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AeroRunway: Diverse Weather and Time of Day Aerial Dataset for Autonomous Landing Training

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Abstract − Acquiring a sufficient amount of diverse and accurate real-world data poses a significant challenge in advancing autonomous systems, which are becoming increasingly popular. Despite the aerospace industry's keen practical and economic interest in autonomous landing systems, readily available open-source datasets containing aerial photographs are scarce. To address this issue, we present a dataset named AeroRunway, comprising high-quality aerial photos designed to aid in runway recognition during the approach and landing stages. The dataset is composed of images using X-Plane, a flight simulator software developed by Laminar Research. It is a highly realistic and detailed flight simulation program that allows users to experience the sensation of piloting various aircraft in a virtual environment. These synthetic images were collected mostly in variable weather conditions above 5000 feet to supplement existing satellite imagery that can be used for extreme situations. This dataset was created from 28 different airports in different weather conditions, such as foggy and rainy, at various times of the day, such as day and night, and consists of 3880 images and is approximately 13.3 GB in size.

Keywords − *Aerodrome detection, spatial awareness, artificial intelligence, deep learning, machine learning*

1. Introduction

Maintaining situational awareness is paramount for pilots, especially during critical phases of flight such as approach and landing. Visual cues aid pilots' orientation and decision-making processes, providing essential information about their surroundings and facilitating safe navigation. However, visually identifying aerodromes amidst diverse and often rapidly changing environments presents significant challenges. Spatial disorientation, a phenomenon where pilots may misinterpret their spatial position and orientation relative to the ground, poses a considerable risk during flight. This can be exacerbated by poor visibility, inclement weather conditions, or complex terrain features. Additionally, aerodromes exhibit varying characteristics and visual appearances, ranging from large international airports with distinctive runway layouts to smaller regional airfields nestled amidst rural landscapes.

In response to these challenges, the study introduces a dataset designed to leverage the power of Deep Learning (DL) algorithms for real-time aerodrome detection from aircraft. By harnessing the capabilities of machine learning and computer vision, this dataset offers a revolutionary solution to enhance pilots' situational awareness and improve flight safety. The dataset comprises a comprehensive collection of high-resolution aerial images capturing diverse aerodrome environments worldwide. These images are meticulously annotated with precise aerodrome boundaries, runway configurations, taxiway markings, and other distinctive features,

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facilitating robust training and validation of DL models.

By training DL algorithms on this dataset, pilots can benefit from advanced onboard systems capable of autonomously detecting and identifying aerodromes in real time, even under challenging conditions. This technology promises to revolutionize cockpit instrumentation, providing pilots with invaluable assistance in navigating complex airspace environments and mitigating the risks associated with visual navigation errors. Incorporating DL-based aerodrome detection systems into aircraft avionics represents a significant leap forward in enhancing flight safety and efficiency. By empowering pilots with cutting-edge technology, this initiative aims to redefine the standards of situational awareness in aviation, ensuring safer skies for passengers and crew alike. These methods employ neural networks to extract pertinent features and have demonstrated effectiveness in computer vision applications [1].

Northwestern Polytechnical University (NWPU) created the NWPU-RESISC45 dataset [2], a standard for Remote Sensing Image Scene Classification (RESISC). There are 700 photos in each of the 45 scene classifications in this dataset's 31,500 photographs. The NWPU-RESISC45 proposal includes a large number of scene classes and total images. It has significant changes in translation, spatial resolution, perspective, object posture, lighting, background, and occlusion and has a high level of both within-class and between-class variability.

10 classes of openly accessible geographic object identification NWPU VHR-10 dataset [3-5] is another resource we can reach in this field. An aircraft, ship, storage tank, baseball diamond, tennis court, basketball court, running track on the ground, harbor, bridge, and vehicle are among the ten categories. This collection consists of 800 Very High-resolution (VHR) remote sensing photos that specialists carefully annotated after being clipped from the Vaihingen and Google Earth datasets. This 10-class dataset for geographic object recognition may be used to find both single-class and multi-class items. A total of 800 VHR optical Remote Sensing Images (RSIs) were used to create this dataset, from which 477 vehicles, 757 airplanes, 302 ships, 655 storage tanks, 390 baseball diamonds, 524 tennis courts, 159 basketball courts, 163 ground track fields, 224 harbors, and 124 bridges were manually annotated with axis-aligned bounding boxes. 715 color images from Google Earth were acquired with spatial resolutions ranging from 0.5 to 2 meters, and 85 pan-sharpened Color Infrared (CIR) images from Vaihingen data [6] were acquired with a spatial resolution of 0.08 meters.

A diverse dataset [7] is constructed by collecting RGB imagery using Google Earth technology. This collection consists of a total of 3092 images measuring approximately 4800 x 2703 pixels each. This was achieved by sourcing photographs from renowned international airports such as Paris-Charles de Gaulle, John F. Kennedy International Airport, and Frankfurt Airport, among others, and aircraft boneyards such as Davis-Monthan Air Force Base. To properly label each photograph's aircraft, they used the help of HyperLabel software where they manually created individual bounding boxes surrounding them, which included quality control measures using external independent visual inspectors who maintained accuracy during this process. This led them to label a staggering amount of about eighteen thousand four hundred seventy-seven airplanes overall. Once labeled, their dataset was portioned into three smaller sets with different usage criteria. These subsets were separated accordingly into training (70%, 2166 images), validation (20%, 615 images), and testing (10%, 311 images) to cover all bases respectfully. The DIOR dataset [8] for object detection in optical remote sensing images consists of 20 object classes, 23463 images, and 192518 object instances annotated with horizontal bounding boxes. DIOR-R is an expanded version of DIOR that uses the same images as DIOR but is annotated with orientated bounding boxes. Images in the collection are 800 by 800 pixels in size, with spatial resolutions varying from 0.5 to 30 meters. Similar to most current datasets, this one was gathered from Google Earth (Google Inc.) by specialists in interpreting earth observation data. As opposed to dataset NWPU VHR-10, which has only 800 images, the 23463 remote sensing images in the proposed DIOR collection span over eighty countries. These images are carefully gathered in various weather situations, seasons, imaging settings, and image quality. As a result, for each object class in the DIOR dataset, there are richer variations in perspective, translation, lighting, backdrop, object position and appearance, occlusion, etc.

Military Aircraft Recognition dataset (MAR20) [9] is a publicly accessible remote sensing image collection intended solely for research. This collection consists of 22341 instances, 20 categories, and 3842 images with orientated and horizontal bounding boxes annotated.

A large-scale Dataset for Object Detection in Aerial images (DOTA) [10] collects 2806 aerial images from different sensors and platforms. Each image is around 4000 by 4000 pixels and includes items with a broad range of sizes, orientations, and forms. Experts in aerial image interpretation then annotate these DOTA images using 15 common item categories. There are 188,282 occurrences in the completely annotated DOTA images, and each one is given a random (8 d.o.f.) quadrilateral label.

Scene semantic categories are used to identify the 10 million scene images in the Places Database [11], which provides a comprehensive catalog of the many sorts of surroundings seen across the globe. The Place Database's data-collecting procedure is comparable to the picture collection in other widely used datasets, such as ImageNet [12] and COCO [13]. Based on the synset of WordNet [14], the categories for the ImageNet dataset have been defined. Using the collection of WordNet synonyms, potential images are retrieved from several image search engines. Contrarily, the COCO dataset focuses on adding additional scene information to the object instances inside the images. Places database as a benchmark has four subsets: Places205, Places88, Places365-Standard, and Places365-Challenge.

FAIR1M [15] is another benchmark dataset for recognizing fine-grained objects in high-resolution remote sensing images. It contains more than 1 million instances and more than 15,000 images. From several stations dispersed throughout numerous nations and regions, remote sensing images with resolutions ranging from 0.3 to 0.8 meters are gathered. All items in the FAIR1M dataset have oriented bounding boxes that annotate them about 5 categories and 37 subcategories.

Comparing the FAIR1M dataset to other datasets, it has several unique traits. The first thing that makes it unique is its vastly increased number of samples and pictures, which offers more thorough, fine-grained category information. The collection includes items from remote sensing photographs, which offer useful geographic data like latitude and longitude. Another important aspect is the dataset's high resolution, attained through a careful data-cleaning process that guarantees superior image quality.

Another method uses an open-source virtual globe to replicate the surroundings around airport runways. Virtual globes have been employed in many research projects over the past ten years as common instruments for data collecting, exploration, and modeling [16]. Google Earth Studio [17, 18], a sophisticated animation tool for obtaining and creating Google satellite pictures, is considered in this work. Landings of civil aircraft are represented by the Landing Approach Runway Detection (LARD) dataset [19]. So, based on the information supplied by aviation standards, we first define a general landing approach cone. It next designs a method to create a dataset of images with appropriate labels from this description. It consists of 14.433 images with a resolution of 2448x2648 that were collected from a total of 32 runways at 16 distinct airports. Approximately 451 images are taken for each approach (or runway). Although most of the dataset is made up of artificial pictures, they include hand-tagged photos from actual landing footage to provide the detection job with a more realistic context. They provide a generator to create these artificial front-view images and automatically annotate the runway corners using geometric transformations.

This paper is structured to comprehensively address developing and utilizing a synthetic dataset for runway recognition, which is crucial for enhancing autonomous landing systems in aviation. It begins with an introduction that highlights the significance of the problem and the motivation behind the research. The methodology section details the X-Plane simulator's data collection process, including the specific conditions and parameters considered, such as weather variations and different altitudes. Following this, the results and discussion section presents the findings from the dataset, emphasizing the impact of weather conditions, day/night operations, and altitude on runway recognition. High-resolution images and their standardized dimensions are also discussed to underline the dataset's precision and applicability. The conclusion synthesizes the key insights and underscores the potential of machine learning in improving autonomous landing systems, advocating for the value of large datasets in facilitating advanced algorithms. Finally, the paper includes author contributions, conflict of interest statements, and a references section to ensure comprehensive attribution and context for further research.

2. Data Description

Today, object detection studies are integrated into our lives in many areas. It has an important place in aviation as pilot assist systems. To contribute to these studies, many dataset studies are presented. In our study, a dataset study was conducted to contribute to this literature. The images were systematically created for 16 airports. These airports included Adana Incirlik Airport (LTAG), Adıyaman Airport (LTCP), Alanya Gazipasa Airport (LTFG), Ankara Esenboga Airport (LTAC), Antalya Airport (LTAI), Balıkesir Koca Seyit Airport (LTFD), Çanakkale Airport (LTBH), Chios Island Airport (LGHI), Diyarbakır Airport (LTCC), Elazıg Airport (LTCA), Erzincan Airport (LTCD), Erzurum Airport (LTCE), Hatay Airport (LTDA), Istanbul Airport (LTFM), Istanbul Ataturk Airport (LTBA), Izmir Adnan Menderes Airport (LTBJ), Kayseri Erkilet Airport (LTAU), Kocaeli Cengiz Topel Airport (LTBQ), Konya Airport (LTAN), Malatya Airport (LTAT), Nevsehir Kapadokya Airport (LTAZ), Rhodes Diagoras Airport (LGRP), Şanlıurfa Airport (LTCS), ¸Sırnak Airport (LTCV), Tekirdag Airport (LTBU), Trabzon Airport (LTCG), Van Airport (LTCI), Zonguldak Çaycuma Airport (LTAS). When we examined the studies in the literature in which artificial intelligence was used in this field, we saw that most of the datasets used were on clear images regardless of weather conditions. That's why we wanted to make a different contribution and add difficult weather conditions to our dataset for the development of algorithms. It was seen that the same situation was valid for the altitude parameter. Thus the lower altitude status was preferred to the higher altitude status. The images were taken for different weather conditions, such as clear, cirrus, scattered, broken, foggy, and stormy at different altitudes. Hereafter,' altitude' refers to the height above an aerodrome. High-altitude images were taken above 10000 feet. Lower-altitude images were taken between 5000 and 10000 feet. Images were not included for altitudes below 5000 feet because other public datasets, like the Places dataset, contained most such low-altitude images. The altitudes were combined with different distances from the aerodrome to the aircraft approximately between 2 and 70 nautical miles, such that the aerodrome was visible from the aircraft. The weather conditions included precipitation variations, cumulus cloud varieties, cirrus clouds, and stratus clouds. The images were taken from different camera angles to create diversity. Figure 1 shows images taken at different times, such as day and night. In contrast, Figure 2 shows examples of images in different weather conditions, such as foggy and rainy, respectively. In Figure 3, low and high-altitude images of the same airport are shown, respectively.

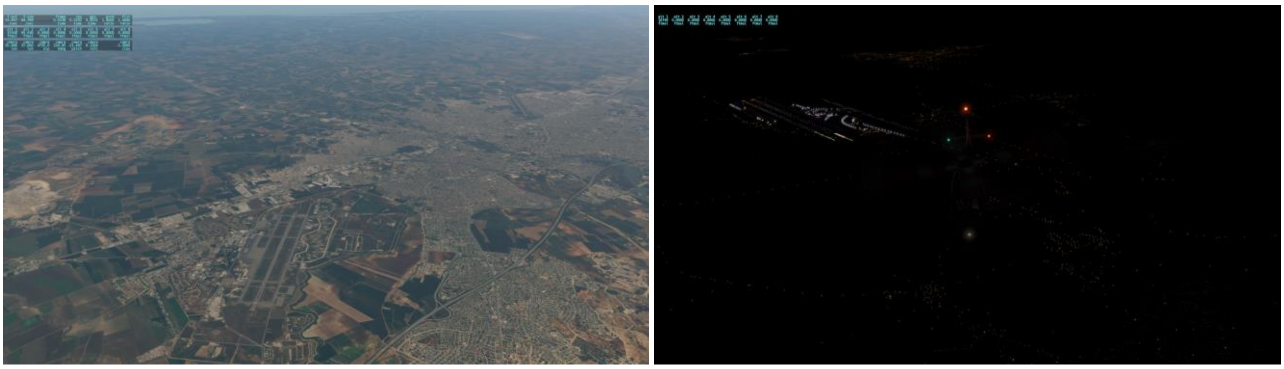

Figure 1. The left side of the figure represents a daytime image, and the right side represents a nighttime image

In addition to helping the algorithms acquire better features, adjusting the camera angle also makes the detection independent of the location of the mounted camera. Images were captured from the sides and as the aircraft approached an airfield in the direction of each runway. Images are captured with the entire airport visible in each view, and partial views of the airport and rotations of views are included. Because bad weather conditions, such as foggy weather are also considered. To use it for aerodrome detection even in closed weather conditions such as foggy rain, attention was paid to the fact that a part of the runway, if not the whole, was visible while creating the dataset.

Figure 2. The left side of the figure represents a foggy image, and the right side represents a rainy image

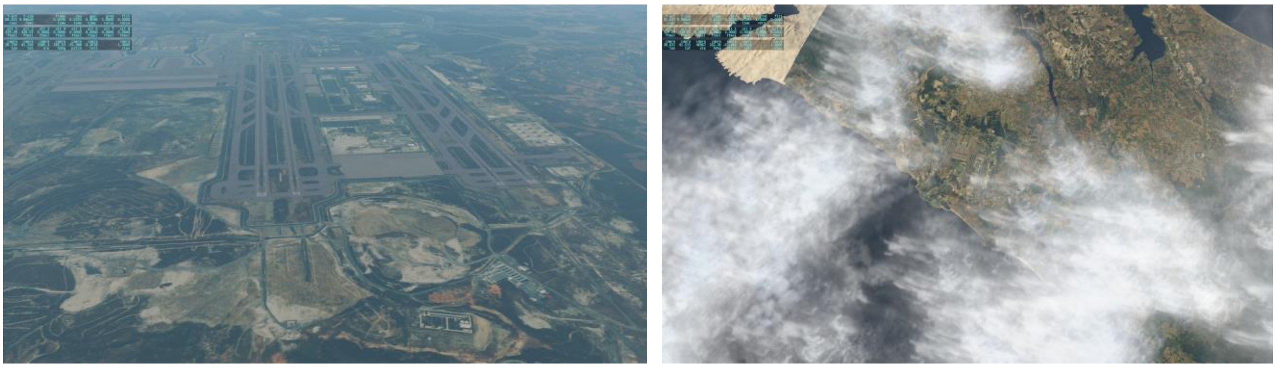

Figure 3. The left side of the figure represents a low-altitude image, and the right side represents a high-altitude image

3. Image Acquisition

This dataset was collected using X-Plane 11, a sophisticated flight simulation software developed by Laminar Research, renowned for its realistic flight physics based on "blade element theory". Widely used by aviation enthusiasts and professionals, it offers detailed global scenery, customizable environments, and a wide range of aircraft models. The simulator supports multiple platforms, including Windows, macOS, and Linux, and even offers Virtual Reality (VR) capabilities for an immersive experience. Additionally, X-Plane 11 is recognized by the Federal Aviation Administration (FAA) for its high level of realism, making it suitable for professional flight training and certification purposes. Simulations were run on equipment featuring an NVIDIA GeForce RTX 3060 GPU and an AMD Ryzen 7 6800H with Radeon Graphics CPU. Ortho4XP v1.15 was combined with X-Plane to create overlays and custom scenery. It is a tool widely used by flight simulation enthusiasts to enhance the realism of X-Plane by creating custom, photo-realistic ground textures. It allows users to generate detailed scenery by downloading satellite imagery and integrating it with elevation data, producing high-resolution orthophotos that accurately represent real-world landscapes. Designed specifically for X-Plane, Ortho4XP replaces the default terrain textures with these realistic images, significantly improving the visual experience of the simulator. Supported by an active community, the tool enables users to customize and enhance specific regions, making flights in X-Plane more immersive and visually accurate. The images were exported by taking screenshots at multiple angles and heights, ensuring the frame rate was above 50. In each image, values such as height, camera angle, frame rate, etc., are displayed in the upper left corner by the sensor opened in the image.

When the literature was reviewed, it was observed that there was a lack of image dataset studies in extreme weather conditions, particularly in Türkiye, in datasets created with X-Plane, as stated in this article. This dataset offers several key advantages compared to existing ones, particularly regarding its diversity and relevance to autonomous landing systems. One of the primary benefits is the inclusion of images captured under challenging weather conditions such as fog, rain, and storms. This is significant because many existing datasets predominantly feature clear weather scenarios, which restricts the performance of trained models in adverse conditions. The trained models' robustness is enhanced by including these challenging scenarios, enabling better performance in real-world situations with varying visibility and weather conditions.

Additionally, a wide range of altitudes, from 5,000 to 70,000 feet, is covered by this dataset, which is crucial for simulating different phases of approach and landing. This variation allows models to be trained on images representing both low and high-altitude approaches, improving their ability to recognize runways from various distances and perspectives.

The superiority of this method is underscored by these enhancements, which provide a more representative and challenging dataset for training deep learning models. These benefits are believed to significantly advance the field of autonomous landing systems and offer a valuable resource for improving model performance in real-world conditions.

The effectiveness of the dataset is further contributed to by the high-resolution images and diverse aircraft types used in the simulations. By capturing images from multiple aircraft and camera angles, various perspectives and viewpoints are ensured, enhancing the generalization capabilities of the models.

In this dataset, 3880 images of 28 different airports around Türkiye are taken with different angles, weather conditions, and aircraft. The total size of this dataset is approximately 13.3 GB. Lighting is important in airport and runway determinations, as it becomes difficult to detect the landforms from the air after dark, that is, at night. In addition, for the sake of diversity and being closer to reality, multiple aircraft were used to obtain the images. This distribution can be seen in the pie chart in Figure 4. The largest part of the data set, which is approximately a quarter slice, was obtained with the CirrusSF50 type aircraft model, and the other large slices consist of Cessna_172SP, Cessna_172SP_G1, and L5_Sentinel type model aircraft. There is not much difference between the number of images obtained from the remaining aircraft models and they are proportionally close to each other.

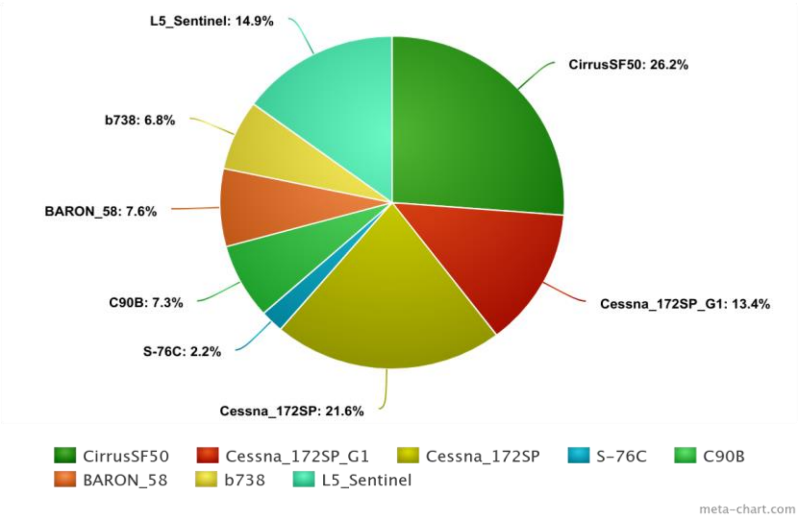

Figure 4. Distribution of aircraft types

To be close to real scenarios and to cover extreme conditions, images containing these weather conditions were also obtained, apart from clear images. The detailed table showing the number distributions of these parameters is included in Table 1. When the distribution of the number of images taken from 28 different airports is examined, it is seen that the airport with the most images is Adıyaman Airport, with 202 images, and the airport with the least images is Ankara Esenboga Airport, with 37 images.

In addition to the weather conditions, the number distribution of the feet where the flights are made and the day/night conditions during the flights according to the airports are shown in Table 2 in more detail. When the distribution is made by considering the feet parameter, the observability of the airport generally increases at low feet, and the observability decreases with higher feet as one moves away from the airport. Considering the literature, since there are not many sources at high altitudes, adding high-altitude images to the dataset is important.

While obtaining images of existing airports, it was imperative to ensure a minimum actual frame rate (f-act) of 50 frames per second (FPS) on the video card, guaranteeing smooth and accurate rendering of the dynamic airport environments. This requirement is crucial for various applications, including real-time air traffic monitoring, surveillance, and security measures, where even minor delays or lags can have significant implications for operational efficiency and safety.

The images' diversity spans from ground level to an impressive altitude of 70,000 feet. It extends up to 70 nautical miles in range, providing a comprehensive aerial perspective of the airport surroundings. This extensive coverage enables comprehensive monitoring and analysis of airport infrastructure, surrounding terrain, and airspace dynamics, offering valuable insights for airspace management, flight planning, and emergency response procedures.

Table 1. Image counts in each airport folder

Airports	Image Count
Adana İncirlik Airport (LTAG)	173
Adıyaman Airport (LTCP)	202
Alanya Gazipaşa Airport (LTFG)	148
Ankara Esenboğa Airport (LTAC)	37
Antalya Airport (LTAI)	184
Balikesir Koca Seyit Airport (LTFD)	155
Canakkale Airport (LTBH)	113
Chios Island Airport (LGHI)	154
Diyarbakir Airport (LTCC)	157
Elazığ Airport (LTCA)	148
Erzincan Yıldırım Akbulut Airport (LTCD)	150
Erzurum Airport (LTCE)	126
Hatay Airport (LTDA)	142
Istanbul Airport (LTFM)	180
Istanbul Ataturk Airport (LTBA)	48
Izmir Adnan Menderes Airport (LTBJ)	136
Kayseri Erkilet Airport (LTAU)	130
Kocaeli Cengiz Topel Airport (LTBQ)	117
Konya Airport (LTAN)	105
Malatya Airport (LTAT)	165
Nevşehir Kapadokya Airport (LTAZ)	43
Rhodes Diagoras Airport (LGRP)	188
Şanlıurfa GAP Airport (LTCS)	130
Şırnak Şerafettin Elçi Airport (LTCV)	161
Tekirdağ Çorlu Airport (LTBU)	152
Trabzon Airport (LTCG)	160
Van Ferit Melen Airport (LTCI)	140
Zonguldak Caycuma Airport (LTAS)	136
Total	3880

High-resolution imaging techniques were employed to ensure optimal image quality and facilitate the easy detection of landforms and infrastructural details. High-resolution images offer enhanced clarity and precision, enabling precise identification of runway markings, terminal buildings, navigation aids, and other critical elements essential for air traffic management and airport operations. To achieve this, rendering options were meticulously configured to operate at the highest settings, maximizing image fidelity and detail resolution.

The images in the dataset adhere to standardized dimensions, with pixel values of 1920 in width and 1080 in height. Standardizing image dimensions ensures consistency and compatibility across various visualization and analysis platforms, facilitating seamless integration into airport planning, simulation, and management software systems. This standardized approach streamlines data processing and analysis, enabling efficient extraction of relevant insights and actionable information from the vast repository of airport imagery.

While 803 flights are categorized under 'Not Clear' conditions at 28 airports, indicating adverse weather conditions such as fog, rain, or snow, the number of flights marked as' Clear' stands at 394. This discrepancy highlights the significant impact that weather conditions can have on flight operations, underscoring the importance of robust safety protocols and the expertise of air traffic controllers and pilots in navigating challenging weather scenarios to ensure passenger safety.

In addition to weather conditions, the distinction between Day and Night operations also plays a crucial role in aviation. The fact that 730 flights were conducted during the day compared to 467 flights during the night emphasizes the preference for daytime operations, which often offer better visibility and favorable weather conditions, contributing to smoother and safer flights. However, it's essential to note the vital role of nighttime operations, particularly in facilitating cargo transportation and accommodating international flight schedules across different time zones.

Moreover, altitude is another critical factor influencing flight operations. Of the total flights, 817 were operated at High Altitude, exceeding 10.000 feet above sea level. High-altitude flights typically involve long-haul routes and require specialized equipment and training due to reduced oxygen levels and lower temperatures. Conversely, 409 flights were conducted below the 10.000 feet threshold at Low Altitudes.

Table 2. Table of situations

Airport	Clear	Not Clear	Day	Night	High Alt	Low Alt	Total
LTAG	106	67	139	34	123	50	173
LTCP	143	59	170	32	165	37	202
LTFG	109	39	111	37	49	99	148
LTAC	20	17	11	26	31	6	37
LTAI	112	72	112	72	130	54	184
LTFD	82	73	115	40	64	91	155
LTBH	68	45	88	25	63	50	113
LGHI	90	64	116	38	33	121	154
LTCC	64	93	125	32	106	51	157
LTCA	89	59	115	33	109	39	148
LTCD	62	88	117	33	111	39	150
LTCE	21	105	105	21	112	14	126
LTDA	38	104	123	19	95	47	142
LTFM	101	79	135	45	112	68	180
LTBA	11	37	30	18	26	22	48
LTBJ	94	42	107	29	56	80	136
LTAU	81	49	105	25	111	19	130
LTBQ	65	52	97	20	69	48	117
LTAN	32	73	76	29	83	22	105
LTAT	42	123	118	47	142	23	165
LTAZ	1	42	43	0	42	1	43
LGRP	110	78	142	46	133	55	188
LTCS	19	111	121	9	95	35	130
LTCV	41	120	135	26	102	59	161
LTBU	40	112	127	25	94	58	152
LTCG	82	78	117	43	83	77	160
LTCI	72	68	111	29	128	12	140
LTAS	69	67	87	49	67	69	136
TOTAL	394	803	730	467	817	409	3880

Low-altitude flights often encompass short-haul journeys, regional routes, and flights approaching or departing from airports, necessitating different navigation procedures and considerations for air traffic management and terrain clearance.

The 28 airports and the aircraft type of the obtained images were named in Figure 5 to be read systematically. The airport's ICAO code is made up of four letters. These codes are created using divisions made between nations and regions. The first letter identifies the geographical area where the airport is located, while the second letter identifies the nation. Usually, the other two letters are given in alphabetical sequence. The first part of naming the images is to provide an ICAO code of which airports they belong to. For example, naming the images of ADANA INCIRLIK Airport, ALANYA GAZIPASA Airport, ANKARA ESENBOGA Airport, ANTALYA Airport, BALIKESIR KOCA SEYIT Airport, and CANAKKALE Airport airports start with LTAG, LTFG, LTAC, LTAI, LTFD, and LTBH respectively. After the ICAO part, naming is done according to aircraft types. Finally, the sample number concat and forms the image name. According to all these rules mentioned above, the file name of the first image of the "ADANA INCIRLIK Airport" species and with the "CirrusSF50" aircraft will be "LTAG_CirrusSF50_01.png". Figure 6 shows the structure of the dataset.

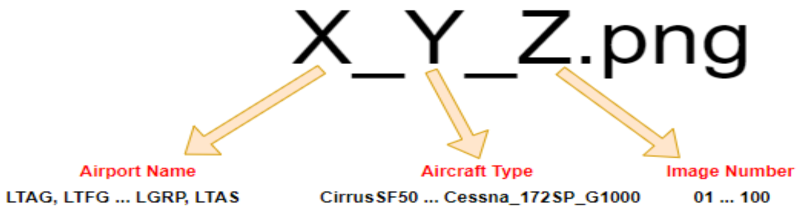

Figure 5. Renaming files

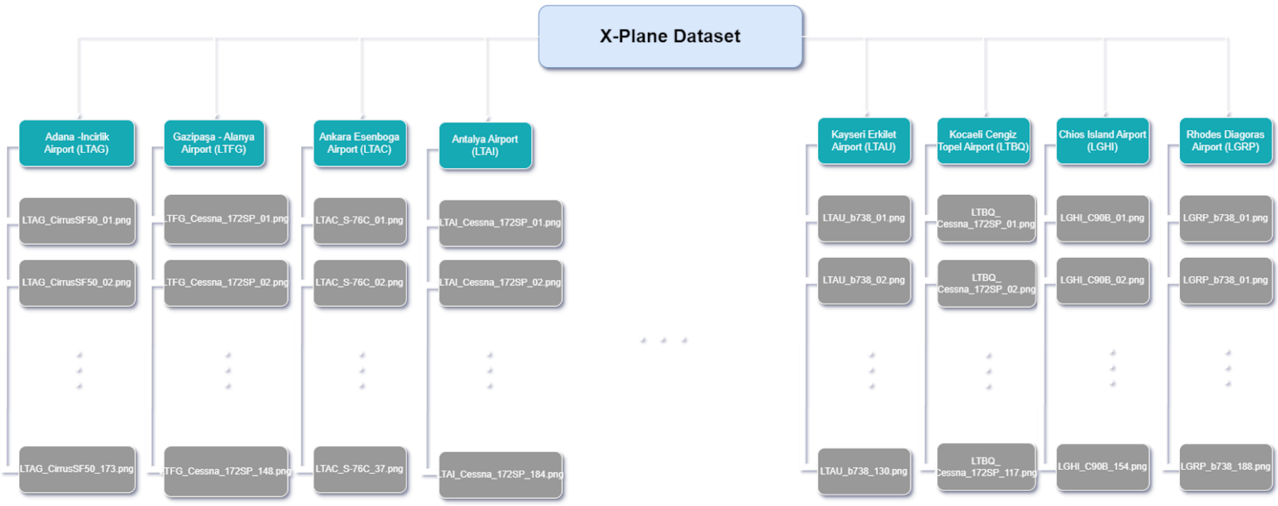

Figure 6. File structure of the dataset

4. Conclusion

As autonomous systems gain popularity, a significant hurdle lies in acquiring enough relevant real-world data. The aerospace industry, particularly autonomous landing systems, has a strong practical and economic interest. However, open-source datasets are scarce, specifically focused on aerial images. To solve this problem, we offer a collection of aerial images for runway recognition during the approach and landing phases. The collection consists of synthetic images from the X-Plane simulator, which attempted to create a dataset based on improving detection under various weather conditions and periods, especially in poor visibility. Few image datasets are available, including runways seen from the aerial front view. One way to solve this issue is to use synthesized data, which enables the construction of more scenarios at a lesser cost. Using a flight simulator is a frequent remedy to this well-known issue in aviation [20]. Pilots, for instance, may practice emergency maneuvers and familiarize themselves with flight controls and protocol owing to simulators. The requirements and rules of the relevant authorities, such as the FAA in America and the EASA in Europe [21], determine the complexity and realism of such simulators.

Based on EASA and [22] findings, a significant portion of non-commercial airplane accidents happen during the landing phase under favorable weather conditions. These accidents are frequently attributed to human errors, with perception being identified as the most critical risk factor. This underscores the importance of developing safer landing systems. Implementing autonomy in these systems can serve as an initial measure to address this problem, beginning with pilot assistance and gradually progressing toward fully autonomous landings in the distant future. The advancement in this direction will inevitably depend on utilizing Artificial Intelligence for runway detection, which facilitates the computation of the aircraft's position. In this article, we have provided a clear and precise description of this task, emphasizing the significance of large datasets to facilitate the application of DL algorithms. Utilizing machine learning can create innovative technology that enhances cockpit capabilities and pilots' awareness of their surroundings. This dataset seeks to help with the value machine learning can bring to this field by highlighting this potential through the visual detection of airports.

Based on the study results, future research could explore the integration of this dataset with real-world aerial imagery to further enhance the robustness of autonomous landing systems. Expanding the dataset to include more diverse airport environments and extreme weather conditions could provide deeper insights and improve algorithm performance. Leveraging advancements in deep learning and artificial intelligence, it is also recommended to develop adaptive models that dynamically adjust to new and unforeseen variables, ensuring even greater reliability and safety in autonomous aviation operations. This forward-looking approach will pave the way for significant advancements in autonomous flight technologies.

One key direction for future research is the integration of our synthetic dataset [23] with real-world aerial imagery. Combining synthetic data with actual flight data could enhance the robustness and accuracy of autonomous landing systems by providing a more comprehensive dataset that includes real-world variability not captured by simulations alone. This integration could also help validate the effectiveness of models trained on synthetic data in operational environments.

Author Contributions

The third author directed the project and supervised this study's findings. The second and third authors devised the main conceptual ideas and developed the theoretical framework. The first author performed the data collection. The first author wrote the manuscript with support from the second and third authors. The second and the third author reviewed and edited the paper. All authors read and approved the final version of the paper.

Conflicts of Interest

All the authors declare no conflict of interest.

Ethical Review and Approval

No approval from the Board of Ethics is required.

References

[1] Z.-Q. Zhao, P. Zheng, S.-t. Xu, X. Wu, *Object detection with deep learning: A review*, IEEE Transactions on Neural Networks and Learning Systems 30 (11) (2019) 3212–3232.

[2] G. Cheng, J. Han, X. Lu, *Remote sensing image scene classification: Benchmark and state of the art*, Proceedings of the IEEE 105 (10) (2017) 1865–1883.

[3] G. Cheng, J. Han, P. Zhou, L. Guo, *Multi-class geospatial object detection and geographic image classification based on collection of part detectors*, ISPRS Journal of Photogrammetry and Remote Sensing (98) (2014) 119–132.

[4] G. Cheng, J. Han, *A survey on object detection in optical remote sensing images*, ISPRS Journal of Photogrammetry and Remote Sensing (117) (2016) 11–28.

[5] G. Cheng, P. Zhou, J. Han, *Learning rotation-invariant convolutional neural networks for object detection in VHR optical remote sensing images*, IEEE Transactions on Geoscience and Remote Sensing 54 (12) (2016) 7405–7415.

[6] *2D semantic labeling - Vaihingen dataset*, https://paperswithcode.com/dataset/isprs-vaihingen, Accessed on 21 June 2023.

[7] T. Bakirman, E. Sertel, *HRPlanes: High resolution airplane dataset for deep learning*, International Journal of Engineering and Geosciences 8 (3) (2022) 212-223.

[8] G. Cheng, J. Wang, K. Li, X. Xie, C. Lang, Y. Yao, J. Han, *Anchor-free oriented proposal generator for object detection*, IEEE Transactions on Geoscience and Remote Sensing (60) (2022) 1–11.

[9] W. Yu, G. Cheng, J. Wang, Y. Yao, X. Xie, X. Yao, J. Han, *MAR20: A benchmark for military aircraft recognition in remote sensing images*, National Remote Sensing Bulletin 27 (12) (2024) 2688–2696.

[10] J. Ding, N. Xue, G.-S. Xia, X. Bai, W. Yang, M. Y. Yang, S. Belongie, J. Luo, M. Datcu, M. Pelillo, L. Zhang, *Object detection in aerial images: A large-scale benchmark and challenges*, IEEE Transactions on Pattern Analysis and Machine Intelligence 44 (11) (2022) 7778–7796.

[11] B. Zhou, A. Lapedriza, A. Khosla, A. Oliva, A. Torralba, *Places: A 10 million image database for scene recognition*, IEEE Transactions on Pattern Analysis and Machine Intelligence 40 (6) (2017) 1452–1464.

[12] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, L. Fei-Fei, *ImageNet large scale visual recognition challenge*, International Journal of Computer Vision (115) (2015) 211–252.

[13] T.-Y. Lin, M. Maire, S. Belongie, L. Bourdev, R. Girshick, J. Hays, P. Perona, D. Ramanan, C. L. Zitnick, P. Dollár, *Microsoft COCO: Common objects in context*, in: D. Fleet, T. Pajdla, B. Schiele, T. Tuytelaars (Eds.), Computer Vision–ECCV 2014: 13th European Conference, Zurich, 2014, pp. 740-755.

[14] G. A. Miller, *WordNet: A lexical database for English*, Communications of the ACM 38 (11) (1995) 39–41.

[15] X. Sun, P. Wang, Z. Yan, F. Xu, R. Wang, W. Diao, J. Chen, J. Li, Y. Feng, T. Xu, M. Weinmann, S. Hinz, C. Wang, K. Fu, *FAIR1M: A benchmark dataset for fine-grained object recognition in high-resolution remote sensing imagery*, ISPRS Journal of Photogrammetry and Remote Sensing (184) (2022) 116-130.

[16] L. Yu and P. Gong, *Google Earth as a virtual globe tool for Earth science applications at the global scale: progress and perspectives*, International Journal of Remote Sensing 33 (12) 2012 3966–3986.

[17] Google. *Google Earth studio*, https://www.google.com/intl/eng/earth/studio/, Accessed on 21 June 2023.

[18] Google. *Google Earth studio*, https://www.google.com/earth/about/versions/, Accessed on 21 June 2023.

[19] M. Ducoffe, M. Carrere, L. Féliers, A. Gauffriau, V. Mussot, C. Pagetti, T. Sammour, *LARD – Landing approach runway detection – dataset for vision based landing*, arXiv preprint arXiv:2304.09938 (2023).

[20] A. T. Lee, Flight simulation: Virtual environments in aviation, Routledge, New York, 2017.

[21] T. Longbridge, J. Burki-Cohen, T. Go, *Flight simulator fidelity considerations for total airline pilot training and evaluation*, AIAA Modeling and Simulation Technologies Conference and Exhibit,

Montreal, Quebec, 2001, pp. 4425

[22] G. Balduzzi, M. F. Bravo, A. Chernova, C. Cruceru, L. van Dijk, P. de Lange, J. Jerez, N. Koehler, M. Koerner, C. Perret-Gentil, Z. Pillio, R. Polak, H. Silva, R. Valentin, I. Whittington, G. Yakushev, Neural network based runway landing guidance for general aviation autoland, U.S. Department of Transportation Federal Aviation Administration, New Jersey, 2021.

[23] N. Bor, (2024). AeroRunway, *Zenodo.* https://zenodo.org/records/11577457, Accessed on 22 September 2024.