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UAV-based studies in railway infrastructure monitoring

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Abstract

This review paper provides a comprehensive overview of Unmanned Aerial Vehicles (UAV) applications in railway infrastructure studies, with a specific focus on railway track infrastructure. The paper covers various aspects, including UAV types, flight performance, selection criteria, and regulations for railway environments. It explores sensor technologies used in drone-based inspections, such as imaging sensors, LiDAR, and infrared thermography. The application of UAVs in railway tracks, bridges, and tunnels is discussed in detail. The identified future prospects and challenges underscore the need for advancements in sensor technologies, the integration of AI and machine learning, and the importance of regularly updating regulatory frameworks. Overall, the integration of UAVs in railway infrastructure monitoring holds promise for enhancing safety, refining maintenance strategies, and improving operational efficiency in the railway industry.

Keywords

Railway monitoring; UAV; Imaging; LiDAR; Infrared thermography

1 Introduction

The transport sector relies heavily on the railway industry due to its reliable and efficient means of moving people and goods over long distances. As railway networks continue to expand and evolve, it becomes imperative to prioritise the safety and maintenance of railway infrastructure to ensure its integrity and optimal functioning. One critical aspect of maintaining a safe and reliable railway system is the regular inspection and assessment of the infrastructure's condition. Railway infrastructure is subject to various factors that can lead to degradation and wear over time. Factors such as heavy train loads, environmental conditions, and constant exposure to dynamic forces necessitate a proactive approach to monitoring and maintaining the infrastructure [56]. Traditional inspection methods have been employed for decades, relying on visual inspections and manual measurements carried out by trained personnel [8]. However, these methods are time-consuming, labour-intensive, and limited in coverage. With the rapid advancements in technology, new inspection techniques such as unmanned aerial vehicles (UAVs) are emerging that offer significant improvements in efficiency, accuracy, and safety [59]. UAV also known as a drone, is an acronym used to refer to an aircraft that operates without human pilots on board. UAVs are designed to navigate and travel through the air autonomously [32]. The term UAS (Unmanned Aerial System) encompasses the full system to control a UAV remotely, including the ground control station, pilot and crew, communication systems, flight software, and additional hardware [70,93,97].

UAVs have revolutionised monitoring practices across various fields due to their versatility, efficiency, and ability to access hard-to-reach areas (Fig. 1). In agriculture, UAVs are extensively used for crop monitoring, allowing farmers to assess crop health, optimise irrigation, and detect pest infestations with high precision [23]. Environmental monitoring also benefits from UAV technology, as drones can survey large and remote areas to track wildlife (e.g., waterbird colonies) [61], measure air and water quality with gas/environmental sensors [9], and assess the impacts of natural disasters using multi-spectral sensors and infrared cameras [21]. In the construction industry, UAVs provide real-time progress updates, inspect structures for safety compliance, and create detailed 3D models of building sites [55]. Additionally, in the field of public safety, drones are instrumental in search and rescue missions, and surveillance, providing critical information without putting human lives at risk [64]. The integration of UAVs into these diverse applications underscores their significant role in enhancing monitoring capabilities, improving efficiency, and ensuring safety across multiple sectors.

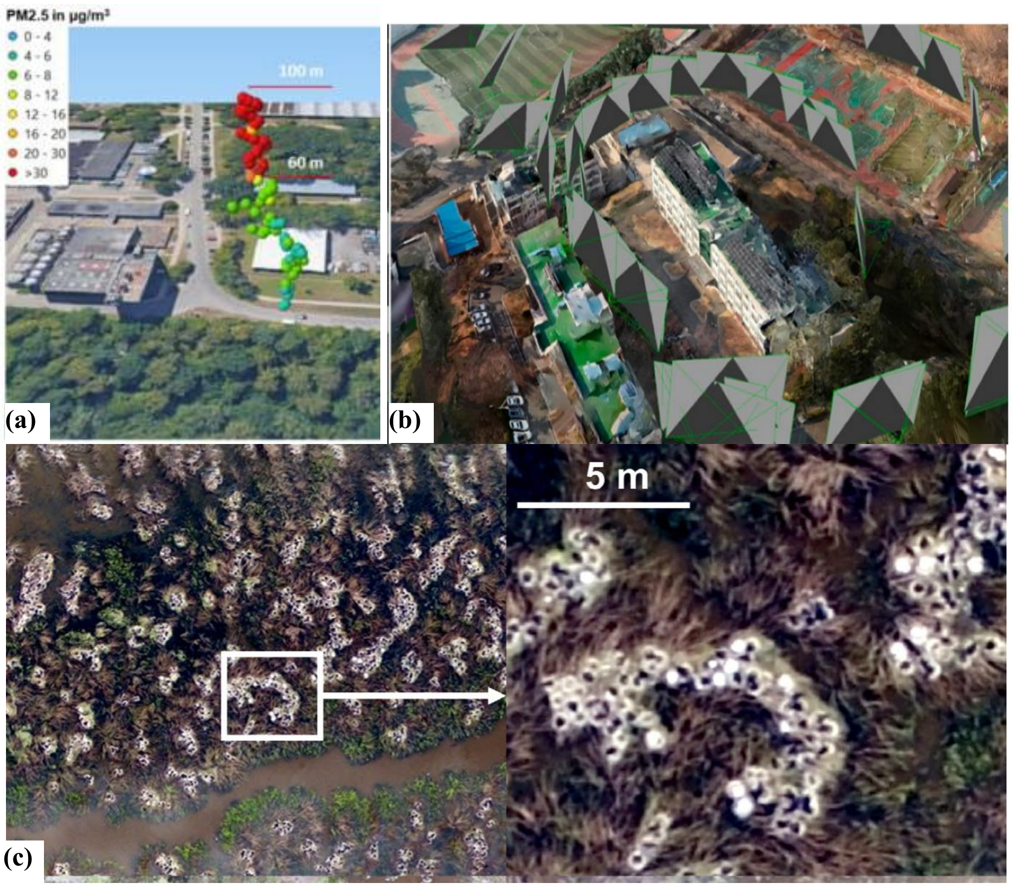


Fig. 1 UAV applications: (a) Air quality assessment [87], 3D modeling of the building site [55], Variation in nest types and environments across a colonial waterbird [61]

1.1 UAV market size

As shown in Fig. 2a, the global market size for commercial drones is projected to reach approximately USD 47.38 Billion by the year 2030, experiencing robust growth at a compound annual growth rate (CAGR) of 28.58% from 2022 to 2030. Fig. 2b presents the growth rates of the drone industry across various sectors, in which infrastructure demonstrates the highest growth rate at 45.2%, indicating the substantial adoption of drone technology in infrastructure inspections, surveying, and mapping [3]. Security exhibits a notable growth rate of 10%, signifying the use of drones in surveillance, monitoring, and emergency response. Other sectors such as agriculture, transport, media & entertainment, insurance, telecommunications, and mining also demonstrate growth rates, indicating the expanding applications of drones in these industries. Fig. 2c depicts the projected global drone market size in billion U.S. dollars, categorised by different regions, including the U.S., Asia-Pacific, Europe, the Middle East and Africa, and the rest of the world [19]. In 2020, the U.S. held the largest market size at 8 billion USD, followed by the Asia-Pacific region at 4 billion USD. By 2030, the United States is forecasted to have a market size of 34 billion USD, while the Asia-Pacific region is projected to reach 30 billion USD. Europe is estimated to have a market size of 16 billion USD, followed by 5 billion USD in the Middle East and Africa, and 7 billion USD in the rest of the world region. The data indicates the shifting dynamics of the global drone market across different regions, with significant growth expected in the U.S. and Asia-Pacific regions in the coming years.

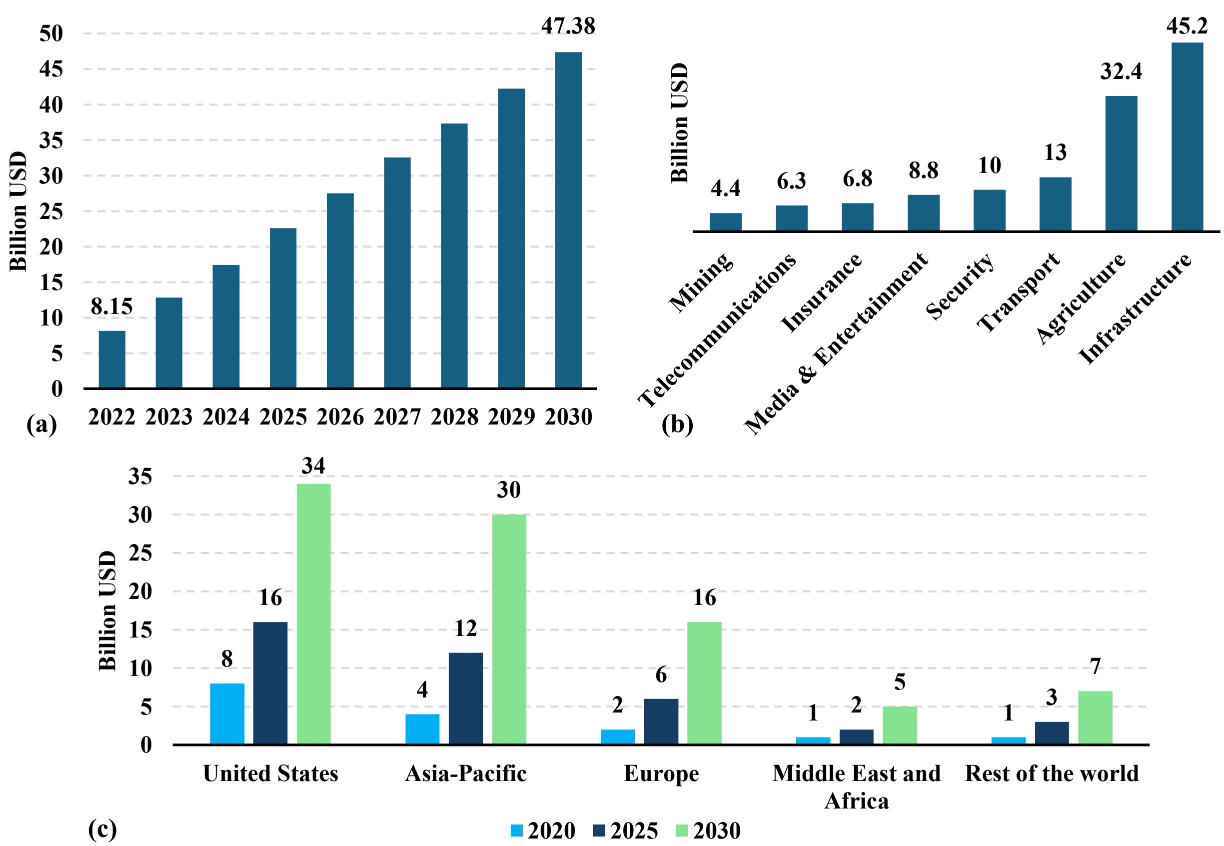


Fig. 2 Global commercial drone market size a) by year [52], b) by discipline [3], and c) by region [19]

1.2 Research methodology

The current study aims to systematically review research efforts focused on UAV considerations and applications within railway problems. Fig. 3 provides an overview of the four key stages of the review process, namely search inquiry, refining, snowballing, and analysis.

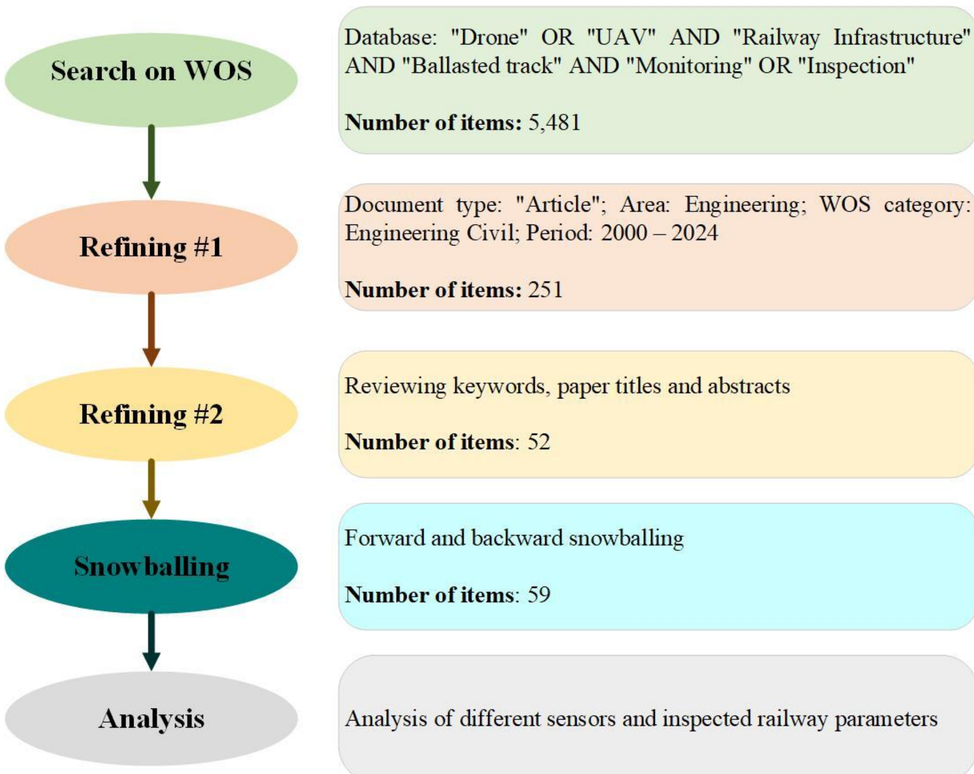


Fig. 3 Review process stages

The review process commenced by executing a search query in the WOS database, utilising specific keywords such as "Drone" or "UAV," "Railway Infrastructure," "Ballasted track," and "Monitoring" or "Inspection." This initial search yielded a substantial number of over 5,480 research items. Subsequently, the results were refined by applying filters including document type ("Article"), research area (Engineering), and a specific time period (2000 – 2024). After applying these filters, approximately 250 items remained for further evaluation. The titles, abstracts, and keywords of the remaining articles were then scrutinised to exclude any that did not align with the scope of the review paper. After this screening process, a final set of 52 articles specifically focused on UAV-based monitoring of railway problems was identified. To ensure comprehensive coverage, forward and backward snowballing techniques were employed to identify any additional relevant articles. Forward snowballing involved examining the references cited within the initially identified articles, and backward snowballing involved reviewing articles that cited the initially identified ones. Ultimately, a total of 59 articles were considered for the review. In the following, scientometric analysis is conducted to identify the most recurring keywords in UAV-related studies on railway problems and to analyse the publishing sources and years. This systematic analysis aimed to identify and compare various aspects of UAVs, including UAV types, flight performance, selection criteria, regulations, sensor technologies, and their applications.

1.3 Scientometric analysis

The significance of UAV-based inspection lies in its ability to overcome the limitations of traditional methods. While traditional inspections require personnel to physically access the infrastructure, drone-based inspections offer a non-intrusive and efficient alternative. UAVs equipped with cameras, sensors, and other specialised equipment can capture high-resolution imagery and collect data from multiple perspectives [93]. The background of this study stems from the increasing utilisation of UAVs in various industries, including infrastructure inspection. A review of 250 papers on UAV applications in railways, as reported by Web of Science, reveals several prominent keywords that are frequently mentioned, including UAV, computer vision, inspection, remote sensing, railway detection, and photogrammetry (Fig. 4). As shown in Fig. 5a, these publications span across various disciplines, with the most significant contributions from Electrical and Electronic Engineering (93 publications), Transportation Science Technology (41 publications), and Telecommunications (54 publications). The analysis also highlights the origin countries of the studies, with a significant number of investigations conducted in China, the US, Germany, India, Turkey, and Spain. The publications span from 2006 to 2023, with a growth in recent years, indicating the growing interest and advancements in this field (Fig. 5b).

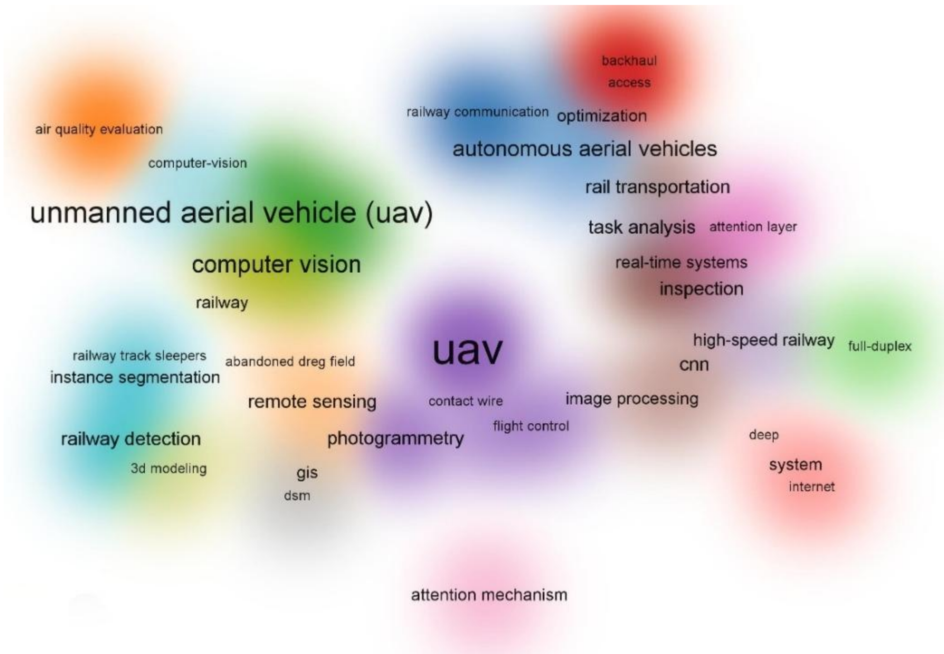


Fig. 4 Most repeated keywords in UAV-related studies on railway problems

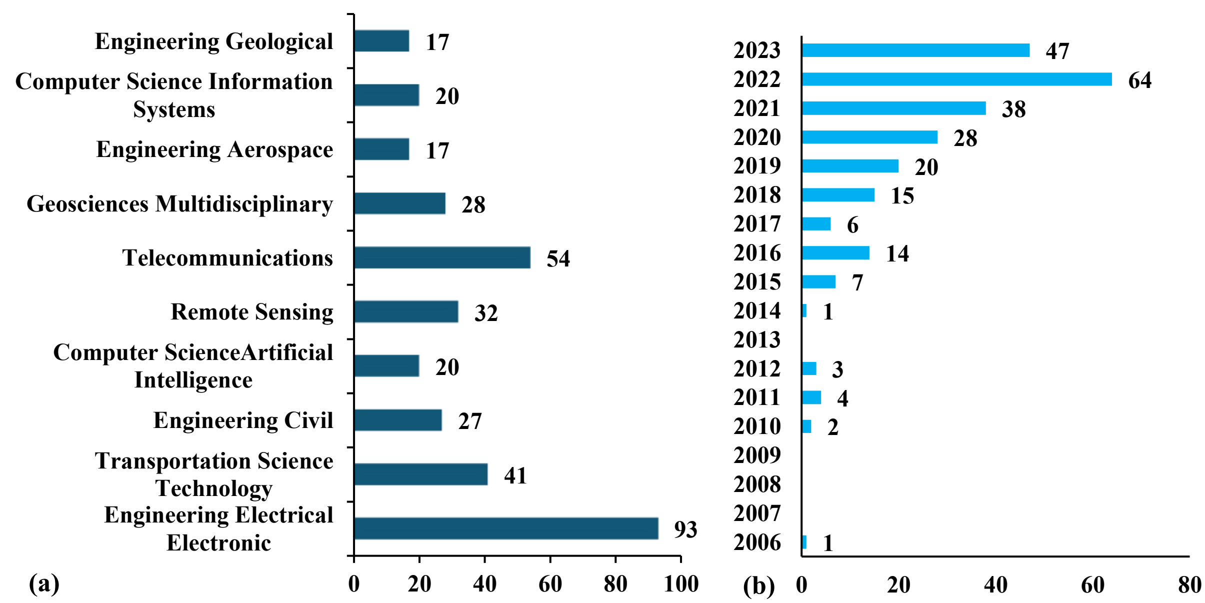


Fig. 5 Number of publications regarding a) discipline, and b) year

Several reviews have explored UAV applications across diverse fields such as transportation [11], agriculture [23,82], mining [83], the military [50], and civil construction [36,67]. However, there is a noticeable gap in the literature concerning a comprehensive review of existing research on UAVs for railway infrastructure monitoring. Key parameters such as track monitoring time limits, image resolution, and the extensive length of railways differentiate the suitability of UAV types for railway monitoring from those used in other fields of study.

This review aims to highlight the methodologies, technologies, and findings of previous studies, providing a thorough background and context for our work. The main contributions of this review include detailed case studies, practical implementations, and an examination of monitoring challenges, regulations, and guidelines associated with the use of UAVs in railway applications. The objective of this review paper is to enhance the understanding of the benefits and challenges associated with UAV-based inspections and to address regulatory considerations. The scope encompasses all aspects related to UAV-based studies in railway infrastructure, including tracks, bridges, tunnels, and associated components. Additionally, it explores different UAV platforms, imaging and sensing technologies, and data processing methods. Lastly, this review identifies gaps in current research and suggests areas for future research and development in UAV-based studies for railway infrastructure.

2 Systemic review

The identified articles were analyzed to examine the main aspects of rutting measurement methods and technologies. The investigated aspects of rut measurement methods included indices, measurement algorithms, and reporting schemes. Another primary focus of the study was measurement technologies. A comprehensive analysis of the processing techniques, performance, and performance determinants associated with the application of the leading technologies was conducted. Finally, the applications of rutting measurement were thoroughly reviewed.

UAVs are found in a wide range of applications across various sectors, including economic, commercial, recreational, military, and academic fields, demonstrating their versatility and widespread usage. Mohsan et al. [66] provided extensive insights into various aspects, including the potential applications of UAVs, their characteristics, different types, swarm technologies, classifications, charging methods, and regulatory considerations. Up to now, little is known about the specific conditions associated with railway track monitoring. In the following, the highlights related to UAV specifications are explained.

2.1 UAV types

UAVs exhibit various specifications, equipment, sizes, ranges, and configurations. Mohanty et al. [65] described different UAV components, including actuator, receiver, sensors, battery, GPS, gyroscope, motors, and processing units. UAV classification involves various factors, with weight, payload, and flight time being some of them, as discussed in previous studies [7,16,105]. Additionally, UAVs are commonly categorised based on their shape, including fixed-wing, single-rotor, multirotor, and other configurations, as depicted in Fig. 6 [66]. Fixed-wing UAVs consist of a main body, wings, propeller, and motor. These UAVs necessitate specialised training for control and are unsuitable for aerial surveillance. These UAVs are commonly employed for tasks such as aerial mapping and power line inspection, but they lack the ability to hover. A hybrid fixed-wing UAV portrays a single-rotor UAV. However, single-rotor UAVs are mechanically complex and susceptible to challenges such as vibrations with limitations in their effectiveness in monitoring tasks [49]. Conversely, multirotor UAVs are relatively cost-effective and straightforward to construct. These UAVs are frequently utilised for image and video surveillance purposes. As shown in Fig. 6c, Quadcopters are the most commonly employed among multirotor UAVs [41]. Quadcopters have gained popularity due to their ability to vertically land and manoeuvre swiftly, low cost, and compact size. The SuperVolo UAV is a recently developed hybrid aircraft with both fixed-wing and rotor-wing capabilities, as shown in Fig. 6e [101]. Developed and tested by the Alaska Center for UAS Integration (ACUASI), it utilises battery-powered rotors for vertical take-off and landing (VTOL), transitioning to a fixed-wing mode with a gas engine and onboard generator for sustained flight. This unique hybrid design presents classification challenges but offers various advantages. However, it is important to consider the potential drawbacks associated with this type of UAS. The summary of different UAV types is presented in Table 1. More details on UAV types can be found in [1].

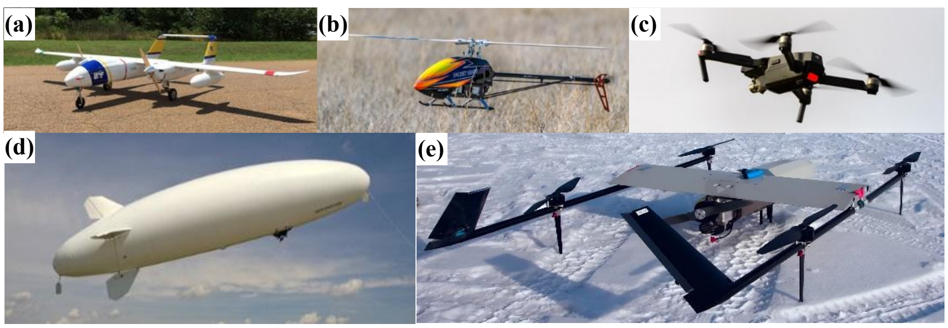


Fig. 6 a) Fixed-wing, b) Single-rotor, c) Multirotor, d) Others, e) SuperVolo [101]

Table 1 Summary of different UAV types

Ref.	Type	Specifications
[47,92]	Fixed-wing	Long endurance; Large area coverage (up to 200,000 km); High flight speed
[92]	Single-rotor	Hovering and VTOL; Long endurance (with fuel); Heavier payload capacity
[92]	Multi-rotor	Ability to hover and VTOL; Ease of use; Accessibility

2.2 UAV flight performance analysis

The successful implementation of UAV-based monitoring systems relies heavily on understanding and analyzing the flight performance of UAVs. Kalra et al. [48] highlighted challenges in UAV-based monitoring, including movement, variations in lighting conditions, drone altitude, and camera sensitivity. The proximity between the drone and the individuals being monitored is found to have a negative impact on these factors. Table 2 presents formulas for estimating UAV flight performance considering parasitic drag, skin friction coefficients, stall speed, gliding range and endurance, powered flight range and endurance, and maximum rate of climb. These calculations are vital to assess the UAV's capabilities and determine if it can accomplish its mission objectives.

Table 2 Equations used for flight performance analysis of the UAV [65]

Category	**Equation**	**Category**	**Equation**
Parasitic Drag	$C_{D_0} = \frac{KC_f S_{wet}}{S}$	Stall Speed	$U_{stall} = \sqrt{\frac{2W}{\rho S C_{l_{max}}}}$
Skin Friction Coefficient (Turbulent Flow)	$C_f = \frac{0.455}{[\log_{10}(Re_L)]^{2.58}}$	Gliding Range	$R = \frac{H}{\tan(-\gamma)}$
Skin Friction Coefficient (Laminar Flow)	$C_f = \frac{1.328}{\sqrt{Re_L}}$	Gliding Endurance	$E = \frac{H}{\dot{Z}} = \frac{H}{\sqrt{\frac{2W}{\rho S} \times \frac{C_D^2}{(C_L^2 + C_D^2)^{3/2}}}}$
Battery Power	$P_b = n_{tot} \times V \times \frac{C}{Rt}(\frac{Rt}{t})^{1/n}$		
Powered Flight Range	$R_{max} = (Rt)^{1-n} \times \left(\frac{n_{tot} \times V \times C}{\left(\frac{1}{\sqrt{\rho S}}\right) C_{D_0}^{\frac{1}{4}} (2W\sqrt{k})^{3/2}}\right)^n \times \sqrt{\frac{2W}{\rho S} \times \sqrt{\frac{k}{C_{D_0}}}} \times 3.6$		
Powered Flight Endurance	$E_{max} = (Rt)^{1-n} \times \left(\frac{n_{tot} \times V \times C}{\left(\frac{2}{\sqrt{\rho S}}\right) C_{D_0}^{\frac{1}{4}} (2W\sqrt{k/3})^{3/2}}\right)^n$		
Max Rate of Climb	$n_{tot} \times \frac{V}{W} \times \frac{C}{Rt}(\frac{Rt}{t})^{1/n} - \frac{1}{2}\rho U^3 \frac{S}{W} C_{D_0} - \frac{2Wk}{\rho U S}$		

K: Form factor; S_{wet}: Surface area of the component; C_f: Coefficient of friction; S: Wing planform area
U: Velocity; W: Weight; ρ: Air density; C_D: Drag coefficient; C_l: lift coefficient; γ: Flight path angle; R: Range of the aircraft; H: Altitude; V: voltage; C: Battery capacity, AR: Wing aspect ratio;
η_{tot}: Total propulsive efficiency, e: Oswald efficiency factor; n: Peukert coefficient

2.3 Regulations and guidelines for drone operations in railway environments

The rapid growth of UAVs has presented a significant challenge for policymakers worldwide. While some countries have established clear and comprehensive laws governing UAS operations, others are still grappling with developing regulations to keep pace with advancing technology. This discrepancy creates difficulties for international UAS operators seeking to navigate through a patchwork of local regulations and policies. Recognizing the need for unified laws and flight regulations, several countries have called for a standardised approach.

The International Union of Railways (UIC) has implemented regulations to govern the usage of UAVs based on different risk categories [72]. In the ***Open*** Category, which involves low-risk operations, UAVs weighing below 25 kg and falling within classes C0 to C4 can operate without prior authorisation. However, certain conditions must be met, such as maintaining a maximum height limit of 120 m, ensuring a safe distance from people, and operating within a visual line of sight (VLOS). UAVs in this category are prohibited from carrying dangerous goods or dropping any material. In the ***Specific*** category, which entails increased risk, additional requirements apply, including obtaining operational authorisation, conducting a risk assessment, and setting operational limitations through the authorisation. This category applies to operations over assemblies of people, transportation of people, and carrying dangerous goods, and requires certification of both the UAV and the UAV pilot. Regarding high-risk operations, the ***Certified*** category of UAV usage regulation encompasses operations involving flying over assemblies of people, transportation of people, and carrying dangerous goods. In this category, both the UAV and the UAV operator are required to obtain certification. Certification of the UAV involves meeting specific standards and requirements, while the UAV operator must obtain a license as a remote pilot. These measures are implemented to ensure the highest level of safety and compliance in situations where there is an increased risk associated with UAV operations.

In the meantime, countries like France, Japan, New Zealand, South Africa, and the United Kingdom have emerged as leaders in introducing UAS technology into their airspace. However, it is important to note that while many countries are actively establishing legislation, some have taken the extreme step of banning UAV operations altogether. Table 3 presents an overview of the regulations governing UAVs taken by different countries in the utilisation of UAV technology.

Table 3 Regulatory frameworks governing the commercial use of UAVs implemented by various countries [73,84,93]

Parameter	Ctry	Description
Commercial operations	US	UAS under 55 lbs flown for commercial purposes are regulated under 14 CFR Part 107.
	UK	All commercial operations must be approved by the UK's Civilian Aviation Authority.
	GR	Operators of UAVs heavier than 2 kg need certification or a pilot's license.
	FR	Limitations and safety requirements for commercial use of UAVs in different scenarios.
	CA	Special Flight Operations Certificate required for non-recreational and UAVs over 35 kg.
	JP	Operations require permission from Ministry of Land, Infrastructure, and Transportation.
	NZ	Certification is required for operations exceeding standard requirements.
	SA	Non-private operations require approval and a certificate of registration from the CAA.
Visual Line of Sight (VLOS)	US	The UAS must remain within the VLOS of the remote pilot or visual observer.
	UK	The pilot of a small UAV must maintain direct, unaided visual contact with the aircraft.
	GR	UAVs lighter than 5 kg must be kept within the operator's VLOS at all times.
	FR	UAVs may be flown outside of the pilot's line of sight with certain conditions.
	CA	UAVs must be operated within VLOS or under specific exemptions.
	JP	UAS flights must be monitored by the operator's own eyes.
	NZ	Operations are limited to unaided visual line of sight during daylight hours.
	SA	Different ratings for VLOS, extended VLOS, and BVLOS operations.
Maximum altitude	US	Maximum altitude of 400 ft above ground level, or within 400 ft of a structure if higher than 400 ft.
	UK	The vehicle may not fly at a height of more than 400 ft above the surface.
	GR	UAVs cannot be operated above 100 m.
	FR	UAVs must not fly higher than 150 m above the ground or 50 m above certain objects.
	CA	Altitudes are limited based on specific regulations or exemptions.
	JP	UAVs must keep more than 30 m from people and objects.
	NZ	Altitude is limited to 120 m above ground level unless conditions are met.
	SA	Altitude limited to 400 ft above ground level.
Restricted areas	US	No operations from a moving vehicle, except over sparsely populated areas.
	UK	Near congested areas, vessels, vehicles, structures, and people.
	GR	Near people, public gatherings, airports, and other sensitive locations.
	FR	Military installations, nuclear power plants, historical monuments, etc.
	CA	Restrictions based on specific regulations or exemptions.

	JP	Over certain areas, such as airports and government buildings.
	NZ	Consent is required for flying above someone or specific areas.
	SA	Airfields, restricted airspace, and sensitive locations.
Certification/ Approval	US	Holding a remote pilot airman certificate with a small UAS rating.
	UK	Holding a certificate of airworthiness, a permit to fly, and a licensed flight crew.
	GR	Certification or pilot's license is required for operators of UAVs over 2 kg.
	FR	Certification may be required for certain categories, while others require authorisation.
	CA	Special Flight Operations Certificate or exemptions required for certain operations.
	JP	Permission is required from the Ministry of Land, Infrastructure and Transportation.
	NZ	Certification or operating certificate is required based on the type of operation.
	SA	Letter of approval and certificate of registration are required for non-private operations.

US: United States; UK: United Kingdom; GR: Germany; FR:France;
CA: Canada; JP: Japan; NZ: New Zealand; SA: South Africa

2.4 Sensor technologies for UAV-based railway inspection

In the realm of UAV-based railway inspection, the effective utilisation of sensor technologies assumes a pivotal role in acquiring indispensable data for diverse applications. Bayomi et al. [13] extensively documented the sensors currently accessible along with their respective specifications. Within the domain of remote sensing, a fundamental contradiction arises in the form of passive and active sensing techniques [90]. Passive sensors rely upon the unassisted emanation of electromagnetic radiation, encompassing sunlight or thermal emissions, to apprehend pertinent information on the Earth's surface and atmosphere. Conversely, active sensors proffer an autonomous energy source, facilitating the dissemination of specific signals or energy, such as microwave or laser pulses, and subsequently monitoring the resultant reflected signal. Shahmoradi et al. [89] compiled a comprehensive inventory of sensors commonly utilised in the mining industry. On the other hand, Partheepan et al. [74] provided a list of sensors used for Bushfire Management. In the present review, the authors primarily provided a detailed description of the sensors employed specifically for addressing issues related to railways.

2.4.1 Imaging sensors (RGB, DIC, multispectral)

Imaging sensors play a crucial role in drone-based railway inspection, enabling the capture of visual information and data acquisition for analysis and assessment. This subsection focuses on three primary types of imaging sensors used in this context: RGB, Digital Image Correlation (DIC), and multispectral sensors (Fig. 7). RGB sensors are the most common imaging sensors found in drones. They capture images in the visible spectrum, similar to what the human eye perceives. RGB sensors provide high-resolution colour imagery, allowing inspectors to visually assess the condition of railway infrastructure. They are particularly useful for identifying surface defects, cracks, and corrosion on tracks, and bridges. Additionally, RGB sensors facilitate the creation of ortho mosaics and 3D models, aiding in the accurate mapping and visualisation of the inspected area. However, RGB sensors have limitations when it comes to capturing data beyond the visible spectrum, such as temperature variations or specific material properties.

Also, it is important to address the challenges posed by foggy or hazy conditions in imagery railway inspection. UAV images captured in such conditions often suffer from degradation, which can limit the efficiency of inspection. Wu et al. [110] developed a novel end-to-end network "DPRnet" using a pyramidal network structure consisting of dense residual blocks and enhanced residual blocks to exploit feature maps and increase depth at different scales. Additionally, a new loss function incorporating the structural similarity index was introduced to preserve more structural information, resulting in improved dehazing performance.

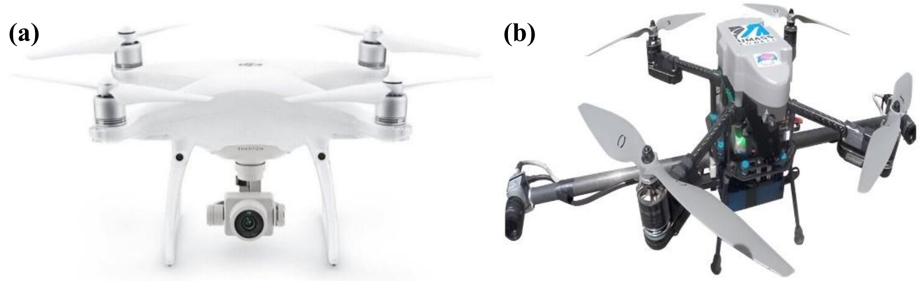


Fig. 7 UAV with different cameras: a) Digital camera [27], and b) DIC [71]

2.4.2 LiDAR technology for 3D mapping and point cloud generation

LiDAR (Light Detection and Ranging) is a remote sensing method that uses laser pulses to measure distances to targets. It operates by emitting a laser pulse, which reflects off the target's surface and returns to the sensor's receiver (Fig. 8a). LiDAR systems emit laser pulses and measure the time it takes for the pulses to bounce back after hitting objects in their path. By analysing the return time and intensity of the laser pulses, LiDAR sensors can create highly detailed and precise 3D models of the inspected area [101].

A LiDAR system consists of several components, such as a laser emitter, a scanner and mirror system, and a receiver or photodetector (Fig. 8b). The system also relies on a Global Navigation Satellite System (GNSS) and an Inertial Measurement Unit (IMU) to determine the sensor's position and orientation. Different types of LiDAR include topographic LiDAR, which uses near-infrared laser beams to penetrate vegetation, and bathymetric LiDAR, which can measure water depth. LiDAR data can be processed to create detailed 3D models or point clouds, which find applications in terrain mapping, vegetation and forest monitoring, infrastructure inspection, archaeological surveying, disaster management, and precision agriculture [15,34].

In railway inspection, LiDAR technology offers several advantages. Firstly, LiDAR enables the creation of high-resolution digital elevation models (DEMs) and topographic maps of railway infrastructure. This information is crucial for assessing the alignment, gradient, and curvature of tracks, as well as identifying areas prone to erosion or subsidence. Accurate DEMs provide valuable insights into the overall condition of the railway network and can guide maintenance and repair efforts. Secondly, LiDAR facilitates the generation of point clouds, which are dense collections of 3D spatial points representing the surfaces of objects. Point clouds derived from LiDAR data offer detailed information about the geometry and structure of railway infrastructure. They can be used to detect deformations, settlements, and wear on tracks, bridges, and other components. By comparing the point clouds captured over time, inspectors can monitor changes in the infrastructure's shape and identify potential signs of damage. Furthermore, LiDAR technology enables the identification of clearance issues along railway corridors. By scanning the surroundings and capturing the precise spatial information of overhead structures, such as bridges and tunnels, LiDAR sensors can detect any potential obstructions that may pose a risk to train operations. However, it is important to note that LiDAR technology has some limitations. It is sensitive to environmental factors such as weather conditions, vegetation density, and surface reflectivity. Adverse weather conditions, such as heavy rain or fog, can affect the accuracy and reliability of LiDAR data. Vegetation interference can also hinder the detection of subtle infrastructure details. Additionally, LiDAR systems can be costly and require specialised expertise for data processing and analysis. Despite these limitations, LiDAR technology continues to advance, with improvements in sensor capabilities and data processing techniques. As technology becomes more accessible and affordable, its integration with drone platforms in railway inspection is expected to increase, contributing to more efficient and comprehensive infrastructure assessment and maintenance practices.

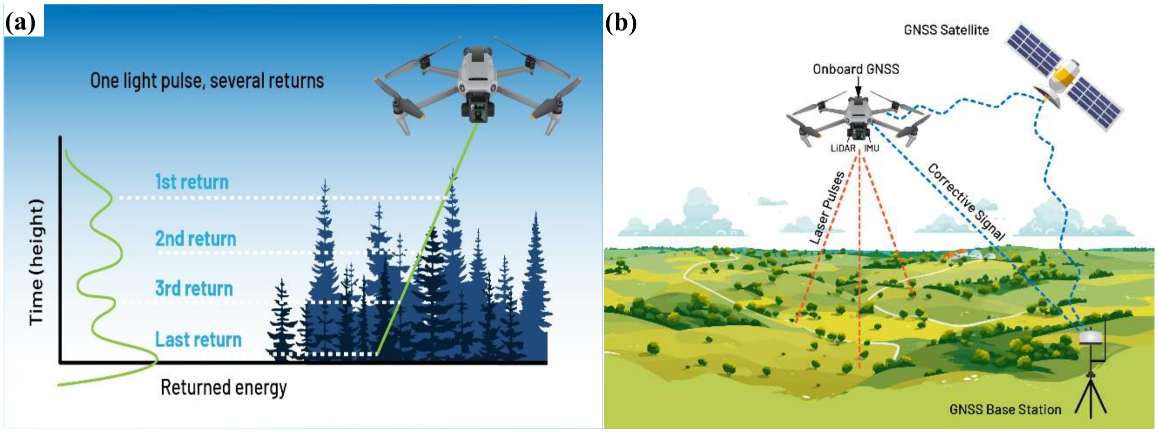


Fig. 8 a) LiDAR mechanism, b) LiDAR System Components [101]

2.4.3 Infrared thermography for heat detection and analysis

Thermal sensors, also known as infrared sensors, capture thermal radiation emitted by objects. These sensors detect temperature variations, making them valuable for identifying anomalies related to heat, such as overheating components or electrical malfunctions in railway infrastructure. Thermal sensors can identify hotspots, track insulation issues, and detect potential friction points. By visualising temperature differences, inspectors can identify potential risks and prioritise maintenance activities. These sensors offer a more comprehensive view of the inspected area by capturing data beyond what RGB sensors can detect. Infrared sensors operate within the infrared bands of the electromagnetic spectrum, which are categorised into two types: reflected IR bands and emitted/thermal IR bands (Fig. 9). Reflected IR bands, including Near Infrared (NIR) and Short-Wave Infrared (SWIR), measure the solar radiation reflected off a target. Analysis of reflected infrared signals enables the assessment of surface characteristics, such as vegetation health, land cover classification, mineral exploration, and urban area monitoring. Emitted/thermal IR bands detect the heat energy emitted by objects above absolute zero temperature. By capturing this emitted radiation, infrared sensors provide valuable information on surface temperatures and are used in various applications, such as monitoring climate patterns, studying urban heat islands, assessing volcanic activities, and evaluating crop stress and irrigation efficiency [101].

Reflective IR sensors consist of an optical system, detector, readout electronics, and a signal processing unit. The optical system focuses incoming infrared radiation onto the detector, which converts it into an electrical signal. Readout electronics amplify and digitise the signals, which are then processed and converted into images for further analysis. Thermal IR (infrared) sensors share similar components with reflective IR sensors but also include a cooling mechanism to reduce detector noise. Cooling mechanisms can include cryogenic coolers for high-performance applications or thermal electric coolers (TECs) for less demanding applications, based on the Peltier effect.

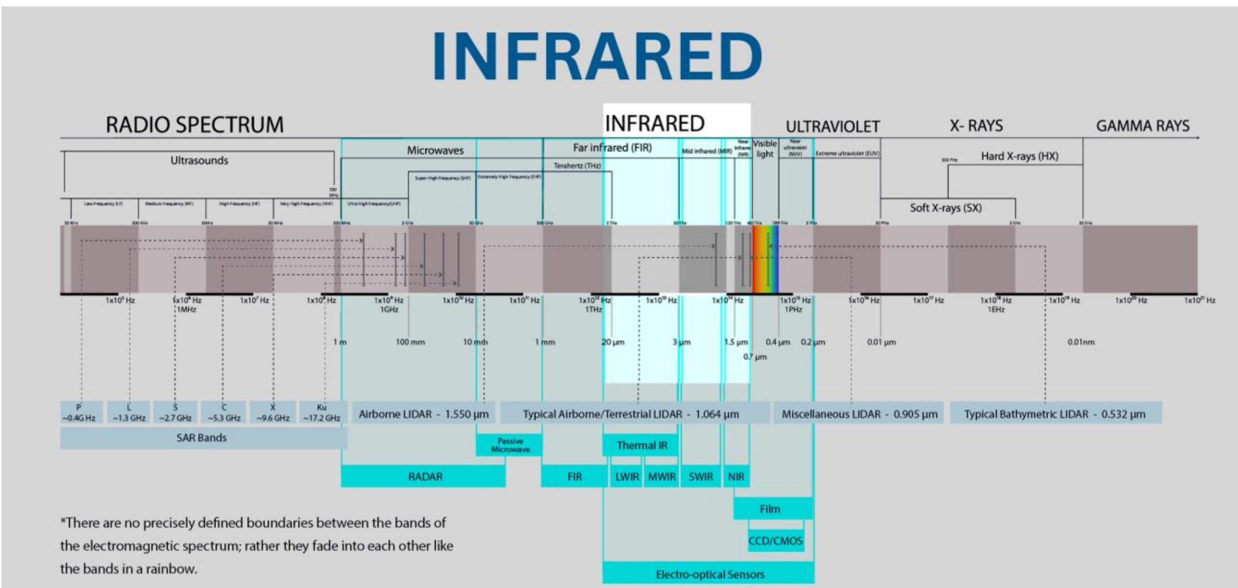


Fig. 9 Electromagnetic spectrum considering reflective infrared (0.78 - 1.5µm), and thermal infrared (3 - 14µm) [101]

These infrared sensor technologies have significant implications for remote sensing applications, enabling the monitoring and analysis of various environmental factors and surface characteristics. In railway inspection, multispectral sensors can aid in vegetation management along tracks, identify areas prone to landslides or erosion, and assess the condition of the ballast and subgrade. However, multispectral sensors tend to have lower spatial resolution compared to RGB sensors, which can impact the level of detail in the captured imagery.

2.4.4 Ground-penetrating radar

Ground-penetrating radar (GPR) is a powerful technology utilised for subsurface inspection of the infrastructure. This subsection explores the application of GPR in assessing the condition of the subsurface layers of railway tracks, embankments, and other critical components. GPR operates by transmitting electromagnetic waves into the ground and measuring the reflections and echoes that occur when these waves encounter different underground materials and interfaces. By analysing the received signals, GPR systems can create detailed subsurface profiles, revealing the composition, thickness, and condition of various layers. GPR can be applied for railway inspection regarding the assessment of ballast and subgrade conditions. GPR can penetrate the ballast layer and detect variations in its thickness, density, and fouling content. This information helps identify areas of inadequate ballast support, which can lead to track deformations, settlement, or instability. One advantage of GPR is its ability to provide real-time data during inspections.

The combination of UAVs and GPR systems is highly appealing due to contactless subsurface sensing and imaging, allowing for rapid scanning of challenging environments. This integration merges the advantages of UAV technology with the capabilities of GPR, creating efficient and effective solutions for subsurface exploration. As shown in Fig. 10, UAV-borne GPR is composed of (I) flight control subsystem consisting of a UAV flight controller and, in some cases, a microcomputer like Raspberry Pi. (II) a positioning and georeferring subsystem comprising an inertial measurement unit (IMU), barometer, compass, and GNSS receiver. (III) A communications subsystem for communication between the UAV and the pilot, (IV) potentially a ground station, which typically includes a radio controller (R/C) transmitter and receiver modules, and (V) GPR subsystem includes the radar module, the transmit and receive antennas.

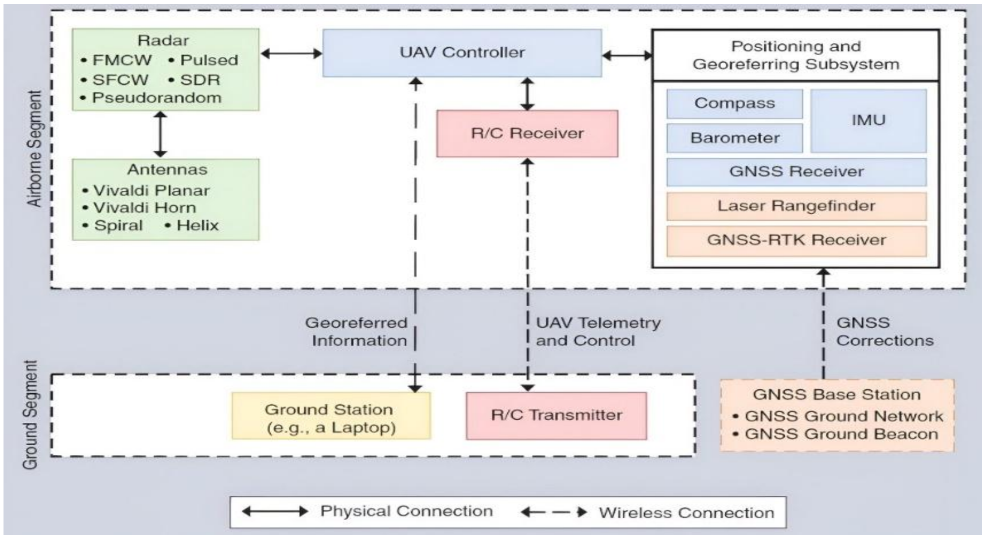


Fig. 10 The architecture of integrated UAV-borne GPR system [60]

As UAVs equipped with GPR technology fly over the railway corridor, they can capture the subsurface data, allowing inspectors to analyse and interpret the results promptly. This facilitates efficient decision-making and enables targeted maintenance and repair efforts. However, GPR does have limitations. The accuracy and depth of penetration depend on factors such as soil composition, moisture content, and the frequency of the GPR system used. Complex subsurface conditions, such as high moisture levels or highly conductive materials, can attenuate the signals and reduce the effectiveness of GPR. Additionally, interpreting GPR data requires expertise in understanding the subsurface characteristics and distinguishing between different underground features. Fig. 11 represents the comparison of the above-mentioned sensors as UAV payloads.

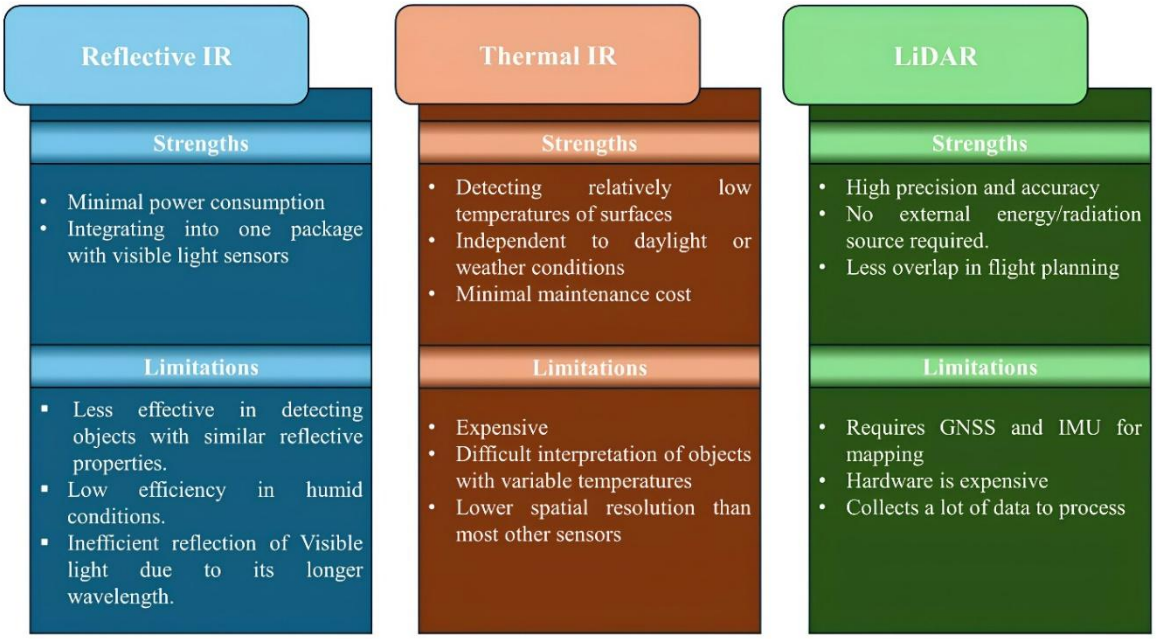


Fig. 11 Comparison of different imagery sensors as UAV payloads

2.5 UAV selection criteria

When selecting a UAV for railway infrastructure applications, several factors need to be considered. The UAV should have sufficient flight time and range to cover the inspection area without frequent battery changes. Currently, the measurement speed of UAVs can reach 30 km/h [44]. It should possess stability and maneuverability features for capturing high-quality data, even in challenging environmental conditions. Accurate GPS and navigation systems are essential for precise data collection and mapping. Safety features such as obstacle detection, RTH functionality (return to home), and fail-safe mechanisms are crucial. Reliable data transmission and onboard storage capabilities are required for real-time data transmission and secure data storage [79]. A user-friendly interface and compatible software enhance the usability of the UAV. Regulatory compliance and cost considerations, along with the availability of technical support and maintenance services, should also be taken into account. Payload capability in UAVs refers to their capacity to carry different weights, ranging from small loads of a few grams to heavier loads of several hundred kilos [46,104]. The ability to carry greater payloads allows for the transportation of more equipment and accessories, such as sensors, video cameras, and even cellular devices like tablets and mobile phones [2]. The necessary sensors include cameras, LiDAR sensors, thermal imaging cameras, or any other specialised sensors required for data collection. Considerations for the payload capacity of UAVs are presented in Table 4.

Table 4 Considerations for UAV payload capacity in railway monitoring [57,93]

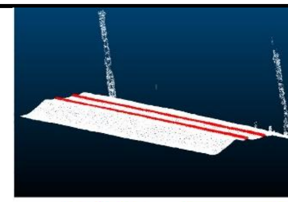
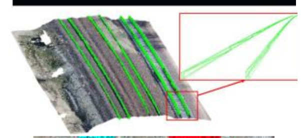
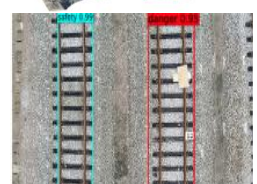
Aspects	**Considerations**
Weight restrictions	Stay within the maximum allowable weight
Power and propulsion	Ensure sufficient power for payload
Payload size and dimensions	Compatible with UAV's payload bay
Sensor and camera	Consider the size and weight of the required equipment
Environmental conditions	Account for wind and turbulence, path planning problem
navigation and accurate positioning	Inclusion of GPS and RTK modules

Given the criteria outlined above, rotor-based UAVs are predominantly employed for inspecting specific infrastructure issues [96]. For example, the DJI Matrice 300 RTK, a multi-rotor UAV, was recently utilised with a camera payload to achieve an accuracy of approximately 2 cm, creating a highly detailed 3D map of around 40 ground control points per square kilometre within 20 minutes [30]. Similarly, the Phantom 4, another multi-rotor UAV, is used for visual inspections and detecting track failures such as landslides, drainage clogs, and sleeper displacement [51]. For rapid railway infrastructure surveys, Dippel [22] proposed using the DJI Mavic, a hybrid UAV, which demonstrated survey track mapping 3-4 times faster than the Phantom 4.

2.6 Applied UAV areas in railway infrastructure

UAVs have emerged as a promising technology for various applications in the railway industry, including track monitoring and design. Table 5 summarises selected studies that have explored the use of UAVs in this context, highlighting the UAV models, sensors used, monitored parameters, and specific specifications. These studies demonstrate the diverse capabilities of UAVs and the valuable insights they can provide for efficient and effective railway infrastructure management. By leveraging UAV technology, railway authorities, and maintenance teams can improve their monitoring and inspection processes, leading to enhanced safety, reduced downtime, and optimised maintenance strategies.

Table 5 Potential applications of UAV for railway track monitoring and design

Ref.	Year	UAV	Sensor	Parameters	Specifications	View
[108]	2023	DJI Mavic Pro	CMOS camera	Track gauge	✓Accuracy range is ±1mm ✓Processing time is in seconds ✓Suitable for track curves	
[86]	2020	DJI Phantom 4	-	3D track model	✓Projection-based process ✓Accuracy of ±30 mm	
[42]	2023	DJI Phantom 4	PTZ camera	Object detection	Fused-ConvLSTM module: ✓high accuracy ✓computational efficiency	
[103]	2021	BG300	Camera	Rail damage Rail gauge	✓Maximum speed of 20 km/h ✓Inspected track length of 200 km	
[18]	2023	DJI Mavic 2	Camera	3D bridge model	✓Iterative closest point (ICP) technique for data optimisation ✓Image quality of 1.04 mm/pixel ✓9 mm deviations between UAV and TLS-based models	

2.6.1 Railway track

- ***Track geometry***

UAVs can effectively analyse and inspect various components of track geometry, including but not limited to track alignment, gauge, cross-level, and sleeper spacing [35,63] (Fig. 12). By capturing high-resolution aerial imagery and utilising specialised sensors, UAVs can provide accurate measurements and identify deviations or abnormalities in these track geometry components.

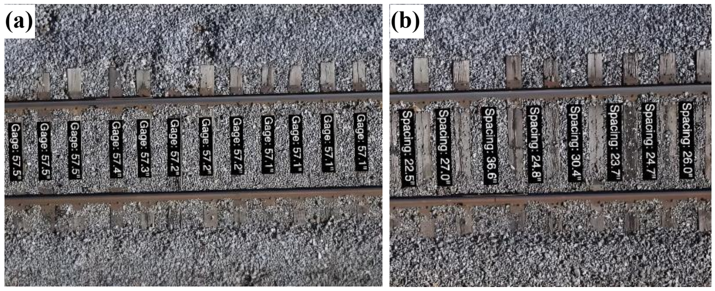
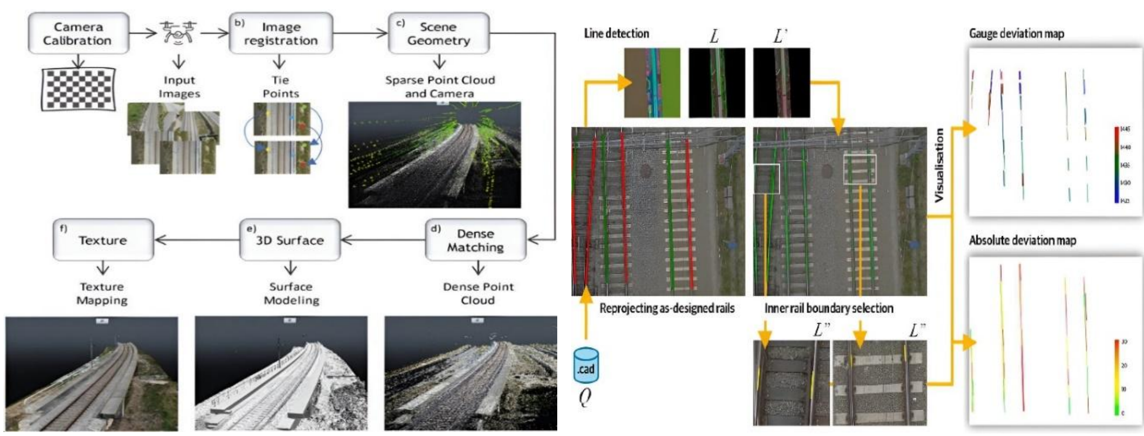


Fig. 12 UAV application for measurement of a) track gauge, b) sleeper space [6]

Reconstruction of the 3D track model is an approach that was extensively conducted using UAVs [17]. Reality capture involves creating digital models of real-world objects using active or passive vision systems. Active systems use their illumination source, while passive systems rely on ambient light. Hybrid systems aim to combine the advantages of both approaches. LiDAR sensors are a key technology in active systems, capturing geometric attributes by emitting light beams and measuring their travel time or phase shift [76]. Passive systems use cameras and geometric principles for scene reconstruction, employing techniques like Structure from Motion (SfM) and Multi-View Stereo (MVS). Photogrammetry involves multiple steps, including camera calibration, feature correspondence, geometry extraction, and texture mapping as shown in Fig. 13a. Selecting the right data processing workflow is crucial for converting raw sensor data into actionable insights. There are numerous photogrammetry solutions available, from user-friendly commercial packages for simplified workflows to advanced open-source options, as reported by Bayomi et al. [13].

Yang et al. [112] proposed a discretisation-filtering-reconstruction (DFR) method for high-precision railway detection in UAV imagery, leveraging deep networks and the intrinsic characteristics of railway lines. The DFR method segments railway images, filters background clusters, and reconstructs the connected components into a polynomial curve, resulting in continuous and smooth railway lines. Experiments show that the DFR method significantly improves the accuracy of railway detection. In addition, Cuypers et al. [24] introduced an unsupervised pipeline for rail boundary detection and measurement of deviations using UAV photogrammetry (Fig. 13b). Various line extraction methods, including Canny, Holistically-Nested Edge Detection (HED), DexiNed, Segment Anything Model (SAM), and Mobile Line Segment Detection (M-LSD), are compared. The workflow involves preprocessing, rail boundary detection, inner rail boundary pair selection, and visualisation of positioning. The advantages of UAV-based inspections are highlighted, emphasizing their affordability and safety compared to traditional methods.



(a) Fig. 13 Reconstructing a 3D scene using photogramme (b) [77], b) Planimetric rail positioning using UAV [24]

- ***Obstacle detection***

Obstacle detection using UAVs in the context of railway tracks has gained significant attention within the field of artificial intelligence. The rising number of derailment accidents caused by obstacles like boulders and fallen trees poses a serious threat to railway safety [80]. Traditional manual monitoring methods by human workers are inadequate and dangerous, particularly in high-risk areas. Real-time monitoring of railway tracks presents numerous challenges. As a result, researchers have turned to aerial imagery and deep neural network models, to address this problem.

To facilitate the development and evaluation of obstacle detection algorithms, researchers have created datasets specifically tailored for rail obstacle detection. Given [20,31,111] and Table 6, the You Only Look Once (YOLO) algorithm has undergone significant development and refinement, emerging as one of the most widely utilised methods for real-time detection and classification of multiple targets. By utilising UAVs, real-time aerial images of railway tracks are captured for analysis. These datasets undergo preprocessing to ensure optimal input for the deep neural network models mentioned earlier. Each model is then individually trained on the dataset. The experiment takes into account various metrics, including training time and performance, to assess the effectiveness of the models. The results are carefully visualised, evaluated, and compared, leading to the identification of the most effective deep neural network models for detecting obstacles on railway tracks. Fig. 14 demonstrates an example of obstacle detection along railway tracks.

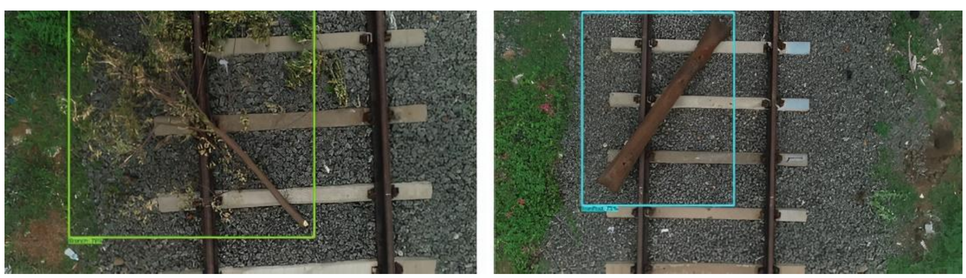


Fig. 14 Obstacle detection along the railway tracks [80]

Table 6 Studies on obstacle/trespasser detection

Ref./ Year	UAV	Sensor	Algorithm	Output
[80] 2022	DJI Phantom 4	Sony DSC-RX1RM2	CenterNet, Hourglass, EfficientDet, RCNN, SSD Mobile Net, SSD ResNet, YOLO, RODD	✓ High accuracy methods: ✓ SSD Mobile Net = 96.75% ✓ Faster RCNN = 84.75%
[33] 2020	DJI F550	HERO camera	Hough transform, Perspective transformation, threshold method	✓ Effectively detects and segments the areas of intrusion.
[58] 2022	-	-	YOLO-v5	✓ Detecting plastic waste with an overall accuracy of 85.4%.
[12] 2019	DJI Matrice 200 UAV	Zenmuse X4s/ FLIR camera	N/A	✓ Limited sight distance hindered surveillance for detecting trespassers in forested areas.

RODD: Rail Obstacle Detection Dataset

- ***Superstructure defects***

UAVs have emerged as valuable tools for detecting and monitoring defects in the superstructure of railway tracks. Given Table 7, this section focuses on the assessment and identification of defects in key components of the superstructure, including the rail, fastening systems, sleepers, and ballast.

The rail is a critical element of the superstructure, and UAVs equipped with high-resolution cameras and sensors can provide detailed imagery for inspecting its condition. These UAVs can capture close-up images and videos of the rail, enabling inspectors to identify defects such as cracks, corrosion, wear, and corrugation, as shown in Fig. 15a-b [81]. By examining the rail's surface and cross-section, UAVs contribute to the early detection of structural issues that could compromise the safety and functionality of the railway track. Fastening systems, which secure the rail to the sleepers, are prone to defects that can lead to track instability and increased maintenance needs. UAVs equipped with thermal imaging cameras can detect irregularities in the fastening systems, such as loose or damaged clips, bolts, or spikes. The thermal imaging capabilities of UAVs enable inspectors to identify temperature variations, indicating potential issues with the fastening systems that may require immediate attention. Sleepers, also known as ties, provide support and stability to the rail. UAVs play a crucial role in inspecting sleepers by capturing high-resolution images that allow for the detection of various defects. These defects can include rot, decay, cracks, or improper alignment of the sleepers (Fig. 15c). By detecting sleeper defects early on, railway authorities can take proactive measures to replace or repair them, ensuring the overall integrity and safety of the track. Ballast, the layer of crushed stones beneath the sleepers, is another component critical for track stability. UAVs equipped with advanced sensors and LiDAR technology can assess the condition of the ballast by measuring its depth, density, and uniformity

(Fig. 15d). This allows for the detection of issues such as ballast settlement, erosion, or contamination. Identifying ballast defects enables timely maintenance interventions, ensuring proper drainage and load distribution along the track.

The use of UAVs for superstructure defect detection offers several advantages. Firstly, the aerial perspective of UAVs allows for efficient and comprehensive inspections of large stretches of railway tracks, reducing the time and resources required for manual inspections. Additionally, UAVs with advanced imaging technologies can capture detailed data, enabling inspectors to assess defects accurately. However, there are challenges associated with UAV-based inspections of superstructure defects. Factors such as varying weather conditions, wind speeds, and limited flight endurance can impact the effectiveness of UAV operations. Additionally, interpreting collected data requires skilled professionals to accurately analyse the imagery and sensor readings to identify and classify defects.

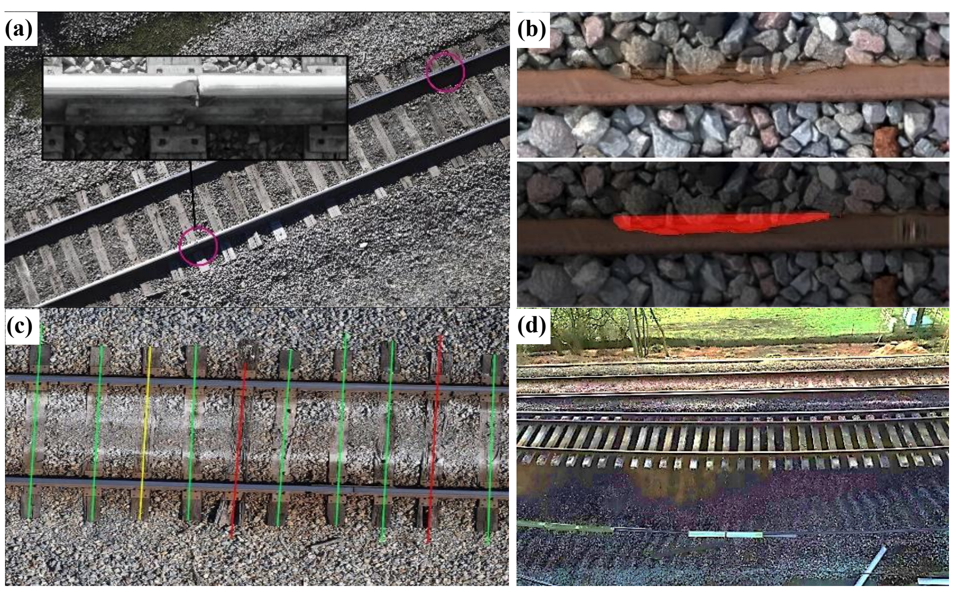


Fig. 15 Damage detection at a) rail joint [6], b) rail head [14], c) sleeper positioning [6], and d) ballast washout [69]

Table 7 UAV applications for detecting superstructure defects

Ref.	Year	UAV	Sensor	Parameters	Specifications and Results

[109]	2018	DJI M600	Camera Zenmuse-Z30	Rail surface	✓Local Weber-like Contrast for image enhancement ✓Grey stretch maximum entropy for defect segmentation ✓93.75% for T-I defects and 94.26% for T-II defects
[114]	2018	Hybrid UAV	1080p camera	Rail profile	✓3d reconstruction of rail profile using MVS algorithm ✓RMS error was 4.18 for a heavily damaged railhead
[14]	2021	Vogel R3D	Ultra 4K camera	Railhead	✓Damage detection using FCN-8 ✓Detecting split defects with a width > 6.9% of rail width ✓81% accuracy of rail defect detection
[25]	2022	-	-	Rai fastener	✓Damage detection using YOLO-v5 ✓The ideal model was YOLOXs-lite_s, with ShuffleNet V2 backbone and YOLOX-s head
[94]	2022	DJI Phantom 3	Sony 4K camera	Sleeper positioning	✓Sleeper position detection using RCNN and ResNet101+FPN ✓Average precision of 95.42
[28]	2023	DJI Mavic	Ultra 4K camera	Sleeper damage	✓Canny operator edge detection ✓Capture 8.4 km of railway line in 1 hour

FCN: Fully Convolutional Network; RCNN: Region-based convolutional neural networks
FPN: Feature Pyramid Network; MVS: Multi-View Stereo

- ***Vegetation detection***

Vegetation detection using drones has become increasingly important for monitoring vegetation growth and health along railway tracks. UAVs equipped with specialised sensors, such as multispectral or LiDAR cameras, can capture detailed imagery and data that enable a precise analysis of vegetation density, encroachment, and potential hazards. By conducting aerial surveys along the railway track, UAVs provide a cost-effective and efficient way to identify areas where vegetation may pose a risk to train operations, such as overhanging branches or dense growth near tracks. There are various vegetation indices where Equations (1) and (2) can be effectively applied to distinguish the plant layer from the soil, as outlined below [23]:

$$\text{Normalised Green-Red Difference Index (NGRDI)} = \frac{Green-Red}{Green+Red} \quad (1)$$

$$\text{Soil-Adjusted Vegetation Index (SAVI)} = \frac{NIR-Red}{NIR+Red+L}(1+L) \quad (2)$$

L: Plant density (0<L<1)
NIR: Near-infrared

Recently, Sharma et al. [91] employed the YOLO algorithm with aerial footage to identify points of interest (vegetation spots), resulting in the detection of vegetation with an accuracy of 85% (Fig.

16). On the other hand, Rahman et al. [78] developed a modified DCNN architecture further to improve the performance of the vegetation detection task.

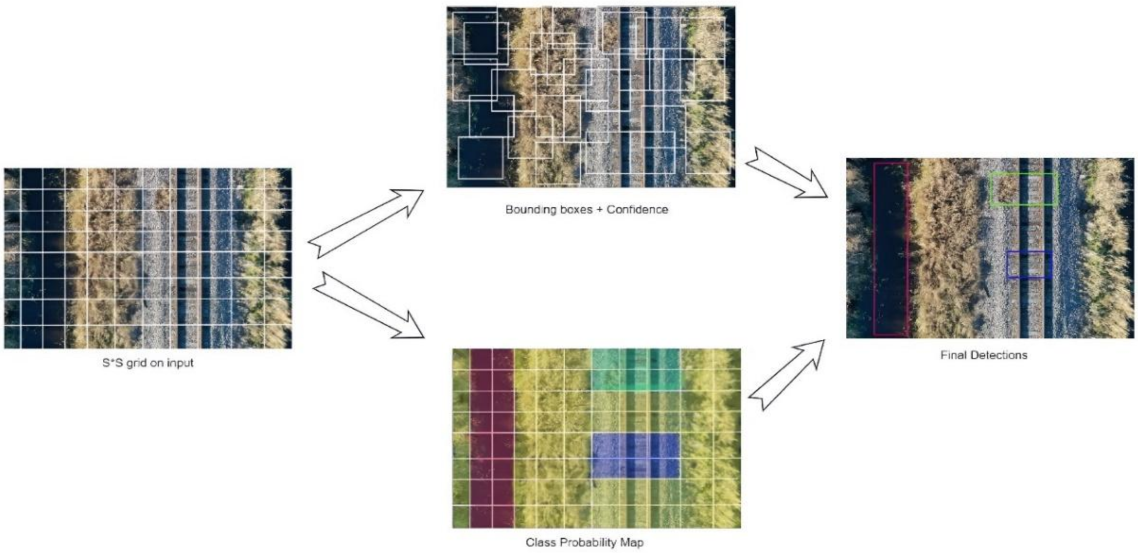


Fig. 16 YOLO-based detection of vegetation along railways [91]

2.6.2 Railway bridge

In the field of UAV applications in railway bridge monitoring, a wide range of sensors can be employed to gather crucial data. These sensors encompass eddy current measurement systems, which aid in determining layer thickness, as well as ultrasonic probes used for cavity detection and wall thickness assessment. Regarding UAV-based railway bridge monitoring, the main challenges are flight planning, georeferencing, and validating the digital model. Regardless of these challenges, Scheithauer et al. [45] indicated that the use of UAVs significantly impacts the factors of safety, accuracy, overview, and time savings in the daily work of construction supervision in railway projects. Narazaki [68] focuses on the development of a framework for automated vision-based post-earthquake inspection of RC railway bridges. The goal of the research is to reduce the time required for railway lines to resume operation after an earthquake by improving the efficiency of structural assessment. As shown in Fig. 17a, this framework consists of four steps: UAV navigation to the bridge location, identification of critical structural components, collection and evaluation of images for structural inspection, and the development of a synthetic environment for testing methods. The research indicates the potential of automated vision-based techniques to enhance post-earthquake inspection and improve the overall efficiency of the process.

UAVs have proven to be a practical solution for the 3D reconstruction of bridges (Fig. 17b). According to Han et al. [38], while UAV oblique photography is more time-consuming than laser scanning for data collection and model reconstruction, the high manoeuvrability of UAVs provides a distinct advantage in surveying hard-to-reach components and locations. Additionally, efficient route planning for UAVs was proposed as of paramount importance in the context of bridge inspection and 3D modelling. Optimised flight planning not only saves time and energy but also contributes to a more comprehensive and precise representation of the bridge structure. However, it is important to note that this particular study focused solely on the bridge alignment, neglecting other geometric shape parameters, such as the deviation of beams in the launching direction at different construction stages or the irregular appearance of piers due to poor concreting quality. Table 8 presents studies conducted on railway bridges using UAVs.

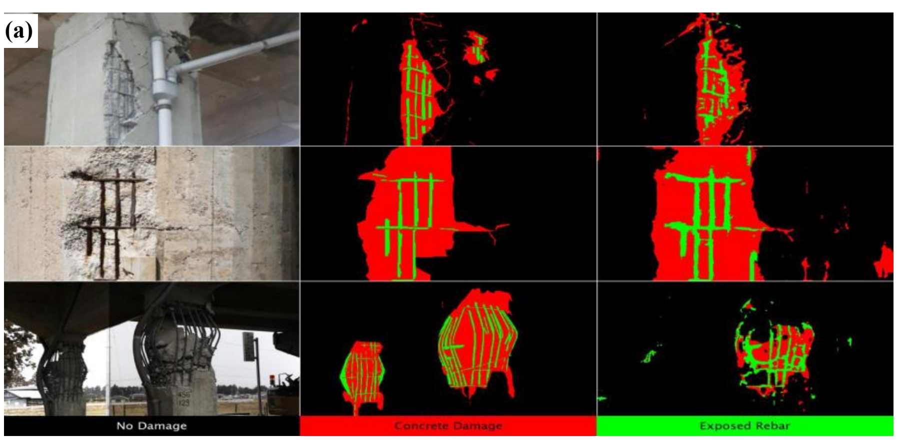


Fig. 17 a) Damage detection on railway concrete bridge [68], b) bridge 3D reconstruction [4]

Table 8 Railway bridge inspections using UAVs

Ref.	UAV	Sensor	Algorithm	Output
[102]	Self-developed	GoPro camera	N/A	✓ Concrete crack and cover
[68]	-	Monocular camera	FCN, SfM, LSD-SLAM	✓ Vision-based rapid post-earthquake bridge inspection. ✓ FCN45 and SegNet45 outperformed SegNet45-S with high accuracy: 70% mean IoU and >85% frequency-weighted IoU.
[4,10]	Multirotor	Camera	Mask R-CNN	✓ UAV-based inspection can cover more desirable observation locations. ✓ Applying displacement and frequency subtraction for camera motion elimination ✓ Low-cost cameras for accurate measurements of vibrations or deflections.
[99]	ROBi-L	Camera, Ultrasonic	Eddy current	✓ Cavity detection or wall thickness assessment
[75]	Aibot X6	Digital camera	SLAM	✓ Detecting superficial defects such as paint absence, efflorescence, and vegetation on structural elements using the software DEEP.
[45]	DJI Inspire 2	Zenmuse X5S	-	✓ Complex drone operations and data requirements require expert involvement ✓ UAVs can not replace the on-site bridge inspection.
[95]	-	StereoDIC	N/A	✓ Camera vibration due to drone rotor dynamics is a critical factor in the measurement system
[54]	DJI Phantom 4	-	ICP registration	✓ Creating a 3D bridge model using UAV-TLS methods. ✓ Monitoring the condition of piers, arch ribs, and other structural elements.

SfM: Structure from Motion; LSD-SLAM: Large Scale Direct Simultaneous Localisation and Mappin
StereoDIC: Stereo digital image correlation system

2.6.3 Railway tunnels

UAVs are increasingly being utilised for inspection and navigation in tunnel and underground environments due to their ability to access areas that are challenging for humans [115]. Current research in this field focuses on enhancing situational awareness in complex, obscured environments, and achieving autonomous positioning without reliance on GNSS. However, challenges such as insufficient communication range, navigation accuracy, high power consumption, and poor interference resistance persist. UAVs are employed in various applications, including natural cave networks, artificial tunnels, urban underground environments, and other GPS-denied locations. Integrating new technologies, such as intelligent group control, integrated robotics, advanced chip technology, and long-range communication facilitates UAV applications in underground problems. By capturing visual data of tunnel interiors, UAVs enable the assessment of tunnel conditions, identification of potential hazards, and evaluation of ventilation efficiency. Additionally, thermal and digital imaging cameras on UAVs can detect temperature anomalies, indicating potential water leakage or cracks in tunnel linings (Fig. 18). By identifying these issues early, maintenance activities can be scheduled promptly to ensure tunnel safety.

Fig. 18 Crack detection along the railway tunnels [81]

Table 9 show a summary of the key information on UAV inspection requirements, challenges, and applications in underground or tunnel environments. This includes the essential features and specifications that UAVs must possess to operate effectively in such challenging conditions. The table also highlights various types of UAVs commonly used for these purposes, details the environmental and structural obstacles they must overcome, and lists the types of sensors that are integral to their functionality.

Table 9 Summary of UAV requirements and challenges for underground monitoring

Category	Details
Requirements [88]	Small size and multiple positioning sensors; Common multi-sensor combination Data fusion techniques, Graphical optimisation, Anti-collision protection
UAV types [115]	DJI and DIY drones: Flyability's Elios, Kespry, Skycatch's Explore, Microdrone's MD4, Precision Hawk, Trimble's quadrotor and Hexrotor UAVs
Challenges [115]	Environmental: air density changes, dust, smoke, water droplets, insufficient light Structural: obstacles, narrow passages, airflow issues Communication: signal blocks, magnetic interference, moisture, and water leakage
Sensors [37,106]	Inertial sensors, Cameras, LiDAR, Ultra-wideband, Radar, Ultrasonic sensors

3 Future directions and challenges in railway infrastructure

The future directions and challenges in railway infrastructure, particularly in the context of UAV applications, are crucial for advancing the field. Table 10 summarises some of the key challenges and potential directions for overcoming them. One significant challenge is the speed limitations of UAVs. To address this, improving UAV power and propulsion systems can enhance speed capabilities. This improvement would enable UAVs to cover larger distances in a shorter time, increasing efficiency and reducing inspection durations. Additionally, implementing obstacle avoidance features becomes crucial, especially when UAVs are flying at higher speeds between 35 and 70 km/h. Incorporating advanced collision detection and avoidance technologies can prevent potential collisions with obstacles and ensure safe operations. Battery life is another challenge in UAV operations. Exploring swarm technology, where multiple UAVs work collaboratively, can help distribute the workload and extend the overall flight time. Additionally, researching energy-efficient designs for recharging stations and investigating wireless power transfer methods can enhance the UAVs' endurance and reduce downtime due to battery limitations. In terms of railway infrastructure monitoring, there are limitations in processing capability, flight time, and energy requirements. Overcoming these limitations can be achieved by cooperatively utilising multiple

UAVs. By coordinating their efforts, UAVs can cover larger areas and complete projects faster, enabling comprehensive inspection coverage of the infrastructure. Furthermore, integrating GPR with digital images emerges as a practical method for accurately measuring damages in ballast. This integration overcomes the limitations of image analysis caused by fouling and provides more precise information about the condition of the ballast, aiding in effective maintenance strategies.

Additionally, monitoring catenary wires is another crucial aspect of railway infrastructure management. The expansion and contraction of these wires due to temperature variations can impact their alignment and clearance with passing trains [100]. UAVs have a crucial role in visually inspecting the wires and verifying their correct positioning and appropriate tension. Regular inspections, temperature measurements, and adjustments to wire tension and clearance are essential for effectively managing the temperature-related effects on catenary system wires.

Table 10 Challenges and Future Directions [53,62,66]

	Challenge/Limitation	**Description**
UAV	Speed limitations [66]	Improving UAV power and propulsion to overcome speed limits
	Obstacle avoidance [66]	Preventing possible collisions at speeds between 35-70 km/h
	Battery life [98]	Exploring swarm technology, energy-efficient designs for recharging stations, and wireless power transfer methods
	Limited payload capability [66]	Expanding the payload capability of lightweight UAVs to carry various sensors, such as laser scanners, ultrasonic, and radars.
	Communications [40,43]	UAV-to-UAV communication possibilities, Integration of UAVs into 5G and satellite
	Weather conditions [110]	Storms, rain, and wind can cause deviations in trajectories, and affect operation time, altitude, and flight direction.
Infrastructure	Ballast condition [5,29,113]	Integrating Ground Penetrating Radar (GPR) and digital images is a practical method for accurately measuring damage in ballast, overcoming the limitations of image analysis due to fouling
	Sleeper/Rail cracks [26,39]	Previously developed UAV-based crack object-detection algorithms (e.g., MUENet) can be used for detecting cracks in sleepers or rails
	Catenary wires [85,107]	Inspecting and validating the accurate positioning and optimal tension of the wires using UAVs.

Challenge/Limitation	Description
Obstacles in tunnels [115]	Using multiple UAVs for simultaneous data acquisition

4 Conclusions

UAVs are used for different purposes in the railway track industry, and track monitoring and mapping are the most favorable ways of using UAV applications. Various aspects related to UAV technology were described, including UAV types, flight performance analysis, drone selection criteria, and regulations and guidelines for drone operations in railway environments. Furthermore, the review focuses on applied sensors and investigated parameters in the railway infrastructure, particularly in ballasted railway superstructure, such as RGB, multispectral, LiDAR, and infrared thermography.

UAV's role in railway track monitoring was explained, which includes the assessment of track geometry, the detection of obstacles, the identification of superstructure defects, and the spotting of vegetation. Using UAVs in railway bridges and tunnels was also delved into, demonstrating their potential for effective inspection and maintenance. Looking forward, numerous future prospects and challenges in the realm of UAV-based railway infrastructure were identified. These include the development of cutting-edge sensor technologies, integrating artificial intelligence and machine learning algorithms for automated analysis, and addressing challenges associated with data management and processing, with YOLO playing a significant role in image-based analyses. Moreover, the importance of regularly updating regulatory frameworks and guidelines to guarantee safe and efficient UAV operations in railway settings was emphasised.

In conclusion, significant potential for boosting safety, refining maintenance strategies, and enhancing overall operational efficiency is offered by the incorporation of UAV technology in railway infrastructure monitoring.

Acknowledgmenet

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