GARD - Gustavo's Awesome Runway Dataset - A Synthetic Runway Image Dataset built with Diffusion Models

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Contents

Introduction

Aviation is regarded as highly safe medium of transportation, and is marked by high-degrees of automation, reducing the biggest cause (85% of the general

aviation crashes) of accidents: pilot error [1]. The increase in automation reduces cognitive, fatigue, and inexperience risks for pilots and is and important factor, alongside better training and safety regulations, to the to the rapidly decrease (1959-2024) in the fatal accidents rate [2].

Although the approach and landing phases are the minority of the flight time, they contribute disproportionally to the number of accidents, this data being corroborated by the two major commercial airplane companies Boeing (7% in approach, 36% in landing) [3], and Airbus (59% in landing, 11% in approach) [4].

Contributing as a risk-factor, the approach and landing phases are flight parts that require heavy human intervention. This has led to an increased interest in the development of autonomous landing (autoland) systems, which are systems that can autonomously navigate the civil aircraft or UAV (unmanned aerial vehicle, e.g. drones) during the landing procedure. Currently, most autoland systems are based on radio signals that provide guidance to the system, such as ILS (instrument landing system) and PAR (precision approach radar).

Radio-based autonomous landing systems have the advantage of allowing the landing in extremely adverse weather conditions and low visibility, but they have a high-cost of deployment and maintenance, can suffer from electromagnetic and radio interference, and require on-the-ground specialized equipment to support the aircraft (e.g. localizer and glideslope). (TODO: add reference?)

The recent advancements in the Computer Vision field have sparked increasing interest [5] in developing vision-based autoland systems, which use visual navigation to guide the aircraft during the approach and landing phases. In [6], the authors describe key advantages of vision-based autoland systems for UAV: autonomy, low cost, resistance to interference, and ability to be combined with other navigation methods for higher accuracy. Vision based landing is especially attractive for drones that often need to land in extreme situations when in military use, environmental monitoring, and disaster relief, where runways may not have the necessary equipment for radio-based systems.

Two key parts of a autonomous landing system is detection and segmentation of runways, the former being responsible for detecting the presence and locating the runway on the image by drawing a bounding box around the runway, and the latter, more granularly, works at the pixel-level, identifying the exact shape of the object on the image.

Detection and segmentation methods can be separated into two broad fields: traditional methods and deep-learning based methods. Traditional methods employ handcrafted features and mathematical rules to segment images, e.g. recognition of texture, line segments, and shape features of runways [7] [8]. They tend to be faster to run and not require training, but because they require handcrafted rules, they often fail to generalize to out-of-sample images and complex real-world scenarios that involve similar objects like roads and multiple runways and adverse weather conditions.

Compared to traditional methods, deep-learning based ones have shown improved generalization and performance on out-of-sample images, with the latest published runway segmentation papers all having used this approach and getting better results than traditional methods [9] [10].

However, because of their data-hungry nature, previous research [10] [9] [11] [12] all note the lack of publicly available, high-quality, large, real-world datasets of aeronautical images to be used in the task of runway segmentation. To close this gap, the researchers have built and published datasets comprised of synthetic images collected from flight simulators such as X-Plane [11] [10], Microsoft Flight Simulator [9], and images collected from Google Earth Studio [12].

While these synthetic datasets have contributed to advancements in the field, there still an opportunity of an open-source, realistic, high-quality dataset that has runway image data encompassing a greater variety of weather and lighting conditions, environments and runway structures, and, even better, an open-source image generator that is capable of generating novel images or augmenting an existing dataset.

In recent years, striking advancements were made in the field of image generation models, with several closed-source and open-source models being published for general use, such as DALL-E [13], Midjourney [14], Kandinsky [15], and Stable Diffusion [16]. These recently state-of-the-art models are latent diffusion models (LDM), which have surpassed in performance the previous state-of-the-art techniques that were based in generative adversarial networks (GANs). These image-generation models are now so capable of generating realistic images that researchers are studying the impacts of generative AI on the spread of fake news [17].

These recent research advancements opened a new opportunity window to use synthetic data to close the gap on the lack of real images in object detection and segmentation tasks. There have already been progress in this idea applied to other areas such as medical images [18], urban applications [19], and apple detection in orchards [20]. But up to my knowledge of public research, that has been no generative AI-based open-source dataset that could be used for the task of runway detection and segmentation.

To address the challenges of lack of data in the context of runway segmentation tasks, this paper introduces a novel, open-source, data augmentation technique based on a multi-step Stable Diffusion pipeline that extracts features existing datasets and outputs images that retain a similar structure but are customizable in respect to scenery, weather, and lighting conditions, guided by a text prompt. The images generated by the pipeline are already labeled and don't require handcraft labelling.

This technique is then used to construct a novel, large-scale, high-resolution, open-source, dataset of labeled runway images with good coverage of image variants in respect to weather, lighting, background, and runway occlusion.

This approach can greatly increase the availability of runway images to be used in other research projects, and, by virtue of being open-source, allow other researchers to generate and augment their own synthetic datasets with their own desired characteristics.

This new dataset is evaluated both theoretically by measuring the similarity of generated images to real images using metrics such as Fréchet Inception Distance (FID) and Structural Similarity Index (SSIM), and practically by introducing a runway detection and segmentation pipeline based on state-of-the-art models and comparing the performance of the model when training it with an existing dataset and when training with the new dataset.

The template chosen for this project is "Gather your own dataset". TODO: explain chapters.

Literature Review

Deep-learning based runway segmentation

In [21], the authors give a broad literature review of the prior work on runway segmentation, that uses traditional methods and deep-learning methods. They break down the traditional methods into two categories: template-based and feature-based approaches, the former uses a template image that is compared to the actual image on a pixel-by-pixel basis, and the latter uses edges, corners, texture, and others to detect and localize the runway. They find that most works that use deep-learning methods are focused on airport detection, and not runway segmentation, showing their paper relevance.

They then propose a two-module pipeline, where the first module is responsible for detecting if a runway is present in the image and the second module is responsible for localizing the runway when it is present. For the detection module, they fine-tune a pre-trained ResNet50 model, achieving an accuracy of 97%. And for the localization module, they experiment with three approaches: hough transform, line segment detector, and a CNN, which performed with a localization score of 0.8 (mean Intersection-over-Union (IoU)).

The study shows that deep-learning methods are a valid and effective pathway to runway detection and segmentation, but there are significants shortfalls with it from a practical point of view on building a vision based landing system. The top-down perspective from the satellite images of the used dataset (*"Remote Sensing Image Scene Classification"* [22]) are unrealistic for fixed-wing aerial vehicles approach and landing, because the onboard system needs to detect and segment runways from the perspective of the aircraft. Secondly, there are no discussions on dataset diversity such as adverse weather and lighting conditions and the performance of the pipeline in those cases.

In [11], the authors note the lack of large-scale, publicly available datasets for the field of runway segmentation. Trying to alleviate this problem, they

propose "*BARS: A Benchmark for Airport Runway Segmentation*", a 10256-image labeled runway dataset, with images collected from X-Plane, a FAA-certified flight simulator. The images were collected from several simulated flights under different weather and at different times, across 40 airports, to generate a diverse dataset and far more suitable for the task of vision based landing than the one used in [21].

To test the efficacy of this new dataset, they experiment with several segmentation methods (e.g. Mask R-CNN, YOLACT, SOLO) and report the trained models' performance, that have a wide range of reported precisions (AP50 of 90.98 for the best performing one, and 62.18 for the worst performing one).

At the same time, using a simulator for generating synthetic images restricts the diversity of scenarios that can be produced (e.g. it is not possible to create scenarios in airports that are not included in the simulator). Also, because it is a closed-source simulator, it is not easy or accessible for other researchers to expand on this dataset by adding more diverse and unseen scenarios. And the manual labelling process using LabelMe [23] also increases the cost of reproducing or expanding the dataset. Another problem of the work is that the authors decided to publish their work on Baidu, which makes it impossible to access the full dataset without installing a third-party program on the computer.

The way the authors decided to test *BARS* experimentally highlights a situation that is similar to the problem encountered by Nobel-winning economist Eugene Fama on his work on Efficient Markets [24] : the joint hypothesis problem. The joint hypothesis problem is the fact that all test of market efficiency are simultaneously tests of market efficiency and the asset pricing model that defines expected returns. Therefore, anomalous market returns might be due to market inefficiency, an inaccurate model, or both.

Similarly, when proposing new datasets, one has to always be mindful that empiric tests of training models on this new datasets is always a joint test of the quality of this new dataset and the performance of the models being trained on it. A model's poor performance might indicate deficiencies in the dataset (e.g., lack of diversity, poor annotation quality, or unrealistic synthetic images), a reflection on the model's limitations of handling a more realistic dataset, with more complex tasks, or both. On the other hand, if a model performs really well, it doesn't automatically prove that the dataset is good. It could just mean that the dataset happens to match what the model is already good at, without really testing how well it would work on real-world runway images.

In [9], the authors propose *ERFE: efficient runway feature extractor*, a runway detection model that is able to extract semantic segmentation and feature lines. Also highlighting the difficulties of runway datasets, the authors propose a new synthetic image dataset *FS2020*, with images extracted from Microsoft's Flight Simulator 2020. They did have access to BARS, but argued that the images from X-Plane were unrealistic, especially in regards to ground texture and lighting condition. Their proposed dataset contains 5587 high-resolution (1920x1080)

images, sampled from different runways, airplane positions, and lighting and weather conditions.

After image collection, the authors used the LabelMe toolbox to provide two types of annotation for each image: segmentation masks and feature lines with 6 categories (left edge, right edge, center line, aiming point front, threshold rear and PAPI lights).

The authors highlight the need for fast and accurate inference in the context of a fast-moving airplane. Thus, they chose to build a deep-learning model based on MobilenetV3, a convolutional neural network designed for mobile phone CPUs. They claim that their trained network has the capacity of processing 200 high-resolution images per second.

Their work excels in demonstrating the feasibility of an onboard runway segmentation system, and their FS2020 dataset is a rich contribution to the field, especially as it is accompanied by segmentation and feature lines labels. At the same time, it is a smaller dataset when compared to BARS, and because it is also based on a closed-source simulator, it has the same trade-offs associated to it. The authors also didn't compare their model's performance when trained with another dataset like BARS, which would make it easier to understand how well their dataset generalizes compared to others. Without this comparison, it is unclear whether their model performs well because of the dataset's quality or simply because the dataset aligns well with the model's training conditions. On the other hand, they chose to host the dataset on Kaggle, a widely used and known platform for hosting public datasets.

In [12], the authors still highlight the lack of open-source datasets of aerial-images of runway and present a novel 17000 image dataset alongside an image generator. They use Google Earth Studio, positioning a camera inside the studio in the perspective of an airplane nose pointing to the runway. They publicly shared their generator scripts that automatically output labeled images without the need of human intervention. Alongside the generated synthetic data, they manually labeled real videos from airplanes landing.

Their method has considerable advantages over simulator-based ones: it is possible to reproduce and generate new images for virtually free, as Google Earth Studio is closed-source, but free tool, and the images are already labeled in the generation process. On the other hand, the images are less realistic than the simulator-based ones, as the ground texture is worse and it lacks different weather conditions and night view is simulated by a simple reduction in ambient brightness.

The authors don't train any detection or segmentation models based on the *LARD* dataset in the paper, but [25] did introduce YOLO-RWY, a YOLO-based [TODO:CITE YOLO] deep-learning model, and trained it using LARD, reporting that it has *"strong generalization and real-time capabilities"* [25]. The authors highlight how the limited nighttime and adverse weather samples in

LARD may affect performance in extreme conditions, and they did include a data augmentation step in their training pipeline.

In [10], the authors built VALNet, a model based on YOLO and that uses band-pass filters to be able to handle large-scale changes and input image angle differences in the context of runway segmentation. Among the reviewed papers on runway segmentation models, it is by far the most advanced, with a novel model architecture and extensive experiments comparing its results with other options, such as YOLOv8 and Mask R-CNN.

The paper also cited the dataset scarcity challenge, and proposes a new dataset called *RLD (Runway Landing Dataset)*, with 12239 images with a resolution of 1280x720. The images are sourced from X-Plane, similarly to the already reviewed BARS. The dataset was also manually labeled using LabelMe, and the dataset is also hosted on Baidu. Although it is the largest simulator-based dataset reviewed in this paper, it has the same advantages and disadvantages previously reviewed simulator-based datasets.

Image generation models

GANs (generative adversarial networks), were introduced by [26], and they consist of two neural networks, the Generator and the Discriminator, engaged in adversarial training. The generator is responsible for creating synthetic images (in the context of image GANs) and the discriminator is responsible for evaluating the authenticity of images. During training, the generator gets better at creating realistic images and the discriminator gets better at differentiating real from synthetic images.

In [27], the authors give a survey on the main issues of GANs and their applications. They show how GANs can be effectively used for data augmentation, and with other GAN architectures such as Semi-supervised GAN (SGAN), there can be a model that outputs labeled images. But, GANs suffer from a well-known problem called "mode collapse", where the generator learns to produce only one or a few specific patterns that fool the discriminator, making the range of images generated by the model less diverse.

Diffusion models, introduced in [28], are a generative approach based on iterative denoising. Diffusion models work by progressively adding noise to an image (called the forward process) and then training a network that learns how to remove noise from the image (the reverse process).

Figure 1: Diffusion forward process

The intuition of Diffusion models is that, if a model can be trained to predict the noise in an image at a *timestep*, we can start at pure noise, then repeatedly

call this model and remove the noise from the image, at each step making a less noisy image.

A key architecture used in diffusion models are U-Nets, introduced in [29]. The U-Net is composed of two parts: an encoder and a decoder. The encoder transforms the image into a compressed form that retains essential features. This compressed data is called a "latent". The decoder can then operate on this latent and output some data related to the input data. In the original paper, they used the U-Net to extract biomedical segmentation data. In Diffusion models, the U-Net is used as the model that predicts the noise from an image.

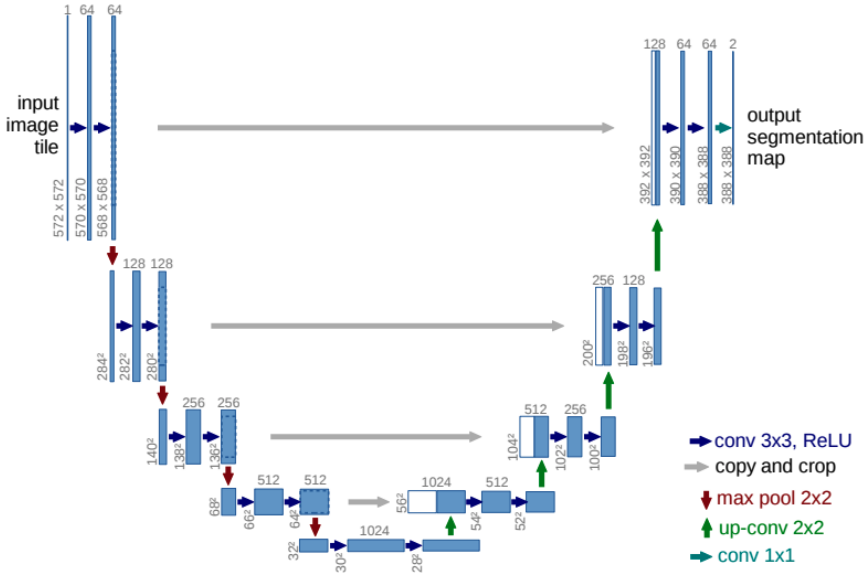

Figure 2: Figure from [29]

Although recently diffusion models have emerged as the new state-of-the-art architecture for image generation [30], they do have disadvantages. Namely, their inference time is slower than of GANs, they have a higher computational cost, and by themselves, they lack mechanisms for precise editing of the image aside from the text prompt.

This problem of controlling the generated image was tackled by [31], that introduced ControlNet. ControlNet is a neural network that allows spatial conditioning to pre-trained text-to-image models. With it, it is possible to use canny edges, human poses, and segmentation masks to control the final result of the image. This allows greater control over the generation of synthetic images, such as the positioning of a runway in an image or control over the markings and detailed paintings on the runway.

Synthetic datasets built with diffusion models

In [18], the authors cite a similar data scarcity problem in the field of medical images, specifically, gastrointestinal images. To solve this problem, they built a pipeline that used diffusion models to generate labeled gastrointestinal polyp images.

They started by clustering the training images and masks into 20 different clusters, and after that, training a four-channel (3 for RGB and a binary one for the mask) DDPM (Denoising Diffusion Probabilistic Models) model for each cluster. The models were trained with a fourth channel so that the model outputs an image and the associated mask along with it, requiring no human labelling. They used the RePaint [32] technique to guide the diffusion process so that the polyp was always generated in a specific area of the images, and they also used styling techniques so that the generated images were realistic.

They compared the diffusion generated images with a GAN model generated images and found that the diffusion images were closer to real ones. The study trains several diffusion models to address the problem of large variation between images in the dataset, making each diffusion model "specialized" in generating images similar to its cluster. The paper shows promising results that we can augment image datasets with diffusion models, but only low resolution images were generated (256x256 pixels) and a larger variety of images would require training more independent models.

In [19], the author explored using text-to-image diffusion model to generate urban traffic images for vehicles detection and classification. The author used the trained Kandinsky 2.2 model to generate images using prompt engineering, the practice of crafting a prompt so the image contains the necessary details. 192 different prompt variants were used to generate 1000 images with different combinations of traffic density, type of vehicle, location, weather condition, time of day, and camera location. The paper shows how far off-the-shelf models are capable of generating realistic images that can be used to train detection algorithms. But, it does not compare images generated by different models and the images have to be manually labeled.

In [20], the authors studied the effectiveness of fine-tuning a pre-trained Stable Diffusion model for the purpose of generating datasets, applied to apple detection in apple orchards. They separated their baseline dataset into two datasets: green apples and red apples. After that, they fine-tuned two Stable Diffusion models with DreamBooth, and then generated a whole dataset. They used a trained apple detection model for baseline image annotations and then manually refined these annotations. To experimentally test the effectiveness of their datasets, they trained multiple YOLO object detectors on the baseline and synthetic datasets and compared the results. In their study, object detectors performed similarly when trained on their synthetic dataset and when trained on real images datasets. Their approach shows promising results in dataset generation with Stable Diffusion, although there is a lack of diversity (e.g. weather conditions,

lighting conditions, different backgrounds, etc...) in both the baseline dataset that makes it easier to generate a synthetic dataset that is similar to the original.

Evaluation of Synthetic Data

Across the previously mentioned works, two types of evaluation were common: theoretical similarity and experimental performance. Theoretical similarity were done using metrics such as FID (Fréchet Inception Distance) [33] and SSIM (Structural Similarity Index) [34], which measure the similarity between two images. Theoretical similarity was used to evaluate the synthetic datasets in [18]. Experimental performance, on the other hand, is about training a real model on the synthetic dataset and comparing the results. Experimental performance was used to evaluate the synthetic datasets in all runway segmentation papers covered in this review, except for LARD, and in [19] and [20].

Both forms of testing are valid and have their trade-offs. Theoretical similarity is faster and easier to measure, but heavily depends on what images are included in the test. And if a dataset contains very different images' structures than the original, even if they are high-quality, the FID/SSIM give worse values. On the other hand, experimental performance tests the dataset in a realistic setting, evaluating how it will be used by other researchers, but suffers from the joint dataset-model problem covered previously.

Design

Project overview

The literature review has shown the importance of large-scale, public, and diverse datasets for deep-learning projects, specifically, in the field of runway detection and segmentation, where there is currently a lack of a dataset of real images with these characteristics. To address this challenge, previous work on the field has relied on synthetic data, mainly collected from flight simulators, which poses a significant cost barrier to the expansion of these datasets as these simulators are usually paid and closed-source, and the collected images require manual labelling.

At the same time, the emergence of diffusion models as the new state-of-the-art technique in image generation has opened a new window of opportunity in building synthetic datasets. Although this idea of using diffusion models to build synthetic datasets has been explored in other fields, there is no known work applying it to the runway segmentation research field.

This project's primary research question is how can a suitable synthetic image dataset be built for computational vision tasks without the need of images extracted from simulators or similar solutions. To answer this question, the project uses the field of vision-based landing and builds a synthetic runway image dataset.

The primary users of this project are researchers that may use the dataset and techniques provided in this project to build models for runway detection. Secondary users might be researchers interested in synthesizing their own datasets for computational vision tasks such as classification or segmentation.

With these end-users in mind, this projects delivers a two-fold contribution: a novel modular data augmentation pipeline that can increase the diversity of an existing dataset, while maintaining key features and structures; and using this data augmentation pipeline to generate a fully synthetic runway images dataset based on existing public datasets.

The proposed research question begs the question of what constitutes a "suitable synthetic image dataset". Here, we rank the following characteristics that make an image dataset suitable:

1. **Human-judged realism**: humans subjectively judge the images as credible and realistic. When comparing side-by-side the images of the generated dataset with other datasets, the perceived quality of the images are the same or better.
2. **Detection by existing models**: fine-tuned models on available datasets can detect the presence and segmentation of the desired data (runways in this project) in the images.
3. **Data diversity**: the dataset has good data diversity, including edge cases and several data variations.
4. **Model training**: an existing architecture can be trained on the dataset and achieve a reasonable performance or a pre-trained model can be fine-tuned and have their performance improved.

Data augmentation pipeline

On earlier prototypes, several diffusion techniques such as prompt engineering, prompt weighting, unconditional image generation, inpainting and textual inversion were tried. Most of them failed to, standalone, generate realistic runway images with detailed and accurate markings. The most successful attempt was using ControlNet with an input canny edge, alongside well-crafted prompts to guide the text-to-image model. Because the canny edge was extracted from an existing runway image, the generated image faithfully respected the runway shape, position, markings and texture. Thus, the data augmentation pipeline is based around using a text-to-image diffusion model with ControlNet.

The data augmentation pipeline is composed of five separate modules, that can each be independently developed and improved, or totally replaced without affecting the overall functioning of the pipeline. This modularity and separation of concerns is good software engineering practice and aids on future research developing on this project.

Template image selection module: this step selects the "template images" that will be used in the pipeline. The template images are existing images

in public datasets that are used to extract the overall structure of the image containing the runway to be used in the image generation step. Ideal template images have clear visibility of the runway and the surrounding background. The output of this module is a folder with pairs of image files and label files. This module could be automated by using a combination of a runway detection software to filter ambiguous images and image description software to filter bad weather or bad lighting conditions. Or, this module could be done with manual help with a tool that allowed the human to either accept or reject an image.

Edge extraction module: this step uses the template images as input, processes them, and outputs canny edge images, to be used as inputs for ControlNet, alongside the according label for that image.

Base Image generation module: this step uses as inputs the canny edges, a list of text prompts, and a number of how many images should be generated for each pair of canny edge and prompt. It then uses a text-to-image model with ControlNet to generate base images. These images should be, similarly to the template ones, images with clear visibility of the runway and its surroundings. Thus, although we expect high-quality images as output, it will not be a diverse set of images. This module also outputs the labels for each image, adding metadata of what model, seed, and prompt was used.

Filtering module: this step filters out the bad images generated in the previous module. Similarly to the template selection module, it can be done manually or automated by a runway detection tool.

Variant image generation module: this module uses as input the filtered base images and a list of "diversity prompts". These diversity prompts are text prompts designed to be an input to an image-to-image model, so that the base dataset generated can be expanded to have more diversity in terms of background scenery, weather, and lighting conditions.

Evaluation

Following the standards of evaluation of synthetic datasets presented in the literature review, and our definition of what constitutes a suitable synthetic dataset, two types of evaluation will be done on the dataset: intrinsic and experimental evaluation.

Intrinsic evaluation measures the quality of a dataset by its intrinsic characteristics, such as image realism, resolution, diversity, and size. Ideally, to judge human-based realism, a group of subject experts would be assembled to judge the images, but because of time-constraints, this won't be done.

Instead, it will be replaced by metrics of image similarity between template images and the generated base images. Through metrics such as FID (Fréchet Inception Distance) and SSIM (Structural Similarity Index) it is possible to know how similar or different the images are from one another, and if they retain

a similar structure such as the runway shape, position, and markings, and a similar background.

Other metrics such as size and image resolution will be reported. Data diversity will also be reported based on the generated images' text prompts. This doesn't guarantee full accuracy as there is a possibility of the model "hallucinating" and not generating a certain desired characteristic (e.g. rain, snow, runway occlusion), but nonetheless allows a good estimate to be reported.

Experimental evaluation is about using the dataset to train one or a collection of models and evaluating their performance empirically. It is an imperfect measurement, as there is a lot of moving parts when training a model, and, as seen on the literature review, a poor performance might be due to the dataset quality or an inherent flaw in the model's architecture. However, this type of evaluation is still widely used and a standard in testing synthetic datasets.

As it is not the focus of this project building a new architecture for runway segmentation, the experimental evaluation will be restricted to training and fine-tuning existing detection and segmentation models, such as YOLO.

Using a pre-trained segmentation model, comparisons will be made between the performance of training on this new synthetic dataset and of existing datasets, and the resulting performance when detecting a real images dataset. Also helping in assessing the realism of the images in the synthetic dataset, the accuracy of a model trained on an existing dataset trying to detect runways on the synthetic dataset will be reported.

Old Design

Methodology

The background research has shown the importance of datasets for researchers working on the field of detecting runways for the task of automated aircraft vision-based landing. Real-image datasets are too small to be used in deep-learning model training. Synthetic datasets bridge the gap of data availability and use simulated images from programs such as X-Plane, Microsoft Flight Simulator and Google Earth to generate the runway images.

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3. **Data diversity**: the dataset has good data diversity, including edge cases and several data variations.
4. **Model training**: an existing architecture can be trained on the dataset and achieve a reasonable performance or a pre-trained model can be fine-tuned and have their performance improved.

Hypothesis and experiments

The emergence of diffusion models for image generation creates a golden opportunity to apply this state-of-the-art technique to the problem at hand. Thus, the project will evaluate the following hypothesis: *"Can diffusion models generate a suitable runway image dataset?"*. This novel idea would be ground-breaking for the runway detection and segmentation field, because it would mean that researchers would be able to use existing techniques in the field of image generation such as *inpainting*, *DreamBooth*, and *LoRAs* to generate their own extensive datasets with images in diverse, specific and complex scenarios.

Suitable image generation To evaluate the hypothesis, a Python project using the *Diffusers* library will be written. The first part of the project will evaluate what main techniques can be used to generate suitable images: Unconditional image generation, text-to-image generation and image-to-image generation.

Secondary to the issue of image generation is the question if diffusion models are able to generate diverse, specific and complex scenarios, such as scenes that vary in relation to runway orientation, weather conditions (e.g., fog, rain, snow), lighting (e.g., dusk, dawn, night, heavy overcast), and background scenery (e.g., airport buildings, natural terrain, distant cityscapes),

Unconditional image generation Unconditional image generation is a good starting point because it allows generation of images that look like those in the training dataset in a simple manner. In the context of generating runway images, we can train models using two approaches:

- Train with images of runways in their background scenery, with, for example, the airport buildings and the terrain;
- Train with cropped images that contain only or primarily the runway;

The hypothesis to be explored here is if it's possible to generate suitable images when training with the original images, because there is a possibility that the model doesn't learn the main concept of the runway and just learns to generate scenery that is found around the runway.

Training with cropped images has a better chance for the model to learn the concept and features of a runway, but it is more limited in the usefulness, as it would require other techniques, such as *Outpainting*, that extends the original image beyond its original boundaries, to generate a complete and realistic image for the dataset.

Text-to-image generation Text-to-image generates an image from a text description, also known as *prompt*. Text-to-image generation is the most powerful and adaptable technique because it would allow the extension of the dataset by generating new custom images using text prompts.

The simplest way to explore the question is to start with *prompt engineering*. Prompt engineering is the technique to tweak and try different text prompts to guide the image generation process.

It is unlikely that prompt engineering alone will be able to generate suitable images for the dataset. In that case, other techniques will need to be tested:

1. **Prompt weighting**: prompt weighting is a technique that emphasize or de-emphasize certain parts of the text prompts by manipulating their embedding values. This allows for more control over the generated image as the model will focus more on certain concepts.
2. **Textual inversion**: fine-tunes the text embedding of the model to learn a new concept.
3. **DreamBooth**: fine-tunes the whole model to learn how to generate contextualized image of a given subject.

Image-to-image generation Image-to-image generation is similar to text-to-image, but in addition to passing a text prompt, an image is also passed as the starting point for the diffusion process. The two techniques selected here to be explored are:

1. **ControlNet**: provides structural guidance to shape the generation of an image. It can be a pose skeleton or segmentation masks, for example, that will have their information retained and use to guide de de-noising process. ControlNet can be used to generate images in a way where the specific position of the runway is determined beforehand.
2. **Inpainting**: Inpainting modifies an existing image. It takes a mask that shows where the model should change the image. The model then tries to generate the content in the masked out area consistent with the surrounding pixels and the given prompt. It can be used to transform a scenery image into a runway image.

And because image-to-image also uses text-to-image, there's the possibility to use techniques such as Prompt weighting, textual inversion and DreamBooth alongside ControlNet and Inpainting for better performance.

Another technique that could be further developed in another project would be to use image-to-image generation to extend existing datasets. For example, the LARD datasets doesn't have different weather conditions for the images. Thus, we could use image-to-image generation to add different weather conditions (e.g., fog, rain, snow).

Evaluation

The evaluation of the synthetic runway image dataset will be both qualitative and quantitative, focusing on the key characteristics defined in the report: realism, detectability by existing models, data diversity, and potential to improve model performance.

Human-Judged Realism:

1. **Approach**: Conduct a small-scale human evaluation. Recruit a few peers to rate the realism of a random sample of generated images compared to a sample of images from established datasets (e.g., LARD or BARS).
2. **Metrics:** Rate images on a Likert scale (1–5) for realism.
3. **Feasibility:** Small-scale user study with at least 5 evaluators, each rating at least 20 images.

Detection by Existing Models:

1. **Approach**: Take a pre-trained runway detection model (e.g., a model pre-trained on LARD or a simple ResNet50 classifier) and test it on a subset of the synthetic dataset.
2. **Metrics**: Accuracy, Precision, Recall, and F1-score for runway detection on the synthetic images.
3. **Feasibility**: This could be done by fine-tuning a lightweight classifier if no pre-trained model is readily available.

Data Diversity

1. **Approach:** Qualitatively check scenarios: generate images under different conditions (weather, lighting, background) and visually inspect variety.
2. **Metrics**: Define a small taxonomy of conditions to be covered such as weather (Clear, Fog, Rain, Snow), lighting (Day, Dusk/Dawn, Night), and background (Urban, Rural, Coastal, Mountainous) and report the number of images in each category.

If time permits, there could be a quantitative metric:

1. **Approach:** Use embedding-based diversity metrics (e.g., CLIP embeddings) to measure intra-dataset variability.

2. **Metrics**: Calculate mean pairwise similarity between image embeddings; lower similarity implies greater diversity.

Model training:

1. **Approach**: (If time permits) Train or fine-tune a basic runway detection or segmentation model.
2. **Metrics**: Comparison in accuracy and segmentation metrics.
3. **Feasibility**: Due to time constraints, this may be done at a small scale.
4. **Critique**: There is the possibility that accuracy metrics decrease when training with the new dataset. If the images in the dataset closely mimic reality, it could be the case that performance decreases because existing models are not suitable for real-world challenges.

Prototype

To demonstrate the feasibility of the project, a small-scale dataset is produced using Unconditional Image Generation. Usually, in image generation models, there are inputs that guide the image generation process such as a prompt or initial starting image. This is not the case in unconditional generation, where the model starts from random noise and has no guidance. The result is that after training, the model should output images that look like the dataset it was trained on.

The training dataset was the FS2020 dataset. It was chosen because it has realistic images in diverse scenarios, that were subjectively judged as more aesthetic pleasing than the other datasets. It is also the easier to download as it is hosted on Kaggle.

How diffusion works

The model for image generation used in this prototype is a Denoising Diffusion Probabilistic Model presented in [28]. Diffusion models work by progressively adding noise to an image (called the forward process) and then training a network that learns how to remove noise from the image (the reverse process).

Figure 3: Diffusion forward process

The intuition of Diffusion models is that, if a model can be trained to predict the noise in an image at a timestep, we can start at pure noise, then repeatedly call this model and remove the noise from the image, at each step making a less noisy image.

U-Net

In ***"U-Net: Convolutional Networks for Biomedical Image Segmentation"*** [29], the authors introduced the U-Net architecture for image segmentation. The U-Net is composed of two parts: an encoder and a decoder. The encoder transforms the image into a compressed form that retains essential features. This compressed data is called a "latent". The decoder can then operate on this latent and output some data related to the input data. In the original paper, they used the U-Net to extract biomedical segmentation data. In Diffusion models, the U-Net is used as the model that predicts the noise from an image.

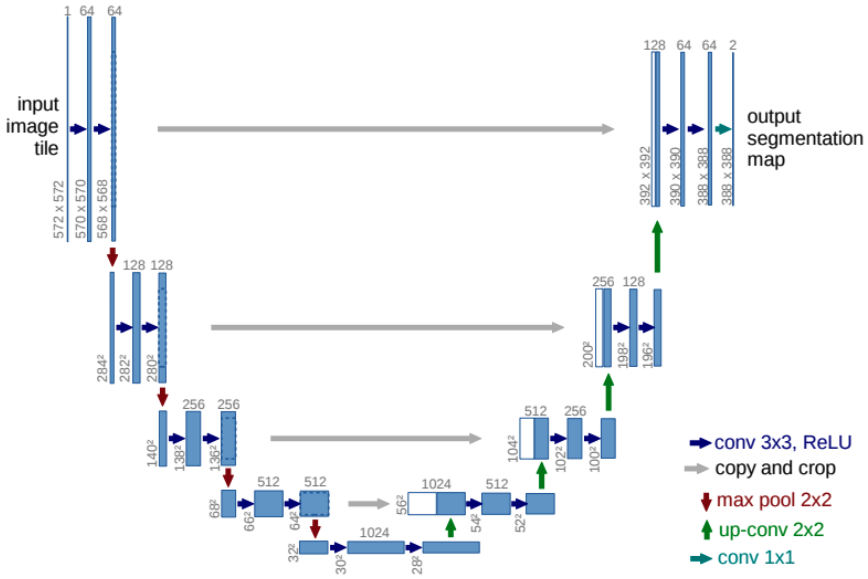

Figure 4: Figure from [29]

Training

Before training, the dataset was preprocessed by applying four operations: resizing to 128x128 pixels, random horizontal flipping, transforming to Pytorch Tensor and normalizing the tensor values.

Following the same methodology as in the DDPM [28] paper, the `UNet2DModel` from Diffusers was chosen. The model was trained for 1000 epochs, with batch size of 16 and using a AdamW optimizer. A `DDPMScheduler` of 1000 timesteps was used, meaning that in training, there were 1000 possible variations of progressive noise added to the images.

Figure 5: Images before and after preprocessing

Results

A dataset of 256 images with the resolution of 128x128 was generated. As the goal of the prototype was to evaluate the feasibility of the research project, it is evaluated by two characteristics: subjective human criticism and data diversity.

For data diversity, a small taxonomy is used and the number of images in each category is reported:

Class	Subclass	Image count
Weather	Clear	116
	Fog	128
	Rain	0
	Snow	12
Lighting	Day	213
	Dusk/Dawn	25
	Night	18
Background	Urban	13
	Rural	55
	Coastal	30
	Mountainous	7
	Unable to detect	30
	Too close to runway	21
Presence	Runway clearly detectable	90
	Hard to detect runway	11
	No runway in image	155

The images (Figure 4) demonstrate the feasibility of the project: Diffusion models are in fact capable of generating suitable images for a runway dataset. The trained model was able to generate runway images with rich and diverse scenery. The model is even capable of generating images at night, a limitation of the synthetic images in the LARD [12] dataset.

Still, there are challenges to be addressed further in the research project. The images have a low-resolution (128x128), some images do not contain a runway, there's too much fog in a lot of images that make the runways unrecognizable, the demarcations and numbers in the runway should follow a specific pattern observed in real runways and the dataset itself needs to be larger. And most importantly, as it uses unconditional image generation, it's not possible to specify desired characteristics to generate an image.

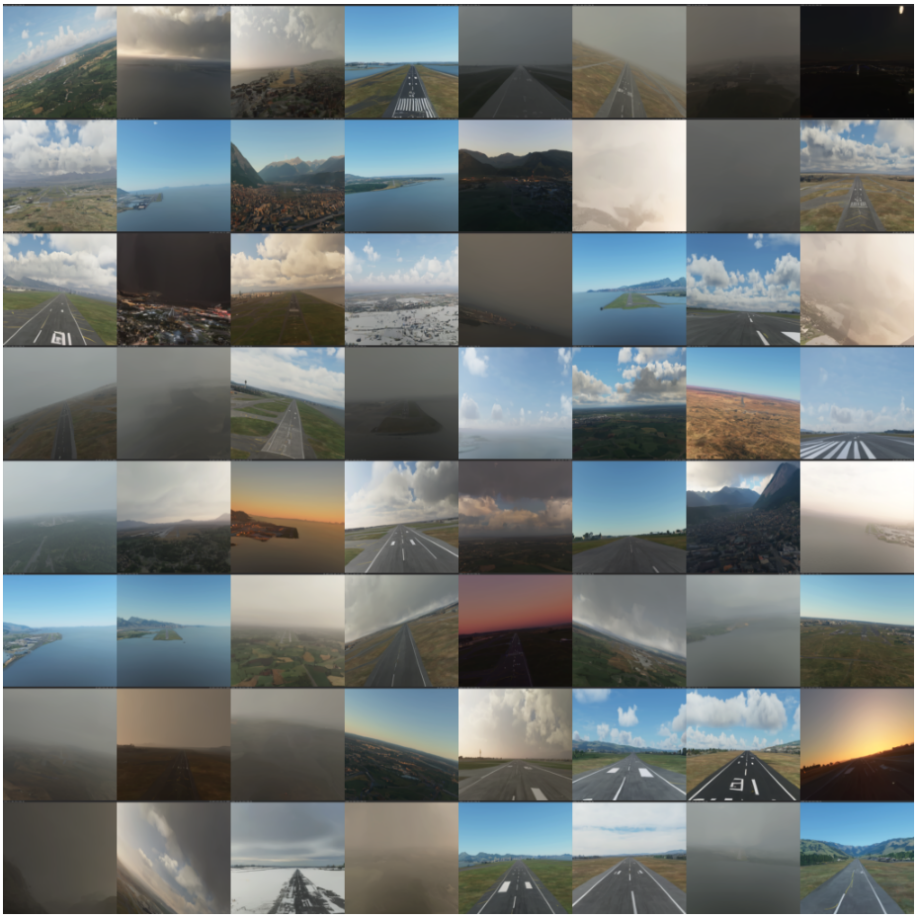

Figure 6: Images 192-256

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