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Empowering automated surface defect inspection with IoT and deep learning techniques: an application in Trunk Road T2 and Cha Kwo Ling Tunnel, Hong Kong

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ABSTRACT

The continuous collection and analysis of data are instrumental in the inspection of tunnel structures. This procedure enables tunnel inspectorates to systematically monitor structural integrity, thereby ensuring the safety and stability of tunnels. Thanks to recent breakthroughs in technologies such as Internet of Things (IoT), deep learning, and robotics, it is now feasible to automate the inspection of tunnel structures. Hong Kong Productivity Council (HKPC), Civil Engineering and Development Department (CEDD), and Hyder-Meinhardt Joint Venture (HMJV) have collaboratively developed an AI-based tunnel structure inspection system that integrates air-ground cooperation. This system leverages cutting-edge techniques, including IoT sensors, Unmanned Ground Vehicle (UGV), and Unmanned Aerial Vehicle (UAV), to facilitate the real-time image data capturing of tunnel structures. Furthermore, it is equipped with the capability to automatically identify defects such as concrete cracks, concrete spalling, and water leakages. Consequently, this advancement not only heightens the efficiency of the tunnel inspection process by diminishing the inspection time and increasing cost savings, but also enhances the site safety and optimises the construction logistics.

KEYWORDS Internet of Things; deep learning; robotics; automate the inspection of tunnel structures; air-ground cooperation
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1. Introduction

The regular inspection of a tunnel's surface is a crucial procedure entailing the continuous collection and analysis of data to evaluate the health status of a tunnel's surface structure. Conventionally, it has been necessary for engineers and inspectors to perform manual inspections on mobile platforms, working in congested tunnel areas, which is time consuming, tedious, and involves safety risks associated with working at height. In recent years, the integration of Internet of Things (IoT) and Deep Learning (DL) techniques has garnered substantial interest in tunnels' surface inspection, promising a transformative impact on the monitoring, inspection, and maintenance of tunnel infrastructure. With the use of sophisticated IoT sensors, e.g., high-resolution cameras, beacons, Light Detection and Ranging (LiDAR), and communication modules, diverse information can be collected automatically, such as environmental conditions, structural integrity, visual information, and communication data. By constantly collecting and analysing these data, the autonomous inspection of tunnel surface defects can be carried out in tunnel construction sites. Consequently, tunnel inspectorates are empowered to detect the evidence of damage or deterioration within tunnels through the intelligent inspection system, thereby enabling prompt responses and advising contractors to rectify any identified defects.

As an abbreviation for "Internet of Things", IoT has become one of the most important technologies in recent years due to the widespread availability of affordable and reliable sensor technology, which allows for the real-time collection and monitoring of various data streams. In the field of civil engineering, the leverage of innovative techniques of IoT allows for monitoring concrete structures and developing inspection and maintenance plans to ensure their long-term integrity (Mijwil et al., 2003). With the years of continuous development of this technology, IoT sensors (Ghosh et al., 2021) have gained considerable traction in the civil engineering industry due to their ability to collect and convey data in real time, alert the relevant individuals and authorities regarding abnormal circumstances, and improve the efficiency of infrastructure monitoring (Mishra et al., 2022). Accordingly, the application of IoT in tunnel inspection, a critical aspect of civil engineering projects, has revolutionised the way that tunnels are inspected and maintained. By empowering the technological progress of real-time data collection and monitoring, engineers can monitor the structural health of tunnels and identify potential issues before they become major problems.

With the utilisation of IoT sensors, a wide range of information can be acquired in real time in construction sites with the use of robotic systems, e.g., tunnel surface image data, the battery level of Unmanned Ground Vehicles (UGVs), driving trajectory of UGVs, the location of UGVs, Unmanned Aerial Vehicles (UAVs), and image data on site. Also, when mounted on a UAV, these sensors can provide valuable insights into inaccessible or challenging-to-reach areas. For example, they are particularly useful for monitoring the condition of infrastructure such as bridges, dams, and pipelines.

On the other hand, the recent advancement in AI has catalysed the adoption of state-of-the-art deep learning techniques in the civil engineering domain, including structural health monitoring, traffic engineering, architectural design, intelligent construction (Kamolov, 2024), construction site safety monitoring (Akinosho et al., 2020), etc. For example, the N-LoLiGan model (Wang et al., 2023), an innovative unsupervised generative adversarial network (GAN) is proposed to detect tunnel surface defects from captured images. This approach is particularly beneficial for IoT applications characterised by the limited training data available, as GANs are adept at generating additional data samples for training purposes. In our previous work (Yang et al., 2022), a deep learning model, You Only Look Once Version 3 (YOLOv3) (Redmon and Farhadi, 2018) was employed to train sample defect images collected from tunnel sites. Stored in an edge computing device on drones, the trained model was then deployed to detect tunnel surface defects, viz. concrete cracks, concrete spallings, and water leakages. Yu et al. (2022) proposed a novel constrained dense convolutional autoencoder combined with a DNN-based semi-supervised strategy to extract the geological information of the tunnel (Yu et al., 2022). Shan et al. proposed a framework for forecasting Tunnel Boring Machine (TBM) performance, aiming at developing real-time models to predict the penetration rate.

In conclusion, there is a plethora of nascent deep learning techniques that can be employed for IoT data analytics in construction sites. These techniques are instrumental in deriving meaningful insights from IoT data and facilitating innovative applications and services on site. After conducting a thorough study and considering the genuine requirements of tunnel inspection from the client, a two-stage tunnel surface inspector for real-time identification and the analysis of tunnel surface defects are proposed. The design and development details will be elaborated in the following sections.

2. The proposed real-time tunnel defect inspector in two stages with the use of IoT and deep learning techniques

This section provides a comprehensive elucidation of the developed tunnel inspectors, which operate in real time and consist of two stages. State-of-the-art techniques of IoT and deep learning are employed in both stages to achieve the real-time inspection of tunnel surface defects.

2.1. Stage 1.0: 3S tunnel defect inspector

The 3S Tunnel Defect Inspector, the first generation of developed tunnel inspectors, is a pioneering tunnel inspection system in Hong Kong that integrates drone technology with on-board artificial intelligence (AI) processing capabilities; it symbolises a digital upgrade in tunnel inspection, allowing engineers to conduct intelligent and safe inspections directly on site. The name “3S” stands for “Safe”, “Smart”, and “on Site”. This system has been successfully developed and deployed in the “Trunk Road T2 and Cha Kwo Ling Tunnel” project (hereinafter referred to as the “T2 project”) in East Kowloon, with the Civil Engineering and Development Department (CEDD) of the HKSAR Government as the client and Hyder-Meinhardt Joint Venture (HMJV) as the consultant.

Co-developed by the aforementioned three parties, the 3S Tunnel Defect Inspector signifies a revolutionary advancement in tunnel inspection. Employing cutting-edge AI algorithms and robotics techniques, this system has been engineered to deliver intelligent inspection capabilities. By using deep neural network and transfer learning to substitute conventional visual inspection approaches, the inspection accuracy can reach the millimetre level, significantly enhancing the efficiency and accuracy of inspection processes.

Initially, the 3S Tunnel Defect Inspector involves deploying a UAV equipped with a high-resolution camera to capture image data of the tunnel surface. The drone is programmed to capture high-resolution images of the tunnel lining surface. The data are then transmitted to an on-board AI chip. This advanced chip, coupled with edge computing-based neural networks, enables faster and more efficient AI-driven detection calculation. This allows engineers to conduct real-time inspections on site and receive immediate inspection results. The detection accuracy is greatly improved to the millimetre scale, covering all parts of the tunnel and enabling operators to identify defects efficiently and accurately.

Additionally, this innovative inspection solution integrates AprilTag with QR code technologies, enabling continuous and stable inspections of tunnel surface defects at different locations and under various environmental conditions, independent of a Global Positioning System (GPS) signal for positioning. Upon the detection of defects, the system automatically generates electronic defect reports, realising the digitalisation of the entire inspection process.

The 3S Tunnel Defect Inspector obviates the requirement for inspectors and engineers to utilise elevated platforms for tunnel inspections, which are often occupied by various tunnel construction logistics. Consequently, the system significantly diminishes the necessity for working at heights and minimises the associated safety risks. The successful upgrade and digitalisation of tunnel inspection practices will substantially bolster the development of intelligent tunnel operations and maintenance. This inspection system is also applicable to the inspection and maintenance of other substantial infrastructure inspections, such as bridges, buildings, pylons, and wind turbines. The 3S Tunnel Defect Inspector in operation is shown in Figure 1.

Figure 1. 3S Tunnel Defect Inspector in operation in the T2 project

2.1.1. Edge computing on the drone

For real-time defect inspection of tunnel surfaces, two devices are installed on the drone. The first device is the DJI Zenmuse H20T camera, an advanced system with a zoom camera and a side camera, capable of capturing RGB and infrared images of surface defects, respectively. Hence, it serves as an efficacious tool for aerial inspections and surveillance, and is particularly well-suited for tunnel inspection.

The second device integrated into the drone is the NVIDIA® Jetson AGX Xavier™ edge computing device, an advanced embedded AI computer designed for autonomous robotics. A distinctive feature of this device is its capability to perform AI inference at the edge, facilitating the rapid training and deployment of neural works. In the context of tunnel inspections, the Jetson AGX Xavier is employed for the AI-driven detection processing of the images captured by the DJI Zenmuse H20T camera. The device is preloaded with AI models that can accurately detect typical tunnel surface defects and water leakage areas. This enables the real-time detection of defects during the inspection phase and facilitates the prompt follow-up action of the contractor for defect rectification.

The integration of edge-AI techniques on the drone in the initial stage of the system confers numerous benefits. Firstly, it empowers the real-time monitoring and detection of surface defects in tunnel linings, such as concrete cracks, concrete spallings, and water leakages. Secondly, it obviates the necessity for the manual inspection of tunnel lining surfaces, which can be time consuming and tedious and involves safety risks associated with working at height.

2.1.2. The YOLOv3 model for tunnel surface defect detection

The system uses YOLOv3, an advanced real-time detection model, for training on the defect images captured by the camera installed on the drone. The YOLOv3 model is renowned for its capability to combine shallow and upsampled deeper layers, generating feature maps of varying scales that facilitate object detection across three distinct scales. This feature is particularly advantageous for the detection of tiny objects, as larger feature maps contain more comprehensive information that aids in identifying these objects. Consequently, the YOLOv3 model outperforms its predecessors in detecting tiny objects by leveraging the shortcut of residual connections with multi-scale features.

For the training of the YOLOv3 detection model, the experimental protocol incorporates both RGB and thermal images. The red, green, and blue channels of the RGB image and thermal image are concatenated to form four input channels, utilising a sensor fusion technique. In the RGB image, water leakages frequently manifest as indistinct and irregularly shaped patches, rendering them difficult to detect due to the absence of distinguishable features. Additionally, the existence of shadows due to uneven illumination in the tunnel can produce similar segments, potentially impacting the visual detection results of defects. In contrast, thermal images highlight the leakage characteristics that are not prominent in RGB images. Hence, the integration of both image sources contributes to a more accurate representation of the defects to be inspected. This enhancement in defect detection accuracy is attributable to the complementary nature of the RGB and thermal images, and provides a more comprehensive view of the defects. Experimental results show an overall (aggregate of the three types of defects) accuracy of 98% for the 3S Tunnel Defect Inspector using the YOLOv3 model after six continuous training sessions.

2.2. Stage 2.0: air-ground cooperative tunnel inspector

In the second stage of the system architecture, an integration of UGV and UAV techniques is employed to conceptualise an air-ground cooperative tunnel inspector, as illustrated in Figure 2. This groundbreaking invention represents the world's first air-ground cooperative robotic system dedicated to tunnel surface inspection, incorporating AI, robotics, precise positioning, and sensor fusion. By leveraging these advanced techniques, the system brings an intelligent, automation, and digital advancement to tunnel inspection in Hong Kong, marking a substantial step forward in the field.

The development of this cooperative tunnel inspector is based on the inadequacies and drawbacks of actual tunnel inspection situations. Despite the growing public interest in UAV and UGV techniques as emerging mobile inspection techniques, the synergistic application of UAVs and UGVs for tunnel defect detection in GPS-denied environments is still a brand-new undertaking in Hong Kong. Until now, there exists no tunnel inspection system that combines the air-ground cooperation techniques to achieve the fully autonomous detection of different categories of defects on the surface of tunnel internal structures, namely thermal barrier, vitreous enamel panel cladding, and carriageway paving.

The system utilises three state-of-the-art techniques. Firstly, the edge computing technique enables real-time data processing and analysis at the edge of the network to achieve on-site AI inspection, reducing the requirement to transmit data to a centralised data centre for further processing. Secondly, heterogeneous multi-robot cooperation is employed to ensure comprehensive inspection coverage within the tunnel environment. Lastly, the system is integrated with automated total stations to facilitate global localisation in non-GPS environments.

This pioneering integration of air-ground cooperation between UAVs and UGVs realises an efficient and autonomous tunnel defect inspection framework. Using SLAM and automated total stations for localisation, the system operates proficiently inside the constructed tunnels with numerous concurrent tunnel construction activities, despite the limited illumination and absence of GPS signals for positioning. This innovation notably diminishes human errors and mitigates safety risks, offering a marked improvement over traditional tunnel inspection techniques.

The proposed tunnel inspector conducts on-site defect detection based on the captured images, thereby facilitating prompt notification to tunnel inspectorates for the initiation of rectification measures. The automated recording of operational processes and the generation of digital reports for subsequent actions are integral to its functionality. Utilising the multi-sensor fusion approach, this inspection system is capable of navigating around obstacles in GPS-denied environments, as well as capturing and inspecting defect images through a combination of RGB and a thermal camera system.

2.2.1. LoRa techniques for data communication in No-GPS tunnel environments

GPS is reliant upon signals transmitted from satellites to determine the position of a receiver on the Earth's surface. However, GPS signals are incapable of penetrating through solid objects such as tunnels, presenting challenges in accurately determining locations within such environments. To address this limitation, conventional wireless communication technologies such as Wi-Fi, Bluetooth, and ZigBee, among others, are employed to furnish locations within tunnel environments. These techniques leverage signal strength and triangulation strategies to ascertain the position of a receiver within a tunnel. Furthermore, the susceptibility to interference in long-distance data transmission diminishes the accuracy of the collected data.

(a)

(b)

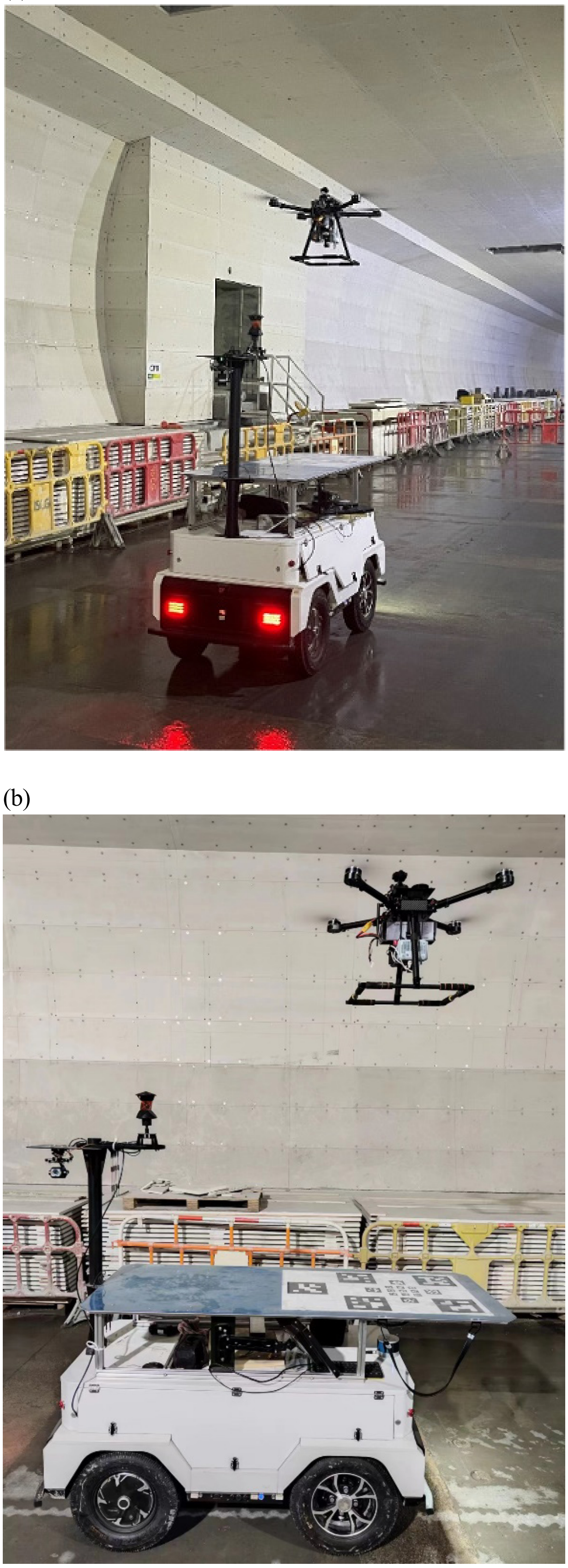

Figure 2. Stage 2 air-ground cooperative tunnel inspector in operation in the T2 project with different views: (a) rear view and (b) side view.

To surmount these challenges, the LoRa (Devalal and Karthikeyan, 2018) (Long Range) wireless communication technology, renowned for its proficiency in transmitting modest data packets across expansive distances, is employed. Compared to traditional IoT techniques, LoRa technology, which has gained prominence in recent years, exhibits exceptional attributes of power consumption and wide coverage. In the study by Zhu et al. (2022), LoRa was employed for tunnel environment monitoring. For the air-ground cooperative tunnel surface inspector in this paper, LoRa techniques were utilised to facilitate real-time communication of the UGV-UAV system and pre-installed total stations in non-GPS tunnel environments. Figure 3 illustrates the self-developed LoRa communication module. A total of four sets of LoRa are integrated into the Stage 2 air-ground cooperative tunnel inspector for the purpose of long-distance data transmission in tunnels. Three sets of LoRa are strategically installed along with the pre-installed total stations, while an additional set is installed on the UGV system. By utilising LoRa for data transmission in non-GPS tunnel environments, real-time communication between the UGV system and the pre-installed total stations can be effectively achieved. The details of the LoRa interface can be found in Table 1.

Table 1. Details of the LoRa interface.

Interface	Remarks
RF ANT	Connects to the LoRa antenna
TS Port	Connects to the total station
Black Port	GEB373 battery to DC 2.5 mm barrel power jack, 12V input
The Green-blue Charging Port	Power supply for both AC 110V and 220V

Figure 3. LoRA communication module.

2.2.2. Air-ground cooperation of the UGV and UAV

In the Stage 2 development of the air-ground cooperative tunnel inspector, the most notable advancement is the integration of air-ground cooperation between the UGV and UAV for real-time defect inspection of the tunnel surface, and a detailed model description can be found in Table 2. For the air-ground cooperative tunnel inspector, the UAV sub-system inspects the upper part of the tunnel, while the UGV sub-system focuses on the lower part, which facilitates a comprehensive and automated 360-degree inspection of the tunnel without the requirement for engineers to perform manual inspections. The system effectively negates the necessity for extensive working platforms required by conventional visual inspections, leading to substantially reduced time and space requirements and significantly bolstering site safety, inspection accuracy, and efficiency.

Table 2. Detailed Model Description of the Air-Ground Cooperative Tunnel Inspector.

Category	Technical parameters	Descriptions
UGV *Brand: SKYWILUNG*	UGV dimensions	- 850 mm*162 mm*186 mm (from the ground to the top of the prism)
	Width of drone airport	- 73 cm
	Weight when fully loaded	- Around 210 kg
UAV *Brand: Customised*	UAV dimensions	- 450*350*450 mm (folded state, payload height not included) - 600*600*500 mm (unfolded without propeller, payload height included)
	Battery	- 220*70*70 mm (single size, total four batteries)
	Weight	- 33.5 kg including the box - 6 kg without the box and with all the necessary accessories - UAV battery: 2.12 kg
UGV camera *Brand: PVL*	Weight	- < 290 g
	Dimensions	- 95*89*102 mm
	Photo resolution	- 8000*6000 - 5496*3672 - (3:2) 5472*3648 - (16:9) 5472*3078
UAV camera *Brand: Easy Balance*	Pixel size	- 1.12 µm (RGB module) - 12 µm (Thermal module)
	Photo resolution	- 4208*3120 - 5496*3672
LiDAR *Brand: LSLIDAR*	Laser band	- 905 nm
	Range accuracy	- ±3 cm
	Detecting range	- 70~200 m
	Laser channel	- 16-channel
	Dimension	- Φ102 mm*78 mm
	Weight	- 1050 g (including 1.2 m cable)/840 g (lightweight, including 1.2 m cable)

3. Applications in the T2 project in Hong Kong

This automated surface defect inspection system has been under development since December 2021. In 2023, HKPC, CEDD, and HMJV collaboratively developed the world's first autonomous air-ground cooperative tunnel inspection system, heralding an era of intelligent, automated, and digitised tunnel inspection practices in Hong Kong. The T2 project is a dual two-lane trunk road spanning approximately 3.4 km, which forms the middle section of Route 6, connecting the Central Kowloon Route (CKR) on the west and the Tseung Kwan O-Lam Tin Tunnel (TKO-LTT) on the east (Civil Engineering and Development Department, 2024). A substantial portion of the T2 project, which is approximately 2.4 km in length, was constructed primarily by TBM underneath the seabed of Victoria Harbour. The location plan of Trunk Road T2 and Cha Kwo Ling Tunnel is depicted in Figure 4.

3.1. Performance of the YOLO model for the air-ground cooperative tunnel inspector

Different from the deep learning model used in Stage 1, the YOLOv7 (Wang et al., 2023) model is used to train the data collected using the air-ground cooperative tunnel inspector. Five types of defects are collected and inspected, which are board gaps, abandoned holes/missing anchors, edge damage, scratches, and water leakages. The model shows satisfactory performance in detecting different defects and achieves an average recall rate of 79.34%, average precision of 86.73%, and mAP@0.5 of 0.812. The detailed performance of the YOLOv7 model can be found in Table 3.

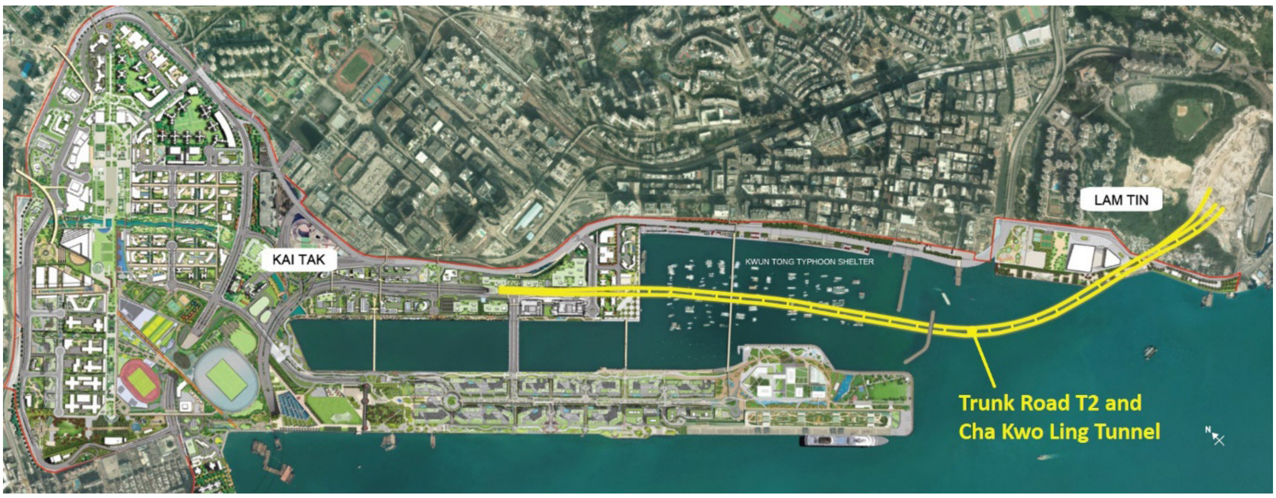

Figure 4. Location plan of the T2 Project in East Kowloon.

Table 3. Performance of the YOLOv7 model for tunnel defect inspection.

Method	Precision	Recall	mAP@0.5
YOLOv7 for board gap using data augmentation	80.98%	75.81%	0.793
YOLOv7 for abandoned hole or missing anchor using data augmentation	67.80%	68.20%	0.563
YOLOv7 for edge damage using data augmentation	95.70%	84.80%	0.906
YOLOv7 for scratches using data augmentation	95.50%	82.80%	0.912
YOLOv7 for water leakage using data augmentation	81.00%	85.60%	0.856
Overall	86.73%	79.34%	0.812

3.2. Limitations

Although the system performed well during the on-site testing in the T2 tunnel, it still has some shortcomings. In Stage 1, the 3S Tunnel Defect Inspector detected three main types of defects: spallings, cracks, and water leakages. In Stage 2, the inspected targets were board gaps, abandoned holes/missing anchors, edge damage, scratches, and water leakages. Due to the small size of the target tunnel defects, there are higher demands on the hardware design and camera resolution of the detection system. Also, the system may not be able to detect defects that are too small or hidden, such as those located behind pipes or cables. Additionally, the system may be affected by external factors such as the lighting conditions. Therefore, further improvements and optimisations are needed to enhance the system's performance and reliability in detecting tunnel defects.

4. Conclusion and future work

This paper provides a thorough exposition of pioneering real-time tunnel surface inspectors, a collaborative effort by HKPC, CEDD, and HMJV across two distinct stages. The system utilises the latest IoT and deep learning techniques to facilitate the real-time monitoring and detection of surface defects within tunnel linings and internal structures in the T2 project in Hong Kong.

In the initial stage of the system, a distinctive inspector is employed, leveraging edge AI on drone technology to enable real-time inspection of tunnel lining surface defects. An integrated setup of a high-performance camera and an edge computing device is mounted on the drone, enabling the capture of RGB and thermal image data of the tunnel surface. Subsequently, these data are transmitted to the edge computing devices, where they are processed utilising the YOLOv3 deep learning algorithms. These techniques enable the prompt identification and response to surface defects such as concrete cracks, concrete spallings, and water leakages. After that, an electronic defect report can be generated on site to digitalise the whole inspection process and significantly reduce the time traditionally required for manual preparation of such report.

In the subsequent stage of the system, the air-ground cooperative tunnel inspector was conceptualised and developed, incorporating the UGV technology. In addition, state-of-the-art techniques in air-ground cooperation, robotics, precise positioning, and sensor fusion are utilised. The UGV and UAV engage in real-time communication and collaboratively capture high-resolution images of a tunnel's internal structures, achieving fully autonomous inspection in non-GPS environments. In contrast to conventional tunnel inspections, which necessitate engineers and inspectors to visually perform inspections from mobile elevated working platforms, the utilisation of this system significantly enhances the inspection efficiency, accuracy, and site safety.

In essence, this developed real-time tunnel surface inspector, comprising two distinct stages, signifies a substantial advancement in real-time tunnel safety and maintenance. By harnessing the synergy of IoT and deep learning techniques, an innovative robotic system capable of swiftly and accurately identifying tunnel surface defects has been engineered, enabling expedited rectification measures to uphold the structural integrity of tunnels. The system's capacity to provide the real-time monitoring and detection of tunnel surface defects constitutes a significant enhancement over traditional inspection methods, which are typically time consuming and tedious and involve safety risks associated with working in the tunnel site.

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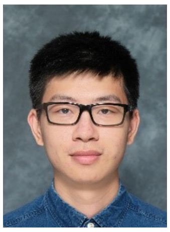

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