achieved a high accuracy rate for drone detection. The study aims to

* Corresponding author. E-mail address: *begumcinkir@gmail.com*
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provide a solution that can be used in drone-based applications and contribute to the existing methods in the literature.

2. Literature Review

Singha et al. used an image-based method for drone classification using a convolutional neural network (CNN). They used the YOLOv4 CNN architecture to detect multiple objects and achieve an accuracy of 95%. They used a common dataset of 2395 drone and bird images, and similar studies using image-based drone classification and CNN show an average accuracy of 80-90% [4]. Nerya et al. propose a new idea for drone swarm characterization and detection using RF signals analysis and various machine learning methods. They applied different frequency transforms such as continuous, discrete and wavelet scattering transform to extract RF features from RF fingerprint and then used them as input for unsupervised classifier. They achieved a classification accuracy of about 95% under total Gaussian white noise with different SNR levels using M100 dataset [5]. Scheller et al. investigated ways to detect drone presence using machine learning. By recording the RF spectrum during a drone's flight and then feeding it to a machine learning system to learn models and model. However, he suggested that more work is needed for improvement[6]. Behera et al. used different methods for drone detection and classification using deep learning. In their study, they used a convolutional neural network (CNN) to train the model with a suitable dataset for 150 epochs. As a result, they concluded that CNN shows an excellent approach for real-time detection of drones compared to other deep learning networks such as YOLOv3 [7]. Dongkyu Lee et al. designed a system that can work on camera drones and conducted a study on drone detection. Their system extracts the location in the image and the vendor model of the drone according to the machine classification obtained from the camera images. They created a data set consisting of drone images and information for the learning process of this system they created using the OpenCV library. As a result of this study, they concluded that the system output showed approximately 89 percent accuracy [8]. Shafiq et al. used the deep learning model YOLOv3 to facilitate drone detection. To further improve the reliability of the system, they incorporated sensor fusion into their work, which provides a stable and accurate real-time system and minimizes the possibility of false detections. According to their study, they found that the YOLOv3 model outperformed other models in terms of both speed and robustness, and They concluded that it achieved a high level of confidence with a score of over 95% [9]. Yasmin Ghazlane et al. conducted a study to distinguish between birds and drones. In her study, she identified different features of birds and drones and used 20,000 data sets with these features for machine learning. He concluded that the EfficientNetB6 model achieved the best performance with 98.12% accuracy, 98.184% precision, 98.115% F1 score and 99.85% AUC. They concluded that EfficientNetB6 results surpassed existing methods in the literature and that using pre-trained models and fine-tuning them on our target dataset achieved better results compared to other existing approaches [10]. Holly Dale et al. conducted a study to detect drone and non-drone objects using convolutional neural networks (CNN). They trained a classifier on radar spectrograms obtained using L-band surveillance radar and compared its performance with a machine learning benchmark. At the end of their study, they concluded that the preliminary results showed that CNN achieved up to 98.89% correct classification performance [11]. Rahman et al. conducted a CNN-based drone classification study. The aim of their study was to create a large database of micro-Doppler spectrogram images of drones and birds in flight. They created two separate datasets with the same images, one consisting of RGB-based images and the other consisting of grayscale images. They used the RGB dataset for training based on the GoogLeNet architecture and the grayscale dataset for training with a set of architectures developed during this study. During training, 20% of the dataset was used as a validation set. As a result of their study, they concluded that the validation and test accuracy of the GoogLenet-based model was around 99% for all cases [12]. Kassab et al. A study on discovering the disadvantages of traditional machine learning techniques such as SVM and RF and examining their value in drone detection

They have realized it. With the results obtained in their study, they modified the study and tested it on SVM and RF with a modified NMS.

As a result, SVM and RF with modified NMS were able to achieve a 25% improvement the evaluation metric. For this reason, they proposed a modified deep learning paradigm to reduce the complexity associated with deep learning methods [13]. Pham et al. conducted a study on drone detection with image processing for restricted areas and special regions where cameras are used for surveillance. They detected drones using captured images based on the training of Haar-like features. They explained that the proposed solution can accurately detect drones in any region or in a limited area. They stated that the average accuracy of their proposed method in their experimental environments was 91.9% [14]. Coluccia et al. conducted a study to distinguish drones and birds. The aim of their study was to detect one or more drones in a video in which birds and other distracting objects may be present along with the motion in the background or foreground. As a result, they concluded that there is a range of difficulty depending on the size and shape of the drone in the videos on different tests, with images recorded by a moving camera and very distant drones being the most difficult

[15]. Patil et al. conducted a study to build a drone detection system using deep learning and deep learning algorithms. They achieved 85% accuracy by classifying military drone images into aircraft category using YOLOV4 model. They claim that their system can distinguish between a drone and other flying objects such as a different type of bird [16]. Zohra et al. conducted a study to propose a new drone detection approach using deep convolutional neural networks. They aimed to propose a method for computer-aided classification using CNN and VGG16 model. They captured drone and non-drone scenes from RGB-based images and used them as a data set. As a result, they concluded that drone can be used for object detection with 94.57% accuracy with deep learning algorithm using CNN [17]. Tzelepi et al. conducted a study on human crowd detection method for the safety of drone flights using convolutional neural networks. They used a CNN architecture that can detect crowded areas in images obtained from drones. As a result of their study, they presented an effective method to enable drones to fly safely in crowded areas [18].

As a result of the researches in the literature, it can be seen that the use of convolutional neural networks (CNN) works with high accuracy rate to distinguish drones, which are frequently used in different fields and in our daily lives, from non-drone objects.

Considering these studies, in this study, we have analyzed various drones and non-drone drones that are similar to drones or that we may encounter in environment, such as birdsrockets, etc. Using a dataset consisting of images of objects, CNN was used to classify drone and non-drone objects.

The contributions of the study to the literature as follows;

Images of drone and non-drone objects are classified with CNN architecture.

A total of 1081 data sets were used, including 597 drone images and 484 images of non- drone objects.

Accuracy metric was used for training and performance evaluation of the CNN model.

It is predicted that the proposed model can distinguish between drone and non-drone objects with deep learning and detect non-drone objects quickly and accurately.

The remaining stages of the article are planned as follows. The third section provides information about the methodology and data set used in the study. In the fourth section, detailed explanations about the studies conducted are given. In the fifth section, the results obtained as a result of the studies and suggestions for those who read the article and want to work in this field are shared.

3. MATERIAL AND METHOD

This section of the paper describes the CNN architecture, dataset, performance metrics, validation and training methods used.

3.1. Data Set Used for Distinguishing and Classifying Drone and Non-Drone Objects

In this paper, images of drone and non-drone objects used in Drone and Non-Drone Classification are used as a dataset [14].

The dataset used consists of images of drone and non-drone objects. These images are divided into three folders named test, train and val and each folder consists of two folders containing images of drone and non-drone objects. In total, there are three folders of drone images and three folders containing images of non-drone objects. Figure 1 and Figure 2 show examples of images of drone and non-drone objects in the test folder.

Figure 1. Drone image in the test folder.

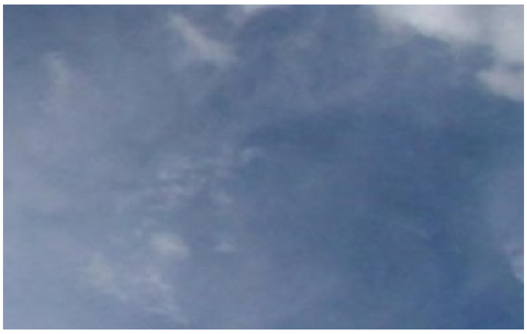

Figure 2. Non-Drone object image in the non drone folder with in the test folder.

Figure 3 and Figure 4 show examples of images of drone and non-drone objects in the Drone and Non-Drone folders in the train folder.

Figure 3. Drone image in the Train folder.

Figure 4. Non-Drone object image in the non drone folder with in the train folder

Figure 5 and Figure 6 show examples of images of drone and non-drone objects in the Drone and Non-Drone folders in the val folder in the folder containing the dataset.

Figure 5. Drone image in the validation folder

Figure 6. Non-Drone object image in the non drone folder with in the validation folder

3.2. Methods Used

In this study, deep learning was used and the classification of drone and non-drone objects was performed quickly and with high accuracy with the Convolutional Neural Network (CNN) architecture.

3.2.1. CNN

Convolutional Neural Network (CNN) is an artificial neural network architecture that is frequently used in image processing, natural language processing, video analysis and other data processing tasks [19, 20]. In this study, firstly, the Convolution layer, which is one of the basic building blocks of the CNN architecture, is used to extract feature maps from the image. Then another layer of the CNN architecture, MaxPooling layers, was added to minimize the feature maps and highlight important features [21]. And so, feature maps from the image extraction process is completed. Dense layer was used to classify the images and the classification process was performed.

3.2.2. Performance Metrics

In this study, Accuracy and Loss are used as the key performance metrics. These two metrics are monitored and compared during training. Accuracy shows the correct classification rate of the model [22, 23]. Loss is used to measure the model's errors and to detect overfitting/underfitting. In this study, since there are samples belonging to more than one class (Drone and Non-Drone), the Categorical Crossentropy Loss function of the Loss metric was preferred. It is a metric that expresses the ratio of correctly classified samples to the total number of samples. The difference between training and validation accuracy/loss helps us understand the overall state of the model [24]. The accuracy metric obtained in the test set is an indicator of how the model will perform in the real world.

4. EXPERIMENTAL RESULTS

In this study, a Sequential CNN model was used to classify drone and non-drone objects with an image processing algorithm using a dataset consisting of images of drone and non-drone objects in order to distinguish between drone and non-drone objects. This study was conducted on an Intel(R) Core(TM) i7-9750H CPU @ 2.60GHz 2.59 GHz, 16 GB RAM, NVIDIA GeForce GTX 1660 Ti GPU and Windows 11 (64-bit) operating system. Python programming language was used in this study.

In the CNN model used, a layer structure was created with increasing filter numbers similar to VGGNet. Convolution and pooling layers were used. Flattening was applied to flatten the multidimensional feature map obtained after convolution and pooling layers. The optimizer parameter was used to optimize the model and the metrics parameter was used to determine the metrics to be used to evaluate the model. In this study, the accuracy metric was used. The train_test_split function was used to distinguish between training and validation sets. And according to the values determined for this function, 20% of the dataset was used for the test set and the remaining 80% was used for the training set.

In the first stage of the study, the dimensions of the images were set to 64x64. Then, normalization process was applied to these images. After the normalization process, the data set was created with the train_test_split function with 80% from the training set and 20% from the test set. After splitting the dataset into training and test data and creating the labels, we used 3 convolution layers and maximum pooling, which we used in the CNN model.

Layer is included in the model. Classification was performed with the Dense layer. And overlearning was prevented with Dropout. After this stage, a probability value was returned for each class in the output layer with the Softmax layer. Adam optimizer was used to compile the model.

The CNN model was then trained for 20 epochs. The accuracy of the model was calculated on the test data with

Then, KNN (K-Nearest Neighbors), RF (Random Forest) and ANN (Artificial Neural Networks) algorithms were used for further analysis with machine learning models using the features of the images obtained from the CNN model. And by comparing the accuracy of KNN, RF and ANN models, the best performing algorithm was determined. Table 1 shows a table showing the accuracy of KNN, Random Forest and ANN models.

Table 1. Table of accuracy values for KNN, Random Forest, and ANN models.

Model	*Accuracy*
KNN	85.00
Random Forest	85.00
ANN	89.99

the model evaluate function. And the training and validation accuracy and loss graphs were created during the calculated training process. The accuracy and loss graphs obtained during training and validation are as shown in Figure 7;

In the continuation of the study, 5 images were randomly selected from the data set. Among the 5 images to be selected by the model, drone images were printed on the drone images and Non- Drone images were printed on the non-drone images. In Figure 8 and Figure 9, the output images of 5 randomly selected images from the dataset are exemplified for classification as Drone and Non-Drone.

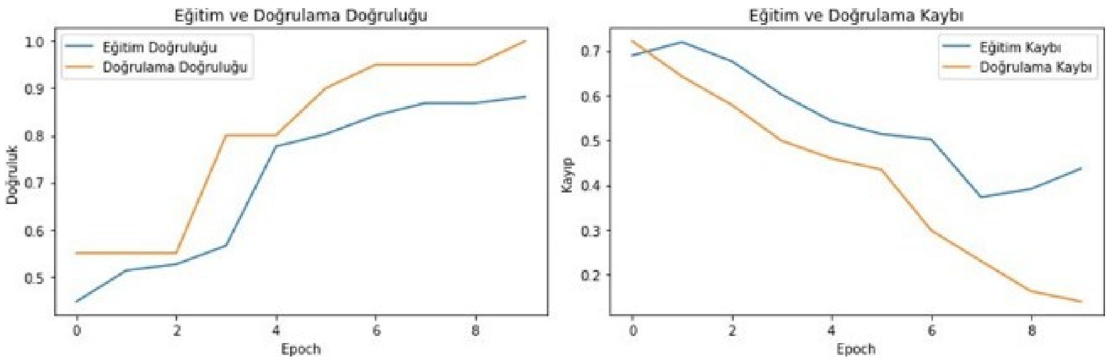

Figure 7. Accuracy and loss plots obtained during training and validation.

Figure 8. Visuals of the classification of drone and non-drone objects.

Figure 9. Visuals on the classification of drone and non-drone objects.

The processes and stages throughout the whole study are shown in the flow diagram in Figure 10.

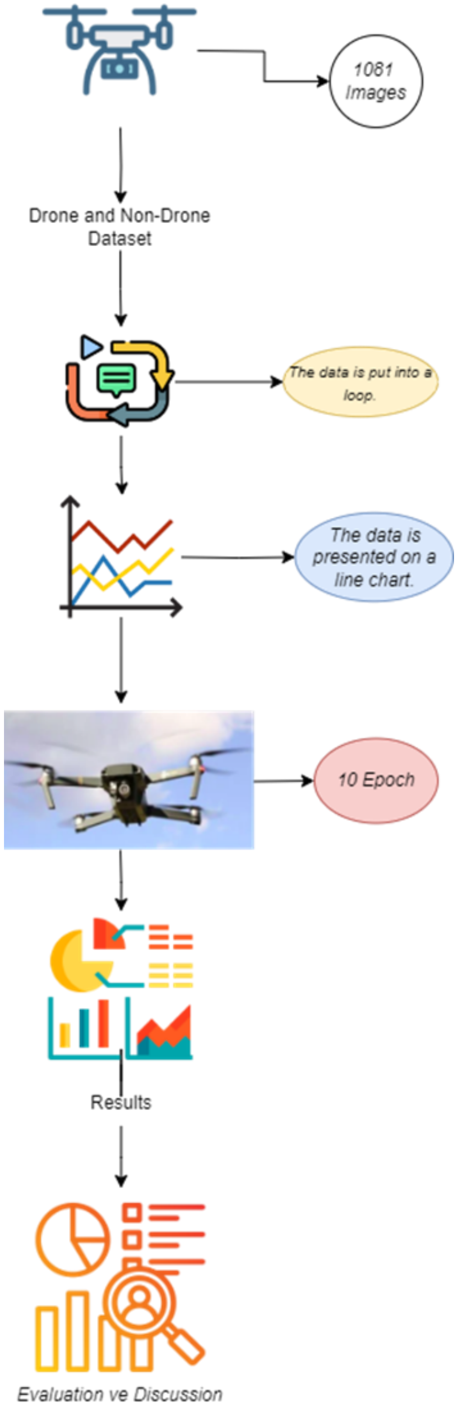

Figure 10. Flow Diagram Showing the Stages of the Study for Feature Extraction and Classification of Drone and Non-Drone Objects Using CNN Model

5. CONCLUSION AND DISCUSSION

In this study, a dataset containing a total of 1081 images in two classes using images of drone and non-drone objects was used. A two-class CNN model was used to extract image features. The extracted features were classified with ANN, KNN and RF machine learning models. According to the results of the study, the CNN model achieved successful results in direct classification and showed a high accuracy rate. ANN model achieved 89.9% classification success, KNN model achieved 85% classification success and RF model achieved 585% classification success. In line with these results, it was determined that the ANN model was the best performing model compared to ANN, KNN and RF models. In general, the results of the study show that the combination of CNN-based feature extraction and machine learning models provides a powerful solution for classification processes.

The results obtained that the proposed method can be used for similar image classification problems such as drone detection and classification. However, the number of images in the dataset used in the study is limited. It is thought that by using a dataset consisting of more images of drones and non-drone objects, the training of the model can be more successful and therefore the classification success can be increased. Thus, it is thought that the objects we see in the air can be remotely controlled to determine whether they are drones or.

Declaration of Ethical Standards

The authors confirm that they have followed all ethical guidelines including authorship, citation, data reporting, and the publication of original research. The article does not contain any studies with human or animal subjects.

Credit Authorship Contribution Statement

All authors contributed to the design and study of the article. BO was responsible for the literature research and preparation of the draft. YST carried out the analysis of data and results. AY arranged the materials, methods, and data.

Declaration of Competing Interest

The authors declare that they have no competing interests.

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Data Availability

The dataset used in this study was obtained from publicly available sources and is available upon request.

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