

Review

Pavement Inspection in Transport Infrastructures Using Unmanned Aerial Vehicles (UAVs)

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Abstract: The growing demand for the transportation of goods and people has led to an increasing reliance on transportation infrastructure, which, in turn, subjects the pavements to high traffic volumes. In order to maintain adequate service and safety standards for users, it is essential to establish effective maintenance strategies that ensure the preservation of pavement conditions. As a result, emerging innovations in pavement surface inspection methods, surpassing traditional techniques in terms of inspection and data processing speed and accuracy, have garnered significant attention. One such groundbreaking innovation in inspection systems that has been tested and used in recent years to assess infrastructure condition is the use of unmanned aerial vehicles (UAVs). This study aims to present a critical open-access literature review on the use of UAVs in the inspection of transportation infrastructure pavement in order to assess the type of equipment used, the technology involved, applicability conditions, data processing, and future evolution. The analysis of relevant literature suggests that the integration of intelligent technologies substantially enhances the accuracy of data collection and the detection of pavement distress. Furthermore, it is evident that most applications and research efforts are oriented towards exploring image processing techniques for the creation of 3D pavement models and distress detection and classification.

Keywords: unmanned aerial vehicles (UAVs); pavement inspection; data collection; image processing; open-access publication



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1. Introduction

1.1. Framework and Objectives

The air and road transport infrastructure systems play a fundamental role in the economic growth and development of regions and nations, ensuring the movement of goods and people. Projections from the International Air Transport Association (IATA) show substantial growth in the passenger air transport sector, with the number of passengers expected to double by 2037 [1]. Similarly, road infrastructure within the European Union (EU) is anticipated to maintain a dominant role in the coming decades, with a significant increase in both passenger and freight transport [2].

As transport infrastructures are heavily used, functional and structural damage to pavements becomes a pressing concern. Therefore, while the composition and design of pavements play a significant role in their performance, proper maintenance of these assets ensures their continued good condition throughout time [3–10]. This underscores the importance of managing pavement maintenance and implementing new, efficient, and cost-effective solutions for assessing its condition, contributing to the sustainability of transportation infrastructure.

To achieve proper pavement maintenance, managers must have access to efficient and effective pavement damage databases. Obtaining updated, relevant, and reliable information on pavement condition often poses a challenge due to its high cost. This demand for accurate data stresses the importance of efficient and up-to-date solutions for pavement inspection [3,8–11].

The study presented in this article focuses on the use of unmanned aerial vehicles (UAVs), a contemporary solution, as a monitoring tool for pavement inspection. It is believed that this solution, characterized by its effectiveness, speed, and cost-effectiveness, will continue to evolve as an essential monitoring instrument [3,8,9]. Recognizing the dynamic landscape of UAV applications, this review study aims to provide a comprehensive view of innovations as well as analyze trends and future directions identified in scientific open-access publications with a focus on the use of UAVs in pavement inspection, highlighting their advantages over traditional inspection methods.

The article is organized into four sections. Section 1 presents the importance of managing pavement maintenance, with a particular focus on pavement inspection significance and technologies. It also presents the use of UAVs as an inspection method for collecting data on the pavement surface condition. Section 2 presents the study design adopted in the selection of the scientific open-access publications considered in the review. Section 3 presents a characterization, analysis, and discussion of the main aspects covered in the selected documents, and Section 4 offers the main conclusions of the study and the main directions reported for future work.

1.2. Pavement Distress Data Collection

The collection of data regarding the condition of the pavement surface is one of the most important components of a road or airport pavement management system (PMS). It is essential for assessing the current pavement status and defining adequate and timely maintenance and rehabilitation strategies. This data is organized and stored in a database, serving as the central component that supports data analysis and system outputs, including prioritization, planning, and budgeting reports [3,5,7,11–13]. The efficiency of a PMS substantially relies on both the quality and quantity of data collected about the pavement [3]. This reliance hinges on the choice of the data collection methods that provide the necessary information to evaluate the condition of the pavement, thus making it an essential factor for the success of the system. This choice depends on several factors, such as the availability of equipment (static or dynamic), pavement type (flexible or rigid), level of data detail, and survey duration. The collected data is encoded based on distress catalogs, which facilitates the identification of distress types and severity levels. These catalogues provide descriptions, examples of severity levels (in the form of photographs), and the applicable measurement method for each type of pavement and distress [3,14–16].

Regarding the inspection method, the collection of surface pavement distress data initially involved a time-consuming process performed on foot. This was primarily due to the absence of available technology for automatic or semi-automatic data collection. Due to operational constraints, which limit access time to heavily trafficked pavements, as well as reductions in funding and available human resources for its execution, the traditional visual inspection (on-foot) pavement became expensive [3,17]. Additionally, issues related to inspectors' judgment and transcription errors were also identified [13]. To address these limitations, entities responsible for managing pavement networks shifted their focus towards seeking automated, efficient, and cost-effective pavement monitoring solutions [8,9,12]. As an alternative to the traditional method, where distress type, severity level, and extent were recorded on paper or in digital forms, methods using equipped land and air vehicles with multifunctional capabilities or even the use of smartphones for capturing and initially processing the collected data have emerged [5,9,12,18].

Examples of devices used in innovative data collection methods include GNSS for location referencing, video logging modules for pavement and 360° imagery, laser systems for crack, rut, and profile measurement, high-resolution odometers for distance measure-

ment, laser profilometers for collecting roughness (IRI—International Roughness Index), macrotexture and longitudinal profile data, and land mobile light detection and ranging systems (LiDAR) [5,13]. In addition, advancements in technology have led to the development of high-resolution optical cameras and image processing techniques that convert two-dimensional (2D) images collected by equipped land vehicles and UAVs into three-dimensional (3D) reconstructed models, providing a cost-effective alternative to 3D laser scanning [19].

1.3. Unmanned Aerial Vehicles (UAVs) in Pavement Inspection

The constant pursuit of creating and developing new technologies capable of identifying, analyzing, and repairing pavement issues in transport networks with precision and speed has led to the exploration of approaches using UAVs. UAV-based approaches have been studied and tested not only for data collection but also for the initial treatment of pavement surface distress data [3,20–22]. Among the main advantages of using UAVs in pavement inspection are their high flexibility, relatively low cost when compared to multifunctional land vehicles, easy maneuverability, reduced ground-level work with enhanced personnel safety, expedited data collection, and the potential to generate 3D models for pavement distress identification, measurement, and data re-evaluation [19,23]. According to [19,24], the main advantages of UAVs over multifunctional land vehicles are the lower on-site inspection process costs and the ability to access locations that are otherwise inaccessible or difficult to reach using other inspection equipment without compromising the integrity of the equipment or the safety of the operator.

To achieve functional systems at an affordable cost, aerial inspection solutions generally only incorporate cameras and positioning systems [13,25–27]. Recent advancements in high-resolution optical cameras and image processing techniques, as well as high-precision satellite-based positioning, such as RTK GNSS and geomatics, enable the creation of 3D models from UAV images with high accuracy and efficiency. This renders image-based 3D models a cost-effective alternative to the presently employed 3D laser scanning in land vehicle inspection systems. Multiple 3D modeling and photogrammetric software options capable of automating these tasks are available on the market [19]. One technique adopted by this software is Structure from Motion (SfM). This technique enables the definition of the shape, dimensions, and spatial position of any object from a set of 2D images. As a result, a three-dimensional reconstruction of the pavement surface is derived from the images captured using UAVs. Approaches that can be employed to evaluate image data collected using UAVs include the Geographic Information System (GIS) and the Convolutional Neural Network (CNN). CNN relies on an object detection approach, while GIS uses visual odometry for pavement mapping and evaluation [8,19,28–30]. Both methods are used to detect and quantify pavement distress and aid in calculating pavement condition indexes.

2. Study Design

This study focuses on the analysis of open-access scientific publications on the use of UAVs for pavement inspection in transport infrastructure. The criteria for selecting open-access publications were based on several parameters. Firstly, open-access publications are freely available to anyone with an internet connection. This means that the information can be accessed by a wider audience, including those who may not have access to subscription-based journals or are unable to pay for individual articles. Using open-access articles in a review ensures that those can be read and verified by the broadest possible audience. Secondly, open-access articles are often subject to rigorous peer review and editorial oversight. This is because open-access journals tend to be newer and smaller, thus relying heavily on their reputation to attract high-quality submissions and maintain a high impact factor [31–34]. Finally, there is a growing trend towards open science and open-access publishing, with many funding agencies and institutions requiring that research be made available in an open-access format. The European Commission is a major supporter of open access, recognizing that open science contributes to better and more

efficient science and innovation in the public and private sectors [32,34]. To align the study with these broader trends in academic communication and contribute to a more open and accessible scientific community, the authors chose to base this review article solely on this type of publication.

The scientific database chosen for searching and collecting the raw data used in the analysis is Scopus, a reputable database from Elsevier created in 2004, containing expertly curated abstracts, articles, and citations. Data collection was carried out between March and April 2023 (last accessed on 3 April). Table 1 and Figure 1 present the phases considered in the document selection/exclusion and analysis process. The rigorous screening process aims to ensure the quality, relevance, and effectiveness of the chosen documents, showcasing an unwavering commitment to high standards of scientific excellence.

Table 1. Document selection process.

Process Phase	Selection Criteria
1	Scopus database search considering all search fields and the expression: (“unmanned aerial vehicles” OR “UAV”) AND (“pavement inspection” OR “pavement condition” OR “pavement evaluation”)
2	Results refined for open access, the final stage, and the English language.
3	Results refined for confirmation of the presence of the words: “UAV”, “unmanned aerial vehicles”, “drone”, or “aerial vehicle”.
4	Documents describing the effective use of UAVs in inspection or image collection (case studies).
5	Documents describing UAV use in pavement inspection within transport infrastructure.

In Phase 1, data was collected through an advanced search, considering all available fields and employing logical operators and a set of keywords relevant to the topic of inspecting pavement transport infrastructure using UAVs. The following keywords and logical expressions were selected as relevant to the document search: (“unmanned aerial vehicles” OR “UAV”) AND (“pavement inspection” OR “pavement condition” OR “pavement evaluation”). In total, 333 documents published in the last 9 years (2015–2023) were found, with the oldest documents dating back to 2015, thus confirming the newness of the research topic.

To narrow down the selection to open-access publications subject to peer review and written in English, results were filtered in Phase 2 using the following criteria: ‘all open access,’ ‘final’ publication stage, and ‘English’ language, which led to the identification of 131 documents. These 131 documents were analyzed and processed based on the research objectives of this review article. In Phase 3, the presence of the acronyms/words ‘UAV’, ‘unmanned aerial vehicles’, ‘drone’, or ‘aerial vehicle’ was checked. This analysis resulted in the removal of 47 out of the 131 publications that did not meet these criteria, leaving 84 publications for further examination. The selected publications were then characterized by their distribution over time, country of origin, thematic area, type of document, authors’ co-citation, and trends.

In Phase 4, the content of the remaining 84 documents was analyzed to verify the effective use of UAVs for inspection or image collection (case studies). This process resulted in the selection of 22 publications. Subsequently, publications describing data collection or analysis methods based on unmanned aerial vehicles for inspecting transport infrastructure pavements were chosen, resulting in 13 documents. Specific approaches to pavement inspection using UAVs are then evaluated in detail in Section 3.2 to identify the field of UAV application regarding factors such as the type of pavement inspected (road or airport; flexible or rigid), the type of UAV and equipment used (balloon, aircraft or vertical take-off and landing (VTOL) vehicle, camera type, GNSS system, etc.), the road environment (urban or rural), the type of application (data collection, data processing, and data analysis), the

type of distress identified (cracking, deformation, wear layer degradation, and material movement), flight height, data processing techniques, precision, and the maturity degree of research (initial, intermediate, or advanced).

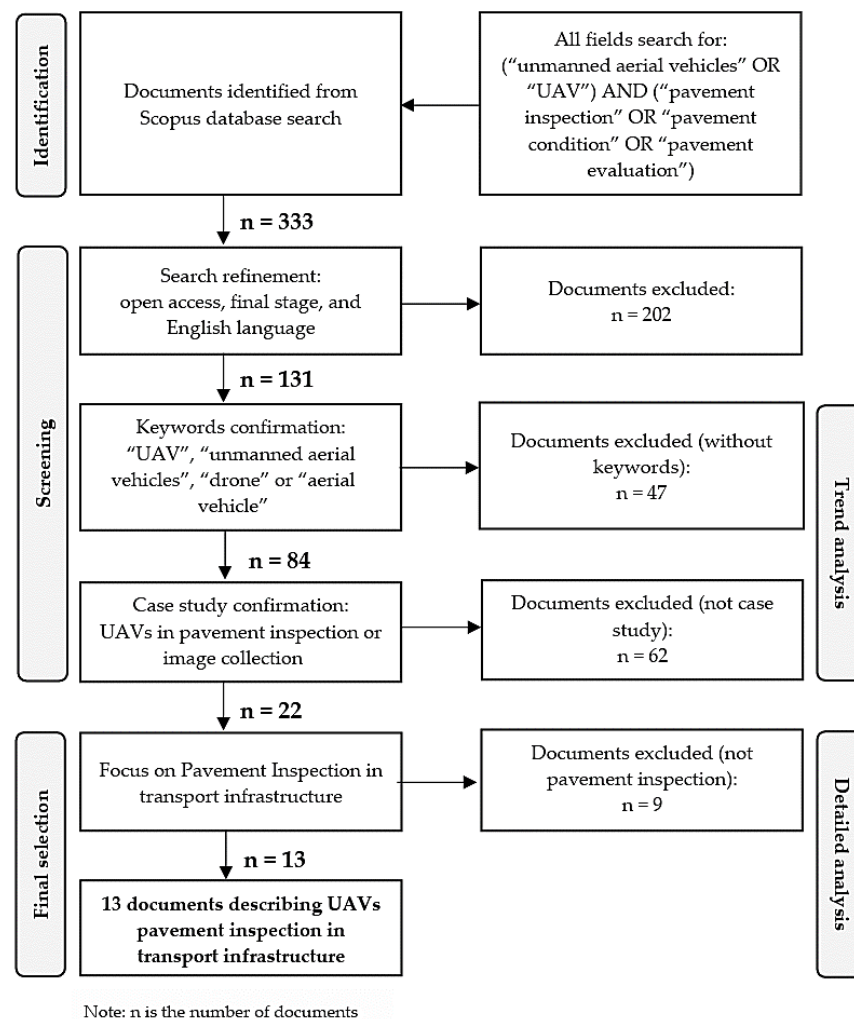


Figure 1. Flowchart of the document selection/exclusion and analysis process.

3. Characterization, Analysis, and Discussion of Results

3.1. Characterization of the Selected Documents

Upon considering the selection performed in Phase 3 (comprising 84 documents), Figures 2 and 3 illustrate the temporal distribution of open-access scientific publications published since 2015 and the distribution of documents by country of origin.

As evident from the data presented in Figures 2 and 3, there has been a significant increase in the number of publications over the years. China emerges as the leading producer of articles within the scope of this research, with a total of 25 publications in the last 9 years. The United States follows closely behind with 15 published documents, representing almost half of China's total. Furthermore, several European countries, such as Italy (12 publications), the United Kingdom, Spain, and the Netherlands (each with 7 publications), have also contributed substantially. The reason for the higher number of publications originating in China and the United States could be attributed to governmental research initiatives and investment priorities. Notably, China has made substantial investments in UAV technology and infrastructure in recent years, which has spurred numerous Chinese companies and research institutions to conduct research on the use of UAVs for various applications, including pavement inspection [35–37].

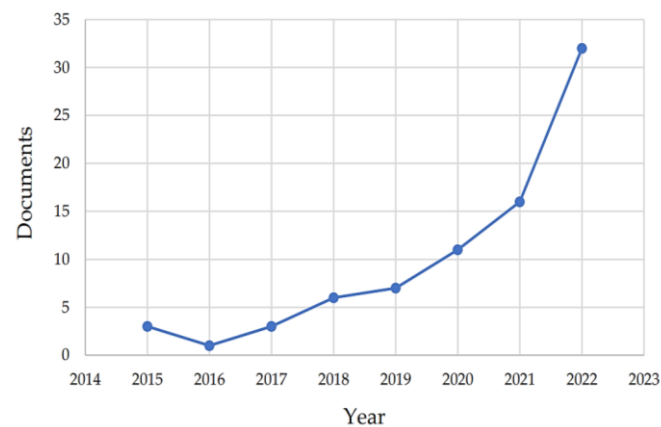


Figure 2. Documents distribution by year (Phase 3).

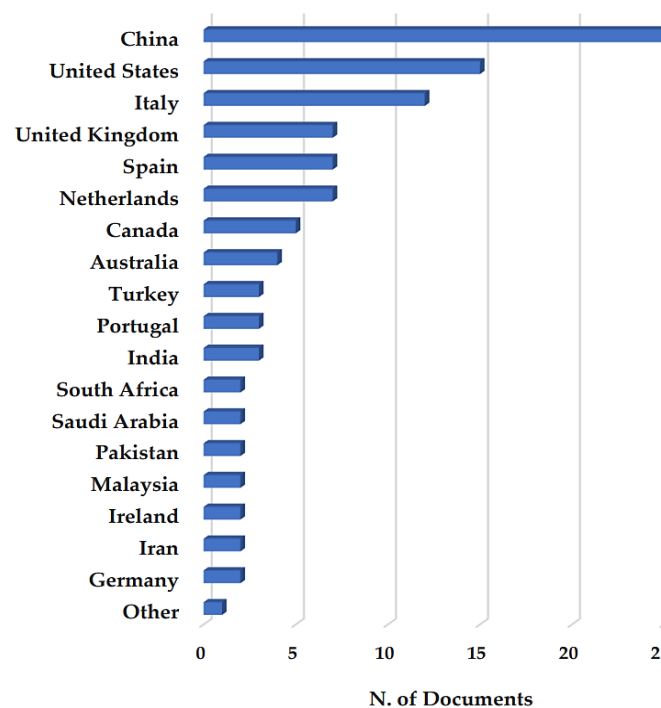


Figure 3. Document distribution by country (Phase 3).

Additionally, Figures 4 and 5 depict the distribution of documents based on thematic area and document type.

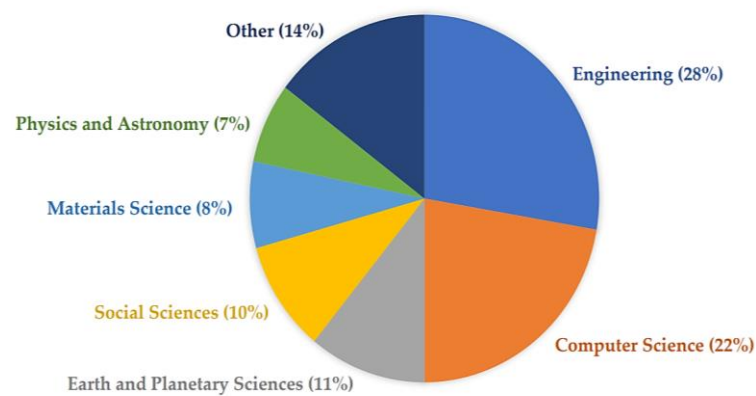


Figure 4. Document distribution by thematic area (Phase 3).

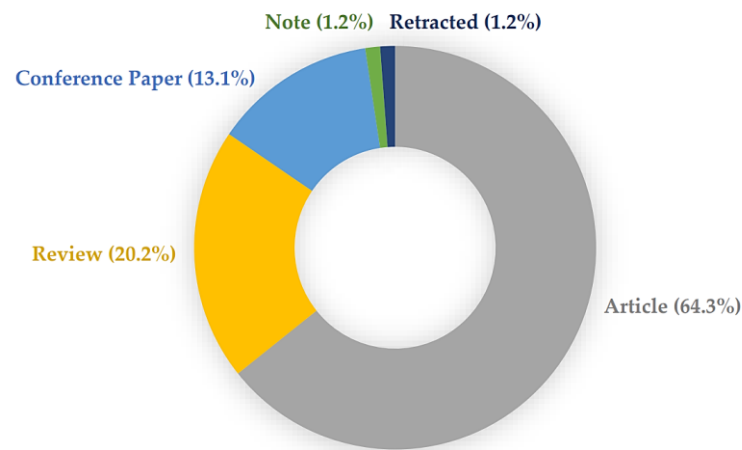


Figure 5. Document distribution by document type (Phase 3).

From Figure 4, as expected, half of the publications are published in engineering and computer science journals. This can be explained by the direct link between infrastructure inspection, monitoring, and engineering, as well as the fact that the processing of data collected by UAVs falls within the realm of computer science expertise. However, it is also noticeable that publications cover several other areas of study, even if to a lesser extent. Figure 5 reveals that more than half of the published documents are articles.

A map reflecting the relationship between co-citations and cited authors for the set of documents selected in Phase 3 was obtained using VOSviewer (see Figure 6). This analysis allowed us to explore the connections between documents and identify highly cited authors. In the set of 84 documents, the analysis identified 12,124 cited authors. Considering the criteria that those with a minimum number of citations equal to 50 are relevant authors in the field under study, 12 authors, divided into two clusters, were identified (see Figure 6). Of these, seven authors, namely Zhang, H., Li, S., Wang, Y., Li, Y., Wang, X., Zhang, X., and Solla, M., hold the authorship of documents included in the set under analysis (84 documents), including five articles considered in Phases 4 and 5 [30,38–41].

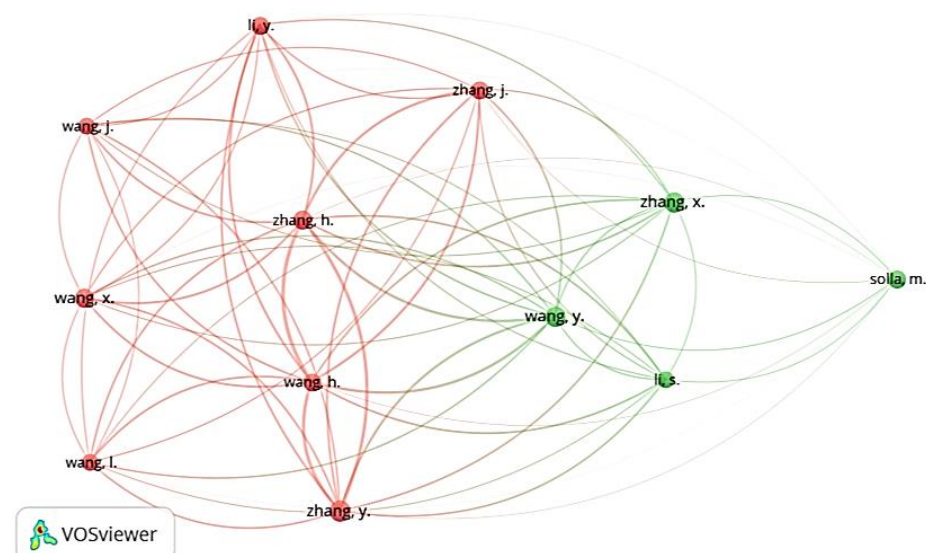


Figure 6. Mapping of cited authors' co-citation analysis (Phase 3).

Upon analyzing Figures 2–6, it becomes evident that the number of scientific publications related to the use of UAVs for infrastructure inspection and monitoring, as well as the emergence of relevant authors in this field, are on a rising trend. Several topics are addressed, including the benefits and challenges of using UAVs for pavement inspection, the types and

suitability of UAVs for inspection operations, and the methods used to process the collected data. The main research trends identified in this set of documents are presented in Section 3.2.

Concerning the 22 documents selected in Phase 4, Table 2 provides basic information related to these documents. Of the 22 documents describing the application of UAVs in a case study (Table 2), 9 did not involve UAVs for pavement inspection. Therefore, these nine documents were excluded from the set considered for a detailed analysis in Phase 5. Recognizing that this advanced technological approach can optimize benefits and reduce costs, the 13 remaining documents that described effective applications of UAVs for transport pavement inspection (Phase 5) were subjected to a detailed analysis in Section 3.3. to assess the suitability of this technique for such a task.

3.2. Research Trend Analysis

This subsection aims to identify the main research trends in UAVs used for infrastructure inspection by analyzing the set of documents selected in Phase 3. The observed trends reveal a notable evolution and common goals in various research areas, as well as the effectiveness of this technology in addressing challenges related to high costs. It also shows the inefficiency associated with manual inspections [20,21,42,43].

In the context of sensor and imaging technology advancement, the integration of innovative sensors, such as high-resolution cameras and multispectral sensors, has significantly propelled data acquisition, providing more detailed and reliable information [42,43]. This progress stands out as a crucial element for the effective understanding and monitoring of infrastructures, including those related to transportation [20,21,23]. This technology has been comprehensively applied to the monitoring and management of construction works [41,44], including those related to road construction [45], and in the management of transport infrastructure assets, such as pavements. Application studies aimed at monitoring [7–9,12,13,46,47] and determining [26] the condition of flexible road pavements are common, with less expression for rigid [47], stone [28], or airport [7,17] pavements. Automatic detection and classification of pavement's damage has received special attention [18,19,25,30,38,47]. The fusion of multiple data sources and the application of advanced image processing techniques, such as Convolutional Neural Networks (CNN) and Support Vector Machines (SVM), highlight the evolution of UAV data processing methods [42,43]. Automation and artificial intelligence emerge as fundamental elements in the current research on the use of UAVs for inspection. Advanced machine learning algorithms and computer vision techniques have played a crucial role in reducing the workload of technicians, resulting in significant improvements in inspection efficiency and accuracy. This technological advancement not only optimizes inspection operations but also paves the way for the implementation of predictive maintenance strategies and early anomaly detection, promoting a proactive approach to infrastructure management.

In addition to transportation infrastructure inspection, several documents focus on the use of UAVs in other sectors, such as the detection of damage in concrete structures (cracks and detachments) [48], defects in buildings and infrastructure [49], and road traffic elements (such as pedestrian lanes, bus stations, parking areas, etc.) [50]. Moreover, UAV images can be used for urban feature classification [51], construction project management [45], and construction and demolition waste management [41]. This sector-specific approach not only demonstrates a more precise and efficient application of UAVs but also drives innovations across various domains, expanding the possibilities of their use in different contexts.

Data processing techniques include the generation of 3D digital models through Structure-from-Motion (SfM) photogrammetry [41,51] and three-dimensional point clouds [41,49], pixel-based segmentation [49] and classification techniques [51], image segmentation using a Fully Convolutional Network (FCN) [41,49], and deep learning techniques for automatic detection and classification [41,45,48,50,51], such as Support Vector Machine [51] and Siamese Convolutional Networks (SCN). The use of You Only Look Once (YOLO) systems for object recognition [48,50] and Geographic Information Systems (GIS) is also reported [7,37,41]. Finally, the use of multiple UAVs is tested to reduce inspection time [48].

Table 2. Basic information related to the documents selected in Phase 4 (Scopus, 2023).

Year	Article Title	Authors	Scientific Area	Journal	UAVs Application in Pavement Inspection		Ref.
					Yes	No	
2015	Classification of urban feature from unmanned aerial vehicle images using GASVM integration and multi-scale segmentation	Modiri, M., Salehabadi, A., Mohebbi, M., Hashemi, A., Masumi, M.	Computer Science and Social Sciences	<i>International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences</i>		X	[51]
2016	Characterizing pavement surface distress conditions with hyper-spatial resolution natural color aerial photography	Zhang, S., Lippitt, C., Bogus, S., Neville, P.	Engineering and Computer Science	<i>Remote Sensing</i>	X		[46]
2017	Crack identification for rigid pavements using unmanned aerial vehicles	Ersoz, A., Pekcan, O., Teke, T.	Engineering and Material Science	<i>IOP Conference Series: Materials Science and Engineering</i>	X		[47]
2017	Object-based and supervised detection of potholes and cracks from the pavement images acquired by UAV	Pan, Y., Zhang, X., Sun, M., Zhao, Q.	Engineering, Computer Science and Social Science	<i>International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences</i>	X		[38]
2018	Human supervised multirotor UAV system design for inspection applications	Shaqura, M., Alzuhair, K., Abdellatif, F., Shamma, J.	Engineering, Computer Science and Social Sciences	<i>2018 IEEE International Symposium on Safety, Security, and Rescue Robotics</i>		X	[52]
2018	Detection of asphalt pavement potholes and cracks based on the unmanned aerial vehicle multispectral imagery	Pan, Y., Zhang, X., Cervone, G., Yang, L.	Engineering and Computer Science	<i>IEEE Journal of selected topics in applied earth observations and remote sensing</i>	X		[30]
2019	Crack junction detection in pavement image using correlation structure analysis and iterative tensor voting	Wang, Y., Huang, Y., Huang, W.	Engineering, Computer Science and Materials Science	<i>IEEE Access</i>	X		[39]
2019	UAV photogrammetry-based 3D road distress detection	Tan, Y., Li, Y.	Engineering, Computer Science and Social Science	<i>ISPRS—International Journal of Geo-Information</i>	X		[40]
2019	A robust pavement mapping system based on normal-constrained stereo visual odometry	Huang, H., Fan, R., Zhu, Y., Liu, M., Pitas, I.	Engineering, Computer Science and Physics and Astronomy	<i>IST 2019—IEEE International Conference on Imaging Systems and Techniques</i>		X	[29]

Table 2. Cont.

Year	Article Title	Authors	Scientific Area	Journal	UAVs Application in Pavement Inspection		Ref.
					Yes	No	
2020	Analysis of optimal flight parameters of unmanned aerial vehicles (UAVs) for detecting potholes in pavements	Romero-Chambi, E., Villarroel-Quezada, S., Atencio, E., Rivera, F.	Engineering, Computer Science, Materials Science and Physics and Astronomy	<i>Applied Sciences</i>	X		[19]
2020	An architectural multi-agent system for a pavement monitoring system with pothole recognition in UAV images	Silva, L., Blas, H., García, D., Mendes, A., González, G.	Engineering, Computer Science and Physics and Astronomy	<i>Sensors</i>	X		[8]
2021	Real-time concrete damage detection using deep learning for high rise structures	Kumar, P., Batchu, S., Swamy S., Kota, S.	Engineering, Computer Science and Materials Science	<i>IEEE Access</i>		X	[48]
2021	Change detection in unmanned aerial vehicle images for progress monitoring of road construction	Han, D., Lee, S., Song, M., Cho, J.	Engineering	<i>Buildings</i>		X	[45]
2021	Building and infrastructure defect detection and visualization using drone and deep learning technologies	Jiang, Y., Han, S., Bai, Y.	Engineering	<i>Journal of Performance of Constructed Facilities</i>		X	[49]
2021	Use of UAV-based photogrammetry products for semi-automatic detection and classification of asphalt road damage in landslide-affected areas.	Nappo, N., Mavrouli, O., Nex, F., Westen, C., Gambillara, R., Michetti, A.	Earth and Planetary Sciences	<i>Engineering Geology</i>	X		[53]
2022	Assessment of visual representation methods of linear discontinuous deformation zones in the right-of-way	Wróblewska, M., Grygierek, M.	Engineering, Computer Science, Physics and Astronomy, Materials Science, Chemical Engineering	<i>Applied Sciences</i>	X		[54]
2022	Evaluation of a multi-mode-transceiver for enhanced UAV visibility and connectivity in mixed ATM/UTM contexts	Schelle, A., Völk, F., Schwarz, R., Knopp, A., Stütz, P.	Engineering, Computer Science	<i>Drones</i>	X		[55]

Table 2. Cont.

Year	Article Title	Authors	Scientific Area	Journal	UAVs Application in Pavement Inspection		Ref.
					Yes	No	
2022	UAV imagery for automatic multi-element recognition and detection of road traffic elements	Huang, L., Qiu, M., Xu, A., Sun, Y., Zhu, J.	Engineering	Aerospace		X	[50]
2022	Super-resolution images methodology applied to UAV datasets to road pavement monitoring	Inzerillo, L., Acuto, F., Di Mino, G., Uddin, M.	Engineering, Computer Science, Social Sciences	Drones	X		[56]
2022	Development of a cognitive digital twin for pavement infrastructure health monitoring	Sierra, C., Paul, S., Rahman, A., Kulkarni, A.	Engineering, Computer Science, Materials Science	Infrastructures	X		[57]
2022	Automatic volume calculation and mapping of construction and demolition debris using drones, deep learning, and GIS	Jiang, Y., Huang, Y., Liu, J., Li, D., Li, S., Nie, W., Chung, I.	Engineering and Computer Science	Drones		X	[41]
2022	Comparative utilization of drone technology vs. traditional methods in open pit stockpile volumetric computation: A case of njuli quarry, Malawi	Matsimbe, J., Mdolo, W., Kapachika, C., Musonda, I., Dinka, M.	Engineering and Social Sciences	Frontiers in Built Environment		X	[44]

With regard to increasing efficiency, accuracy and reliability in UAV operations, including data collection and processing, [29] explored a robust pavement mapping system based on stereo visual odometry with normal constraints to support pavement inspection systems; [44] studied the automated processing of images captured by UAVs using Pix4D mapper 2.2 pro software, resulting in rapid generation of digital surface models and orthomosaics; and [52] proposed the integration of UAVs with onboard sensing and computing, together with a smart laser pointer equipped with built-in sensing and communication capabilities to accomplish a human-supervised system.

A continuous advancement in UAV capabilities and applications, driven by progress in sensors, imaging technology, automation, artificial intelligence, and efficient data collection and processing methods, can be inferred from analysis. Diversification across various sectors and the search for specific solutions to distinct challenges reinforce the ongoing importance of development and research in this field. The research also highlights the growing need to expand applicability, overcome obstacles such as disparities between urban and rural areas, as well as to implement robust data management platforms.

3.3. Relevant Works

3.3.1. Detailed Description

This subsection provides an analysis of the key aspects addressed in the 13 documents selected during Phase 5. A summary of the main aspects identified in the reviewed documents is presented in Table 3, including reference number, country, pavement type (asphalt, concrete), road environment (urban, rural, airport), research focus and maturity, type of pavement distress, UAV and camera types, positioning, flight height, main data processing techniques and ground sampling distance (GSD) precision/error.

From the set of analyzed documents, the first study to demonstrate a practical application of an unmanned aerial vehicle for pavement condition evaluation was published in 2016 by Zhang et al. [46]. The study describes an early-stage application developed for an aircraft-based pavement evaluation method with the aim of assessing the technical feasibility of aerial triangulation (AT) and hyperspatial-resolution natural color aerial photography (HSR-AP). The study utilized images captured at a low altitude (5 m) using a tethered helium weather balloon to characterize pavement surface conditions. These images were captured using millimeter-scale HSR-AP, thus offering a ground sampling distance of 2 mm. Aerial triangulation, also known as Structure from Motion (SfM), was employed to process the images and estimate three-dimensional models from a sequence of two-dimensional images [46]. The results demonstrate that employing HSR-AP for image collection and using AT to process the images for generating orthophotos and millimeter-scale digital surface models (DSMs) can effectively be adopted for characterizing both the horizontal and vertical conditions of pavement surfaces. The results obtained with this technique were statistically comparable to those from conventional on-foot surveys [46], thus validating the potential for fully automating pavement distress evaluation. The pavement distresses studied included rutting, alligator cracking, and transverse cracking.

Table 3. Documents characterization according to the UAV application in pavement inspection (Phase 5) (Scopus, 2023).

Ref.	Country	Pavement Type	Environment	Research Focus	Research Maturity	Type of Pavement Distress	UAV Type	Camera	Positioning	Flight Height	Data Processing Technique(s)	GSD Precision/Error
[46]	USA	Asphalt	Rural and urban roads	Data collection and processing	Initial	Rutting Alligator cracking Transverse cracking	Helium weather balloon	Canon SX260 HS digital camera: 12 MP/CMOS/GPS	Unspecified	5 m	Image restitution AT 3D model construction SfM	GSD = 0.20 cm Error < 1 cm in distress measurements RMSE = 0.40 cm for XY and RMSE = 0.70 cm for Z
[47]	Turkey	Concrete	Urban road	Data collection and processing	Intermediate	Cracks	DJI Inspire 1 Quadcopter	UAV camera: 12.4 MP/CMOS	GPS	0.5 to 3 m	Detection/Classification algorithm SVM	-
[38]	China	Asphalt	Rural road	Data collection and processing	Advanced	Cracks Potholes	fixed wing UAV	MCA camera	Unspecified	30 m	Object recognition eCognition Developer Detection/Classification algorithm KNN, SVM, ANN and RF	1.354 cm/pixel
[30]	China	Asphalt	Rural road	Data collection and processing	Advanced	Cracks Potholes	UAV MSI (Six-spreading-wings)	MCA snap12 camera	Unspecified	25 m	3D model construction Pix4Dmapper Detection/Classification algorithm SVM, ANN and RF	-
[39]	China	Asphalt	Rural road	Data collection and processing	Advanced	Block cracking Alligator cracking	unspecified	camera with 2048 × 1536 pixels	Unspecified	Unspecified	Detection/Classification algorithm Tensor voting	0.20 cm/pixel
[40]	China	Asphalt	Urban road	Data collection and processing	Intermediate	Piling up (bulges) Potholes Subsidence (cavities) Corrugation	DJI Phantom 4 Pro	UAV camera: 5472 × 3648 pixels/20 MP/CMOS	GPS GNSS	15 m	3D model construction Pix4Dmapper	Absolute error of around 1 cm in vertical dimension for measurements ≥ 2 cm
[19]	Chile Spain	Asphalt	Unspecified	Data collection and processing	Initial	Potholes	DJI Phantom 4 Pro	UAV camera: 5472 × 3648 pixels/20 MP/CMOS	GPS GNSS	2 to 40 m	3D model construction SfM-MVS	1.07 cm/pixel The level of error is about 1 cm for flights at 10–15 m height
[8]	Spain Brazil	Asphalt	Rural road	Data collection and processing	Intermediate	Cracks Potholes	Quadcopter DJI Mavic Air 2	4K digital camera: 4000 × 3000 pixels/48 MP/FOV	GPS	60 m	Object recognition YOLOv4	-
[53]	Italy	Asphalt	Rural road	Data collection and processing	Intermediate	Longitudinal and transverse cracks IRI	DJI Phantom 4 Pro	UAV camera: 5472 × 3078 pixels/16.8 MP/CMOS	GPS GNSS	10 m	3D model construction SfM	0.37 cm/pixel The multi-criteria procedure detects and classifies longitudinal and transverse cracks wider than 1 cm

Table 3. Cont.

Ref.	Country	Pavement Type	Environment	Research Focus	Research Maturity	Type of Pavement Distress	UAV Type	Camera	Positioning	Flight Height	Data Processing Technique(s)	GSD Precision/Error
[54]	Poland	Asphalt	Rural road	Data collection	Initial	Discontinuous deformations	Quadcopter weighing over 1.3 kg	Camera with a 1-inch 20 MP sensor	GPS GNSS	60 m	Image restitution Photogrammetry	1.50 cm/pixel Measurement accuracy of ±4 cm (XY) and ±5 cm (Z)
[55]	Germany	Asphalt	Airport	Data collection and flight operations	Initial	-	DJI Matrice 210 RTK v2 + DJI Matrice 600 Pro	UAV camera	GNSS	10 m 25 m	UAV communication and integration MQTT protocol and a collaborative interface with ATC	-
[56]	Italy	Asphalt	Urban road	Data collection and processing	Initial	Cracks Potholes	DJI Mavic 2 PRO	UAV camera: 5568 × 3712 pixels/20.9 MP/CMOS	GPS	30 m 49.7 m 51.6 m	Resolution improvement SRa 3D model construction SfM, Agisoft Metashape	RMSE = 0 to 1.50 cm in distress measurements
[57]	Australia USA	Asphalt	Urban road	Data collection and processing	Advanced	Crocodile cracking Potholes Rutting	DJI Phantom 4 RTK + DRTK 2	UAV camera: 5472 × 3648 pixels/20 MP/CMOS	GPS	60 m	Detection/Classification algorithm U-net: Binary cross-entropy and Jaccard coefficient VGG16 CNN: KNN, RF and XGBoost	Horizontal measurement errors of ±2 cm for 3 m lane width

Note: Initial research maturity—documents that pertain to the collection and initial processing of restitution data and the construction of 3D models; Intermediate research maturity—documents involving advanced data processing for building 3D models and the initial stages of distress detection; Advanced research maturity—documents covering approaches to detecting and measuring distress using AI/machine learning techniques. **Abbreviation Key:** ANN—Artificial Neural Network; AT—Aerial Triangulation; ATC—Air Traffic Control; CNN—Convolutional Neural Network; KNN—K-Nearest Neighbors; MCA—Multiple Camera Array; MQTT—Message Queuing Telemetry Transport; MVS—MultiView Stereo; RF—Random Forest; SfM—Structure from Motion; SRa—Super-Resolution algorithm; SVM—Support Vector Machine; XGBoost—Extreme Gradient Boosting; YOLOv4—You Only Look Once version 4.

In 2017, two articles were published in the field of UAV-based pavement distress identification systems. The study referenced in [38] was carried out on asphalt pavements, with a focus on identifying the most effective learning algorithm for distress classification accuracy. On the other hand, the study referenced in [47] was conducted on concrete pavements. In [38], Pan et al. (2017) performed a study to identify the optimal learning algorithm that guarantees the highest distress classification accuracy (greater than 98%) while minimizing computational time. This study used a set of road pavement digital images in RGB channels collected through a multispectral Micro-Miniature Multiple Camera Array System (MCA) coupled to a UAV. Four common supervised learning algorithms, namely K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest (RF), were employed to identify pavement distresses. The resolution of images collected with the UAV (1 pixel $\approx 13.54 \times 13.54$ mm of pavement area) enabled the use of the Multiresolution Segmentation (MS) algorithm integrated into the software eCognition Developer Software 9.0 to extract information about potholes and cracking from pavement images. MS identifies individual image objects based on pixel size and merges them with neighbors using the relative homogeneity criterion. This criterion combines spectral and shape criteria and is determined by a scale parameter. According to the authors, choosing an appropriate scale parameter to simultaneously extract cracks and potholes is a challenging task. The analysis of the performance of the four learning algorithms showed that the RF exhibited the best results, boasting higher classification accuracy and the shortest running time [38]. The study referenced in [47], carried out by Ersoz et al. (2017), proposes a system that combines image processing and machine learning techniques to identify and classify cracks in rigid pavement. This system consists of two main steps: the detection of crack candidates and crack classification. In the crack candidate detection step, images obtained from UAVs are segmented to separate objects with and without cracks from the background using image segmentation and enhancement techniques. The geometric properties of these objects are then collected and used to train an SVM model for distress classification [47]. To test and validate the performance of the algorithm, 109 images of rigid pavements were collected using the UAV DJI Inspire 1 Quadcopter at different heights (0.5 to 3.0 m). These images were processed, and the crack detection algorithm extracted 157 bodies, of which 124 were cracks. Subsequently, the geometric properties were determined using 80% of cases for training and 20% for testing the SVM model. The performance of the crack classification algorithm was evaluated using a confusion matrix, which revealed an accuracy of 97.0% in distinguishing crack and non-crack regions. The paper concludes that the proposed UAV-based system for monitoring rigid pavements is promising and offers a cost-effective solution compared to existing systems. The authors acknowledge some limitations, such as performance issues related to shadowy or low-resolution images, and suggest future improvements, such as incorporating more cases to enhance algorithm accuracy and addressing additional crack types.

In 2018, Pan et al. (2018) presented an application of a system composed of a multispectral camera attached to a six-rotor drone (UAV MSI) to capture images of the pavement surface. They used RF, ANN, and SVM learning algorithms to detect distress from the collected images [30]. The case study took place in the rural area of the city of Shihezi, Xinjiang, China. Given the high resolution of the pavement images collected, the Multiresolution Segmentation (MS) algorithm incorporated in the eCognition Developer software was employed to conduct the segmentation of the pavement images. The study revealed that spatial features such as texture and geometry contributed more to the accuracy of crack and pothole detection than spectral features. According to the authors, the classification data obtained can achieve better performance and require less running time when using an RF classifier with 18 trees. The overall classification accuracy for cracks, potholes, and non-distressed pavement was 98.3%. A comparative study of several resolution images showed that the spatial resolution should not exceed the minimum scale of pavement distress occurrences to be identified; otherwise, minor damages, such as low-severity cracking,

can be missed during the segmentation procedure [30]. This publication can be considered an extension of the 2017 study conducted by Pan et al. [38], as both articles discuss the use of MCA cameras coupled to a UAV to capture pavement surface images and the application of machine learning algorithms (RF, ANN, and SVM) for pavement distress detection.

In 2019, two articles were published, each describing a different approach to detecting specific types of road pavement surface distress using image data collected by the UAV. The study conducted by Tan et al. (2019) proposes an automatic method for building 3D models aiming to detect road pavement distress from oblique photogrammetric images obtained by UAVs [40]. In their study, the images captured by the UAVs were processed using the standard photogrammetry software Pix4Dmapper 4.1 to build 3D models (also used by Pan et al. (2018) in [30]). The region-growing algorithm (image segmentation method) was then applied to classify the 3D model into two parts: the road pavement and the non-road-paved areas, which allowed for the exclusion of irrelevant surroundings from the pavement surface in the 3D models. Using the 3D models, the authors developed and implemented an algorithm based on the Graham scan algorithm to detect road surface distress and extract measurements such as distress length, width, and height/depth. As a result, it was determined that the approach can precisely detect areas of pavement damage with an approximate margin of error of 1 cm in height/depth measurements [40].

In the same year, Wang et al. (2019) presented a study that aimed at detecting crack junctions (transverse, longitudinal, and alligator cracks) of any type and size through the analysis of pavement surface images [39]. The proposed method was tested using a set of rigid pavement images from a public dataset, the SDNET2018 [58], and flexible pavement images collected by UAVs on the G45 highway in China. The study aimed to characterize crack distress structures from different pavement condition surface images. For this purpose, the contrast between the cracks' junction and pavement background was improved by removing large interferences and background elements, such as lane markings, shadows, and dirt debris. Then, based on the structural characteristics of crack curves, a correlation structure index was proposed to locate possible cracks in the images. After an iterative tensor voting process, the unified ball tensor structure was used to extract actual crack junction data from the crack candidates. This is a mechanism that employs tensor-based structure characterization and propagates the structure indication to neighbors through voting. Through tensor voting, the structure of the crack junction is improved, and some interferences, such as stone mixtures and dirt debris, are gradually eliminated from the images. Thus, the ball tensor is used to uniformly characterize the crack junction of different sizes, types, intensities, or those formed by crack curves with different orientations. The experimental results demonstrated that the method could detect crack junctions with a correctness of 0.891 and a completeness of 0.887, and it can be applied to different crack types and sizes in both rigid and flexible pavements, despite different sources of noise and interference (material texture, imaging condition, etc.) [39].

In 2020, Romero-Chambi et al. (2020) developed a method for measuring the geometric characteristics of flexible road pavement potholes, including their depth, width, and volume, through 3D models generated from images obtained with a UAV and processed using software based on the Motion-MultiView Stereo (SfM-MVS) technique [19]. A case study was conducted to assess the accuracy (error evaluation) of 3D models created from images, considering variations and combinations of different flight and image capture parameters. Specifically, variations and combinations of camera view angles (vertical and oblique), image overlay rate, and flight height were tested. The results indicate that although including image capture angles other than 90° has a positive impact on the accuracy (error reduction) for measuring potholes, it does not justify the additional time spent in acquiring extra images, as the processing time nearly doubled. Additionally, no specific oblique angle or clear trend was found to ensure error reduction. Among the studied geometric characteristics, width exhibited the lowest level of error, followed by depth and volume. The study concluded that the methodology is applicable for flight heights between 10 and 15 m. For higher heights, the error level does not allow for an adequate representation of

the geometric characteristics of the potholes when considering an FOV of 84° and a 20 MP image. On the other hand, for lower image capture heights, the process becomes extremely laborious as it requires manual flights, and the GPS becomes sensitive, leading to a loss of precision [19]. When comparing the approaches proposed by Romero-Chambi et al. (2020) [19] and Tan et al. (2019) [40], it is evident that the former represents a considerable improvement in this field of study, as the error levels presented are less than 1 cm.

Also in 2020, Silva et al. introduced a platform capable of detecting road pavement distress along public transport routes using UAVs and a Multi-Agent System (MAS) based on PANGAEA (Platform for Automatic coNstruction of orGanizations of intElligent Agents) [8]. PANGAEA was responsible for coordinating the various components of the architecture through ubiquitous computing techniques using deep learning algorithms. The platform allows the identification of pavement distresses and provides the most important results from the data collected during inspections, thus optimizing time, costs, and specialized labor. The MAS was used to coordinate and communicate with all the entities involved in this task, allowing for dynamic reconfiguration of the system. The authors emphasize that employing an MAS streamlines case study development and ensures compatibility among the different platform components. The PANGAEA-based system facilitates seamless communication and information exchange between the drone and platform, adapting the work to contextual requirements. The distress identification process relied on the YOLOv4 algorithm, while communication with different agents was facilitated through RFC 149 IRC (Internet Relay Chat), a text-based real-time multi-user message exchange system known for its energy-efficient communication capabilities [8,59,60]. The use of RFC significantly enhanced UAV battery autonomy during flight, thus increasing the energy available for pavement inspection. A total of 600 images were captured, resized, and labeled, resulting in 568 labeled images. To expand the dataset, multiple versions of each image were generated using zooming techniques, effectively doubling the dataset size to 1362 images. These images were utilized for model training and evaluation, with 70% allocated for training, 20% for validation, and the remaining 10% for testing the effectiveness of the trained model. The authors did not observe any variation between the results obtained from 4K video image frames captured at 70 and 90 m height and the UAV's operating speed between 15 and 25 km/h. The level of accuracy in distress detection was notably high, above 95%. However, although several crack detection techniques were tested and analyzed in the study, none yielded results greater than 47%. The authors attribute this lower performance to the dataset used for testing the automatic recognition process, which did not encompass European road cases and featured cracks with notably larger openings (i.e., conditions distinct from those identified in the case study), which primarily included low-severity cracking and small potholes [8].

In 2021, Nappo et al. proposed a methodology for characterizing cracks in asphalt road pavements in areas affected by landslides. This method utilizes 3D models reconstructed from UAV images. The study was conducted in the Province of Como, located in northern Italy, with the primary objective of providing a valuable tool for local authorities. This tool enables them to select and inspect road sections damaged by landslides in areas prone to such geological events. The methodology employs the use of 3D and 2D photogrammetry tools to identify, describe, and classify the severity of both longitudinal and transverse cracks. The research integrates various data sources, including satellite imagery, field surveys, and UAV images, to gather information about the road network and landslide occurrences [53]. The methodology consists of four distinct phases. In the first phase, road segments that are exposed to landslides and potentially have pavement damage are selected based on thematic maps and InSAR (Interferometric Synthetic Aperture Radar) data. Once the relevant road sections are identified, high-resolution UAV images with a resolution of 16.8 MP are collected at an altitude of 10 m using a DJI Phantom 4 Pro with an 80% image overlap. The second phase involves the use of photogrammetric techniques, specifically Structure of Motion (SfM), to create 3D models of the selected road sections. Subsequently, the point cloud obtained from the 3D model is processed to extract road

surface information and analyze pavement deviations and geometric attributes in the third phase of the process. A multi-criteria binary classifier is trained to identify and evaluate the severity of pavement damage. In the final phase, an edge detection algorithm is applied to the 2D orthorectified image to identify damaged edges. These 2D edges are then overlaid with the 3D point cloud to gather additional information and determine the extent of pavement damage [53]. When applied to a practical case study, the results showed a clear correlation between different types of road damage and the presence of landslides. Longitudinal and transverse cracks were mostly observed within the landslide-affected areas, while other forms of damage, such as fatigue cracks, were found both inside and outside these landslide zones [53].

The most recent open-access documents analyzed are from 2022. Among the four selected documents, the first one, authored by Sierra et al., delves into a research study on the use of UAVs for pavement maintenance and monitoring [57]. The study aims to develop an innovative method that combines UAVs, reality modeling, and machine learning algorithms to create a digital twin of the pavement structure. This digital twin facilitates the automated detection of pavement distress. To accomplish this, UAV flights were conducted at an altitude of 60 m over a transited road, and the captured images were used to generate a comprehensive reality model of the pavement. Subsequently, machine learning algorithms, specifically CNNs, KNN, RF, and XGBoost, were applied to identify and assess pavement distress. The study shows that this UAV-based methodology, using reality modeling and machine learning, yields results comparable to traditional approaches while offering cost and time efficiency. Moreover, the researchers also discussed different UAV flight methods for data acquisition, including predetermined flight paths, manual flight control, manual still images, and manual video. Each method presented distinct advantages and disadvantages, with the selection of the most suitable approach contingent on factors such as the road network environment, desired data coverage, level of detail, and available resources. The manual still image method was deemed the most suitable for research purposes, as it provides precise data with minimal waste. Overall, the study emphasizes the considerable potential of UAVs and related technologies, such as reality models and machine learning, in enhancing the assessment and maintenance of pavement structures [57].

The article authored by Inzerillo et al. (2022) describes the use of UAVs for detecting structural cracks in concrete structures and road pavement surfaces [56]. According to the authors, the quality of images collected by UAVs can be affected by vibrations and distances, thus resulting in a loss of critical information that makes crack detection difficult. To address these challenges, the authors employed Super-Resolution Reconstruction (SRR) algorithms aimed at enhancing the resolution and precision of the captured images. In a case study conducted by the authors in Palermo, Italy, low- and high-resolution images of a road surface were collected using a DJI MAVIC 2 Pro UAV equipped with a 20 MP camera. The UAV was flown at heights of 49.7 and 51.6 m. A morpho Super-Resolution algorithm (SRa) was applied to the low-resolution image dataset to improve image quality. This dataset was then compared with high-resolution images and ground-based image sources. The results showed that the super-resolution approach significantly improved the accuracy of the 3D model, as evidenced by a reduction in root mean square error (RMSE) from over 10 cm to a range of 0 to 1.5 cm. By enhancing the quality of low-resolution images, the super-resolution approach effectively enables the detection and measurement of pavement distresses such as cracks and potholes. This, in turn, provides invaluable information for the formulation of maintenance strategies [56].

In the study performed by Schelle et al. (2022), the main objective is to propose a communication and integration system that enables safe and reliable drone flights in controlled airspace. This system addresses various challenges and risks associated with aerial surveying operations, including those related to routine maintenance, such as inspecting airport runways for damage [55]. The document highlights the challenges of integrating an unmanned aircraft system into the European national airspace and introduces the concept

of U-Space, aimed at developing automated, interoperable, and sustainable solutions for Unmanned Traffic Management (UTM). To achieve this, the authors introduced a device called the Multi-Mode Transceiver (MMT), which combines Mode S transponder technology, including ADS-B (Automatic Dependent Surveillance-Broadcast), with a cellular interface. The MMT is designed to enhance the visibility and connectivity of drones in environments involving both manned Air Traffic Management (ATM) and UTM. It plays a crucial role in enabling drones to interact collaboratively with air traffic control (ATC), obtain flight authorizations, and ensure the safety of operations. The system includes various UTM services, such as flight planning management, tracking, and traffic information. The research evaluates the performance of MMT and the collaborative interface with ATC, along with a tactical collision prevention method based on energy reservation. The study provides valuable insights into the implementation and functionality of MMT in a real-world UTM environment, supporting the development of UTM systems for the safe integration of UAVs in airspace [55].

Furthermore, the article by Wróblewska et al. (2022) discusses a research methodology for evaluating pavement conditions, particularly in areas with discontinuous deformations that can affect road safety [54]. The case study was conducted in the southern province of Silesia, where an important regional road was impacted by deep mining activities, resulting in pavement surface irregularities and transverse cracks. The primary aim of the research was to assess pavement regularity and identify discontinuous linear surface deformations through the application and comparison of various measurement methods. These methods included laser profilometry, geodetic measurements (leveling and GPS positioning), and low-altitude UAV photogrammetry to determine the effectiveness of these approaches. For this purpose, a dataset comprising 233 aerial images of the road surface, collected at 60 m height with a UAV equipped with a 1-inch sensor camera with 20 MP high resolution during an 18-min flight, was used. The images were processed using photogrammetry techniques to create a 3D model of the inspected pavement surface, which enabled the identification of discontinuous linear deformations and the generation of a hypsometric map displaying elevation variations. The comparative evaluation of UAV photogrammetry results with other measurement methods, such as mobile laser profilometry, demonstrated that both methods yielded a significant number of measurement points or a high point density. The study concluded that both traditional methods, such as laser profilometry, and modern UAV-based techniques can effectively identify pavement damage. However, it highlighted that UAV-based photogrammetry offers a high level of data detail and efficiency in detecting discontinuous linear surface deformations, complementing the other methods [54].

3.3.2. Discussion

After presenting the main aspects of the 13 selected documents, it is possible to conclude that UAV-based pavement condition assessment practices are promising. Several aspects, including their cost-effectiveness when compared to existing systems, the quality of collected data, and the potential for the development of systems for pavement distress recognition, all point to the full automation of pavement condition assessment in the near future. Most of the studies compare UAV-based approaches with traditional research methods to validate results and identify areas for improvement in UAV pavement inspection. Performance, the incorporation of additional features, different pavement conditions, and several types of distress identification are among the most discussed topics. Notably, the most recently published research (from 2020 to 2022) tends to incorporate the latest advances and technologies, such as 3D modeling [19,53,56] and image data processing techniques [8,19,53,54,56,57], benefiting from the progress made in the field since the first publications on this subject (2016) [46].

When analyzing the authors, Wang, Y., Li, Y., and Zhang, X. are identified as relevant, and there are only two articles [30,38] that share common authors, namely Pan, Y., and Zhang, X. This suggests a collaboration or shared research interests, indicating potential for future

collaboration between the remaining authors. Regarding the country of origin, 31% of studies were developed in China, 46% in European countries, and 23% in other parts of the world, indicating a reasonably diverse range of contributions from different countries. It is also worth noting that only one article [47] focuses on rigid pavement, while the remaining articles study flexible pavement [8,19,30,38–40,46,53–57]. Furthermore, seven articles (approximately 54%) focus on road pavements in rural environments [8,30,38,39,46,53,54], five articles on road pavements in urban environments (approximately 38%) [40,46,47,56,57], and one on an airport environment [55], suggesting the relevance of pavement assessment for different transport infrastructures and environments.

The analysis of the selected documents underscores the fact that most of the studies are directed towards researching UAV image collection and processing techniques to obtain 3D models that represent the pavement surface for distress identification, measurement, and condition evaluation. Four articles present advanced research maturity [30,38,39,57], employing techniques to retrieve and process data on pavement surface distress to identify its characteristics efficiently and operationally, such as type of distress, dimension, and severity. However, none of the studies analyzed more than three different types of distress, usually focusing on cracks and potholes, except for publication [40], which analyzed four, namely piling up (road bulges), potholes, subsidence (road cavities), and corrugation. It is noteworthy that cracks and potholes are the most studied pavement distresses, both being examined together in over 38% of the articles [8,30,38,56,57]. Specifically, crack detection and analysis have been important research areas in pavement condition assessment using UAVs [8,30,38,39,46,47,53,56,57]. Other pavement distresses, such as discontinuous deformations [54], rutting [46,57], subsidence, pilling, and corrugation [40], are mentioned in only one or two articles, suggesting that they are relatively less studied in the context of UAV-based pavement evaluation. This is likely due to UAV-based methods being a recent and developing approach, not yet encompassing the detection of all pavement distress types, thus currently focusing on the most common and significant ones.

Quadcopters, with the DJI Phantom 4 Pro model being notably the most utilized, are prevalent in these studies [8,19,40,47,53–57]. The quadcopters are typically combined with cameras having resolutions ranging from 16.8 MP to 20.9 MP, enabling the capture of highly detailed aerial images. It is noteworthy that none of the articles refer to the spectral or radiometric resolution of imaging sensors. The choice of cameras is driven by the specific needs of each study, taking into account factors such as the desired resolution, georeferenced accuracy, equipment availability, and the objectives of the pavement inspection.

The selection of the positioning system primarily hinges on the required accuracy and prevailing environmental conditions. Among the articles included in this study, GPS/GNSS in UAVs emerges as the most common choice, facilitating precise georeferencing of images [19,40,53,54]. Some articles also mention the exclusive use of GPS [8,47,56,57] or GNSS [55], depending on precision needs and satellite availability.

The choice of flight height for pavement distress inspection exhibits significant variation among the analyzed documents. As depicted in Table 3, UAVs' flight height ranges from 5 to 60 m, with some variations, such as flights as low as 0.5 m in a specific study [47]. The determination of the flight height depends on various factors, including the desired image spatial resolution, the accuracy of distress measurement, terrain characteristics, UAVs' flight regulations, and the specific study objectives. Low-altitude flights are conducted manually and can capture finer details, while higher-altitude flights can cover a more extensive area in a single flight and be automatic. This variability underscores the flexibility of UAV survey techniques to adapt to different research contexts and the specific requirements of pavement analysis.

Regarding the autonomy of UAVs, values ranging from 20 to 30 min per battery charge are typically reported [40,53,54,57,61]. This may require interruptions during inspection; however, it is expected that autonomy will be extended to over 40 min in the near future. The recorded UAV's speed usually varies from 3 to 5 m/s [8,40,47,53–55,57].

Several UAV image data processing techniques have been effectively employed to obtain image restitution, 3D models, and distress detection and classification. In terms of image restitution, the studies under scrutiny have embraced the principles of photogrammetry, such as aerial triangulation (AT) and SfM processes [19,46,53,54,56]. For the creation of 3D models, several software packages, such as Pix4Dmapper, Multi-view Stereo, or Agisoft Metashape, were used [30,40,56]. To enhance resolution, super-resolution algorithms were also used [56]. For object recognition, the eCognition Developer software and the YOLO system were adopted [8,38]. Concerning distress detection and classification (feature extraction), techniques such as the tensor voting algorithm and machine learning algorithms like CNN, KNN, ANN, SVM, RF, and XGBoost were applied [30,38,39,47,57]. Among these, SVM and RF have shown notably high levels of accuracy in detecting pavement damage, often exceeding 98%. Notably, the use of deep learning algorithms and Multi-Agent Systems (MAS) [8] suggests a more advanced approach in terms of computational intelligence.

As for the ground sampling distance (GSD) or spatial resolution of the images, some authors have reported values ranging from 0.20 cm/pixel to 1.50 cm/pixel [19,38,46,53,54]. The former was obtained from UAV data collected at a height of 5 m, and the latter at a height of 60 m. Regarding the verified distress measurement errors, they generally fall below 1 cm for UAV data collected at low altitudes (less than 5 m) [46], around 1 cm for data collected between 10 and 15 m [19,40,53], and more than 1.5 cm for greater heights above ground [54,56,57]. The analysis of the presented studies suggests that flight heights in the range of 25 to 30 m generally allow automatic flights and an acceptable level of pavement distress detection and precision, particularly for medium and high distress severity levels.

Finally, when comparing UAV-based pavement inspection over on-foot and in-vehicle techniques, the main advantages reported by the author include:

- Relative affordability concerning acquisition and operation costs [46,47,49,53,57].
- Reduced data collection time and minimized infrastructure downtime for inspection [38,46,53].
- Easy maneuverability [38,55].
- High flexibility, thus enabling quick and easy inspection of otherwise inaccessible areas [23,38,40,47,53].
- Applicability in high-risk situations without endangering inspector lives [19,23,24,55].
- High-quality information, such as flights close to the pavement surface or other physical assets, allows for the detection and diagnosis of damage and problems [30,38,46,57].
- Potential for semi-automatic or automatic data processing for damage detection and classification [19,30,38–40,53,54].
- Reduced environmental impact when compared to other inspection techniques, such as noise, material waste, and CO₂ emissions [19,23,24].
- However, several disadvantages have also been identified:
- Inoperability in adverse weather conditions, including wind, dust, extreme temperatures, and, in the case of some UAVs, rain [44,46,54].
- Limited autonomy (approximately 20–30 min per battery charge), which may require inspection interruptions [40,53,54,57,61].
- Potential traffic interruption during pavement inspection [47,55].
- Limited load capacity makes it difficult to accommodate certain inspection needs, such as cameras with specialized features, sensors, LiDAR, GPS systems, etc. [30,46].
- Regulatory limitations on their use [47,53].
- Difficulty maneuvering without a GPS signal [23,24].

4. Conclusions

The demand for transportation between regions, cities, and countries has steadily increased over the years. This has led to continuous damage to the pavement of transport infrastructure, thus resulting in a decline in the quality of driving, comfort, and safety for road and airport users. The necessity for pavement maintenance, which encompasses the inspection of pavement surfaces to assess their current condition, predict their future

condition, and develop economically viable maintenance and rehabilitation strategies, calls for cost-effective solutions that enable faster data collection and processing without compromising data quality.

This article contributes to this challenge by presenting an evaluation of recent technological developments in this field, specifically the use of UAVs for inspecting the surface distress of transport pavements. The analysis of the selected documents showed that this is a recent topic that has shown a growing interest in the academic community, with an expected increase in the number of documents and relevant authors in the coming years. Most applications described in the open-access literature reviewed focus on image processing techniques to convert images captured using UAVs into 3D models and on the automatic or semi-automatic extraction of information about the type and geometric characteristics of distresses in road asphalt pavement through the use of machine learning approaches. Practical cases in pavement distress inspection tend to concentrate on the detection and analysis of cracks and potholes, while other types of distress receive comparatively less attention. From the case studies, it is evident that the most suitable inspection technique involves capturing pavement surface images vertically (at 90°). This is because the processing time required for achieving high-precision measurements at other angles is not justified. Recent studies also indicate a precision level of around 1 cm for planimetric and altimetric measurements in UAV image capture at flight heights ranging from 10 to 15 m.

In summary, the reviewed studies suggest that UAV-based pavement surface condition monitoring systems can enhance data collection, reduce processing time, and improve data accuracy. For future work, the most crucial next steps identified in the analyzed documents include:

- Enhancing spatial resolution to improve the accuracy of pavement condition evaluation by capturing low distress severity levels [30,39].
- Increasing the accuracy of 3D models by incorporating stable ground control points (GCP), such as road milestones and other benchmarks with known geographic features [19,40].
- The use of UAV data collection techniques based on LiDAR and radar, leveraging LiDAR's potential to directly acquire elevation information, and evaluating the accuracy of pavement distress detection when considering high-density point clouds and multispectral remote sensing images [8,30,38,39,46].
- Expanding existing datasets with additional UAV pavement images covering different types of roads (highways, motorways, etc.), pavement surfaces (cement, gravel, and stone), and types of damage (rutting, roughness, etc.) to evaluate the performance of models and machine learning algorithms [30,38,39,47,53,54,57].
- Addressing the limitations of images that can be used in automated detection methods, such as image resolution and UAVs' flight height [57].
- Testing other advanced machine learning algorithms for pavement distress detection, such as Convolutional Neural Networks [30,38,39], and integrating software and algorithms through individual coding to speed up detection processes [30,39].

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