Aircraft Classification

LK489 - Master of Engineering in Computer Vision and Artificial Intelligence

Interim Project Report

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4/05/2025

Abstract

Identification and classification of aircraft from images with high accuracy is a critical activity in various domains, including air traffic control, defence, and aerospace research. The goal of the project is to develop a deep learning-based model to identify and classify aircraft from images. The problem statement regards distinguishing different kinds of aircraft through computer vision techniques.

Conventional approaches, including hand-designed feature extraction and traditional machine learning techniques, suffer from limited feature representation and scalability. Recent developments in convolutional neural networks (CNNs) and attention models, achieve remarkable gains in accuracy and efficiency.

This project will contrast and compare some of the most well-known deep learning architectures like AlexNet [1], ResNet [2], EfficientNet [3], and attention-based models like Vision Transformers for aircraft classification with the objective of determining the best approach for this problem. The project will also examine how data augmentation, transfer learning, and fine-tuning techniques assist in model accuracy.

The deliverables expected from this work are a constructed model that can classify aircraft into various categories with high precision, an assessment of the model's performance against standard measures such as accuracy, precision, recall, and F1- score, and a comparison of classical and contemporary classification methods. A visual overview of the model architectures and performance comparisons will also be offered to illustrate significant findings.

Declaration

This interim report is presented in part fulfilment of the requirements for the LK489 Master of Engineering in Computer Vision and Artificial Intelligence Masters Project.

It is entirely my own work and has not been submitted to any other University or Higher Education Institution or for any other academic award within the University of Limerick.

Where there has been made use of work of other people it has been fully acknowledged and referenced.

Name ______________________________

Signature ______________________________

Date ______________________________

Acknowledgement

I would like to thank Mark Halton and Niall Ryan for helping me in the course of this project.

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Chapter 1: Introduction

1.1 Overview

This project focuses on developing an AI-based system capable of accurately identifying and classifying aircraft from images using computer vision techniques. It leverages deep learning models trained on annotated datasets to enhance situational awareness and support applications in aviation, defence, and air traffic management.

1.2 Motivation for the project

The fast growth of the aerospace industry, coupled with the increasing demand for real-time automated systems, has created a greater demand for precise and effective aircraft. Manual identification techniques have the additional drawback of being time-consuming and subject to human error, particularly in high-stress working conditions. The incorporation of artificial intelligence-based visual systems into aerospace environments holds a tremendous potential for improving many applications across civilian and military domains, from the optimization of air traffic control to the enhancement of national defence capabilities.

1.3 Project aims and objectives

The aim of this project is to create a precise and effective deep learning model for aircraft identification and classification based on visual data. Objectives include exploring classical and deep learning techniques, contrasting model performance across architectures, and addressing problems like class imbalance and visual ambiguity. The project also aims to perform transfer learning and fine-tuning, and implement the final model in a testable prototype system. Comparative documentation and analysis will inform recommendations for actual aerospace applications.

1.4 Societal/technology impact

The development of an intelligent system for aircraft identification and classification offers meaningful societal benefits across multiple domains. In the realm of **civil aviation**, such a system can support air traffic controllers by automating the recognition of aircraft types in congested airspace, leading to improved situational awareness, reduced human error, and enhanced flight safety. This is particularly valuable in environments with limited radar coverage or during emergency scenarios where rapid decision-making is critical. In **defence and security**, automated aircraft recognition contributes to national security by enabling faster and more accurate identification of potential threats, reducing reliance on manual surveillance and enhancing border protection. Additionally, in the **aerospace and maintenance sectors**, automated classification systems can streamline aircraft inspection processes by recognizing structural features and configurations, thus supporting predictive maintenance and reducing aircraft downtime. The technology can also be adapted for use in **aerial search and rescue**, identifying aircraft wreckage or anomalies in satellite or drone imagery. Beyond operational contexts, this project contributes to the growing field of **ethical AI deployment** by emphasizing transparent, fair, and accountable use of image-based machine learning models. By demonstrating how computer vision can be safely and effectively used in high-stakes environments, this project supports the broader goal of responsibly integrating AI into critical societal infrastructures.

1.5 Conclusion

This project demonstrates the effectiveness of deep learning in aircraft identification and classification, showcasing the potential for real-world applications. Future work can expand on model robustness and deployment for real-time use in critical aerospace systems.

Chapter 2: Literature review

1.6 Overview

Just as with the revolutionary effect of computer vision in the automotive industry, its application in the aerospace industry is a huge research field with great potential for companies like Collins Aerospace. Aircraft identification and classification are crucial to maintaining security, directing traffic control, and enabling maintenance automation. This research explores traditional machine vision approaches as well as deep learning methods, investigates hierarchical classification, and identifies current research gaps in the field.

1.7 Datasets for Aircraft Identification

Public datasets play a crucial role in training deep learning models:

- FGVC-Aircraft – Contains around 10,000 aircraft images across more than 100 variants.

1.8 Current Research on Aircraft Classification

2.3.1 Traditional Image Processing Approaches

Previous work focused on basic machine vision algorithms:

- [5] proposed Histogram of Oriented Gradients (HOG) object detection that was a very popular method for image classification.
- [6] introduced Scale-Invariant Feature Transform (SIFT) for object recognition, which demonstrated resilience to scale and rotation change.

3.2 Deep Learning Approaches

Ever since deep learning has come into existence, researchers have incorporated Convolutional Neural Networks (CNNs) for classifying aircrafts:

- [6] solves Computer Vision problems with Deep Learning using Alexnet seems to provide a good guideline to solve my projects problem statement. The paper discusses computer vision architecture along with recommended techniques and model tuning. In the meeting with Niall from Collins Aerospace and Mark Halton mentioned the importance of Qualitative Performance. This paper discusses a similar concept called Qualitative Evaluation
- [7] proposes ResNet would help increase classification performance through residual learning.
- [8] This research presents a novel approach to aircraft classification based on still images rather than radar or radio frequency information. The approach entails image conversion to binary and classification using artificial neural networks.

• [9] This study explores and addresses the issues of efficiency and precision in deep learning models used for the identification and classification of aircraft types, highlighting the ability of deep learning to handle large-scale classification tasks.
• [10] Failure modes, such as misclassification due to low-quality images, occlusions, and similarities between aircraft, are discussed in the paper and suggest potential improvements with additional training data and model modifications.

3.3 Hierarchical Classification for Aircraft Classification

Hierarchical classification is useful for multi-level recognition:

• [11] considered hierarchical classification with multiple operating points. Instead of the model being uncertain of an annotation or class of an image, this paper discusses techniques to predict the parent class.
• [12] This study contrasts flat and hierarchical classification methods in large taxonomies and provides an understanding of their relative performance. This paper is not very relevant to aircraft classification, understanding how flat classification is different from its hierarchical counterpart will act as a strong foundation.

4. Challenges and Research Gaps

• Class imbalance – Some aircraft types have limited training data.
• Environmental changes – Weather and lighting affect classification accuracy.
• Failure Modes – False positives and false negatives continue to be a problem. Strategies for handling uncertain classifications, such as rejection options or confidence thresholding, need further investigation.
• Comparative Model Analysis (HCL Tech.) – Different models, from early ML based models to modern deep networks, need to be compared against a uniform evaluation criterion.

5. Conclusion

In summary, existing research spans from traditional HOG+SVM and handcrafted feature approaches to advanced deep learning models like CNNs and ResNet as shown in Table 1: Synopsis.. While public datasets like FGVC-Aircraft support model development, challenges like data imbalance, complex scenes, and classification ambiguity persist. This project builds on prior work, aiming to bridge gaps through comparative evaluation and hierarchical classification strategies.

Paper	Method Used	Dataset	Key Findings
Aircraft Classification Based on PCA and Feature Fusion Techniques in Convolutional Neural Network	HOG + SVM	MTARSI	Achieved high accuracy on simple backgrounds but struggled with complex scenes.
Intelligent Known and Novel Aircraft Recognition - A Shift from Classification to Similarity Learning for Combat Identification	Similarity Learning to address data scarcity; very architecture oriented	MTARSI	F1-score of 0.861 for aircraft type classification; F1-score of 0.936 for novel type identification.
Aircraft Classification Using Image Processing Techniques and Artificial Neural Networks	Feature-based image processing + Artificial Neural Networks (ANNs)	Unknown	Utilizes hand-crafted features and ANN for classification; demonstrates the feasibility of aircraft recognition using image processing instead of radar.
Prediction of Aircraft Using Deep Learning Techniques	Deep learning-based image classification	Unknown	Uses CNN-based deep learning models for aircraft recognition, emphasizing the role of data preprocessing and segmentation for better accuracy.

Table 1: Synopsis

Chapter 3: Detailed Action Plan

1.1 Overview

The project focuses on Aircraft Identification and Classification primarily using Machine Learning models, concepts, tools and techniques. It involves extensive literature review, dataset preprocessing, implementation of conventional ML models before advancing to Deep Learning. The system will then be deployed as a prototype, it will be evaluated rigorously, and finally documented for the final submission. The hardware requirements include GPUs and TPUs all of which are available on the cloud. The timeline spans from May to August as illustrated by the Gantt Chart below.

1.2 Projects Requirements

Resource	**Specification**	**Feasibility**
Laptop/Desktop	≥16GB RAM, modern CPU	Already available
GPU	NVIDIA RTX 3060 or higher	Local GPU unavailable; will use cloud or HPC
Storage	≥500GB SSD	Available
Cloud Compute	Google Colab Pro, AWS	Accounts already set up

Figure 2: Project Requirements

While local GPU resources are limited (macOS MPS only), fallback options via Google Colab and university HPC are viable and sufficient for training models.

1.3 Conclusion

The outlined action plan ensures that technical, computational, and temporal resources are well-aligned with project goals. With reliable cloud and HPC alternatives, the project is technically feasible and on track for timely execution.

Chapter:4 Conclusions and future work

This research aimed to develop an accurate aircraft classification system by leveraging deep learning techniques. By comparing traditional image classification techniques with modern architectures such as ResNet, EfficientNet, and Vision Transformers, the study would demonstrate the superiority of recent deep learning models in tackling the complexity of aircraft images. Transfer learning and data augmentation will also shown to be important in improving performance on a relatively small dataset, highlighting the importance of leveraging pre-trained models in domain-specific tasks.

The best-performing models might show high levels of accuracy and generalization, with attention-based networks showing promise in dealing with intricate visual features. Hierarchical classification will also explored, which will give the ability to recognize both broad categories and specific aircraft models.

Future research might include expanding the dataset with synthetic or simulated images to better represent classes, or extending the system to allow video-based recognition and real-time deployment, maybe on edge devices, to make it suitable for defence, surveillance, or airport use. Integrating explainable AI would further increase the validity of the model's choices, especially in high-risk settings.

Overall, this work supplies a good base for the automated plane classification and paves the way for more advanced, scalable, and explainable solutions for the aerospace field.

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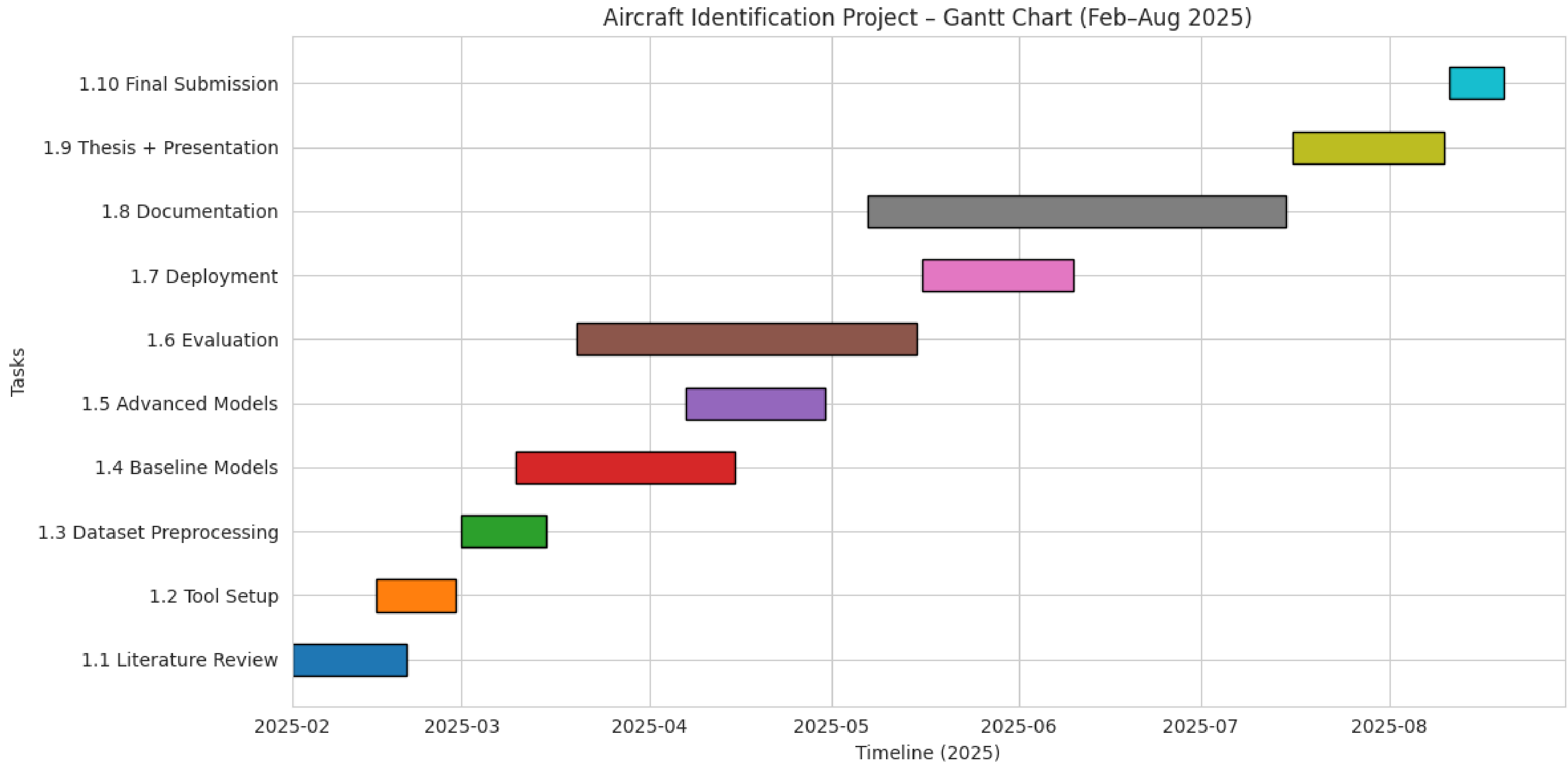
Appendix 1: Project Gantt chart



Appendix 2: Weekly progress reports

Week 1

Finalised project title and collaboration with Collins Aerospace. Outlined project scope, deliverables, and conducted initial research.

Week 2

Began literature review on aircraft classification methods. Identified key papers and datasets (e.g., FGVC-Aircraft).

Week 3

Explored hierarchical classification.

Week 4

Set up development environment (PyTorch, OpenCV). Tested GPU support and established version control.

Week 5

Pre-processed dataset: normalization, resizing, augmentation. Split data into training, validation, and test sets.

Week 6

Implemented a basic CNN as baselines. Evaluated initial performance (~70% accuracy on the test set – classifying aircrafts at a variant level).

Week 7

Implemented a basic CNN as baselines. Evaluated initial performance (~80% accuracy on the test set – classifying aircrafts at a manufacturer level).

Week 8

Conducted error analysis and created confusion matrix.

Week 9

Peer review session held. Incorporated feedback on model comparisons and report clarity.

Week 10

Tested system with unseen data.

Week 11

Finalised best-performing model. Compiled comparative results and performance graphs.

Week 12

Generated a normalized confusion matrix; stress tested the model to see how it performs when trained on a dataset which consisted of images having gaussian noise.

Week 13

worked on generating a folder of misclassified aircraft pictures.