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Comprehensive Review and Analysis of Soiling Detection Technologies in Solar Panels

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ABSTRACT

Soiling, defined as the accumulation of dirt, dust, and other particles on the surface of photovoltaic (PV) panels, is a significant issue that substantially impacts solar panel efficiency and performance. This accumulation leads to energy losses and decreased electricity output. Numerous research papers have proposed various systems to address this issue. This paper provides a comprehensive review of recent publications on soiling detection in solar panels. The review methodology includes literature retrieval, screening, content analysis, and bibliometric analysis, utilizing the Scopus database to compile a final selection of 75 papers. This review identifies gaps in previous research, such as the need for more robust and cost-effective detection systems and the integration of emerging technologies like artificial intelligence and remote sensing. Key findings highlight that deep learning models and advanced sensor technologies show promising results in improving soiling detection accuracy. The review also suggests potential areas for future work, emphasizing the development of innovative inspection tools, models, and cleaning systems that can enhance efficiency and reduce operational costs.

1. INTRODUCTION

In recent years, the global demand for energy has significantly increased. Various power sources have been utilized to meet our daily energy needs, with fossil fuels being the predominant source [1]. However, the environmental impact and finite nature of fossil fuels have necessitated the search for more efficient and sustainable alternatives. Renewable energy sources, particularly solar energy, present a promising solution. Solar energy, harnessed through photovoltaic (PV) systems, offers a clean and virtually infinite power source. This renewable energy not only helps mitigate the environmental issues associated with fossil fuels but also enhances energy security by reducing dependence on finite resources [2].

Several factors have driven the adoption of solar energy, with climate change being the foremost reason. Greenhouse gas emissions and other pollutants from fossil fuel sources are major contributors to climate change. Solar energy can significantly reduce these emissions and mitigate climate change effects since it does not produce greenhouse gases or involve combustion processes. Consequently, solar energy can enhance air quality and public health. Additionally, solar energy contributes to energy security by providing an abundant and consistent supply, reducing reliance on centralized power plants, and improving global energy markets. As the solar energy industry grows and becomes more competitive, its economic advantages are increasingly compelling. The cost of solar technology is becoming more affordable compared to fossil fuels. Furthermore, solar energy offers environmental benefits by conserving land. Unlike traditional energy production, which involves extensive mining and drilling, solar panel installation requires minimal land disruption, helping preserve ecosystems [3].

Despite the significant benefits of solar panels, several challenges can arise, with soiling being one of the most impactful issues. Soiling is defined as the accumulation of dirt, dust, bird droppings, tree branches, snow, and other particles on the surface of PV panels. This accumulation can severely affect the efficiency and performance of solar panels by obstructing sunlight absorption and electricity generation. Soiling generates losses in energy efficiency and decreases electricity output, often underestimated and neglected despite its profound impact. Dust accumulation creates a barrier that prevents the smooth flow of sunlight through PV panels, resulting in reduced light capture and energy conversion. The economic and environmental repercussions of soiling are also significant. Reduced energy production leads to financial losses and necessitates an increased number of solar panels to meet energy demands, thereby requiring more manufacturing processes that impact the environment. Additionally, the buildup of soiling increases the need for frequent maintenance and cleaning of solar panels [4]. Despite advancements in soil detection, certain challenges remain. Many existing detection systems struggle with accuracy under varying environmental conditions, making them less reliable for real-world applications. Additionally, high costs and maintenance requirements limit the adoption of traditional technologies, especially in large-scale solar farms. However, emerging technologies such as deep learning and remote sensing offer promising solutions. These innovations have the potential to overcome current limitations by improving real-time detection, reducing operational costs, and enabling predictive maintenance. Moreover, integrating these advanced techniques with automated cleaning systems could help eliminate the gap between detection and proactive mitigation. This review explores these advancements, highlights their potential, and identifies areas for further development to enhance the efficiency and sustainability of solar energy systems.

This review paper addresses a critical challenge in the solar energy industry. The objective of this review paper is to provide a comprehensive analysis of existing soiling detection technologies for solar panels. Specifically, it aims to identify the most effective tools, evaluate emerging technologies such as artificial intelligence and remote sensing, and highlight research gaps that can inform future advancements. The methodology employed for this review includes literature retrieval, literature screening, content analysis, and bibliometric analysis, utilizing the Scopus database to compile a final selection of 75 papers. The paper identifies key findings, highlights gaps in existing studies, and offers valuable recommendations, making it an essential resource for researchers and practitioners. The paper seeks to answer key research questions, including:

1. What are the most accurate, cost-effective, and widely applicable tools for detecting soiling on solar panels?
2. How do deep learning and machine learning improve soiling detection, and what are their limitations?
3. What key challenges remain in soil detection, and what advancements are needed to improve accuracy and practicality?

By addressing these questions, this review advances the field of soiling detection on solar panels by providing a comprehensive analysis of existing technologies, identifying research gaps, and highlighting emerging solutions. Unlike previous studies, it integrates findings from 75 publications to compare diverse detection methods, including sensor-based systems, AI-driven models, and satellite imaging. By emphasizing the potential of machine learning and real-time monitoring, this study offers insights into improving detection accuracy, reducing maintenance costs, and optimizing solar panel performance. It serves as a valuable resource for researchers and industry professionals, guiding future developments toward more efficient and scalable soiling detection solutions.

The subsequent sections of this paper are structured as follows: First, the methodology employed in selecting the research papers is described, including the criteria and processes used. Second, a comprehensive content analysis is presented, outlining the current state of research, key findings, and insights from previous studies, and identifying research gaps that suggest potential areas for further investigation. This is followed by a detailed bibliometric analysis to examine different research focuses and other relevant details. Finally, the key findings are highlighted, and recommendations are provided to guide future work in the field of soiling detection on solar panels.

2. METHODOLOGY

The methodology in this study follows a systematic process to collect and analyze recent research. A Scopus search was conducted to retrieve relevant studies, followed by bibliometric analysis using VOSviewer to identify key research trends, influential studies, and emerging topics. Finally, content analysis categorized the 75 selected papers into Inspection Tools, Models, and Cleaning Systems, allowing for a structured synthesis of methodologies and findings. This approach ensures a comprehensive, structured and up-to-date assessment of advancements in soiling detection research. It contains four main steps, as defined below:

2.1 Literature retrieval

This step involves the initial stage of selecting appropriate search terms and keywords to gather relevant research papers and publications. A systematic literature review was conducted using Scopus, employing various keywords such as "soiling detection solar," "soiling concentration solar," "dust detection solar," "dust concentration solar," and others. Scopus was used as our primary database because it is one of the most comprehensive and widely recognized academic databases, which covers a wide range of high-quality journals and conference proceedings in engineering, energy, and environmental sciences. Its extensive collection of peer-reviewed publications ensures that our review captures all significant research on soiling detection. Therefore, this process resulted in a total of 683 papers, covering the years 2000 to 2023.

2.2 Literature screening

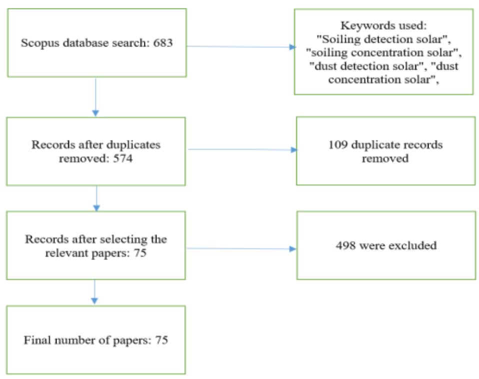

Figure 1. Literature screening approach

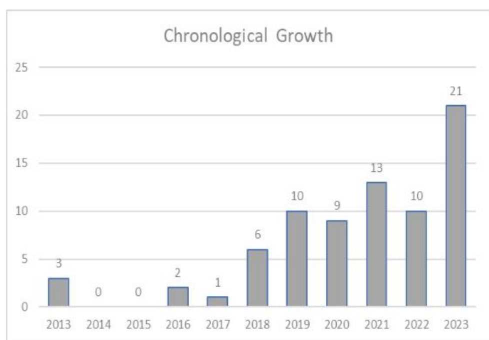

Figure 2. The chronological span of years

The PRISMA statement [5] is utilized in the following step to provide a structured framework for identifying and selecting relevant literature. Initially, a total of 683 papers were identified. After removing duplicates, the count was reduced to 574 papers. Further screening for direct relevance to the topic of soiling detection on solar panels narrowed the selection to 75 papers, with 498 papers being excluded. Each paper was manually reviewed to ensure its relevance, with the inclusion criteria focusing on studies that specifically addressed soiling detection techniques, technological advancements, and their impact on PV performance. Papers that lacked a direct focus on soiling detection, addressed unrelated aspects of solar energy, or provided insufficient technical details were excluded. This thorough screening process enhances transparency and ensures that the selected papers contribute meaningfully to the review. Figure 1 illustrates this selection process. The remaining 75 papers were then classified into three sections: Inspection Tools, Models, and Cleaning Systems. Figure 2 presents the chronological distribution of the selected papers, highlighting the increasing interest and research activity in soiling detection over recent years. This trend underscores the growing importance of this area in the context of enhancing solar panel efficiency and performance.

2.3 Bibliometric analysis

Bibliometric analysis was conducted to systematically evaluate the structure of research in soil detection by analyzing citation patterns, keyword occurrences, and co-authorship networks. Using VOSviewer software, visual representations were generated to highlight key research themes, influential authors, and emerging topics. This approach enabled a deeper understanding of research trends and relationships among various studies by:

- Identifying influential works through citation counts and co-citation networks, determining the most referenced studies in the field.
- Mapping research trends by examining keyword co-occurrence, which helps visualize commonly studied topics and gaps in the literature.
- Analyzing collaboration patterns through co-authorship networks, providing insights into global research contributions and partnerships in soil detection.

The advantage of bibliometric analysis is that it offers quantitative insights into the research landscape, allowing for an objective identification of dominant themes, key contributors, and emerging directions. Additionally, visualized bibliometric maps provide a structured way to observe relationships between studies, guiding future investigations and fostering collaboration. This method also helps highlight emerging topics and research gaps, ensuring that ongoing studies align with industry needs and technological advancements.

2.4 Content analysis

In addition to bibliometric analysis, content analysis was conducted to gain a qualitative understanding of the reviewed studies and systematically categorize key findings. This approach enabled a structured examination of the 75 selected papers, organizing them into three main themes:

- Inspection Tools: Technologies and methods used to detect soiling accumulation on solar panels.
- Models: Statistical, empirical, and AI-based approaches for analyzing and predicting soiling impact.
- Cleaning and Mitigation Systems: Strategies designed to minimize soiling effects and optimize solar panel efficiency.

The research papers in this review were systematically categorized into three key themes: Inspection Tools, Models, and Cleaning Systems to provide a structured and comprehensive analysis of soiling detection and mitigation. These themes were chosen based on a thorough examination of existing literature, ensuring that they capture the core aspects of soiling detection research. This classification ensures a holistic approach, covering detection, analysis, and mitigation, which are the fundamental pillars of soiling research.

By classifying research into these themes, content analysis provided a clear framework for understanding various approaches and their role in soil detection and mitigation. Each study was carefully examined to extract key methodologies, findings, and limitations, enabling researchers to:

- Identify research gaps, such as the need for more cost-effective, real-time soiling detection methods.
- Compare different methodologies, evaluating their advantages, limitations, and applicability under various environmental conditions.
- Highlight technological trends, particularly the increasing role of AI, remote sensing, and automated cleaning in soiling detection.

The advantage of the content analysis is that it offers a structured qualitative synthesis, allowing for a comprehensive comparison of existing detection tools, models, and cleaning systems. This method facilitates the identification of patterns and common themes, helping researchers understand the evolution of soiling detection technologies and guiding future advancements in solar panel efficiency and performance.

3. BIBLIOMETRIC ANALYSIS

In this section, an in-depth bibliometric analysis focusing on the field of soiling detection on solar panels is provided. A comprehensive understanding of current innovations in this field is aimed at by examining a wide collection of articles and publications extracted from the Scopus database. Valuable insights into the methods used for detecting soiling on solar panels are sought through systematic literature screening and data analysis. VOSviewer was used to generate a detailed analysis of the current state of soiling detection on solar panels. Five types of visualization maps were produced to offer a clear understanding and analysis of the topic. These maps include circles representing different items such as terms and publications. The level of activity associated with each item is indicated by the size of the circle and the font used. Larger circles and bigger font sizes signify higher levels of activity, while smaller circles and fonts indicate lower levels of activity. The degree of association between any two terms is shown by the distance between them in the diagram; shorter distances represent stronger correlations, and longer distances indicate weaker correlations.

For the bibliometric analysis, VOSviewer was primarily used to generate co-occurrence networks and visualizations of research trends in soiling detection on solar panels. In addition to VOSviewer, Microsoft Excel was employed for data processing and trend analysis, allowing for deeper statistical evaluation of citation patterns. The analysis considered key parameters such as co-authorship networks to identify prominent researchers, citation counts to determine influential works, and keyword occurrences to highlight key research areas. The selection of influential works was based on citation impact, relevance to the field, and recurring themes in soil detection methodologies. Additionally, a co-occurrence analysis of keywords and index terms was performed to map emerging trends and research gaps.

To analyze key research trends and relationships in soiling detection, a co-occurrence network was constructed using terminology extracted from the titles and abstracts of the reviewed publications. The process involved several systematic steps to ensure accuracy and relevance. First, the dataset of 75 selected papers was processed using VOSviewer software, which automatically identified and extracted frequently occurring keywords and terms. Next, duplicate and irrelevant terms were filtered out to maintain a high-quality dataset. The refined set of terms was then analyzed to establish co-occurrence relationships, where terms appearing together frequently in multiple publications were linked, revealing key thematic connections. Finally, a visual network map was generated, grouping terms into clusters based on their thematic relevance. This method provided valuable insights into the main research focuses, emerging topics, and knowledge gaps in soiling detection, offering a structured representation of the field's development over time.

3.1 Co-occurrence map based on text data

Text data from a total of 75 selected publications was analysed to identify relevant occurring terms. Terms from the titles and abstracts of these publications were extracted to construct a co-occurrence network, linking related terms. A total of 2,114 terms were found, out of which 35 terms met the minimum threshold of 10 occurrences. Additionally, VOSviewer calculated a relevance score for each term to further refine the selection. The top 60% of the most relevant terms were chosen, resulting in 21 terms displayed in the network shown in Figure 3.

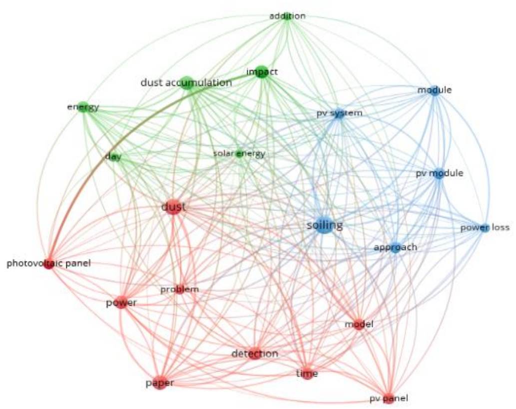

Figure 3. Co-occurrence map based on text data

The findings presented in Figure 3 illustrate the extensive scope of research within the topic of soiling detection on solar panels. This research encompasses various areas, including dust accumulation, PV systems, and power loss. The figure highlights the relationship between soiling and detection, providing insights into the application of detection systems for identifying soiling on solar panels. Additionally, the association between soiling and terms such as "model" underscores the implementation of different models, such as machine learning and deep learning, in detecting soiling on solar panels. The impact of soiling on solar panels raises concerns about power loss and its effect on PV systems, emphasizing the importance of analyzing how different types of soiling can affect the operation of solar panels.

3.2 Co-occurrences map based on keywords

To extend the analysis, frequently occurring keywords from the 75 selected publications were identified. A total of 849 keywords were gathered, with 35 keywords meeting the minimum threshold of 5 occurrences. The analysis included all keywords, encompassing both index keywords and author keywords. Figure 4 illustrates the co-occurrence map of these keywords, providing a visual representation of the relationships between them.

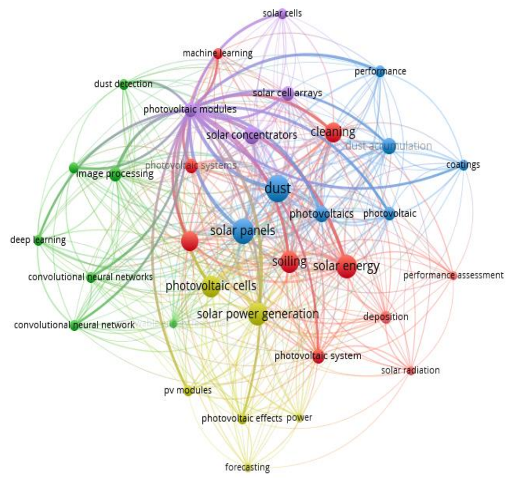

Figure 4. Co-occurrences map of all keywords

The co-occurrence map in Figure 4 highlights the interconnectedness of various research themes within the field of soiling detection on solar panels. By visualizing the frequency and connections of keywords, the map offers insights into prevalent research areas and the intensity of their interrelations. This visualization helps in understanding the primary focus areas and the breadth of research topics explored in the selected publications. The larger circles, such as those for "dust," "solar panels," and "solar energy," indicate a higher frequency of occurrence, reflecting their central role in this research field. The shorter distances between terms such as "dust," "solar panels," and "cleaning" demonstrate strong correlations, suggesting that these topics are frequently discussed together in the literature.

3.3 Co-occurrence map based on country of co-authorship

In addition, the analysis was expanded by examining the geographic distribution of the publications. Figure 5 visualizes the country co-authorships, setting a minimum number of documents per country at 3. Out of the 43 countries with publications, 12 met this threshold. This map highlights the collaborative relationships between countries in the field of soiling detection on solar panels.

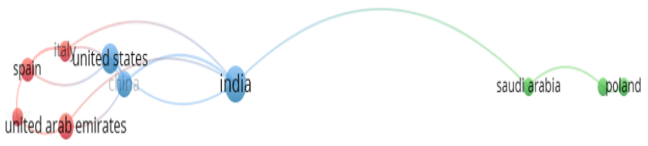

Figure 5. Country of co-authorships

Figure 5 illustrates the international collaboration among researchers in the field of soiling detection on solar panels. The map reveals that India is at the center of multiple co-authorship links, indicating its significant role in fostering international research partnerships. The United States, Spain, and the United Arab Emirates also show strong collaborative ties, reflecting their active engagement in this research area. Additionally, the links connecting India to Saudi Arabia and Poland demonstrate a diverse range of international cooperation, emphasizing the global nature of efforts to address soiling on solar panels. This visualization underscores the importance of cross-border collaborations in advancing research and developing innovative solutions for soil detection.

3.4 Co-occurrence map based on authorship

To further extend the analysis, a network was generated to investigate authorship relationships. The map was created by setting a minimum threshold of 7 citations per author. Out of the 309 authors, 151 met this threshold. Figure 6 shows the resulting network visualization, with the largest set of connected authors consisting of 13.

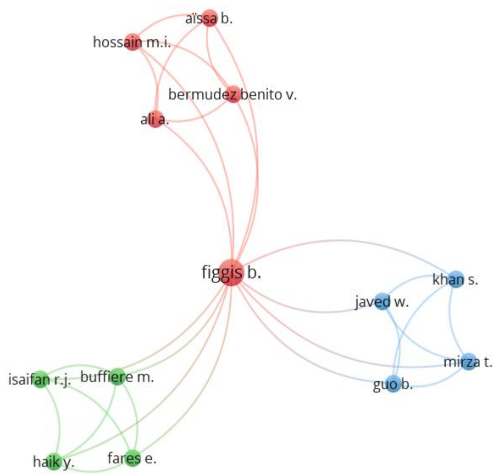

Figure 6. Co-occurrence map of authorship

Figure 6 visualizes the interconnectedness among authors in the field of soiling detection on solar panels. The network demonstrates the collaborative nature of research in this area, highlighting how researchers from diverse educational backgrounds and expertise come together to advance the field. The co-occurrence map offers valuable insights into the main contributors, research trends, and potential collaboration opportunities within the community. It also emphasises the dynamic exchange of knowledge facilitated by these collaborations.

3.5 Data analysis on article sources

A detailed analysis was conducted on the sources of the 75 selected publications, with a unique list compiled and ordered by the number of articles from each source. The sources with the highest number of articles were "Energies" and the "IEEE Journal of Photovoltaics," each contributing five publications. Figure 7 presents a bar graph reflecting the top 10 sources by the number of publications, illustrating the distribution of research across various journals and proceedings. This visualization highlights the significant contributions from sources such as "Solar Energy Materials and Solar Cells," "Solar Energy," and "Applied Energy," indicating a focused interest in renewable energy and PV technologies. The diverse range of sources also suggests a multidisciplinary approach to the research, integrating insights from electrical engineering, materials science, and applied energy sectors. By examining these top sources, a clearer understanding of the key journals and conferences driving the discourse in this field is achieved, providing researchers with insights into potential publication venues for their future work. This analysis underscores the importance of journals like "Energies" and the "IEEE Journal of Photovoltaics," reflecting strong contributions to energy-related and PV research, respectively, and highlighting the integration of advanced computational methods and materials science in solar energy.

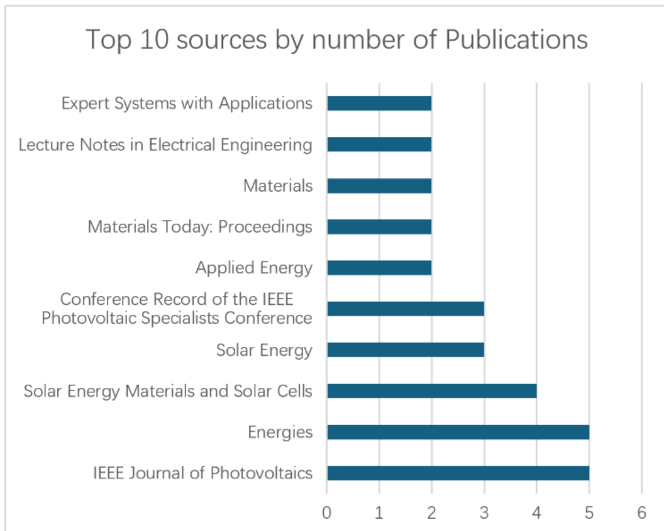

Figure 7. Bar graph reflecting the top 10 sources by number of publications

3.6 Data analysis on document type

In this section, 75 publications were classified according to their document type. Figure 8 presents a bar graph depicting the distribution of different document types, as extracted from Scopus. The analysis reveals that the most common type is "Article," with 36 occurrences, followed closely by "Conference paper" with 34 occurrences. Additionally, "Review" appears three times, while "Book chapter" is represented only once. Lastly, one paper was classified as "Document type." This categorization underscores the prevalence of primary research articles and conference papers in the field, highlighting the importance of both detailed studies and the dissemination of preliminary findings through conference presentations.

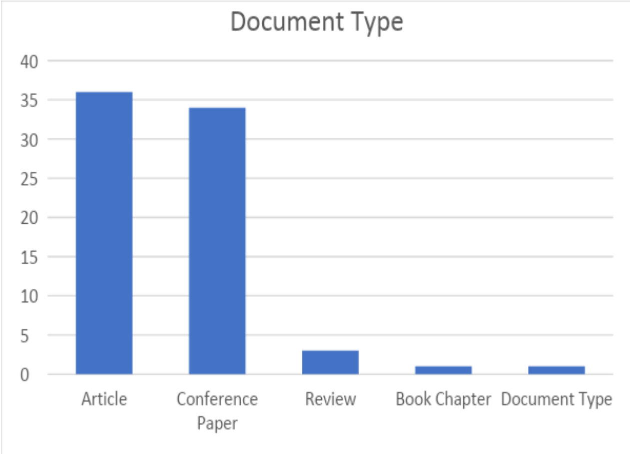

Figure 8. Occurrences of different document types

4. CONTENT ANALYSIS

Significant attention has been garnered by the detection of soiling on solar panels due to its critical impact on the efficiency and performance of PV systems. Various inspection tools and models have been developed and studied, offering promising methods to enhance the effectiveness of solar energy generation. In this section, a comprehensive content analysis of the field is provided, examining the latest advancements, tools, and models used for soil detection. Key findings are highlighted, research gaps are identified, and insights are offered to drive future developments in improving solar panel efficiency and sustainability.

4.1 Inspection tools

In this section, the various inspection tools utilized to detect different forms of soiling on solar panels are explored. The effectiveness of solar panels can be significantly compromised by soiling, making the development and utilization of precise detection tools essential. A wide array of technologies has been employed, including digital and thermal cameras, advanced sensor systems, and drones. By examining these tools, their capabilities, advantages, and limitations in addressing the challenges posed by soiling are understood. A detailed classification of the reviewed papers is provided in Table 1, highlighting the main focus and methodologies employed in each study, thereby offering a comprehensive overview of the current state of research in this critical area.

Table 1. Inspection tools

Theme	Types	Authors	Year	Focus
Inspection tools	Camera	El Ydrissi et al. [6]	2023	Implementing RGB camera images with CNN to detect and measure soiling on solar mirrors.
		Cavieres et al. [7]	2022	Capturing stationary RGB images and applying an ANN to quantify PV power loss from soiling and shading.
		Fan et al. [8]	2022	Applying image analysis to identify uneven dust accumulation and classify dust distribution.
		Abuqaaud and Ferrah [9]	2020	Proposing a computer vision method to classify PV panels as clean or dirty.
		Onim et al. [10]	2022	Developing a CNN-based SolNet architecture for dust detection from camera images.
		Ayyagari et al. [11]	2022	Investigating high-resolution image classification with ML to detect and categorize dust on PV arrays.
		Sriram and Sudhakar [12]	2023	Employing thermal imaging to detect soiling without physical inspection.
		Cardinale-Villalobos et al. [13]	2021	Applying UAV infrared and RGB imaging to detect soiling and shading.
		Zhang et al. [14]	2021	Proposing a SolarQRNN model with surveillance camera images to estimate power loss.
		Tribak and Zaz [15]	2019	Designing an image-processing system with an HD camera to quantify dust concentration and power loss.
		Hwang et al. [16]	2020	Applying AI and RGB images to detect soiling on PV modules.
		Hajar et al. [17]	2023	Developing a YOLOv5-based system for monitoring soiling on PV panels.
		Aji et al. [18]	2023	Creating a smart image-processing system for panel cleaning optimization.
		Saquib et al. [19]	2020	Proposing an ANN model to predict PV power output from image-based analysis.
		Qasem et al. [20]	2016	Employing UAV images under varied lighting to detect dust and optimize PV plant operation.
		Hanafy et al. [21]	2019	Applying ML to terrestrial and aerial UAV images to classify PV cleanliness.
		Czarnecki and Bloch [22]	2022	Using drone video and statistical classifiers to detect and classify PV soiling.
		Hwang et al. [23]	2023	Implementing UAV RGB images with ML for monitoring soiling and planning cleaning schedules.
	Sensors	El Ydrissi et al. [6]	2023	Applying a reflectometer sensor to calculate mirror reflectivity.
		Saquib et al. [19]	2020	Combining a voltmeter, an ammeter, and LDR sensors to predict PV power output.
		Narvios and Nguyen [24]	2021	Proposing an IoT-based system with dust, temperature, and humidity sensors for monitoring soiling.

	Abid et al. [25]	2018	Designing an ACS712-based automatic and periodic PV monitoring system.
	Bodnár et al. [26]	2019	Measuring temperature, voltage, and current to study contaminants' effect on power generation.
	Chockalingam et al. [27]	2023	Integrating multiple sensors with IoT to detect localized hotspots.
	Mehmood et al. [28]	2023	Deploying low-cost sensors with IoT and cloud architecture for soiling monitoring.
	Olorunfemi et al. [29]	2023	Designing an Arduino-based dirt detection and robotic cleaning control system.
	Azouzoute et al. [30]	2021	Employing a pyranometer and meteorological sensors to assess the dust effect on glass transmittance.
	Kavya and Keshav [31]	2018	Applying Arduino with current and voltage sensors to evaluate the soiling impact and cleaning needs.
	Kampira et al. [32]	2022	Using PM, humidity, and electrical sensors to measure soiling impact on PV performance.
	Mohammed et al. [33]	2018	Designing an Arduino-based dust monitoring and cleaning system.
	Ghodki [34]	2022	Introducing a robotic arm using IR sensors for dust removal.
	Soedibyo et al. [35]	2021	Proposing a fuzzy logic model with dust, temperature, and electrical sensors.
	Micheli et al. [36]	2020	Applying a spectrophotometer to estimate soiling transmittance spectra.
	Singh and Rizwan [37]	2023	Using detectors and sensors to predict PV power/irradiation from dust levels.
	Guo et al. [38]	2016	Developing linear and semi-physical models using DustTrak® data for PV cleanness index (CI).
	Sharma et al. [39]	2023	Comparing models on dust mass accumulation impact on PV performance.
	Jaszczur et al. [40]	2019	Identifying deposition parameters via PM2.5/PM10 concentration measurements.
	Skomedal et al. [41]	2019	Applying a pyranometer and temperature sensors to quantify soiling rates.
	Caron and Littmann [42]	2013	Using monitoring stations to study dust impact with irradiance and weather sensors.
	Lopes et al. [43]	2019	Implementing a tracking cleanliness sensor to measure mirror reflectance.
Satellite information	Supe et al. [44]	2020	Applying Google Earth Engine indices and satellite data to detect sand accumulation.
	Silva et al. [45]	2023	Combining NASA satellite and weather data to estimate PV soiling.
	Esposito et al. [46]	2023	Comparing ground irradiance with satellite data to assess soiling.
Visual inspection	Yadav et al. [47]	2021	Employing a stereoscopic microscope to examine dust deposition and cleaning effects.
Scanner	Islam et al. [48]	2021	Designing MOSFET-based I–V scanner to analyze shading and soiling impacts.

Table 1 presents an overview of various inspection tools used for detecting soiling on solar panels, emphasizing their usage, benefits, and findings from multiple studies. Digital and thermal cameras, as well as cameras mounted on unmanned aerial systems (UAS), have been extensively used. Digital cameras capture high-resolution RGB images for soiling detection and measurement through image processing techniques, while thermal cameras detect temperature differences to identify soiling, useful in low-light conditions. UAS-mounted cameras enable remote and comprehensive area coverage. Additionally, a variety of sensors, including reflectometers, dust sensors, temperature and humidity sensors, and voltage and current sensors, have been employed to collect real-time data on soiling and environmental conditions. These sensors provide high precision and accuracy but can be limited by specific environmental conditions. Other tools, such as satellite information from NASA and COPERNICUS, offer remote sensing and frequent updates but can be hindered by weather and data processing complexities. Visual inspection tools, like the Magnus stereoscopic microscope, are cost-effective but prone to human error. I-V scanners provide quantitative performance data under various soiling conditions but require regular maintenance. Together, these tools offer a comprehensive approach to soiling detection on solar panels, each contributing unique strengths and facing specific limitations.

Table 2 offers a detailed summary of the various types of cameras utilized for soiling detection on solar panels, emphasizing their respective advantages and disadvantages [49]. Digital cameras offer clear visual inspection and high-resolution images, which are essential for accurately measuring soiling accumulation. They are non-invasive but may be limited in low-light conditions and can be costly. This type of camera was used in 12 papers. Thermal cameras are known for their sensitivity to temperature differences, making them effective in low-light and nighttime conditions. However, they have reduced spatial resolution. This type of camera was used in two papers. Drones equipped with cameras, such as UAS and UAV, provide excellent accessibility and remote sensing capabilities, covering wide areas without requiring physical access to the panels [50]. Despite their advantages, drones face weather limitations and limited battery life. Cameras on drones were featured in five papers.

Table 3 summarizes the findings related to the use of various sensors for detecting different elements on solar panels. Each type of sensor has been evaluated for its advantages and disadvantages, highlighting their effectiveness in different scenarios [51]. Dust sensors, used in 23 papers, are noted for their precision and accuracy in measuring the level of dust accumulation on PV panels. However, they can be costly. Temperature and humidity sensors are employed to monitor ambient conditions, which can impact the performance and soiling rate of solar panels. Voltage and current sensors collect data on the electrical performance of PV panels, providing valuable insights into the impact of soiling on energy output. Reflectometer sensors measure the reflectivity of solar mirrors, helping to quantify the extent of soiling. TCS3200 color sensors are used for color measurement and calibration, aiding in the detection of dust and other contaminants. Light-dependent resistor (LDR) offers the ability to provide real-time data on light intensity, although they may suffer from damage and have a limited lifespan. Other sensors, such as limit switch sensors, CMP21 Pyranometers, Campbell Scientific CS215 sensors, and NRG #40C Anemometers, are used to measure various environmental and operational parameters. Spectrophotometers measure the transmittance of soiled glass, helping to estimate the impact of soiling on light absorption. The findings from these sensors contribute to a comprehensive understanding of soiling detection and its impact on solar panel performance. Each sensor type brings unique strengths and limitations, emphasizing the need for a multi-faceted approach in soiling detection strategies.

Table 2. Summary of the findings of the camera usage

Usage of Camera				
	Types of cameras	Advantages	Disadvantages	Number of papers
Camera	A digital camera stationary camera HD camera surveillance cameras	-Clear visual inspection -High resolution -Non-invasive	-Limited in low light conditions -Can be costly	12
Thermal camera	Thermal camera	Sensitivity to temperature differences	Reduced spatial resolution	2
	UAS with thermal camera	Works in low light and at night	Initial cost	
Drones with camera	UAS	Accessibility	Weather limitations	5

Table 3. Summary of the findings of the sensor's usage

Usage of Sensors			
Types of sensors	Advantages	Disadvantages	Number of papers
Dust sensor temperature and humidity sensor Voltage sensor Current Sensor Reflectometer sensor TCS3200 colour sensor	Precision and accuracy	Cost	23
LDR Limit switch sensor CMP21 Pyranometer Campbell Scientific CS215 sensor NRG #40C Anemometer spectrophotometer	Ability to provide real-time data	Damage and limited lifespan	

Table 4. Summary of the findings of using satellite information, visual inspection and I-V scanner

Usage of Satellite Information			
Sources of information	Advantages	Disadvantages	Number of papers
NASA Copernicus	Frequent data update Remote sensing	Weather limitations Data processing complexity	3
Usage of Visual Inspection			
Sources of information	Advantages	Disadvantages	Number of papers
Magnus stereoscopic microscope	Low cost No data requirement	Human error Limited accuracy	1
Usage of I-V Scanner			
Sources of information	Advantages	Disadvantages	Number of papers
I-V scanner	Quantitative data Remote monitoring	Maintenance needs Complexity	1

Table 4 outlines the findings related to the use of satellite information, visual inspection, and I-V scanners for detecting soiling on solar panels [52]. Each inspection tool has been utilized by different authors, with distinct advantages and disadvantages highlighted in the table. Satellite information, particularly from NASA, offers the advantage of frequent data updates, making it highly reliable for continuous monitoring. However, its effectiveness can be limited by weather conditions. This source was referenced in three papers. COPERNICUS satellite data provides excellent remote sensing capabilities, which are advantageous for large-scale and remote monitoring, though the complexity of data processing remains a significant drawback. Visual inspection tools, such as the Magnus stereoscopic microscope, offer a low-cost solution for inspecting solar panels. However, these methods are prone to human error, which can affect accuracy. General visual inspection requires no data and can be a straightforward method for detecting soiling, but it suffers from limited accuracy, especially when detailed quantitative analysis is needed. The use of the Magnus stereoscopic microscope was noted in one paper. I-V scanners, on the other hand, provide robust quantitative data, making them effective for detailed performance analysis of solar panels under different soiling conditions. They also support remote monitoring, which enhances their utility. However, I-V scanners require regular maintenance and involve complexity in their operation. The use of I-V scanners was documented in one paper. The findings from Table 4 illustrate that each inspection tool offers unique benefits and challenges. Satellite information is valuable for its broad coverage and frequent updates, though it can be hampered by weather conditions and data processing complexities. Visual inspection methods, while cost-effective, may lack the precision needed for thorough analysis. I-V scanners provide detailed quantitative data but require maintenance and can be complex to operate. Together, these tools contribute to a comprehensive strategy for detecting and mitigating soiling on solar panels.

The inspection tools used for detecting soiling on solar panels have yielded several significant findings. Various types of cameras, including standard digital cameras, thermal cameras, and drones equipped with cameras, have been employed to gather detailed information about soiling on PV panels. Digital cameras provide clear visual inspections and high-resolution images, which are crucial for precise measurement of soiling accumulation through image processing techniques. While fixed cameras offer localized monitoring, flexible or drone-mounted cameras can cover wider areas, enhancing the scope of inspection. Thermal cameras, known for their sensitivity to temperature differences, are particularly effective in low-light and nighttime conditions. They detect soiling by capturing temperature variations on the panels. The use of drones equipped with cameras has revolutionized remote sensing capabilities, allowing comprehensive inspections without physical access to the panels, which is especially useful in large-scale solar farms.

Additionally, various sensors, such as dust sensors, temperature sensors, voltage sensors, and current sensors, have been extensively used to gather real-time data on soiling levels and panel performance. Dust sensors measure the level of dust accumulation by detecting particulate matter size and concentration, while temperature sensors monitor ambient and panel surface temperatures, aiding in the detection of soiling that affects thermal properties. Voltage and current sensors provide data on electrical performance, helping to quantify the impact of soiling on energy output. Other inspection tools, including satellite information, visual inspection tools like microscopes, and I-V scanners, have also been employed. Satellite data, combined with tools like the Google Earth Engine, is used to monitor soiling patterns over large areas, particularly in arid regions. Visual inspection tools offer detailed observations of soiling particles and their impact on panel surfaces, while I-V scanners analyze the electrical characteristics of PV panels under different soiling conditions, helping to understand performance variations.

The integration of various inspection tools provides a comprehensive approach to detecting soiling on solar panels. Cameras, with their high-resolution imaging capabilities, are highly effective but may face limitations in certain weather conditions. Sensors offer precise real-time data but can also be affected by environmental factors. Combining these tools with advanced technologies like drones and satellite data enhances inspection capabilities and provides a holistic view of soiling impacts.

Future research should focus on integrating advanced technologies such as artificial intelligence and machine learning with existing inspection tools to improve the accuracy and efficiency of soiling detection. Developing AI algorithms that can analyze data from multiple sources, including cameras, sensors, and satellites, in real-time could significantly enhance detection capabilities. Research should also aim to develop more robust and weather-resistant sensors that can operate effectively in diverse environmental conditions. Exploring the use of novel materials and technologies for sensors to improve their sensitivity and accuracy is another promising area.

Moreover, investigating cost-effective solutions for soiling detection that can be widely adopted, especially in large-scale solar farms, is essential. Developing low-cost, high-efficiency tools that can be easily maintained and deployed will facilitate broader adoption. Emphasis should also be placed on comprehensive data analysis techniques that can integrate data from various inspection tools to provide a more accurate assessment of soiling. Utilizing big data analytics to identify patterns and trends in soiling across different geographical locations and environmental conditions can further advance the field.

By addressing these future research directions, the field of soiling detection on solar panels can advance significantly, leading to improved solar panel efficiency and performance.

4.2 Models

This section examines various research papers focusing on the use of models in the field of soiling detection on solar panels. Table 5 summarizes the studies, highlighting the types of models employed, their authors, years of publication, and specific focuses. The models explored include statistical and regression models, stochastic models, empirical models, and deep learning models, each offering unique approaches to analyzing and predicting the impact of soiling on PV systems. The effectiveness, advantages, and limitations of these models are discussed, providing a comprehensive understanding of their application in optimizing solar panel performance and maintenance.

Table 5 details a comprehensive overview of various models used for soiling detection on solar panels, covering their applications, benefits, and specific focus areas. Statistical and regression models have been used to compare the effectiveness of visual inspection and infrared thermography, study the impact of surface contaminants on energy generation, and predict daily CI changes based on environmental variables. These models also investigated the impact of dust accumulation using transmittance loss, PM deposition-based, and empirical models. Stochastic models, such as dynamic models using Markov chains, accounted for dust accumulation and seasonal variations. Empirical models analyzed the effect of dust on transmittance and quantified soiling rates using a temperature-corrected performance ratio (CPR). Deep learning models utilized convolutional neural networks for dust detection and classification, while machine learning models employed various algorithms to detect cleanliness levels and estimate soiling. These studies highlight the diverse approaches and technologies used to enhance the detection and analysis of soiling on solar panels, each offering unique benefits and facing specific challenges.

Table 5. Models for soiling detection

Theme	Types	Authors	Year	Focus
Models	Statistical and regression models	Cardinale-Villalobos et al. [13]	2021	Comparing RGB visual inspection and infrared thermography with statistical analysis to detect soiling and shading.
		Bodnár et al. [26]	2019	Correlating surface contaminants (leaves, dust, bird droppings) with electrical parameters to quantify energy loss.
		Guo et al. [38]	2016	Developing linear and semi-physical models to predict daily CI from environmental variables.
		Sharma et al. [39]	2023	Comparing transmittance, PM deposition, and empirical models to estimate soiling losses on PV panels.
		Supe et al. [44]	2020	Using Google Earth Engine and satellite indices (NDSI, RNDSI, DBSI, LST) to monitor sand accumulation and PV soiling.
		Esposito et al. [46]	2023	Creating soiling indices to assess irradiance instrument dirt deposition using ground and satellite data.
		Kalimeris et al. [53]	2023	Using regression models to estimate PV soiling ratio by learning optimal performance from data.
		Ma et al. [54]	2023	Establishing a linear relation between illumination and PV power to detect panel cleanliness.
	Stochastic models	Caron and Littmann [42]	2013	Studying dust effects on PV in California and using the I-V curve technique to measure soiling rate.
		Cheema et al. [55]	2021	Applying the Markov chain model to predict PV power output with dust accumulation and seasonal variations.
	Empirical models	Azouzoute et al. [30]	2021	Measuring transmittance loss of soiled glass and estimating energy/soiling ratio with mathematical equations.
		Skomedal et al. [41]	2019	Using temperature-CPR to quantify soiling rates and detect cleaning events.
		Kumar et al. [56]	2023	Developing a model to estimate PV power loss from soiling using meteorological derating factors.
		Abid et al. [25]	2018	Using a wireless system to periodically monitor PV panels and classify faults, including soiling.
		Imran et al. [57]	2019	Linking PM size distribution with PV soiling losses; developing a theoretical model for prediction.
		Coello and Boyle [58]	2019	Modeling PV soiling losses with tilt, tracking, rain, and PM concentration (PM2.5/PM10).
		Li and Niu [59]	2018	Developing a physical model of dust deposition to predict light transmittance reduction.
		Rosas et al. [60]	2019	Modeling dust layer thickness over time under varying environmental conditions.
		Alfaris [61]	2023	Using an AI-based expert system to estimate solar radiation and detect dust without external devices.
		Zhou et al. [62]	2019	Using the CMAQ model to estimate aerosol particle deposition and soiling impact across locations.
		Peterson et al. [63]	2022	Developing a soiling data processing algorithm (SDPA) to calculate daily/monthly/yearly soiling rates.
	Deep learning	El Ydrissi et al. [6]	2023	Using CNN and RGB photos to classify dust density on solar mirrors.
		Cavieres et al. [7]	2022	Applying ANN with image analysis to quantify PV power loss from soiling and shading.
		Onim et al. [10]	2022	Using SolNet CNN to detect dust accumulation on solar panels.
		Ayyagari et al. [11]	2022	Combining CNN and LSTM to detect and classify dust/soil on PV arrays using images and meteorological data.
		Zhang et al. [14]	2021	Developing SolarQRNN probabilistic model to estimate PV power loss from surveillance images.
		Tribak et al. [15]	2019	Quantifying dust particle concentration on PV panels using image processing.
		Hwang et al. [16]	2020	Using AI and image processing to detect PV soiling.
		Hajar et al. [17]	2023	Using YOLOv5 and CNN for automated soiling detection.
		Aji et al. [18]	2023	Developing a smart image-based detection system to optimize PV cleaning.
		Qasem et al. [20]	2016	Using image processing to optimize PV plant operation by analyzing panel surfaces.
		Sun et al. [64]	2023	Reviewing dust detection techniques using image processing and deep learning approaches.
		Fan et al. [8]	2022	Using a deep residual neural network (DRNN) to analyze dust concentration and distribution.
		Abuqaaud and	2020	Applying computer vision methods to detect dust/soil on PV surfaces.

	Ferrah [9]		
	Saquib et al. [19]	2020	Using ANN and dust/irradiance data to predict PV power output.
	Sriram and Sudhakar [12]	2023	Detecting PV soiling using a thermal imaging system.
	Singh and Rizwan [37]	2023	Comparing LSTM, 1D CNN, and BiLSTM models to forecast PV power and irradiation under dust.
	Hanafy et al. [21]	2019	Using ML algorithms and UAV images to classify PV cleanliness levels.
	Czarnecki and Bloch [22]	2022	Applying statistical classifiers to categorize PV panels based on soiling.
Machine leaning	Silva et al. [45]	2023	Applying regression, Random Forest, MLP, Decision Tree, and LSTM to estimate soiling.
	Martin et al. [65]	2021	Using ML techniques to detect soiling in residential solar installations.
	Hwang et al. [23]	2023	Integrating image processing, statistics, and ML to monitor soiling and support cleaning schedules.
	Mehmood et al. [28]	2023	Proposing a system, conversion recovery system (SCRS) with IoT, cloud, and ANN to remotely monitor PV soiling.

Table 6. Summary of the findings of using statistical and regression models, stochastic models and empirical models

Usage of Statistical and Regression Models				
Examples of models	Used for	Advantages	Disadvantages	Number of papers
Regression model	Measuring the soling ratio	Easy to understand	Cannot work well in case of input data error	9
Linear model	Predicting the daily change in the CI of PV panels	Its output is easy to predict	Does not work well with a large number of variables	
		Can include all variables	Does not deal with categorical variables	
Usage of Stochastic Model				
Example of models	Used for	Advantages	Disadvantages	Number of papers
Markov chain model	Predicting PV output power	It is totally explicit about the assumptions being made	Sensitivity to model parameters	1
		It monitors whether the predictions of a model are within the bounds one would expect	It is quite complex to perform	
Usage of Empirical Models				
Examples of models	Used for	Advantages	Disadvantages	Number of papers
Brownian motion, impaction and sedimentation	Estimating the thickness of the accumulated dust layer on PV panels	Adaptability	Data dependency	11
	Power loss			
Mathematical model	Estimate the thickness of the accumulated dust layer			
Lambert-Beer law	Impact of dust deposition on the light transmittance	Simplicity	Limited adaptability	
Average spectral transmittance	Soiling ratio	It has high reliability	Difficulty with complex patterns	

A concise overview of the findings from the application of statistical and regression models, stochastic models, and empirical models in detecting soiling on solar panels is presented in Table 6 [66, 67].

Statistical and regression models, utilized in nine papers, include regression and linear models, which are widely used to analyze relationships between environmental factors and soiling accumulation. These models effectively predict trends in soiling ratios and estimate power loss due to dust accumulation. Their key strength lies in their simplicity and interpretability, making them useful for initial assessments and historical data analysis. However, their performance can be limited by input data errors, and they struggle with handling complex, nonlinear relationships and large datasets with multiple interacting variables. Empirical studies have shown that while regression models provide a reasonable estimation of soiling effects, they lack the adaptability required for dynamic environmental conditions.

Stochastic models, such as the Markov chain model used in one study, introduce probabilistic approaches to capture the randomness in soiling accumulation. These models are particularly useful in scenarios where environmental variables fluctuate unpredictably, allowing for more robust predictions. The primary advantage of stochastic models is their ability to incorporate uncertainty, making them suitable for long-term soil forecasting. However, they are highly sensitive to parameter selection and require extensive historical data for calibration. While these models provide more flexibility than deterministic approaches, their computational complexity and reliance on extensive data make them challenging to implement in real-time applications.

Empirical models, discussed in eleven papers, cover a range of applications, including estimating the thickness of accumulated dust layers and assessing power loss. Examples include transmittance loss models, PM deposition-based models, and mathematical models based on Brownian motion, impaction, and sedimentation. The main advantage of empirical models is their adaptability to specific locations and conditions, as they are derived directly from experimental data. However, their performance is highly dependent on the availability of high-quality data, and they often require periodic recalibration. While these models are effective for short-term predictions, they may lack generalizability across different climatic regions.

Table 7 features a concise summary of the findings from the use of deep learning models in detecting soiling on solar panels [68]. Deep learning models, particularly CNN and ANN, have revolutionized soil detection by enabling automated feature extraction from images and sensor data. CNNs have demonstrated exceptional performance in detecting soiling patterns using aerial and terrestrial images, reducing the need for manual inspection. These models excel in feature learning and can generalize well to new datasets when trained effectively.

Table 7. Summary of the findings of using deep learning

Usage of Deep Learning			
Type of models	Advantages	Disadvantages	Number of papers
CNN	Feature learning Transfer learning	Data intensity Computational complexity	11
DNN	Representation learning Transfer learning	Data intensity Computational complexity	1
CLCM	Texture analysis Low computational complexity	Feature engineering dependence Limited adaptability	1
ANN	Versatility Representation learning	Data intensity Computational complexity	2

Table 8. Summary of the findings of using machine learning

Usage of Machine Learning			
Type of models	Advantages	Disadvantages	Number of papers
K-means clustering KNN Neural networks Random forest SVM	Easily identifies trends and patterns	Data acquisition	6
Naïve Bayesian classifier Fisher's linear discriminator Multilayer perception XGBoost model	No human intervention needed	Interpretation of results	

Table 9. Comparative summary of each model

Model Type	Predictive Capabilities	Strengths	Weaknesses
Regression models	Trend estimation, power loss prediction	Simple, interpretable	Limited handling of nonlinear relationships, sensitive to input data errors
Stochastic models	Long-term forecasting under uncertainty	Accounts for randomness, flexible	Computational complexity, data-intensive
Empirical models	Site-specific predictions	Adaptable, easy to implement	Requires recalibration, limited generalizability
Machine learning models	Pattern recognition, automated soiling detection	High accuracy, improves with data	Requires large datasets, computationally intensive, potential overfitting
Deep learning models	Image-based soiling detection	Automated feature extraction, high accuracy	Data-intensive, requires high computational resources, interpretability concerns

CNNs, for example, analyze pixel-level variations to detect dust accumulation on solar panels, improving accuracy in classification tasks. They can outperform traditional machine learning models by learning hierarchical features directly from raw image data. ANNs, on the other hand, are well-suited for nonlinear relationships between environmental conditions and soiling accumulation, providing robust predictive capabilities. However, deep learning models are data-intensive and require high computational power, making their deployment challenging in low-resource settings.

Despite their advantages, deep learning models also have limitations. Their effectiveness heavily relies on the availability of large, high-quality labeled datasets, and they are prone to overfitting when trained on limited or unbalanced data. Computational requirements can also pose a challenge, as training complex networks requires substantial processing power and memory. Furthermore, interpretability remains a concern, as deep learning models function as "black boxes," making it difficult to understand how predictions are generated.

Empirical studies highlight that while CNNs achieve state-of-the-art accuracy in soiling detection, their dependence on large labeled datasets remains a key limitation. Some research suggests that transfer learning techniques and data augmentation methods can mitigate these issues by leveraging pre-trained models and enhancing dataset diversity. Additionally, hybrid models combining deep learning with traditional machine learning techniques have shown promise in improving accuracy and reducing computational complexity.

A concise summary of the findings from the use of machine learning models in soiling detection for solar panels is shown in Table 8 [69]. Machine learning models have gained recognition in soiling detection due to their ability to process large datasets and identify complex patterns in soiling accumulation. These models, including K-means clustering, K-Nearest Neighbor (KNN), Neural Networks, Random Forest, Support Vector Machines (SVM), Naïve Bayesian classifiers, Fisher's Linear Discriminator, Multilayer Perceptron, and XGBoost, excel in detecting soiling from image-based data and sensor measurements, offering higher accuracy compared to traditional statistical methods.

A key advantage of machine learning models is their adaptability to diverse environmental conditions and their ability to improve over time as more data becomes available. For instance, Random Forest and XGBoost, both ensemble learning techniques, demonstrate high predictive accuracy by aggregating multiple decision trees. SVMs are effective in distinguishing between clean and soiled solar panels based on feature extraction techniques, while KNN models leverage similarity-based learning to classify different levels of soiling.

Despite their strengths, machine learning models also have limitations. Their performance depends heavily on the availability of high-quality training data, and they require significant computational resources for real-time applications. Moreover, certain models, such as SVMs and neural networks, can be challenging to interpret, making it difficult to understand the decision-making process. Additionally, overfitting remains a common concern, particularly when models are trained on limited or biased datasets.

Different models have been implemented to process data for detecting soiling on solar panels, each with distinct strengths and limitations. Statistical models mathematically represent relationships between variables, making them effective for analyzing data and making predictions when patterns are clear. They are particularly useful for identifying trends in historical data, but struggle with complex and nonlinear relationships.

Stochastic models incorporate randomness or uncertainty to account for probabilistic factors such as weather patterns. These models are valuable for long-term soiling predictions but require large datasets for accuracy and are less efficient with smaller datasets. Empirical models, which rely on observed data and experiments, offer adaptability and simplicity but are heavily dependent on data availability and site-specific conditions.

Machine learning models enhance soiling detection by identifying trends and anomalies across diverse environmental conditions. They excel in tasks such as image recognition and real-time monitoring, but require extensive data for training. Deep learning models provide advanced capabilities in feature learning and predictive modeling, making them ideal for analyzing complex data structures like image-based assessments of solar panels. However, both machine learning and deep learning models demand significant computational resources and large training datasets.

A comparative analysis highlights the effectiveness of these models under different conditions. Statistical and regression models, such as linear and empirical models, are valued for their simplicity and ability to establish clear relationships between variables, but are best suited for structured data with well-defined patterns. Stochastic models, like the Markov chain model, effectively incorporate randomness and seasonal variations, making them useful for long-term soil predictions, though their accuracy depends on large datasets.

Empirical models estimate the impact of soiling on transmittance and energy loss, offering practical insights but relying heavily on high-quality experimental data. In contrast, machine learning models, including decision trees, SVM, and artificial neural networks, provide superior predictive capabilities by identifying complex patterns and trends in large datasets. These models are particularly well-suited for adaptive soiling detection and real-time monitoring. Deep learning approaches, such as CNNs and LSTM networks, achieve the highest accuracy in image-based soiling detection, making them ideal for automated inspection systems, though they require extensive computational resources and large training datasets to maintain performance.

The choice of model depends on the specific requirements of the application. Empirical and statistical models are advantageous for rapid estimations with minimal computational costs, while machine learning and deep learning models excel in automated detection and large-scale monitoring. Future research should explore hybrid approaches that integrate multiple models, leveraging their strengths to improve accuracy and efficiency in diverse environmental conditions.

To provide a clearer comparison, Table 9 summarizes the predictive capabilities, strengths, and weaknesses of each model discussed.

4.3 Cleaning and mitigation systems

This section examines various research papers focused on cleaning and mitigation systems for soiling detection on solar panels. Table 10 provides an overview of the studies, highlighting the authors, publication years, and specific focus areas. These systems employ a variety of innovative approaches, including IoT technologies, robotic systems, anti-soiling coatings, and automated cleaning mechanisms, to address the challenges posed by dust and dirt accumulation on PV panels. The effectiveness, advantages, and limitations of these cleaning and mitigation strategies are discussed, offering insights into their application for optimizing solar panel performance and maintenance.

Various publications focus on designing and proposing mitigation and cleaning systems to address dust accumulation on solar panels. Shields, such as 1D and 2D shields, have been used to mitigate dust, demonstrating effective results. Studies have shown that 1D shields perform better than 2D shields. Additionally, combining 1D shields with antistatic coatings and vibrating the panels yielded encouraging results in dust mitigation. Electrostatic cleaning devices have also been employed, providing high efficiency in cleaning performance.

Other proposed systems for dust mitigation or removal include automatic cleaning using Arduino Uno microcontrollers, automated robotic systems, and anti-soiling coatings. Automatic cleaning systems using Arduino Uno microcontrollers have maintained solar panel performance through washing mechanisms activated upon detecting dust accumulation. The use of automated robotic systems has highlighted efficiency and safety improvements, as well as enhancements in PV performance. Coated mirrors have shown a lower soiling index compared to uncoated mirrors, effectively reducing dust particles.

Future research should focus on a comprehensive analysis of cleaning systems to identify the most cost-effective and accurate solutions. Comparisons between existing systems should be made to recommend the best approach. Additionally, new systems leveraging emerging technologies and trends should be proposed, aiming to surpass the performance of existing systems. Evaluating and comparing the challenges and maintenance requirements of proposed and new systems is essential to ensure long-term effectiveness and sustainability.

Table 10. Cleaning and mitigation systems

Theme	Authors	Year	Focus
Cleaning and mitigation systems	Narvios and Nguyen [24]	2021	Developing an IoT-based monitoring system with an integrated cleaning mechanism for PV dust removal.
	Chockalingam et al. [27]	2023	Creating an IoT-based non-invasive method to detect hotspots and quantify affected PV areas.
	Olorunfemi et al. [29]	2023	Designing an Arduino-based system for dirt detection and automated cleaning.
	Mohammed et al. [33]	2018	Proposing an Arduino Uno-based system for dust detection, power monitoring, and automatic cleaning.
	Ghodki [34]	2022	Introducing a robotic arm using an IR sensor-based cleaning technique.
	Lopes et al. [43]	2019	Evaluating anti-soiling coatings for CSP mirrors with economic analysis.
	Pouladian-Kari et al. [70]	2022	Proposing NightFlip system: inverting panels at night to use condensation for cleaning.
	Eisa et al. [71]	2023	Adding windshield protection to mitigate dust on PV panels powering light posts.
	Altıntaş and Arslan [72]	2021	Exploring electrostatic cleaning to remove dust from PV panels.
	Yerramsetti et al. [73]	2021	Designing a robotic system to clean floating solar panels.
	Patil et al. [74]	2018	Developing a dust cleaning mechanism to restore panel efficiency.
	Alghamdi et al. [75]	2019	Proposing an automated PV cleaning system for desert conditions.
	Dahlioui et al. [76]	2022	Using dew flow as a natural soiling mitigation method.
	Najeeb et al. [77]	2018	Developing automated dust cleaning technology to reduce soiling losses.
	Hossain et al. [78]	2022	Reviewing anti-dust technologies, mitigation methods, and influencing factors.
	Aldawoud et al. [79]	2022	Proposing a motorized curtain system to protect PV modules during dust storms and nights.
	Fares et al. [80]	2021	Reviewing critical issues of PV soiling in the Gulf Cooperation Council.
	Rudnicka and Klugmann-Radziemska [81]	2021	Reviewing self-cleaning and anti-dust coatings for restoring PV performance.
	de Jesus et al. [82]	2018	Investigating hydrophilic/hydrophobic coatings for CPV dust mitigation.
	Joshi et al. [83]	2021	Analyzing dust accumulation impact on PV arrays under different deposition patterns.
	Hirohata et al. [84]	2013	Studying PMMA anti-soiling layers for PV panels.
	Kumar et al. [85]	2021	Reviewing solar tracker technologies for improving PV efficiency.
	Sayyah et al. [86]	2013	Examining dust accumulation on CPV and different cleaning methods to reduce energy loss.

5. ECONOMIC AND ENVIRONMENTAL IMPLICATIONS OF SOILING AND MITIGATION STRATEGIES

Soiling on solar panels has significant economic and environmental implications, making effective detection and mitigation strategies essential for optimizing PV performance and long-term sustainability. Economically, soiling reduces energy output, leading to financial losses for solar farm operators, residential users, and industrial-scale energy producers. This decline in efficiency increases the levelized cost of electricity (LCOE) and reduces the overall return on investment for solar energy projects. Moreover, the costs associated with manual cleaning, labor, and downtime can be substantial, particularly in utility-scale installations where frequent maintenance is required.

Implementing advanced soiling detection and mitigation techniques can significantly reduce these costs. AI-driven monitoring systems, drone-based inspections, and automated robotic cleaning technologies offer real-time detection and precise maintenance scheduling, ensuring cleaning is performed only when necessary, rather than on a fixed routine. This predictive maintenance approach not only minimizes operational expenses but also extends the lifespan of PV panels by preventing unnecessary physical interventions that may degrade their surface over time. Future research should focus on developing cost-efficient sensor technologies that integrate with IoT-based monitoring systems to provide real-time, remote soiling detection with minimal human intervention.

From an environmental perspective, traditional water-based cleaning methods pose challenges, particularly in arid and drought-prone regions where water scarcity is a major concern. In many cases, large-scale solar farms require thousands of liters of water per cleaning cycle, contributing to water depletion and increasing operational costs. The development of water-free cleaning solutions, such as electrostatic, hydrophobic, and self-cleaning coatings, presents a sustainable alternative to reduce environmental impact. Additionally, robotic cleaning systems that utilize compressed air, vibration, or mechanical brushing are being explored as eco-friendly alternatives to water-intensive methods.

Another critical environmental consideration is the impact of soiling on land use and material efficiency. When PV efficiency decreases due to soiling, more panels may be required to generate the same amount of power, leading to increased land usage and material waste. By enhancing soiling detection accuracy and mitigation efficiency, energy output can be optimized, reducing the need for excessive panel installations and minimizing the environmental footprint of solar farms.

To further advance the economic and environmental sustainability of soiling detection and mitigation strategies, future research should explore cost-benefit analyses, life-cycle assessments, and policy frameworks that encourage the adoption of advanced soiling detection methods. Governments and industry stakeholders should evaluate incentive programs for adopting automated and sustainable cleaning technologies in large-scale solar farms. Additionally, interdisciplinary research integrating material science, AI, and environmental engineering can help develop next-generation coatings, sensors, and autonomous cleaning systems that are both cost-effective and environmentally friendly. Addressing these economic and environmental challenges, innovative soiling detection and mitigation solutions will play a crucial role in enhancing the reliability, efficiency, and sustainability of solar energy systems worldwide.

6. CONCLUSIONS AND FUTURE RESEARCH

The issue of soiling on solar panels has become increasingly critical, necessitating the development of innovative methods and technologies to detect and mitigate the effects of dust and dirt accumulation. To address this challenge and enhance the performance and reliability of solar energy systems, a comprehensive analysis of 75 publications was conducted, identifying key findings and research gaps in the field of soiling detection and mitigation.

Initially, a comprehensive content analysis of the literature in the field was conducted. This analysis provided key insights into current studies on the detection of soiling on solar panels. Publications were classified into three themes: inspection tools, models, and cleaning and mitigation systems, to obtain key findings and identify possible research gaps. Following the content analysis, a bibliometric analysis was performed. This included examining a total of 683 papers extracted from the Scopus database, which were then narrowed down to 75 publications after screening and removing duplicates. The bibliometric analysis studied aspects such as co-occurrence maps based on text data, keywords, and country of co-authorship. This analysis highlighted the significant growth in research on soiling detection, particularly from 2018 to 2023, and identified key trends and collaborations in the field.

Various inspection tools, including cameras, sensors, and drones, have been employed to detect soiling on solar panels. These tools provide detailed observations and real-time data crucial for accurate soiling detection. The integration of these tools with advanced technologies like AI and machine learning has shown promise in enhancing detection capabilities and offering a comprehensive understanding of soiling impacts. Different types of cameras, such as digital, thermal, and high-resolution cameras, along with sensors like dust and temperature sensors, have been widely used. These tools are essential for identifying and measuring the extent of soiling, which directly affects the efficiency of PV systems.

Different models have been explored to analyze and predict the impact of soiling on PV systems. These include statistical, stochastic, empirical, and machine learning models. Each model type has demonstrated effectiveness in different scenarios, with machine learning models showing particular promise due to their ability to identify trends and patterns without human intervention. The application of deep learning models, particularly convolutional neural networks, has proven effective in processing large datasets and improving the accuracy of soiling detection. These models have been used to quantify power loss, predict soiling patterns, and optimize maintenance schedules.

Innovative cleaning systems, such as IoT-based solutions, robotic systems, and anti-soiling coatings, have been proposed to address the challenges posed by dust and dirt accumulation. These systems aim to optimize the performance and maintenance of solar panels by mitigating the impact of soiling. IoT-based cleaning systems enable remote monitoring and automated cleaning processes, ensuring consistent maintenance without manual intervention. Robotic cleaning systems and anti-soiling coatings have also shown potential in maintaining the cleanliness of PV panels, thus enhancing their efficiency.

Future research should focus on developing and integrating advanced inspection tools that offer higher efficiency and cost-effectiveness. Key research questions include:

- How can AI-driven inspection tools improve the accuracy of soiling detection in real-time?
- What are the most cost-effective and scalable sensor technologies for monitoring soiling in different environmental conditions?

To address these questions, studies should explore the application of deep learning techniques, for example, convolutional neural networks, for image-based soiling detection and the use of IoT-enabled sensor networks for continuous monitoring. Additionally, field experiments comparing AI-based models with traditional detection methods will help validate their effectiveness.

Further investigation is needed into the best models for soiling detection. Research should aim to:

- Compare and benchmark different AI models, for example, neural networks, SVM, and decision trees, to assess their performance, efficiency, and reliability.
- Develop hybrid models that integrate statistical, empirical, and machine learning approaches to enhance predictive accuracy.

A combination of simulation studies and real-world field trials will be necessary to determine the robustness of these models under varying environmental conditions.

Comparative studies on different cleaning systems should also be conducted to identify the most effective and cost-efficient solutions. Key questions include:

- Which cleaning mechanisms, for example, robotic, electrostatic, or hydrophobic coatings, offer the best balance of efficiency and sustainability?
- How do environmental factors such as humidity, temperature, and dust composition impact the effectiveness of different cleaning methods?

Experimental comparisons of cleaning technologies in diverse climate conditions will provide valuable insights into their long-term viability and maintenance requirements.

Additionally, research should explore emerging trends such as integrated sensor technologies, self-cleaning surfaces, and the use of big data analytics to identify patterns and trends in soiling. Exploring the potential of combining IoT with machine learning algorithms could lead to more advanced and efficient soiling detection and mitigation systems. Further, investigating the environmental and economic impacts of these technologies will be essential for their widespread adoption.

Addressing the challenges of soiling on solar panels requires a multi-faceted approach that includes the development of advanced inspection tools, the application of robust models, and the implementation of effective cleaning systems. By focusing on these areas, future research can contribute to improving the efficiency and performance of solar panels, ultimately supporting the advancement of renewable energy technologies. This paper has laid the groundwork for future studies by providing a comprehensive overview of current research, identifying key findings, and suggesting directions for further exploration.

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