Airport Runway Crack Detection to Classify and Densify Surface Crack Type



Abhilasha Sharma, Aryan Bansal

Abstract: With the extensive development in infrastructure, many airports are being built to satisfy the travel needs of people. The frequent arrival and departure of numerous planes lead to substantial runway damage and related safety concerns. Therefore, the regular maintenance of runways has become an essential task, especially for detecting and classifying cracks due to the intensity heterogeneity of cracks, which results in low realtime performance and time-consuming manual inspections. This paper introduces a new dataset named ARID, comprising eight distinct crack classes. A runway crack detection model based on YOLOv5 and Faster R-CNN has been proposed, which is trained on 8,228 annotated datasets. Then, the model is trained with different parameters to obtain the optimal result. Finally, based on experimental results, the crack detection precision has improved from 83% to 92%, while the recall has increased from 62.8% to 76%.

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Keywords: Crack Segmentation, Google API, Pavement Detection, Runway Crack, Runway Distresses Detection.

I. INTRODUCTION

In recent decades, extreme travel and transportation exchanges have been tremendously increased across the globe. The aviation industry has witnessed significant advancements in technology, leading to safer and more comfortable flights. Modern aircraft are equipped with stateof-the-art navigation systems, advanced safety features, and improved cabin amenities, making air travel a more enjoyable experience for passengers. While increased transportation activity can indirectly impact the service performance and service life of infrastructure, the development of surface cracks is influenced by some factors. Thus, regular maintenance has become an essential task, particularly for detecting and classifying cracks on the runway. The structural degradation of runways can potentially compromise safety, reduce service life, and lead to economic losses. Crack-based damage has the potential to impair performance and present safety risks. They become the most common defect that appears on airport runways, lowering the stress state and potentially causing accidents. If this damaged pavement is not repaired promptly, the problem will worsen due to recurring environmental or human factors.

Manuscript received on 02 August 2023 | Revised Manuscript received on 19 January 2024 | Manuscript Accepted on 15 February 2024 | Manuscript published on 28 February 2024. *Correspondence Author(s)

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Repairing a crack before it deteriorates will decrease the cost of maintenance, reduce environmental impact, and extend the asphalt's lifespan. If the maintenance tasks of crack removal are completed on time, the price for crack rehabilitation can be kept up to 80%.

In recent years, the rapid growth in the Indian economy has led to a pace of airport development that is driving the aviation industry to recover from pre-pandemic levels, with new routes and startup carriers on the horizon. By 2025, the government hopes to build 220 additional airports. According to Jyotiraditya Scindia, the Minister for Civil Aviation, India is expected to have 1,200 planes and 400 million passengers by 2027. The nation is building new greenfield airports using public financing and public-private partnerships in a market that is expected to experience tremendous growth. Eight of the 21 greenfield airports are already operational. As more people opt to fly, various types of runway damage will inevitably result. The runway is extensively tainted with fuel stains and aircraft wheel Moreover, fragile cracks are often present, marks. indicating a significant risk of failure. These images are extremely noisy and feature a variety of characteristics, including tiny fractures, fuel stains, and textured surfaces. Automated crack detection technologies have revolutionized the analysis process in intelligent transportation systems by providing rapid and reliable results, replacing the slow and subjective traditional approaches. A computerised crack detection system can efficiently evaluate the condition of a runway and aid airport authorities (International Civil Aviation Organisation (ICAO)) in organising and prioritising repair activities aimed at increasing the runway's useful life. Computer vision (CV) enables machines to learn from the features of digital images and videos. Using visual data improves understanding of features and patterns. For these research domains, a vast amount of visual data is available via cellphones and digital cameras.

Various researchers have explored the concept behind deep architecture-based crack detection approaches, as explained in further detail. Gopalakrishna et al. [1] gives a chronicle review on deep-learning approaches grounded on crack detection. To eliminate road markings from the track image, Otsu's enhanced threshold segmentation algorithm is applied. After the markings have been eliminated and the crack has been produced, the enhanced adaptive threshold segmentation algorithm is used to segment the image. Oliveira et al. [2] employed a variety of image analysis techniques to identify and describe cracks on road surfaces.



While these methods have proven effective in detecting cracks in high-quality image datasets [3], it is essential to note that they may not be sufficiently precise to differentiate cracks from the intricate background in low-quality images.

Critical surface cracks must be identified and analysed to design an effective distress detection model for pavements. Traffic volume, climatic conditions, layering structure, age of layers, and layer quality are several factors that might impact the pace of surface crack detection. Once the cracks have been identified and classified, road administrators can utilise the data to develop pavement repair strategies based on the nature, scope, and severity of the problems. Prior research has attempted to do this, but it falls short in some areas. For example, the work done by CrackNet [4] was only on defining the presence of distress surfaces, meanwhile the method didn't diagnose distinct types of damage within the surfaces, whereas Zalama et al. [5] examined both horizontal and vertical varieties of distress in their study, whereas the classification of distresses into three types, namely horizontal, vertical, and alligator, was proposed by Akarsu et al. [6]. Other studies have focused on recognising blurry road markings, as well as classifying different types of cracks, plus sealed cracks. The quality of the data used in the training and testing sets is crucial for achieving better efficiency with the deep learning technique. Labelled datasets are essential for creating a reliable distress surface dataset for airport runways. In this paper, a new dataset is introduced, namely the 'Airport Runway Image Dataset' (ARID). Here, initially 8,228 images were extracted from 10 different surface sections. Images were collected from street views using the Google Application Programming Interface (API). The first step is to annotate each image set by designing a bounding box near each segment to recognized distress surface. The dataset is evaluated using two deep learning approaches, namely YOLO v5 and Faster R-CNN.

Based on a deep learning methodology, two deep learning (DL) models are improved and implemented in a single outline, as shown in Figure 1. The significant contributions of this paper are as follows:

- A new dataset has been introduced that enables the simultaneous categorization and quantification of surface cracks utilizing a range of camera viewpoints, including top-down and wide-view perspectives. The top-down photos were used to determine the density of damage, while the wideangle images were used for categorisation.
- The wide-view images have been marked with a total of 9 types of cracks, identified along with their respective crack IDs, i.e., D0-D8. These include reflecting, transverse, block, longitudinal, alligator, sealed transverse, sealed longitudinal, and lane longitudinal cracking, as well as the presence of potholes, which are deemed critical for assessing crack surface quality.

The proposed model is implemented using two deep learning approaches, namely YOLO v5 and Faster R-CNN, and trained on the dataset above.



Fig. 1. Outline for Airport Runway Crack Detection and its Classification

The rest of the paper has been organised as follows: Section 2 provides a detailed literature survey of the chosen area. Section 3 discusses the proposed methodology. Section 4 evaluates the experimental results and discusses their analysis. Section 5 concludes the research paper.

II. RELATED WORK

Researchers have recently explored the machine learning areas that could benefit from their ability to classify data. These techniques, like SVM (Support Vector Machine), RF (Random Forest) and NN (Neural Network), can achieve improved precision by extracting manually created features [7]. However, as NNs continue to evolve, they are likely to replace the local features used in traditional algorithms. Deep learning refers to a machine learning approach that utilises neural networks with multiple layers to identify and extract relevant features effectively.

The detection of cracks has been explored using various approaches in deep learning, including image classification (IC) and semantic segmentation (SS) techniques. To build on recent successes, a Convolutional Neural Network (CNN) was utilised for image classification, specifically for identifying images with cracks.

A. Image Classification (IC)

The proposed crack detection model's decision process entirely relies on the input image, and the trained architecture determines whether the image contains a crack. The initial aspect of this architecture is responsible for extracting meaningful features from raw images layer by layer. This is accomplished through the use of a sequence of convolutional layers and max-pooling layers that gradually turn the input picture into a more abstract representation.



Retrieval Number: 100.1/ijeat.A42731013123 DOI: 10.35940/ijeat.A4273.13030224 Journal Website: www.ijeat.org

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The following section of the CNN consists of Fully Connected Layers (FCL) and categorises the feature extraction. Wang et al. [8] examined the use of the principal component analysis (PCA) method for crack type classification using a CNN to detect crack. Park et al. [9] presented a multi-class classification method based on CNN applied to road images to classify road regions into intact areas, road markers and cracks. Li et al. [10] achieved a crack type classification task with five classes using four CNN models with varying depths, inspired by AlexNet [11] and LeNet [12]. The models were compared to one another. Furthermore, Wang et al. [13] utilised a sizable dataset comprising 5000 3D pavement images, which included a diverse range of examples. The objective was to facilitate the architecture's understanding of possible complexities and variations in road surfaces. Table 1 presents a taxonomy of techniques for segmenting cracks based on an image classification using deep learning approaches.

 Table 1: Taxonomy of Deep Crack Segmentation

 Approaches on Image Classification

Author, Year	Description	Methods
Yokoyama et al., 2017 [31]	Presented the first application of DL for crack classification.	-
Cha et al., 2017 [32]	During the testing phase, images of any resolution were scanned using the sliding window algorithm.	Mat Conv Net
Pauly et al., 2017 [33]	Worked on the effectiveness of the number of convolutional layers and max-pooling on the crack image performance for crack detection.	-
Wang et al., 2017 [8]	Worked on the effectiveness of patch size in images on the performance, and the types of cracks are classified by using PCA.	-
Feng et al., 2017 [24]	Identified the crack type classification by using active learning during the training phase.	ResNet
Eisenbach et al., 2017 [35]	Worked on a shallow network application along with ANIVOS architecture to achieve deep-crack detection and collect the publicly available GAP's dataset.	LeNet., AlexNet, VGG- 16
Dorafshan et al., 2018 [36]	Demonstrates various AlexNet applications, comparing them in two training approaches: scratch and transfer learning.	AlexNet
Da et al., 2018 [37]	Performing crack detection for image classification using CNN depends on transfer learning approaches.	VGG-16
Kim et al., 2018 [39]	Worked on pretrained AlexNet applications on the "ImageNet" dataset to accomplish detection for cracks while assuming a richer dataset, including non-crack objects.	AlexNet
Kim et al., 2019 [38]	Comparison of FCL and CNN- based robust feature approaches.	AlexNet
Park et al., 2019 [9]	Mainly worked in black-box images for its crack detection and	-

	its classification into crack, road marking and whole targeted areas.	
Li et al., 2020 [10]	Worked on the effectiveness of the receptive field size of images with multiple classes of distinct crack types.	AlexNet, LeNet
Kim et al.,2021 [59]	Proposed a shallow CNN-based architecture employed for concrete surface crack detection, which consists of fine-tuning of the LeNet-5 architecture with the METU self-made dataset.	Optimized LeNet
Oui et al., 2023 [56]	Work is proposed to integrate YOLO into an unmanned aerial vehicle for real-time crack detection in tiled sidewalks.	ResNet50-based YOLOv2 and YOLOv4-tiny

B. Semantic Segmentation (SS)

Semantic segmentation involves classifying images at the pixel level. In computer vision, SS has a variety of applications, such as autonomous driving [14], 3D-reconstruction [15], in medical analysis [16] and also in robotic area. In the context of crack detection, the result of a semantic segmentation framework is an input picture in which crack pixels are distinguished from background pixels using a distinct colour. Deep crack segmentation strategies may be roughly categorized into hybrid and pure approaches.

C. Hybrid Semantic Segmentation

The first step to detect cracks is to locate patches, and then to segment the pixels that correspond to cracks within those patches. Various techniques can be used for this purpose, like RFED (Random Forest edge detection) [17], tubularity flow [18], Otsu's thresholding [19] and block-wise segmentation [20], implemented using the Image Processing Toolbox (IPT) as well as shallow fully convolutional network (FCN). FCNs can be employed for performing semantic segmentation on bounding boxes that densify areas that exhibit cracks [17][21]. Author Ni et. al. [27] worked to detect patches containing cracks, the classifiers GoogLeNet [22] and ResNet [23] [34] were used. Following the detection of crack patches, the usual method for crack segmentation involves applying Otsu's thresholding, followed by the use of median filtering and the 'Hessian matrix' to remove the effects of lighting and enhance the features of the cracks, respectively. In another work [20], a previously trained architecture using the ImageNet dataset was used to identify crack patches using transfer learning. While crack detection is done at the level of pixels using a semantic segmentation technique, crack quantification has also been studied in this area using various approaches [28][19][22]. Table 2 presents a taxonomy of deep crack segmentation approaches in the Hybrid SS setting.



Author, Year	Description	Methods
Zhang et al., 2018 [20]	Worked on transfer learning applications to detect cracks, especially sealed crack segments. A fast block- wise segmentation method using linear regression was applied to identify crack segments.	IC+IP
Zhang et al., 2018 [40]	Worked on pretrained AlexNet on "ImageNet" data to detect & classify road crack images, especially in sealed cracks, along with background images.	IC+FCN
Tan et al., 2019 [41]	Worked in pavement image datasets to detect cracks.	OR+FCN
Fang et al., 2019 [42]	Worked on crack segmentation, which was performed on faster R-CNN in conjunction with a Bayesian probability algorithm to conquer false detection.	OR+IP
Kalfarisi et al., 2020 [17]	Review on 2-crack segmentation outlines with structured Random Forest edge detection (FED)and Mask R-CNN.	OR + IP and OR + FCN
Kang et al., 2020 [18]	Working on crack segmentation with a modified tabularity flow field, and also working on crack quantification using an improved transform method.	OR+IP
Chen et al., 2023 [58]	Proposed a pavement fracture segmentation method based on the U- Net model, and its type by taking factors like the length, width and areas of the crack are measured as per the segmentation results	IC+FCN (U-Net)

 Table 2: Taxonomy of Deep Crack Segmentation

 Approaches on Hybrid SS Setting

D. Pure Semantic Segmentation

The crack detection process can also be carried out without identifying crack patches or candidate regions. The substitution of fully connected layers with convolutional layers in the typical architecture used for image classification creates an encoder-decoder structure known as the fully convolutional network (FCN) [24], which can be utilized to accomplish this. The updated version of CrackNet [4] i.e., CrackNet-II [25] & CrackNet-V [26] technique provides enhanced learning capabilities as well as reduced processing time. These are the DL-based algorithms developed for the semantic segmentation of 3D crack images, whereas the original CrackNet framework used both DL and handcrafted features. These algorithms refrain from using max-min pooling layers while preserving the width and height of pictures throughout the convolution layers. This approach enables them to perform pixel-level classification under the supervision of labelled data. To extract high-level and complex features, a backbone architecture is employed for semantic segmentation, utilising an encoder-decoder framework. The use of a series of convolution, pooling, and activation layers performs this. After passing through the backbone architecture, the dimensions of the input image, specifically its width and height, drop. Therefore, a decoder module is used to resize the features back to match the original dimensions of the input image. The decoder module is made up of a sequence of deconvolution layers (also called transposed convolution or fractionally strided convolution). The restoration of feature size enables this pixel-level categorization.

In the computer vision area, multiple architectures have been suggested to carry out semantic segmentation (SS), like the U-Net architecture [27], SegNet architecture [28], and FC-Dense Network architecture [29]. These architectures

Retrieval Number: 100.1/ijeat.A42731013123 DOI: <u>10.35940/ijeat.A4273.13030224</u> Journal Website: <u>www.ijeat.org</u> have also been extensively used in the crack detection. According to certain studies, the use of basic encoderdecoder structures was investigated, without incorporating any technique for addressing the merging of feature maps at varying scales, as documented in references [30]. Table 3 presents a taxonomy of deep crack segmentation approaches on the Pure SS setting.

Table	e 3: T	axonom	iy of D	eep C	rack	Segme	ntation
	Арр	roaches	on the	e Pure	SS S	etting	

Author, Year	Method	Description
Zhang et al., 2016 [43]	crack pixels at the centre of the patches	The first application of crack segmentation is feature extraction on raw data using ConvNet.
Zhang et al., 2018 [25]	Consecutive conv layers with an invariant spatial size	Proposed an improvised version of CrackNet called CrackNet II that shows increased efficiency in both accuracy and speed.
David et al., 2018 [44]	Encoder– decoder (U-Net)	The U-Net architecture was first utilized in the field of crack detection to address various drawbacks of using CNNs.
Fan et al., 2018 [45]	Centre crack pixels in the patches	Using CNNs to forecast the crack structure. An approach to address the issue of imbalanced classes.
Zhang et al., 2019 [46]	RNN	CrackNet-R, an enhanced version of CrackNet that utilizes a new recurrent unit based on RNN, has been introduced.
Li et al., 2019 [47]	Encoder– decoder (FC- DenseNet)	A more comprehensive FCN architecture has been proposed for detecting four types of concrete damage, eliminating the need for a sliding window technique.
Bang et al., 2019 [48]	Encoder– decoder (ResNet + SegNet, FCN, ZFNet)	Using deep learning methods for the detection of Black-Box on road cracks.
Zou et al., 2019 [52]	Encoder– decoder (SegNet)	A new neural network, end-to-end trainable and based on the SegNet architecture, has been developed for reliable crack detection.
Zhang et al., 2020 [49]	Encoder– decoder (U-NET as generator)	A CrackGAN framework is proposed that utilises a GAN architecture and can operate effectively with partially annotated ground truth data.
Mei et al., 2020 [50]	Encoder– decoder (FC- DenseNet)	Application in the DL for feature fusion utilizing skip connection. Implementing the depth-first search algorithm for post-processing improves accuracy.
Chen et al., 2020 [51]	Encoder– decoder (SegNet)	"Adadelta" optimiser and cross- entropy loss function are implemented with the SegNet architecture for crack segmentation.





Fei et al., 2020 [26]	Consecutive conv layers with an invariant spatial size	CrackNet-V (an enhanced version of CrackNet) is proposed to generate better efficiency in terms of accuracy and speed, and to boost the accuracy of crack segmentation for shallow cracks. A new activation function is considered.
Yang et al., 2020 [53]	Encoder– decoder (feature fusion)	A feature pyramid and hierarchical boosting network are being proposed to address the challenge of imbalanced classes and enhance the robustness of feature representation.
Mei et al., 2020 [54]	Encoder– decoder (FC- DenseNet as generator)	Proposing a crack segmentation technique that employs a conditional Wasserstein GAN and connectivity map to improve the accuracy of the segmentation outcome.
Youzhio et al., 2021 [60]	Encoder- Decoder based on ResNet-34 (EDNet)	Worked to overcome the imbalance in quantity within the crack & non- crack pixels images based on an encoder-decoder network for pavement crack segmentation.
Deng et al., 2023 [57]	Hybrid Lightweight Encoder- Decoder Network (HLEDNet)	Worked on real-world images captured via several concrete bridges, which are based on an ad- hoc crack segmentation and measurement system.

III. PROPOSED METHODOLOGY

This section presents the proposed model, based on YOLO v5 and Faster R-CNN, which consists of two phases: Detection and Segmentation, respectively. In the first phase, YOLO v5 was utilised as a classification detection method, trained on image patches to search for areas with cracks or damage on the runway. Moreover, the images' background noise and unnecessary bits are removed. The second phase involved pixel-level segmentation in small areas to distinguish runway cracks from the original photos. The block diagram of the proposed model for detecting road cracks and its segmentation is represented schematically in Figure 2, where a max-pooling layer follows each CNN layer within the YOLO v5. The first phase employs YOLO v5 as a detection technique, which is trained using sample image patches to identify areas within the runway that have cracks. Additionally, it cleans up the images' background noise and removes superfluous elements. In the second phase, runway cracks are segmented into discrete areas within the original images. And finally, the combined method has compensations for both phases, i.e., detection and segmentation.



Fig. 2. Block Diagram of Proposed Model for Detecting Road Cracks and its Segmentation

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Fig. 3. YOLO v5 Architectural Diagram

A. YOLO v5 Model

A deep learning framework termed YOLO v5 [55] is used to detect and also classify its types of cracks, automatically. Figure 3 provides the architectural diagram of the YOLO v5 deep learning model. A relatively new object detection approach called YOLO appears to offer the best accuracy for developing deep learning-based approaches. For the proper execution of object detection, YOLO first reframes the object detection process, looking at a single image only once. Most recently, CNN classifiers have been utilised by object identification algorithms to accelerate detections. The algorithm can forecast class probabilities simultaneously in this way. Table 4 lists the details of the CNN architecture, showing the series of layers along with their respective kernel sizes, strides, and output pixel shapes for model implementation.

B. Faster R-CNN Model

This model includes the 2-stage crack-targeted detection method. It gives three leading caterers for the marked area: (i) Informative Region Selection (IRS); (ii) Feature Extraction Classification (FEC); (iii) Location Refinement (LR) within the framework. Here, initially, the model splits crack images into small segments. After that, each segment is passed through a sequence of convolutional filter layers for feature extraction. Then, it passes through a classifier, where the probability of crack image areas for the output region is collected, including the type of crack.

Table 4. CNN Architecture for the Proposed Model

#Layer	Kernal-Size	#Stride	Output Shape
Input			[416,416,3]
Convolutional Layer	3x3	1	[416,416,6]
Max Pooling	2x2	2	[205,205,16]
Convolutional Layer	3x3	1	[205,205,32]
Max Pooling	2x2	2	[104,104,32]
Convolutional Layer	3x3	1	[104,104,64]
Max Pooling	2x2	2	[52,52,64]
Convolutional Layer	3x3	1	[52,52,128]
Max Pooling	2x2	2	[26,26,128]
Convolutional Layer	3x3	1	[26,26,256]



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Max Pooling	2x2	2	[13,13,256]
Convolutional Layer	3x3	1	[13,13,512]
Max Pooling	2x2	1	[13,13,512]
Convolutional Layer	3x3	1	[13,13,1024]
Convolutional Layer	3x3	1	[13,13,1024]
Convolutional Layer	1x1	1	[13,13,35]

IV. EXPERIMENTAL EVALUATION

This section describes the implementation details of the entire setup. The model has been implemented on the newly collected dataset as described in Section 4.1. The selection of hyperparameters during training is also discussed in Section 4.2. The experiments are performed on a machine equipped with an AMD Ryzen 5 5600H processor and Radeon graphics, featuring a 3.30 GHz graphics core, 8 GB RAM, and an NVIDIA GeForce RTX GPU.

A. Dataset

In general, pavement cracks are categorized into nine types as shown in figure 4: (i) Reflective Runway Crack (ii) Transvers Runway Crack (iii) Block Runway Crack (iv) Longitudinal Runway Crack (v) Alligator Runway Cracks (vi) Sealed-Reflective Runway Crack (vii) Lane-Longitudinal Runway Crack (viii) Sealed-Longitudinal Runway Crack.



Fig. 4. Airport Runway Distress Crack Types with their Crack ID

For implementation on the airport runway crack, we introduce a new dataset called as ARID which comprises of 8,228 images obtained via 10 different airports in India collected by via camera of Iphone11 having 12 MP, f/1.8, 26mm (wide), 1/2.55", 1.4 μ m, dual pixel PDAF, OIS, 12 MP, f/2.4, 120°, 13mm (ultrawide), 1/3.6". Additionally, through the Google API, distress surface images are automatically extracted by requiring GPS coordinates, including camera and image parameters. Herein, the starting and ending points are selected on the runway for each marked area. Different images of the same cracks are combined at a particular coordinate point, with a pitch angle of -60 ° and -90 ° for the camera, for runway crack classification. In the dataset, an image size of 640 x 640 pixels is used for all collected images. Then, the wide-view

Retrieval Number: 100.1/ijeat.A42731013123 DOI: <u>10.35940/ijeat.A4273.13030224</u> Journal Website: <u>www.ijeat.org</u> images are annotated using a software annotation tool to depict nine distinct runway cracks, i.e., D0-D8. A total of 8,228 wide-view images were taken, from which 5,760 images were used for training and 2,468 images for testing.

B. Model Accuracy

This section covers metrics, such as precision, recall, and F1-score, that are used for the performance evaluation of runway crack classification and its detection. These metrics can be defined as:

$$Percision = \frac{tp}{(tp+fp)} \tag{1}$$

$$Recall = \frac{tp}{(tp+fn)}$$
(2)
F1 - score = $\frac{2*Precision*Recall}{Precision+Recall}$ (3)

where the '*tp*' indicates the number of True-Positives, 'fp' indicates the number of False-Positives and 'fn' shows the number of False-Negatives.

The proposed model is trained on a total of 5,760 images and evaluated on 2,468 images for 20,000 iterations, along with 10 epochs, using a learning rate of 0.01. For the estimation of accuracy, we first calculate the overlapping area between the ground-truth values and the predicted bounding boxes. While measuring, if the predicted bounding box captures over 20% overlap with the ground truth bounding box values, the prediction is considered correct, i.e., a true positive (TP). And if this predicted bounding box has an overlap area of less than 20% with the ground truth box, it is considered a false positive (FP). Additionally, if the overlap had a 20% area between the prediction box and the ground truth values, then the classification was deemed incorrect and referred to as a false positive (FP). If the proposed model is not able to predict any crack, then it's assigned as fn.

The red and green colour bounding boxes represent the ground truth values and the predicted bounding box, respectively. Fig. 5(a) provides the descriptions of cracks that are correctly detected and classified with an IoU of over 20% for each segment crack class (referred to as true-positive 'tp'). Fig. 5(b) covers the area with an IoU overlap of less than 20% with the ground truth. False negative 'fn' those cracks that are not detected via the proposed model, which is illustrated in Figure 5(b) and Figure 5(c). The unlabeled cracks left behind during the tedious, manual annotation process are illustrated in Figure 5(d). Hence, it displays the high-level performance of the proposed model in YOLO v5.







Fig. 5. Classification of Predicted Runway Crack for Validation Set

Table 5: Confusion Matrices Gained on the Classification (a) YOLO v5 (b) Fast R-CNN Models

YOLO V5	D0	D1	D2	D3	D4	D5	D6	D7	D8	
D0	0.99	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	
D1	0.02	0.97	0.01	0.00	0.00	0.00	0.00	0.00	0.00	
D2	0.00	0.00	0.99	0.00	0.00	0.00	0.00	0.00	0.00	
D3	0.00	0.00	0.01	0.98	0.00	0.00	0.01	0.00	0.00	
D4	0.00	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.00	
D5	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	
D6	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00	
D7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	
D8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	
				a)					
Fast R-CNN	DO	D	1 D	02 I	03	D4	D5	D6	D7	D8
DO	0.9	6 0.0	0.	01 0.	.00 (0.00	0.01	0.00	0.00	0.00
DI	0.0:	5 0.9	1 0.	04 0.	.00 (0.00	0.00	0.00	0.00	0.00
D2	0.0	0.0	1 0.	97 0.	.02 (0.00	0.00	0.00	0.00	0.00
D3	0.0	0.0	0 0.	07 0	.92 (0.00	0.00	0.01	0.00	0.00
D4	0.0	0.0	0 0.	00 0.	.00 (0.97	0.00	0.01	0.00	0.01
D5	0.0	1 0.0	0 0.	00 0.	.00 (0.00	0.99	0.00	0.00	0.00
D6	0.0	0.0	0 0.	00 0.	.01 (0.00	0.00	0.99	0.00	0.00
D7	0.0	0.0	0 0.	00 0	.00 (0.00	0.00	0.01	0.99	0.00
D8	0.0	0.0	0 0.	00 0	.00 (0.07	0.00	0.00	0.00	0.93

Table 5 presents the resulting confusion matrices for the YOLO v5 and Faster R-CNN models. It shows that both models' accuracies yield better results, but the YOLO v5 model achieves greater accuracy. Comparatively, confusions between classes arose far more often in the Faster R-CNN than in the YOLO v5.

Table 6: Results for the Crack Detection and **Classification of 9 Types of Level Distress Runway** Cracks

Crack ID	#Crack_ Class	YOLOv5 Model			Faster	R-CNN	Model
		Preci sion	Recal 1	F1- Score	Precisi on	Recall	F1- Score
D0	Reflective Runway Crack	0.92	0.75	0.83	0.72	0.71	0.71
D1	Transvers e Runway Crack	0.89	0.82	0.85	0.74	0.73	0.74
D2	Block Runway Crack	0.92	0.78	0.84	0.81	0.58	0.67
D3	Longitudi nal Runway Crack	0.91	0.83	0.87	0.66	0.43	0.52
D4	Alligator Runway Crack	0.91	0.74	0.82	0.81	0.43	0.57
D5	Sealed Transvers e Runway Crack	0.93	0.83	0.87	0.83	0.68	0.75
D6	Sealed- Longitudi	0.92	0.78	0.84	0.82	0.53	0.64

Crack ID	#Crack_ Class	YOLOv5 Model			Faster	R-CNN	Model
	nal Runway Crack						
D7	Lane longitudin al Runway Crack	0.94	0.57	0.71	0.75	0.30	0.42
D8	Pothole Runway Crack	0.96	0.78	0.86	0.83	0.78	0.80
	Average Mean	0.92	0.76	0.83	0.77	0.57	0.64

The results for the detection and classification of YOLOv5 and Faster R-CNN for nine crack classes are presented in Table 6. In Faster R-CNN, the longitudinal and alligator lane cracks result in lower performance metrics, including precision, recall, and F1 scores. The F1 scores for the classes in the YOLOv5 model are higher than those for the Faster R-CNN model. The precision and recall values for the YOLO v5 model are 93% and 77%, respectively. The high values of precision, recall, and the F1 score of 84% in our proposed YOLO v5 model suggest the benefit of using labelled datasets in developing runway crack detection models with their type ID.

Figure 6 illustrates the comparative results between YOLO v5 and Faster R-CNN for detecting runway cracks in top-down images. Obstacles such as sunlight images and shadow images (for example, trees, crew buses) are used to challenge the robustness of both models. In Figure 6, the black bounding boxes represent the ground truth values of cracks, whereas the blue and green colour bounding boxes represent the predicted crack detections on the runway. Both models accurately detect runway cracks for obstacle images as well.



Runway Crack Detection using Faster R-CNN Model

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V. CONCLUSION AND FUTURE SCOPE

This research introduces a new dataset, namely the Airport Runway Image Dataset (ARID). The proposed model, along with the dataset, has been utilised for automated surface crack classification, its detection, and monitoring the depth of the crack on airport runways for training deep learning approaches. This dataset comprises two types of images: (i) wide-view images and (ii) top-down images, also presenting the nine types of surface distresses on airport runways. The wide-view images are used to classify the runway cracks, while the top-down view images are used for estimating the density of the cracks. The main goal is to demonstrate how deep learning approaches and wide-view images can be utilised to categorise surface cracks. The F1 scores, which are often used for model accuracy calculations, are attained at 83% for YOLO v5 and 64% for the Faster R-CNN models. Both models are also capable of accurately detecting cracks in obstacles. Finally, the proposed model is reliable and adaptable, with the ability to identify and predict cracks from various camera viewpoints, enabling practical, economical, and precise surface crack evaluation and monitoring of the runway and its management. Therefore, for future reference, the work may be extended to improve the model's robustness and focus on developing enhancements in the Faster R-CNN analysis to integrate images from Google Maps directly.

DECLARATION STATEMENT

Funding	No funding was received for this work.
Conflicts of Interest/ Competing Interests	The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval or consent to participate, as it presents evidence that is not subject to interpretation.
Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	Abhilasha Sharma: Visualisation, Supervision, and editing of the manuscript. Aryan Bansal: Conceptualised and conceived of the study, and designed the model. Carried out the related studies, in sequence alignment and drafting the manuscript, along with performance and statistical analysis.

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Airport Runway Crack Detection to Classify and Densify Surface Crack Type

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