

Priority management for public road repairs using digital twins and UAVs

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Abstract

The problems of road pavement degradation caused by the growing number of transport vehicles and seasonal damage related to weather conditions (e.g. after winter) are well known. This problem affects not only municipal, provincial and local authorities, but also all road users. Limited budgets and resources of road maintenance crews contribute to the accumulation of problems and difficulties in planning road repairs and renovations. The article proposes the use of unmanned aerial vehicles to collect photogrammetric data as information for creating a digital twin of cities in order to increase certainty in prioritising road repairs and restoring them to full functionality as quickly as possible. The article proposes the concept of a digital twin of road infrastructure and a model for the automatic acquisition of information on road damage in order to integrate this data with existing pavement management systems.

Keywords: city digital twin; UAV; photogrammetry; smart cities development; urban planning; systems integration; pavement management system;

1 Introduction

1.1 *The problem of road surface degradation and budget constraints*

Road surface degradation problems resulting from increasing traffic volumes and seasonal weather damage pose a significant challenge for transport systems in cities and urban areas, particularly for local government authorities (Talahat et al., 2024). Damage occurring after winter periods is particularly noticeable, leading to a reduction in road safety and user comfort.

Traditional pavement management systems (PMS) are largely based on a reactive approach, which involves taking action only after visible damage occurs. This approach is considered to be less cost-effective than proactive solutions based on regular monitoring of technical condition and forecasting of pavement degradation (Consilvio et al., 2023; Topu et al., 2025). In addition, man-made field inspections are labour-intensive, time-consuming and involve the risk of human error and subjective assessment, which makes it difficult to compare results over time and space and limits the possibility of objective prioritisation of repairs (Lv et al., 2025; Samadzadegan et al., 2024).

1.2 *The practice of management and inspection of municipal and district roads in Poland*

The management of municipal and district roads in Poland is based on periodic inspections and actions taken in response to current reports and observations in the field. The WR-D-83 guidelines (Ministerstwo Infrastruktury, 2023a) indicate that decisions regarding road surface maintenance are based on the findings of basic inspections (carried out at least once a year) and extended inspections (carried out every five years). These sources are supplemented by information obtained between inspections, including road lane monitoring, reports from services and users, and data resulting from maintenance works.

In practice, visual inspection remains the dominant method of assessing the condition of local roads. This is in line with WR-D-83 (Ministerstwo Infrastruktury, 2023b), which describes the principles of conducting field assessments, segmenting sections for inventory purposes, and cataloguing typical pavement damage.

Control and diagnostic activities are carried out both by the administrators themselves (inspections, patrols, photographic documentation) and by commissioning external entities to perform inspections, especially in the case

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of extended inspections. It is common practice to commission periodic inspections of district roads, including five-yearly inspections, aimed at assessing the technical condition and suitability for use of road elements and their surroundings.

Guideline WR-D-83 allows for the documentation of the road lane through photo and video recording as methods supporting the identification of changes and damage in the road corridor (Ministerstwo Infrastruktury, 2023a, 2023b). At the same time, they define the scope of assessments performed as part of annual and five-year inspections and the rules for classifying the condition of the road surface, with visual assessment and image recording serving as tools to support the inspection process (Ministerstwo Infrastruktury, 2023b, 2023a). In practice, recording activities are periodic and are carried out in conjunction with formal inspections, which means that there is an information gap between successive scheduled inspections regarding the current condition of the road surface, which is particularly important in urban conditions due to the likelihood of faster surface degradation. In this context, the cyclical acquisition of photogrammetric data from UAVs can be considered a potentially effective, complementary source of information. It allows for objective and repeatable documentation of changes occurring between inspections and the use of this data in the ongoing process of local road management.

2 Literature review

In smart cities, Urban Digital Twins (UDTs) are used for traffic management, spatial planning and resource optimisation (Dawkins & Kitchin, 2025; Sacoto-Cabrera et al., 2025). DT maturity is described using models such as DUET, where the highest level ('Intelligent Twins') uses AI to predict events and automatically adjust decisions to long-term policies (Marçal Russo et al., 2025).

The literature indicates that DT in road engineering integrates geometric modelling (BIM), spatial information (GIS) and data obtained from sensors (Yan et al., 2025). Research focuses on creating 3D models from point clouds and using numerical methods (e.g. FEM) to predict the fatigue life of pavements (Oditallah et al., 2025; Talaghat et al., 2024).

Modern systems such as RIOMS use spatio-temporal data to improve decision-making processes in road maintenance (Lv et al., 2025). The integration of DT with decision support systems (DSS) allows for automatic analysis of degradation risks and assessment of Key Performance Indicators (KPIs), which translates into maintenance cost savings (Consilvio et al., 2023).

Deep learning algorithms, especially those from the YOLO family (e.g. v7, v8), are revolutionising road inspections by offering high precision and speed in detecting cracks, potholes and patches (Samadzadegan et al., 2024; Yıldızlı et al., 2025). A key photogrammetric parameter is GSD (Ground Sample Distance) – the size of a pixel in the field; a smaller GSD allows even microcracks several millimetres wide to be detected (Guan et al., 2023; Lv et al., 2025).

A digital twin (DT) is a dynamic, virtual representation of a physical asset which, thanks to the integration of data from sensors and historical records, enables real-time monitoring of the condition of the object (El-Agamy et al., 2024; Yan et al., 2025). In the context of road infrastructure, DT not only allows for the mapping of geometry, but also for the simulation of pavement behaviour under the influence of operational loads and environmental factors (Sacoto-Cabrera et al., 2025).

One of the key sources of data for digital twins of road networks are unmanned aerial vehicles (UAVs), which enable rapid acquisition of high-resolution photogrammetric data, forming the basis of the model's information layer (Zhang et al., 2025). This data can be used for automatic detection of pavement defects using machine learning methods, in particular deep learning algorithms, and then integrated into the DT model to support decision-making processes.

Recent research focuses not only on detection, but also on automating the repair planning process. Mehta et al. (Mehta et al., 2025) and Sacoto-Cabrera et al. (Sacoto-Cabrera et al., 2025) proposed a data-driven framework for fleets of autonomous ground vehicles (UGVs) repairing potholes. They mathematically expressed the pothole repair time as a function of its geometry. This approach allows for precise planning of maintenance schedules in a digital twin environment, optimising the use of materials and equipment resources.

A review of the literature indicates that the majority of existing research on digital twins in infrastructure has focused on motorways, bridges, or tunnels. Sources confirm that research on DT in road engineering is still rare and scattered, and there is a lack of work focused on the micro-level of pavement condition in local (municipal) administration, where budgetary challenges are greatest.

Manual road inspections are subjective and labour-intensive, and advanced laser scanning systems (MLS) are very expensive and require powerful computing equipment. The use of drones is considered a promising direction, but still requires the development of a unified framework for regular monitoring. There is a need for solutions that are not overly detailed but focus on decision-making utility. Many existing PMS (Pavement Management Systems) are complex tools that are difficult to implement in small municipalities due to financial barriers and a lack of specialised personnel

3 Purpose and novelty elements of the article

An analysis of the current WR-D-83 guidelines indicates that procedures for the maintenance of local authority roads are explicitly formulated within an interventionist approach and do not incorporate a preventive approach, i.e. measures planned ‘in advance’ on the basis of a continuous flow of data (Ministerstwo Infrastruktury, 2023a, 2023b). The guidelines specify the scope and methods of assessment (including visual inspections, diagnostics and the use of video recording), but do not define a low-cost, implementable mechanism for regularly feeding data into the decision-making process between scheduled inspections, nor do they address how this relates to the prioritisation of repairs at the local network level (Ministerstwo Infrastruktury, 2023b, 2023a). At the same time, a review of the literature shows that DT and automated inspection solutions more often concern high-priority infrastructure (motorways, engineering structures) or require costly measurement technologies, whilst there is a lack of work focused on a simple and cost-effective operational model for local roads that would provide direct, transparent support for maintenance decisions.

The aim of this study is to present a practical operational model of a digital twin (DT) for local road networks, which integrates low-cost UAV photogrammetry with an objective repair prioritisation system. The system has been designed to enable small local government units to transition from costly, subjective manual inspections to data-driven management (actionable intelligence). The article describes the architecture of a system integrating automatic damage detection with decision support tools, tailored to the operational realities of local authorities.

A novel feature of the presented approach is the proposed data processing procedure, which automatically sends detection results directly to the DT database, feeding into the repair prioritisation process. The cost-effectiveness of the system was adopted as a key factor, resulting in the use of a drone as the primary data source instead of a fleet of inspection vehicles. The combination of widely available drones (e.g. DJI Matrice 4E) with deep learning algorithms (YOLO) as the main source of data for the DT eliminates the cost barrier associated with expensive MLS scanning systems.

A key innovation of the proposed solution is its focus on the network of local roads, considering their specific role in urban logistics (e.g. the last mile).

Another innovation is the replacement of subjective ratings with objective measures. Here, we utilise, amongst other things, an adaptation of the formula from (Mehta et al., 2025) to parameterise the cost and time indicator (C), which allows for the precise calculation of the required resources directly from the 3D model generated by a drone.

4 Assumptions of the digital twin concept for the local road network

4.1 The scope of DT

In the proposed approach, the digital twin of the local road network is understood as an operational information model, the primary purpose of which is to support decision-making regarding repair priorities. The spatial scope covers the local road network within the administrative boundaries of the local authority. To balance the cost of data acquisition with the clarity of decision-making, a moderate level of detail has been adopted. It is assumed that the road network is divided into sections, each with individual identifiers and attributes relating to condition and operation. This division enables the mapping of damage detection to segments and the creation of a repair ranking without the need to fully model every geometric detail. The scheme for dividing the network into sections is determined in consultation with the administrator of the road in question. Sections are the basic unit of analysis in terms of monitoring their condition and determining maintenance needs. The proposed DT assigns importance attributes to sections based on their role in maintenance and traffic safety. These include, among others, sections:

- with particularly heavy traffic,
- adjacent to facilities critical to public safety (hospitals, police stations, fire stations).

The DT also stores time-related data, i.e. each section may have a history of inspections, detected defects and work carried out. As a result, the DT serves as a condition record and a database for analysing trends in the rate of deterioration.

4.2 Data model and system architecture

The DT data model is based on four information layers.

The first layer is the geometric layer (GIS/3D) – it contains the network’s georeferencing, division into sections, and basic geometric parameters (length, width, axis alignment). The minimum requirement is a linear GIS layer (road centreline + segmentation). 3D models (e.g. from point clouds) are treated as an optional resource – used when they enhance the reliability of the assessment (e.g. when assessing deformation, rutting or estimating the depth of potholes). The source material for this layer should be existing registers and inventories maintained by road authorities. These registers are usually records of roads/streets identified primarily by number/name and length, often divided into sections. Data from these registers will become DT objects with identification and location parameters, forming the basis for assigning information in subsequent layers.

Figure 1 shows an example network of six roads. Each road has been divided into sections approximately 100 m long. Road No. 1 is the southern entrance to the town; it begins at a level crossing marked with a yellow box numbered 1 (section 1.1). The road comprises 13 sections. A primary school (yellow box 2) is located near sections 1.1 and 1.2, which leads to temporary increases in traffic volume. Road No. 2 runs around the pond in the central part of the village; it is characterised by heavy traffic and comprises 14 sections. The Volunteer Fire Brigade station is located near sections 2.8 and 2.9 (yellow box 3). Roads No. 3 and 4 provide access to residential properties. They consist of 9 and 7 sections respectively. Road No. 5 is the north-eastern entrance to the village; there are no critical facilities along it, but it is heavily used. It consists of 19 sections. Road No. 6 is an access road to properties and consists of 19 sections.

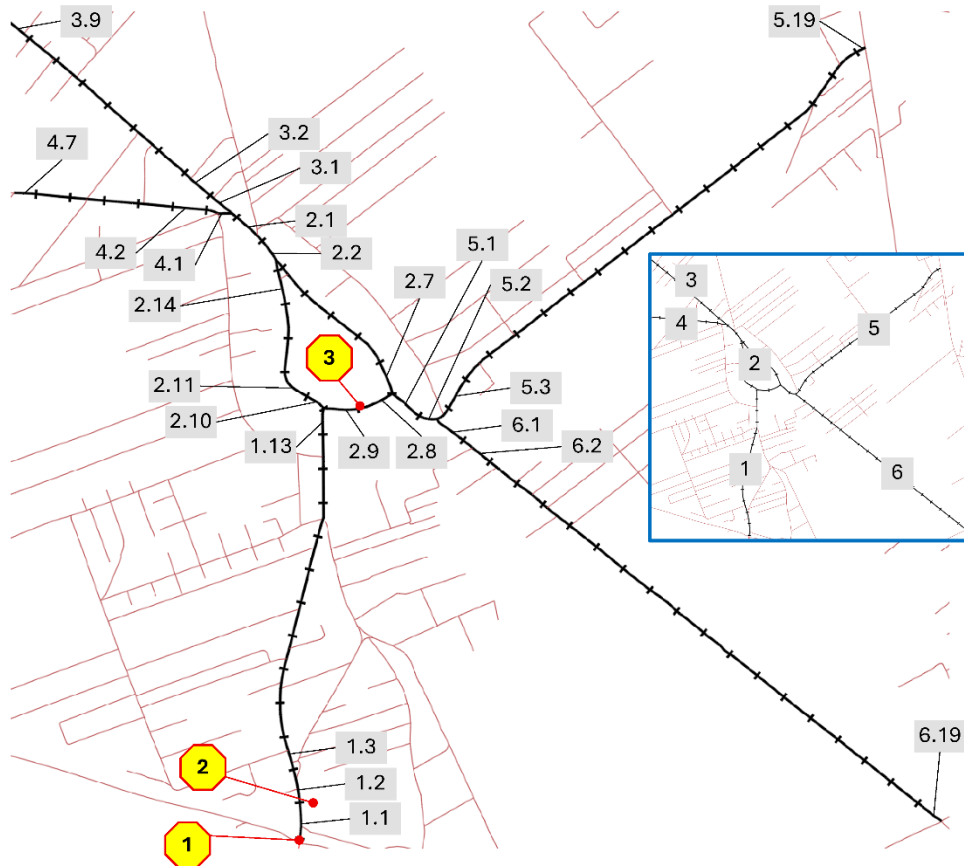


Fig. 1. An example of a road network covered by DT, broken down into sections. Own study.

The example provided is a simplified one. In reality, the area under analysis comprises a much larger number of public roads; however, the focus has been placed on selected roads for the sake of clarity.

The second layer of the DT consists of information on the current and historical condition of the surface of each section (defect register) – this is the key layer of the DT. Each defect constitutes a record with a unique identifier and attributes, e.g.:

1. defect type (e.g. potholes, cracks, patches),
2. location (coordinates or reference to the section + kilometre marking),
3. geometric parameters (area, length/width; optionally depth),
4. date and method of detection (UAV, resident report, manual inspection),
5. detection reliability (so-called confidence parameter, operator verification flag),
6. information on change over time (new/persistent/growing/repaired).

Digital twin operational layer – stores attributes affecting the significance of a section and the rate of degradation, e.g. road class, speed limit, proportion of heavy goods vehicles, approximate traffic volume, function within the network (access to public services). Figure 1 shows three example points marked with octagonal labels – a railway crossing (1), a school (2) and a fire station (3).

Decision-making layer – contains indicators aggregating information from layers (2) and (3) for prioritisation purposes:

1. safety risk indicator (e.g. depending on the type and size of the defect and its location on the track),
2. estimated repair costs and the cost of delays,

3. task status (reported, approved, scheduled, in progress, completed),
4. logistical information supporting the grouping of repairs (area, team availability, time slot).

This layered structure allows for a balance between detail and simplicity of implementation: a local authority can begin building the system with geometry and a defect register, and only later enhance the DT with operational data and a full decision-making layer.

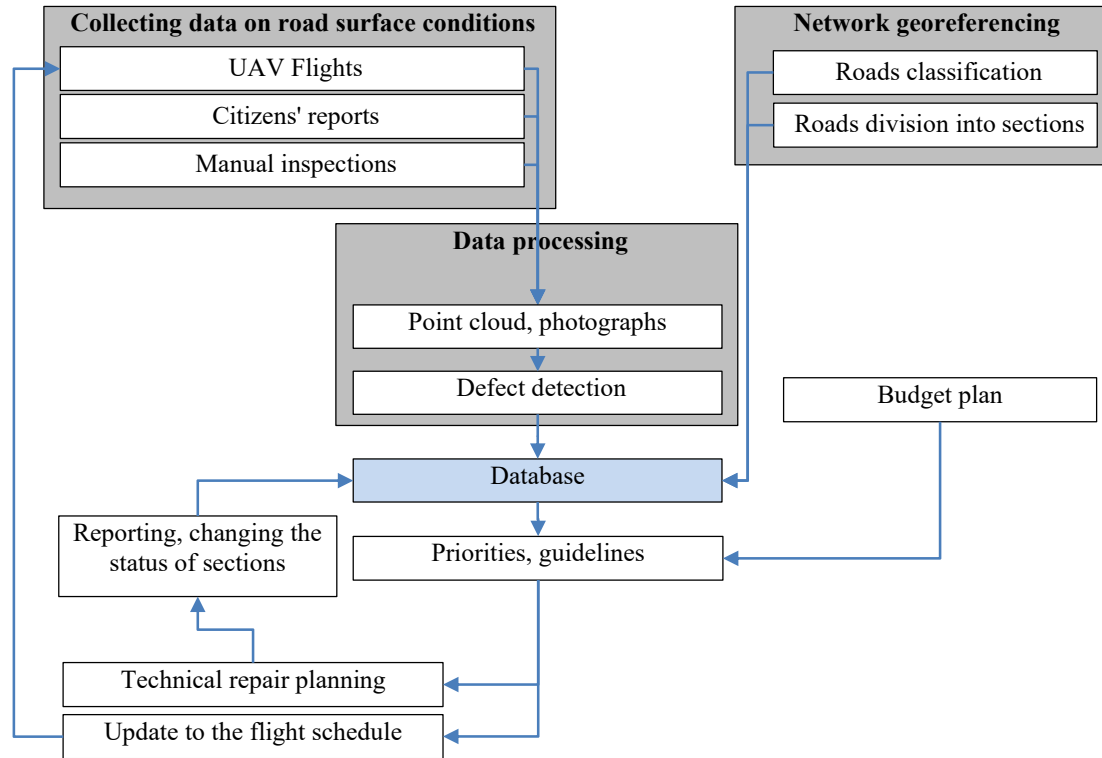


Fig. 2. The modular architecture of the digital twin. Own study.

The main source of data consists of UAV flights carried out at intervals tailored to the road class. Each flight is recorded as an event (time, parameters, coverage). Additional data sources may include reports from residents via a dedicated app or web portal. Manual inspections may be introduced as a supplement and for periodic verification.

The results of pavement defect detection should be recorded in a way that allows for both automated processing and rapid operator verification (e.g. rejection of incorrectly identified defects).

The DT database stores: the road network plan and its segmentation (GIS), the defect register, data from each UAV flight (time, mission parameters, range, resolution), and road operational data (indicators, costs, statuses). Data is made available via API services so that DT can integrate with existing tools (municipal GIS, PMS, reporting system, work planning dashboard). DT has at least two user groups:

- decision-makers/officials responsible for planning the budget and priorities,
- maintenance teams carrying out tasks.

Depending on requirements and permissions, the database interface should provide access to:

- a map showing sections by priority class (colour coding),
- a view of defects and their attributes,
- tracking of implementation status and activity history,
- reports (ranking, costs, justifications).

This architectural design supports the main objective of the project: a rapid transition from UAV data to repair decisions, whilst maintaining transparency for the local authority and allowing for further expansion (e.g. to include additional data sources or more advanced decision-making methods).

This approach also allows for varying the frequency of data collection (e.g. more frequent UAV flights for sections of higher importance or greater risk), without affecting existing periodic inspections – DT serves here as an extension of the existing records with a regularly updated road condition layer.

5 A module for inspecting road surfaces using drones

5.1 Configuration of the UAV platform and sensors

The study utilised a DJI Matrice 4E unmanned aerial vehicle (UAV) equipped with a high-resolution visual camera based on three CMOS image sensors measuring 1/1.3 inches, 1/1.5 inches and 4/3 inches, enabling the collection of visual data at a maximum resolution of 48 MP. The drone is additionally equipped with a laser rangefinder capable of measuring distances between 1 and 3 m with a measurement error of <0.3 m. Control and planning of automated missions can be carried out using a controller fitted with a touchscreen. The controller can connect to Wi-Fi networks and mobile networks for two-way synchronisation of data relating to planned or completed missions. Additionally, the unmanned aerial vehicle is equipped with distance sensors. Automatic obstacle detection and avoidance is achieved through a multi-directional, binocular vision system, supplemented by an infrared sensor.

Mission planning, data collection, and subsequent data processing and analysis are carried out using dedicated software provided by the drone manufacturer, DJI. Both DJI FlightHub 2, accessible via a web browser, and DJI Pilot 2, accessible via a touchscreen controller, can be used for mission planning, route mapping and setting mission parameters. The collected visual and spatial data is organised and processed in DJI Terra.

The technical parameters of the data obtained depend on the flight altitude, the type of sensor used, the image resolution and the focal length of the optical path. Based on this data, it is possible to estimate the ground sampling distance (GSD) – the actual distance on the ground covered by a single pixel of the image. To calculate the GSD, the general photogrammetric formula from (Luhmann et al., 2020) can be used:

$$GSD = \frac{H \cdot S_w}{f \cdot I_w} \quad (1)$$

where:

GSD – ground sampling distance [cm/px],

H – flight altitude [cm],

S_w – image sensor width [cm],

f – lens focal length [cm],

I_w – number of horizontal image pixels.

For example, to achieve an accuracy of 0.5 cm of terrain per 1 pixel of the image, one would need to use a 1/1.3-inch sensor with an image sensor width of 0.96 cm, a resolution of 21 MP (5280 x 3956 px) and a focal length of 1.23 cm. Under these conditions, the drone should fly at an altitude of approximately 18.6 m.

5.2 Configuration of the UAV platform and sensors

Research procedure for the adopted assumptions regarding damage identification and integration of information from the digital twin:

- collection of image data;
- collection of geographical data;
- 2D/3D data processing;
- automatic identification of defects;
- classification of voids;
- quantitative assessment of damage;
- qualitative assessment of damage;
- assessment of the significance of damage based on type and location;
- statistical analysis of results;
- assessment of the feasibility of integrating image data with the digital twin resources of the municipality/county.

5.3 Automatic defect detection

Automatic data collection requires subsequent processing in order to extract quantitative and qualitative information. It is essential to apply appropriate methods of video image processing. Advances in computer graphics and increased computing power have made it possible to use visual information for the automatic interpretation of real-time situations in road transport. The first publications began to appear in the first half of the 1980s. In parallel with the growing interest in the use of CCTV images in road transport, there has been a development of mathematical methods for automatic image processing and their further analysis. Articles (Ali & Dagless, 1992; Dickinson & Waterfall, 1984; Wigan & Cullinan, 1984a, 1984b) describe devices and techniques for the digital acquisition and processing of images for the purposes of automatic monitoring of road traffic flow, vehicle

classification and identification, as well as for assessing the potential application of these methods to the monitoring of road condition.

Image processing and analysis algorithms can be divided into two main categories based on the type of mathematical methods used. The first category comprises those based on conventional mathematical methods, whilst the second consists of algorithms based on machine learning. Machine learning (ML) is a branch of artificial intelligence (AI) and enables systems to analyse data and draw conclusions based on previously acquired knowledge. Building an ML model involves two key phases: training and testing. During training, the system learns from labelled or unlabelled data, creating a representation in feature space. Subsequently, in the testing phase, it uses this experience to predict outcomes for new, unlabelled data. The effectiveness of the model depends, amongst other things, on the required accuracy and the quality and scope of the learning process (Aldahiri et al., 2021).

The YOLO (You Only Look Once) algorithm was used for the quantitative and qualitative analysis of road damage. It is based on single-pass convolutional neural networks. It was first presented in 2016 in publication (Redmon et al., 2016). Compared to other convolutional networks based on fast region classification (F-RCNN), which result in multiple predictions for different regions in the image, the YOLO architecture is more similar to a Fully Convolutional Neural Network (FCNN) and analyses an $n \times n$ image only once, through a single network, with the output being a prediction region of dimensions $m \times m$. This architecture divides the input image into regions using a grid and, for each grid, generates two bounding boxes and evaluates the probability of object classification for these boxes. Figure 3 shows a general diagram of the operation of a Single Shot Detector (SSD) network, on which the YOLO algorithm's architecture is based.

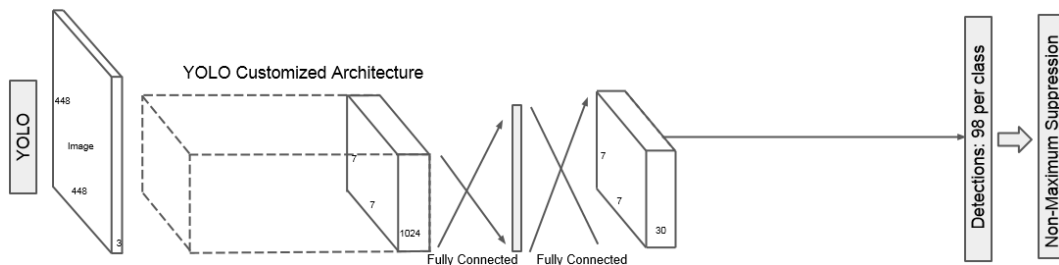


Fig. 3. A diagram illustrating how the YOLO algorithm works to identify objects in an image. Source: (Liu et al., 2016).

The collected data undergoes quantitative and qualitative analysis to identify types of damage and pavement degradation. The data obtained and processed in this way, and the information derived from it, can make a significant contribution to the digital twin of the road network. Information on the technical parameters of road surface defects, such as length, width and depth, allows the damage to be classified into the following types:

- potholes (bumps);
- cracks (mesh, fatigue);
- ruts;
- surface subsidence;
- edge damage;
- spalling and surface degradation;
- transverse and longitudinal cracks;
- binder bleeding (bleeding).

The type of damage can have a significant impact on the decision to undertake immediate repair work or to assign an intensive monitoring plan to a given section of road.

5.4 Mission planning and flight schedules

In the proposed approach, UAV mission planning is intended to ensure the comparability of data across successive inspection cycles and to enable the gradual development of a database detailing the condition of the road surface. It is crucial to maintain consistency in data acquisition: a fixed flight path logic over the road network and consistent recording parameters (including adequate image coverage), so that differences observed in subsequent flights result primarily from changes in road surface condition, rather than from differing data acquisition conditions.

The article uses an example road network area shown in the figure (Fig. 1), in which roads are divided into sections with unique identifiers (e.g. 1.1, 1.2 ... 2.1, 2.2, etc.). This numbering system serves as a common 'address' for planning and archiving aerial surveys: each mission is assigned to the list of sections it covers, and the inspection results (location of identified defects and their parameters) can be automatically linked to the relevant section identifier in the DT database. In practice, this reduces the need for manual recording of results and facilitates the comparison of data between successive monitoring cycles.

Mission planning requires the definition of reference segments, which serve as the unit for flight planning and for the aggregate presentation of inspection results. In this example, the segments (e.g. 1.1, 1.2...) have been defined in such a way as to, on the one hand, enable the unambiguous location of damage, and on the other, limit the number of records and the volume of photogrammetric products. It is assumed that longer units (of the order of 150–200 m) can be used on homogeneous and straight sections, whereas in areas with complex geometry, dense development or potential obstructions (e.g. trees, junctions, crossroads), a finer division (of the order of 50 m) is recommended. This approach represents a compromise between the resolution of the description and the efficiency of data processing and storage.

The proposed option adopts a monthly inspection cycle as the baseline schedule for the area under review. At the same time, it allows for more frequent inspections in situations where the risk of rapid pavement degradation increases or where there is a need to assess the condition following exceptional events. This applies in particular to transitional periods (e.g. thaws and freeze-thaw cycles), heavy rainfall, as well as situations reported by users or observed by maintenance services. An adaptive schedule allows for a consistent, comparable monitoring rhythm to be maintained, whilst also enabling a response to conditions conducive to the development of damage.

The inspection of each section should include two flyovers in opposite directions, which enhances the completeness of the documentation and minimises the impact of obstructions and changes in lighting on defect detection. To ensure comparability across successive cycles, it is recommended that flights be conducted along a fixed track, close to the centreline of the right-hand carriageway or at a distance of approximately 1 m from the right-hand edge of the carriageway. Maintaining adequate longitudinal and transverse coverage of the images is a prerequisite for obtaining material of a quality that enables both automatic defect detection and analysis of changes between successive flights. An example visualisation of the result of a single mission (identification and geolocation of defects as a photogrammetric image) is shown in Fig. 4.

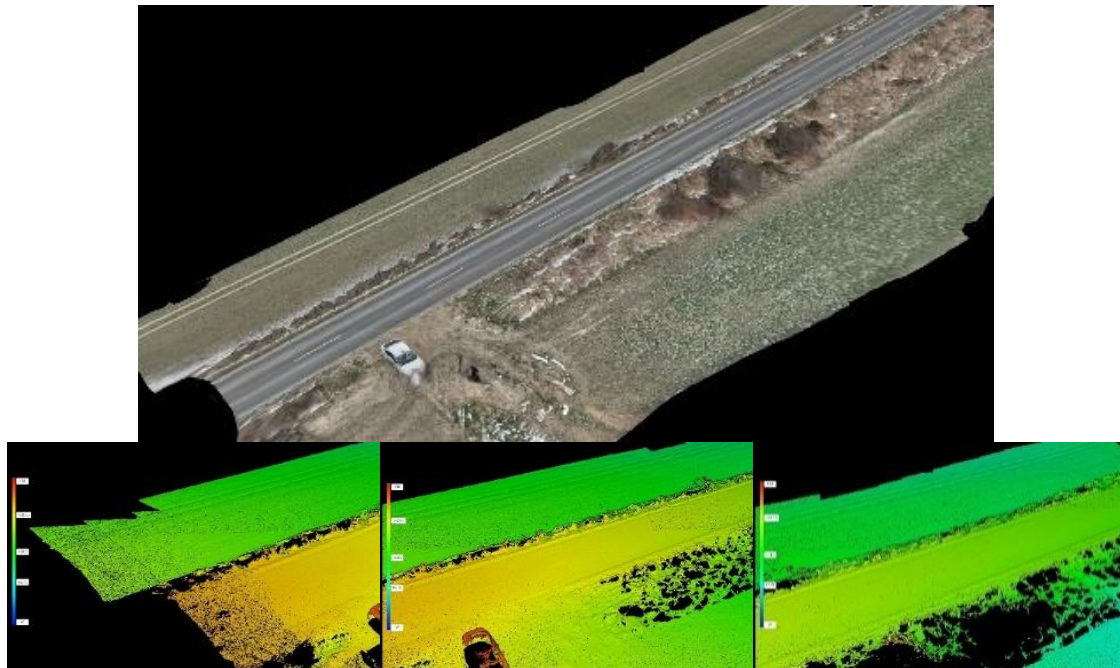


Fig. 4. An example of how UAV inspection results might be visualised (illustrative material showing how the results are presented). Own study.

The visualisation shown in Fig. 4 is supplemented by a tabular record in the form of defect records, which enables the results to be archived unambiguously and processed further within the digital twin. In the proposed approach, a defect record contains at least the section identifier (e.g. 1.2), the type of damage, the location within the carriageway cross-section (e.g. right-hand side/centre/left-hand side), basic geometric parameters (dimensions or derived measurements), as well as the geolocation and date of the mission. A record organised in this way constitutes a common input data format for further processing (summary of results, analysis of changes, support for maintenance decisions). This paper proposes the use of the defect record format presented in Table 1 as the standard for reporting UAV inspection results.

Table 1. Proposed format for recording UAV inspection results (defect record).

No	Section ID (1.2, 1.3, etc.)	Defect type	Position in the road cross-section	Dimensions [cm] (L×W×D) / derived measures	Mission date
1	right / centre / left
2	right / centre / left
3	right / centre / left

(In practice, the table may contain any number of records; the rows shown are merely examples.)

6 A model for prioritising and scheduling repairs

6.1 Classification of road sections

The main objective of the proposed model is to transform raw photogrammetric data and the results of automatic damage detection into an objective ranking of maintenance activities. This model bridges the gap between a reactive approach to repairs and a modern, proactive asset management system (PMS), tailored to the realities of small local authorities.

The decision on the order of repairs is based on the classification of road sections according to their functional importance within the road network covered by the digital twin. A higher class is assigned to sections with heavier traffic, an increased risk of incidents, and sections providing access to facilities critical to public safety. The proposed model adopts the following classes of sections.

- S0 – standard (local) sections: sections with a local function, serving commuter and local residential traffic, with no specific critical functions; no direct impact on the continuity of service to key facilities and no high-risk locations (e.g. highly complex traffic junctions).
- S1 – sections of heightened importance: sections with increased traffic volume or a higher risk of incidents (e.g. in the vicinity of junctions, roundabouts, road junctions, pedestrian crossings, bus stops), as well as sections playing a significant role in serving local transport and public transport,
- S2 – critical sections: sections providing access (including emergency access) to critical facilities (e.g. fire stations, hospitals, police stations) or key transport routes for which the organisation of diversions is significantly impeded (limited availability of alternative routes, high social cost of closure to traffic).

The classification of road sections should be updated at least once a year and whenever there are significant changes to traffic management or land use (e.g. changes to public transport routes, the construction or change of function of public facilities, changes to the availability of alternative routes). This requires the conduct or use of traffic volume surveys and the monitoring of developments not only in the road network but also in public facilities, critical institutions, public transport (stops), pedestrian crossings, and seasonal fluctuations in the population of residents and road users (e.g. in tourist areas).

Figure 5 shows a proposed classification of road sections in an example town. Traffic volume and the critical facilities described in subsection 4.2 were taken into account.

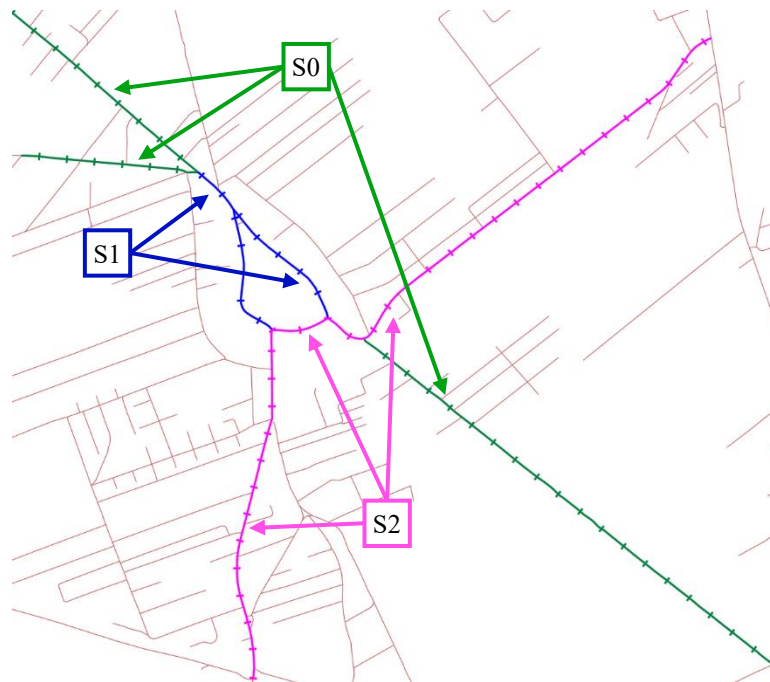


Fig. 5. Classification of sections of a sample road network. Own study.

6.2 Classification of road defects

Following each inspection, identified surface damage is also classified based on the type of defect (e.g. pothole, crack), its geometry (surface area, depth) and location in relation to the traffic lane (centre of the lane, edge). The following damage classes are proposed:

- D0 – minor damage: localised cracks, small depressions or small-scale spalling, not causing a significant deterioration in safety or traffic flow under the applicable speed limit; no indication of rapid progression in the short term,
- D1 – moderate (developing) damage: defects impairing driving comfort and with the potential to develop under operational conditions (e.g. as a result of water infiltration and freeze-thaw cycles), as well as clusters of minor damage whose combined impact is significant on the section under analysis,
- D2 – serious defects (road safety hazard): defects posing a threat to road safety (risk of vehicle damage, loss of stability, ejection of material) which, in practice, require urgent intervention or temporary measures (signage, speed restrictions); under normal conditions, it is possible to avoid them by changing course
- D3 – critical defects: defects causing a significant restriction of traffic flow or a high risk of an incident, including situations requiring immediate intervention (e.g. closure of a lane/section or securing the site), where safe passage is not possible under permissible traffic conditions.

If there are multiple defects on a road section, the defect with the highest severity class is used for the repair priority analysis.

6.3 Prioritising repairs

Figure 6 shows a flowchart outlining the procedure for determining repair priorities for each section of the road network under analysis. The green box highlights the area addressed on an ongoing basis following each scheduled inspection and any unscheduled reports of damage.

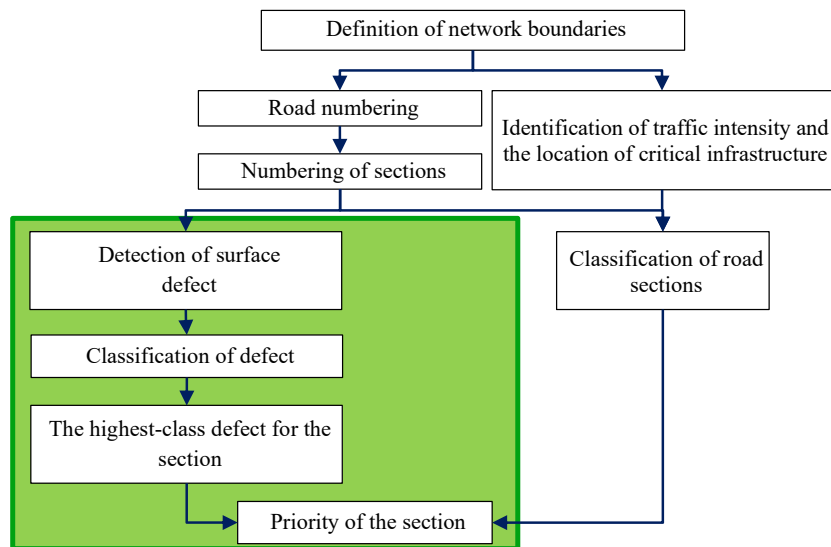


Fig. 6. Procedure for prioritising road section repairs. Own study.

Using the values of the two variables – the section class and the damage class – the repair priority can be determined on the basis of the proposed Table 2.

Table 2. The priority of repairing a section as a function of two variables

		Defect class			
		D0	D1	D2	D3
Section class	S0	P0	P1	P2	P3
	S1	P1	P1	P2	P3
	S2	P1	P2	P3	P3

Based on the section class (S) and the predominant damage class (D), a repair priority (P) is determined, interpreted as follows:

- P0 – low: monitoring / scheduled repair during routine maintenance works.
- P1 – moderate: inclusion in the works plan in the short term (planning within the current cycle).
- P2 – high: urgent repair; prioritised in the schedule, possibly with temporary measures (e.g. signage/speed restrictions) and additional weekly visual inspections until the damage is rectified.
- P3 – emergency: immediate intervention and securing of the site; immediate action.

6.4 Scheduling repairs

Once the repair priority has been determined, the next step is to estimate the scope of work for each intervention, which enables the creation of a schedule and resource planning. Using data from UAV photogrammetry, the system can automatically determine the surface area of the defect and – approximately – its volume. To estimate the workload (repair time), a simplified linear model adapted from research on repair automation (Mehta et al., 2025) is used:

$$T = (a \cdot V) + (b \cdot S) + c \quad (2)$$

where T is the repair time, V is the volume of the defect, S is the surface area of the defect, and a , b , c are coefficients determined empirically on the basis of data from previous repairs (for a given technology, work organisation and local conditions).

The calculated T parameter can be used directly to assess traffic restrictions (lane closure time) and for preliminary planning of material consumption. For example, given V , the requirement for mineral-asphalt mix can be estimated based on a density of approximately 2400 kg/m³ (an approximate value depending on the type of mix). In practice, repair costs can be further determined on the basis of T (unit cost of labour and equipment) and indirect costs arising from the organisation of the works.

However, estimating the time T and cost is not sufficient to draw up a realistic work plan, as organisational constraints and the possibility of grouping tasks into work packages also play a significant role in scheduling. At the scheduling stage, in addition to priority P and estimated time T , logistical constraints are taken into account: the availability of teams and equipment, the possibility of grouping repairs in a given area, and alignment with time windows (e.g. constraints arising from traffic volume, local events or weather conditions). This allows repairs of similar priority to be carried out in a more organisationally efficient manner, whilst maintaining safety criteria for top-tier interventions.

7 Preliminary studies

7.1 Assumptions

Preliminary studies were conducted to test the effectiveness of damage detection and classification, the visualisation of results, and the analysis of the correctness of the designed information flow within the proposed DT. The studies involved carrying out pavement condition inspections and planning repairs in accordance with the proposed procedure.

The study site was a sample town, the road network plan of which is shown in Figures 1 and 5. Six roads were identified within the network, with the following lengths:

- road 1 – 1281 m,
- road 2 – 1390 m,
- road 3 – 901 m,
- road 4 – 640 m,
- road 5 – 1805 m,
- road 6 – 1887 m.

In accordance with the system specifications and in compliance with UAV flight safety regulations governing visual line-of-sight (VLOS) flights, 14 flights were carried out, with an average flight segment length of 565 metres. Taking into account a 60% overlap, 950 photographs were taken for each individual road segment. The total number of images was 13,300, occupying approximately 105 GB of disk space. The total flight time for all 14 missions, excluding the time required for take-off and landing procedures between individual missions, was 21 minutes.

7.2 Inspection results

As a result of the aerial inspections, seven instances of surface damage were identified. Two of these are fairly large areas of asphalt spalling. On section 2.3, several instances of spalling were recorded; these were treated as a single instance, and their lengths and widths were added together (Fig. 7). The remaining defects are unevenness of an extensive but relatively mild nature. A summary of the results is provided in Table 3, which follows the format of Table 1 (Subsection 5.4).

Table 3. Results of the UAV inspection

No	Section ID	Defect type	Position in the road cross-section	Dimensions [cm] (L×W×D)	Mission date
1	2.1	collapse	centre	300x200x5	25.02.2026
2	2.3	group of crushing	right+centre	70x50x5	25.02.2026
3	2.14	crumbling	left	100x100x5	25.02.2026
4	3.3	ruts	right	800x100x7	25.02.2026
5	3.4	ruts	right	500x50x8	25.02.2026
6	6.7	ruts	right+centre+left	800x100x6	25.02.2026
7	6.8	ruts	right+centre+left	500x100x8	25.02.2026



Fig. 7. Photographs of damage (spalling) on section 2.3. Own study

To convert the aerial photographs into a 3D model, the standard photogrammetric process described in section 5.2 was used. The photographs are merged into a coherent spatial model, which yields a point cloud; following densification of this cloud, a three-dimensional surface model is produced in the form of a triangular mesh with an applied texture. This processing chain can be carried out both in software dedicated to drone data (used in this study) and in external photogrammetric tools based on photographs, including free solutions (e.g. Meshroom/MeshLab). An example of the result of the process in the form of a point cloud and a textured mesh model is shown in Fig. 8.

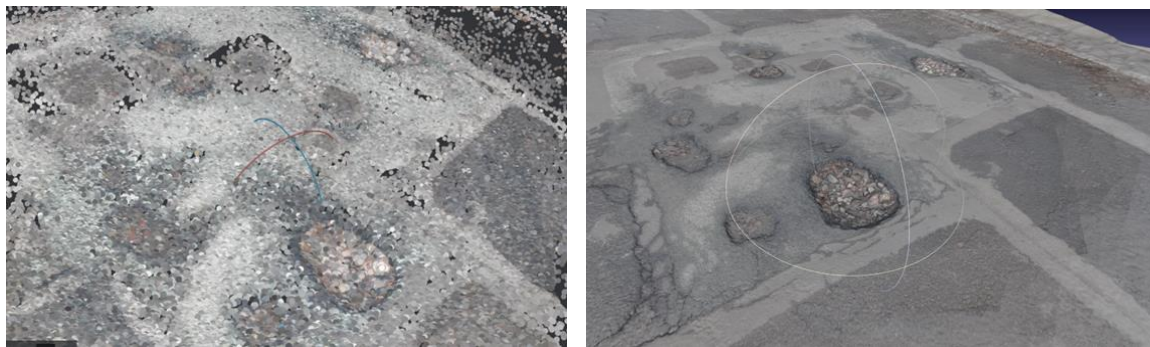


Fig 8. A damage model derived from aerial imagery and photogrammetric data, presented as a point cloud (left) and a textured mesh (right). Own study

7.3 Results of the repair prioritisation study

The procedure shown in Fig. 6 was used to prioritise repairs. The classification of road sections shown in Fig. 5 was adopted. Each damage was classified on the basis of its dimensions, location and a visual assessment based on photographic documentation. Three of the damages are fairly large areas of asphalt spalling. The spalling on section 2.3 is classified as D1 and D2. The highest class on this section, i.e. D2, is used for the repair priority analysis. The damage was classified in accordance with the guidelines described in subsection 6.2. The summary of results is presented in Table 4.

Table 4. Results of the repair prioritisation

No	Section ID	Section class	T	Section repair priority
1	2.1	S1	D1	P1
2	2.3	S1	D2	P2
3	2.14	S1	D2	P2
4	3.3	S0	D0	P0
5	3.4	S0	D0	P0
6	6.7	S0	D0	P0
7	6.8	S0	D0	P0

It can be seen that one section has been given a moderate priority (P1), whilst two have been given a high priority (P2). This means that sections 2.3 and 2.14 should be marked immediately and subjected to additional monitoring inspections until they are repaired. The repair itself should be scheduled as soon as possible.

Fig. 9 shows a possible extension of the digital twin with a visual layer on which road sections are marked in colour according to their current repair priority. Such a map will change dynamically as further inspection results are delivered and information on completed repairs is entered.

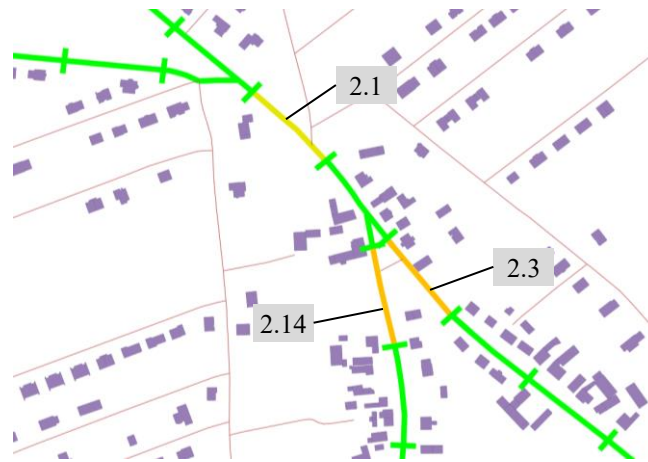


Fig 9. A section of the road network showing, in colour, the sections requiring priority repairs. Own study

8 Conclusions and future work

This article presents the concept and results of pilot studies on a practical operational model for a digital twin (DT) of a local road network. The proposed system integrates low-cost UAV photogrammetry with automatic damage detection and an objective repair prioritisation model.

Key innovative elements of the proposed approach include:

- Scale adaptation: Unlike most market solutions and literature focusing on motorways or strategic engineering structures, this model is tailored to the needs of municipal and district road networks, where budgetary challenges are greatest.
- Source efficiency: It has been demonstrated that unmanned aerial vehicles can serve as the primary data source for DT, eliminating the need to maintain an expensive fleet of MLS inspection vehicles.
- Transparency in decision-making: Automatic defect detection has been combined with a clear system of indicators (classes S, D, P), which provides local authorities with objective criteria for the allocation of budgetary resources.

Preliminary results of the pilot study confirm that the synergy between UAV technology and deep learning enables reliable detection of pavement defects, while simple priority indices constitute an effective decision-support tool for road administrators.

Further development of the system will focus on several key areas aimed at increasing the precision and practical usability of the model:

- Enhancing the level of spatial data detail: A transition is planned from the analysis of 2D imagery to the use of dense photogrammetric point clouds. This will enable the automatic generation of digital elevation models (DEM) and road surface meshes, allowing for precise assessment of pothole depth and rutting. In subsequent

stages, a quantitative comparison between UAV-derived data and publicly available datasets (e.g., national geoportal data) will be conducted in order to evaluate the influence of ground resolution on reconstruction accuracy.

- Expansion of the analytical layer: Dedicated deep learning (DL) models (e.g., YOLOv8 or Vision Transformer – ViT) will be trained on locally specific datasets, which is expected to improve the detection accuracy of micro-cracks under challenging lighting conditions. Integration with municipal GIS systems will enable full automation of the information workflow, from defect detection to maintenance order generation.
- Social dimension and advanced modelling: An important development direction involves incorporating resident-generated data (crowdsourcing) into the model, which may increase public acceptance of planned road maintenance activities. The application of Agent-Based Modelling (ABM) will allow simulation of the impacts of maintenance works, such as traffic delays or the effects of detours on residents' behaviour and urban logistics. This approach, inspired by recent trends in Urban Digital Twins, will enable the assessment of the social costs of road repairs prior to their implementation (Marçal Russo et al., 2025).
- Integration with the Internet of Things (IoT): Ultimately, the Digital Twin (DT) system will be extended with data from sensors embedded in road pavements and Vehicle-to-Infrastructure (V2I) systems. This will enable real-time monitoring of road conditions and facilitate the transition to a higher level of digital twin maturity—from a descriptive model to a predictive one.

References

- Aldahiri, A., Alrashed, B., & Hussain, W. (2021). Trends in Using IoT with Machine Learning in Health Prediction System. *Forecasting*, 3(1), 181–206. <https://doi.org/10.3390/forecast3010012>
- Ali, A. T., & Dagless, E. L. (1992). A parallel processing model for real-time computer vision-aided road traffic monitoring. *Parallel Processing Letters*, 2, 257–264.
- Consilvio, A., Hernández, J. S., Chen, W., Brilakis, I., Bartoccini, L., Gennaro, F. Di, & van Welie, M. (2023). Towards a digital twin-based intelligent decision support for road maintenance. *Transportation Research Procedia*, 69, 791–798. <https://doi.org/https://doi.org/10.1016/j.trpro.2023.02.237>
- Dawkins, Oliver, & Kitchin, Rob. (2025). Urban digital twins: Digital twins for participatory steering. *New Media & Society*, 27(8), 4402–4419. <https://doi.org/10.1177/14614448251338280>
- Dickinson, K. W., & Waterfall, R. C. (1984). Video image processing for monitoring road traffic. *IEE Conference Publication*, 105–109.
- El-Agamy, R. F., Sayed, H. A., AL Akhatatneh, A. M., Aljohani, M., & Elhosseini, M. (2024). Comprehensive analysis of digital twins in smart cities: a 4200-paper bibliometric study. *Artificial Intelligence Review*, 57(6), 154. <https://doi.org/10.1007/s10462-024-10781-8>
- Guan, S., Liu, H., Pourreza, H. R., & Mahyar, H. (2023). *Deep Learning Approaches in Pavement Distress Identification: A Review*. <http://arxiv.org/abs/2308.00828>
- Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. Y., & Berg, A. C. (2016). SSD: Single shot multibox detector. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 9905 LNCS, 21–37. https://doi.org/10.1007/978-3-319-46448-0_2
- Luhmann, T., Robson, S., Kyle, S., & Boehm, J. (2020). *Close-Range Photogrammetry and 3D Imaging*. De Gruyter. <https://doi.org/doi:10.1515/9783110607253>
- Lv, Z., Hao, Z., Zhu, Y., & Lu, C. (2025). A Review on Automated Detection and Identification Algorithms for Highway Pavement Distress. *Applied Sciences*. <https://api.semanticscholar.org/CorpusID:279023673>
- Marçal Russo, L., Dane, G., Helbich, M., Ligtenberg, A., Filomena, G., Janssen, C. P., Koeva, M., Nourian, P., Patuano, A., Raposo, P., Thompson, K., Yang, S., & Verstegen, J. A. (2025). Do urban digital twins need agents? *Environment and Planning B: Urban Analytics and City Science*. <https://doi.org/10.1177/23998083251317666>
- Mehta, S., Yusuf, A. B., & Ghafari, S. (2025). Data-driven framework for pothole repair automation using unmanned ground vehicle fleets. *Automation in Construction*, 174, 106176. <https://doi.org/https://doi.org/10.1016/j.autcon.2025.106176>
- Ministerstwo Infrastruktury. (2023a). *Wytyczne utrzymania nawierzchni jezdni i poboczy dróg samorządowych Część 1: Wymagania podstawowe*.
- Ministerstwo Infrastruktury. (2023b). *Wytyczne utrzymania nawierzchni jezdni i poboczy dróg samorządowych Część 2: Diagnostyka*.
- Oditallah, M., Alam, M., Ekambaram, P., & Ranjha, S. (2025). Review and Insights Toward Cognitive Digital Twins in Pavement Assets for Construction 5.0. *Infrastructures*. <https://api.semanticscholar.org/CorpusID:277075700>

- Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2016-Decem*, 779–788. <https://doi.org/10.1109/CVPR.2016.91>
- Sacoto-Cabrera, E. J., Pérez-Torres, A., Tello-Oquendo, L., & Cerrada, M. (2025). IoT, AI, and Digital Twins in Smart Cities: A Systematic Review for a Thematic Mapping and Research Agenda. *Smart Cities*. <https://api.semanticscholar.org/CorpusID:282170516>
- Samadzadegan, F., Javan, F. D., Mahini, F. A., Gholamshahi, M., & Nex, F. (2024). Automatic Road Pavement Distress Recognition Using Deep Learning Networks from Unmanned Aerial Imagery. *Drones*. <https://api.semanticscholar.org/CorpusID:270290258>
- Talaghat, M. A., Golroo, A., Kharbouch, A., Rasti, M., Heikkilä, R., & Jurva, R. (2024). Digital twin technology for road pavement. *Automation in Construction*, 168, 105826. <https://doi.org/https://doi.org/10.1016/j.autcon.2024.105826>
- Topu, M. M., Anik, M. A., Wasi, A. T., & Ahsan, M. M. (2025). *Digital Twin-Driven Pavement Health Monitoring and Maintenance Optimization Using Graph Neural Networks*. <https://arxiv.org/abs/2511.02957>
- Wigan, M. R., & Cullinan, M. (1984a). MACHINE VISION AND ROAD RESEARCH: NEW TASKS, OLD PROBLEMS. *Proceedings - Conference of the Australian Road Research Board*.
- Wigan, M. R., & Cullinan, M. C. (1984b). Digital image processing: an applications review for road research applications. *Australasian Conference on Computer Graphics, 2nd, 1984, Melbourne, Australia (AusGraph)*.
- Yan, Y., Ni, L., Sun, L., Wang, Y., & Zhou, J. (2025). Digital Twin Enabling Technologies for Advancing Road Engineering and Lifecycle Applications. *Engineering*, 44, 184–206. <https://doi.org/https://doi.org/10.1016/j.eng.2024.12.017>
- Yıldızlı, T., Bayraktar, M., & Güldür Erkal, B. (2025). Automated Road Damage Detection Using UAVs and Deep Learning: A Scalable Solution for Infrastructure Maintenance. *E-Journal of Nondestructive Testing*, 30(10). <https://doi.org/10.58286/31691>
- Zhang, Y., Chen, J., Wu, Z., Guo, X., & Jia, S. (2025). Optimizing pavement distress detection with UAV: A comparative study of vision transformer and convolutional neural networks. *KSCE Journal of Civil Engineering*, 29(6), 100095. <https://doi.org/https://doi.org/10.1016/j.kscej.2024.100095>