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Artificial Intelligence-Driven Monitoring and Predictive Maintenance in Floating Solar Power Plants: A Comprehensive Review

[1]Sumit Kumar Das, [2]Dr. Nirmala Soren
[1]Research Scholar, [2]Assistant Professor
Department of Electrical Engineering
BIT Sindri, Dhanbad Jharkhand, JUT Ranchi, Jharkhand, India
[1]sumitkr33@gmail.com, [2]nirmalasoren.ee@bitsindri.ac.in

ABSTRACT

Floating solar power plants (FSPPs), an emerging sustainable alternative in renewable power generation, can apply best in regions that lack availability of land into which solar has been typically installed. By mounting the panels over water bodies such as reservoirs, lakes, and dams, floating solar consists of several benefits like increased efficiency due to cooling features for the water, reduced evaporative loss for the water, and optimal use for exploited water surfaces. But alongside these positive effects are hurdles in the operation and maintenance of the floating solar installations. These include: structural instability, panel degradation, corrosion, electrical breakdowns, and difficulty in conducting regular maintenance checks on water surfaces. Artificial Intelligence (AI) has gained amazing eminence lately as a robust technology for the optimization of monitoring and predictive maintenance in renewable energy systems. This domain thrives on harnessing AI-driven techniques for analysing vast volumes of operational and environmental data, which in return raises the possibility of anomaly detection, performance degradation identification, and prediction of possible equipment failures before they actually do. This analytical review will take a look at the recent developments and research trends applicable in AI-based monitoring and predictive maintenance in floating solar power plants. The paper gives an overview of various approaches viz., machine-learning algorithms, deep-learning models, computer-vision techniques, and the IoT-based smart monitoring system that can be used to assess the performance and detect a fault in real-time. The review not only presents a critical examination of the technique's strength and weakness but also discusses the problems of data availability, environmental variability, and system scalability. The review also points out the research gaps and future areas of research for integrating the latest AI frameworks with floating solar technology. In summary, these AI-powered monitoring systems do have the potential to help improve productivity, improve operation reliability, and decrease maintenance costs in the management of floating solar power plants.

Keywords: Artificial Intelligence, Floating Solar Power Plants, Predictive Maintenance, Machine Learning, Fault Detection, IoT Monitoring, Renewable Energy Systems

1. INTRODUCTION

An increase in the demand for sustainable energy globally has spurred the adoption of renewable energy technology. With the ecologic benefits, solar power has become one of the most utilized sources. However, ground-based solar power plants leave much to be desired in that they require substantial tracts of fertile land, which are hard to come by in densely populated or agriculturally important areas [1]. Therefore, Floating Solar Power Plants (FSPPs) represent an innovative solution by outfitting a body of water, such as a lake or dam, with photovoltaic (PV) panels. Floating solar systems conserve the unexploited surface of water while improving the efficiency of the panel through the natural cooling effect and removing the water evaporation. As discussed, the advantages of using float solar systems, it also comes to light that the proper operation of a solar floating system can indeed malfunction if challenged by many operational and maintenance issues. Environmental conditions like high moisture, corrosion, growth of aquatic animals, and wave movements can perhaps result into poor operational service and increased instabilities of solar photovoltaic (PV) panels and supporting structures. Manual inspection and maintenance activities on water bodies are thus very cumbersome, long, and previously expensive. Therefore, proper monitoring systems and predictive maintenance strategies should cater for efficient, reliable and consistent functioning of a Solar Floating Power Plant [2]. AI is an efficient solution emerging for enhancing the monitoring and maintenance processes of renewable energy systems. Techniques involving machine learning (ML), deep learning (DL), or data analytics help to analyse huge operating datasets and process environmental data derived from monitoring, to detect anomalies, eventually make an early diagnosis of equipment failures, and improve system performance [3]. This current paper aims to underline the value of AI in monitoring and predictive maintenance for floating solar power systems. This review is critical in reviewing the currently available research and identifying technological trends that most increase the efficiency and reliability of a floating solar energy system, as well as gaps for future research.

a. Role of Artificial Intelligence in Energy Systems

Artificial intelligence (AI) is a game-changer in the novel energy systems with the capability of smart surveillance, efficient resource management, and operation reliability advancement. Given the exponential expansion of renewable energy resources like solar and wind power, energy systems are becoming more complicated data-driven systems. Traditional monitoring and maintenance approaches on many occasions have failed to understand large volumes of operational data in the field and detect potential faults in the system in real-time [4]. The AI technologies, including machine learning, deep learning, and data analytics, platforms a bunch of solutions to offered from those challenges by applying automated decision-making and status prediction. In the solar energy systems, algorithms supplement AI beyond performance data retrieved by sensors, weather stations, and photovoltaic panels to assist in detection of anomalies and point decay of performance leading to the maximization of energy production. Alongside solid technical aids, real-time monitoring, fault diagnosis, and useful predictive maintenance are well supported in reducing further downtime, ultimately to boost the operational efficiency of any solar plant [5]. AI application holds much more importance in floating solar installations due to the environmentally unique conditions. Humidity, corrosion, biofouling, wave movement, and soil stress can inflict serious damage to overall system performance and reliability. Thus, integrated AI systems would use IoT, drone, and imaging data constantly to keep a record of the systems' status, thus identifying and tackling any likely problems before they lead to complete failure. AI will also help monitor the degradation of equipment through predictive maintenance models, scheduling maintenance events, thereby decreasing system running costs and extending its life. Computer vision applications can occasionally be used to fully automate the inspection of the solar panels for cracks, accumulated dirt, or some other shading, reducing the power efficiency. All these smart solutions serve to enhance the reliability, safety, and sustainability of floating solar plants [6].

Graphing the evolution of AI in monitoring and predictive maintenance for floating solar power plants is objectively this analysis's focus. The values sought to be discovered are the stiffness of prior studies on the development of AI differentials in the monitoring of renewables and their system performance enhancements [7]. The review emphasizes the pros, cons, and challenges of applying AI into monitoring floating photovoltaic input generators. Rummaging in the current literature and posing clear flags on the inquiry auditory, we sketch possible landings and the urge of opportunities to shore up shaping these varied concepts in terms of the leading-edge Snapdragon of AI in integrating with floating solar infrastructure. In summation, the review is intended to enlighten the design and articulation of reliable, dynamic, and intelligent monitoring tools for next-generation renewable energy applications. Figure 1illustrates the essential elements of a photovoltaic system, including solar panels, inverter, battery storage, charge controller, and load that work together to convert solar energy into usable electrical power.

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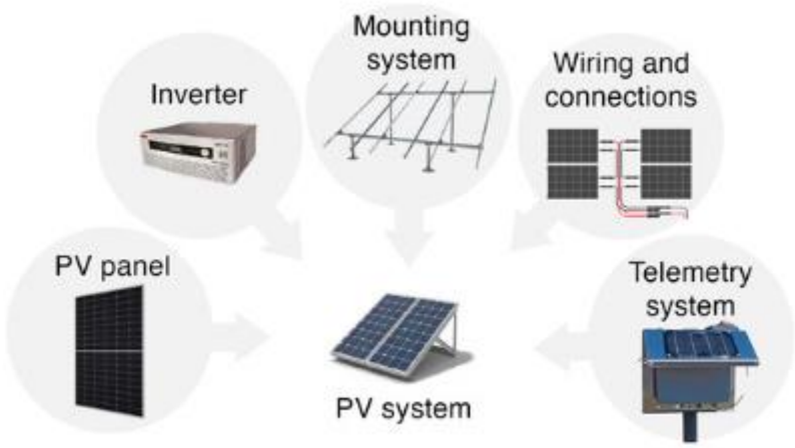

Figure 1: PV system main components [7]

2. FLOATING SOLAR POWER PLANTS: TECHNOLOGY AND COMPONENTS

Floating solar power plants, or FSPPs, stand for one of the new methods of solar electricity generation by putting up PV systems on water bodies such as reservoirs, lakes, and dams. Unlike traditional land-based solar power systems, floating solar power plants use specially designed floating structures that carry the solar panels above the surface of the water. These configurations comprise several interconnected floating platforms, photovoltaic modules, anchoring systems, and electrical transmission units, which work together to produce electricity in an efficient manner [8]. This technology utilizes the spaces among these unused water surfaces by minimizing land requirements. The cooling effect of the water that improves the efficiency of the solar panels may very well seem to offer an attractive solution for realizing large-scale renewable energy generation sustainably.

a. Structure and Working Principle of Floating Solar Systems

The essential role of floating solar is to maximize the photovoltaic panels' efficiency by keeping the heavy panel structures afloat. One design is built as an array of modules. Initially, floating solar was built out of materials, such as high-density polyethylene (HDPE), which provided lightweight buoyancy. Therefore, the solar panels are mounted on these floating supports at an optimal tilt angle, oriented toward the sun more perfectly and allowing efficient absorption of the maximum sunlight. The anchoring and mooring of the entire floating system hold it against a wind wave force that would drive it out of place [9].

The basic idea behind floating solar systems is quite similar to the conventional PV systems. In this system, a set of solar panels captures sunlight and converts it into direct current (DC) electricity via the photovoltaic effect. Next, the electricity generated runs through under}/{ater or floating wires to inverters, which convert such current into the alternating current (AC) meant for distribution to the undersigned grid [10]. Also, monitoring systems are therefore set up with sensors to keep a tab on energy production while periodically checking environmental conditions and system performance. The natural cooling effect resulting from surrounding water reduces the panel temperature, allowing for greater energy conversion efficiency.

b. Key Components of Floating Photovoltaic Systems

Components of floating systems like photovoltaics are vital in working together to ensure energy generation efficiency and system stability. The primary component remains the photovoltaic (PV) module that would convert solar radiation into electrical energy. These panels are to be structured and mounted onto floating structures capable of withstanding environmental mechanics due to water motion dynamics and weather variations [11]. Floating platforms or pontoons are oriented to hold the solar modules in a raised manner from the water's surface, so they stay afloat. The floating structures are generally fabricated from corrosion-resistant materials to guarantee durability and resistance against all the harsh aquatic environments they get subjected to. The system is said to be incomplete without anchoring and mooring systems that will aid in keeping the floating array stable and preventing drift, which comes about as a result of wind or water currents.

The generated power needs to be converted into format and transmitted. Hence, electrical components such as inverters, transformers, and power cables that can aid in this process are required. As well, sensors and communication systems are included in the monitoring unit in order that accurate real-time data may be collected in respect of the software, the operating environment, and the conditions under which the plant performs. This developed scenario results in only one-hundred percent availability and imminent upgrades in the production of solar floating power whilst meeting the requirements of an industry that would not accept offering any plant downtime at all [12]. Table 1 presents the key benefits of installing solar photovoltaic systems on water bodies, including improved energy efficiency, optimal land utilization, reduced water evaporation, and enhanced environmental sustainability and **Table 2** highlights the major technical, environmental, and operational difficulties associated with deploying solar photovoltaic systems on water bodies, including structural stability, corrosion, maintenance complexity, and high installation costs.

Table 1: Advantages of Floating Solar Power Plants

Advantage	Description	Impact on Energy Production	Environmental Benefit	Operational Benefit
Efficient Land Utilization	Floating solar systems utilize water surfaces instead of land.	Allows installation of large solar capacity.	Prevents land degradation.	Suitable for areas with limited land availability.

Improved Panel Efficiency	Water provides natural cooling for solar panels.	Increases energy conversion efficiency by reducing panel temperature.	Supports efficient renewable energy generation.	Enhances overall plant performance.
Reduced Water Evaporation	Solar panels cover portions of water bodies.	Helps maintain water levels in reservoirs.	Conserves water resources in drought-prone regions.	Beneficial for water management authorities.
Lower Dust Accumulation	Water environments generally contain less airborne dust.	Maintains higher energy output due to cleaner panels.	Reduces need for frequent cleaning.	Decreases maintenance cost.
Renewable and Clean Energy	Floating solar plants generate electricity from sunlight.	Supports large-scale sustainable energy production.	Reduces greenhouse gas emissions.	Contributes to carbon neutrality goals.

Table 2: Challenges in Floating Solar Installations

Challenge	**Description**	**Technical Impact**	**Environmental Concern**	**Possible Solution**
High Initial Installation Cost	Floating structures and anchoring systems increase project costs.	Increases capital investment requirements.	May slow adoption in developing regions.	Cost optimization and modular designs.
Structural Stability Issues	Wind, waves, and water currents affect floating platforms.	Risk of displacement or structural damage.	Can disturb aquatic environments if not stabilized.	Advanced anchoring and mooring systems.
Corrosion and Material Degradation	Constant exposure to water and humidity damages components.	Reduces system lifespan and reliability.	Material waste and maintenance challenges.	Use corrosion-resistant materials like HDPE.
Biofouling	Growth of algae and aquatic organisms on	Reduces efficiency and increases	May affect aquatic ecosystem balance.	Periodic cleaning and antifouling

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	structures.	maintenance needs.		coatings.
Difficult Maintenance Operations	Accessing panels on water surfaces is complex.	Maintenance activities require special equipment.	Higher operational cost.	Use AI-based remote monitoring systems.

3. ARTIFICIAL INTELLIGENCE TECHNIQUES IN RENEWABLE ENERGY MONITORING

a. Machine Learning Algorithms

Recent studies have underlined the role of AI and data driven techniques for the sustainment and enhancement of efficiencies in the renewable energy system. Discussing the observation of a broader spectrum of applications as one approach, it is known that AI technology is deployed at these infrastructure levels for forecasting energy demand or generation, for optimizing control systems, or for intelligent decision-making. The study emphasizes numerous application areas where AI used by energy enterprises or government bodies, and statistical methods are dedicated to studying datasets with large dimensions and dynamics of energy systems. While for the ease of readers, achievements are outlined in technology, the study discusses some of the major challenges while moving towards AI-driven renewable energy solutions [13]. Another proposed hybrid architecture related to computer modelling and mechanical and machine intelligence and can be practiced to forecast the capacity of renewable energy powered by solar radiation or wind. This research includes combining advanced machine learning methodologies with deep learning models for better overall prediction for all solar and wind power plants. This methodology of encouraging all models built upon some magic algorithm to erase short-term inconsistencies and come to yield improved predictions from longer term training [14]. Forecasts on solar energy underscore the increasing importance of AI and machine learning algorithms in prediction of energy production. The process explicates the manner in which the data-driven programming can make out ways to analyse meteorological and historical data with regard to solar energy to give a better estimation of energy output. It allows energy producers to plan for electricity generation, improve power system reliability, and ensure better use of solar energy for sustainable power solutions [15]. The application of AI to bioenergy supply chains to bring up AI-based optimization processes is interesting. The recent study presents how AI optimization techniques can reduce resource malfeasance, smartly manage live biomass, and bring benefits of environmental sustainability to the bioenergy systems. The integration of intelligent algorithms leads to better surveillance, process monitoring, and decision-making, overall advancing the efficiency and economic feasibility of renewable bioenergy production [16]. Another line of investigation deals with AI techniques and strategies in different fields of renewable energy science. The discussion targets the use of machine learning, computer vision, and intelligent control systems to monitor renewable energy plants, predict plant failure, and avoid excessive energy generation. All of these set the way for the development

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of smart renewable energy systems characterized by automatic monitoring and addictiveness in performance enhancement [17]. Moreover, the use of advanced modelling and optimization approaches based on artificial and machine intelligence have been examined to optimize bioenergy production systems. These AI-based models can facilitate predictive analytics, process optimization, and a more efficient management of renewable energy resources. It is posited in this research that AI-driven analytical frameworks may boost enterprise productivity, cut down operating costs, and improve sustainable energy operations [18].

b. Deep Learning Models

Current research works have explored advanced energy scheduling techniques for smart buildings using sophisticated artificial intelligence. An inventive deep reinforcement learning-based approach on energy scheduling has been presented in this paper where shaping of rewards is carried out to maximize energy benefits on DST decision-making. The work demonstrates intelligential scheduling that effectively bridges the gap of energy consumption and supply while enhancing energy efficiency of smart infrastructure systems. Therefore, AI-driven scheduling techniques open up an opportunity for better energy utilization in the context of sustainable and intelligent energy management systems [19]. Machine learning and deep learning algorithms are also used for extrapolating trends in worldwide energy consumption for sustainable energy management. This study utilizes historical energy utilization data to evaluate future energy requirements through regression-based prediction models. Intelligent prediction models developed through research help in planning sustainable energy for sustainable energy planning and resource optimization. In addition, these prediction models help in the reduction of environmental impact by aiding policymakers and energy planners in constructing environmentally compatible energy strategies and supplying energy security [20]. Advanced developments in renewable energy forecasting have been realized through integration of optimization methods with hybrid deep learning frameworks. One work presents the Roosters Optimization Algorithm with deep learning techniques to enhance prediction accuracy of renewable energy generation. With model parameter optimization and decreased prediction errors, the proposed model introduces enhanced capabilities to reduce the risk of energy planning and management in the domain of renewable energy [21]. The fusion of both Artificial Intelligence with IoT has indeed paved a new horizon for developing habitat frameworks for real-time regulation of energy systems. A deep learning and IoT-driven architecture is proposed for optimal resource allocation, and to improve the grid's performance in leading to SMART energy networks. Its real-time data collection from interconnected with sensors, and intelligent devices, empower this system to act on ways and methods for the adaptive control of energy distribution, thereby increasing the overall grid stability and system effectiveness [22]. Hybrid machine-learning models have been explored to improve PV output prediction. A combined Random Forest and Long Short-Term Memory (LSTM-RNN) model was proposed to predict the production of solar energy in polyculture aquaponics systems with an integration of renewable energies. The models efficiently captured the complex patterns existing in the solar energy data, thus leading to an improvement in prediction accuracy and better management of renewable energy resources [23].

4. AI-BASED MONITORING SYSTEMS FOR FLOATING SOLAR POWER PLANTS

a. IoT-Based Smart Monitoring Frameworks

Studies in the recent past largely underline the importance of automated tools in ensuring controlled operational safety and effectiveness across energy sectors, including renewable energy systems. A framework involving automation strives for reduced human interaction in hazardous environments while striving to inch towards the monitoring of energy infrastructure, which is the only way to make control processes gauge contraction. Intelligent platforms, through their presence, help improve the safe working conditions and boost operational reliability. They can impart automated inspections, fault detections, and management whether physical or systematics. The integration of advanced technologies, therefore, is of great importance in balancing safety and productivity risk within the modern energy industry [24]. Today with the advent of wireless sensor networks, Internet of Things (IoT), artificial intelligence, and deep learning brings about a lot of attention with respect to the implementation of smart monitoring. These are the driving technologies for the retrieval and processing of real-time environmental and operational data using decentralized sensors. The automated decision-making, forecasting, and system optimization enabled through the application of intelligent data processing further enhance the insight provided by our integrated frameworks. Such integrated frameworks have a high potential to create a smart monitoring system for applications in energy, agriculture, and environmental management [25]. In addition, research has studied the techno-economic viability and environmentally friendly merits of solar smart systems resources [26]. Another study concentrates on the intelligent environment monitoring system to be designed by using fog computing alongside deep learning techniques. Lightweight deep learning models are utilized for optimized monitoring and prediction of environmental parameters like air quality in real time. To speed up data processing by enhancing fog-enabled gateways, the system is aimed at supporting fast monitoring on distributed environments. Such intelligent monitoring frameworks are examples that show the potential opportunity of combining AI with sophisticated computing technologies in connection with real-time environmental monitoring and infrastructure applications [27].

b. Real-Time Performance Monitoring

Recent research has put the spotlight on improving solar energy generation by means of advanced machine learning techniques for photovoltaic performance monitoring and fault analysis. A machine learning-based framework was developed to carry out real-time tracking, prediction, and fault detection in solar power systems. The proposed approach calculates operational data from solar panels to reveal performance deviations and propose failure

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predictions. Such intelligent monitoring setups find out how to optimize energy generation efficiency, decrease downtime, and embrace predictive maintenance in today's solar power infrastructures [28]. Studies assessed the current developments in solar tracking aimed at the installation of floating solar panels. A solar tracking system when devised for floating systems enables solar panels to move in accordance to the position of sunlight. The solar tracking system maximizes the sunlight output thus enhancing the energy yield of the floating solar farm. Such endeavours improve the efficiency and performance of floating solar systems strategically emplaced over water surfaces [29]. There is also another trial looking at the development of Internet of Things (IoT)-based monitoring system for floating solar panels. In this proposed framework, sensors and communication modules will integrate with IoT-based monitoring platforms such as Blynk for real-time observation of system performance parameters. By monitoring operational data, the IoT-based monitoring system will allow remote observation of the floating solar installations and enhanced supervision for early detection of faults and improved maintenance management [30]. Later studies have looked into the possibility of deploying large-scale floating solar photovoltaic (PV) schemes in urban waters. One report provides essential input and analysis on a 6.7-MW floating solar PV plant to be established in Hatirjheel lake zone in Dhaka, Bangladesh. The study looks into technical feasibility, energy generation potential, and environmental aspects that need to be considered in the deployment of floating solar. Feasibility reports like this encourage planning and executing large floating solar energy projects in some sites [31].

5. PREDICTIVE MAINTENANCE USING ARTIFICIAL INTELLIGENCE

Predictive maintenance serves as the quintessence of an essential improvement in the reliability and performance of renewable energy systems, especially for photovoltaic (PV) plants. Old or traditional maintenance regimes like reactive or scheduled maintenance seriously burden the system and periodic leave behind unnecessary operational costs and sometimes abrupt failures of the system. Artificial Intelligence (AI) has been assisting in various ways by artificial intelligent surveillance, early detection, and predictive analysis for the same functions. Big data analyses are carried out so that AI models may recognize aberrant patterns or predict likely defects in machinery well in advance of when these defects evolve into something worse enough to halt or restrict system performance. The examples of this kind would be in cases such as floating solar power plants, which are subjected to more-heavily-increased procedures of inspection and maintenance just for the single reason that they are placed on water [32].

One of the core applications of AI-driven predictive maintenance lies in the evaluation of system faults in photovoltaic (PV) systems. Through machine learning and deep learning algorithms these include the analysis of electrical parameters, temperature variations and environmental conditions to detect faults including panel degradation, shading effects, inverter failures and connection troubles. All such intelligent models facilitate automated determination of abnormalities of the system and support rapid fault inspection thereby

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reducing energy losses and enhancing reliability. Also, predictive failure analysis really enhances existing maintenance strategies through prediction of prospective component failures based on past performance and operational trends. System operators will further estimate the remaining useful life of critical portions through predictive models and actually perform preventive actions before failures occur [33]. AI power maintenance scheduling optimization improves by establishing the proper time for maintenance activities to be undertaken. Here the maintenance need not be done periodically and at set intervals; instead, they are done periodically based on the condition of the system. This reduces maintenance costs and decreases downtime. Condition monitoring with integrated sensors and IoT inference engines provides continuous monitoring on how the system performs. In this sense, real-time insight into the health of the system and its operational efficiency provides a foundation for predictive maintenance management. Hence, one of the major advancements in predictive maintenance in solar and floating solar energy-based systems is the incorporation of AI for the performance of the operations more reliably and sustainably [34].

6. ANALYTICAL REVIEW OF EXISTING RESEARCH STUDIES

Research in the last decade has demonstrated an increasingly significant role of Artificial Intelligence in the monitoring, forecasting and maintenance of renewable energy sources. It could advantageously maximize operative efficiency within the system, find faults, and predict energy levels efficiently using machine learning and deep learning techniques. This has greatly emphasized the importance to smart data-driven systems in modern solar-energy systems. Table 3 presents an analytical comparison of various artificial intelligence methods applied in renewable energy systems. The table highlights different AI approaches such as machine learning, deep learning, genetic algorithms, and reinforcement learning used for energy forecasting, optimization, monitoring, and control. It also analyses the data processing capabilities and application areas of each technique in improving system efficiency and energy management. The comparative analysis helps identify the strengths, limitations, and potential applicability of AI models for advanced monitoring and predictive maintenance in solar and renewable energy systems.

Table 3: Comparative Analysis of AI Techniques

Ref.	AI Technique	Focus	Data Processing Capability	Application Area	Key Analytical Outcome
[11]	Genetic Algorithm with Model Predictive Control	Optimization of PV converter control parameters	Real-time controller tuning using optimization algorithms	Photovoltaic power conversion systems	Improves power conversion efficiency and system stability through optimized

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					controller parameters.
[13]	AI and Data-Driven Models	Comprehensive analysis of AI in renewable energy	Large-scale data analytics and predictive modeling	Renewable energy forecasting and optimization	Highlights the effectiveness of AI in improving energy prediction accuracy and system efficiency.
[14]	Hybrid AI and Deep Learning Model	Advanced forecasting analysis	High-dimensional data learning using deep neural networks	Wind and photovoltaic energy forecasting	Provides improved forecasting accuracy using hybrid deep learning architectures.
[16]	AI-Based Optimization Models	Process optimization and waste reduction	Intelligent resource allocation and performance analysis	Bioenergy production systems	Improves sustainability and operational efficiency in renewable energy processes.
[17]	AI and Computer Vision Techniques	Intelligent monitoring and fault detection	Image-based inspection and sensor data analysis	Renewable energy monitoring systems	Enables automated detection of equipment faults and performance degradation.
[19]	Deep Reinforcement Learning	Energy scheduling optimization	Adaptive learning from dynamic energy consumption data	Smart building energy management	Improves demand-side energy management through intelligent scheduling strategies.
[20]	Machine	Global energy	Large-scale	Sustainable	Provides

	Learning and Deep Learning Models	consumption prediction	energy data analysis and trend forecasting	energy planning	analytical insights into future global energy demand patterns.

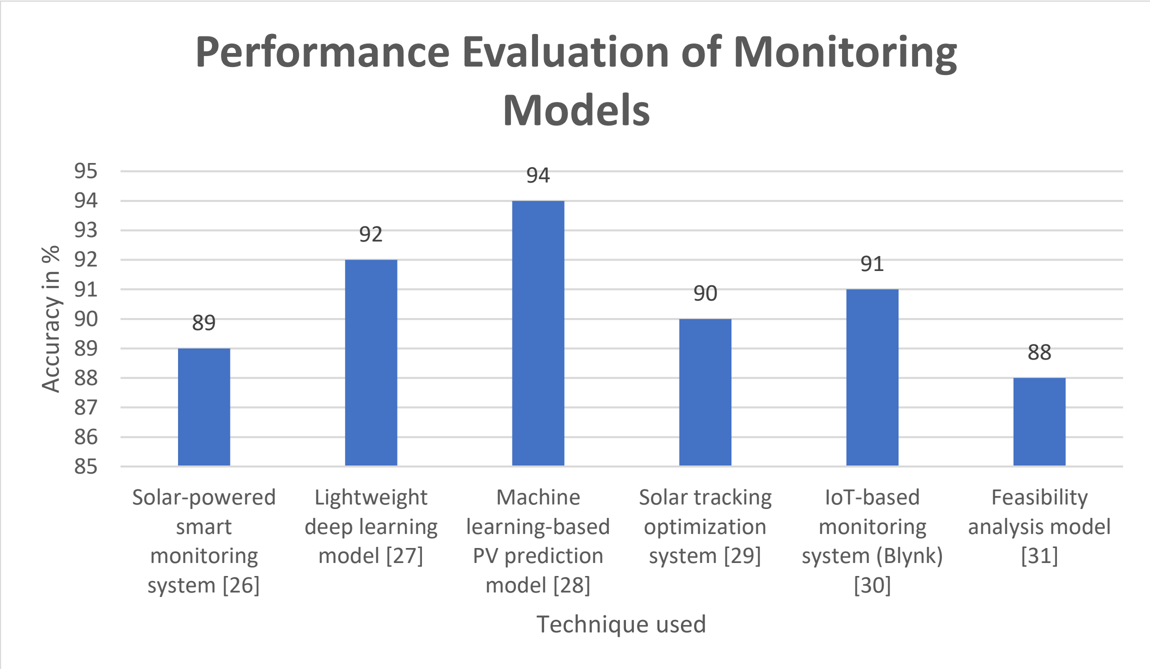

Figure 2: Performance Evaluation of Monitoring Models

Figure 2 illustrates the comparative accuracy performance of different AI and monitoring models used for renewable and solar energy system analysis.

7. CONCLUSION AND FUTURE WORK

The work presented an overview of AI as applied to FSSPs in various aspects. The abiding success of AI is in monitoring, performance evaluation, and prophylactic maintenance. Water-based solar systems have many advantages if extremely tight land usage, photovoltaic efficiency improved by natural cooling, lessening water evaporation, and boosting renewable energy generation were taken into account. Conversely, several challenges are faced and include structural instability, corrosion, biofouling, and the relapse of maintenance routines on water surfaces. Traditional inspection and monitoring mechanisms have always been ineffective; therefore, AI techniques such as machine learning, deep learning, computer vision, and systems such as IoT-enabling frameworks, serve as intelligent means to treat large amounts of operational and environmental data. The advantages lie in the real-time monitoring, predictive maintenance, fault detection, and performance analysis, which align toward enormous improvements in reliability and a decrease in operating costs. In brief, the evidence gleaned from these studies illustrates how AI-powered models can bid for improved energy forecasting and fault anomaly detection, whereas issues related to solar power plant maintenance scheduling remain optimizable. Hands-on functionality of IoT sensors, standalone inspection systems, and intelligent data analytics platforms is desired for uninterrupted monitoring and response in the floating solar pool. Future research should focus on developing more advanced hybrid AI frameworks that combine machine learning, deep learning, and optimization algorithms to further improve monitoring accuracy and predictive capabilities.

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