AN IMPROVED FRAMEWORK FOR AEROSOL AND DUST SEVERITY PREDICTION ON PHOTO VOLTAIC PLANT PERFORMANCE USING AI TECHNIQUE: A SYSTEMATIC REVIEW

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Abstract: *The rising demand for electricity, the swift depletion of fossil fuels, and global environmental challenges have led to the widespread adoption of solar photovoltaic (PV) plants. These PV plants are crucial for contemporary infrastructure as they provide the energy needed for lighting, heating, cooling, and powering various devices and machinery. However, maintaining optimal power output in PV power plants poses a significant challenge, particularly due to environmental factors like the accumulation of dust and aerosols, which hinder energy efficiency. The buildup of these particles on PV panels greatly impacts their performance and energy efficiency, creating barriers to sustainable solar energy production (SE). Advanced techniques, such as artificial intelligence (AI), can address these issues. This study presents an enhanced framework for predicting the effects of aerosols and dust on PV plant performance using advanced AI methods. Compared to traditional methods, the proposed framework offers improved predictive accuracy and robustness by integrating machine learning algorithms (ML) with meteorological and environmental data. Additionally, this study explored the relationship between dust severity, weather conditions, and PV effectiveness through an AI-driven analysis to enhance operational strategies and maintenance planning.*

Objective:
The objective of this research is to create a more effective predictive model for evaluating how dust and aerosols affect the performance of photovoltaic (PV) plants, thereby aiding in the sustainable production of solar energy (SE).

Methods:
A framework enhanced by AI was introduced, utilizing machine learning algorithms in conjunction with meteorological and environmental data. This system aims to model and forecast the degradation of PV performance caused by the accumulation of dust and aerosols, also will predict the severity of dust and aerosol.

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1. INTRODUCTION

Electricity systems are experiencing worldwide transformation. The global reliance on and demand for electric power are increasing. With environmental issues becoming more urgent, there is a significant emphasis on cutting greenhouse-gas emissions [1]. To meet the growing global demand for sustainable energy, it is essential to reduce greenhouse gas emissions and harness renewable energy sources, especially solar power. This strategy ensures that future energy needs are met while minimizing climate change effects and supporting environmental stewardship [2]. As nations and companies transition to green energy solutions, photovoltaic (PV) technology has become a prominent method for capturing solar energy, driven by the pressing need to reduce carbon emissions and encourage sustainable energy practices worldwide [3]. By adopting PV systems, communities can advance significantly toward energy independence and environmental accountability, highlighting the vital role of advanced technology in achieving global sustainability objectives [4]. However, PV systems face various operational challenges that can greatly impact their efficiency and overall energy output [5]. These challenges include problems such as the buildup of dust and dirt on panels, which reduce their ability to capture sunlight effectively, and the deterioration of materials over time due to exposure to environmental conditions like UV radiation and temperature fluctuations [6]. Environmental factors, such as dust and aerosol accumulation, have been identified as major contributors to performance decline in solar power plants, especially in arid and semi-arid regions where dust storms and aerosol levels are common [7]. The cycle of factors affecting the impact of dust accumulation on PV panels is depicted in Figure 1.

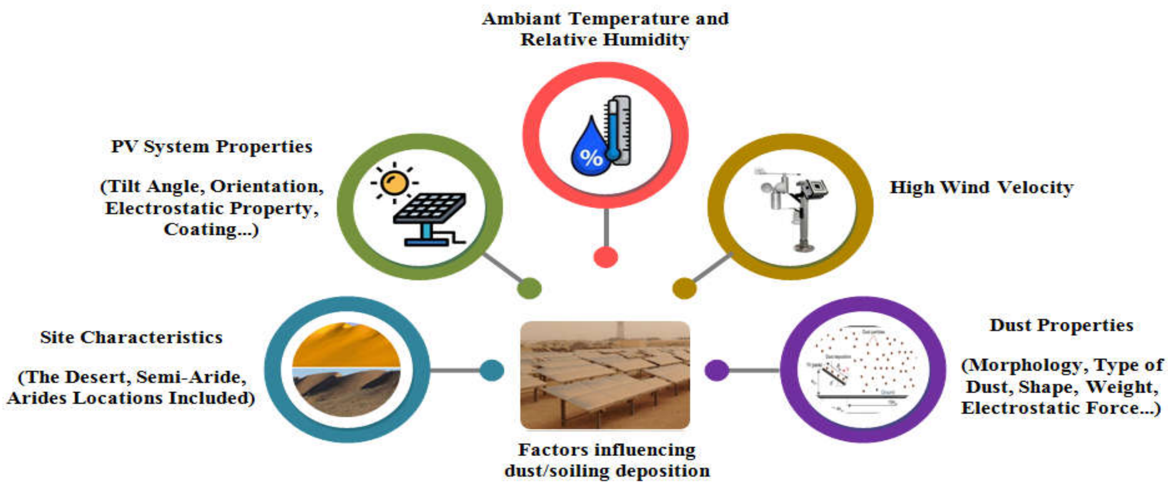

Figure 1: *Cycle of factors contributing to dust accumulation impact in PV panels*

Particles in the atmosphere, like dust and aerosols, diminish the amount of sunlight that photovoltaic (PV) panels receive [8]. When these particles accumulate on the panels, the efficiency of the system declines [9]. Accurately predicting the impact of dust and aerosol accumulation on PV systems is essential for effectively managing solar power facilities in the regions affected [10]. Advanced AI methods enhance prediction accuracy, as conventional approaches fall short. Machine Learning (ML) and Deep Learning (DL) are capable of *handling extensive datasets and identifying patterns in environmental modeling [11]. This review paper seeks to equip PV plant operators with a tool to optimize efficiency through AI techniques [12]. Additional section headings are illustrated in Fig. 2.*

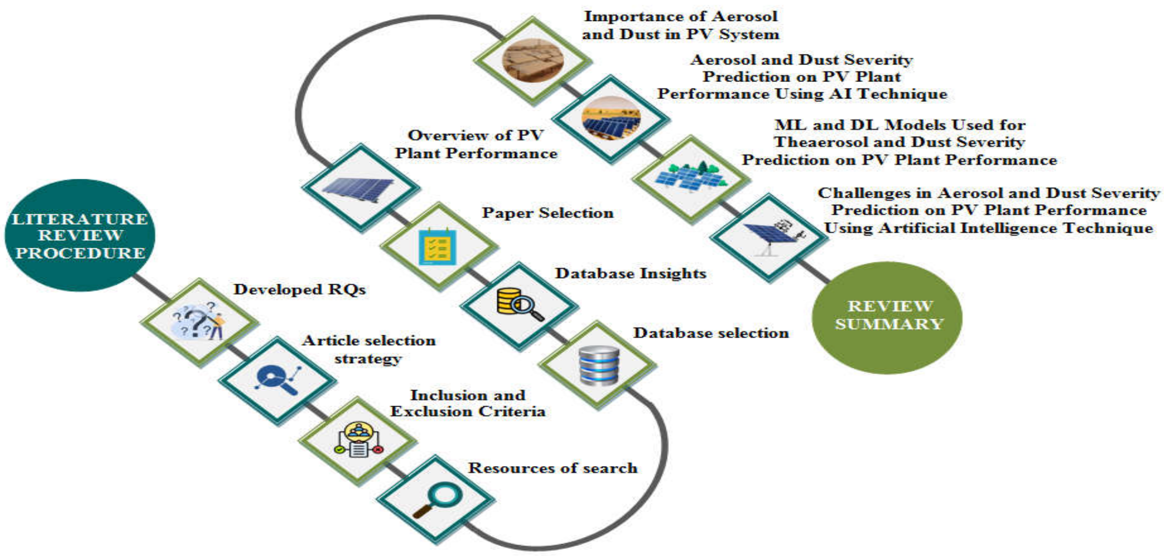

Figure 2: *Further section headings*

2. RESEARCH QUESTION AND ARTICLE SELECTION STRATEGY

Research questions

In developing a literature review, the Research Question (RQ) is essential for directing the review and establishing the foundation of the research project. Examining RQs within the literature review clarifies the main components. The RQ identifies the topics and subheadings to highlight, ensuring they align with the study's goals.

Development of RQs

The research questions were crafted to systematically examine the primary components of the subjects. These questions explore topics such as the impact of aerosols and dust on the efficiency of photovoltaics, the role of AI in predicting environmental changes, and possible enhancements to models. Figure 3 provides an illustration of these research questions.

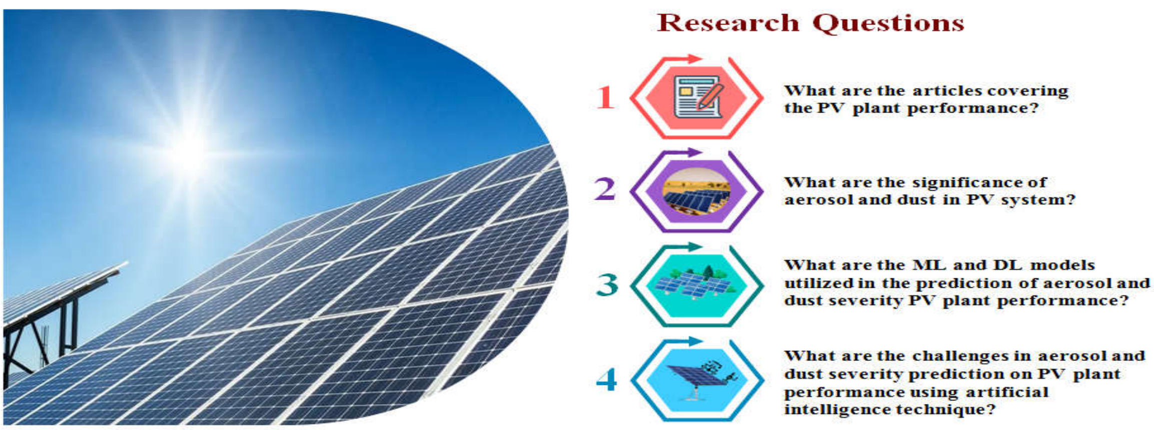

Figure 3: *Developed RQs*

This research aims to investigate how cutting-edge AI techniques can improve the accuracy of forecasts and the efficiency of PV plants by tackling these issues. It seeks to examine the combination of AI with environmental forecasting, providing important insights and solutions for the field of renewable energy.

Article selection strategy

Choosing the right articles is essential for performing systematic reviews of research, using a methodical approach that matches the objectives. This selection process ensures that the research is pertinent to the aim. It involves identifying, evaluating, and synthesizing existing studies, theories, and methods to comprehend the impact of aerosols and dust on PV performance and the role of AI.

2.1. Inclusion and Exclusion Criteria

This research incorporated English-language papers due to the broad understanding of this language. The analysis concentrated on studies carried out between 2015 and 2023.
Inclusion criteria: *The study investigated how aerosols and dust impact the efficiency of photovoltaic systems and the role of AI in predicting environmental conditions. This review encompassed research conducted between 2015 and 2024.*
Exclusion criteria: *Studies that concentrated exclusively on AI were omitted. Research highlighting the difficulties in forecasting the effects of aerosols and dust on the performance of PV plants using AI has not been examined.*

2.2. Resources of search and selection strategy

Here, the resources utilized for the literature search and review procedures are explained.
Resources: *To select articles, academic search engines such as Google Scholar, Springer, Elsevier, and IEEE Xplore were utilized, as they contain information pertinent to their specific areas of focus.*
Database selection: *The literature review involved selecting articles from key databases such as Web of Science (WOS), Science Citation Index Expanded (SCIE), and Scopus.*

Database Insights: *ScienceDirect is notable for its extensive array of peer-reviewed article summaries and references. These databases provide benefits for evaluating both appearance and content.*

The Prisma methodology was employed to select articles. PRISMA specifies the steps for review-based studies, ensuring that objectives, methods, and results, including study characteristics and meta-analyses, are clearly outlined. It provides details on the records identified, the data included or excluded, and the reasons for exclusion. Figure 4 illustrates the prismatic framework.

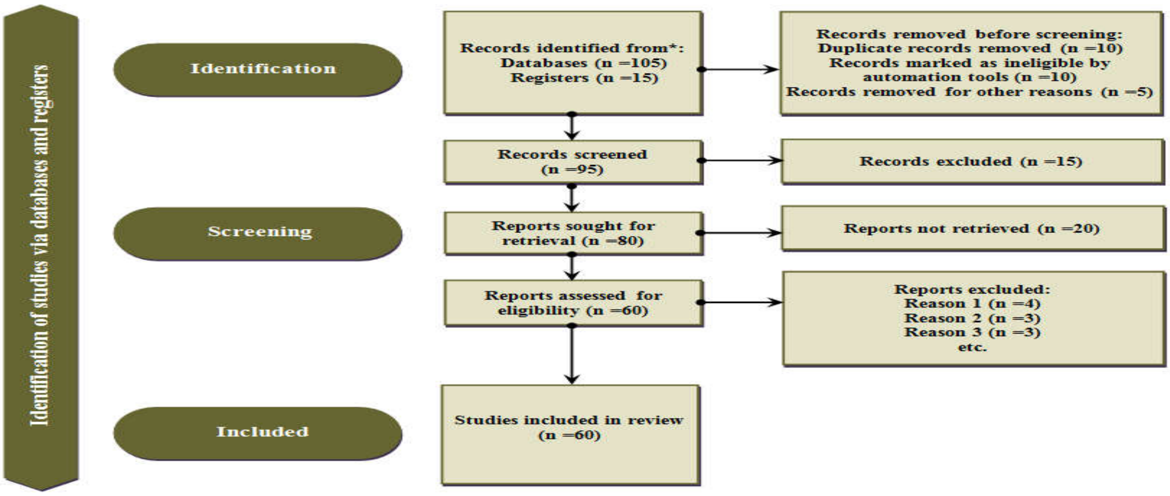

Figure 4: *PRISMA framework*

3. LITERATURE REVIEW

Accumulation of dust and aerosols primarily diminishes efficiency, while environmental conditions influence the performance of photovoltaic (PV) plants. Gaining insight into these impacts is essential for boosting the effectiveness of PV systems. A range of artificial intelligence (AI) approaches have been created to forecast the severity of dust and aerosols in PV facilities. AI methods, such as machine learning (ML) and deep learning (DL), enhance environmental predictions and offer maintenance guidance. Nonetheless, implementing AI encounters obstacles like data quality, environmental factors, and system integration. Overcoming these hurdles with AI aids in optimizing PV plant efficiency and promotes the global adoption of renewable energy.

3.1. OVERVIEW OF PV PLANT PERFORMANCE

Photovoltaic (PV) plants play a crucial role in evaluating the efficiency and sustainability of solar energy systems. The performance of these systems is influenced by various factors, including the efficiency of PV cells, environmental conditions, system design, and maintenance practices [13, 14]. Advances in technology have led to improvements in PV cell efficiency, thereby boosting energy output [15]. The interplay between technology, environmental factors, and maintenance is key to optimizing solar energy as a sustainable power source [16].
Satish et al. [17] evaluated the performance of rooftop solar photovoltaic power systems in northern India. Their study concentrated on a 5-kW rooftop solar installation, examining its efficiency and the impact of temperature. The recorded efficiencies for the system, inverter, and array were 10.02%, 88.38%, and 11.34%, respectively. The results reveal that energy loss peaked in May, which was also the month with the highest temperatures.

Shiva et al. [18] carried out an assessment of a 10 MW solar photovoltaic power plant linked to a grid in India. They determined the Performance Ratios (PR) and identified various power losses, which included those caused by (i) temperature, (ii) internal networks, (iii) power electronics, and (iv) grid connections. Furthermore, they compared the plant's performance outcomes with simulation values derived from PV-GIS and PV-System software. The plant's annual PR was recorded at 86.12%, and its final yield (YF) varied between 1.96 and 5.07 hours per day.

Maria et al. [19] conducted an evaluation of the performance and deterioration of large-scale grid-connected (GC) solar photovoltaic (PV) power plants situated in a tropical semi-arid area *of India. To assess degradation, they employed statistical methods such as (A) the Holt-Winters seasonal model (HW), (B) Seasonal and Trend decomposition using loess (STL), (C) Linear Least-Squares Regression (LLS), and (D) Classical Seasonal Decomposition (CSD). The calculated annual degradation rates over a period of 50 months were 0.27, 0.32, 0.50, and 0.27%, respectively.*

Andrés et al. [20] performed an extensive study to assess how solar technology influences the economic outcomes of photovoltaic (PV) power plants across Europe. They examined the three most common PV technologies to identify the optimal installation type for each nation. A minimal feed-in tariff remuneration indicator was employed. These results are beneficial for stakeholders interested in fostering global investments in the PV industry and for policymakers who aim to make well-informed decisions to boost renewable energy sources.

Vikas et al. [21] reported on a 5 MW GC PV plant situated in western India. To evaluate the projected performance of the PV facility, a quality assessment of global horizontal irradiation data was performed. The month of March showed the highest anticipated capacity utilization factor (CUF) at 24.25%, while July recorded the lowest at 3.16%. On average, the performance ratio (PR) and CUF for different months were 74.29% and 18.50%, respectively.

Kodami et al. [22] conducted an evaluation of a 33.7 MW solar photovoltaic plant situated in a developing nation. Their research calculated the Energy Payback Time (EPBT) for a 33.7 MWp photovoltaic system connected to the grid in Zagtouli, Burkina Faso, and assessed its environmental impact through a life cycle assessment in line with ISO 14040 and 14044 standards. The sensitivity analysis revealed that modifying the power mix could potentially decrease the impacts on climate change, the depletion of fossil resources, and the EPBT by roughly 30%.

3.2. IMPORTANCE OF AEROSOL AND DUST IN PV SYSTEM

Aerosols and dust have a significant impact on the performance of PV systems [23]. When these particles settle on photovoltaic (PV) panels, they obstruct the passage of light to the solar cells. As a result, the system's ability to convert sunlight into electricity is diminished [24]. This problem is especially severe in dry and desert regions, where dust buildup is prevalent [25]. Additionally, aerosols can scatter and absorb solar radiation, affecting the efficiency of PV systems. Therefore, it is crucial to regularly clean and maintain the PV panels [26].

Claudia et al. [27] investigated how aerosols affect the spatial and temporal variations in photovoltaic (PV) energy production throughout the Euro-Mediterranean area. The research aimed to assess the impact of aerosols on PV energy output over both seasonal and multi-decadal timescales. The results indicated that aerosols significantly influence the long-term trends, seasonal patterns, and the complex spatial distribution of PV generation. Central Europe, in particular, where PV production is highly sensitive to aerosols, experienced the most significant effects.

Zeki et al. [28] investigated the effects of various dust pollutants on the efficiency of photovoltaic (PV) systems. They revised and evaluated how these pollutants impact PV performance. The effect of dust pollution was strongly associated with the local air quality where the PV system was situated, suggesting that it differed depending on the location. As a result, applying a single model universally is challenging. However, there is an urgent requirement for a comprehensive model that takes into account different types of pollutants and accurately replicates the impact of various dust types on PV performance.

Silveira et al. [29] investigated how aerosols affect PV SE generation in Goias, Brazil. The primary goal of their research was to compare data on PV power generation with *geostationary satellite information to assess the influence of human-made aerosols on electricity production. The study established a connection between aerosol indicators and PV SE generation. It found positive correlations between electric voltage and aerosol products, while current and electric power showed negative correlations.*

Patricio et al. [30] investigated the optical losses in solar cells caused by the buildup of aerosols, emphasizing the role of particle refractive index and size. To examine FL in relation to particle size and complex refractive index, scattering calculations were conducted to model how light interacts with particles on surfaces. The results reveal that larger particles with a smaller imaginary component of the refractive index experience greater backscattering losses. Conversely, smaller particles with a larger imaginary component of the refractive index tend to have more absorption losses.

Ahmed et al. [31] investigated the effect of dust on the efficiency of solar PV systems in the UAE's climate. They carried out an experimental study to assess the properties of dust and its influence on the electrical performance of photovoltaic (PV) modules in Sharjah, United Arab Emirates. The analysis of dust samples showed that the particles were small, with sizes ranging from 1.61 to 38.40 µm, and displayed a variety of shapes. The indoor experiments indicated a linear relationship between dust density and normalized PV power, with a decrease of 1.7% per g/m2.

Elias et al. [32] investigated how surface dust and aerosols influence the performance of GC PV systems. Their approach involved three steps: calculating the PR, assessing the normalized efficiency, and applying a mathematical model for reference forecasting. The findings indicated that only surfaces with substantial dust buildup significantly impacted PV performance, leading to a 5.6% decrease. Conversely, light or moderate soiling had a smaller effect on PV performance.

Aslan et al. [33] conducted a study to examine the impact of dust accumulation on the efficiency of photovoltaic (PV) systems. The research was carried out in Tehran, Iran, commencing on May 9, 2017, and spanning a duration of 70 days to assess the effect of dust on PV performance. The results indicated that, in the absence of rainfall, 6.0986 (g/m2) of dust accumulated on the surface, leading to a 21.47 (%) reduction in power output. Furthermore, with a power capacity of 4.845 kW, there was a corresponding decrease of 289 kWh in energy production.

3.3. AEROSOL AND DUST SEVERITY PREDICTION ON PV PLANT PERFORMANCE USING AI TECHNIQUE

Advanced algorithms in artificial intelligence (AI) are used to forecast the effects of aerosols and dust on the performance of photovoltaic (PV) plants by analyzing environmental data [34]. By examining both historical and current data, AI improves PV system design, optimizing its size and configuration [35]. AI is also capable of predicting failures and facilitating preventive maintenance to reduce downtime. Machine learning (ML) and deep learning (DL) assess the impact of dust and aerosols by evaluating factors such as solar irradiance, temperature, humidity, and dust concentration to estimate energy losses [36].

3.3.1. ML and DL models used for the aerosol and dust severity prediction on PV plant performance

Machine learning models are employed to predict how aerosols and dust influence the performance of photovoltaic (PV) plants, thanks to their capacity to manage extensive datasets and identify patterns. These methods forecast dust storms that impact PV efficiency. Random forest is a machine learning technique that enhances prediction accuracy by utilizing multiple decision trees through ensemble learning [37]. Artificial Neural Networks (ANNs), especially *multilayer perceptrons (MLPs), model nonlinear interactions and forecast dust buildup on PV panels, thus aiding in maintenance scheduling [38].*

Due to their capacity to process extensive datasets and identify patterns, deep learning models are used to predict the effects of aerosols and dust on the performance of photovoltaic plants [39]. These models encompass Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), multilayer perceptrons (MLP), and Long Short-Term Memory (LSTM) [40]. Table 1 presents research articles on machine and deep learning models that forecast the severity of aerosols and dust on PV plant performance, outlining their objectives, findings, and limitations.

***Table 1:** Research articles associated with the ML and DL models utilized for the aerosol and dust severity prediction on PV plant performance with their aim, findings, and limitations*

Models	***Predictions***	***Findings***	***Limitations***	***Authors' name***
Grey wolf optimization (GWO)-MLP	*Aerosol*	*According to the model's results, (i) normalized mean bias error (NMBE), (ii) normalized mean absolute error (NMAE), along with (iii) normalized root-mean-square error (NRMSE) were 2.267%, 4.681%, and 6.67%, respectively.*	*The accuracy of aerosol data could be affected by the spatial and temporal variability of aerosol concentrations, making it challenging to obtain precise results.*	*Astitva, et al [41]*
MLP, KNN and DT	*Aerosol*	*The MLP model worked particularly well in desert regions with clear skies, frequent dust storms, and high airborne ODS (> 0.4).*	*Models might require continuous calibration and validation to account for changing environmental conditions.*	*Abdullah, et al [42]*
CNN	*Dust*	*98% (accuracy) was attained in tests that lasted a few minutes using the applied technique, which could automatically categorize the thermographic images from the system's CNN.*	*One major challenge was the requirement for huge labeled training data to achieve high accuracy, which could be time-consuming and expensive to collect.*	*Giovanni, et al [43]*
LSTM and RF	*Dust*	*Predictions from LSTM networks performed better with a R-value of 0.9759.*	*LSTM models, while effective in capturing longer-term dependencies in time-series data,*	*Kadir, et al [44]*

			could be computationally intensive and require significant processing power.	
LSTM-KNN	*Dust*	*The accuracies of the hybrid LSTM-KNN, LSTM, along with KNN models in predicting dust-related PV panel losses were 98.22%, 95.51%, and 61.49%, respectively.*	*The accuracy of predictions heavily relied on the quality along with the quantity of input data like solar radiation, humidity, and temperature.*	*Tuba, et al [45]*
ANN	*Dust*	*The predicted power accuracies of the six PV modules were 97.5%, 97.4%, 97.6%, 96.7%, 96.5%, and 95.5%.*	*ANNs require significant computational resources and time for training, which could be a challenge for real-time applications.*	*Jabar, et al [46]*
ANN	*Aerosol*	*The Aerosol Index (AI)-based applied models had an MSE of 4.67%.*	*The complexity of integrating multiple environmental factors, such as aerosol concentrations and temperature variations, could complicate the model design.*	*Astitva, et al [47]*

Yutong et al. [48] outlined a technique for forecasting short-term photovoltaic power using a CNN. To discern the features of influencing factors, a hybrid CNN-BiLSTM algorithm was applied, with BiLSTM being used for timing predictions. The findings reveal that this model outperforms traditional prediction models in terms of forecast results, training time, and prediction accuracy. Moreover, it meets the requirements for practical applications in PV energy-generation prediction.

Jun et al. [49] proposed an updated model for predicting PV power that utilizes aerosol index data. This model incorporates AI data as an extra input to improve prediction accuracy. To estimate the PV power outputs for the upcoming 24 hours based on seasonal weather trends, the back-propagation (BP) ANN technique was used. The outcomes from this PV power prediction model were closely aligned with the actual measurement data and showed enhanced accuracy compared to traditional ANN-based approaches.

Rahma et al. [50] investigated fault classification through a deep learning model and studied how dust accumulation impacts solar PV modules. In their study, they applied dust to a 240 Wp module to generate hotspots and evaluate the solar panel's power output. Recently, deep-

learning algorithms have been employed to identify defects in PV systems. From these results, Alex Net showed a higher accuracy of 99.70% compared to Squeeze Net.

Seghir et al. [51] utilized an MLP ANN to forecast how dust accumulation impacts the electrical efficiency of PV modules. The ANN simulations, particularly NARX and FFDTDNN, were used to estimate the decline in electrical performance due to dust presence. This model was validated as suitable for such purposes. All performance metrics, including R2, RMSE, and MARE, showed favorable outcomes.

Rashmita et al. [52] improved the performance of solar panels by applying a machine-learning approach. They employed a Deep Belief Network (DBN) to predict the accumulation of dust on solar panels arranged in a large array. A simulation was carried out to test the model's effectiveness in cleaning the panels and to evaluate the accuracy, precision, recall, and F-measure of the outcomes. The results showed that the model achieved an accuracy rate of over 99%, outperforming other methods.

3.4. CHALLENGES IN AEROSOL AND DUST SEVERITY PREDICTION ON PV PLANT PERFORMANCE USING ARTIFICIAL INTELLIGENCE TECHNIQUE

Utilizing AI techniques to forecast the impact of aerosols and dust on the performance of photovoltaic (PV) plants involves several obstacles [53]. These challenges stem from environmental influences, the quality of data, and the limitations of AI algorithms [54, 55]. Making precise predictions is essential for planning maintenance to minimize efficiency losses due to dust and to maintain the optimal functioning of PV systems [56]. The primary challenges include Environmental and Meteorological Data, the Effects of Dust and Aerosols, and the Complexity of Environmental Variability [57].

Ali et al. [58] investigated the use of AI for predicting defects in photovoltaic (PV) systems. Their method is particularly effective in detecting and categorizing faults in PV systems, while also addressing the limitations of AI-based fault detection in thermal imaging and current-voltage (I-V) curve analysis. The study revealed that AI models, such as neural networks, SVMs, random forests, decision trees, logistic regression, KNN, and naive Bayes, each have distinct advantages in identifying defects, but none can fully address all the challenges faced by PV systems.

Challenges: *There remains significant potential for progress, as demonstrated by challenges such as the lack of publicly available datasets and complexity of existing methods.*

Jonas et al. [59] explored the application of RNNs in identifying satellite malfunctions. Their research, which involved thorough testing on a simulated PV system, revealed a fault sensitivity as low as 5%. The study achieved an accuracy rate of 96.9% ± 1.3% when using precise weather data and 86.4% ± 2.1% with satellite weather data.

Challenges: *Existing PV fault-diagnosis classifiers struggle with faults that are not part of the training dataset.*

Mutaz et al. [60] investigated AI Forecasting methods to minimize uncertainties in renewable energy applications. The ANN time-series model effectively determined the PV energy, irrespective of the input data resolution. The accuracy of the forecasting results was maintained with input resolutions of 15, 30, and 60 minutes.

Challenges: *Predicting future levels of dust and aerosols is challenging due to the uncertainties present in climate change models and the unpredictability of local weather conditions.*

4. SUMMARY OF THE STUDY

This research introduces an innovative framework that leverages AI techniques to predict how aerosols and dust affect the efficiency of photovoltaic (PV) plants. The accumulation of dust and the presence of aerosols significantly diminish the performance of PV systems, especially in dry and semi-dry regions. Conventional methods for assessing these impacts often rely on empirical or statistical models, which struggle to adapt to varying environmental conditions and locations. This framework overcomes these challenges by integrating a wide array of data sources, including meteorological, environmental, and operational parameters, to create a robust predictive model. The AI-driven approach enhances prediction accuracy and streamlines the scheduling of maintenance activities, such as cleaning and performance optimization, thereby reducing operational expenses and boosting energy production. The framework's core components consist of sophisticated machine learning algorithms and data-processing pipelines that analyze patterns and relationships between dust accumulation, aerosol levels, and the degradation of PV performance. Figure 3 illustrates that the research question was grounded in various research concepts, including significance, components, policies, perspectives, and challenges. Five types of research questions were identified: 01, 02, 03, 04, and 05. Table 2 displays the questions and their corresponding answers.

Table 2: *Research questions and responses*

Sl no	***Questions***	***Responses***
01	*What are the articles covering the PV plant performance?*	*These question answers were explained in detail in section 3.1 from the references 17 to 22.*
02	*What is the significance of aerosol and dust in PV systems?*	*The significance of aerosol and dust in PV systems was explained in section 3.2.*
03	*What are the ML and DL models utilized in the prediction of aerosol and dust severity PV plant performance?*	*This question response was explained in detail in section 3.3. by mentioning different ML algorithms like SVM, RF, etc, and DL algorithms like CNN, LSTM, etc.*
04	*What are the challenges in aerosol and dust severity prediction on PV plant performance using AI techniques?*	*This question response was explained in detail in section 3.4 with different research articles from 58 to 60.*

This research lays the groundwork for future studies aimed at enhancing and expanding the framework by integrating additional environmental factors and optimizing the computational efficiency. These advancements are essential for verifying the reliability and performance of PV technologies under diverse environmental conditions, as SE continues to be pivotal in the global shift towards sustainable energy.

5.RESULT

The AI-driven approach demonstrated superior predictive accuracy and consistency compared to traditional methods. Additionally, the study identified notable correlations between dust severity, weather conditions, and the performance of photovoltaic systems, providing data-driven insights for enhanced maintenance planning.

6. CONCLUSION

The framework designed to predict the effects of aerosols and dust on the efficiency of PV plants highlighted significant improvements in accuracy and efficiency over traditional approaches. By incorporating meteorological, environmental, and operational data, the model delivers dependable real-time forecasts through advanced AI techniques. This approach allows PV plant operators to make well-informed decisions about cleaning schedules and maintenance planning, potentially lowering operational expenses and boosting energy efficiency. The reviewed research articles indicate that AI-driven models outperform conventional statistical or empirical methods in forecasting performance impacts. However, the review did have some limitations. The main limitation was that the framework was primarily validated for specific geographic areas and climatic conditions, and applying it to regions with vastly different environmental factors might require additional tuning or retraining of the AI models. Future research should address this limitation and concentrate on refining the AI models used in the analysis. Ultimately, this study highlights the transformative potential of AI in enhancing predictive maintenance strategies and sets a benchmark for improved PV plant performance management.

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