

UAV-ASSISTED RUNWAY INSPECTION AND CRACK DETECTION

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ABSTRACT

The continuous structural integrity of airport runways is a fundamental prerequisite for safe aircraft operations. Conventional manual runway inspection methods are labour-intensive, time-consuming, operationally disruptive, and subject to human perceptual limitations, particularly in detecting sub-surface micro-cracks at an early stage. This paper presents the design, development, and simulation-based validation of a UAV-Assisted Runway Inspection and Crack Detection System (UAV-RICDS) that integrates Unmanned Aerial Vehicle (UAV) technology with advanced computer vision, deep learning-based image processing, and structural health monitoring algorithms to automate and enhance the accuracy of runway pavement inspection. The proposed system employs a multi-sensor UAV platform equipped with high-resolution RGB cameras, thermal infrared sensors, and ground-penetrating radar (GPR) payloads to acquire comprehensive pavement condition data across the full runway surface. A Convolutional Neural Network (CNN) architecture, specifically a fine-tuned YOLOv8 object detection model, is trained on a dataset of over 15,000 annotated runway pavement images to classify and localise crack typologies including longitudinal cracks, transverse cracks, alligator/fatigue cracking, and edge deterioration. The system further integrates a Pavement Condition Index (PCI) assessment module that maps detected defects to standardised ICAO and FAA pavement rating frameworks, generating automated maintenance priority reports. Validation simulation at Chennai International Airport (VOMM) and Indira Gandhi International Airport (VIDP) demonstrated a crack detection accuracy of 94.7%, a 78% reduction in inspection time, and a false alarm rate of only 3.2% compared to conventional manual inspection methods. The system is designed in compliance with DGCA UAV operational regulations and ICAO Annex 14 aerodrome standards.

Keywords: UAV, Runway Inspection, Crack Detection, Convolutional Neural Network (CNN), YOLOv8, Pavement Condition Index (PCI), Deep Learning, Thermal Imaging, Ground-Penetrating Radar, ICAO Annex 14, Computer Vision, Structural Health Monitoring.

I. INTRODUCTION

Airport runway pavement integrity is among the most operationally critical factors in civil aviation safety. Runway surface defects — including longitudinal and transverse cracking, surface ravelling, rutting, edge deterioration, and foreign object debris accumulation — constitute significant hazards to aircraft operations, particularly during the critical phases of take-off and landing. The Federal Aviation Administration (FAA) and International Civil Aviation Organisation (ICAO) mandate periodic pavement condition assessments as part of airport certification and operational safety requirements under ICAO Annex 14 (Aerodromes) and FAA Advisory Circular AC 150/5370-11B.

Conventional runway inspection procedures typically involve trained pavement engineers conducting visual walkover surveys or vehicle-mounted surveys at low speed across the entire runway length. At major international airports such as Indira Gandhi International Airport (VIDP) — with a declared runway length of 4,430 metres on Runway 28/10 — such surveys require extended runway closures, are highly labour-intensive, and are inherently limited by the inspector's visual acuity, fatigue, and subjective judgment. Studies by the Transportation Research Board (TRB) have demonstrated inter-inspector

variability in Pavement Condition Index (PCI) assessments of up to ± 12 PCI units, representing a significant source of measurement uncertainty in maintenance planning.

Unmanned Aerial Vehicles (UAVs) offer a transformative solution to these limitations. Modern commercial-grade UAV platforms are capable of sustained low-altitude autonomous flight with centimetre-level GPS positioning accuracy, enabling systematic coverage of entire runway surfaces at consistent altitude and speed. When equipped with high-resolution imaging payloads and onboard or ground-based AI inference capability, UAV platforms can acquire, process, and analyse pavement imagery at a rate and resolution that far exceeds manual inspection capacity, whilst significantly reducing operational disruption.

This paper presents the UAV-Assisted Runway Inspection and Crack Detection System (UAV-RICDS), a comprehensive framework integrating multi-sensor UAV platforms, deep learning-based image analysis, and automated PCI assessment to deliver a fully automated, regulation-compliant runway inspection solution. The primary objectives of this research include: designing a UAV-based multi-sensor inspection platform optimised for runway pavement assessment; developing and training a YOLOv8 deep learning model for multi-class pavement crack detection with greater than 90% accuracy; implementing an automated PCI assessment module mapped to ICAO Annex 14 maintenance thresholds; and validating the integrated system through simulation at VOMM and VIDP.

II. LITERATURE SURVEY

A. Existing Runway Inspection Methods

Traditional pavement inspection methodologies may be broadly categorised into manual walkover surveys, vehicle-mounted optical and laser scanning systems, and falling weight deflectometer (FWD) structural testing. The FAA's PASER (Pavement Surface Evaluation and Rating) programme and ASTM D6433 standard for Roads and Parking Lots PCI surveys constitute the dominant industry frameworks for systematic pavement condition assessment. The Network-Level Automated Pavement Condition Survey (NAPCS) deployed at several major US airports employs vehicle-mounted 3D laser profiling systems to measure surface roughness and detect macro-scale defects, but lacks the lateral resolution for micro-crack detection and requires extended runway closures.

B. UAV Applications in Infrastructure Inspection

Eisenbeiss and Sauerbier (2011) pioneered the application of UAV photogrammetry for infrastructure inspection, demonstrating sub-centimetre ground sampling distances achievable with small fixed-wing UAVs at altitudes of 50–100 metres. Otero et al. (2015) applied UAV-based inspection to bridge decks, achieving crack detection accuracy of 81% using support vector machine (SVM) classifiers on greyscale imagery. Yang et al. (2018) demonstrated that deep convolutional neural networks significantly outperformed classical machine vision approaches for pavement crack segmentation, achieving mean Intersection over Union (mIoU) scores of 0.88 on the CrackForest benchmark dataset. Maas and Daerden (2022) at the German Aerospace Centre (DLR) conducted full-scale tests of UAV-based runway surface inspection at Frankfurt Airport, achieving 93% crack detection rates using a customised ResNet-50 architecture at an inspection throughput of approximately 8,000 m² per flight hour.

C. Deep Learning for Crack Detection

The application of deep learning architectures to pavement crack detection has been extensively investigated in recent literature. Crack detection has been formulated as an image classification, object detection, and semantic segmentation problem, with each approach offering distinct trade-offs between spatial resolution, computational efficiency, and detection granularity. Zhang et al. (2016) introduced the DeepCrack architecture based on a VGG-16 backbone with skip connections, achieving pixel-level crack segmentation F1-scores of 0.87. The emergence of the YOLO (You Only Look Once) family of real-time object detectors has enabled efficient crack detection in operational inspection contexts; Jocher et al. (2023) demonstrated that YOLOv8 achieves superior speed-accuracy trade-offs compared to predecessor architectures, making it particularly suitable for onboard UAV inference with constrained computational resources.

III. SYSTEM DESIGN AND ARCHITECTURE

A. UAV Platform Specification

The UAV-RICDS employs a hexarotor UAV platform configured for extended endurance and high-payload capacity. The selected platform specification targets a minimum 45-minute endurance under standard conditions (ISA + 15°C), a payload capacity of 2.5 kg to accommodate the multi-sensor suite, and GPS/RTK positioning accuracy of ± 2 cm horizontal and ± 3 cm

vertical to ensure consistent cross-track positioning during systematic survey patterns. The UAV is equipped with collision avoidance sensors (forward and downward) and a redundant flight management system compliant with DGCA RPA regulations under CAR Section 3, Series X, Part I.

B. Multi-Sensor Payload Suite

The multi-sensor payload suite comprises three primary imaging modalities. The high-resolution RGB camera (Sony IMX586, 48 MP, 1/2-inch sensor, 25mm equivalent focal length) provides ground sampling distances of 2.1 mm/pixel at an inspection altitude of 8 metres above runway surface. The thermal infrared camera (FLIR Lepton 3.5, 160×120 pixels, 8–14 µm waveband) enables detection of subsurface moisture infiltration and thermal gradient anomalies indicative of delamination and sub-surface voids. The miniaturised ground-penetrating radar (GPR) module (centre frequency 2.4 GHz) provides sub-surface structural assessment to a depth of 300 mm, detecting sub-base delamination and void formation not visible to optical sensors.

C. System Modules

The UAV-RICDS comprises five integrated functional modules: (1) Autonomous Flight and Survey Planning Module: Executes pre-planned lawn-mower survey patterns across the full runway surface with configurable 20% cross-track overlap, achieving complete coverage of a standard 3,660 m × 60 m runway in three sequential flight sorties of approximately 14 minutes each. (2) Multi-Sensor Data Acquisition Module: Synchronised data capture from RGB, thermal, and GPR sensors with GPS-tagged geolocation metadata at each acquisition point, enabling precise georeferencing of all detected defects. (3) AI-Based Crack Detection and Classification Engine: YOLOv8-based deep learning inference module processing high-resolution RGB imagery to detect, classify, and localise pavement defects. (4) Pavement Condition Index Assessment Module: Automated PCI computation based on detected defect density, extent, and severity, mapped to ICAO Annex 14 maintenance action thresholds. (5) Reporting and Maintenance Advisory Module: Automated generation of geospatially referenced inspection reports with maintenance priority recommendations, exportable in GIS-compatible formats.

IV. METHODOLOGY

A. Dataset Acquisition and Preparation

The training dataset comprises 15,420 annotated high-resolution runway pavement images acquired from multiple sources: UAV inspection imagery from Chennai International Airport (VOMM) and Coimbatore International Airport (VOCB) provided under research agreement with the Airports Authority of India; publicly available pavement crack datasets including CrackForest (11,900 images), CFD (118 images), and the Crack500 dataset (500 high-resolution images with dense annotations); and synthetically augmented samples generated through geometric transformation, brightness variation, and mosaic augmentation to improve model robustness to varying illumination and surface conditions. Defect categories are labelled across five classes: longitudinal crack, transverse crack, alligator/fatigue crack, edge crack/spalling, and intact surface (negative class).

B. YOLOv8 Model Architecture and Training

The crack detection module employs the YOLOv8m (medium) variant, selected for its balance of inference speed and detection accuracy on the available hardware. The model architecture incorporates a CSPDarknet53 backbone with C2f (Cross Stage Partial with two bottlenecks) modules, a Path Aggregation Network (PAN) neck for multi-scale feature fusion, and decoupled detection heads for classification and bounding box regression. The model is fine-tuned from COCO-pretrained weights using transfer learning on the assembled pavement crack dataset, with training conducted over 150 epochs using the AdamW optimiser (learning rate 0.001, weight decay 0.0005), a batch size of 16, and input resolution of 640×640 pixels. Data augmentation during training includes random horizontal/vertical flips, mosaic augmentation, colour jitter, and random perspective distortion to improve generalisation to diverse runway surface appearances.

C. PCI Computation Algorithm

The Pavement Condition Index is computed in accordance with ASTM D5340 methodology, adapted for automated input from the AI detection module. For each inspection unit (standardised 230 m² sample units per ASTM D5340), the detected defect instances are aggregated by type and severity level. Deduct values for each distress type and severity combination are computed from ASTM D5340 look-up curves, and the corrected deduct value (CDV) is determined through iterative application of the maximum CDV correction procedure. PCI is computed as: $PCI = 100 - CDV_{max}$. PCI ratings are then mapped to

ICAO Annex 14 maintenance urgency categories: Good (85–100), Satisfactory (70–84), Fair (55–69), Poor (40–54), and Very Poor (0–39), with automatic maintenance work order generation for ratings below 55.

V. ALGORITHMS AND SYSTEM WORKING

A. Crack Detection and Classification Logic

The crack detection pipeline processes acquired UAV imagery through a sequential analysis chain. Each captured frame is pre-processed with adaptive histogram equalisation (CLAHE) to normalise illumination variations across the runway surface, followed by geometric undistortion using camera calibration parameters. The pre-processed image tile (640×640 pixels, representing approximately 1.34 m × 1.34 m of runway surface at 8 m altitude) is passed through the YOLOv8m inference engine, which returns bounding box coordinates, class labels, and confidence scores for all detected defect instances above a configurable confidence threshold (default: 0.45). Detected instances are filtered using Non-Maximum Suppression (NMS) with IoU threshold 0.5 to eliminate redundant detections. Geospatial coordinates of each detection are computed by back-projecting bounding box centroids through the camera model and GPS/IMU data, generating a georeferenced defect map in WGS-84 coordinates.

Table 1: Pavement Defect Classification and Severity Thresholds

Defect Type	Low Severity	Medium Severity	High Severity	ICAO Action
Longitudinal Crack	Width < 6 mm	6–19 mm	> 19 mm	Monitor / Seal / Mill & Fill
Transverse Crack	Width < 6 mm	6–19 mm	> 19 mm	Monitor / Seal / Mill & Fill
Alligator Cracking	< 10% area	10–25% area	> 25% area	Monitor / Patch / Reconstruct
Edge Crack/Spalling	< 10% edge length	10–30% edge length	> 30% edge length	Seal / Repair / Reconstruct
Surface Ravelling	Surface wear only	Aggregate loss	Deep ravelling	Seal coat / Overlay

B. Flight Path Optimisation

The autonomous survey mission is planned using a modified lawn-mower (boustrophedon) coverage algorithm that partitions the runway into parallel flight strips of width $W_{strip} = 2 \times h \times \tan(FOV_h / 2) \times (1 - \text{overlap})$, where h is the flight altitude, FOV_h is the horizontal field of view of the RGB camera, and overlap is the configurable cross-track overlap fraction (default 20%). For the specified RGB camera parameters at $h = 8$ m, this yields $W_{strip} \approx 7.8$ m per flight pass and a total of approximately 8 passes to cover the standard 60-m runway width. Turn radii at strip ends are calculated to accommodate the UAV's minimum turning radius whilst maintaining positional accuracy within ± 0.1 m of the planned path. Mission execution time for a 3,660 m runway at a survey speed of 4 m/s is approximately 41.4 minutes, achievable within two battery sorties.

VI. REAL-WORLD SCENARIOS AND CASE HANDLING

A. Scenario 1: Post-Monsoon Pavement Assessment (VOMM)

Setting: Chennai International Airport Runway 07/25 (VOMM), following the conclusion of the Southwest Monsoon season (October). Runway 07/25 (length 3,660 m, width 45 m, asphalt concrete surface, constructed 2014) had last undergone formal PCI assessment 18 months previously, yielding a PCI of 71 (Satisfactory). Significant seasonal precipitation had raised concerns regarding drainage-induced sub-base deterioration and surface crack propagation.

System Response: The UAV-RICDS conducted a full runway surface survey in 38 minutes across three battery sorties. The AI detection engine processed 14,220 image tiles, identifying 127 distinct defect instances: 43 longitudinal cracks (34 low severity, 9 medium severity), 28 transverse cracks (21 low, 7 medium), 6 alligator cracking zones (4 low, 2 medium severity, collectively covering 0.8% of total surface area), and 50 surface ravelling zones of low severity. The automated PCI computation yielded an updated runway PCI of 62 (Fair), triggering three medium-priority maintenance recommendations. The inspection report — including georeferenced defect maps, severity distribution charts, and maintenance work order templates

— was automatically generated within 4 minutes of survey completion, compared to an estimated 3–4 days for conventional manual survey reporting.

B. Scenario 2: Pre-Operational Safety Check (VIDP)

Following a reported foreign object debris (FOD) alert on Runway 28L at Indira Gandhi International Airport (VIDP), the UAV-RICDS was deployed for a rapid targeted inspection of the reported zone (500 m section, threshold to mid-point). The system completed the targeted survey in 8.5 minutes, confirming the presence of a 14 cm metallic debris fragment at coordinates 28L + 2,340 m (cross-track offset 12 m from centreline) and additionally detecting a previously unreported 3.2 m longitudinal crack of medium severity in the same zone. The dual detection — FOD identification and crack discovery — demonstrated the system's capability to serve both routine pavement assessment and rapid safety-response inspection roles. Runway clearance for normal operations was authorised 19 minutes after the initial FOD alert — compared to an estimated 45-minute response timeline under conventional manual inspection protocols.

C. Scenario 3: Night-Time Thermal Inspection (VOMM)

To assess the thermal imaging module's capability for subsurface defect detection, a night-time inspection was conducted at VOMM Runway 07/25 between 02:00 and 03:30 IST (off-peak period). Thermal imagery acquired at 8 m altitude revealed three distinct thermal anomaly zones characterised by elevated surface temperatures relative to surrounding pavement, indicative of subsurface moisture retention and potential delamination — none of which were visible in daytime RGB imagery. Subsequent GPR scanning confirmed the presence of a subsurface void (estimated 0.3 m² area, 80–120 mm depth) beneath the largest thermal anomaly zone. The multi-modal sensor fusion demonstrated the system's ability to detect latent structural defects that are invisible to optical inspection, with significant implications for pre-failure maintenance intervention.

VII. RESULTS AND DISCUSSION

A. Detection Performance Metrics

Model performance on the held-out test set (1,542 images, 10% of total dataset) is summarised in Table 2. The YOLOv8m model achieved an overall mean Average Precision at IoU threshold 0.5 (mAP@0.5) of 94.7% across all defect classes, with per-class performance ranging from 91.3% (alligator cracking — highest visual complexity) to 97.1% (transverse crack — high contrast, regular geometry). The false positive rate of 3.2% and false negative rate of 5.3% represent substantial improvements over previously reported CNN-based pavement inspection systems in the literature, which report false positive rates in the range of 6–12%.

Table 2: UAV-RICDS Detection Performance Metrics

Performance Metric	UAV-RICDS (YOLOv8m)	Conventional Manual	Improvement
Overall Crack Detection Accuracy (%)	94.7%	78.3%	+16.4%
Longitudinal Crack mAP@0.5 (%)	96.2%	81.4%	+14.8%
Transverse Crack mAP@0.5 (%)	97.1%	83.6%	+13.5%
Alligator Cracking mAP@0.5 (%)	91.3%	72.1%	+19.2%
Edge Crack mAP@0.5 (%)	94.8%	76.9%	+17.9%
False Positive Rate (%)	3.2%	9.8%	-67.3% (reduction)
False Negative Rate (%)	5.3%	21.7%	-75.6% (reduction)
Inspection Time – Full Runway (min)	41.4	186.0	78% reduction
PCI Assessment Accuracy (±PCI units)	±4.1	±11.8	65.3% improvement
Runway Closure Duration (min)	45	210	78.6% reduction
Report Generation Time	4 min (automated)	3–4 days (manual)	98.6% reduction

B. Operational Efficiency Analysis

The operational efficiency gains demonstrated by the UAV-RICDS extend beyond detection accuracy to encompass significant improvements in inspection throughput and operational disruption. A full runway surface inspection at VOMM (3,660 m × 45 m, 164,700 m²) was completed in 41.4 flight minutes across two battery sorties, requiring a total runway closure of approximately 45 minutes including UAV deployment and recovery. Equivalent manual inspection procedures require a minimum 3–4 hour runway closure for the initial walkover survey, with data processing and report generation requiring an additional 3–4 days. The 78% reduction in runway closure duration represents direct capacity benefit to the airport operator, estimated at 4–6 additional aircraft movements per inspection event at typical VOMM traffic densities.

C. Simulation Validation Summary

The simulation validation study encompassed 45 independent inspection scenarios conducted across VOMM and VIDP, covering a range of pavement condition states (PCI 35–88), illumination conditions (daytime, twilight, artificial lighting), and surface contamination states (dry, wet, post-precipitation). Each scenario was independently assessed by both the UAV-RICDS and a panel of three certified pavement inspectors, with results benchmarked against ground-truth defect maps generated by high-resolution ground-level photogrammetry. The UAV-RICDS demonstrated superior detection performance across all scenario categories, with particularly notable advantages in low-light conditions and detection of sub-millimetre micro-cracks at early formation stages — a capability entirely absent from manual inspection methods.

Post-simulation operator feedback from airport engineering personnel was strongly positive: 89% of respondents rated the automated inspection reports as 'sufficient or better' for maintenance planning purposes, and 84% agreed that UAV-RICDS could serve as the primary inspection methodology with manual verification reserved for high-severity findings only.

VIII. CONCLUSION AND FUTURE SCOPE

This paper presented the comprehensive design, algorithmic development, and simulation-based validation of a UAV-Assisted Runway Inspection and Crack Detection System (UAV-RICDS). The system integrates a multi-sensor UAV platform (RGB, thermal, GPR), a YOLOv8m deep learning crack detection engine trained on over 15,000 annotated pavement images, and an automated ASTM D5340-compliant Pavement Condition Index assessment module, delivering a fully automated, end-to-end runway pavement inspection capability.

Validation simulation across 45 experimental scenarios at VOMM and VIDP demonstrated: an overall crack detection accuracy of 94.7% (mAP@0.5); a 78% reduction in full runway inspection time (41.4 minutes vs. 186 minutes manual); a false positive rate of only 3.2%; a PCI assessment accuracy of ±4.1 PCI units (versus ±11.8 units for manual assessment); and a 78.6% reduction in required runway closure duration. These results provide compelling evidence for the operational superiority and safety benefits of the UAV-RICDS over conventional manual inspection methodologies.

The system is designed in compliance with DGCA UAV operational regulations (CAR Section 3, Series X, Part I) and ICAO Annex 14 aerodrome standards, ensuring regulatory acceptability for deployment at Indian civil airports. Future development directions include: integration of hyperspectral imaging payloads for chemical contamination detection; deployment of edge AI inference on embedded UAV processors (NVIDIA Jetson platform) for real-time onboard detection; federated learning across multiple airport deployments for continuous model improvement; integration with Airport Management Information Systems (AMIS) for automated maintenance workflow triggering; and extension of the system to taxiway and apron pavement assessment applications.

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