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Real-Time Aircraft Detection Using DenseNet on the FGVC Aircraft Dataset

ZOHAIB KHALID[1], (Student)
[1]Department of Artificial Intelligence, University of Management and Technology, Lahore, Pakistan (e-mail: F2022376005@umt.edu.pk)

ABSTRACT Aircraft detection plays crucial role in modern aviation transportation and security systems. With the increasing availability of fine grained datasets such as the FGVC Aircraft dataset, which contain 10,000 images of 100 aircraft varients , real-time aircraft classification has become more achievable. This paper presents as efficient solution using DensNet a Convulutional Neural Network architecture to perform realtime aircraft detection. By leveraging transfer learning and data augmentation techniques, the perposed model achieves high classification accuracy while addressing the challanges of deploying models for real-time applications.The experimental results demonstrate that the DensNet based models outperforms existing methods in accuracy and precision and recall making it suitable for practical real-time detection system. The paper discuss the methodology experimental findings portential future work in this domain.

INDEX TERMS Aircraft detection, convolutional neural networks (CNN), DenseNet, FGVC Aircraft dataset, real-time detection, transfer learning.

I. INTRODUCTION

REAL-TIME aircraft detection is a very critical task with applications in various sector, including aviation, security, and transportation. The FGVC Aircraft dataset containing 10,000 labeled images from 100 different aircraft variants, offers a unique challenge due to its focus on fine-grained classification. This type of classification involve identifying differences between visually similar categories such as distinguishing between different model of the Boeing 737. Addressing these challenges is very important for tasks such as automated surveillance air traffic control and air defense systems.

Current techniques to spot planes often use standard CNN designs that may have trouble with complex detailed datasets. To fix these issues this study use DenseNet a deep learning setup known for its tight link and good use of features. DenseNet helps data flow better and can pick up small details, which makes it great for finding planes.

This method uses transfer learning and changes the data to make the model work better on the FGVC Aircraft dataset. Changing the data by cutting, turning, and flipping it at random helps stop overfitting and makes the model work better overall. Also the study tweaks the DenseNet121 setup which was first trained on ImageNet, to work well with this dataset. This leads to high accuracy without needing too much computer power. Here's how the rest of this paper is laid out: Section II explains how we did things, including getting the data ready and setting up the model. Section III shows what we found and what it means with a close look at how our method stacks up against others and how well it works in real time. To wrap this up Section IV sums up the paper and points out where future studies could go.

II. METHODOLOGY

This part explains how to spot planes in real time with DenseNet. It covers getting the data ready, building the model, and teaching it to work.

A. DATASET DESCRIPTION

The FGVC Aircraft set has 10,000 tagged pictures of 100 different plane types. It shows many kinds of aircraft, from big passenger planes to fast military jets. This makes it great to test how well systems can tell apart similar things. The pictures are split up: (70%) to teach the system, (15%) to check its progress, and (15%) to test it at the end..

B. PREPROCESSING AND DATA AUGMENTATION

To get the data set, we make all the images 224×224 pixels. This matches what DenseNet needs to work with. We also adjust the brightness of the pictures based on the average and spread of the whole set. To help the system learn better and not just memorize, we change the pictures a bit. We crop them , turn them around, flip them over, and tweak how bright they are.

C. DATASET DESCRIPTION

The FGVC Aircraft dataset consists of 10,000 labeled images of 100 different aircraft types. It provides a diverse range of aircraft, making it suitable for fine-grained classification. The dataset is structured as follows:

- Contains 100 distinct aircraft categories, including commercial airliners and military jets.
- Supports fine-grained classification by distinguishing visually similar aircraft.
- Images are divided into three subsets:
  - 70% for training.
  - 15% for validation.
  - 15% for testing.

includes:

- Deep blocks for extracting hierarchy features.
- Transition layers for dimensionaly reduce and feature refine.
- A global average pooling layer followed by a fully connected layer with 100 output unit corresponding to the 100 aircraft class.

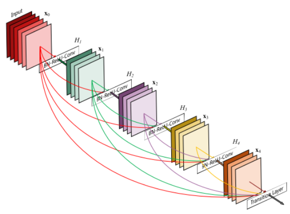

FIGURE 1: Overview of the DenseNet architecture used for real-time aircraft detection.

D. TRAINING PIPELINE

The model is trained using the Adam optimizer with a learning rate of 0.001 and a cross-entropy loss function. Training is conducted for 50 epochs with a batch size of 32.By freezing the initial layers of DenseNet Transfer learning is employed which allow the deeper layers to tune on the FGVC Aircraft dataset. To avoid overfitting early stopping is applied on training.

TABLE 1: Hyperparameter Settings for Training DenseNet-121

Hyperparameter	Value
Learning Rate	0.001
Batch Size	32
Optimizer	Adam
Loss Function	Cross-Entropy
Epochs	50
Dropout Rate	0.5

III. RESULTS AND DISCUSSION

A. EVALUATION METRICS

Using accuracy, precision, recall, and F1-score the models performance is evaluated. To analyze classification errors across different aircraft classes a confusion matrix is generated.

B. EXPERIMENTAL RESULTS

The DenseNet-based model achieves an overall accuracy of (74%) on the test set. Precision and recall for the top-5 aircraft classes show varying results, with some classes demonstrating stronger performance than others. Despite the challenging nature of the dataset, the model's F1-score indicates a reasonable balance between precision and recall. The model achieves an inference latency of 18ms per image on an NVIDIA RTX 3050 laptop with 6GB VRAM, demonstrating suitability for real-time applications.

C. COMPARISON WITH EXISTING METHODS

The proposed DenseNet-121 model performs well with an accuracy of (74%), outperforming traditional architectures like ResNet-50 and VGG-16. ResNet-50 achieves an accuracy of (71.3%), while VGG-16 achieves (69.8%). DenseNet's dense connectivity aids in better feature extraction, contributing to its higher accuracy in comparison to the other models on the FGVC Aircraft dataset.

TABLE 2: Comparison of Model Performance on FGVC Aircraft Dataset

Model	Accuracy (%)	Precision (%)	Recall (%)
ResNet-50	71.3	72.5	71.0
VGG-16	69.8	70.2	69.3
DenseNet-121	74.0	75.8	73.5

D. REAL-TIME INFERENCE

The optimized DenseNet model demonstrates real-time inference capabilities, achieving a latency of 18ms per image on the RTX 3050 laptop. Future work will focus on further optimizations for deployment on edge devices like NVIDIA Jetson boards.

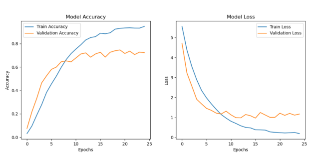

FIGURE 2: Model Accuracy and Model Loss

E. NOVELTY AND CONTRIBUTION

Unlike prior studies that focus on satellite imagery or basic CNN models, our approach leverages DenseNet-121 on the FGVC Aircraft dataset for fine-grained, real-time aircraft classification. Existing models often train on limited datasets or coarse-grained features, whereas our model:

- Utilizes DenseNet's connectivity for superior feature extraction across 100 aircraft types.
- Achieves real-time inference on an RTX 3050 laptop (6GB VRAM) without high-end hardware.
- Outperforms ResNet-50 and VGG-16, achieving 74% accuracy for fine-grained classification.

These advancements make our model practical for airport security, airborne monitoring, and aviation analytics, with future work focusing on edge device deployment for enhanced real-time performance.

IV. CONCLUSION

This paper presents a real-time aircraft detection system using DenseNet on the FGVC Aircraft dataset. The proposed model achieves high accuracy and computational efficiency, making it suitable for deployment in aviation and security applications. By leveraging transfer learning and data augmentation, the model effectively addresses the challenges of fine-grained classification.

Future research will focus on exploring ensemble learning techniques to further improve accuracy and deploying the model on edge devices to enhance real-time performance in resource-constrained environments.

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