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A Dataset for Autonomous Aircraft Refueling on the Ground (AGR)

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***Abstract*—Automatic aircraft ground refueling (AAGR) can improve the safety, efficiency, and cost-effectiveness of aircraft ground refueling (AGR), a critical and frequent operation on almost all aircraft. Recent AAGR relies on machine vision, artificial intelligence, and robotics to implement automation. An essential step for automation is AGR scene recognition, which can support further component detection, tracking, process monitoring, and environmental awareness. As in many practical and commercial applications, aircraft refueling data is usually confidential, and no standardized workflow or definition is available. These are the prerequisites and critical challenges to deploying and benefitting advanced data-driven AGR. This study presents a dataset (the AGR Dataset) for AGR scene recognition using image crawling, augmentation, and classification, which has been made available to the community. The AGR dataset crawled over 3k images from 13 databases (over 26k images after augmentation), and different aircraft, illumination, and environmental conditions were included. The ground-truth labeling is conducted manually using a proposed tree-formed decision workflow and six specific AGR tags. Various professionals have independently reviewed the AGR dataset to keep it no-bias. This study proposes the first aircraft refueling image dataset, and an image labeling software with a UI to automate the labeling workflow.**

Keywords*—*image crawling, image augmentation, benchmark, classification, scene detection

I. Introduction

Autonomous aircraft ground refueling (AAGR) is a relatively new concept in the aviation industry that aims to automate the aircraft ground refueling (AGR) process. The early idea of AAGR was proposed around the 1980s, and the solutions were mainly conducted by adding figure landmarks next to the refueling port to support image processing and robotic solution [1], [2]. However, AGR detection is a challenging task in practice because of variant illumination conditions, refueling ports, and obstructors (see Fig. 1 for AGR conditions). AAGR technology is still being developed [3], while the advances in big data, machine vision, robotics, and artificial intelligence have made AAGR become more feasible and accurate in recent years. The AAGR development can potentially revolutionise the way aircraft refuel on the ground.

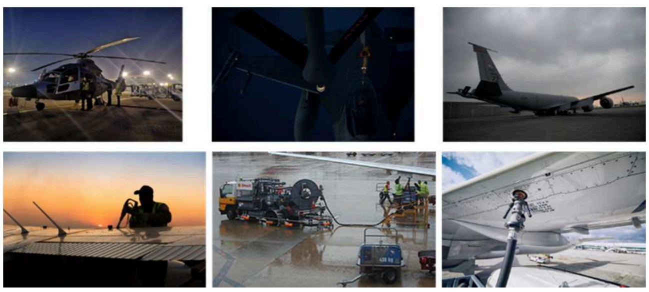

Fig. 1. The aircraft ground refueling conditions. (All images are available under a creative, non-commercial, or commercial license.)

Several factors drive the AAGR developments, including safety, efficiency, and cost-effectiveness [4]. AGR is a hazardous task involving flammable liquids, vapors, and machinery [5]. Automating the AGR can significantly reduce the accident risk to human operators and possible human error [5]. Furthermore, the traditional AGR process is time-consuming and requires a substantial workforce. AAGR can streamline the process, allowing aircraft to be refueled quickly and efficiently, reducing the turnaround time for airlines and other operators. Therefore, AAGR is potentially more cost-effective in time and labor costs, which can further decrease fuel consumption and increase aircraft utilization.

There are many critical challenges of AAGR deployment in applying big data, machine vision, robotics, and artificial intelligence technologies. First, the available data in real-world settings for AAGR research is limited. AGR systems are typically proprietary, and manufacturers may not share the data for competitive reasons. Second, the AAGR deployment needs to be interoperable with existing refueling infrastructure and protocols. Third, human-robot integration (HRI) is another challenge of the AAGR deployment. It is essential to study the human operators' interaction with it, including developing intuitive user interfaces and training workflow to ensure safe and efficient operation. Finally, the visual condition can significantly influence the AAGR performance. Thus, it is important to improve the robustness of the variant visual conditions of the AAGR system.

The aim of this study is to investigate the feasibility of deploying an autonomous image classifier to the crawled image of aircraft ground refueling (AGR) scenarios. The target is to explore the advantage of image crawling and image classification to big online multimedia data usage and autonomous scene identification. Although manufacturers may keep most of the AGR images confidential, the huge online multimedia in the big data era still contain significant valid images to support the AAGR study. However, these images are highly unprocessed, and some are not free of copyright for research usage. This study generates a new AGR

[1] The AGR dataset is made available to the community, which can be accessed at: https://doi.org/10.17862/cranfield.rd.22337473.v1.

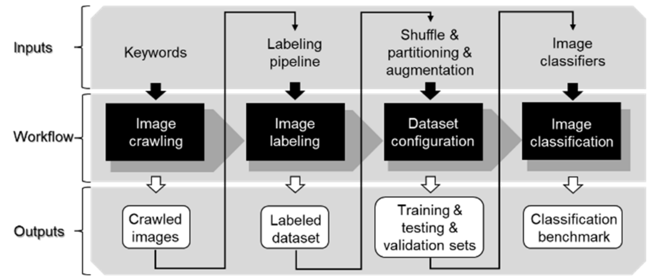

Fig. 2. The flowchart of the proposed method.

dataset by integrating image crawling, license filtering, and image augmentation, and further evaluates using an advanced image classifier.

Image classification has been extensively studied with advances in deep learning and machine vision techniques. The common classifiers include traditional methods such as support vector machine (SVM), decision tree, and random forest [6]–[8], as well as deep learning methods, such as convolutional neural networks (CNN) [9]. Compared with traditional classifiers, CNN can automatically extract image features and learn complex features, so it has achieved better performance in image classification. ResNet [10] (Residual Network)-based classifier is an image classifier that has shown significantly better performance than other CNN classifiers, effectively solving the challenge of vanishing gradient and exploding gradient when neural network depth increases by using residual blocks to transmit the gradients across the layers [11].

The contributions of this study can be summarized as follows. First, this study creates a new aircraft ground refueling image dataset (AGR dataset), which have been made available to the community. As far as the authors are aware, this is the first aircraft refueling image dataset, which has the potential to support further study on image segmentation, scene sensing, and image style transformation. Second, this study designs an image labeling software with a human-robot integrated user interface for the crawled aircraft refueling images. The software can potentially improve the accuracy, standardization, efficiency, and reusability of the image labeling process.

This study is organized as follows. Section II describes the method, including image crawling, image labeling, dataset configuration, and image classification. Section III depicts the corresponding results and discussion. The conclusion is made in Section IV.

II. Method

The method of this study can be divided into four workflow modules: image crawling, image labeling (manual), dataset configuration, and image classification. Fig. 2 is a flowchart of the method, which consists of three layers. The top layer indicates the inputs of each module, the middle layer refers to the four workflow modules, and the bottom layer is the outputs of the workflow modules (see the left brackets in Fig. 2). Arrows across layers indicate the data flow in the flowchart, and each column packages the function of the workflow module. The image crawling module refers to the image searching process from big online image databases, which uses keywords to search potential images. The image labeling module conducts the manual labeling process to provide ground-truth tags, which also designed the professional aircraft refueling labeling tags to standardize the labeling process. The data configuration module divides the crawled and labeled images into three subsets, and then uses data augmentation and shuffle to increase the diversity of the overall dataset. An aircraft ground refueling image dataset is then achieved, the AGR dataset[1]. The image classification module applies different advanced classifiers and tests with different hyperparameter settings, and a benchmark is achieved accordingly.

A. Image crawling

The image crawling module searches potential images from the image databases using the keywords, which are "aircraft" and "refueling" in this study. The balance between the search scope and specificity of keywords is essential and challenging. Keywords that are too broad can introduce too many irrelevant images, while keywords that are too specific can exclude relevant images from the crawling scope. The target scene detection of this study is aircraft ground refueling, which is a subset of aircraft refueling. This study ensures the integrity of crawled image scope through the inclusion relationship. Furthermore, aircraft refueling is a topic highly related to aircraft ground refueling, which can suppress irrelevant image range.

Algorithm 1: Keywords-based image crawler	
Inputs:	kws, opt, num_{max}, dir_{imgs}
Outputs:	$imgs_{crawled}$

$database_{img}$ = **choose**(opt)
set $list_{license}$ = [creative, non-commercial, commercial]
for i **in range**(num_{max}):
  img = **icrawler**(kws) in $database_{img}$
  if $database_{img}$ [i] != end:
    read $license$ of img
    if $license$ is one of $list_{license}$:
      if img.**size**() ≥ $(100, 100)$:
        Rename img use i
        append img to $imgs_{crawled}$
      else continue
    else continue
  break
save $imgs_{crawled}$ to dir_{imgs}

The image crawling module can be presented using Algorithm 1. The input of Algorithm 1 is the keyword list (kws), the option of selecting database (opt), the maximum number of the crawled images (num_{max}), and the output directory (dir). This study uses two keywords, "aircraft" and "refueling" (kws = ["aircraft", "refueling"]). The image crawler is designed with 13 $opts$ (corresponding to 13 image databases, *Baidu*, *Bing*, *Flickr*, *Google*, *Creative Commons Search*, *Freepik*, *Pexels*, *Picjumbo*, *Pixabay*, *Rawpixel*, *StockSnap*, *Unsplash*, and *Wikimedia Commons*). The num_{max} is limited to 800 images per database. The image resolution and size have no rigorous limitation in principle because the practical condition varies due to visual conditions and camera distance. The steps of the image crawling module are as follows. First, the crawling database is selected according to opt. Second, the user needs to specify the list of available image certificates ($list_{license}$). To avoid potential copyright issues, Algorithm 1 only uses images that have declared image certificates as "creative", "commercial", or "non-commercial". Third, Algorithm 1 crawls num_{max} images maximum. Fourth, image crawling is performed on the dataset according to kws. Fifth, it is detected whether the traverse for all crawled images in the corresponding database is completed. If the traverse is completed, the crawling task is

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Fig. 3. The user interface of the designed image labeling software for aircraft refueling.

terminated, and all $imgs_{crawled}$ images will be stored in dir_{imgs}. Otherwise, the sixth step reads the license of the image. A "continue" is triggered to enter the next image if the license is not on the $list_{license}$. The seventh step measures whether the image size is not less than 100×100. Some databases can return some website logos or thumbnails, and the size filtering can avoid prominent invalid images.

B. Image labeling

The image labeling module designs an image labeling software for the crawled aircraft refueling images. This software packages the image labeling mission into an automatic process associated with a user interface (UI) (see Fig. 3). The proposed software has the following advantages compared to existing labeling software. First, some existing software is not free, while the free version can only use limited tags. Second, some existing software integrates too many unnecessary functions, which causes redundant computing costs. Third, no existing software specifically for aircraft refueling with standardized tags exists. Therefore, a user-friendly, highly packaged, and professional crawled aircraft refueling image annotation system is necessary [12].

This image labeling software consists of six panels. First, the software title panel indicates the purpose and function of the software. Second, the observation panel displays the image. Thirdly, the navigation panel can select the image to be labeled or exit the labeling software. Fourth, the labeling panel provides standardized tags for the crawled aircraft refueling images. Fifth, the progress panel uses percentages and image numbers to depict the task progress. Sixth, the information panel prints out the labeled image information. The red box in Fig. 3 indicates the interactive area composed of the navigation, label, and process panels.

The image labeling module uses a tree-formed bifurcation structure to design the labeling pipeline of the image labeling module. The tree-formed design standardizes the labeling criteria and unifies the definition, which can reduce bias and increase efficiency. Fig. 4 depicts the tree-formed labeling pipeline, while the definition and explanation of decision blocks are listed in the upper left corner. The steps are as follows: First, the labeling software deletes the corrupted images. Second, the "refueling" decision block determines the image according to the definition, and "No"-images are categorized into the first category. Third, for the "Yes"-images, the "aircraft refueling" decision block determines the category, and "No"-images go to the second category. Fourth, the labeling tree repeats the same process for "aircraft ground refueling" and "not visible" decision blocks, achieving the

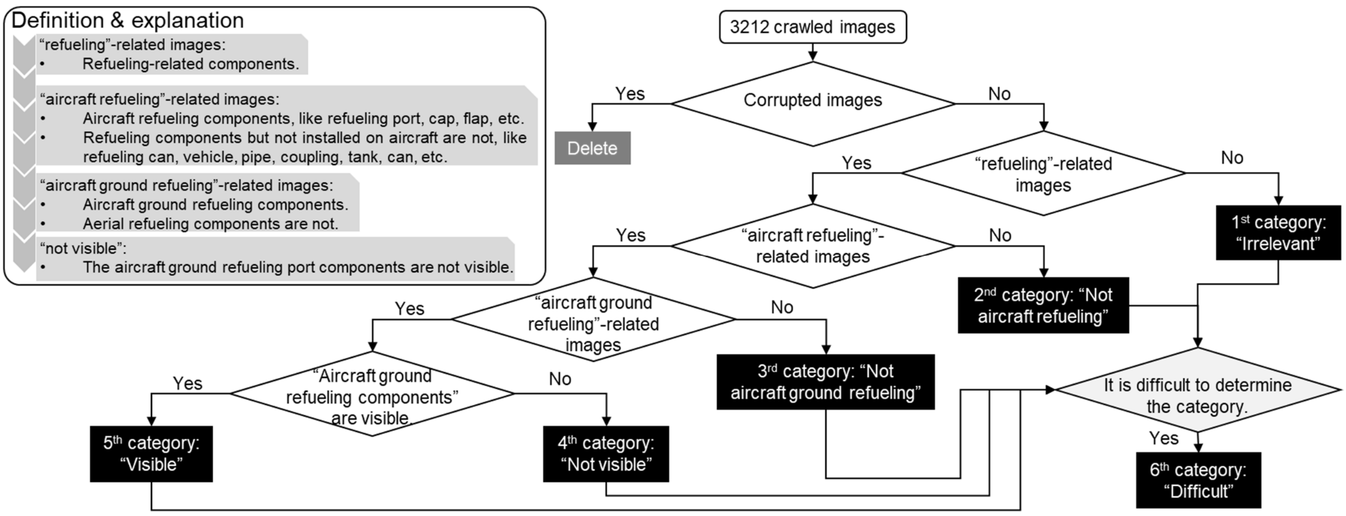

Fig. 4. The tree-formed labeling pipeline and the definition/explanation of the decision blocks.

[1] The AGR dataset is made available to the community, which can be accessed at: https://doi.org/10.17862/cranfield.rd.22337473.v1.

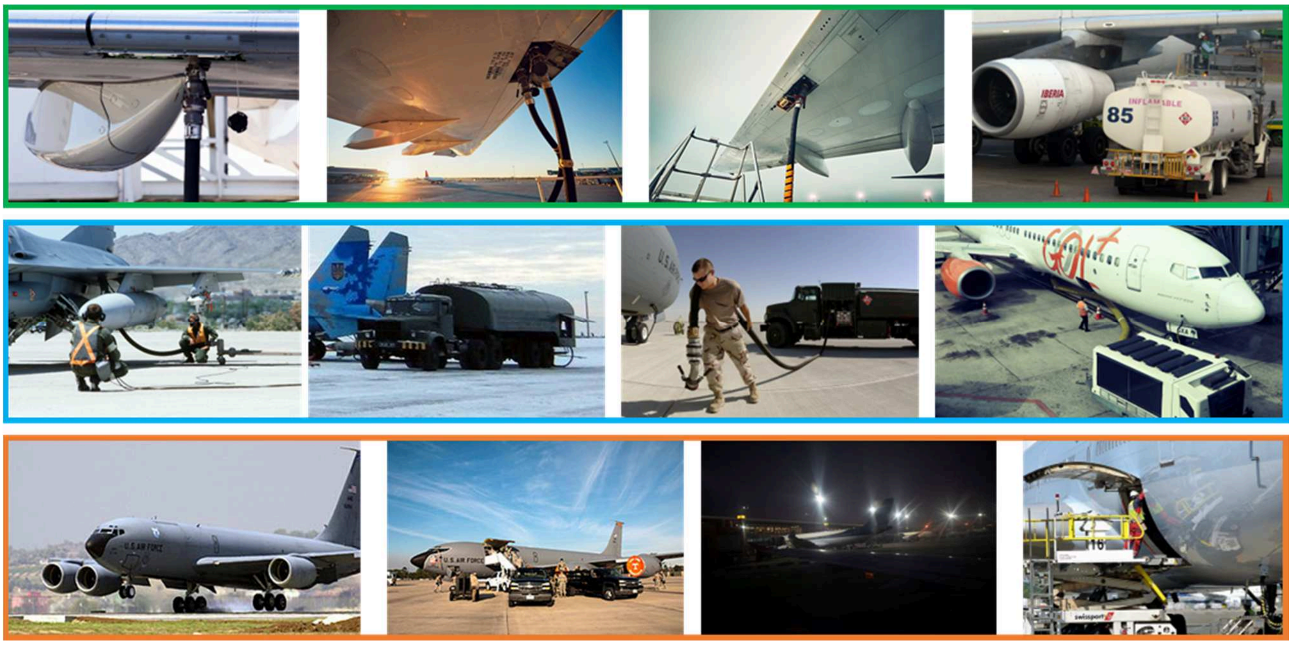

Fig. 5. Some examples of the crawled image.

```
├── /AGR_Dataset
   ├── ORIG
   |   ├── irrelevant
   |   ├── not_aircraft_refueling
   |   ├── not_aircraft_ground_refueling
   |   ├── not_visible
   |   ├── visible
   |   └── difficult
   ├── TTV-S
   |   ├── train
   |   ├── test
   |   └── valid
   └── AUG
       ├── train
       ├── test
       └── valid
```

Fig. 6. The file directory of the proposed AGR dataset.

third and fourth categories. Fifth, the final remaining images are labeled as visible images. Sixth, images that are difficult to determine in each decision module are categorized into the "difficult" tag, the sixth category. Finally, three professionals independently reviewed the labeled images to reduce the labeling bias, and they all have sufficient backgrounds in aerospace, machine vision, automation, machine learning, and robotics. The review process follows a “majority rule” to balance the difference between professionals.

It is noteworthy that the image classification module (Section II.D) does not use the "difficult" images. Difficult images refer to an image that is difficult for human perception. It is not the scope of this study to make machine learning that has better ability than human perception. However, the "difficult" category has been included in the dataset configuration, which leaves freedom for future aircraft refueling scene recognition study to explore and improve further.

C. Dataset configuration

The dataset configuration module applies partitioning, augmentation, and shuffling to the labeled images from Section II.C. An aircraft ground refueling dataset (AGR dataset) is created and made available to the community, and the AGR dataset has been presented in three versions: the original data (ORIG), training/testing/validation-set partition and shuffling dataset (TTV-S), and augmented dataset (AUG). Fig. 6 describes the file directory of the proposed AGR dataset. The ORIG version contains six sub-folders corresponding to six standardized tags in the image annotation software. The image in ORIG is renamed using the tag names. TTV-S version firstly shuffles the images in each sub-folder in the ORIG version, then secondly, partitions into training, testing, and verification images according to the ratio of 70%, 15%, and 15%, and finally, all training, testing, and verification images are merged and reshuffled to build the training, testing, and validation sets. The images in TTV-S are renamed again using labeling tags and the corresponding partition name. The AUG version uses eight data augmentation schemes, including shifting, brightness adjustment, zooming, flipping, cropping, and rotation. The image names in AUG are further extended by adding the augmentation scheme name.

Table 1. The experimental designs of the image classification module.

Index	Classifier	Trainable	Task	Tags: Irrelevant	Tags: Not aircraft refueling	Tags: Not aircraft ground refueling	Tags: Not visible	Tags: Visible	Tags: Difficult
ResM	Resnet50+DNN (Transfer learning)	True	Multiple	o	o	o	o	o	o
ResB1			Binary	o	o				x
ResB2				x	o	o			x
ResB3				x	x	o	o		x
ResB4				x	x	x	o	o	x

“o” and “x” refer to the tag that is enabled or disabled for the classification task.

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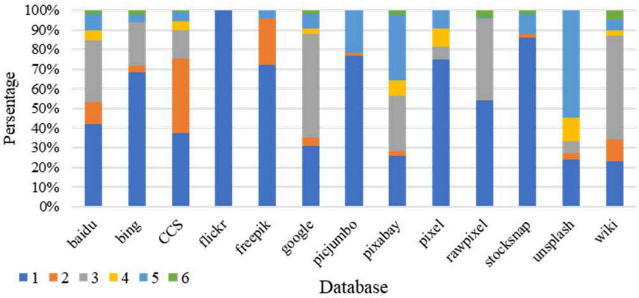


Fig. 7. The category distribution by the image tags among databases. "CCR" and "wiki" refers to the *creative commons search* and *Wikimedia commons* databases, respectively.

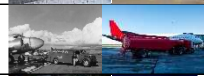
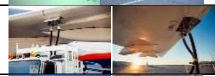
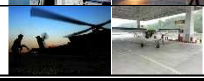
D. *Image classification*

The image classification module adopts an advanced image classifier (ResNet) and provides multiple metrics to evaluate the classification effectiveness of the proposed AGR dataset. The ResNet classifier is the implementation in TensorFlow 2.10 (tf.keras.applications.resnet50.ResNet50()). Evaluation metrics apply accuracy, cross-entropy, and root mean square error (RMSE). Considering that the label of AGR is a layered tree-formed structure, the classification task can be conducted using either the multi-classification approach or the multiple binary classifications approach. The multi-classification approach reduces the overall training time and improves real inference time ability. However, multi-classification classifies all categories in parallel, which ignores the layered tree-formed structure in Section II.B. Each decision block in the tree structure can be a classification task, and the layered tree-formed structure can also logically help the all-tags image classification. However, splitting multi-classification into multiple single-classifications increases the training time and reduces the real inference time ability of the overall solution. Table 1 presents the experimental designs of the image classification module, where "o" and "x" refer to enabling or disabling the corresponding tags.

Table 2. The image crawling results for each database.

Database	Number (images)	Database	Number (images)
Baidu image	800	*Bing image*	170
Flickr	500	*Google image*	649
Creative Commons Search	269	*Freepik*	100
Pexels	33	*Picjumbo*	60
Pixabay	40	*Rawpixel*	140
StockSnap	59	*Unsplash*	33
Wikimedia commons		519	

Table 3. The number of images in each tags.

Category	Number (images)	Example images
Irrelevant	1305	
Not aircraft refueling	270	
Not aircraft ground refueling	1000	
Not visible	92	
Visible	213	
Difficult	63	

A. *Crawled images*

Table 4. The results of partitioning and data augmentation.

Subset (images)	Training set (≈ 70%)	Testing set (≈ 15%)	Validation set (≈ 15%)
Number	2,059	438	446
Augmentation			
Number	18,477	3,933	4,014

Image crawling searches image collections close to the target domain defined using keywords. Fig. 5 presents some examples of the crawled image. From a human perception point of view, Fig. 5 visualizes the related, possibly related, and irrelevant images of the aircraft refueling using green, blue, and orange frames. Therefore, image mining can find effective AGR-related images but still introduces much irrelevant content.

Table 2 presents the image crawling results for each database. *Baidu*, *Google*, *Flickr*, and *Wikimedia commons* all provide more than 500 images per dataset, while *Pexel*, *Picjumbo*, *Pixabay*, *Stocksnap*, and *Unsplash* only provide less than 100 images per dataset. Therefore, the number of images provided by different datasets is not same, and some image might be duplicated.

B. *Labeled images*

Manual labeling provides ground-truth tags for the further classification (or scene recognition) task. Fig. 6 presents the category distribution by the image tags among databases, where the index of "1", "2", "3", "4", "5", and "6" refer to the "irrelevant", "not aircraft refueling", "not aircraft ground refueling", "not visible", "visible", and "difficult" tag, respectively. All images from *Flickr* are irrelevant, and *Stocksnap*, *Pixel*, *Picjumbo*, and *Freepik* contains more than 70% "irrelevant" images. *Unsplash*, *Pixabay*, and *Picjumbo* provide high ratio of "visible" images. Table 3 present the number of images for each of the tags. The labeling speed can reach 50 images per hour when using the designed UI labeling software, and it can be used to review some of the difficult

Table 5. The results of ResNet50 on the AGR dataset

Index	Cross-entropy			Accuracy			RMSE			Callback
	Train	Test	Valid	Train	Test	Valid	Train	Test	Valid	
ResM	0.0037	3.9926	2.4491	99.92%	73.08%	75.82%	0.0172	0.3163	0.3003	256 epochs
ResB1	1.2903×10^{-03}	9.8486	2.7217	99.99%	75.23%	76.10%	4.8580×10^{-11}	0.4935	0.4808	157 epochs
ResB2	0.0019	0.8291	0.5087	99.96%	92.37%	92.47%	0.0191	0.2669	0.2590	74 epochs
ResB3	0.0028	0.5327	0.3311	99.89%	96.03%	95.85%	0.0289	0.1905	0.1965	161 epochs
ResB4	0.0628	1.5312	1.7673	97.97%	76.77%	77.78%	0.1294	0.4454	0.4517	117 epochs

III. Result and Discussion

This section verifies the feasibility to the AGR scene detection task of the workflow proposed in Section II. Sections III.A, III.B, III.C, and III.D correspond to the results and discussion of image crawling (Section II.A), image labeling (Section II.B), dataset construction (Section II.C), and image classification (Section II.D), respectively.

[1] The AGR dataset is made available to the community, which can be accessed at: https://doi.org/10.17862/cranfield.rd.22337473.v1.

cases. Furthermore, considering the recruiting keywords are "aircraft" and "refueling", the AGR dataset can support a wide range of aircraft refueling research, such as aerial refueling, refueling component detection, refueling environment transformation, and environmental perception. However, further processing is recommended for non-AGR studies.

C. Configured dataset

The dataset construction module first partitions the proposed AGR dataset into training, testing, and verification subsets according to the ratio of 70%, 15%, and 15%. Then, this study augments the AGR dataset, further expanding it to increase diversity. It is worth noting that data augmentation should be performed after data partitioning. Otherwise, it can increase the risk of information leakage among subsets. Table 4 shows the results of partitioning and data augmentation.

D. Scene recognition

In this study, an advanced classifier model is used to conduct experiments on the proposed dataset, which can verify the AGR dataset's effectiveness. Table 5 shows the results of ResNet50 on the AGR dataset. Although the overall accuracy result is only 75.82%, this result has verified the effectiveness of the proposed dataset and workflow as an initial result. The classifier can be a promising baseline for further study on activity recognition, refueling component detection, and semantic scene sensing of AGR. Further improvements to the results will require systematic research and further improvements to the training process and classifier design.

IV. Conclusion

This study presents an image dataset of aircraft ground refueling (AGR dataset), the first open dataset of AGR. The source is 3212 crawled images from 13 online multimedia databases. This study designed a tree-formed labeling pipeline that proposed six standardized labels (irrelevant, not aircraft refueling, not aircraft ground refueling, not visible, visible, and difficult). The overall labeling pipeline is packaged as an automatic process with a labeling-software, which is a user-friendly, highly packaged, and professional UI system. This annotation software helps relevant researchers to efficiently re-implement the annotation process. The labeled images are expanded to over 26k after eight augmentation schemes. The AGR dataset has three versions. ORIG only contains ground-truth labels, TTV-S has been partitioned and disordered, and AUG is augmented. Users can choose the corresponding version of the AGR dataset according to the requirements. This study used an advanced neural network-based classifier (ResNet) to verify the proposed AGR dataset, the image crawling-based dataset creation process, and the effectiveness of the tree-formed labeling pipeline.

The diversity of the AGR dataset was expanded through the method of image augmentation. However, image processing-based augmentation is challenging to simulate real-world changes in visual conditions, such as weather, lighting, and camera angle. A promising method is to use the generative model-based image-style transformation technology. However, none of the existing image style transformation technologies are specific to aircraft ground refueling scenarios, which requires further investigation.

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