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Real Time Web-based System to Detect Military Aircraft Using RESNET-50 Algorithm

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Abstract. *As target detection in remote sensing imaging depends on aircraft type recognition, it is essential in both civil and military applications. The job is made more difficult by the existence of fine-grained features, which can result in significant intra-class changes due to variations in size, posture, and angle, as well as modest inter class changes due to very similar subcategories. This kind of system can be helpful for military security as recognition of the type of aircraft is very critical to the decisions being made. There are several existing ways which uses methods like Radar System and Radio footprints, Speed etc., to detect type of Aircraft. Although these methods are massively costly and still cannot detect the type of Aircraft accurately. In this paper aircraft is detected using ResNet-50, Advance State of Art Object Detection Algorithm implementing in Anaconda tool with train accuracy is 98% & validate accuracy is 75%. A crucial area of artificial intelligence is object detection, which enables computer systems to perceive their surroundings by identifying things in visual pictures or movies. In case of any dangerous Aircraft, the system will have capability to raise alarm and Alert using Audio Sirens. The software requirement for this project is python, 3.6/anaconda, or newer and necessary python modules.*

Keywords*- Aircraft Detection, Python, Tensorflow, Keras, RESNET-50*

1. INTRODUCTION

There are many tasks associated with applied computer vision, including object detection. At times, it can be difficult to perform in some applications, such as satellite image processing. It has been a focus for researchers in a variety of areas. This paper focuses on aircraft detection. Airplanes are major field of development for India. Aircrafts come in a variety of sizes, shapes, weight, functions and wing configurations. Uses of airplane in board spectrum include recreation, transportation of goods and people, military, and research. Uses makes people need, so detection of aircraft become important need for civilians and military to get information about aircraft and the type of aircraft, either civilian's aircraft or fighter jet for war. Analysis and optimization algorithm based on real time web-based image data to detect military is a hot issue in recent years. With the images they have captured, the commander may quickly and accurately identify the number of enemy aircraft available on the battlefield as well as the landing and takeoff scenario. The key benefit of aircraft detection is that it provides a solid information security guarantee for operational decisions that will be made in the future and is crucial to winning the war. As a result, military research on aircraft detection in photos is quite popular.

2. LITERATURE REVIEW

C. Chen [1], with the help of SSD (Single Shot multi-box Detector) based aircraft detection system for airport video surveillance is presented in this study. When it comes to speed and accuracy, the original SSD falls short of what is needed for real-time applications like airport surveillance. The findings demonstrate that the ResNet50-SSD method's detection speed is increased from 200 milliseconds to 99 milliseconds, and its average detection accuracy is increased from 80% to 83%.

L. Zhang and Y. Zhang [2], this research proposes a unique airport detection and aircraft recognition approach for high-resolution broad area remote-sensing images based on the two-layer visual saliency analysis model and support vector machines (SVMs). According to the experimental findings, the suggested method not only detects targets in high-resolution, wide-area remote sensing photographs consistently and effectively, but it also generates more reliable results in complicated settings. This method's accuracy rate is 85.04%, and its false-report rate is displayed as being 24.66%.

Chen X, J. *et al.* [3], they presented a unique aircraft target detection method in this study that is based on tiny training samples. Region proposal and target identification are the two key phases of the coarse-to-fine system. The findings indicate that the suggested technique may detect aircraft targets in RSIs more rapidly and precisely and perform better. The proposed method's stated average precision is 0.934.

Han, J. *et al.* [4], the automatic detection of objects in remote sensing photos has always been a popular topic, as this study demonstrates. There are a lot of negative samples in the generated region proposal when using the traditional deep convolution network based on region proposal for detection, which would decrease the model's detection efficiency and precision. When there are 400 negative samples, the data show that the detection accuracy is at its highest.

Feng Xu, j. *et al* [10], an end-to-end aircraft detection algorithm for large scene spaceborne synthetic aperture radar (SAR) imagery is put forth in this study. The results of the experiments demonstrate that the suggested strategy produces good results at a reasonable cost of computation. A scenario measuring 26 km by 27 kmcan be analysed in 24.7 seconds, and aircrafts are spotted with a false alarm rate of 7.7%. Some of the limitations from these papers cannot be focused on small target detection and have uneven illumination and occlusions, false ratio is more.

3. MATERIALS & METHODOLOGY

Deep residual networks are convolutional neural networks (CNNs) with more than 50 layers, like the well-known ResNet-50 model. An Artificial Neural Network (ANN) called a Residual Neural Network (Res Net) builds a network by piling residual blocks on top of one another. This paper will go over residual neural networks including the most well-known Res Nets, such as ResNet-34 and ResNet-50, in detail. Data collection is important to collect data from better site to get better accuracy and check the performance of the system. The input data (Allowed Extension = set [“png”, “jpg’, “jpeg’, “gif’]) and details about aircraft is collected from google sites and fetched to the system to train the data for analyze or predict the output results and accuracy. In this paper, the aircraft pictures are taken from this following url (https://www.pexels.com/search/aircraft/). The output result includes model of aircraft & details about aircraft.

Training the data

To train the system there are 10658 input data samples (aircraft images) are collected from google and fetched to the model to be trained which is called pre-trained data, using this pre-trained data the system tests and validate the input data and predict the aircraft. [11] The dataset needs to be divided into two sections: a training section and a validation section. The model is trained upon this training subset as each period progresses. Then, it evaluates both its effectiveness as well as precision on the validation subset.

Deep Residual Learning

While tackling a computer vision difficulty with deep convolutional neural networks, machine learning experts stack more layers. These additional layers help in the more efficient resolution of complex problems since the different layers may be educated for a range of activities to generate extremely accurate answers. The properties of the model may be improved by the number of stacked layers; however, the degradation issue may be seen in a deeper network. In other words, once the accuracy levels of the Neural Network reach a particular threshold, they may get saturated and start to gradually decline. As a result, both the training data and the testing data show a deterioration in the model's performance. Overfitting did not cause this deterioration. Alternatively, it can be the result of the network's setup, an optimisation function, as well as pertinently issue with disappearing or ballooning gradients.

ResNet-50 Architecture

Because of worries about how long it will take to train the layers, the building block was altered into a bottleneck design in this case. This made use of a three-layer stack. In order to create the Resnet 50 design, each of the 2-layer blocks in Resnet34 was changed to a 3-layer bottleneck block. Compared to the 34-layer ResNet model, this has substantially greater accuracy. The performance of the 50- layer ResNet is 3.8 billion FLOPS.

ResNet50 With Keras

KERAS is a well-liked deep learning API since it makes it easy to create models with it. Everyone may utilise Keras' built-in pre-trained models for their experiments, including Resnet50. Thus, it's quite easy to create a residual network in Keras for computer vision applications like picture categorization. The following expressions are used for refining the images using kernel convolution method.

$$a\ g(x, y) = \omega * f(x, y) = \sum_{dx=-a} b \sum_{dy=-b} \mathrm{m}(dx, dy)\, f(x - dx, y - dy) \qquad (1)$$

Where $g(x, y)$ is the filtered image, $f(x, y)$ is the original image, ω is the filter kernel. Every element of the filter kernel is considered by $-a \leq dx \leq a$ and $-b \leq dy \leq b$.The method in which we take a tiny number matrix (known as the kernel or kernel filter), apply it to our picture, and then modify it according to the values of the filter. It is only a convolutional procedure between the kernel filter and the input image. The input picture is represented by f and our kernel by g in the formula above, and subsequent feature map values are computed in accordance with those values. The indices of the result matrix's rows and columns are indicated with the letters x and y, respectively. Depending on the element value, kernel cause wide range of effects. Some of them can be seen in following images.

FIGURE 1. BE200 Aircraft Identity

FIGURE 2. BE200 Aircraft Edge Detection

FIGURE 3. BE200 Aircraft Sharpen

FIGURE 4. BE200 Aircraft Box blur

FIGURE 5. BE200 Aircraft Gaussian Blur 3x3

FIGURE 6. BE200 Aircraft Gaussian Blur 5x5

Algorithm using RESNET-50

The Algorithm for aircraft detection using ResNet-50 technique can show as per the diagram. The algorithm describes training and testing method of aircraft. Initially aircraft data about 12000 images are fetched to the system and trained, then the input image is fetched, and the features of the aircraft are tested from the trained data then it classifies the type and model of aircraft and give the details of aircraft detected.

Data collection: The data is collected in Allowed Extension = set [“png”, “jpg’, “jpeg’, “gif’] on the web.

Data Annotation: The data is set to required size, format and cast the image into a float32, normalize all values in the range [0,1] [0,1], resize the image from its original shape.

Data Augmentation: Here the performance of the system is increased by training models on several slightly modified copies of existing data.

ResNet-50: Here the input data is operated in convolution method using keras module and detection the type of aircraft.

Aircraft classification: After the detection of aircraft, it specifies either it is civilians or military aircraft.

In this system if the aircraft is not detected an alerting alarm is activated otherwise it gives the model and details of the aircraft.

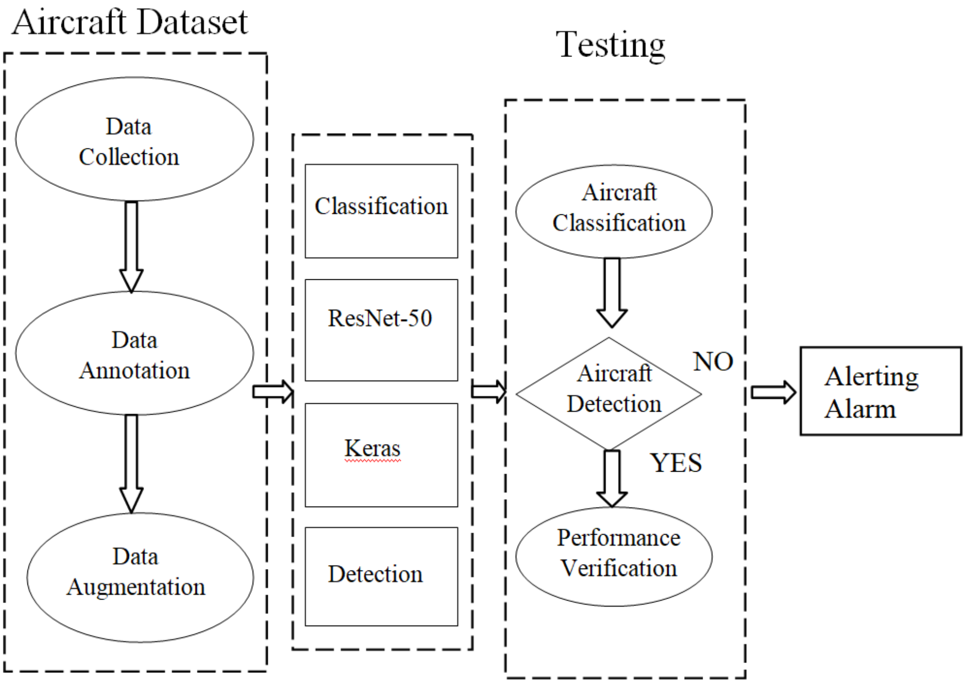

FIGURE 7. Algorithm of proposed system

Features of Aircraft

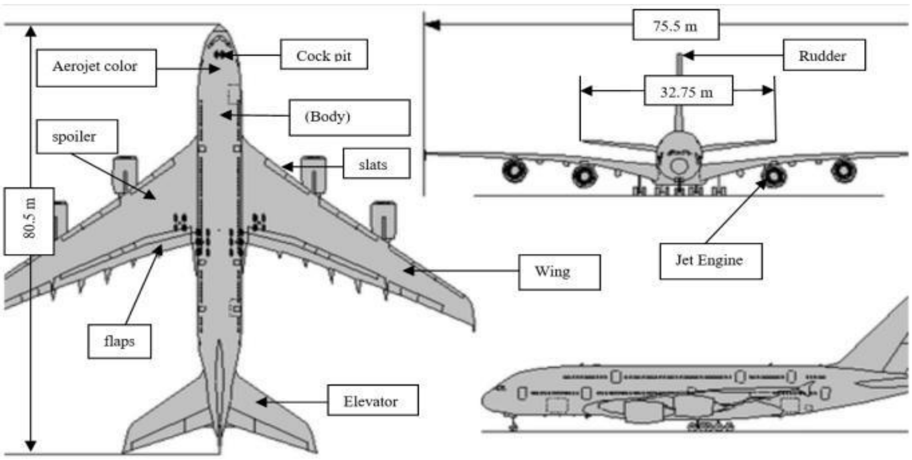

FIGURE 8. Aircraft Testing Features

Figure 8 shows the features of aircraft based which our system (ResNet-50) detects the type of aircraft. The features which describe common in all aircraft are the jet engine, wings, cock pit, color, elevator, rudder, flaps, size and height. This research flips and rotates the input data (aircraft images) from all angles and checks the features of the aircraft, so the rotation in all direction gives fast and better accuracy.

4. RESULTS & DISCUSSION

In this paper aircraft images are collected from web sites, and given to the proposed system, which is based on ResNet-50 architecture and the images are trained based on convolution operation and predict the output response. There are 50 layers which train and classify the type of aircraft. The aircraft tested is BE200 model and the output accuracy is 75% and the speed of the execution is 171ms/step are shown. This system can check and predict anytype of aircraft from any angle or any quality of image (identity, edge detection, sharpen, box blur, gaussian blur 3x3and gaussian blur 5x5) which are shown above also it can classify either it is military or civilians' aircraft. Hence, Aircraft detection using ResNet-50 can predict very accurate and faster response than other existing methods.

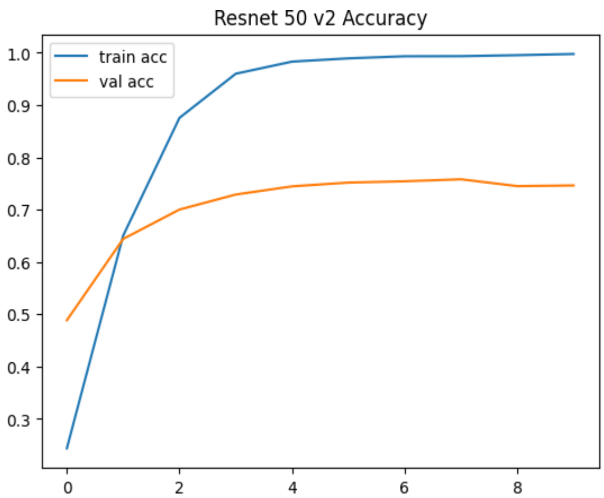

FIGURE 9. Aircraft detected accuracy

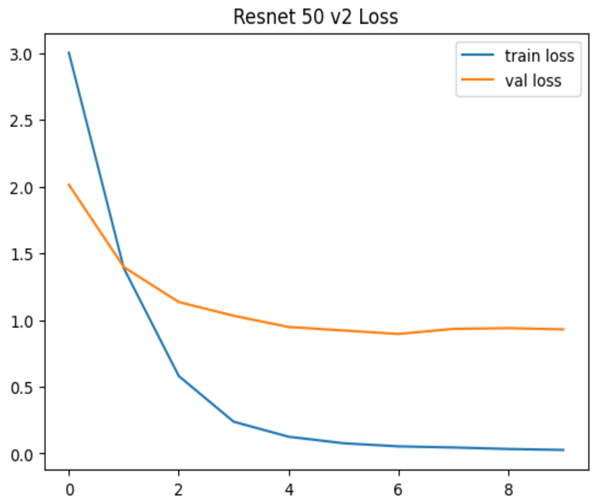

FIGURE 10. Aircraft detection loss

Figure 9 describes the training and validate accuracy of the system. Blue line indicates the training data and red line indicates the validate data. While figure 10, describes the training and validate loss of the system. Similarly, blue and red lines indicate the training and validate data. As the system gets more data than this loss percentage can also be minimized. Output Screenshots

Output Screenshots

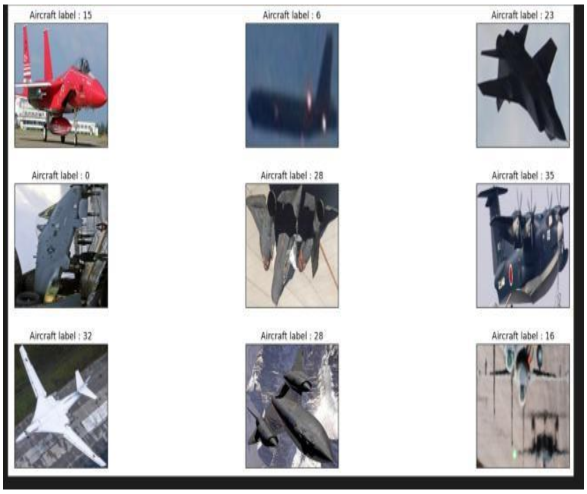

FIGURE 11. Detected aircraft by the system.

Runtime Screenshot

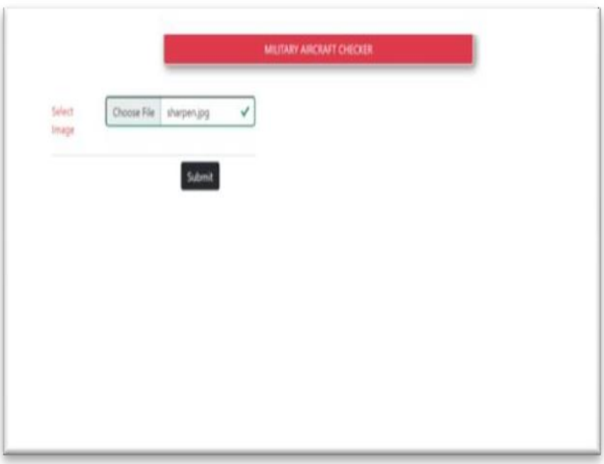

FIGURE 12. Input Aircraft checker on web

FIGURE 13. Output aircraft result prediction on web

TABLE 1. Comparison table between competing methods and proposed methods

S. No.	Methods	Accuracy	Speed/step
1.	**Single Shotmulti-box Detector**	80%-83%	200ms-99ms
2.	**Two-layervisual saliency analysis model**	85.04%	200ms
3.	**ResNet-50**	75%	171ms

Hence, the accuracy and speed of the aircraft detection shows the proposed method has better response and faster execution.

5. CONCLUSION

The use of deep learning and specifically ResNet-50 in the detection of aircraft details has shown promising results, train accuracy is 98% & validate accuracy is 75% and the train loss is 0.1 & validate loss is 0.93. By training the network on a large dataset of aircraft images, the model can accurately identify the type of aircraft, its features, and other important details. The advantage of using deep learning for aircraft detection is that it can handle a wide variety of aircraft types and conditions, even in noisy or cluttered backgrounds. Here the detected aircraft is BE200 which is shown in output aircraft result prediction page and observed the results. Additionally, it can automatically learn and adapt to new aircraft models or changes in lighting or weather conditions. Overall, the use of deep learningand ResNet-50 in aircraft detection has the potential to significantly improve in accuracy and to provide faster response than the existing methods and improve aviation safety and security by providing real-time identification of aircraft in different situations. It also has many other applications such as aircraft maintenance, air traffic control, and aviation research. The Dataset was collected through the internet and different models like Resnet50 and Resnet101 are trained and compared to choose the best model. Finally, the Data Pre-processing and Data Augmentation and Training the Models multiple times by tuning hyperparameters, the final Test Accuracies achieved is around 75% for Resnet50v2.

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