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Systematic Review

Automated and Intelligent Inspection of Airport Pavements: A Systematic Review of Methods, Accuracy and Validation Challenges

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Abstract

Airport pavement condition assessment plays a critical role in ensuring operational safety, surface functionality, and long-term infrastructure sustainability. Traditional visual inspection methods, although widely used, are increasingly challenged by limitations in accuracy, subjectivity, and scalability. In response, the field has seen a growing adoption of automated and intelligent inspection technologies, incorporating tools such as unmanned aerial vehicles (UAVs), Laser Crack Measurement Systems (LCMS), and machine learning algorithms. This systematic review aims to identify, categorize, and analyze the main technological approaches applied to functional pavement inspections, with a particular focus on surface distress detection. The study examines data collection techniques, processing methods, and validation procedures used in assessing both flexible and rigid airport pavements. Special emphasis is placed on the precision, applicability, and robustness of automated systems in comparison to traditional approaches. The reviewed literature reveals a consistent trend toward greater accuracy and efficiency in systems that integrate deep learning, photogrammetry, and predictive modeling. However, the absence of standardized validation protocols and statistically robust datasets continues to hinder comparability and broader implementation. By mapping existing technologies, identifying methodological gaps, and proposing strategic research directions, this review provides a comprehensive foundation for the development of scalable, data-driven airport pavement management systems.

Keywords: airport pavement inspection; functional condition; automated distress detection; machine learning; big data; unmanned aerial vehicles (UAVs); vehicle-inspection systems

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1. Introduction

1.1. Framework

Airport pavements are critical structural components, essential not only for the safety and operational efficiency of air traffic but also for ensuring the economic sustainability of airports. Responsible for bearing the high and concentrated loads of aircraft, these structures must maintain functional characteristics over time, such as load-bearing capacity, surface regularity, and skid resistance. The deterioration of these properties directly compromises safety during landings, takeoffs, and ground maneuvers, while also generating significant operational and economic impacts [1–4]. Several studies have shown that pavement performance depends on both functional and structural integrity, which are influenced by operational, environmental, and maintenance factors.

Evaluation systems such as the Aircraft Classification Number/Pavement Classification Number (ACN/PCN), Pavement Condition Index (PCI), International Roughness Index (IRI), and the Coefficient of Friction (COF) are essential to ensure compatibility between aircraft and infrastructure and to monitor performance over time [5–9]. While the ACN/PCN system verifies structural adequacy under applied loads, the PCI, IRI and COF assess functional aspects, such as surface distresses and ride quality [8–12]. With the growth of air traffic and the intensification of operations, however, the need for more accurate, frequent, and automated inspection methods has become evident. To address this challenge, composite indicators have been continuously refined to better capture the cumulative effects of surface irregularities, friction loss, and distresses associated with operational safety [13–17].

In addition, sustainability plays a central role in modern pavement management, requiring that adopted strategies consider not only economic factors but also environmental, operational, and social impacts throughout the entire infrastructure life cycle [5]. The rational use of resources, combined with the timely planning of technically appropriate interventions, contributes to pavement longevity and ensures the continuity of airport operations with high standards of safety and efficiency.

1.2. Airport Pavement Management System (APMS)

Airport Pavement Management Systems (APMSs) have emerged as strategic tools by integrating historical data, field surveys, and predictive modeling, thereby enabling rational and technically informed management practices [3,18–21]. The systematic and continuous evaluation of airport pavement conditions is essential to support effective and sustainable maintenance decision-making. The lack of reliable diagnostics accelerates the progression of pavement distresses, significantly increases corrective maintenance costs, and compromises the operational availability of runways.

In the context of continuous air traffic growth and the natural aging of runway assets, these systems facilitate more accurate and evidence-based decision-making throughout the pavement life cycle. They guide maintenance and rehabilitation activities based on objective, technical, and measurable criteria. Their primary objective is to maximize pavement durability while minimizing costs through intelligent prioritization of interventions, long-term planning, and efficient allocation of available resources [19–22].

The operation of an APMS is structured around a set of interdependent components that support the collection, storage, analysis, and projection of pavement performance data. The main components include [3,23–26].

1. Network Inventory: Systematic cataloging of the physical and functional components of airport infrastructure, including runways, taxiways, and apron areas. The inventory encompasses detailed information on materials, geometric characteristics, construction history, past maintenance activities, and traffic load intensity.
2. Condition Assessment: Evaluation of the functional and structural condition of pavements using visual inspections, as well as destructive and non-destructive testing methods. Key performance indicators include the PCI and the ACN/PCN. This component also incorporates advanced technologies such as multifunctional vehicles, Unmanned Aerial Vehicles (UAVs), and Light Detection and Ranging (LiDAR) systems.
3. Database: Centralized and structured storage of all data collected throughout the various stages of pavement management. Ensuring the integrity and continuous

updating of the database is essential to perform consistent analyses and to support informed, data-driven decision-making.
4. Data Analysis: Application of predictive models and simulations to estimate pavement distress progression, determine the optimal timing for interventions, and compare maintenance scenarios. This component also encompasses economic analyses focused on cost-effectiveness, return on investment, and overall sustainability.
5. System Outputs: Generation of reports, charts, and thematic maps that prioritize maintenance and rehabilitation actions based on technical, functional, and financial criteria. These outputs provide objective and actionable support for informed decision-making by airport pavement managers.
6. Intervention: Implementation of maintenance, rehabilitation, or reconstruction actions according to the priorities and technical recommendations generated by the APMS. This stage ensures that planned strategies are effectively executed in the field, bridging the gap between diagnostic assessment and practical application, and directly influencing pavement longevity and operational safety.
7. Feedback Loop: Continuous refinement of predictive models through the integration of real-world data obtained from inspections and monitoring. This dynamic process enhances the accuracy of future forecasts and supports adaptive pavement management strategies.

The overall structure of an APMS and its interrelated components is illustrated in Figure 1.

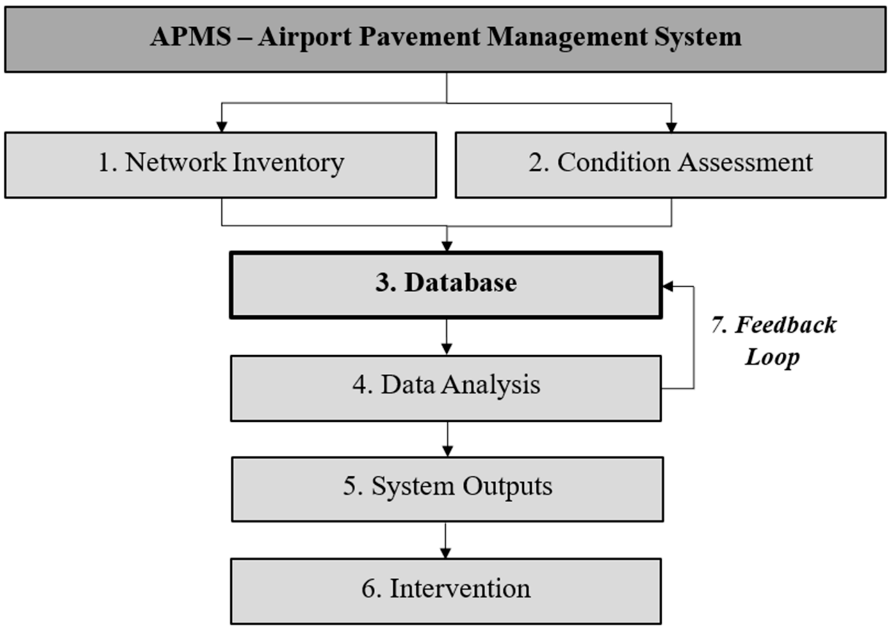

Figure 1. Main components of an APMS.

As demonstrated in [15], even during the early stages of implementation, APMSs offer tangible benefits, such as process simplification and more rational decision-making. Among the components that comprise an APMS, the database functions as the central core of the system. Its reliability directly influences the effectiveness of predictive models and operational processes [20–22]. In this regard, automated technologies have significantly improved data collection and processing by enhancing accuracy, speed, and standardization, thereby optimizing pavement management workflows.

The adoption of preventive strategies based on structured data can significantly reduce maintenance costs and prevent critical failures. Studies indicate that delays in necessary interventions may lead to increases of up to 50% in total costs and substantially reduce the service life of pavement structures [2,20–22]. The overall effectiveness of the system relies on the continuous calibration of data, tailored to local conditions such as traffic volume and climate.

In this context, the pursuit of more effective inspection methods is essential to ensure the integrity, reliability, and representativeness of the data feeding the APMS. The limitations of traditional techniques, such as on-foot visual inspections, have accelerated the adoption of technological approaches that integrate precision, efficiency, speed, and broader spatial coverage. Recent advances have further expanded data collection capabilities through the adoption of non-destructive methods and approaches based on artificial intelligence (AI). Among the most prominent inspection methods are multifunctional vehicles equipped with high-resolution sensors and UAVs, which improve data acquisition, processing, and interpretation, thereby increasing the robustness of decision-support models [27–32].

Despite these advances, many studies remain limited to descriptive analyses and lack objective validation criteria. This is particularly evident when considering the applicability of these methods in airports with varying operational profiles and environmental conditions. There is still a shortage of research that systematically evaluates the effectiveness of automated inspection approaches across diverse operational contexts. Furthermore, the absence of standardized metrics undermines results replicability and hinders the reliable large-scale implementation of these technologies [8,30–33].

1.3. Objectives

Given the challenges described, it is essential to conduct a rigorous evaluation of automated methods for the functional inspection of airport pavements. Aspects such as accuracy, repeatability, and practical applicability must be assessed based on reliable data and robust statistical analysis, moving beyond subjective perceptions and providing quantitative evidence. This is particularly relevant in a context where maintenance decisions and investment planning directly depend on the precision and reliability of the information produced.

Accordingly, this systematic review of the literature aims to identify the evolution and analyze the main technological methods employed in the functional inspection of airport pavements. The study encompasses the characterization of data acquisition techniques, the procedures used for processing and interpreting field data, and the validation criteria applied to assess their accuracy, applicability, and efficiency. Furthermore, statistical validation of these methods is considered a critical step to ensure the robustness of the results and their reliability for integration into inspection systems. Ultimately, this review seeks to map recent advances, identify methodological limitations, and highlight existing gaps in the literature, thereby contributing to the improvement of inspection practices and to the generation of more consistent and reliable data to support the technical management of airport infrastructure.

2. Airport Pavements: Types and Significance of Distress

Airport pavements play a vital role in ensuring the safety and operational efficiency of airport infrastructure. To guarantee optimal performance throughout their service life, three functional characteristics are crucial [4,6,9,23–26,34,35]:

- Structural capacity: ensures the integrity of the infrastructure under repeated and heavy loads generated by aircraft.
- Surface regularity: essential for stability during aircraft movement, preventing structural damage and supporting safe performance.

- Skid resistance: maintains adequate friction levels, particularly under adverse conditions such as wet pavements.

The progressive development of pavement distresses directly compromises operational safety and drives up corrective intervention costs. To mitigate this, periodic inspections and systematic monitoring are crucial for anticipating failures, optimizing maintenance planning, and accurately assessing distress levels to support timely preventive or corrective actions. Pavement distress progression is a central concern in airport pavement management, as extensive cracking, depressions, friction loss, and plastic deformations compromise the functional performance of runways, especially during takeoff and landing under adverse conditions. In addition, loose particles and structural failures increase the risk of Foreign Object Debris (FOD), endangering aircraft integrity and passenger safety [9,35,36].

In this context, it is essential to understand the structural differences between flexible and rigid pavements, as well as the distress mechanisms to which they are subjected [3,23,37]. Rigid pavements, composed of Portland Cement Concrete (PCC) slabs, exhibit high flexural strength and are preferred in areas exposed to intense static loads, such as apron zones. However, they are more vulnerable to structural distresses and extreme weather conditions. Flexible pavements, consisting of bituminous and granular layers, are widely used on runways and taxiways due to their flexibility and ability to adapt to dynamic traffic loads. Nonetheless, they are more susceptible to distresses caused by repeated loading.

Each pavement type responds differently to climate variations, cyclic traffic loads, and wear processes, requiring specific techniques for measurement, diagnosis, maintenance, and rehabilitation. Therefore, understanding the different types of distress and their underlying causes is essential to guide effective intervention strategies. The ASTM D5340-23 standard [38] provides a detailed and standardized classification of the distresses affecting airport pavements. It establishes criteria for their identification, quantification, classification, and evaluation, with direct application in the determination of the PCI. The standard includes 17 types of distress for flexible pavements and 16 types for rigid pavements, detailing visual inspection procedures as well as severity and extent parameters [38].

For the purposes of analysis and maintenance prioritization, pavement distresses are often grouped into functional categories. The functional categorization adopted in this study was developed to organize the various types of distress according to their impact on pavement performance, grouped into four main categories: irregularity, skid resistance, FOD-generating distresses, and structural capacity integrity (see Figure 2). Figure 2 presents a flowchart of the main types of airport pavement distresses, as outlined in ASTM D5340-23 [38], which defines the criteria for PCI evaluation and calculation. Each type of distress is associated with the pavement type (flexible or rigid) and with its predominant causes, which may be related to climatic factors (such as temperature variations, freeze–thaw cycles, and water infiltration) or to repeated loading from air traffic.

Distresses grouped under “Irregularity” are generally caused by repeated traffic loads or significant climatic variations. These conditions, such as block cracking, depression, corrugation, rutting, shoving, swell, and settlement, affect surface uniformity and ride quality [26,39]. These issues can lead to instability, discomfort, and reduced operational performance.

Distresses related to “Skid resistance” are associated with surface wear or contamination, reducing friction levels and increasing the risk of hydroplaning or skidding [23,26]. Common examples include bleeding, polished aggregate, oil spillage, scaling, and spalling. These distresses are particularly critical in wet or icy conditions, where skid resistance is vital for safe aircraft operations.

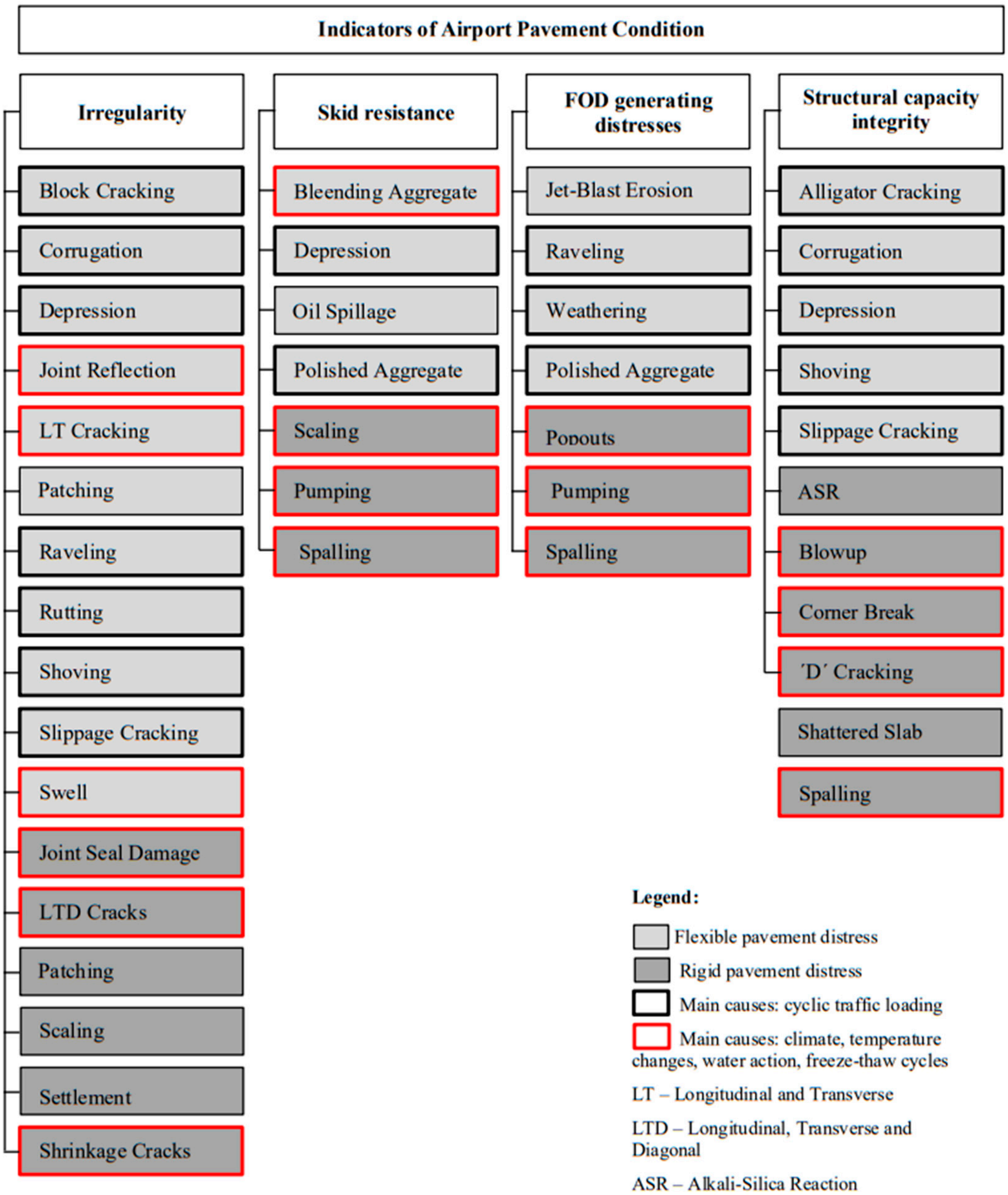

Figure 2. Functional classification of airport pavement distresses developed based on ASTM D5340-23 [38].

The category "FOD-generating distresses" includes surface failures that contribute to the detachment of particles or fragments, such as popouts, pumping, and spalling, typically occurring in high-traffic areas and worsened by mechanical actions like jet-blast erosion and environmental exposure. These failures significantly increase the risk of FOD-related incidents, threatening aircraft integrity and passenger safety.

Finally, "Structural capacity integrity" encompasses distresses that indicate a loss of structural performance, often resulting from fatigue due to repeated aircraft loads, internal reactions in the concrete, or extreme thermal expansion. These include alligator cracking, slippage cracking, 'D' cracking, corner break, blowup, and shattered slab, which may severely compromise the load-bearing capacity of the pavement and require urgent rehabilitation [23,39].

The progression of distresses poses serious risks to operational safety, including aircraft control loss, premature tire wear, and FOD events, especially in high-traffic zones such as runways and taxiways [23,25]. Moreover, untreated surface failures may accelerate structural distress, increase corrective maintenance costs, and reduce the operational availability of airport infrastructure [23,39].

In light of these challenges, the ability to accurately detect, quantify, and classify surface distresses is essential for ensuring the safety, functionality, and cost-efficiency of airport pavements. This underscores the increasing relevance of advanced inspection technologies and data-driven analytical methods, which have become central to the development of more reliable and proactive pavement management strategies.

3. Search Method and a First Glance at Publications

This study aimed to identify, characterize, and analyze the main methods and technologies used in the functional inspection of airport pavements, with a focus on surface distress detection, evaluation, and the accuracy of inspection techniques. To this end, a systematic review was conducted using the Scopus database, Elsevier's renowned bibliographic platform, established in 2004, which indexes peer-reviewed articles, abstracts, and citations curated by subject matter experts. Scopus is considered one of the most comprehensive databases for scientific publications in the fields of engineering and transportation infrastructure.

The data collection was performed on 29 November 2024. The publication selection criteria were based on several parameters, including peer-reviewed articles published in scientific journals and relevant international conference proceedings that specifically addressed methodologies applied to airport pavements. Table 1 and Figure 3 present the stages considered in the document screening, exclusion, and analysis process. This rigorous selection procedure aims to ensure the quality, relevance, and scientific rigor of the documents included, reflecting a strong commitment to high standards of academic excellence.

Table 1. Document selection process.

Process Phase	Selection Criteria
1	Initial search in the Scopus database was conducted using terms extracted from the titles, abstracts, and keywords of relevant articles. The following combined search expressions were applied: ("pavement inspection" OR "pavement condition" OR "pavement evaluation" OR "machine learning" OR "big data" OR "artificial intelligence" OR "multifunctional vehicles" OR "laser scanning" OR "Pavement Condition Index" OR "PCI") AND ("airport pavement" OR "airfield pavement" OR "runway pavement management").
2	Refined of results by subject areas (engineering, materials science, computer science), document type (article, conference paper, conference review, review), publication status (final stage), and language (English).
3	Abstract screening was performed to exclude studies focused solely on structural evaluation (e.g., deflectometer tests) or non-airport pavements.
4	Full-text review of the screened documents, with retrieval of non-open-access articles through author contact when necessary.
5	Final selection of documents that explicitly describe inspection activities or data collection procedures related to airport pavements (e.g., case studies).

Adhering to the PRISMA 2020 statement [40], this systematic review's protocol was deposited on the Open Science Framework (OSF). The registration received the identifier 10.17605/OSF.IO/ET6GV.

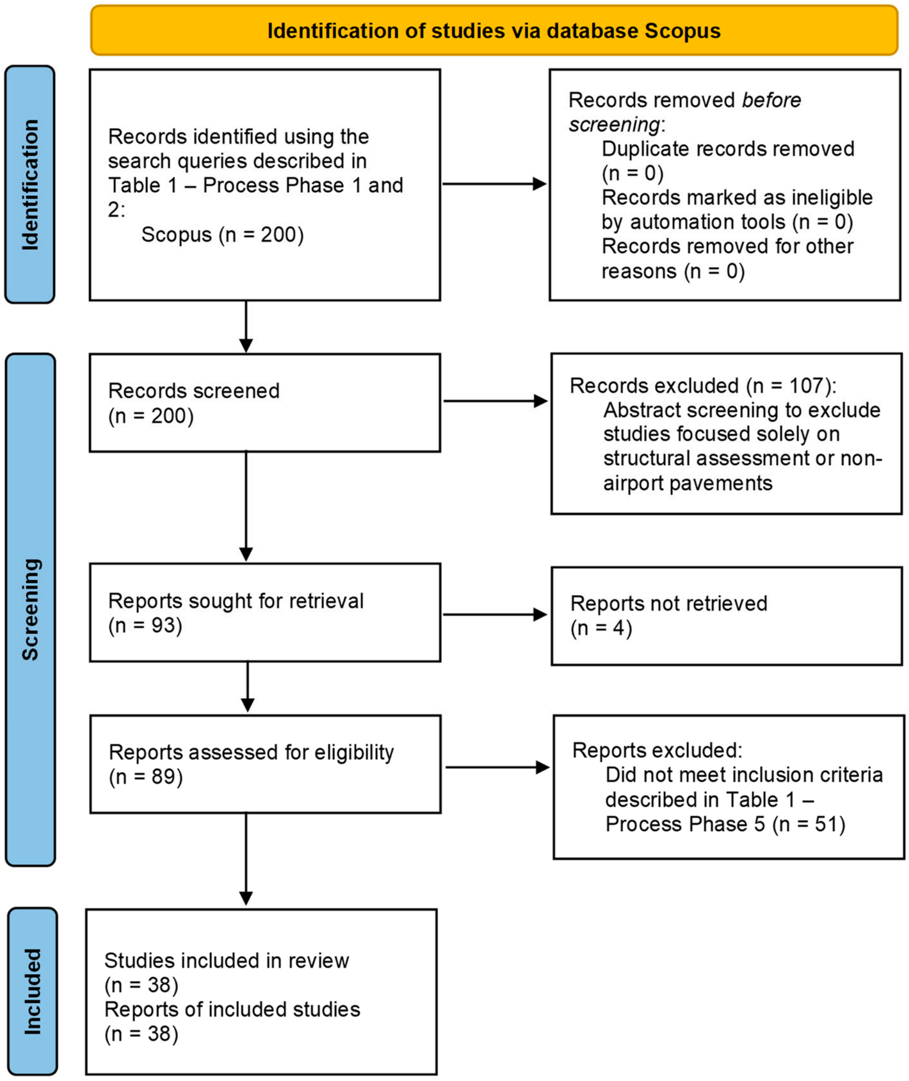

Figure 3. PRISMA 2020 flow diagram of the systematic review process.

The document selection process for this review was carried out in five distinct phases, as presented in Table 1. In Phase 1, an initial search was conducted in the Scopus database using terms extracted from the titles, abstracts, and keywords of the documents. Boolean search expressions related to airport pavement infrastructure inspection were applied to ensure broad topic coverage. This search strategy was designed to capture both conventional approaches and advanced technological methodologies, including automated techniques and applications of artificial intelligence.

The search strategy employed a broad set of 13 terms to maximize the retrieval of relevant studies, given previous findings indicating that research specifically on airport pavements remains limited when compared to road pavements [30,31].

Phase 2 involved refining the results based on relevance criteria, restricting the documents to specific subject areas and to scientific publications written in English and published in their final version. No publication date restrictions were applied, as the scope allowed the inclusion of documents published between 1975 and 2024, enabling an assessment of thematic evolution over time. A total of 200 publications were retrieved. However, the final selection (Section 4.2) consists predominantly of studies published from 2013 onward, which represent 81.6% of the included documents and reflect the period of accelerated technological development in automated inspection systems.

In Phase 3, abstract screening was performed to exclude studies clearly focused on structural evaluation, non-airport pavements (e.g., highway or urban pavements) or reviews focused exclusively on general pavement material properties. This step resulted in the exclusion of 107 documents, leaving 93 publications for further analysis.

In Phase 4, 93 documents were reviewed in full. Only those describing functional inspection activities and data collection and/or processing procedures related to airport pavement distress, including case studies, were retained. Among these documents, 19 were not available through the resources accessible at the time, which required contacting the corresponding authors directly. Fifteen authors responded positively and provided the requested material, resulting in a total of 38 documents included for in-depth analysis.

During Phase 5, these 38 publications constituted the final set of studies analyzed in detail in Section 4.2. They were characterized according to temporal distribution, country of origin, authorship, title, and main research focus, as well as research maturity level (initial, intermediate, or advanced). Additional criteria included the technical focus (e.g., database, processing, analysis), the type of pavement inspected (PCC or AC), the inspection methods and equipment used (e.g., multifunctional vehicles, UAVs, manual inspection with cameras, GNSS systems), the types of distress identified (e.g., alligator cracking, longitudinal cracking, raveling), data processing techniques, the use of machine learning and other artificial intelligence applications, big data, 3D modeling, measurement accuracy, evaluation and validation methodologies (e.g., statistical analysis), and key research trends.

A potential risk of bias is acknowledged for publication selection, as the rigorous search strategy was executed exclusively within the Scopus database (despite its breadth) and restricted to English-only publications. To counter this limitation, inclusion and exclusion criteria were rigorously and consistently applied (Table 1). Additionally, direct contact with authors was made to secure full-text articles that were initially unavailable. Given that only four documents ultimately remained unobtainable, it is concluded that the steps taken were effective in minimizing the overall bias.

The complete process of document identification, screening, and selection for this review is summarized in the PRISMA flow diagram (Figure 3). This flowchart outlines each step described in Table 1, detailing the number of records initially retrieved, the criteria applied at different phases, and the subsequent exclusions that led to the final set of included studies.

4. Data Characterization, Trend Analysis, and Discussion

4.1. Document Characterization

The bibliometric analysis conducted in Phases 2 and 5, comprising 200 and 38 documents, respectively, enabled the identification of key quantitative and qualitative aspects of the scientific literature related to the functional inspection of airport pavements. It also facilitated a comparison between the overall trends observed in the full dataset and those reflected in the PRISMA-selected studies.

Figure 4 shows the temporal distribution of the total publications identified since 1975. A consistent increase in publication volume is observed over time, with a marked rise beginning in 2017 and peaking in 2021. This trend reflects a recent surge in scientific interest in the application of emerging technologies, such as artificial intelligence and automated sensing systems, for airport pavement management.

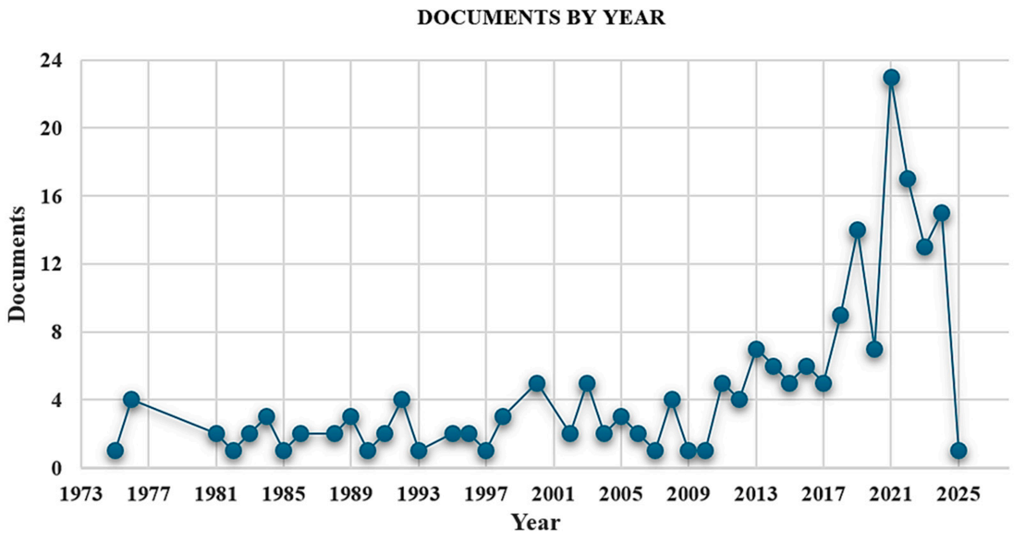

Figure 4. Document distribution by year (Phase 2).

Figure 5 presents the geographical distribution of publications in Phases 2 and 5.

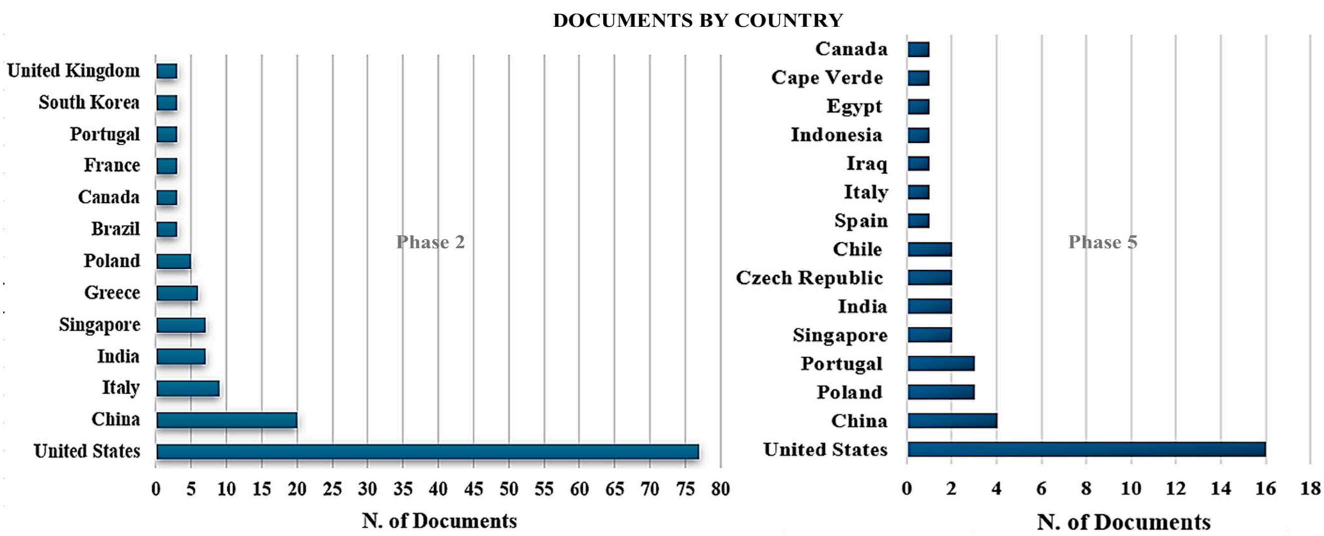

Figure 5. Distribution of documents by country in Phase 2 and Phase 5.

In both phases, the United States leads by a wide margin, with 77 publications in Phase 2 and 16 in Phase 5. China ranks second, with 20 publications in Phase 2 and 4 in Phase 5. Other contributing countries in Phase 2 include Italy (9), India (7) and Singapore (7). In Phase 5, although the total number of documents is smaller, many of these same countries continue to appear, indicating a consistent, though more selective, contribution to the field. Notably, Poland (3) and Portugal (3) stand out, now appearing in 3rd and 4th place. This comparison reflects not only the predominance of countries with extensive airport infrastructure and strong research activity in pavement engineering, but also how the PRISMA filtering narrows the focus to nations producing the most thematically aligned and methodologically robust studies.

The high number of publications from the United States and China may also reflect national policies that promote research funding and strategic investment in infrastructure and air transportation. In China, substantial government investment in UAV technologies and airport infrastructure has driven research on pavement inspection. In the United States, agencies such as the Federal Aviation Administration (FAA) have awarded millions of dollars in grants for research and training in Unmanned Aircraft Systems (UAS). Additionally, recent federal legislation has allocated hundreds of millions more to support UAV-based inspection of critical infrastructure [30,41–43].

Regarding document type, Figure 6 shows that in Phase 2 the dataset is composed primarily of journal articles (49%) and conference papers (42%), with smaller contributions from conference reviews (6%) and review papers (3%). After applying the PRISMA selection criteria in Phase 5, the composition shifts slightly: journal articles represent 47% of the final set, while conference papers increase to 53%. Review and conference review documents are no longer present in the final selection, which underscores the need for studies that consolidate existing knowledge. This deficiency was identified as a gap in both phases and is one that this review seeks to address.

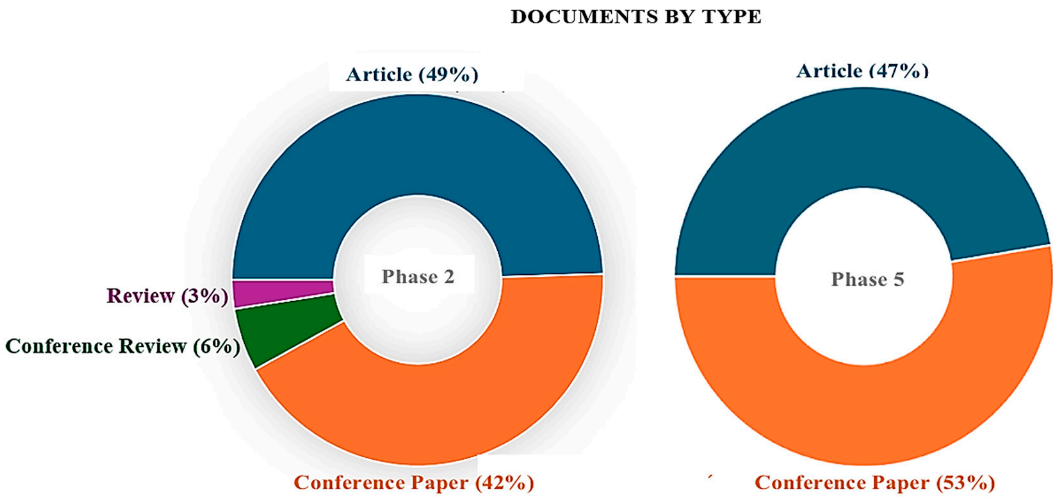

Figure 6. Distribution of documents by type in Phase 2 and Phase 5.

Overall, these results indicate that both phases are dominated by primary research outputs, with Phase 5 showing a stronger concentration of conference papers closely aligned with emerging technological developments in automated airport pavement inspection.

With regard to the subject areas of the publications, Figure 7 shows that in Phase 2 the documents are concentrated primarily in Engineering, which accounts for 58% of the studies, consolidating its position as the dominant technical domain. However, related fields such as Social Sciences (9%), Computer Science (8%), and Materials Science (8%) are also represented, underscoring the interdisciplinary nature of the topic. Publications from other areas were identified as well, although in smaller proportions.

After applying the PRISMA criteria in Phase 5, the dominance of Engineering becomes even more pronounced, increasing to 69% of the selected studies. Computer Science also shows a proportional increase, rising to 10%, reflecting the growing integration of automation, machine learning, and sensing technologies in airport pavement inspection. By contrast, fields such as Social Sciences (5%) and Materials Science (6%) represent smaller shares of the final dataset, consistent with their more peripheral relevance to the core technological focus of this review.

This multidisciplinary profile reflects the increasing integration of digital technologies, data analysis, and organizational approaches in airport infrastructure management.

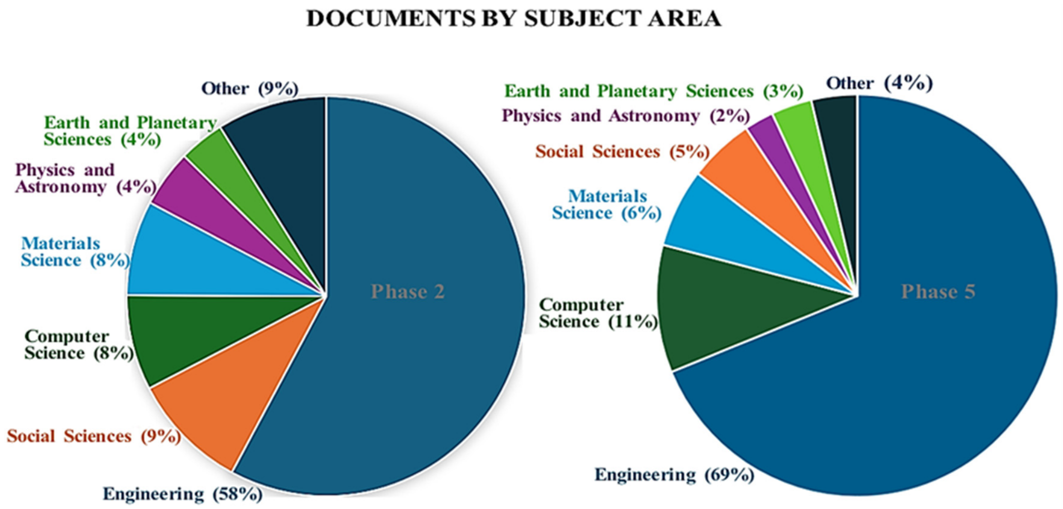

Figure 7. Distribution of documents by thematic area in Phase 2 and Phase 5.

The thematic and intellectual characterization of the selected publication set was further explored through two complementary approaches. First, a keyword co-occurrence analysis was conducted for Phase 5 to examine the thematic relationships among the studies included after PRISMA filtering. Second, an author co-citation analysis was carried out using the broader Phase 2 dataset, allowing us to compare the intellectual structure of the full body of retrieved research with that of the final curated set (Phase 5). Both analyses were performed using VOSviewer 1.6.20 software (see Figures 8–10).

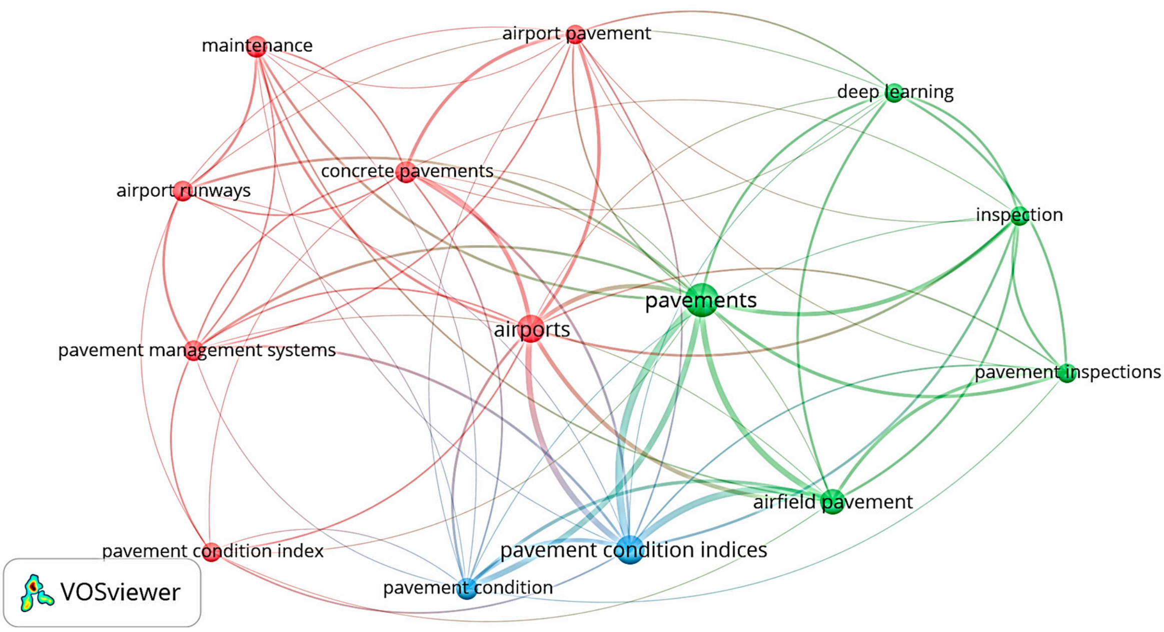

Figure 8. Keyword co-occurrence mapping of the selected studies (Phase 5).

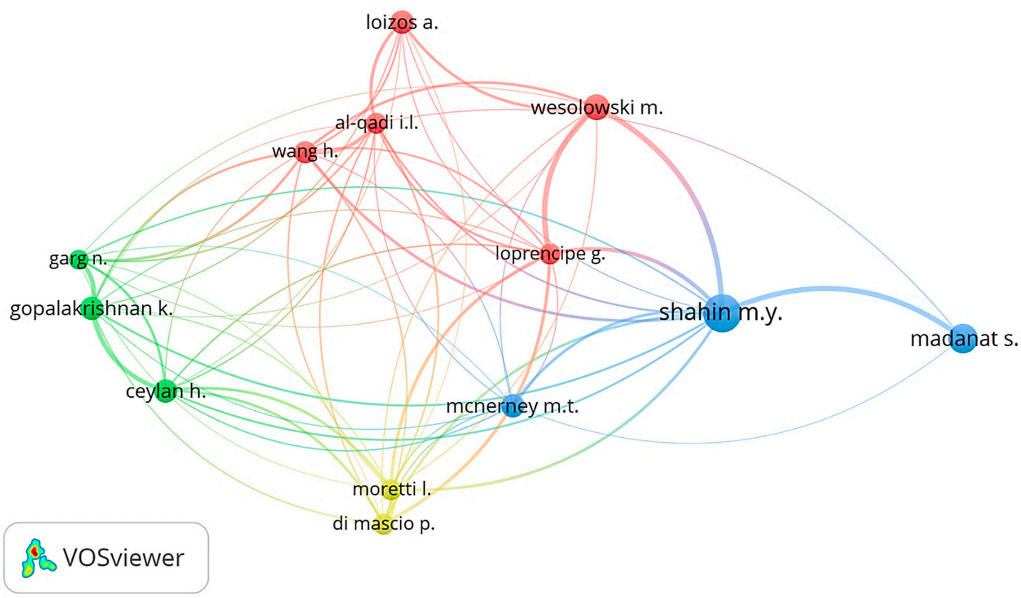

Figure 9. Co-citation mapping of cited authors from the selected studies (Phase 2).

Figure 10. Co-citation mapping of cited authors from the selected studies (Phase 5) (Minimum threshold: 6 citations).

Figure 8 presents the keyword co-occurrence map based on the most frequently used terms in the titles, abstracts, and keywords of the analyzed documents. A total of 381 keywords were identified, of which 6 met the minimum threshold of 14 occurrences, resulting in the formation of four thematic clusters. Each color in the map represents a distinct thematic grouping:

- Red cluster: This cluster groups keywords such as “maintenance,” “airport pavement,” “airport runways,” “pavement management systems,” and “concrete pavements.” It reflects studies focused on infrastructure management, maintenance strategies, and operational aspects of airport pavements.
- Green cluster: This cluster includes terms such as “pavements,” “deep learning,” “inspection,” and “pavement inspections,” indicating research centered on automated inspection techniques, machine learning applications, and sensing technologies.
- Blue cluster: This cluster is organized around “pavement condition” and “pavement condition indices,” representing studies dedicated to evaluating pavement damage, performance indicators, and condition-based assessment methodologies.
- Additional cluster: The smaller connections forming the remaining cluster involve terms such as “airfield pavement,” showing how these concepts bridge condition assessment, airport pavement characteristics, and inspection methodologies.

Overall, the map reveals a strong conceptual integration between pavement condition evaluation, automated inspection technologies, and airport pavement management systems, highlighting the main thematic directions of current research in this field. This structure reinforces the interdisciplinary nature of the topic, connecting transportation engineering, data science, asset management, and technological innovation.

Figures 9 and 10 complement the analysis by presenting the author co-citation map, which reflects the intellectual structure of the field by identifying authors frequently cited together in the analyzed documents.

Within the set of 200 documents, a total of 4.453 cited authors were identified. Applying a relevance threshold of at least 20 citations, 13 authors were selected and grouped into four clusters. Among them, six authors—Shahin, M.Y., McNerney, M.T., Wesolowski, M., Ceylan, H., Moretti, L., and Di Mascio, P.—are also listed as authors of publications included in Phase 5, representing eleven articles from the final dataset [16,44–53].

In Phase 2, Shahin, M.Y. stands out as the most central node in the network, frequently co-cited with Madanat, S., reflecting his seminal contributions to the development of the Pavement Condition Index (PCI) and Pavement Management Systems (PMS). Other relevant clusters include researchers such as Loizos, A., Wesolowski, M., Al-Qadi, I.L., and Wang, H., who are associated with technical and experimental approaches to pavement characterization. Authors such as Garg, N., Gopalakrishnan, K., and Ceylan, H. form a cluster with an emphasis on technological innovations, including sensor applications and machine learning. The co-citation network also highlights the role of researchers such as Di Mascio, P. and Loprencipe, G., suggesting the presence of a European research stream focused on performance modeling and functional analysis of rigid and flexible pavements in airport environments.

Evidence of the strong links identified in Phase 2, along with the European cluster, continues to be present in the Phase 5 co-citation analysis.

The integrated analysis of Figures 4–10 reveals sustained growth in the scientific literature on the functional inspection of airport pavements, reflecting both the consolidation of key research lines and an expanding interest in the topic. The studies cover a broad range of themes, with particular emphasis on advances in inspection automation, the applicability of methods across different operational stages, and strategies for data processing and interpretation. These findings contribute to mapping recurring thematic trends, identifying connections among influential authors, and outlining the conceptual structure of the field, offering valuable insights to guide future research and promote interdisciplinary collaboration.

Nevertheless, it is noteworthy that relatively few studies have focused on the rigorous assessment of the accuracy and reliability of the applied methods, particularly concerning the use of statistical techniques for result validation. This gap highlights the need for more robust validation frameworks to support the establishment of automated tools and AI-based models as dependable solutions for airport infrastructure management.

The analysis underscores the growing scientific interest in the functional inspection of airport pavements, the consolidation of relevant topics, and the diversification of methodological approaches. At the same time, it identifies important gaps, especially regarding the validation of applied techniques. These findings provide a solid foundation for the technical analysis presented in the next section, which explores inspection methodologies, emerging technologies, data processing, validation techniques, Big Data, and artificial intelligence.

4.2. Trend Analysis

A total of 38 studies, specifically focusing on procedures for the collection, processing, or analysis of surface distresses, were included in the detailed technical analysis presented in this section.

The primary objective of this analysis is to identify methodological trends, recurring technical challenges, and innovation opportunities in the field of airport pavement functional inspection. To achieve this, key information was extracted and organized from each study, covering three dimensions: (i) study metadata (year of publication, author, country); (ii) technical scope (pavement type, inspection methods and equipment, types of distress addressed, data processing techniques); and (iii) advanced aspects (application of statistical validation, Big Data and artificial intelligence (AI), implementation of 3D modeling, and quality indices for pavement performance evaluation).

The selection of these variables was guided by their technical and scientific relevance in characterizing the maturity level of the approaches, the degree of technological innovation involved, and the practical applicability of the proposed methods. Additionally, these dimensions support a robust comparative analysis across the studies, facilitating the identification of gaps, patterns, and noteworthy contributions.

The results of this analysis are presented in Tables 2–4. Table 2 synthesizes both the metadata and the main research focus of the reviewed studies, providing a concise thematic overview of literature. Table 3 summarizes the methodological scope and research maturity levels, while Table 4 highlights advanced aspects, including validation frameworks, Big Data applications, and artificial-intelligence-based approaches. Based on the insights derived from these tables, the following analytical subsections examine in greater depth the assessment methods employed: airport pavement inspection methods (Section 4.3.1), emerging technologies in pavement inspection (Section 4.3.3), and the results achieved in terms of cost, time, accuracy, and complexity (Section 4.3.4).

Table 2 reveals clear trends regarding the temporal evolution and geographical distribution of the studies analyzed. A notable concentration of publications has emerged since 2020, peaking in 2023 and 2024, coinciding with the rapid adoption of automated inspection tools and artificial-intelligence-driven analysis. This growth aligns with the advancement and wider implementation of technologies such as unmanned aerial vehicles (UAVs), high-resolution sensors, and deep-learning-based data processing applied to airport infrastructure management.

Geographically, the United States leads in the number of studies, reflecting substantial investment in applied research within the airport sector and the country's extensive network of airport facilities [41,42]. China, Portugal, India, Poland, and the Czech Republic also show growing participation, indicating the global diffusion of advanced inspection technologies and the diversification of research contexts across different climatic and operational conditions.

Table 3, in turn, highlights the functional and methodological dimensions of the studies. Most address the inspection of both rigid (PCC) and flexible (AC) pavements, with combined approaches being common. Flexible pavements appear more frequently, which is consistent with their predominance in secondary runways and small- to medium-sized airports, where traffic conditions and climate make maintenance a continuous challenge.

In addition, the most common technical objectives span both data collection and subsequent processing stages. Regarding inspection and data acquisition, there is a clear shift from traditional on-foot surveys toward the adoption of embedded and automated systems, such as multifunctional ground vehicles and UAVs equipped with high-resolution sensors. These advances reflect a growing concern with efficiency, reproducibility, and the reduction of inspector subjectivity during data collection. Beyond acquisition, objectives are concentrated in the stages of database development (organization of records and historical data), data processing (treatment and interpretation of raw data), data analysis (quantitative and visual evaluation of distresses), and change detection (identification of variations over time). Together, these categories demonstrate an evolution not only in the collection but also in the structuring and exploitation of data, reinforcing their role as the foundation for reliable and informed decision-making.

Finally, Table 4 emphasizes the advanced methodological aspects of the reviewed studies. A clear progression in focus is observed according to the research maturity level. Initial-level research tends to rely on traditional on-foot data collection and the visual categorization of pavement distresses, often with a descriptive or comparative approach. Intermediate-level studies demonstrate increased use of embedded systems (e.g., multifunctional vehicles) and analysis software, with particular emphasis on the integration of Geographic Information Systems (GIS) and statistical tools. This stage also includes methods that focus on pavement data analysis for maintenance and rehabilitation planning, even when traditional inspection techniques such as manual surveys are used. Advanced-level studies, on the other hand, incorporate more sophisticated techniques, including AI, integrated sensors, and automated data processing workflows, with an emphasis on precision, reproducibility, and scalability. This progression reflects a clear technological transition, from conventional visual practices to intelligent, data-driven, and predictive inspection systems, consolidating the role of airport pavement management within the broader paradigm of smart infrastructure.

Table 2. Research trend analysis: metadata and thematic focus.

Ref.; Year; Country	Author	Title	Main Focus
[7]; 2024; Indonesia	Wibowo, A.; Subagio, B.S.; Rahman, H.; Frazila, R.B.	Evaluation of the airport pavement condition index in the aircraft lateral wander area	Modeling PCI using lateral wander area
[54]; 2024; India	Kumar, P.; Gowda, S.; Gupta, A.	Implementation of airfield pavement management system in India	Developing an Airport Pavement Management System for India
[55]; 2024; United States	Frye, J.J.	Climate change impacts on Arctic airfields	Assessing climate impact on airfield pavement performance in Arctic regions
[44]; 2024; United States	Sourav, M.A.A.; Ceylan, H.; Brooks, C.; Dobson, R.; Kim, S.; Peshkin, D.; Brynick, M.	Use of small unmanned aircraft systems in airfield pavement inspection: implementation and potential	Evaluating UAV-based imagery for automated pavement distress inspection and PCI calculation
[45]; 2024; United States	Sourav, M.A.A; Ceylan, H.; S. Kim, S.; Brynick, M.	Integration of small unmanned aircraft systems and deep learning for efficient airfield pavement crack detection and assessment	Detecting airfield pavement distresses automatically using YOLOv8
[46]; 2024; United States	McNerney, M.T.; Bishop, G.; Saur, V.	Using AI and change detection in geospatial UAS airfield pavement inspection for pavement management	Identifying pavement distresses and performing change detection using AI-enabled UAV imagery
[47]; 2023; United States	McNerney, M.T.; Bishop, G.; Saur, V.	Experiences gained and benefits from using uncrewed aerial systems to calculate pavement condition index at over 80 airports in the United States	Implementing full-scale UAV-based inspection for airport pavement PCI evaluation
[28]; 2023; Spain	Alonso, P.; Gordoa, J.A.I.; Ortega, J.D.; García, S.; Iriarte, F.J.; Nieto, M.	Automatic UAV-based airport pavement inspection using mixed real and virtual scenarios	Segmenting pavement defects using UAV imagery and synthetic datasets through deep learning

Table 2. *Cont.*

Ref.; Year; Country	Author	Title	Main Focus
[56]; 2023; Czech Republic	Maslan, J.; Cicmanec, L.	A system for the automatic detection and evaluation of the runway surface cracks obtained by unmanned aerial vehicle imagery using deep convolutional neural networks	Detecting and measuring transverse cracks on concrete runways using UAV and YOLOv2
[57]; 2023; Iraq	Kareem, N.M.; Ibraheem, A.T.	Developing a frame design for airport pavements maintenance management system	Developing an expert system for airport pavement maintenance decision support
[32]; 2022; United States	Pietersen, R.A.; Beauregard, M.S.; Einstein, H.H.	Automated method for airfield pavement condition index evaluations	Assessing PCI through partially automated UAV imagery and CNN modeling
[58]; 2022; Chile	Cereceda, D.; Medel-Vera, C.; Ortiz, M.; Tramon, J.	Roughness and condition prediction models for airfield pavements using digital image processing	Estimating IRI and PCI using automated digital image processing
[59]; 2022; China	Wu, J.; Zhang, Y.; Zhao, X.	Multi-task learning for pavement disease segmentation using wavelet transform	Segmenting pavement diseases with a multi-task deep-learning network
[60]; 2022; China	Li, Z.; Zhao, K.; Zheng, P.	Research on airport pavement condition information system	Developing an integrated airport pavement condition information system with intelligent distress management
[61]; 2021; Czech Republic	Maslan, J.; Cicmanec, L.	Setting the flight parameters of an unmanned aircraft for distress detection on the concrete runway	Optimizing UAV flight parameters for pavement crack detection
[62]; 2021; China	Liu, Z.; Gu, X.; Dong, Q.; Tu, S.; Li, S.	3D visualization of airport pavement quality based on BIM and WebGL integration	Integrating BIM and WebGL for 3D visualization of airport pavement condition
[63]; 2021; United States	Hafiz, A.; Celaya, M.; Jha, V.; Frabizzio, M.	Semi-automated method to determine pavement condition index on airfields	Calculating PCI semi-automatically using 3D laser scanning and Distress Inspector software developed by the authors.
[64]; 2020; Portugal	Santos, B.; Feitosa, I.; Almeida, P.G.	Validation of an indirect data collection method to assess airport pavement condition	Validating a low-cost in-vehicle pavement distress inspection system for APMS applications
[65]; 2020; India	Vyas, V.; Singh, A.P.; Srivastava, A.	Quantification of airfield pavement condition using soft-computing technique	Prioritizing airfield pavement maintenance using fuzzy AHP methodology
[49]; 2020; Poland	Iwanowski, P.; Wesołowski, M.	Evaluation of the cement concrete airfield pavement's technical condition based on the APCI	Developing the APCI integrating structural and surface parameters
[16]; 2020; Poland	Wesołowski, M.; Iwanowski, P.	Evaluation of asphalt concrete airport pavement conditions based on the Airfield Pavement Condition Index (APCI) in scope of flight safety	Applying a comprehensive APCI-based method for technical pavement assessment
[9]; 2019; Portugal	Carvalho, A.F.C.; Picado Santos, L.G.D.	Maintenance of airport pavements: the use of visual inspection and IRI in the definition of degradation trends	Analyzing PCI and IRI evolution trends for pavement condition assessment
[66]; 2019; Cape Verde and Portugal	Lima, D.; Santos, B.; Almeida, P.G.	Methodology to assess airport pavement condition using GPS, laser, video image and GIS	Validating a vehicle-mounted inspection method for PCI evaluation in Cape Verde

Table 2. *Cont.*

Ref.; Year; Country	Author	Title	Main Focus
[50]; 2019; Italy	Di Mascio, P.; Moretti, L.	Implementation of a pavement management system for maintenance and rehabilitation of airport surfaces	Applying an integrated APMS for maintenance prioritization in Italian airport pavements
[67]; 2019; Egypt	Fathalla, S.; El-Desouky, A.	Evaluation of pavement surface conditions for Luxor International Airport	Evaluating pavement surface condition at Luxor International Airport using PCI and Micro PAVER
[51]; 2018; Poland	Zieja, M.; Blacha, K.; Wesołowski, M.	Assessment method of the deterioration degree of asphalt concrete airport pavements	Estimating airport pavement deterioration using a multicriteria weighted assessment method
[68]; 2017; United States and Chile	Sahagun, L.K.; Karakouzian, M.; Paz, A.; Fuente-Mella, H.D.L.	An investigation of geography and climate induced distresses patterns on airfield pavements at US Air Force installations	Analyzing climate-induced distress patterns on U.S. Air Force airfield pavements
[69]; 2016; United States	Dabbiru, L.; Wei, P.; Harsh, A.; White, J.; Ball, J.E.; Aanstoos, J.; Donohoe, P.; Doyle, J.; Jackson, S.; Newman, J.	Runway assessment via remote sensing	Assessing runway surface roughness using microwave remote-sensing techniques
[70]; 2016; United States	Parsons, T.A.; Pullen, B.A.	Relationship between climate type and observed pavement distresses	Correlating climate regions with pavement distress types on USAF airfields
[71]; 2015; China	Ling, J.-M.; Du, Z.-M.; Yuan, J.; Tang, L.	Airfield pavement maintenance and rehabilitation management: Case study of Shanghai Hongqiao International Airport	Developing a decision-tree approach for maintenance and rehabilitation planning at Shanghai International Airport
[72]; 2013; United States	Graves, S.W.	Electro-optical sensor evaluation of airfield pavement	Integrating electro-optical FOD detection systems for pavement condition monitoring
[73]; 2004; Canada and Singapore	Huang, B; Fwa, T.; Chan, W.T.	Pavement-distress data collection system based on mobile geographic information system	Designing a mobile GIS-based data-collection system for airport pavement distress surveys
[74]; 2003; Singapore	Fwa, T.F.; Liu, S.B.; Teng, K.J.	Airport pavement condition rating and maintenance-needs assessment using fuzzy logic	Developing a fuzzy logic-based system for pavement condition rating and maintenance needs
[75]; 1992; United States	Rada, G.R.; Schwartz, C. W.; Witczak, M.W.; Rabinow, S. D.	Integrated pavement management system for Kennedy International Airport	Implementing an Integrated Airport Pavement Management System at John F. Kennedy Airport
[76]; 1992; United States	Hall, J.W.; Grau, R.W.; Grogan, W.P.; Hachiya, Y.	Performance indications from army airfield pavement management program	Evaluating pavement condition and maintenance alternatives for U.S. Army airfields
[77]; 1992; United States	Eckrose, R.A.; Reynolds, W.G.	Implementation of a pavement management system for Indiana airports—a case history	Developing a statewide Airport Pavement Management System for Indiana airports
[78]; 1991; United States	Beaucham, E.B.	Evaluating army airfields	Assessing pavement strength using nondestructive testing (FWD) and PCI evaluation
[53]; 1982; United States	Shahin, M.Y.; Kohn, S.D.	Airfield pavement performance prediction and determination of rehabilitation needs	Predicting airfield pavement performance and rehabilitation needs

Table 3. Research trend analysis: methodological scope.

Ref.; Pavement Type	Research Maturity/ Technical Focus	Inspection Method	Inspection Tools	Type of Pavement Distress
[7]; AC	Initial: data processing & analysis; change detection; pavement management	Traditional on-foot	Image recording, ruler	Cracking (alligator, LT, block, slippage); rutting; raveling; weathering; patching; bleeding; depression
[54]; AC and PCC	Intermediate: database; data processing & analysis; change detection; pavement management	Multifunctional vehicle	Automated Road Survey System (ARSS), Pavement Surface Imaging System (PSIS)	Cracking; raveling; weathering; corrugation; rutting; depression
[55]; AC and PCC	Intermediate: database; data processing & analysis; predictive modeling	Traditional on-foot	NDT/Geotechnical: rotary drilling rigs, automatic weather stations	Permafrost settlement; thermal and frost-related cracking; rutting; drainage distress; joint and edge deterioration
[44]; AC and PCC	Intermediate: database; data processing & analysis; validation study; pavement management	Traditional on-foot and UAV-based	UAV: DJI Mavic 2 Pro (RGB, 20 MP), 2 x M2EA (Quad Bayer RGB, 48 MP), FLIR thermal sensor, Bergen Hexacopter, Tarot X6 (Nikon D850, 45.7 MP), GPS tablets	Cracking (alligator, corner, block, LTD, D-cracking, shrinkage); joint damage; patching; spalling; popouts; scaling; shattered slabs; ASR; settlement/faulting; raveling; weathering; swelling; depression; shoving
[45]; AC and PCC	Advanced: database; data processing; change detection; pavement management	UAV-based	DJI Mavic 2 Enterprise Advanced (RGB, 48 MP/Thermal sensor)	Cracking (corner, LTD); shattered slabs
[46]; AC and PCC	Advanced: database; data processing & analysis; change detection; pavement management	UAV-based	High-resolution geospatial sensors	Spalling (joint/corner); joint seal damage; depression; raveling; weathering; swell; ASR
[47]; AC and PCC	Advanced: database; data processing & analysis; change detection	UAV-based	Silent Falcon platform	Cracking (block, joint, LT); rutting; raveling
[28]; PCC (virtual)	Initial: data processing & analysis	UAV-based virtual	AirSim simulated UAV (physical hardware: NVIDIA Jetson AGX Xavier)	Cracking; other minor surface distress
[56]; PCC	Intermediate: database; data processing & analysis; pavement management; validation study	UAV-based	DJI Mavic 2 Enterprise Dual (RGB/Thermal), DJI Pilot v2.5.1.10	Transverse cracking
[57]; AC and PCC	Initial: database; data processing & analysis; pavement management; validation study	Traditional on-foot	Not specified	Cracking (block, corner, LT, D-cracking; map); scaling; ASR; spalling
[32]; AC	Advanced: database; data processing & analysis; change detection; validation study; pavement management	UAV-based	Custom MAV Hexcopter (FLIR Duo Pro R camera, Mission Planner 1.3.74 software)	LT cracking; patching; rutting; raveling
[58]; PCC	Advanced: database; data processing & analysis; validation study; pavement management.	Multifunctional vehicle	Van-type vehicle, LCMS, HD camera	Cracking (block, LT); roughness; scaling; spalling

Table 3. *Cont.*

Ref.; Pavement Type	Research Maturity/ Technical Focus	Inspection Method	Inspection Tools	Type of Pavement Distress
[59]; PCC	Intermediate: database; data processing & analysis; change detection; validation study; pavement management	Traditional on-foot	Grayscale camera	Cracking, patching; repair marks
[60]; AC and PCC	Intermediate: Data processing & analysis; pavement management	Multifunctional vehicle	DAQ tools (handheld/ vehicle-based), control software (DAQ), lighting system, GPS	Not specified
[61]; AC and PCC	Initial: data processing; validation study	UAV-based	DJI Mavic 2 Enterprise Dual (RGB/Thermal), DJI Pilot application (version V01.00.0860)	Cracking (unspecified)
[62]; PCC	Initial: database; data processing & analysis; pavement management	Traditional on-foot	Not specified	Patching; joint damage; subsidence/faulting; punchout
[63]; PCC	Intermediate: database; data processing & analysis; pavement management; validation study	Multifunctional vehicle	3D LCMS, HD cameras, LiDAR (LDTM), AID-ITV (Integrated Testing Vehicle)	Not specified
[64]; AC	Intermediate: database; data processing & analysis; change detection; validation study; pavement management	Traditional on-foot and multifunctional vehicle	Measuring wheel, chalk/ruler, metallic structure, pickup vehicle, 20 mW laser beams, Garmin Elite video camera, GPS setup (Trimble 4000SSi, GeoXT), laptop	Cracking (alligator, LT); patching; weathering; raveling; depression
[65]; AC	Initial: database; data processing & analysis; pavement management	Traditional on-foot and NDT (HWD; GPR)	NDT: Dynatest HWD 8081, GPR (400 MHz antenna), ELMOD 6 software	Cracking (alligator, fatigue, block); raveling; patching; depression; rutting; corrugation; potholes
[49]; PCC	Initial: database; data analysis	Traditional on-foot	Not specified	Cracking (slotted, edge, corner); spalling; joint damage; scaling; deep cavities
[16]; AC	Initial: database; data analysis	Traditional on-foot	Not specified	Cracking, chipping; rutting; fracturing; raveling
[9]; AC	Initial: database; data processing & analysis; validation study; pavement management	Traditional on-foot and multifunctional vehicle (IRI)	Survey vehicle (tri-laser sensor system—one central, two lateral sensors)	Cracking (alligator, block, LT); patching; raveling; rutting; corrugation; depression
[66]; AC	Initial: database; data processing & analysis; pavement management	Traditional on-foot and multifunctional vehicle	Measuring wheel, chalk/ruler, metallic structure, pickup vehicle, 2 × 20 mW laser generators, Garmin Elite video camera, GPS setup (2 Trimble 4000SSi), laptop	Cracking (alligator, LT); patching; rutting; raveling; depression; corrugation
[50]; AC	Initial: database; data processing & analysis; validation study; pavement management	Traditional on-foot and multifunctional vehicle	Multifunctional vehicle (FWD; HWD, laser texture scanner, high-resolution cameras, crack scale, laser profilers)	Cracking (alligator, block, LT)

Table 3. *Cont.*

Ref.; Pavement Type	Research Maturity/ Technical Focus	Inspection Method	Inspection Tools	Type of Pavement Distress
[67]; AC and PCC	Initial: database; data processing & analysis; pavement management	Traditional on-foot	Not specified	Cracking (block, LTD, D-cracking, corner, shrinkage); depression; raveling; weathering; patching; oil spillage; polished aggregate; joint damage; scaling; spalling; ASR; popouts; bleeding
[51]; AC (implicit)	Initial: database; data analysis; pavement management	Traditional on-foot	Not specified	Distress and repair (types not specified)
[68]; AC and PCC	Initial: data analysis; pavement management	Traditional on-foot	Not specified	Cracking (alligator, corner, D-cracking, shrinkage, linear); raveling; joint damage; patching; scaling; shattered slab; spalling
[69]; AC	Initial: data processing & analysis; validation study	Remote sensing (SAR satellite + LiDAR)	SAR (TerraSAR-X, TanDEM-X, X-band), LiDAR (Leica ALS70), GPS (Leica 500 dual-frequency), DEM (Grafnet/Leica Office)	Not specified
[70]; AC and PCC	Initial: data analysis; validation study	Traditional on-foot	Not specified	Cracking (alligator, block, corner, D-cracking, joint reflection); bleeding; raveling; popouts; scaling; rutting; swelling; ASR
[71]; PCC	Initial: data analysis; pavement management	Not specified	Not specified	Cracking (transverse, corner); joint damage; spalling; popouts; scaling; patching
[72]; AC and PCC	Initial: database; data processing; validation study; pavement management	Traditional on-foot and electro-optical sensor	iFerret sensor system, standard camera, steel strips (simulated cracks), ImageJ software	LT cracking; joint spalling; patching; shattered slab; faulting
[73]; AC	Initial: database; data processing; pavement management	Traditional on-foot with mobile GIS (GPS/PDA-based)	PDA: DGPS receiver (Topcon Turbo G2), Spectec SD digital camera, mobile GIS (ArcPad), Pocket PC (Compaq iPAQ H3700)	Cracking; raveling
[74]; AC	Intermediate: data processing & analysis; pavement management	Traditional on-foot	Ruler and standardized forms	Cracking; potholes
[75]; AC and PCC	Intermediate: data processing & analysis; pavement management	Traditional on-foot	Ruler and standardized forms	Cracking; rutting; spalling
[76]; AC and PCC	Intermediate: data processing & analysis; pavement management	Traditional on-foot	Ruler, standardized forms, FWD/NDT	Cracking; rutting
[77]; AC and PCC	Intermediate: data processing & analysis; pavement management	Traditional on-foot	Ruler, standardized forms, APMS software	Cracking; raveling; rutting; spalling

Table 3. *Cont.*

Ref.; Pavement Type	Research Maturity/ Technical Focus	Inspection Method	Inspection Tools	Type of Pavement Distress
[78]; AC and PCC	Initial: data processing & analysis; pavement management	Traditional on-foot	Ruler, standardized forms, NDT	Not specified
[53]; AC and PCC	Intermediate: data processing & analysis; pavement management	Traditional on-foot	Ruler and standardized forms	Cracking (alligator, LT, block, joint reflection, edge); raveling; bleeding; patching; weathering

Abbreviation Key: ASR—Alkali Silica Reaction; D—Durability; DAQ—Data Acquisition; DEM—Digital Elevation Model; FWD—Falling Weight Deflectometer; HWD—Heavy Weight Deflectometer; IRI—International Roughness Index; LCMS—Laser Crack Measurement System; LDTM—Laser Dynamic Texture Measurement; LT—Longitudinal and Transverse; LTD—Longitudinal, Transverse and Diagonal; NDT—Non-Destructive Testing; PDA—Personal Digital Assistant; SAR—Synthetic Aperture Radar.

In addition to the methodological and technological dimensions synthesized in Tables 2–4, the studies also differ in the type and scope of pavement distresses addressed. The most frequently investigated distresses include longitudinal and transverse cracks, patches, bleeding, weathering, raveling, and plastic deformations such as depressions and rutting. These distresses are particularly critical for the safe and continuous operation of runways, as they directly affect structural performance, ride quality, and the risk of FOD. Early detection is therefore essential for implementing effective preventive maintenance strategies and ensuring the reliable management of airport infrastructure.

Notably, many studies employing advanced technologies, such as UAVs, machine learning, or integrated sensors, tend to concentrate primarily on visible cracking, as it is more easily identified in surface imagery. This focus is largely due to the fact that most automated segmentation and classification models are still trained on datasets centered around crack detection, with less attention given to more complex or less visually prominent distresses such as bleeding, patching, utility cuts, subtle plastic deformations, drainage deficiencies, or chemical reactions like alkali–silica reaction (ASR) and D-cracking.

This trend indicates that while advances in computer vision and remote sensing have enhanced the accuracy of detecting certain distress types, significant gaps remain in the automated detection of other critical categories. These limitations hinder the complete replacement of visual inspections and underscore the need for hybrid approaches that combine remote sensing with on-site technical analysis. Additionally, expanding training datasets and developing more inclusive models is necessary to better capture the full spectrum of pavement conditions.

As such, field validation of automated methods and the development of robust algorithms capable of addressing multiple defect classes are crucial next steps. For airport managers, this means carefully evaluating the technological maturity and contextual suitability of inspection systems before implementation.

This body of evidence lays a strong foundation for the deeper analysis of evaluation methods and emerging technologies presented in the following sections.

Table 4. Research trend analysis: advanced aspects.

Ref.	Data Processing Technique(s)	Accuracy	Statistical Analysis/ Validation	Big Data/ Volume	Quality Index	3D Modelling	AI
[7]	Not specified	-	Regression; standard deviation analysis; and scenario comparison	No: not specified	PCI CDF	-	-
[54]	GIS-based and PAVER	-	-	No: not specified	PCI	-	-
[55]	PAVER; statistical modeling; climatic and geotechnical data analysis	-	Correlation analysis between pavement distress and environmental factors; predictive modeling for deterioration trends	Yes: data from 4 airfields; climatic/ geotechnical data (no quantify)	PCI	-	-
[44]	Photogrammetry (Agisoft Metashape); DEM and hillshade generation; GIS-based spatial alignment; PCI calculation (FAA PAVEAIR)	Pearson correlation R = 0.79–0.90	PCI comparison (UAV-based vs. FOG) and correlation analysis	No: not specified	PCI	DEM; hillshade (3D surface view)	-
[45]	Image annotation (LabelImg); data augmentation; YOLOv8 (nano to large); Roboflow platform; Python-based image splitting	mAP50: 0.65–0.69; precision up to 0.74; recall up to 0.72	-	No: 5.273 images; high-resolution (8000 × 6000 px); real-time processing possible (nano/ small models)	-	-	DL with YOLOv8
[46]	AI (DL) and change detection software	-	Comparison with traditional methods (not specified)	Yes: data from over 100 airports (no quantity)	PCI	-	DL (not specified)
[47]	Orthorectification of images and 3D modelling	-	Correlation analysis between UAV-derived PCI and manual inspections	Yes: data from over 80 airports (no quantity)	PCI	Orthoimage; 3D modelling	-
[28]	DNN-based image segmentation (EfficientNet + Feature Pyramid Network—FPN)	F1-score; IoU; ODS; and OIS	Performance comparison on synthetic and real datasets	Yes: multiple public datasets (no quantity)	-	Unreal Engine 5 (virtual 3D simulation); DAQ	CNN
[56]	Orthoimage generation (Agisoft); image annotation/ labeling (Matlab Image Labeler); DL segmentation/ detection (Matlab DL Toolbox).	Detection performance evaluated using Precision, Recall, F1-score, AP, IoU, LAMR	-	No: 3.279 images	-	Orthomosaic (Agisoft Metashape); DEM; sparce/dense point cloud	YOLOv2; ResNet-50 (MATLAB)
[57]	RPC software developed by the authors; comparison with MicroPaver 5.3.2; and EPCM	R^2	Regression model (PCI vs. IRI) and coefficient of determination (R^2)	No: not specified	PCI; PSI/PSR-reg. (indirect data)	-	-

Table 4. *Cont.*

Ref.	Data Processing Technique(s)	Accuracy	Statistical Analysis/ Validation	Big Data/ Volume	Quality Index	3D Modelling	AI
[32]	Orthoimage generation (Agisoft); data augmentation; semantic segmentation (DeepLabV3+); IoU evaluation	≤94% GA and 0.72 IoU in distress detection	-	No: not specified	PCI	Orthoimage mapping; 3D-printed mount (SolidWorks CAD)	DeepLabV3 (CNN); ResNet-18/-50; Xception; Inception-ResNet-V2 (MATLAB)
[58]	LCMS data processing with MATLAB	R^2	Non-linear regression analysis (Levenberg- Marquardt); R^2 validation	Yes: 24.825 images	PCI; IRI	LCMS–3D surface profiling	-
[59]	DWT; semantic segmentation; channel attention mechanism; and feature fusion branch	CPA: 82.67%; IoU: 49.17% (best:69.96% for light, worst:11.59% for crack)	Model comparison: U-Net, DeepLabv3, DeepLabv3+, BiSeNet, BiSeNetv2; and ablation study	No: 3.467 images	-	-	CNNs: ResNet; MTSSN-WT; PyTorch; SGD
[60]	DL; GIS; and image processing software	-	-	Not specified	PCI; SCI	-	DL (not specified)
[61]	Digital photogrammetry (Agisoft); sparse/dense point cloud reconstruction; ortho-mosaic/DEM generation; MATLAB	MSE; RMSE; R^2; and adjusted R^2	Regression; theoretical vs. actual spatial resolution (GRD & GSD) validation	No: 3.361 images	-	Point cloud reconstruction; surface mesh; DEM	-
[62]	JSON-OBJ conversion; PCI view (color/height); WebGL and Three.js.	Not specified	-	Not specified	PCI	BIM (Autodesk Revit); parametric 3D modelling	-
[63]	Image stitching; GPS alignment correction; point cloud analysis; DI; PCI; export to Paver/XML and GIS/KML	Not specified	-	Yes: 50 units—LCMS and point cloud (moderate volume)	PCI	3D laser scan; point cloud data	-
[64]	GNSS-based image processing; GIS-based visualization; distress digitization; and PCI calculation	Strong correlation with on-foot inspection (R^2 = 0.8993)	Normal tests (Kolmogorov–Smirnov, Shapiro–Wilk), paired *t*-test; Wilcoxon signed-rank test; PCI; distress metric comparison (on-foot vs. vehicle)	No: 2.000 images	PCI	-	-
[65]	Back calculation (HWD/ELMOD 6); GPR thickness analysis; deflection bowl analysis; PCI calculation; and fuzzy AHP for section prioritization	-	-	No: 22.000 data points (HWD; GRP; on-foot inspection)	ACN/PCN; PCI; layer moduli-BC	-	-
[49]	-	-	-	No: not specified	PCI; APCI	-	-
[16]	-	-	-	No: not specified	PCI; APCI	-	-

Table 4. *Cont.*

Ref.	Data Processing Technique(s)	Accuracy	Statistical Analysis/ Validation	Big Data/ Volume	Quality Index	3D Modelling	AI
[9]	Regression; statistical significance testing; and residual analysis	High for PCI models (adjusted $R^2 \leq 88\%$); low for IRI models (data/fit issues)	Regression; hypothesis testing (*t*-test); residual analysis; model comparison; data interpolation	No: not specified	PCI; IRI	-	-
[66]	GNSS-based image processing; GIS-based visualization; distress digitization; and PCI calculation	PCI variation ≤ 5 points between methods	PCI comparison in-vehicle vs. on-foot inspections	No: 2.000 images	PCI	-	-
[50]	Back-calculation (HWD); laser-based ETD/PCI; chromatic mapping; profilograph analysis; MFV-based IRI, RUT, and skid resistance processing	Not specified	Based on reference thresholds	No: not specified	PCI; IRI; RUT; EDT; ACN/PCN	-	-
[67]	MicroPAVER 5.2 software	-	-	No: not specified	PCI	-	-
[51]	Statistical analysis with distress indices	Not specified	Histograms; regression; probability analysis (distress indices/condition classification)	No: not specified	Degree Index (D)	-	-
[68]	Statistical analysis and geostatistical modeling (kriging via ArcMap)	-	Weighted averaging; normalization; regression; hypothesis testing (t-/Mann–Whitney tests); comparison between zones; kriging; spatial trend analysis	Yes: 50.000+ distress records from 77 USAF installations	-	-	-
[69]	LiDAR-based DEM; TRI calculation; linear and polynomial regression	$R^2 \leq 0.46$ (radar vs. TRI)	Regression; R^2 as fit metric; correlation analysis (radar backscatter vs. TRI; validated with ground-truth LiDAR)	No: high- resolution data with localized scope	TRI	DEM from LiDAR-based	-
[70]	PAVER database and statistical analysis	-	ANOVA; main effect analysis; interaction effect analysis	Yes: 17.565 extrapolated records from >435 k distresses data points	-	-	-
[71]	Not specified	-	-	No: not specified	PCI	-	-
[72]	Image processing: background subtraction, image subtraction, feature measurement (RGB error, pixel sizing, contrast plots)	-	PCI manual comparison; image inspection; and crack simulation with physical targets	No: 39 slabs analyzed; simulated images (iFerret)	PCI	-	-
[73]	Real-time GPS conversion; chainage mapping; spatial indexing; GIS query	Location accuracy ≈ 0.5 m (DGPS)	-	No: not specified	PCI	-	-

Table 4. *Cont.*

Ref.	Data Processing Technique(s)	Accuracy	Statistical Analysis/ Validation	Big Data/ Volume	Quality Index	3D Modelling	AI
[74]	Fuzzy logic inference system (fuzzifier, rule engine, defuzzifier); decision rules	-	No; only expert review	No: not specified	PCI	-	-
[75]	Database-driven PMS with forecasting and analysis tools; GIS integration	-	-	No: not specified	PCI	-	-
[76]	PCI vs. age trends; core evaluation; decision criteria	-	No; qualitative comparisons (PCI vs. age trends; core–design; method-based decisions)	No: not specified	PCI	-	-
[77]	PCI-based condition scoring; capital improvement program via software; forecasting	-	-	No: not specified	PCI	-	-
[78]	Not specified	-	-	No: not specified	PCI	-	-
[53]	Empirical modeling with PCI methodology (precursor to PAVER)	-	-	No: not specified	PCI	-	-

Abbreviation Key: ACN/PCN—Aircraft/Pavement Classification Numbers; AHP—Analytic Hierarchy Process; AP—Average Precision; APCI—Airfield Pavement Condition Index; BC—Backcalculation of layer moduli; BiSeNet—Bilateral Segmentation Network; CDF—Cumulative Damage Factor; CNN—Convolutional Neural Network; CPA—Class Pixel Accuracy; DAQ—Data Acquisition; DEM—Digital Elevation Model; DL—Deep Learning; DI—Distress Quantification Index; DWT—Discrete Wavelet Transform; EDT—Effective Depth of Texture; ELMOD—Evaluation of Layer Moduli and Overlay Design; EPCM—Evaluation of Pavement Condition Model; FOG—Fiber Optic Gyroscope; GA—Global Accuracy; GRD—Ground Range Detected; GSD—Ground Sample Distance; HWD—Heavy Weight Deflectometer; IoU—Intersection over Union; IRI—International Roughness Index; JSON-OBJ—JavaScript Object Notation; LAMR—Log-Average Miss Rate; LCMS—Laser Crack Measurement System; LDTM—Laser Dynamic Texture Measurement; MFV—Mean Feature Vector; MSE—Mean Squared Error; MTSSN-WT—Multi-Task Semantic Segmentation Network with Wavelet Transform; ODS—Optimal Dataset Scale; OIS—Optimal Image Scale; PCI—Pavement Condition Index; PSI—Present Serviceability Index; PSR-reg.—Pavement Surface Rating (regression); ResNet—Residual Network; RMSE—Root Mean Squared Error; RPC—Rating of Pavement Condition; RUT—Rutting index; R^2—Coefficient of Determination; SCI—Structural Condition Index; SGD—Stochastic Gradient Descent; TRI—Terrain Ruggedness Index; WEB-JL—Web-based Joint Locator; YOLO—You Only Look Once.

4.3. Discussion

4.3.1. Airport Pavement Inspection Methods

The systematic review summarized in Table 2 reveals a wide range of pavement evaluation approaches, reflecting varying levels of technological sophistication and research maturity. Based on the inspection methods adopted, the studies were grouped into three main methodological categories:

1. Traditional on-foot inspection, still predominant in early-stage research [7,9,16,43,48–50,52,54,56,58,61,63–67,69,71–77];
2. Vehicle-mounted systems, including LCMS, LiDAR, and optical sensors [9,50,54,58,60,63,64,66,69,72];
3. Unmanned Aerial Vehicles (UAVs), which dominate recent studies [28,32,44–47,56,61].

The following subsections explore these approaches in greater detail, highlighting their practical applications, limitations, and recent developments.

Most studies still rely on traditional on-foot visual inspection, especially in exploratory research or initial diagnostics [7,51,53]. However, a notable increase is observed in the use of advanced technologies, such as multifunctional vehicles and UAVs equipped with high-resolution sensors, RGB cameras, LiDAR, and LCMS, reflecting a pursuit of greater efficiency, safety, and accuracy in data collection [44–46,64].

The Pavement Condition Index (PCI), standardized by ASTM D5340 [38], remains the primary functional condition indicator used to quantify the overall state of airport pavements. Based on visual inspections of surface distresses, it provides a numerical score representing the pavement's general condition and is widely adopted by international authorities such as the Federal Aviation Administration (FAA) and the International Civil Aviation Organization (ICAO). Large-scale studies, such as that by Covalt et al. (2017) [79], demonstrate its robustness and reliability, applying it in statistical analyses across thousands of airport runways in the United States.

Functional evaluation methods have diversified beyond the traditional PCI, incorporating indicators such as the International Roughness Index (IRI), the Airfield Pavement Condition Index (APCI), and composite indices developed through multicriteria decision-making techniques [9,16,49,50,57,58]. This expansion seeks to overcome PCI's limitations in detecting early-stage functional issues and to integrate broader performance parameters.

Recent studies have also begun to consider extreme climatic conditions, such as runways located in polar regions or subject to freeze–thaw cycles [55]. A study by the United States Air Force (USAF), based on more than 17.000 PCI records, demonstrated significant correlations between climatic zones (such as cold-dry climates) and specific types of distress, such as frost cracking [70]. This underscores the importance of incorporating geoclimatic variables into predictive models.

Thus, manual methods are gradually giving way to semi-automated and fully automated solutions based on remote sensing, computational intelligence, and spatial data, promoting more efficient and evidence-based airport pavement management.

On-Foot Visual Inspection

Traditional on-foot visual inspections account for a significant portion of the studies included in the systematic review (Table 2). This approach consists of direct observation of surface distresses by trained inspectors, who manually record distress types, severity levels, and extent.

Approximately 40% of the reviewed studies adopt this method, relying on basic equipment such as rulers, digital cameras, measuring wheels, and manual PCI forms [7,51,53,57,64,66,74–78]. These studies primarily focus on small to medium-sized airports, where the availability of embedded technologies remains limited, reflecting the widespread use of this approach in operational contexts with budgetary or technological constraints.

In addition to its standalone use, traditional visual inspection has increasingly been integrated with digital tools and semi-automated analysis methods. Classic studies such as Huang et al. (2004) [73] introduced data collection systems using PDAs with GPS and digital cameras, embedded in mobile GIS platforms, enabling georeferenced recording of distresses with real-time spatial indexing during on-foot inspections.

Furthermore, the studies of Frye (2024) [55] and Parsons & Pullen (2016) [70] examined the influence of climate on pavement deterioration using large datasets collected through on-foot visual inspections, reaffirming the ongoing relevance of this method as a primary data source for systems like PAVER, and as a benchmark for validating and improving emerging automated techniques [55,70].

Complementarily, Graves (2013) [72] explored the use of fixed electro-optical sensors such as iFerret to continuously capture pavement surface imagery, later processed via segmentation and contrast enhancement software, partially automating the interpretation of visual distresses. This type of research illustrates the early steps toward hybrid and automated inspection systems, bridging traditional visual methods with the more advanced vehicle-mounted platforms discussed below.

While effective for localized or structural assessment, these methods face limitations in scalability, dependence on inspector judgment, and reduced operational efficiency in large airport environments.

Multifunctional Vehicle Inspection

With advances in embedded systems, vehicle-mounted inspection platforms have become increasingly prominent in airport pavement evaluation. These multifunctional vehicles, often equipped with high-resolution sensors, cameras, GNSS systems, and integrated processing units, enable continuous and automated data collection along runways. As a result, inspection time is significantly reduced and personnel exposure to operational areas is minimized.

Among the most used technologies are Laser Crack Measurement Systems (LCMS), LiDAR, and high-definition cameras, typically coupled with differential GPS. These tools enable detailed 3D surface mapping and the detection of cracks, depressions, rutting, corrugations, and other surface distresses. The collected data is frequently processed using software such as Agisoft Metashape, MATLAB (Matrix Laboratory), or MicroPAVER, generating accurate indicators such as PCI and IRI [54,57,58,63,64].

Studies by Cereceda et al. (2022) and Hafiz et al. (2021) show that the use of LCMS, cameras, and LiDAR sensors facilitates objective distress quantification with less subjectivity, while also supporting 3D analyses and GIS-based visualization [58,63]. For example, Santos et al. (2020) [64] developed a low-cost system combining embedded lasers and cameras, validated through comparison with manual inspections, achieving high correlation (R^2 > 0.89) and PCI variation under five points.

Integrated data acquisition and analysis platforms such as the AID-ITV (Automated Integrated Distress—Inspection and Testing Vehicle) have also been implemented in recent studies. These systems enable faster and safer inspections, particularly on long or high-traffic runways. Automated data collection and spatial visualization contribute to the continuous updating of pavement management systems, integrating historical records and enabling temporal performance analysis [63].

Beyond operational efficiency, vehicle-mounted technologies offer improved statistical reliability in pavement assessments. The combination of sensors and algorithms allows for more accurate pattern recognition, facilitating intervention prioritization based on objective criteria. The growing adoption of these systems reflects a clear trend toward replacing traditional visual inspection with hybrid or fully automated methods, especially in medium and large airports, where scalability is a key requirement [54,58,64].

UAV-Based Inspection

In parallel with multifunctional ground vehicles, aerial platforms based on Unmanned Aerial Vehicles (UAVs) have emerged as a complementary and increasingly prominent solution for airport pavement inspection. The systems enable the rapid, safe, and wide-area collection of high-resolution georeferenced imagery, making them particularly useful in hard-to-access zones or high-traffic airports [44–47,56].

Most recent studies classified as having intermediate or advanced research maturity employ UAVs equipped with high-definition RGB cameras, thermal sensors, and GNSS systems [28,44–47,56]. Combined with digital photogrammetry and Digital Elevation Model (DEM) generation, these platforms support the accurate detection of cracks, depressions, patches, and structural failures.

Studies by Sourav et al. (2024) [44,45], McNerney et al. (2023) [47], and Maslan & Cicmanec (2023) [56] demonstrate that data collected via UAV systems can be used to estimate the PCI with strong correlation to traditional visual inspections. Some approaches integrate UAV imagery with deep learning (DL) models capable of automatic image segmentation and distress classification, either in real-time or during post-processing [28,45,56].

Notable examples include the application of advanced algorithms such as YOLOv2, YOLOv8, DeepLabV3+, and EfficientNet-FPN, which have achieved global accuracy levels above 90% and Intersection over Union (IoU) scores exceeding 0.70 [28,32,45,56,59]. For instance, Alonso et al. (2023) [28] validated Convolutional Neural Networks (CNNs) trained on both real and simulated datasets generated using Unreal Engine and AirSim, demonstrating their generalizability across different environmental conditions.

Moreover, UAVs equipped with edge computing units, such as those based on the NVIDIA Jetson AGX Xavier, have enabled real-time distress detection during flight, significantly improving inspection efficiency. This capability is especially valuable in time-sensitive scenarios, such as post-event assessments or intensive maintenance regimes [28].

Despite their potential, UAV adoption still faces challenges. Onboard edge processing units such as the Jetson AGX Xavier remain costly, power-intensive, and difficult to integrate with small UAV platforms, limiting their use mainly to experimental or high-budget contexts. Broader barriers include airspace regulations, sensor calibration, workflow standardization, and battery autonomy, which restrict long-duration or large-area missions [28,44–47,56]. Nevertheless, the growing adoption of UAVs and continued advancements in hardware and algorithms indicate that this technology is poised to become a central component of modern airport pavement maintenance and management programs.

4.3.2. Functional and Structural Indexes

Beyond data acquisition technologies, a key dimension of functional inspection lies in the indices used to quantify pavement condition. Around 80% of the studies analyzed use the PCI as the primary indicator of functional condition, confirming its dominance in current pavement maintenance practices. The PCI's standardization has provided a consistent model for performance comparison across airports, supporting uniform maintenance criteria and long-term infrastructure investment planning [9,50,58,79].

MicroPAVER plays a central role in this context, as it enables PCI calculation based on standardized methodologies, while also allowing historical tracking of pavement conditions over time. This makes it a strategic tool for integrated management and decision-making in airport maintenance programs [57,67].

Complementarily, approximately 12% of the reviewed studies apply the International Roughness Index (IRI), typically in conjunction with the PCI, especially for evaluating ride quality and operational safety [9,50,58,79]. Carvalho & Santos (2019) [9] emphasize that functional issues such as longitudinal irregularities may not be adequately captured by the PCI and are better assessed using the IRI, which is based on dynamic measurements of the longitudinal surface profile. Studies such as those by Cereceda et al. (2022) [58], Di Mascio & Moretti (2019) [50], and McNerney et al. (2023) [47] confirm the value of combining IRI with PCI in contexts characterized by heavy traffic, adverse climatic conditions, or severely distressed surfaces.

Other indices have been proposed to address specific contexts. The Airfield Pavement Condition Index (APCI), used in about 5% of the cases, incorporates operational safety parameters and is particularly suited for rigid pavement applications [16,49].

Finally, less than 10% of the studies explore composite or multicriteria approaches, mostly in experimental or early-stage research. These methods, based on fuzzy logic, the Analytic Hierarchy Process (AHP), or other soft computing techniques, combine functional, structural, and environmental variables. Their advantage lies in enabling more comprehensive assessments adapted to the operational reality of each airport, supporting robust and evidence-based decision-making for maintenance prioritization [65,69,74].

Overall, while the PCI continues to dominate due to its standardization and global adoption, the literature indicates a gradual diversification toward complementary and hybrid indices. This evolution reflects the search for more nuanced, reliable, and context-specific evaluation metrics capable of guiding airport pavement management in increasingly complex operational environments.

4.3.3. Emerging Technologies in Pavement Inspection

Building on the methodological transition outlined in the previous sections, from on-foot visual inspection to automated and integrated approaches, several emerging technologies have significantly expanded the scope and effectiveness of airport pavement functional inspection. This expansion is clearly demonstrated by the studies analyzed in Tables 3 and 4.

In terms of data acquisition, there has been a growing use of electro-optical sensors, high-resolution cameras, and mobile platforms integrated with GIS/GPS, which enhance measurement accuracy and reduce operational errors. These solutions have proven especially effective in large-scale or high-traffic airport environments, enabling safer, faster, and more comprehensive inspections [63,64,66,72,73].

At the same time, advances in data processing have been strongly driven by Deep Neural Networks (DNNs) and other Machine Learning (ML) algorithms, which have enhanced the ability of inspection systems to detect, classify, and predict distress patterns with high accuracy and scalability. The integration of real-world datasets with simulated synthetic data has increased model robustness, representing a milestone in the evolution of automated pavement evaluation [9,28,32,45,56,59].

Complementarily, 3D simulation environments have been employed to train algorithms and test inspection scenarios under controlled conditions. Notable examples include the use of Unreal Engine 5 and AirSim, combined with edge computing hardware like the Jetson AGX Xavier. These systems replicate realistic conditions for data collection and classification workflows, offering a safe and efficient framework for algorithm training [28].

In parallel, pavement management systems (PMS) have evolved into intelligent platforms that integrate distress models, historical records, and predictive simulations. Studies such as Kareem & Ibraheem (2023) [57] and Di Mascio & Moretti (2019) [50] highlight the development of these systems, while more recent approaches have incorporated interactive

3D visualizations using Building Information Modeling (BIM) and WebGL, expanding spatial diagnostic capabilities and decision support [62].

These innovations directly address several limitations inherent in traditional methods, including reliance on on-foot inspection, limited scalability, and difficulties in detecting less visible distresses. Collectively, these emerging technologies represent a new frontier in data-driven, proactive airport pavement management, enabling not only more accurate diagnostics but also the integration of continuous historical, geospatial, and operational data streams into intelligent decision-support platforms.

Data Processing

Data processing has become a central component in recent airport pavement management methodologies, especially with the widespread adoption of automated data collection technologies via UAVs, multifunctional vehicles, and embedded sensors. The transformation of raw data and imagery into interpretable information is critical for ensuring accurate, consistent, and scalable infrastructure assessments.

Among the most common techniques used are digital photogrammetry, orthophoto generation, point cloud reconstruction, and Digital Elevation Modeling (DEM), widely applied in both UAV-based and multifunctional vehicles. Software tools such as Agisoft Metashape are frequently used to reconstruct parametric 3D surface models of pavement structures, supporting detailed mapping and the identification of surface distresses [28,32,44,56].

In more advanced applications, imagery is processed through semantic segmentation techniques powered by deep learning architectures. Algorithms such as DeepLabV3+, EfficientNet-FPN, and detectors like YOLOv2 and YOLOv8, along with CNNs, are used to automate distress classification based on visual patterns, delivering high spatial and semantic accuracy [28,32,56]. These approaches have shown strong performance in detecting surface cracking and other types of distress. For instance, Pietersen et al. (2022) [32] achieved an IoU of 0.72 and global accuracy of 94% using DeepLabV3+, while Maslan & Cicmanec (2023) [56] reported average precision (AP) up to 0.89 using YOLOv2, along with high F1-scores for transverse cracking. Similarly, Alonso et al. (2023) [28] obtained consistent F1-score, ODS, and OIS values by applying EfficientNet with FPN across both real and simulated datasets.

Beyond image analysis, the integration of geospatial data into GIS platforms enables spatial visualization (e.g., thematic maps), correlation with historical maintenance records, environmental conditions, and functional zoning of runway sections, enhancing contextual analysis. Studies such as Huang et al. (2004) [73] and Li et al. (2022) [60] illustrate how georeferenced positioning, when combined with structured digital databases, supports more complete diagnostics and strategic maintenance planning.

Tools such as PAVER and MicroPAVER remain in use, particularly within traditional workflows or in low-automation environments [55,70]. Meanwhile, more advanced systems, such as BIM and WebGL-based rendering libraries, have been integrated into pavement management platforms to simulate distress, visualize their progression over time, and support maintenance prioritization [62].

Some studies apply classical statistical models, such as linear regression, ANOVA, and multivariate modeling, for predictive purposes or to validate new inspection methods. Examples include Santos et al. (2020) [64], who used linear regression to correlate PCI values resulting from traditional visual inspection with those obtained from multifunctional in-vehicle inspection data, and Carvalho & Santos (2019) [9], who applied ANOVA to assess the statistical significance of differences between manual and digital inspection methods. Other works explore multivariate models combined with composite indices derived from fuzzy logic methods, such as the Fuzzy Condition Index and Maintenance Needs Index, which integrate multiple functional and operational criteria to estimate pavement performance and prioritize maintenance under various operating conditions [74].

In addition to regression and ANOVA, other studies employ statistical group comparison tests, such as paired *t*-tests, Mann–Whitney, and Wilcoxon tests, particularly to validate significant differences between traditional and automated inspection methods. For instance, Santos et al. (2020) [64] used *t*-tests and Wilcoxon tests to compare the results of traditional on-foot inspections and multifunctional vehicle-based assessments, while Sahagun et al. (2017) [68] applied the Mann–Whitney test to evaluate regional variations in distress manifestations. These nonparametric tests are especially valuable when data do not follow a normal distribution or when sample sizes are limited, making them essential for reinforcing the statistical validity of research findings.

Despite these contributions, relatively few studies rigorously apply intermediate or advanced statistical techniques, highlighting a critical gap in the literature that limits the generalizability of results. In engineering contexts, the reliability of conclusions depends directly on the robustness of the data and the validity of the analytical methods employed. The absence of thorough quantitative validation compromises not only the practical application of new automated methods but also their comparability across different inspection frameworks [14,28,30]. The consistent adoption of validation methods is not only desirable, but essential to ensure the scalability, reliability, and operational relevance of proposed models [14,28,30,64].

In parallel, other authors have explored computational intelligence, based decision support techniques such as fuzzy logic, AHP, and soft computing, with a focus on pavement section prioritization for maintenance and rehabilitation, while considering multiple criteria simultaneously. They offer a more technically grounded basis for prioritization, especially when decision criteria span multiple dimensions and degrees of uncertainty [65,69,74]. Based on the studies summarized in Table 4, Table 5 presents the main data processing and validation techniques identified, grouped by their technical nature and observed frequency of use.

Table 5. Data processing techniques by technical type and frequency of use.

Technique Type	Data Processing Techniques	Frequency
Geometric and visual techniques	Photogrammetry/Orthoimage/DEM	High
	Georeferencing and spatial indexing	Moderate
AI and computer vision techniques	Deep learning (e.g., CNNs, YOLO, etc.)	High [1]
	Semantic segmentation (e.g., DeepLab, FPN, etc.)	High
Statistical and model-based methods	Basic statistical modeling (e.g., linear regression)	Moderate
	Advanced and intermediate statistical modelling (e.g., multivariate analysis, ANOVA, etc.)	Low
	Fuzzy logic/Soft computing/AHP	Moderate
	PAVER/MicroPAVER/GIS	High [2]

[1] Rapidly growing in recent years, especially in advanced-level studies; [2] Commonly used in early-stage or traditional inspection frameworks.

The information in Table 5 reinforces the recent growth of techniques based on artificial intelligence and computer vision, reflecting a trend toward modernization in the field. These findings also confirm the points discussed earlier and help contextualize the transition to more advanced approaches, such as those based on Big Data.

Big Data and Artificial Intelligence (AI)

Recent advancements in airfield pavement inspection and data processing have increasingly integrated Big Data principles and AI-driven analytics, not as stand-alone tools, but as core components of comprehensive decision-support systems. Rather than focusing solely on the detection of visible surface damage, these approaches enable the identification of long-term distress patterns by leveraging heterogeneous datasets, including geospatial, climatic, operational, and historical variables.

As illustrated in Figure 11, which is based on the studies of Kitchin & McArdle (2016), Younas (2019), Ishwarappa & Anuradha (2015), and Geerts & O'Leary (2022) [80–83], Big Data is characterized by the "5 Vs": volume, variety, veracity, velocity, and value. Each of these characteristics poses specific challenges and opportunities for pavement management applications.

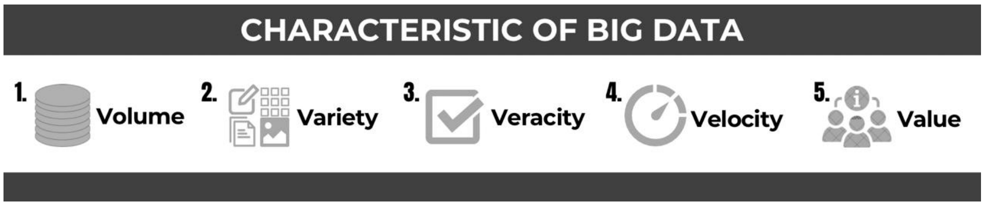

Figure 11. The 5 vs. of Big Data, adapted from [80–83].

Volume refers to the massive scale of data, typically ranging from terabytes to petabytes. Variety encompasses the diversity of formats and sources, including structured, semi-structured, and unstructured data. Veracity concerns the reliability and quality of the data, requiring the mitigation of noise, inconsistencies, and uncertainty. Velocity relates to real-time or high-frequency data generation, as seen in sensor networks, IoT devices, or continuous data streams. Finally, value reflects the potential to extract meaningful and actionable insights from these data sources [80–83].

Based on the analysis of the studies included in the systematic review (Table 2), only about 15% of the publications exhibit characteristics consistent with a Big Data framework, typically involving UAVs with georeferenced sensors, geotechnical sensor networks, high-volume aerial imagery, or integrated historical pavement databases. These studies stand out due to their broader geographic scope, multimodal data integration, and the application of predictive models and machine learning with enhanced generalizability [47,55,57,70].

Most studies, however, rely on small or moderate-sized samples that do not fully meet Big Data criteria. Although these studies may be scalable in theory, they often lack clear reporting on data volume, which hinders cross-study comparisons and compromises result reproducibility.

Table 6 summarizes a classification framework adapted from Ishwarappa & Anuradha (2015) and Geerts & O'Leary (2022) [82,83], tailored to the context of airport pavement inspection.

Table 6. Data processing techniques by technical type and frequency of use, adapted from [82,83].

Category	Size Criterion	Scope
Small data	≤1.000 records/images	Pilot studies, tests, spot inspections
Moderate data	1.000 to 10.000 records/images	Local or single-task datasets
Large data	10.000 to 100.000 records	Regional studies, multivariate models
Big Data	>100.000 records or featuring the 5Vs [1]	Integrated sources, sensor networks, real-time data, high variety

[1] 5Vs—Volume, Velocity, Variety, Veracity, Value.

Based on the classification framework proposed in Table 6, most of the studies listed in Table 4 fall into the "small data" or "moderate data" categories, typically relying on datasets of 2.000 to 5.000 images or a few dozen physical samples. Some more advanced works reach up to 25.000 images, which is substantial for computer vision tasks, particularly when high-resolution imagery and manual labeling are involved [28,32,56]. However, the lack of source diversity, extended temporal series, and operational integration limits their classification as true Big Data applications. In many cases, essential metadata fields, such as dataset volume, are either marked as "no" or "not specified" in Table 4. This lack of transparency restricts the ability to assess methodological robustness and undermines the comparability and generalization of findings across studies.

Studies based on synthetic or simulated data also do not meet Big Data criteria. For instance, Graves (2013) [72] used only 39 physical samples and a small set of simulated images with the iFerret system. While the study employed sophisticated computational techniques, it did not significantly expand the actual volume of data for analytical purposes.

Although currently a minority, the use of Big Data in airport pavement inspection is expected to grow, driven by the digitalization of inspection processes, integration of GIS platforms, onboard sensors, and external databases such as climate records [83]. This expansion is also fueled by the demand for robust, context-aware predictive models capable of linking environmental conditions to distress patterns or simulating pavement life cycles based on historical performance data [70].

In parallel, approximately 30% of the studies included in this review already incorporate artificial intelligence [28,32,59]. However, most of these models still operate in controlled environments or rely on limited datasets, which restricts their ability to generalize across different pavement types, environmental conditions, or operational scenarios.

Deep learning methods—particularly CNNs, YOLO-based object detection models, and semantic-segmentation architectures such as DeepLab and Feature Pyramid Networks (FPN)—have become central to modern automated pavement-distress detection. These approaches enable high-precision visual feature extraction and are capable of identifying small-scale surface anomalies from both aerial and ground-based imagery.

In broader applications of airport pavement inspection, YOLO-based detectors and semantic-segmentation methods (e.g., DeepLab, FPN) have achieved detection accuracies above 90% in controlled scenarios [84–87]. These methods offer significant advantages, including automated feature extraction, scalability to large datasets, and adaptability to heterogeneous pavement conditions. However, their performance remains affected by limitations such as dependence on large annotated datasets, sensitivity to illumination and surface variability, and the need for specialized hardware for real-time processing [28,45,56,86].

CNNs remain the backbone of most AI-based visual-inspection pipelines in the reviewed literature, particularly for identifying cracking patterns, surface defects, and distress severity. Their integration with UAV platforms and ground-based systems is expanding the potential for real-time, autonomous inspection workflows supported by onboard sensors and edge-computing devices.

To date, none of the studies included in this review implement a fully integrated AI pipeline encompassing all stages—automated data acquisition and detection, model training/validation/test, cross-validation, and operational deployment within airport pavement management systems. This gap highlights the need for more robust end-to-end frameworks to ensure technological scalability and real-world applicability.

4.3.4. Results Achieved in Terms of Cost, Time, Accuracy, and Complexity

In addition to the methodological and technological innovations discussed earlier, the systematic review reveals significant differences in practical outcomes, particularly in terms of operational cost, execution time, method accuracy, and implementation complexity.

Studies with low or intermediate maturity levels typically rely on traditional, low-cost methods such as on-foot visual inspections, handheld digital photography, and software tools like MicroPAVER and GIS [7,44,57,67]. Although these approaches have low implementation costs, since they require minimal equipment, they incur high operational costs due to the extensive field time and labor needed to manually document distresses. This reliance on human judgment also increases subjectivity and reduces reproducibility, further elevating indirect costs—particularly when frequent inspections are required.

In contrast, modern solutions using UAVs, LiDAR, and LCMS demand higher initial investment but lead to substantial long-term operational savings, particularly in large airports. These systems minimize the need for runway closures, increase inspection frequency, and reduce manual effort, improving preventive maintenance cycles [32,44,45,47,63,64].

In terms of time efficiency, automated methods significantly outperform traditional ones. Technologies such as multifunctional vehicles and UAVs enable data collection in hours instead of days, even on large-scale or high-traffic runways.

Accuracy varied according to the technique. Approaches based on AI and computer vision, especially those using deep learning and semantic segmentation, demonstrated high performance metrics such as overall accuracy, IoU, and F1-score, outperforming traditional methods in reproducibility and generalization [28].

Some studies applied basic statistical validation methods like linear regression and correlation analysis (R^2) [9,64]. However, the use of advanced statistical validation techniques, such as multivariate analysis or cross-validation remains limited, which weakens the generalizability of proposed models.

Finally, implementation complexity correlates with the technological level and required infrastructure. Tools like MicroPAVER remain common due to standardization and simplicity, despite scalability limitations. Advanced methods involving AI, 3D modeling, GIS integration, and embedded sensors offer greater analytical potential but demand specialized hardware and technical expertise, which still limits adoption in smaller or resource-constrained airports.

To provide a clearer understanding of the relative performance of the main inspection technologies, a quantitative comparison was conducted considering both technical and economic parameters. These include the initial investment required for equipment, sensors, and software, as well as recurring operational costs related to field deployment, personnel, maintenance, and data processing. Combined with technical indicators such as ground resolution, inspection speed, crack-detection performance, and required field time per kilometre, these dimensions offer a comprehensive view of the trade-offs among the available pavement-inspection solutions. The main quantitative differences across technologies, based on approximate ranges derived from the studies listed in Tables 2–4, are summarised in Table 7.

The results indicate that vehicle-mounted LCMS and UAV-based platforms provide substantially higher spatial resolution and faster acquisition rates compared with on-foot visual surveys, reducing field time by more than an order of magnitude. LCMS vehicles achieve high precision with only 8–12 min required to survey 1 km of pavement, while UAVs typically require 15–25 min per kilometre for RGB photogrammetry and 20–30 min for LiDAR-based acquisition. In contrast, on-foot PCI surveys may require 3–4 h per kilometre, limiting scalability in large airfields.

UAV-based approaches, particularly when combined with deep-learning segmentation models such as YOLOv8 and DeepLabV3+, achieve F1-scores between 0.81 and 0.90 and IoU values around 0.70–0.75, closely matching the accuracy obtained from vehicle-mounted systems but at significantly lower operational cost. Multifunctional vehicles remain advantageous for high-traffic or large-runway environments due to their stability, multisensor integration, and high measurement consistency, whereas UAVs offer superior flexibility and access to constrained or obstructed areas.

Table 7. Quantitative comparison of airport pavement inspection technologies in terms of resolution, accuracy, cost, and efficiency.

Technology/Platform	On-Foot Visual	Multifunctional Vehicle	UAV (RGB)	UAV (LiDAR)	AI/DL Pipeline
Main Sensors	Digital camera, ruler, GPS	LCMS + RGB + DMI + GNSS	RGB 20–100 MP	LiDAR + RGB + GNSS + SAR	CNN/YOLO/DeepLab/FPN pipelines
Typical Ground Resolution (mm/pixel)	0.5–1.0 [9,16,50,59,64,66,77]	Transverse laser resolution ≈ 1 mm; depth ≈ 0.5 mm; profile spacing ≈ 150 mm [58,63]	1.0–3.0 (consolidated) 0.7–7.3 [44]; 1.5 [46]; 6.4–8.6 [56]; High-res RGB [28,45]	5.0–10.0 mm UAV LiDAR (point spacing); (SAR: ~500 mm/pixel; airborne Lidar: ~180 mm) [69]	Varies according to dataset [28,32,56,59]
Average Inspection Speed (km/h)	0.25–0.35 [9,16]	10.0–15.0 [58]	3.0–6.0 [28,44]	Minor fix 3.0–5.0 km/h (consistent with UAV LiDAR surveys) [69]	Depending on image acquisition platform
Crack Detection (F1/IoU)	–	–	F1 = 0.81–0.90 [28,32,56]; IoU = 0.70–0.75 [28,32]	–	F1 = 0.81 [56]; IoU = 0.72 [32]; Acc > 90% [28,45]
Correlation with PCI (R^2)	–	$R^2 \approx 0.89$ [63]	$R^2 \approx 0.79$–0.90 [44]	–	–
Implementation Costs (10 km)	Low	High	Medium	High	Medium-High
Operational Cost (10 km)	High	Medium	Low	Medium	Low
Field Time (1 km)	6–10 h [9,16]	8–12 min [58,63]	15–25 min [28,44–46,56]	20–30 min [69]	–
Notes/Key Limitations	Subjectivity; operational disruption	High accuracy, high upfront cost	Limited battery; regulatory constraints	High cost; superior 3D data	Depending on dataset & validation protocol

On-foot inspection, while still valuable for calibration, ground truthing, and validation of automated methods, demonstrates limited reproducibility and high operational cost due to the extensive field time required. The incorporation of AI pipelines further enhances detection performance and automation potential, although final accuracy remains dependent on dataset representativeness, annotation quality, and cross-validation strategies.

Overall, automated inspection technologies provide marked improvements in efficiency, safety, and data consistency. Although they require higher initial investment, these costs are offset by substantially reduced field time and operational expenditure over repeated inspections.

5. Conclusions and Future Directions

This review highlights a clear methodological shift in airport pavement functional inspection, characterized by the gradual replacement of traditional visual methods with automated, intelligent, and data-driven approaches. While manual techniques remain widely used, especially in small airports, their limitations in accuracy, execution time, and reproducibility are becoming increasingly evident.

Emerging technologies such as UAVs, LiDAR sensors, LCMS, and AI-based models have shown significant improvements in in-situ operational efficiency and surface distress detection. Recent studies using deep learning, digital photogrammetry, and statistical modeling have reported accuracy levels above 90% and IoU scores exceeding 0.7, demonstrating the technical maturity of these solutions.

While still in an early stage within the airport sector, the convergence of Big Data and AI holds high transformative potential. As digitalization accelerates and historical pavement datasets expand, it will become feasible to deploy evidence-based predictive maintenance models, enabling more accurate, proactive, and adaptive decision-making.

Nevertheless, the large-scale adoption of these emerging technologies faces significant barriers, including high implementation costs, the need for specialized workforce and technical infrastructure, and a lack of standardized validation protocols. Moreover, there is a shortage of studies with representative samples and rigorous statistical validation, which limits model generalizability and undermines result reliability.

In this context, two paradigms coexist: traditional methods, which are accessible and simple but limited in performance and scalability; and emerging methods, which are more accurate, agile, and analytically advanced, yet require greater investment, technical capacity and robust statistical validation. Ensuring a gradual transition between these paradigms remains the key current challenge.

To support this evolution, the following future directions are proposed:

- Methodological standardization, through the development of integrated protocols covering data collection, processing, and validation, particularly for AI-based methods, where heterogeneous practices hinder result comparability.
- Gradual and hybrid adoption of technologies, combining well-established traditional methods with low-cost automated solutions. This strategy enables scalable transitions, allowing airports with technical or budgetary constraints to progressively adopt innovations.
- Strengthening statistical validation, through robust inferential testing and cross-validation, to ensure reliable, generalizable, and replicable results.
- Integration of Big Data sources to enhance AI applications, enable more accurate predictive modeling, and support better-informed decisions.
- Customization of inspection solutions, tailored to local operational and budgetary contexts.

The future of airport pavement management will depend on the ability to align technological innovation with practical feasibility, fostering proactive, scalable, and evidence-based systems. Achieving this balance will be essential to ensuring the long-term safety, efficiency, and sustainability of airport infrastructure.

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