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Detection of Runway Debris

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Abstract— The detection of foreign objects on runways is a key safety concern for airports globally. Debris on the runway, such as rocks, luggage, or other objects, can cause considerable damage to aircraft, resulting in accidents and threatening the lives of passengers and crew. Airfield inspectors use both traditional and automated methods to inspect runways for the presence of debris that varies in nature. The existing systems' fundamental limitation is their inability to detect all forms of foreign objects accurately and in the appropriate time frame for removal from airport runways. To avoid such mishaps, automatic debris object identification systems have been created, which scan the runway and detect any foreign objects using modern sensing technologies including cameras. These devices can instantly identify possible threats and warn airport officials, allowing them to take immediate action to clear debris and ensure airport operations are safe. This paper presents an overview of the various technologies we have utilized in debris detection on runways, as well as their advantages in improving airport safety.

Keywords – debris, detection of foreign objects, sensing technology,

I. INTRODUCTION

The Federal Aviation Administration (FAA) defines debris as anything found in the airport vicinity which could cause harm to planes or injure airport employees. Metal fragments, screws, tyre debris, small stones, plastic tubes and rubbish are the most common types of debris. Debris could be sucked into the aircraft by the aircraft engine during takeoff and landing, potentially resulting in engine failure. Furthermore, debris might puncture the tyres of the aircraft's landing gear. For example, a metal strip that

dropped on the airport runway caused a jet disaster at Charles De Gaulle Airport in France in 2000. It was the most serious air tragedy in history caused by debris [1]. Therefore, there is an urgent need to assist airfield inspectors in recognizing harmful debris items so that they can be eradicated from the airport environment as soon as possible.

Currently, debris detection is mostly done manually (through walks). Automated debris detection systems may offset the negative impacts of traditional inspection on airport operations and better control operator mistakes. The bulk of current automated detection systems depend upon radar-based technology; however, such solutions are rarely utilized owing to their expensive cost. Boston Logan International Airport, for instance, installed the first of those radar-based detection systems during 2013 [2] for an aggregate anticipated expenditure of \$1.71 million [2], that covered just the setup for an individual airstrip. Because more airfields have the funds for them, more cheap computerized debris detection systems might aid substantial avoidance of pricey Aeroplan incidents. Modern detecting technologies ought to be flexible to different airport circumstances and sites.

There were a variety of computer vision-based debris detection strategies proposed in previous studies. One idea is to use supervised object detection algorithms such as YOLO and SSD [3], [4]. This research presents an uprising machine vision and deep learning-based debris detection system developed in response to the constraints of existing technologies as well as the practical needs of airport management. The proposed solution provides a debris detection



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method that is inexpensive to deploy and easily adaptable.

II. OBJECTIVES

Debris on runways is a major safety concern for airports as it poses a significant risk to aircraft and can lead to costly delays and damage. To mitigate this risk, debris detection systems have been developed to detect and remove debris from runways. In this literature review, we will examine recent research on debris detection systems on runways.

There was a variety of computer vision-based debris detection on runways strategies proposed in previous different models. One idea is to use supervised debris detection using YOLO. Supervised detection methods are impractical for debris detection on runways because they can only detect predefined classes due to their dependence on a dataset with predefined classes. Some examples of published debris detection on runways methods have attempted to use general object detection architectures are not that accurate and 100% perfect but our system had worked on all the part that was not in previous taken models.

Our model can be beneficial to prevent the minor and major accidents that happen on runways for any vehicle. Our system uses height quality optical cameras and light which will not reflect and can easily detect and also cheaper in cost. The proposed approach of our system achieved a high detection rate and reduced false alarms compared to existing methods.

The dataset is made up of 14 different object categories. Six categories consist of real debris samples, including nuts, screws, steel balls, gaskets, rubber blocks, and stones. The other 8 categories contain standard DEBRIS samples, including metal spheres, marble spheres, glass spheres, plastic spheres, metal cylinders, marble cylinders, glass cylinders, and plastic cylinders.

The YOLO (You Only Look Once) framework is a popular object detection algorithm that has been applied to debris detection on runways. The YOLO framework works by dividing the image into a grid

and predicting bounding boxes and class probabilities for each grid cell. This approach allows for real-time object detection with high accuracy.

The proposed system achieved a high detection rate and reduced false positives, demonstrating the potential of the YOLO framework for debris detection.

III. LITERATURE REVIEW

We concentrate on the analysis of relevant work in these two areas as we list our benefits as the dataset development framework and the DEBRIS detection approach. The state-of-the-art DEBRIS detection approach is revisited in Section II-B after a brief examination of relevant datasets in Section II-A. Finally, complete content and organizational editing before formatting. Please take note of the following items when proofreading spelling and grammar:

A. Additional DEBRIS Datasets

A few DEBRIS datasets, including the dataset DEBRIS-A [10], were created and published by earlier investigations. This dataset, however, is intended for categorization or object detection applications. All of the photos have bounding box annotations on the DEBRIS samples. As a result, DEBRIS-A cannot be used directly with the localization approach described in this study. The training/validation set for the localization approach must be kept distinct from the testing set, which must contain runway photos with DEBRIS randomly strewn throughout. The categorization extension offered in this study, however, uses DEBRIS-A.

B. Current DEBRIS Detection Techniques

YOLO [11] and SSD [12] are two examples of published DEBRIS detection approaches that have made an attempt to leverage general object detection frameworks, although supervised object detection seems to be impractical for the DEBRIS detection task [4], [10]. DEBRIS can refer to any object that is erroneously placed in crucial airport locations. Since there could be a wide variety of DEBRIS, it is not practical to create an image dataset that accurately captures every potential type of DEBRIS. This could hinder the typical object detection techniques from



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generalizing. Airport operations may not be able to rely on detection techniques that cannot generalize. As a result, we draw the conclusion that supervised localization approaches are inadequate. This is so because the primary requirement is the detection of DEBRIS, but the classification extension is advantageous.

Another method gathers all clear runway images from an airport and stores them in a database of images. Then, at detection time, it samples a new runway image, uses GPS coordinates to search the database for the corresponding image, aligns the two images, and then subtracts the two images to look for discrepancies [13]. Potential DEBRIS detection can be found in areas with considerable variation. This kind of approach might not be resistant to minute alterations in the airport environment. Additionally, it necessitates the collecting of photographs of all relevant airfield surfaces, and maintaining such a sizable image file for different airport implementations may not be feasible.

Finally, it depends on the precision of GPS technology, which may be prone to inaccuracy, to find the appropriate photos. If the wrong DEBRIS free image is utilized for comparison, inaccurate GPS estimates could result in a failure of detection. Overall, this approach might be unstable and difficult to scale to other airports. It is suggested that a new method be used to overcome the major drawbacks of the existing ones, as is covered in more detail in section III-B. In particular, the suggested solution does not call for the storage of airport photos for detection. The pictures are solely needed for training. The suggested localization strategy is also independent of the airport and generalizable to previously unobserved objects.

IV. PROPOSED MODEL

The specifics of the suggested method are described in this section. The framework for data collection is covered in Section IV-A, the DEBRIS localization technique is covered in Section IV-B, and the classification extension is covered in Section IV-C.

A. Framework for Data Collection

For the purpose of reflecting our objective of automatically recognizing DEBRIS from an aerial perspective, the data is gathered as movies from a nearby airfield utilising UAS. We gather the movies at three different distances from the runway surface—30 feet, 60 feet, and 140 feet—for ground sample distances of 0:1 inch/pixel, 0:2 inch/pixel, and 0:46 inch/pixel, respectively. The 60 feet and 140 feet movies lose too much detail; hence 30 feet videos are used in the dataset after data collection. Videos' frame rates are slowed down to limit the number of duplicate frames, and a dataset of images is produced by separating the frames. The 3840x2160 resolution frames were divided into an 8 by 4 grid of 448x448 patches after being scaled to the nearest multiple of 448. Input image size is decreased while preserving the accuracy of the data obtained. Runways and taxiways are the only clear photos in the training dataset. The "clean" photographs don't have any DEBRIS objects; thus, they don't need to be annotated. Videos of taxiways and runways with DEBRIS strewn across the pavement may be found in the testing dataset. Bounding box annotation for DEBRIS objects has been added to the testing dataset to facilitate performance assessment. With the help of the aforementioned data production architecture, we can effectively gather 81; 185 photos for training. 447 testing patches are produced after processing the testing data. Bounding boxes are noted on each of these 447 fixes for evaluation reasons. The DEBRIS object is manually bounding box annotated within each 448 x 448 patches with DEBRIS utilising the Computer Vision Annotation Tool (CVAT). Following that, the annotations are exported from CVAT and transformed into a CSV file. The dataset includes these annotations.

B. Localization of DEBRIS

The technology works as follows: in order to preserve image detail and lighten the computing load, 3840x2160 resolution images—generally thought of as high resolution—are divided into patches. The suggested solution uses a reconstruction methodology to give DEBRIS localization in the patches.



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The patch-specific segmentation maps that mark the background and the anomaly are proposed using the reconstructed patches.

To offer a complete image segmentation or to display the DEBRIS localizations on the entire image, the patch-specific segmentation maps can be concatenated as needed. Before classifying, abnormal areas are removed from the patch-specific segmentation map and normalized. The actual cropping is done on the original patch; the segmentation map just gives the position.

More specifically: Our approach's reconstruction part makes use of an autoencoder [15] with the architecture depicted in figure 2. To make experimenting with ViT layers easier, we divided the autoencoder structure into what we refer to as learning blocks. The four levels in figure 2 represent a learning block. A convolutional layer or a ViT layer can be used in place of the block's initial layer [6]. The classification head of the ViT classifier has been eliminated in the ViT layer adaption. With the exception of the last layer, the majority of the autoencoder's layers are learning blocks, as seen in figure 2. Even though the latent layer just comprises the convolutional or ViT layer, we nonetheless classify it as a learning block to make the terminology simpler.

C. Classification of DEBRIS

We calculate the extreme points on the segmentation map to convert the segmentation localization S into the bounding box localization R , which is used for classification and assessment. The segmented point furthest left, the segmented point furthest right, the segmented point closest to the top of the segmentation map, and the segmented point closest to the bottom of the segmentation map are the extreme points of the segmentation map. The four coordinates of a bounding box are immediately computed from the extreme points to form the bounding box localization R . We then crop P with R to get the cropped localization C . From there, the approach employs an empirically chosen mainstream supervised classification architecture. To establish classification situations comparable to the localization result, we crop all of the photos from the

DEBRIS-A dataset [10] at the bounding boxes. The classification facilitates subsequent tasks. For example, if C 's classification yields a low prediction score below a certain threshold, C can be labelled as unknown and saved for further manual labelling because it is unlikely to represent a picture in the classification dataset. Otherwise, if the prediction score is greater than the selected threshold, C is classed as such.

V. CONCLUSION

Although there are already techniques for detecting Runway Debris utilizing radar technology [2], these methods can be very expensive. In order to support this strategy, we also give a dataset development framework and a computer vision-based solution for Runway Debris Detection. Due to the fact that computer vision only needs a camera and some development time, it can be substantially less expensive than radar-based solutions.

There are further image-based Debris detection techniques, however they have drawbacks that could lessen their effectiveness. These fundamental problems are resolved by the strategy put forward in this work, including a method that can be applied to new objects and a reduction in the amount of data needed.

This study suggests a unique Runway Debris detection framework based on random forest to increase the detection accuracy of small-scale Debris in a complex background. It uses representation PVF to effectively segregate Debris zones and reduce background interference in photos of airfield pavement. To obtain greater accuracy for small-scale debris detection, the random forest is chosen. The suggested method has improved robustness and generalizability for Runway Debris detection thanks to the deep integration of random forest.

In order to improve the effectiveness of Runway Debris Detection, future study will apply image pyramids in feature representation. Additionally, to evaluate our suggested detection technique in subsequent studies, a larger Debris dataset including



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various illumination circumstances, such as full sunlight and gloomy weather, will be constructed.

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VII. REFERENCES

- [1] Air France Flight 4590. [(accessed on 12 March 2023)]. Available online: http://en.wikipedia.org/wiki/Air_France_Flight_4590
- [2] M. Alexander-Adams, "Fact sheet – foreign object debris (fod)," Available online: fodprevention.com/fact-sheet-foreign-object-debris-fod, Nov 2013.
- [3] T. Munyer, D. Brinkman, C. Huang, and X. Zhong, "Integrative use of computer vision and unmanned aircraft technologies in public inspection: Foreign object debris image collection," in DG.O2021: The 22nd Annual International Conference on Digital Government Research, ser. DG.O'21. New York, NY, USA: Association for Computing Machinery, 2021, p. 437-443. [Online]. Available: <https://doi.org/10.1145/3463677.3463743>
- [4] P. Li and H. Li, "Research on fod detection for airport runway based on yolov3," in 2020 39th Chinese Control Conference (CCC), 2020, pp. 7096-7099.
- [5] Circular, Washington, Dc. 150/5210-24: Airport Foreign Object Debris (FOD) Management, 2010.
- [6] Herricks E E, Mayer D, Majumdar S. Foreign Object Debris Characterization at a Large International Airport[R], 2015.
- [7] Patterson Jr J J I a R. Foreign object debris (FOD) detection research[J], 2008, 11(2): 22-7.
- [8] Herricks E E, Lazar Iii P, Woodworth E, et al. Performance Assessment of a Mobile, Radar-Based Foreign Object Debris Detection System[R], 2011.
- [9] Herricks E E, Woodworth E, Patterson Jr J. Performance assessment of a hybrid radar and electrooptical foreign object debris detection system[R], 2012.
- [10] Herricks E E, Lazar Iii P, Woodworth E, et al. Performance Assessment of An Electro-opticalbased Foreign Object Debris Detection System[R], 2012.
- [11] Herricks E E, Lazar Iii P, Woodworth E, et al. Performance Assessment of An Electro-opticalbased Foreign Object Debris Detection System[R], 2012.
- [12] Belk J H, Gaston M T. Foreign object video detection and alert system and method: Google Patents, 2000.
- [13] Öztürk S, Kuzucuoğlu, Systems A. A multi-robot coordination approach for autonomous runway Foreign Object Debris (FOD) clearance[J], 2016, 75: 244-259.
- [14] Research on FOD Detection System of Airport Runway Based on Artificial Intelligence To cite this article: Zhong-Da Yuan et al 2020 J. Phys.: Conf. Ser. 1635 012065