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Airport Runway Crack Detection to Classify and Densify Surface Crack Type

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Abstract*: *With the extensive development in infrastructures, many airports are built in order to satisfy travelling needs of people. The frequent arrival and departure of numerous plans lead to substantial runway damage and related safety concerns. So, the regular maintenance of runway has become an essential task specially for detection and classification of cracks in terms of owing to the intensity heterogeneity of cracks such as low real-time performance and the long time-consuming manual inspection. This paper introduces a new dataset named as ARID with 8 different crack classes. A runway crack detection model based on YOLOv5 and Faster RCNN has been proposed which is annotated on 8,228 collected datasets. Then the model is trained with different parameters for training to obtain the optimal result. Finally, based on experimental result, the crack detection precision has improved from 83% to 92%, while the recall has increased from 62.8% to 76%.

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

I. INTRODUCTION

In recent decades extreme travelling and transportation exchanges has been tremendously increased across globe. The aviation industry has witnessed significant advancements in technology, leading to safer and more comfortable flights. Modern aircraft are equipped with state-of-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 via some factors. Thus, regular maintenance has become an essential task specially for detection and classification of cracks on the runway. The structural degradation of runway can potentially endanger safety and diminish service life as well as may cause loss in economics growth. Crack-based damages has the potential to impair performance and present safety risks. They become the most common defect that appears on airport runways that lowers the stress state and potentially causes accidents. If this damaged pavement is not repaired timely, the problem will worsen due to recurring environmental or human factors.

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Repairing a crack before it deteriorates will decrease the cost of maintenance, reduce the impact on the environment, and lengthen the life of the asphalt. If the maintenance tasks of crack removal are achieved in time, the price for the crack rehabilitation can be kept upto to 80%.

In recent years, the quick growth in Indian economy has a pace of airport development which leads the aviation industry to recover from pre-pandemic levels, and new routes and startup carriers are on the horizon. By 2025, the government hopes to build 220 additional airports. According to Jyotiraditya Scindia, the minister for civil aviation, India would 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. 8 of 21 greenfield airports are already operating. As more and more people opt to fly, various types of runway damage will unavoidably result. The runway is extensively tainted with fuel stains and aircraft wheel marks. Moreover, there are often very thin cracks present which can indicate the possibility of significant failure These images are extremely noisy and feature a variety of characteristics including very small 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. An automated crack detection system can efficiently evaluate the condition of a runway and aid airport authorities {(International Civil Aviation Organization (ICAO)} in organizing and prioritizing repair activities aimed at increasing the runway's useful life. Computer vision (CV) fabricates machine by learning from the features of digital images and videos. By using visual data, it improves understanding of features and patterns. For these research domains, there is a vast amount of visual data available via cellphones and digital cameras.

Various researchers have been gone through the concept behind deep architecture-based crack detection approaches as explained further. 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.

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While these methods have proven effective in detecting cracks in high-quality image datasets [3], it should be emphasized 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 analyzed in order 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 found and classified, road administrators can utilize the data to create pavement repair strategies depending on the nature, scope, and severity of the problems. Prior research attempted to do this but fails to do in some areas. For example, the work done by CrackNet [4] was only on defining the presence of distress surfaces, meantime 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 recognizing 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 set is necessary to achieve the better efficiency of deep learning technique. Labeled datasets are crucial for creating a reliable distress surface dataset for airport runways. In this paper, a new dataset has been introducing namely 'Airport Runway Image Dataset,' or (ARID). Here, initially 8,228 images were extracted from 10 different surface sections. Images were collected from street-view 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 through by using of two deep learning approaches i.e., YOLO v5 and Faster R-CNN.

Based on a deep learning methodology, two DL (deep learning) models are improved and implemented in a single outline as given in figure 1. The major 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 for determining the density of damage while the wide-angle images were used for categorization.
- The wide-view images have been marked with total 9 types of cracks are identified along with its crack id i.e., D0-D8. That are reflecting, transverse, block, longitudinal, alligator, sealed transverse, sealed longitudinal, and lane longitudinal cracking, as well as the existence of potholes deemed critical for assessing crack surface quality.

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

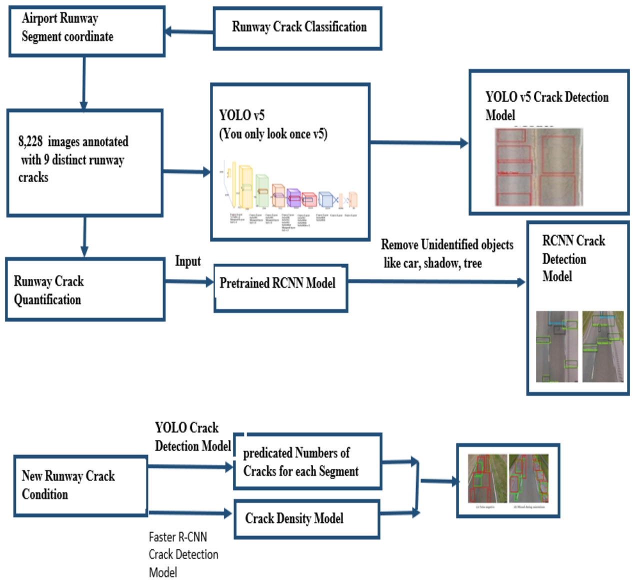

Fig. 1. Outline for Airport Runway Crack Detection and its Classification

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

II. RELATED WORK

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

The detection of cracks has been explored using different approaches in deep learning such as image classification (IC) and semantic segmentation (SS) techniques. To build on recent successes, Convolutional Neural Network (CNN) was utilized for image classification, specifically for the identification of images that have 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 or not the image has a crack. The initial aspect of this architecture is in charge of extracting meaningful features from raw images layer by layer. This is accomplished through the use of a sequence of convolutional layer and max-pooling layers that gradually turn the input picture into a more abstract representation.

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The following section of the CNN is made up of Fully Connected Layers (FCL) and categorizing the features 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], a crack type classification task with five classes was achieved using four CNN models with fluctuated depths, inspired by AlexNet [11] and LeNet [12]. The models were compared to one another. Further, Wang et al. [13] utilized a sizable dataset consisting of 5000 3D pavement images, which included a diverse range of examples. The objective was to facilitate the learning of possible complexities and variations in road surfaces by the architecture. Table 1 presents a taxonomy of techniques for segmenting cracks based on an image classification using deep learning approaches.

Table 1: Taxonomy on 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]	In testing phase, images were of any resolution and scanned using the sliding window algorithm.	Mat Conv Net
Pauly et al., 2017 [33]	Worked on the effectiveness of number convolutional layers and max-pooling on the crack image performance for crack detection.	-
Wang et al., 2017 [8]	Worked on the effectiveness in patch size of images on the performance and the types of crack type get 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 shallow network application along with ANIVOS architecture to achieve deep-crack detection and collecting the publicly available GAP's dataset.	LeNet., AlexNet, VGG-16
Dorafshan et al., 2018 [36]	Shows various the AlexNet applications with its comparison in 2 ways of training i.e., scratch and transfer learning approaches.	AlexNet
Da et al., 2018 [37]	Performing crack detection for image classification using CNN depend on transfer learning approaches.	VGG-16
Kim et al., 2018 [39]	Worked on pretrained AlexNet applications on "ImageNet" dataset to accomplish detection for crack while assuming a richer dataset including the where non-crack objects included.	AlexNet
Kim et al., 2019 [38]	Comparison among FCL and CNN based robust features 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 receptive field size of images with multi-class of distinct cracks type.	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]	Worked on the integration of YOLO into an unmanned aerial vehicle is proposed to achieve real-time crack detection in tiled sidewalks.	ResNet50-based YOLOv2 and YOLOv4-tiny

B. Semantic Segmentation (SS)

Semantic segmentation involves the classification at the pixel level of images. 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 the crack pixels are distinguished from the background pixels by using a distinct color. 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] were used. Following the detection of crack patches, the usual method for crack segmentation involves the application of Otsu's thresholding, followed by the utilization of median filtering and the 'Hessian matrix' to remove any effects of lighting and improve 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 on deep crack segmentation approaches on Hybrid SS setting.

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Table 2: Taxonomy on Deep Crack Segmentation Approaches on Hybrid SS Setting

Author, Year	Description	Methods
Zhang et al., 2018 [20]	Worked on transfer learning applications to detect cracks, especially sealed crack segments. Fast block-wise segmentation using linear regression are used to identified crack segments was applied.	IC+IP
Zhang et al., 2018 [40]	Worked on pretrained AlexNet on "ImageNet" data to detect & classify road crack images especially in sealed crack 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 collective with modified tabularity flow field and also worked on crack quantification using an improved transform method.	OR+IP
Chen et al., 2023 [58]	Proposed a pavement fracture segmentation method based on U-Net model, and the its type by taking the factor like the length, width and areas of crack are measured as per segmentation results.	IC+FCN (U-Net)

D. Pure Semantic Segmentation

The crack detection process can also be carried out without the identification of 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 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 images throughout the convolution layers. This approach enables them to perform pixel-level classification under the supervision of labeled data. To extract high-level and complex features, a backbone architecture is used for semantic segmentation utilizing an encoder-decoder framework. This is performed by the use of a series of convolution, pooling, and activation layers. 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). This pixel-level categorization is enabled by the restoration of feature size.

In computer vision area, multiple architectures have been suggested to carry out semantic segmentation (SS) like U-Net architecture [27], SegNet architecture [28], and FC-Dense Network architecture [29]. These architectures have also been extensively used in the crack detection. According to certain studies, the use of basic encoder-decoder 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 on deep crack segmentation approaches on the Pure SS setting.

Table 3: Taxonomy on Deep Crack Segmentation Approaches on the Pure SS Setting

Author, Year	Method	Description
Zhang et al., 2016 [43]	crack pixels on center in the patches	The first application of task of Crack segmentation is feature extraction on raw data by 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 deeper and more comprehensive FCN architecture has been proposed for detecting four types of concrete damage, which eliminates the need for a sliding window technique
Bang et al., 2019 [48]	Encoder–decoder (ResNet + SegNet, FCN, ZFNet)	Using deep learning methods for detection of Black-Box on road cracks.
Zou et al., 2019 [52]	Encoder–decoder (SegNet)	A new neural network that is 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 being proposed that applies GAN architecture and can function 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 hence improving the accuracy.
Chen et al., 2020 [51]	Encoder–decoder (SegNet)	"Adadelta" optimizer and cross-entropy loss function is implemented with SegNet architecture for crack segmentation.

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Fei et al., 2020 [26]	Consecutive conv layers with an invariant spatial size	CrackNet-V(enhanced version of CrackNet) is proposed generating in better efficiency in terms of accuracy and speed and to boost the accuracy of crack segmentation for shallow cracks, new activation function is taken into consideration..
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 Resenet-34 (EDNet)	Worked to overcome the imbalance quantity within the crack & non-crack pixels images based on 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 is 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 model that consists of two-phase i.e., Detection and Segmentation respectively. In the first phase, YOLO v5 utilized as a classification detection method which is trained on image patches to search for any areas having cracks or damage on runway. Moreover, the images' background noise and unnecessary bits are removed. The second phase covered with the pixel-level in small areas for segmenting runway cracks from the original photos. The block diagram of proposed model for detecting road cracks and its segmentation is represented schematically in figure 2, where each CNN layer within the YOLO v5 is followed by max-pooling layer. The first phase employs YOLO v5 like a detection technique which is trained using sample image patches to look for any areas within the runway that have cracks. Also, it cleans up the images' background noise and superfluous bits. In the second phase, runway cracks are segmented in discrete areas within the original images. And finally, the combined method has compensations for both phases i.e., detection and segmentation.

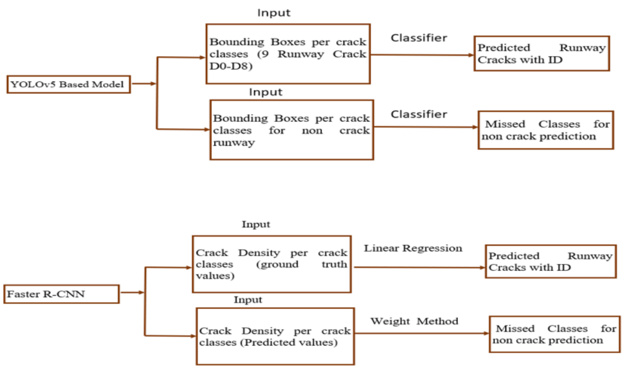

Fig. 2. Block Diagram of Proposed Model for Detecting Road Cracks and its Segmentation

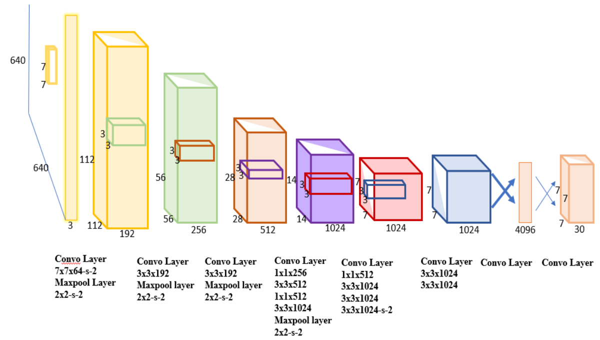

Fig. 3. YOLO v5 Architectural Diagram

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 YOLO v5 deep learning model. An object detection approach called YOLO, which is relatively new, seems to offer the best accuracy for developing deep learning-based approaches. For proper execution of object detection, YOLO first reframes the object detection process just looking at a certain image only one time. Most recently, CNN classifiers have been used by object identification algorithms to speed up detections. The algorithm can forecast class probabilities simultaneously in this way. Table 4 enlists the details of CNN architecture and shows the series of layers along with each kernel size, strides with the output shape of pixel for model implementation.

B. Faster R-CNN Model

This model includes the 2-stage crack-targeted detection method. It gives 3 main 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 segment. After that each segment is passes through a sequence of convolutional-filter layers for feature extraction, then it passes through a classifier. The probability of crack image areas for outputs region collected via this classifier including its type.

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]

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Convolutional Layer	3x3	1	[26,26,256]
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 about the implementation details of whole setup. The model has been implemented on the newly collected dataset as described in Section 4.1. The selection of hyper parameters during training are also discussed in Section 4.2. The experiments are performed on machine having AMD Ryzen-5 processor, 5600H- Radeon, having 3.30 Gigahertz Graphics, RAM: 8 GB, GPU NVIDIA GETFORCE RTX.

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.

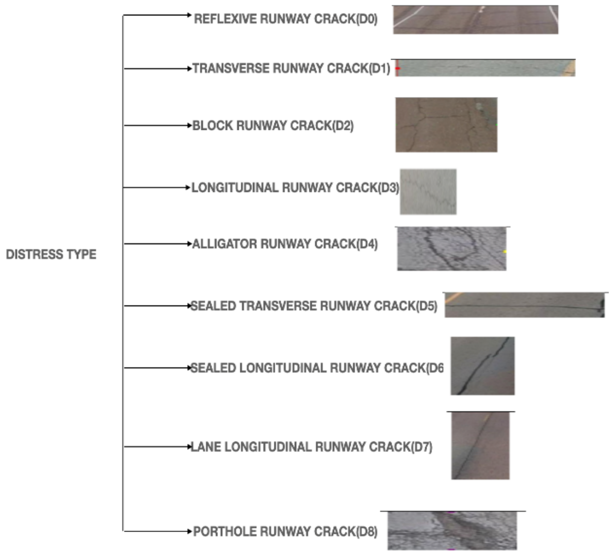


Fig. 4. Airport Runway Distress Crack Types with its Crack ID

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", 1.4µm, dual pixel PDAF, OIS, 12 MP, f/2.4, 120˚, 13mm (ultrawide), 1/3.6". Also, by means of the Google API, distress surface images automatically get the extraction by requiring GPS coordinates inclusive of camera and image parameters. Herein, starting and ending points are selected on the runway for each marked. Different images of same cracks are together at particular coordinate point having pitch angle for camera of -60◦ and -90◦ for runway crack classification. In the dataset, 640*640 pixels image size is taken for all collected images, then the wide-view images are annotated through software annotation tool to depict 9 distinct runway cracks i.e., D0-D8. Total 8,228 wide-view images are taken from which 5,760 images are taken for training & 2,468 images for testing data.

B. Model Accuracy

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

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

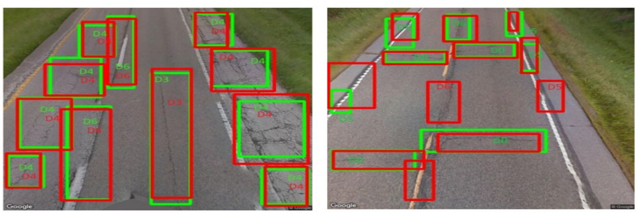
$$Recall = \frac{tp}{(tp+fn)} \quad (2)$$

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

where the ***'tp'*** indicates numbers of True-Positive, ***'fp'*** indicates numbers False-Positive and ***'fn'*** indicates numbers False-Negative images.

The proposed model is trained on total of 5,760 images and evaluated on 2,468 images for 20,000 iterations along with 10 epochs by setting the learning rate to 0.01. For estimation of accuracy, we firstly calculate the overlapping area among ground-truth values and predicting bounding boxes. While measuring, if this predicted bounding box are captured over 20% overlap area with ground truth bounding box values, then the prediction founds to be correct i.e., *tp*. And if this predicted bounding box has under 20% overlap area of ground truth box which considered as *fp*. Also, if the overlap had 20% area among the prediction box and the ground truth values then classification found to be incorrect referred as *fp*. If the proposed model not able to predict any crack, then it's assigned as *fn*.

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



(a) True positive (b) False positive & False negative

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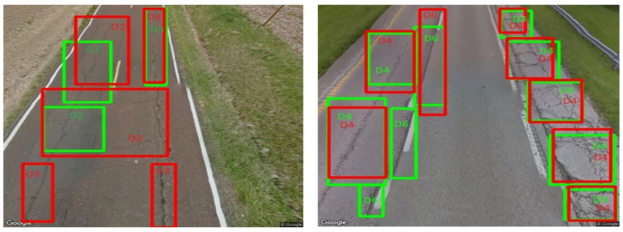


(c) False negative (d) Missed during annotations

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	D0	D1	D2	D3	D4	D5	D6	D7	D8
D0	0.96	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.00
D1	0.05	0.91	0.04	0.00	0.00	0.00	0.00	0.00	0.00
D2	0.00	0.01	0.97	0.02	0.00	0.00	0.00	0.00	0.00
D3	0.00	0.00	0.07	0.92	0.00	0.00	0.01	0.00	0.00
D4	0.00	0.00	0.00	0.00	0.97	0.00	0.01	0.00	0.01
D5	0.01	0.00	0.00	0.00	0.00	0.99	0.00	0.00	0.00
D6	0.00	0.00	0.00	0.01	0.00	0.00	0.99	0.00	0.00
D7	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.99	0.00
D8	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.93

b)

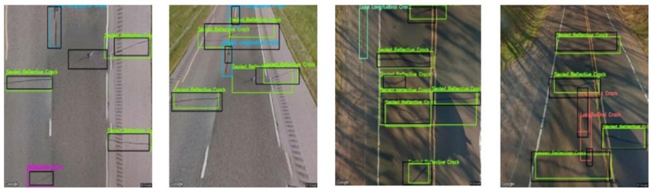
Table 5 shows the resultant confusion matrices for YOLO v5 and Faster R-CNN models. It shows that both models' accuracies come out to be better result, but the YOLO v5 model's achieves greater accuracy. Comparatively, confusions between classes arose far more often in the Faster R-CNN than the YOLO v5.

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		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score
D0	Reflective Runway Crack	0.92	0.75	0.83	0.72	0.71	0.71
D1	Transverse 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	Longitudinal 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 Transverse Runway Crack	0.93	0.83	0.87	0.83	0.68	0.75
D6	Sealed-longitudinal Runway Crack	0.92	0.78	0.84	0.82	0.53	0.64
D7	Lane longitudinal 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**

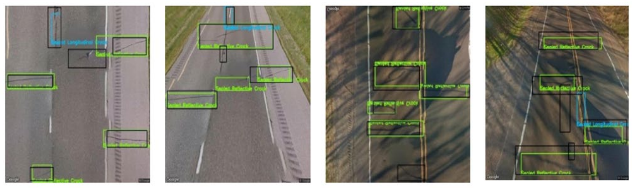
The result for detection and classification of the YOLO v5 and Faster R-CNN for 9 crack classes are shown in Table 6. In Faster R-CNN, the longitudinal, alligator and longitudinal lane cracks the performance metrics results to be lesser precision, recall and F1 scores. The F1 scores for the classes in the YOLO v5 model are higher than the scores 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 suggests the benefit of using labeled datasets in developing runway crack detection models with its type ID.

Figure 6 illustrate the comparative results among YOLO v5 and faster R-CNN for detecting runway cracks as of top-down images. The obstacle like sunshine images and shadow's images (for example trees, crew bus) are taken to challenge the robustness of both models. In figure 6, the black bounding-boxes represent ground truth values of cracks whereas blue color and green color bounding-boxes represents the predicted crack detections on runway. Both the models are accurately detecting runway cracks for obstacle images also.



top-down image plain wide-view image shadowed top-down image shadowed wide view image.

(i)



top-down image plain wide-view image shadowed top-down image shadowed wide view image.

(ii)

Fig. 6. (i) Runway Crack Detection using YOLO v5 Model. (ii) Runway Crack Detection using Faster R-CNN Model

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V. CONCLUSION AND FUTURE SCOPE

This research, introduces a new dataset i.e., Airport Runway Image Dataset (ARID). The proposed model along with the dataset has been utilized for the purpose of automated surface cracks classification, its detection & also monitoring the depth of the crack on airport runways for training the deep learning approaches. This dataset comprises via two ways: (i) wide-view images and (ii) top-down images; also presenting the nine types of surface distresses of airport runway. 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 crack. The main goal is to show how the deep learning approaches and wide-view images can be utilized to categories surface cracks. The F1 scores, which are often used for model accuracy calculation are attained as 83% or YOLO v5 and 64% or the Faster R-CNN models. Both the models are able to accurately detect cracks in obstacles also. Finally, the proposed model is reliable and adaptable, with the ability to identify and predict the crack from various camera viewpoints for practical, economical, and precise surface crack evaluation, monitoring the runway and its management. Therefore, for future reference the work may be extended on improving the robustness of model and focuses on developing enhancements in the Faster R-CNN analysis to directly integrates from Google maps images.

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Authors Contributions	Abhilasha Sharma: Visulazation, Supervision and editing in manuscript. Aryan Bansal: Conceptulization and conceived of the study & in desiging of model. Carried out the related studies, in sequence alignmnet and drafting the manuscript along with performance and statistical analysis.

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