CHAPTER 1

INTRODUCTION

Systems developed to analyze the images obtained from unmanned aerial vehicles (UAVs) and to find solutions to existing problems arouse great interest. In this context, For example, solutions are proposed for the processing of images obtained by UAV in many fields such as the determination of the stability problem on the rails, land object recognition, classification of diseases in agriculture, building recognition, which can be counted as examples in different branches of science. It is also known that UAVs, which can fly autonomously or semi-autonomously without an operator, are an important factor in object recognition and detection. The field where object detection and recognition performed by machine learning is most used and needed is the defense industry. Thanks to machine learning, compelling operations such as classification and statistics are easily performed.

Today with the help of Deep learning algorithms, which is one of the machine learning methods, object detection and recognition are performed faster and more efficiently. In the recent literature, it has been observed that deep learning methods are mainly used in studies on object detection and recognition.

By using Convolutional Neural Networks (ESA), the gains obtained by adjusting the pedestrian, cyclist, car, tree and streetlamp images obtained from the UAV to the desired dimensions are examined. the implications of automatic license plate recognition study using Masked Regional CNN (MBESA), which is one of the deep learning techniques, are presented. Autoencoders (AE) architecture called Diabolo network is used for fabric defect detection. In order to meet the need in the military field, the weapon detection study was carried out by choosing one of the deep learning algorithms, Regional Based CNNs (RCNN).

In this study, it is suggested to keep the threat elements to be detected at the time of discovery and observation more comprehensively. High accuracy rate is of great importance in deep learning applications.

In this study, a database consisting of 11 different threatening element images has been prepared. Deep learning architectures Faster-RCNN and YoloV4, which are frequently encountered in the literature, are used for object detection and recognition. For the

Inception V2 Coco and YoloV4 model, which is one of the types of Faster-RCNN architecture, the classification of the types of objects is carried out by using the Darknet architecture. Machine learning training was done separately for two different models. In the scaling stages, the inferences obtained by checking the graphically presented loss values are evaluated.

Object detection and recognition were performed using images obtained by ˙IHA. As a result of the experiments, the accuracy rates obtained with the suggested deep learning methods were compared and the outputs related to the performance analyzes were presented. of the study. The proposed methods are explained in detail in methods. In this chapter, the accuracy rates of the deep learning architectures used in the study are compared. Inferences from lost value graphs and test results are presented in this section. In the last section, the obtained results are interpreted.

CHAPTER 2

RELATED WORK

In this study, it is suggested to keep the threat elements to be detected at the time of discovery and observation more comprehensively. High accuracy rate is of great importance in deep learning applications. In this study, a database consisting of 11 different threatening element images has been prepared. Deep learning architectures Faster-RCNN and YoloV4, which are frequently encountered in the literature, are used for object detection and recognition.

2.1 RESEARCH REGARDING UAV’s

Artificial Genius experts are particularly interested in computer ingenuity and foresight in drones. Drones with Genius will tackle a wide range of real-world issues. Object recognition, item tracking, and object counting are all useful computer vision tasks for keeping track of a variety of situations [2]. Altitude, digital camera angle, occlusion, and action blur, on the other hand, make it a more difficult assignment.

A specific literature evaluation focusing on object recognition and monitoring the use of UAVs in beautiful applications was carried out in this study [3]. This paper reviews recent research findings and underlines the gaps that must be filled.

The strategies used to recognize objects in UAV photographs are defined and identified. The following is a list of UAV datasets relevant to object detection requirements. [3] Summarizes the present condition of work search in many functions. Finally, in precision agriculture, a robust object identification framework with an impermeable onboard processing device is given to address observed look up gaps.

In this study, the sequence of events, approval, and public accessibility of another neural organization-based PC that attempts to distinguish the maker and, shockingly, the model group of a pacemaker or defibrillator from a chest radiograph are completely criticized. A clinical group prefers to choose the model of a pacemaker or defibrillator as quickly and accurately as possible (cardiovascular mood gadget). A modern approach is evaluating a device's radiological appearance using an information float graph.

Artificial Genius experts are really interested in computer inventive and prescient in drones. Providing Genius to drones will solve many real-world problems. Object identification, item tracking, and object counting are excellent computer imaginative and prescient responsibilities for monitoring distinctive situations. Altitude, digital camera angle, occlusion, and action blur, on the other hand, make it a more challenging assignment.

This paper presents a unique literature review focusing on object detection and monitoring the use of UAVs in unusual applications. This article highlights the findings of recent research publications and indicates research gaps. Object detection algorithms used in UAV photographs are labelled and expanded upon. There is a list of UAV datasets that are specific to object detecting duties. Existing lookup functions for certain uses are summarized. Finally, in precision agriculture, an impenetrable onboard processing device based on a strong object detection framework is proposed to close known lookup gaps.

CHAPTER 3

METHODOLOGY

In the first place, CNNs, one of the profound learning strategies, are utilized to prepare for AI on the items in the proposed procedure. It is trusted that by utilizing the Faster RCNN and YoloV4 profound learning designs, the precision accomplished all through the preparation stage can measure up. Informational indexes containing photographs gathered from differed climate, land conditions, and timeframes of the still up in the air for use in the preparation and testing phases of the suggested philosophies. The model for distinguishing and perceiving perilous things has been prepared utilizing 2595 photographs. The innovation for distinguishing and perceiving things is being assessed utilizing military activity photographs and information caught by UAVs.

3.1 WORKING MODEL OF PROPOSED SYSTEM

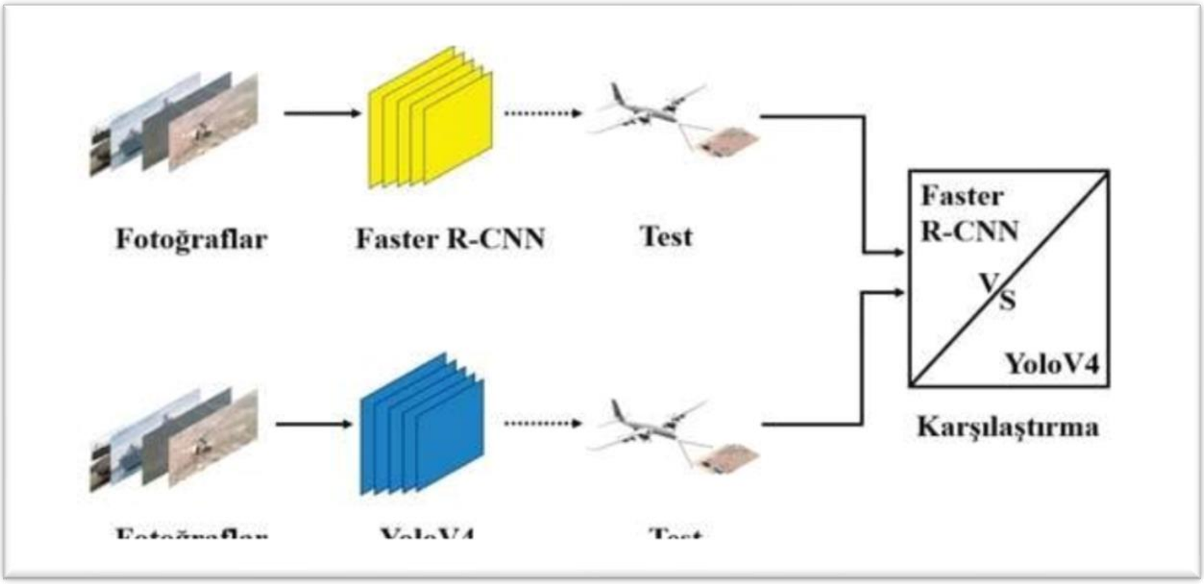

Figure 3.1: System Model of Proposed System

Object detection and recognition were performed using images obtained by ˙IHA. As a result of the experiments, the accuracy rates obtained with the suggested deep learning methods were compared and the outputs related to the performance analyzes were presented. of the study. The proposed methods are explained in detail in the section. III. In this chapter, the accuracy rates of the deep learning architectures used in the study are compared. Inferences from lost value graphs and test results are presented in this section. In the last section, the obtained results are interpreted.

3.2 METHODS

3.2.1 CNN

CNNs (CNN) are used in a range of applications. It is, besides a doubt, the most extensively used deep studying architecture. The good sized reputation and efficacy of convnets has contributed to the latest amplify in pastime in deep learning. Alex Net sparked activity in CNN in 2012, and it has grown hastily seeing that then. Researcher's superior from eight-layer Alex Net to 152 layer Reset in simply three years. CNN is now the go-to mannequin for each image-related issue. They outperform the rivals in phrases of accuracy. It has additionally been used efficaciously in recommender systems, herbal language processing, and different areas.

The integral gain of CNN over its predecessors is that it routinely discovers substantial points barring the want for human intervention. For example, given a giant quantity of pics of cats and dogs, it learns distinguishing facets for every type on its own. CNN is additionally pretty environment friendly in phrases of computing. It performs parameter sharing and makes use of exclusive convolution and pooling algorithms. This approves CNN fashions to run on any device, making them attractive to a vast vary of users. Overall, this sounds like pure magic. We're working with a very superb and environment friendly mannequin that makes use of automated function extraction to attain superhuman accuracy (yes CNN fashions now do picture classification higher than humans). Hopefully, this article will aid us in uncovering the secrets and techniques of this awesome technology.

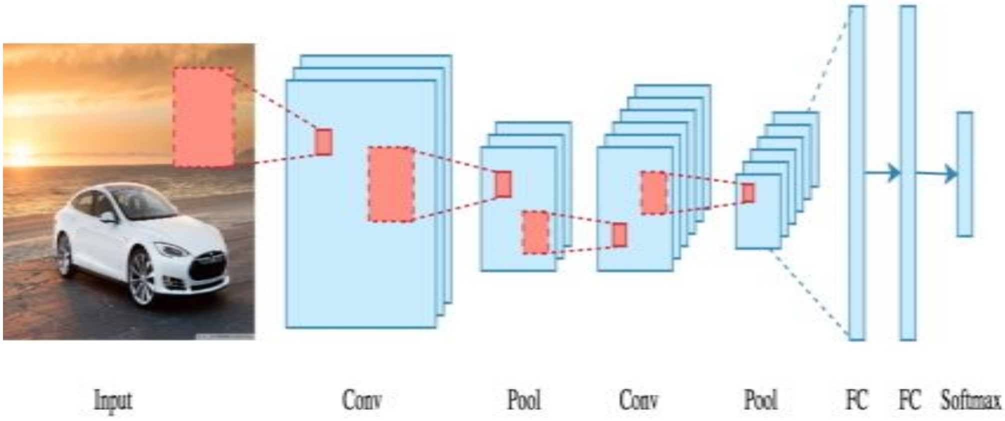

Figure 3.2.1.1: Architecture

The VGG16 CNN model was proposed by K. Simonyan and A. Zisserman of the University of Oxford in their publication, "Very Deep Convolutional Networks for Large-Scale Image Recognition." The model achieves 92.7 percent top-5 test accuracy in ImageNet, a dataset with over 14 million images classified into 1,000 classes. It was one of the most well-known models from the ILSVRC-2014. It outperforms Alex Net by replacing large kernel-sized filters with a sequence of 33 kernel-sized filters (11 and 5 in the first and second convolutional layers, respectively). For weeks, VGG16 was trained on NVIDIA Titan Black GPUs

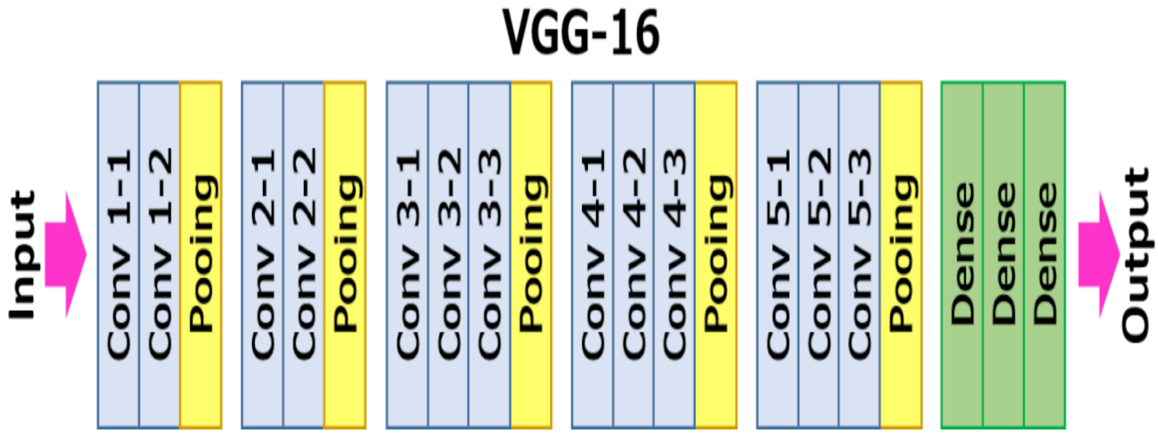

Figure 3.2.1.2: VGG-16

3.2.2 Faster-RCNN

The first model used for machine learning is trained to recognize 11 different threatening elements. The training is on the graphical processing unit (GPU) to make the process go faster. A virtual environment is created. CUDA, CuDNN and Anaconda programs have been installed in the virtual environment. All operations are coded in the object-oriented, unitary and interactive high-level Python programming language. Tensorflow, pillow, lxml, matplotlib, pandas and OpenCV libraries are used in the training. In the data set used for machine learning, images obtained from videos of military exercises, which are available on the internet and held as standard all over the world, were used in terms of the variety of objects

The found images were labeled in PascalVOC format using the LabelImg program and their files in xml format were created. Next, the xml files are converted to csv format. 80% of the photos were transferred to the train file and 20% to the test file. The photos were converted to record format to be given as input to the module, and the data set needed for the model was completed by creating the labelmap. pbtxt file in which the element names are classified. Necessary adjustments for machine learning have been made and training has been started. Image processing was performed using images taken from the UAV. In this study, firstly, the Faster-RCNN model in Figure 3, one of the deep learning architectures in machine learning algorithms, is used. The picture taken as input is converted to matrix format so that it can be understood by the machine. 3 3 filters are applied in order to obtain data over the picture. The operation performed is defined in (1).

$$s(t)= (x * w)(t)= \sum_{a=-\infty} x(a)w(t-a) \qquad (1)$$

Here, the filter w, input x, time to be applied on the image t, the result is expressed as s. A 32 32 gray image is given to the algorithm as a 32 32 matrix. If the input image is two-dimensional, the mathematical operation specified in (2) is applied

$$s(i,j)= (x * w)(i,j)= \sum_{m}\sum_{n} x(i,j)w(i-m,j-n) \qquad (2)$$

Here i and j represent the positions of the new matrix to be obtained. Each position of the filter is represented by the terms n and m. The image converted to matrix format is passed through the CNN. As output, feature map is obtained. A region recommendation network is created, and the region is determined [14]. Pooling is done to equalize the dimensions of the picture without losing its properties [15]. The output size of the pooling layer is shown in (3.2.1.1).

3.2.3 YOLOv4

YOLOv4 is a one-stage object detection model that improves on YOLOv3 by including a plethora of tricks and modules from the literature. The tricks and modules used are described in greater detail in the components section below. YOLOv4: Fastest and Most Accurate Object Detection

3.2.4 Faster-RCNN

R-CNN uses selective search to extract a number of regions from the given image, and then tests to see if any of these boxes contain an item. We first extract these regions, and then CNN is utilized to extract specific features for each region. Finally, these characteristics are employed to detect things. Unfortunately, because of the several steps involved in the process, R-CNN becomes slow.

3.3 COMPARITIVE ANALYSIS

	Faster R-CNN	YoloV4
Askeri Gemi	97.2	94.2
Tank	97.8	92.2
Silah	92.4	82.6
Helikopter	95.6	94.7
Bıçak	86.0	80.8
El Bombası	87.0	81.6
İHA	94.5	93.8
Zırhlı Araç	98.7	93.7
Havan Topu	95.8	85.5
Kompozit Başlık	90.4	83.4
Füze Rampası	91.3	90.1

Figure 3.3: Comparative analysis

shows the results of the accuracy rates obtained by using two different deep learning algorithms on 11 different threatening elements as a result of performance tests. Test operations were carried out on the image in which there are 3 threatening elements in a photo frame. The accuracy rates in the table show the average test results. It is observed that the accuracy rates of large objects such as armored vehicles and military ships reach high values in both models. Smaller objects such as grenades and knives have lower accuracy rates in the YoloV4 model than in the FasterRCNN model. When the object detection and recognition times on the images were evaluated, it was observed that the Faster-RCNN model found around 0.2 seconds, and the YoloV4 model found it in 0.032 seconds. It has been determined that the accuracy rates in both training models reach the recommended percentage of success. In Figure 9, the accuracy rates obtained as a result of the evaluation of a threatening sample image taken from the UAV with FasterRCNN and YoloV4 models are given.

CHAPTER 4

ADVANTAGES AND DISADVANTAGES

4.1 ADVANTAGES

1. Monitoring and Surveillance

Controlled remotely, drones are small enough to fly over the areas where humans can't possibly reach. UAVs are a safe way to monitor locations that are otherwise vulnerable to possible hazards.

Monitoring dangerous sites is one of the greatest advantages of drones in military operations, as it may save many soldiers from casualties. Drones can also ensure worker's safety, especially in hazardous situations like radiation monitoring, inspecting high-voltage lines.

2. Aerial Photography

Aerial photography is one of the fun and unique ways to capture images. Drones, when used with HD cameras, better the image and video quality. Also, it gives a new dimension to imagery. Drones are widely used in the film industry because they add more creativity to videos making them more entertaining.

Drone photography is a great tool to accumulate accurate information about particular sites such as mines, rivers, forests, and radioactive sites. The data gathered by **drone cameras** can further be used for research and to identify hazardous elements in disaster-prone areas.

3. Drone Delivery System

As said above, Drone technology has transformed ways of conducting business. As mankind drives more towards modernization, Drone technology will have numerous applications in daily lives. Amazon has already announced to use of Drone technology to ship consumer products. The renowned eCommerce giant will use the Prime Air Delivery system for users in future.

The system guarantees to deliver the package (up to 3 kg) to the delivery destination within half an hour. The **Amazon drones** will be limited to fly up to 25 km range. An express delivery system is something the American users were keenly waiting for.

4. Affordability is one of the main advantages of drones

Drones are not limited to defence systems; UAVs are a common tool for businesses. This technology comes at an affordable price which is under $500. You don’t have to have a pilot’s license to fly a drone; you need to have specialized skills. If you want drones with advanced features, they are also available at an affordable price.

The drone is more economical to buy, and you don’t have to worry about running out of fuel as rechargeable batteries power it. No maintenance and no cost of refilling sounds like more advantages of drones over helicopters and planes

4.2 DISADVANTAGES

Drone technology will bring many benefits to businesses and society. However, from user privacy and safety to legal issues and unfair use, many factors contribute to the disadvantages of drones.

PRIVACY - While drone's benefits are endless, drone technology has several downsides to it. UAVs can quickly fall prey to manipulation and trespass a group or individual's privacy. Though many desire to utilize drones for retaining safety, it could violate numerous individual liberties in the name of public security.

1. Legal Issues

Even though UAVs or drones are used for various purposes, there are still concerns about their misuse and abuse. These concerns are why many state law authorities still have rules for the regulation of drone use. Laws for Property protection from aerial trespassing are still in the making.

Thus, UAV technology functions in a judicial **grey zone**. There are flaring arguments between governmental regulations and any state or city laws to manage airspace property rights. Since a drone pilot can fly anywhere, many people may not like the idea of being watched by the unknown.

2.Drone technology can be hacked

Vulnerability to hackers is one of the **major disadvantages of drones**, whether it's military operations or business use. Drones run on programmed instructions and algorithms. The navigation and flight operations are only possible because of the internet system.

Hackers can easily attack a drone's central control system and become the drone's original controller. They may acquire full control of UAVs without the knowledge of the original controller. Hackers can also retrieve private information, corrupt or damage the files, or even leak data to unauthorized third parties.

3.Technical Glitches

Lithium-ion batteries, sensors, weight, and atmospheric pressure are too much to bear for a drone. In addition, an inexperienced pilot may be more dangerous as they have to avoid possible obstacles in mid-air.

Software or hardware malfunctions come as the biggest **cons of drones** that carry ammunition as it may cause numerous casualties. Drones are still in the process of improvement to limit accidents that can compromise the safety of human lives.

CHAPTER 5

CONCLUSIONS

- It is critical in this study for the military and defense sectors. There are 11 different threatening elements of UAVs that carry out missions.

- We describe a deep learning-based detection and recognition approach. type. Deep learning techniques' CNNs Using the YoloV4 and Faster-RCNN models of the process's accuracy rates were compared.

- Threatening 2595 pictures obtained by IHA are utilized for identification and recognition of elements in military operations. In the Faster-RCNN architecture, object detection and recognition are roughly 93 percent accurate.

- In the YoloV4 design, the validity ratio is roughly 88 percent. Accuracy was achieved. When all parameters are considered, the Faster-RCNN training model looks to perform better.

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