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Real-Time Internet-based Technology Applying Machine Learning Algorithm to Identify Airplane

Muhammad Ibrar[1], Saif Ur Rehman[1], Tahir Zaidi[2], Rida Javaid[2], Manzoor Ellahi[1], Wajih H Hashmi[2]

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Abstract: Aircraft target detection is critical in remote sensing for both civil and military purposes. The main challenge arises from subtle characteristics that cause significant variation within the same segment, such as differences in size, posture and angle. while only minor differences exist. Among similar subcategories, it is important to accurately identify aircraft types such as radar systems, although commonly used, and often lacking accuracy. Anaconda, a state-of-the-art object recognition algorithm for aircraft target recognition in the environment where impossible of other technologies like radar, achieves 98% training accuracy and 75% artificial intelligence accuracy by allowing computer systems to recognize objects from visual images or videos. Using algorithms Allows for analysis. The system is further equipped with an audio alert feature that activates when a potentially dangerous aircraft is detected. The project uses Python 3.6 (or later) and the necessary Python modules is, which makes it efficient and effective.

Keywords: - Algorithm, Accuracy, Airplane, recognition.

1- Introduction

Applied computer vision involves a wide range of problems, one of which is object recognition. In some cases, like satellite image processing, it might be challenging to execute. Scholars from several fields have directed their attention on it. The topic of this study is airplane recognition. India's primary area of development is Airplane. The sizes, forms, weights, purposes, and wing arrangements of Airplane vary widely.

Recreation, military use, passenger and cargo transportation, and research are among the uses of airplanes in the spectrum. People require things for which they have uses, thus it is crucial for both the military and civilian population to detect airplanes in order to get information about them and their types—fighter jets for combat or civilian Airplane. The recognition of military activity using real-time web-based visual data for analysis and improvement has been a popular topic in recent years.

The commander can swiftly and precisely determine the quantity of enemy Airplane present on the battlefield and the conditions surrounding the landing and takeoff with the help of the photographs they have taken. The main advantage of Airplane recognition is that it is essential to winning the war and offers a strong information security assurance for future operational choices. Therefore, there is a lot of interest in military research on Airplane recognition in photographs.

*[1]*Department of Electrical Engineering, The Superior University, Lahore, Pakistan.*
[2]*Department of Avionics Engineering, The Superior University, Lahore, Pakistan.*
*[1]md.ibrar@superior.edu.pk

2- Literature Review

This study introduces a system for aircraft recognition in airport video surveillance, using a Single Shot multi-box Detector (SSD) as developed by C. Chen [1] as a standard SSD. The accuracy and speed of the model show that by implementing the ResNet50-SSD architecture, the recognition speed increases from two hundred million to 83%. This increase to 99 milliseconds Airport monitoring highlights the benefits of combining ResNet50 to strengthen system capabilities.

In their research, L. Zhang and Y. Zhang [2] introduce an advanced technique for airport recognition and classification of aircraft in high-resolution, wide-area remote sensing images. This method uses support vector machines (SVMs) integrated with a two-layer visual saliency analysis model. Their experimental results show that this approach provides better accuracy in challenging environments, successfully identifying targets within high-resolution, wide-area remote sensing images. This method achieves a remarkable accuracy rate of 85.04% with a false report rate of 24.66%. Overall, this technique has great potential to enhance remote sensing applications in the aviation sector.

Chen X, J. et al. [3] presented a unique approach to airplane target recognition using minimal training samples in this study. The two most crucial phases in the coarse-to-fine system are target identification and area recommendation. The findings suggest that the suggested approach could work better and find aircraft targets in RSIs more rapidly and accurately. The recommended method's average accuracy is 0.934, as shown.

Han, J. et al. [4] state that this study demonstrates the long-standing problem of automatically recognizing objects in remote sensing photos. Traditional deep convolutional networks that rely on region proposals for recognition often include a significant number of negative samples within the generated proposals. This can reduce both the efficiency and accuracy of the model. Based on statistical analysis, the optimal recognition accuracy is attained when 400 negative samples are present.

The study by Feng Xu, J. et al. [10] proposes an airplane identification method using spaceborne synthetic aperture radar (SAR) images across large scenes. The experimental outcomes show that the method is effective with a reasonable computational cost. A scene measurement 26 km by 27 km can be analyzed in 24.7 seconds, with a 7.7% false alarm rate for aircraft recognition. However, limitations of this approach include a higher false ratio, challenges with inconsistent lighting and occlusions, and difficulties in focusing on small target recognition.

3- Methodology

Convolutional neural networks (CNNs) that contain more than fifty layers, such as the popular ResNet-50 model, are classified as deep networks. These networks fall under the broad umbrella of artificial neural networks (ANNs), now commonly referred to simply as neural networks. The ResNet architecture distinguishes itself by using a novel methodology that integrates different building blocks to form a powerful network. This research aims to illustrate the complexities of centralized networks, focusing specifically on the widely used ResNet models. It will explore ResNet-34 and ResNet-50, emphasizing their features and applications. Through this investigation, we aim to deepen the understanding of these important models in the field of deep learning. It is important to get information from various reliable sources to increase accuracy and measure your body's performance. Information about the aircraft and input data (permission extension = location ["png", "jpg", "jpeg", "gif"]) were taken from the Google website and entered into the system to be trained for analysis or prediction. output. the truth of what happened. Airplane images used in this article are taken from https://www.pexels.com/search/Airplane/. Results include information such as aircraft models.

3.1 Preparing the data

Pre-trained data is the set of 10658 input data samples (pictures of Airplane) that are retrieved from Google and used to train the model. The system uses this pre-trained data to evaluate the input data and make predictions about the Airplane. [11] Two components of the dataset must be created: a training section and a validation section. As each period goes on, the model is trained using this training subset. Next, it assesses its accuracy and efficacy on the validation subset.

3.2 Deep Residual Learning

Machine learning experts add additional techniques when using deep convolutional neural networks to solve computer problems. These additional processes help solve more complex problems, as single processes can be trained on many tasks to produce very precise answers. Stacking the number of layers can improve the properties of the structure but can suffer from decay problems with deep connections. In other words, when the real level of neural networks exceeds a threshold, they saturate and start to slowly decrease. As a result, the model's performance degrades as shown by the testing and training sets of data. This degradation was not brought on by overfitting. On the other hand, it may be the outcome of how the network is configured, an optimization function, or a relevant problem with gradients that vanish or inflate.

3.3 ResNet-50 Architecture

The architecture was redesigned into a bottle shape to tackle issues related to the extensive training duration for each layer, implementing a three-layer strategy. To enhance the ResNet 50 framework, all layer 2 bottleneck blocks in ResNet 34 were substituted with layer 3 blocks. This change led to improved accuracy when compared to the 34-layer ResNet model. The upgraded design consists of fifty layers, which significantly enhances its overall performance. Remarkably, the ResNet demonstrated a remarkable 3.8 billion FLOPS, showcasing its computational strength. These modifications ultimately lead to more efficient training processes and improved accuracy in the model.

3.4 ResNet50 with Keras

Keras is ease of use facilitates the construction and training of models in a clear and efficient manner. Anyone can use Keras' pre-trained models like Resnet50 for their experiments. Therefore, it is very easy to create domains for computer studies like image classification in Keras. Use kernel convolution to tune the image using the following equation.

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

$$dy{=}{-}\mathrm{ab}$$

In this case, ω represents the filter kernel. The primary picture is $f(x, s)$, and the filtered image is $g(x, s)$. The filter kernel is applied to each member, with $-a \le dx \le a$ and $-b \le dy \le b$ defining the range of the kernel. This process creates the filtered image from the original input. This technique involves applying a small number matrix, referred to as the kernel or kernel filter, on our image, altering it based on the filter's values. The only process that occurs between the input picture and the kernel filter is convolution. In the formula above, the input image is represented by f and our kernel by g. The values of the feature map are then calculated based on those values. The letters x and y, respectively, stand for the row and column indices of the result matrix. The consequences of the kernel vary widely depending on the element value. A few of them are seen in the pictures below.

Fig. 1. Identification of Airplane

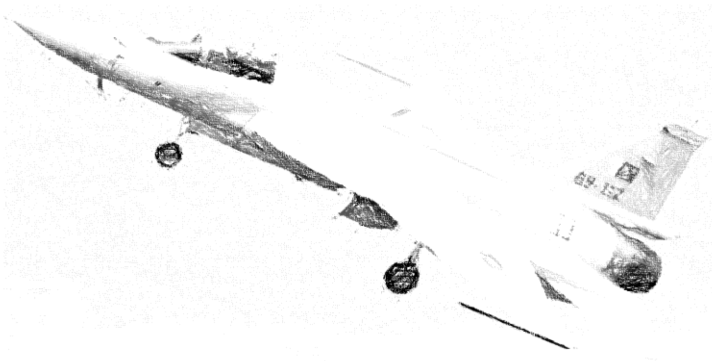

Fig. 2. Edge Recognition of Airplane Edge Recognition

Fig. 3. Sharpen of Airplane

Fig. 4. Box of Blur Airplane

Fig. 5. Gaussian Blur 3 by 3 of Airplane

Fig. 6. Gaussian Blur 5 by 5 of Airplane

3.5 Algorithm using RESNET-50

Based on the diagram, the algorithm for recognizing airplanes with the ResNet-50 approach may be displayed. The airplane training and testing procedure is described by the algorithm. For training, the system first downloads over 12,000 images of airplanes. Following the download of the input image, the characteristics of the aircraft are compared to the learnt data, and the system classifies the kind and model of the aircraft in addition to providing information on any that are found.

3.5.1 Data collection: Recognized Extension = set ["jpg','png","jpeg',"gif'] is where the material is gathered from the internet.

3.5.2 Data Annotation: Data values are rounded to the range [0,1] to maintain uniformity. The image is resized to meet the required dimensions and formatted for subsequent operations. Finally, the image is converted to float 32 type to increase computational efficiency.

3.5.3 Data augmentation: Training models using different slightly modified versions of existing data improves system performance. This strategy facilitates better generalization and flexibility. As a result, the model adjusts to different situations. is more adept at doing." gets done, thereby increasing its overall performance.

3.5.4 ResNet-50: In this case, the input data is processed using the convolution approach to identify the kind of aircraft by utilizing the Keras module.

3.5.5 Classification of aircraft: It indicates whether the aircraft is military or civilian after it has been detected.

If the airplane is not detected, an alert alarm is triggered. If detected, the system provides the airplane's model. It also displays detailed information about the airplane. The system continuously monitors for airplane presence. Alarms and information updates happen in real-time.

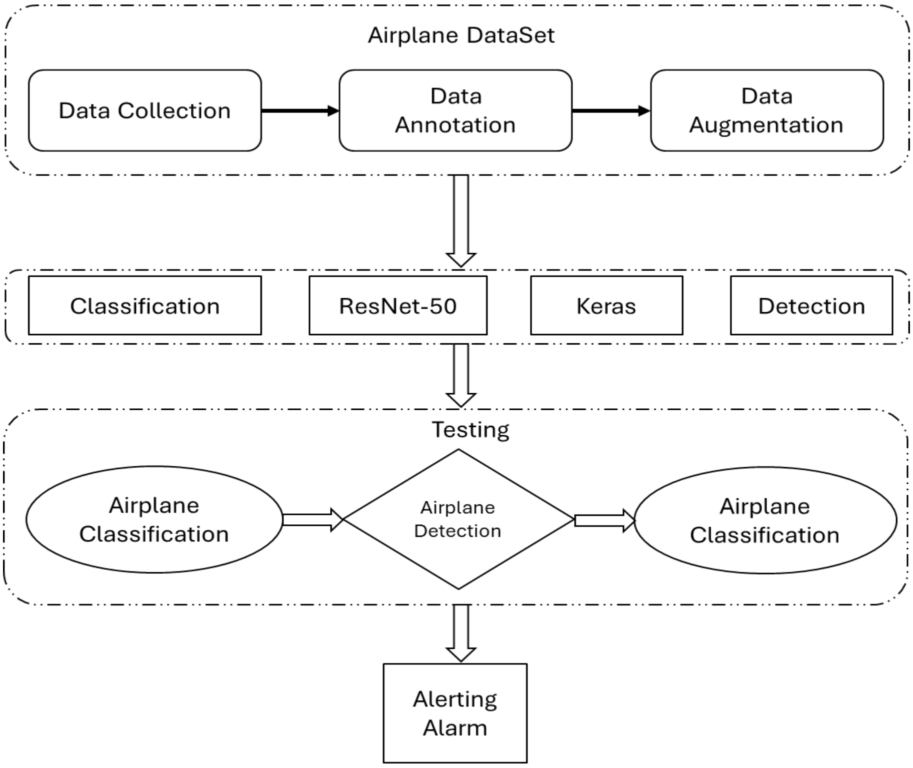

Fig. 7. The proposed system's algorithm

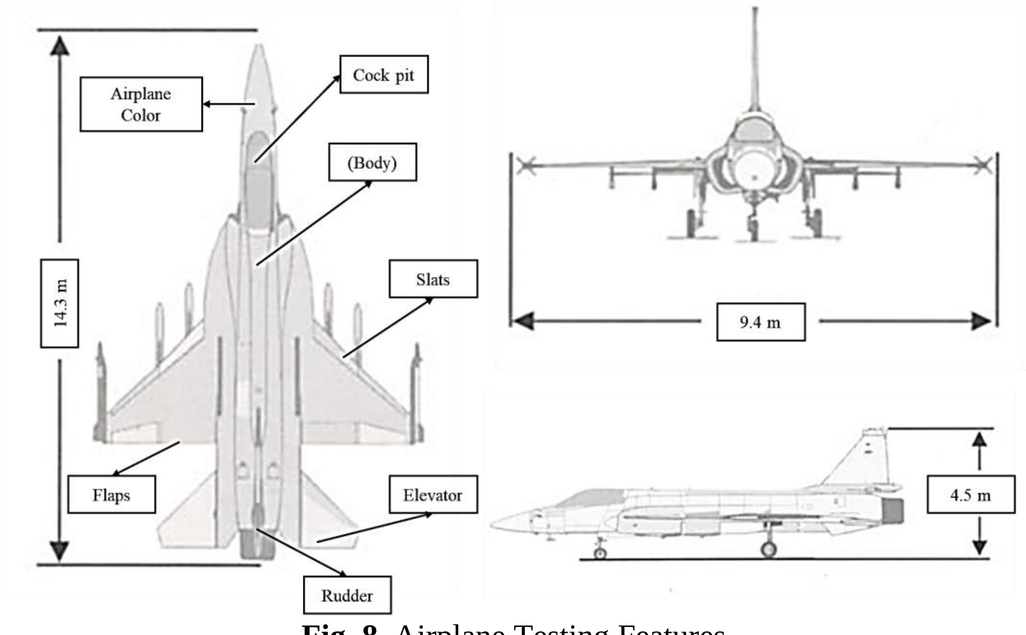

Fig. 8. Airplane Testing Features

The attributes of an airplane, based on which our system (ResNet-50) determines the kind of aircraft, are displayed in Fig. 8. It shared the characteristics by all airplanes. This study rotates and flips the input data (photos of airplanes) in all directions while examining the aircraft's attributes. This rotation provides quicker and more accurate results.

4- Results and Discussion

The suggested system in this article, which is built on the ResNet-50 architecture, is fed airplane photos that are gathered from websites. The images are then trained using convolution operations to anticipate the output response. The kind of aircraft is trained and classified using fifty layers. The JF-17 Thunder model aircraft was used for the test, and the results indicate that the output accuracy was 75% and the execution speed was 171ms/step.

This system can identify and predicting aircraft images from any angle, with advanced features such as sharpening, box blur, and applying Gaussian blur with 3x3 and 5x5 kernels. It enhances the clarity of images while offering different levels of blur for analysis. The system also verifies the type of aircraft and provides accurate forecasts. Its versatile functions make it suitable for a variety of image processing and aviation-related applications. This robust system is designed to handle complex tasks efficiently. It can also determine whether the aircraft is military or civilian. Therefore, compared to other current approaches, ResNet-50's airplane identification can anticipate highly accurate and faster reaction times.

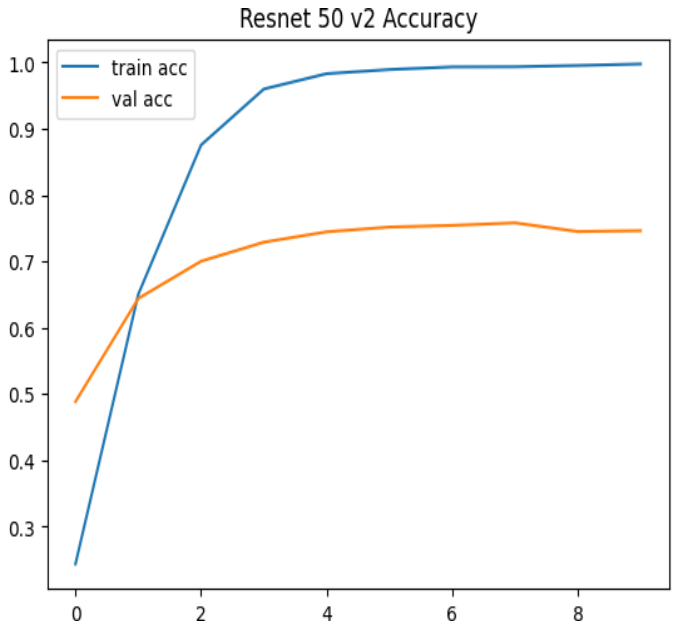

Fig. 9. Airplane detected accuracy

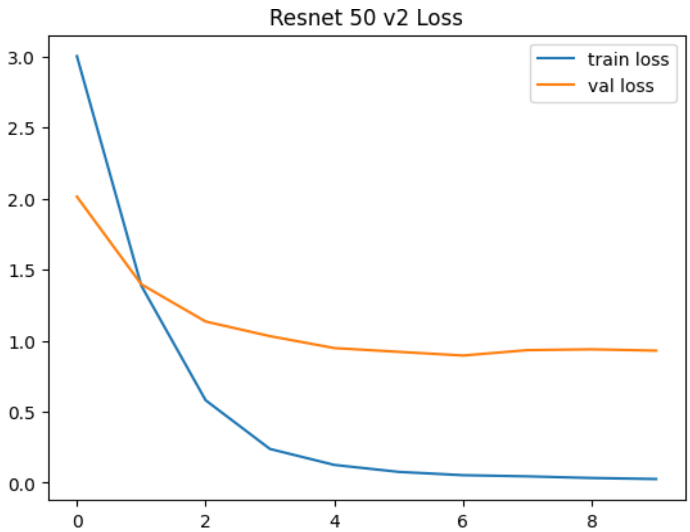

Fig. 10. Airplane recognition loss

Fig. 9 shows the accuracy trends for both the training and validation phases of the system. The blue line shows the accuracy of the training data, while the red line shows the accuracy of the validation data. This graphical the representation facilitates a straightforward comparison between the two. In a similar manner, Fig. 10 shows the training and validation losses associated with the system. While the validation loss serves as a measure of the model's generalizability, the data provide valuable insight into the model's training behavior and its effective generalization ability. Below are output screenshots.

Table 1. Table of comparisons between the suggested and opposing approaches

S. No.	Procedure	Accuracy (%)	Speed/step (ms)
I.	**Single Short Multi-Box Detector**	80-83	200-99
II.	**2 Layer Visual Saliency Analysis Model**	85.04	200
III.	**Resnet-50**	75	171

As a result, the suggested technique exhibits improved responsiveness and quicker execution based on the accuracy and speed of the airplane recognition.

5- Conclusion

Promising results have been observed when using deep learning, and more especially ResNet-50, to recognize airplane features. The training model achieved 98% accuracy, while validation accuracy reached 75%. The training loss was 0.1, and the validation loss was recorded at 0.93. The model, trained on a large dataset of aircraft images, effectively recognizes different types of aircraft and their characteristics. A key advantage of deep learning is its ability to detect aircraft in a variety of settings. capability, including noise or clutter. For this example, the model successfully identified the JF-17, which is reflected in the aircraft's prediction results. Additionally, the model can recognize new types of aircraft, variations in lighting, and changes in weather conditions. Overall, using deep learning and ResNet-50 for real-time aircraft identification in diverse scenarios can significantly increase accuracy, provide faster response time than conventional methods, and aviation I can improve safety and security. The technology has numerous applications, including air traffic management, aircraft maintenance, and aviation research. To determine the most efficient model, different architectures, such as ResNet50 and ResNet101, are trained and evaluated using datasets obtained from the Internet. Following data pre-processing, augmentation, and multiple rounds of model training with adjusted hyperparameters, the final test accuracy achieved by Resnet50v2 was approximately 75%.

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