ERURJ **2025**, *4*, 4, 3314-3335
(Review)

A Review of Deep Learning and AI Techniques for Enhanced Sun Detection in Solar Power Applications

Alaa Eesa[1] * and Wafaa Mostafa[1]

[1]*Mechatronics Engineering Department, Faculty of Engineering, Egyptian Russian University Badr City, Cairo 11829, Egypt.*

* Corresponding author: Alaa Eesa, Alaa-eesa@eru.edu.eg

Received: 16th November 2024, Revised: 11th August 2025, Accepted: 30th October 2025. DOI: 10.21608/erurj.2025.336928.1205

ABSTRACT

This review article explores the evolution and recent innovations in solar tracking systems, with a specific focus on the integration of deep learning and artificial intelligence (AI) techniques for enhanced sun detection. The paper highlights the strategic importance of renewable energy, particularly in Egypt, and discusses Concentrated Solar Power (CSP) systems especially Parabolic Trough Systems (PTS) as a sustainable energy solution. Traditional and modern solar tracking techniques are critically analysed, showing how AI-driven methods significantly improve tracking accuracy, system adaptability, and energy efficiency across various environmental conditions. Key findings demonstrate that deep learning approaches, such as Convolutional Neural Networks (CNNs) and ANFIS, can boost tracking precision by over 90%, reduce error margins to under 0.1°, and improve energy yield by up to 76% in dual-axis systems. The review concludes that the integration of AI and machine vision not only enhances the reliability and scalability of solar tracking systems but also opens new pathways for autonomous, low-cost, and high-performance renewable energy applications.

***Keywords**:* Solar tracking systems, deep learning, YOLO, concentrated solar power, renewable energy.

1. Introduction

In 2015, the United Nations launched the Sustainable Development Agenda, with Goal 7 aiming to provide sustainable energy for all by 2030. After a temporary 5.8% decrease in CO_2 emissions in 2020 due to the COVID-19 pandemic, transitioning to low or zero-carbon energy sources is essential to achieve net-zero emissions by 2050. Renewable energy's share in global electricity generation is expected to rise from 19% in 2019 to 79% by 2050. Egypt accounts for about 8% of Africa's renewable energy production, which is equivalent to approximately 93 million tons of oil. Although its share is relatively small on both regional and global scales, Egypt has vast potential for renewable energy. The estimated capacity for concentrated solar power is 73,656 TWh/year, wind energy at 7,650 TWh/year, and photovoltaic solar energy at 36 TWh/year. Additional resources include biomass (15.3 TWh/year), geothermal (25.7 TWh/year), and hydropower (80 TWh/year). Currently, Egypt's total installed energy capacity is around 54.5 GW, with a small portion coming from renewable sources. With immense untapped resources and ideal conditions for renewable energy generation, Egypt aims for renewable sources to account for 42% of its electricity generation by 2035, as shown in Figure 1. **Error! Reference source not found.**. Solar energy is one of the leading renewable resources, offering clean and reliable power. The solar radiation reaching Earth is 27 times higher than global commercial energy consumption, making it a highly attractive renewable option. Situated in the "Sun Belt," Egypt enjoys high direct solar radiation ranging from 5.5 to 9.0 kW/m² per day, with sunlight lasting between 9 to 11 hours daily. The country has over 125 solar power stations generating up to 9 GW, reducing carbon dioxide emissions by 9 million tons annually. Several solar projects are either underway or completed, particularly in Upper Egypt and along the Red Sea coast [1], [2], [3].

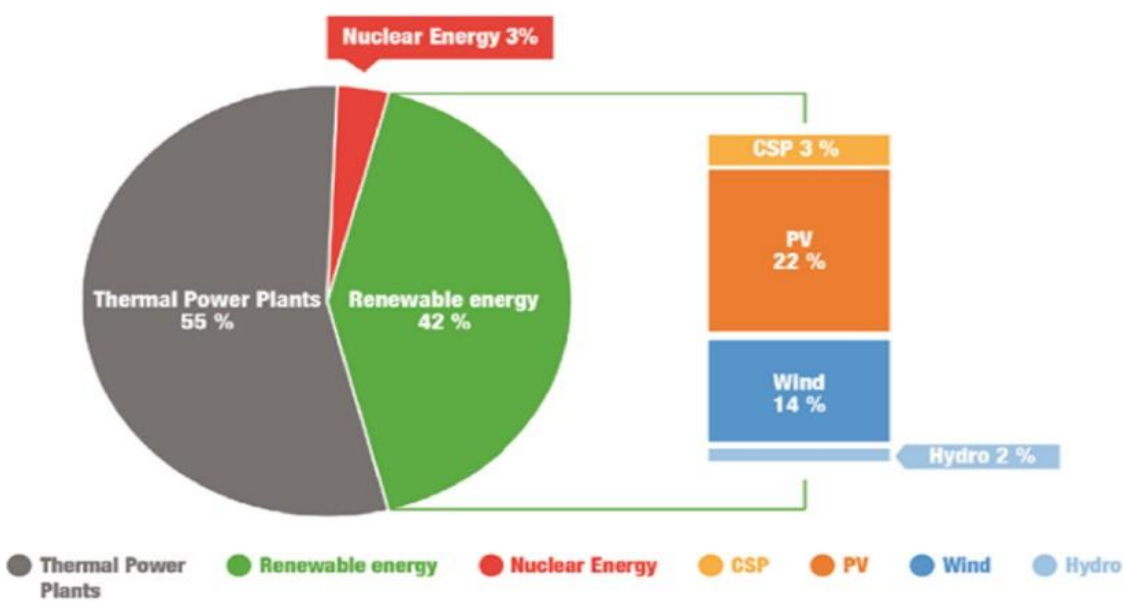

Figure 1. Electricity production future plan classification [2].

Concentrated Solar Power (CSP)

Concentrated Solar Power (CSP) systems represent an established and efficient approach to sustainable energy generation, harnessing concentrated solar irradiance to produce both thermal and electrical energy. These systems are particularly suitable for applications requiring medium to high operating temperatures. CSP technologies employ reflective surfaces, typically mirrors, to focus solar radiation onto a defined focal line or point. Linear-focus configurations—such as Parabolic Trough Collectors (PTCs) and Linear Fresnel Collectors (LFCs) utilize single-axis tracking mechanisms to direct sunlight along a focal line. Conversely, point-focus configurations, including solar tower systems and parabolic dish systems, employ dual-axis tracking to concentrate solar flux onto a discrete focal point, enabling higher concentration ratios and thermal efficiencies.

Parabolic Trough Collectors (PTCs)

PTCs are regarded as the most mature and widely used CSP technology. These systems consist of concave structures fitted with mirrors to direct sunlight towards receiver tubes situated at the focal line. The technology's main purpose is to capture direct solar energy and focus it onto the receiver tubes for optimal heat transfer. Regular maintenance and operational support are essential for ensuring the systems operate efficiently and have a long service life as shown in Figure 1 and Figure 2.

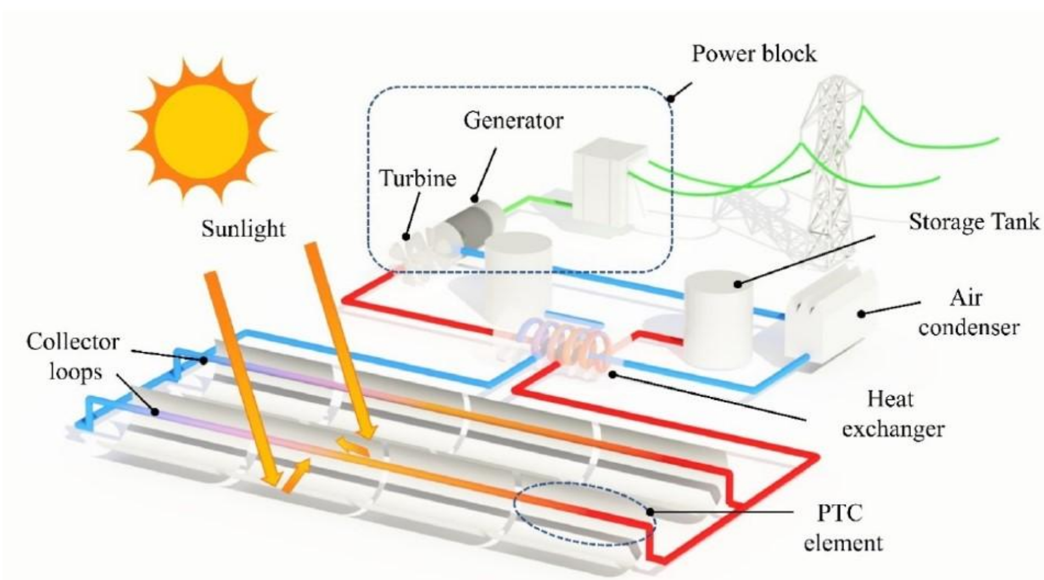

Figure 1 Schematic diagram of a solar parabolic trough collector system [4].

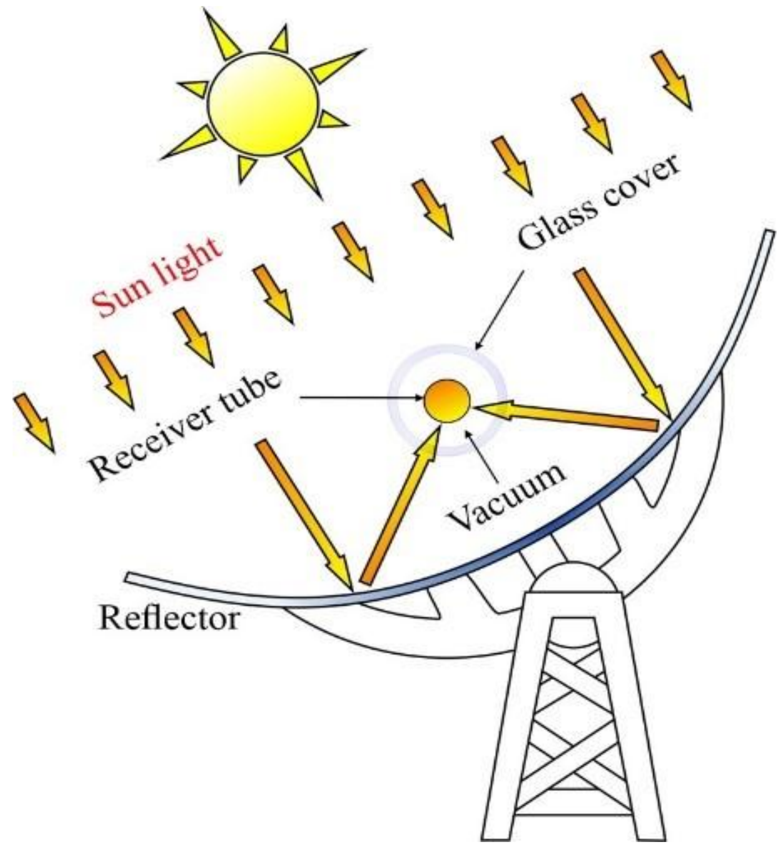

Figure 2 Diagram of PTS [5]

However, various errors can occur in Parabolic Trough Collector (PTC) systems, affecting their optical, thermal, and electrical performance. Examples of these errors include tilt deviations, shape imperfections, tracking inaccuracies, and dust accumulation, all of which can lead to significant degradation in the system's optical performance and cause noticeable optical losses. This study aims to provide a comprehensive review of methods for addressing tracking errors, ranging from traditional techniques to the use of artificial intelligence and deep learning for detecting and locating the sun's position. The system then dynamically adjusts the tracking mechanism to ensure that solar rays strike the mirrors perpendicularly. This alignment guarantees optimal reflection of sunlight onto the receiver tube. These approaches offer an effective and reliable means of maintaining accurate solar tracking, thus enhancing the overall performance of the PTC system.

2. Literature review

2.1 Renewable Energy in Egypt

According to Mostafa et al. (2024), Africa holds 40% of the global solar energy potential but contributes only 1.48% to global production. In Egypt, where solar radiation ranges from 5.5 to 9 kWh/m² per day, efforts are underway to increase renewable energy's share from 10% to 42% by 2035, supported by projects like the Benban Solar Park. The study emphasizes the importance of collaboration between academia and industry to advance renewable energy development [1], [3].

As stated by Moharram et al. (2022), Egypt has significant potential in renewable energy, particularly solar and wind energy. The country benefits from approximately 3050 hours of sunlight annually, making it ideal for solar projects such as the Benban Solar Park, expected to become the largest photovoltaic facility in the world. Additionally, Egypt has substantial wind energy resources, especially in areas like the Sinai Peninsula and the Gulf of Suez, where wind speeds range from 8 to 10 m/s. The country also supports initiatives like "net metering," which encourages the installation of solar panels and the sale of excess energy to the national grid [2].

This study explores Egypt's solar energy potential, specifically identifying the most suitable strategic locations for installing photovoltaic (PV) systems to support the country's electricity needs, especially in rural and desert areas. Seven key sites were evaluated using data from four stations to validate the ERA5 reanalysis dataset. The results indicate that El-Golf, Shiab-Elbanat, and Saffaga are the most cost-effective sites for PV system installation, owing to their favorable solar radiation levels and low energy production costs, making them ideal for sustainable energy development in Egypt [6].

Solar energy, particularly through photovoltaic (PV) panels, has seen significant advancements in recent years, but faces challenges related to energy storage and efficiency during non-sunny periods. Concentrated Solar Power (CSP) systems address these issues by using mirrors to concentrate sunlight, generating high temperatures to produce steam for electricity generation. CSP can store thermal energy, enabling electricity production even during cloudy periods or at night, enhancing its efficiency compared to PV systems. It also produces high-quality thermal energy for industrial use.

A study by Elshafey et al. (2018) highlights the potential of solar thermal power plants to meet global energy demands, reduce fossil fuel dependence, and mitigate pollution, while discussing challenges faced by a 140 MW integrated solar power plant in Egypt [7].

2.2 Parabolic Trough Systems (PTS)

In recent years, solar energy systems have seen significant advancements due to continuous technological progress. Among these systems, the Parabolic Trough Collector (PTC) system is one of the most efficient in converting solar energy into thermal energy. This system relies on a design that enhances the concentration of sunlight onto a receiver containing a heat transfer fluid, increasing its efficiency in various applications such as electricity generation and heating.

According to Himanshu et al. (2022), a comprehensive review of parabolic solar collectors was conducted, highlighting the importance of proper geometric dimensions and optimized materials to improve thermal efficiency, with a focus on the use of nanofluids for enhanced heat transfer[8].

Additionally, Wassila et al. (2022) emphasized the significant improvements in heat transfer with the use of nanofluids and turbulators, noting that fin inserts were more effective than nanofluids, despite their higher costs [9].

Kai et al. (2024) developed a strategy to enhance the efficiency of parabolic trough collectors (PTCs) by integrating multiple concentration ratios (CRs) within a single loop. The results showed a 6.7% increase in optical efficiency and a 4.5% rise in thermal efficiency compared to traditional systems, improving the overall system performance [4].

Ayoub et al. (2023) introduced the Heat Loss Out System (Heat LOS) for assessing temperature distribution in CSP plants using an infrared camera mounted on a vehicle. The system demonstrated a 93% accuracy rate using deep learning, helping to improve the lifespan and operational efficiency of CSP systems [11].

Bouarfa et al. (2024) developed advanced optical and thermal models for PTC systems using the Tonatiuh software and MCRT method. The results showed a high correlation with experimental data, highlighting the potential of solar energy for industrial processes in semi-arid climates [12].

Building on the technological advancements and performance optimization strategies discussed for CSP and PTC systems, the next section explores solar tracking systems, which play a critical role in maximizing energy capture by ensuring continuous alignment with the sun's position.

2.3 Solar Tracking Systems

Solar panels have become more efficient due to advancements in materials and solar tracking systems. Solar tracking allows collectors to follow the sun's path, maximizing energy capture and improving overall efficiency. By aligning the collector with the sun throughout the day, tracking systems optimize energy absorption, reduce reflection losses, and enhance solar energy conversion.

Solar tracking systems can be classified into different types based on their axis of movement and operational mechanism. Table 1 summarizes the main categories, highlighting their operating principles, advantages, and limitations.

Table 1 Classification of Solar Tracking Systems

System Type	Operating Mechanism	Advantages	Disadvantages
Fixed	Panels are positioned at a constant tilt throughout the day	Low cost, minimal maintenance	Lower efficiency, cannot adapt to the sun's movement
Single-Axis Tracking	Moves along one axis (East–West or North–South)	Higher energy yield compared to fixed systems, moderate cost	Less efficient than dual-axis systems
Dual-Axis Tracking	Moves along two axes to track the sun precisely	Maximum energy yield, optimal tracking	Higher cost, increased maintenance

M.A. Ben Taher et al. (2023) introduced a design for parabolic trough collectors (PTC) that uses the Monte Carlo Ray-Trace (MCRT) method to predict solar flux distribution. The study achieved an optical efficiency of 83.01% and a heat flux uniformity of 92.24%, highlighting the importance of optimizing collector design for improved heat transfer and solar flux distribution [10].

GARIP et al. (2023) explored a solar cogeneration system with a small-scale Stirling engine adapted for solar applications, capable of producing 1 kW of electricity and 3 kW of heat. The system, equipped with a dual-axis tracking system, showed a significant reduction in required collecting surface area, although the high cost of Stirling micro-cogenerators remains a challenge for widespread adoption [13].

Balaji et al. (2022) developed a Selective Power Point Tracking (SPPT) technique for photovoltaic (PV) systems, which tracks reduced power during partial shading and varying irradiation conditions. The algorithm, integrated with Salp Swarm Perturb and Observe (SSPO), demonstrated a tracking efficiency of over 98% and response times of less than 1 second, proving effective in PV system control [14].

Abdel-hamed et al. (2022) presented an efficient single-axis solar tracking system using the Harris Hawks Optimization (HHO) algorithm, optimizing sun-tracking control through the Weighted Goal Attainment Function (WGAF). Simulation results showed significant improvements in performance, indicating the system's potential for practical applications in solar-powered systems [15].

Nguyen et al. (2016) highlighted the importance of alignment in the performance of trough solar concentrators. Their research demonstrated the effectiveness of automatic control systems in tracking the sun's movement and enhancing the efficiency of parabolic trough concentrators by adjusting the collector's position in response to changing solar radiation [16].

Hariri et al. (2022) compared single-axis solar tracking systems (SAST) with sensor-based solar tracking systems (STS), showing that sensor-based STS outperforms SAST in terms of energy output and consumption. The sensor-based system improved tracking accuracy and reduced energy consumption, offering a more effective solution for PV energy generation [17].

Adolfo et al. (2017) developed a vision-based solar tracking sensor that ensures accurate sun alignment by measuring the angle of incidence of solar rays. This sensor, validated through experimental testing, achieved a high level of accuracy and was proven effective for use in solar tracking systems [18].

Satué et al. (2020) introduced an automated calibration algorithm for high concentration photovoltaic (HCPV) systems, improving sun tracking accuracy and power output. The method significantly reduced startup time and installation costs, while enhancing power performance by 5% to 7% compared to manual calibration [19].

Tiwari et al. (2023) presented a closed-loop solar tracking system that enhances PV panel efficiency through real-time sun tracking. Their system demonstrated improved current output and resilience to wind pressure, showing promise for reducing solar energy costs and improving system reliability [20].

Sappaniran et al. (2023) developed a sensorless dual-axis solar tracking system using a Particle Filter (PF) to improve energy generation. The system demonstrated a 20.1% increase in energy output compared to fixed systems and performed well in varying weather conditions, suggesting potential for autonomous energy systems [21].

Coronado et al. (2023) introduced a dual closed-loop control strategy for single-axis solar trackers in parabolic trough systems. Their approach, which combines photodiode-based solar sensors with a shadow-based visual device, reduces solar tracking error by 78%, improving system stability and performance under diverse weather conditions as shown in Figure 3 [22].

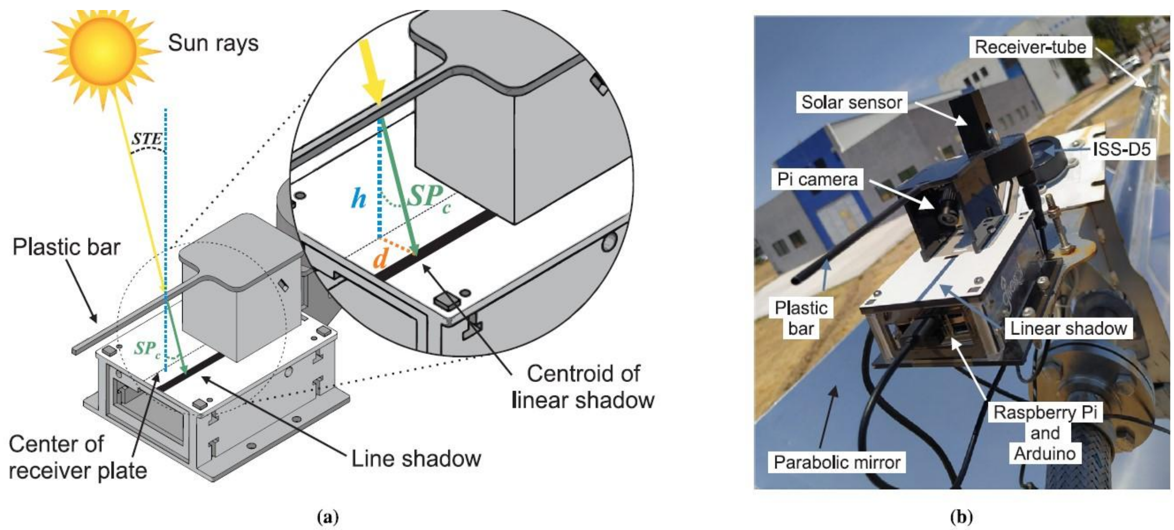

Figure 3 Proposed SBVD: (a) CAD design and (b) construction and installation [22].

Tchao et al. (2023) developed a dual-axis solar tracking system for concentrating solar power plants, utilizing a computer vision-based controller that incorporates a webcam, light sensor, Arduino microcontroller, and stepper motors to track the sun's position. This system achieves high accuracy in sunlight detection by monitoring the shadow of a stick on a transparent plate, with initial tests demonstrating precise tracking with minimal operational costs. The team plans to integrate machine learning models in future research to further improve accuracy under varying weather conditions as shown as Figure 4 [23].

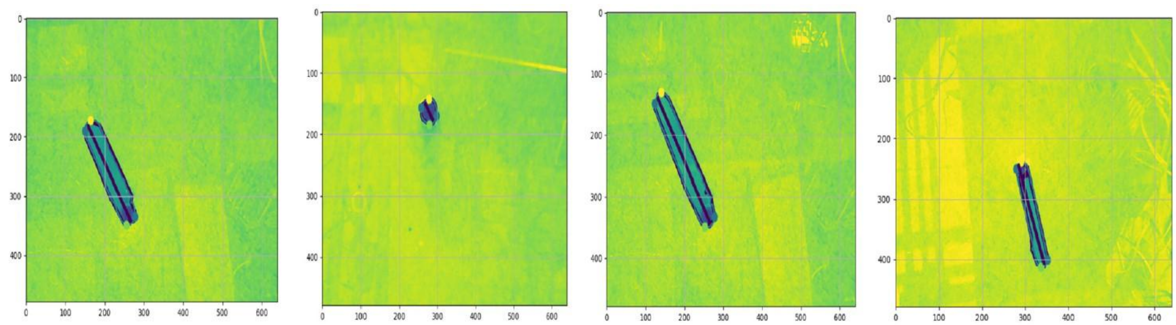

Figure 4 Locating the Stick's Shadow to Compute its Length [23].

Saeedi et al. (2021) focused on enhancing photovoltaic (PV) panel efficiency through the design of a dual-axis solar tracker (DAST). Their system uses an analog control mechanism combining a Wheatstone bridge circuit with light-dependent resistors (LDRs) to ensure optimal alignment of the PV panels relative to the sun. This design allows for significant improvements in energy absorption, with experimental results indicating a notable increase in power output by accurately tracking the sun's position throughout the day, surpassing the performance of fixed panels [24].

Bhattb et al. (2022) introduced a dual-axis solar tracking system controlled by a programmable logic controller (PLC). This system integrates a multi-quadrant photoelectric detector and a solar orbital tracking scheme to enhance solar positioning accuracy. The system achieves tracking accuracy of less than 0.07 degrees, demonstrating its effectiveness in real-world applications. Future developments will focus on refining the mechanical components and improving performance under varying environmental conditions [25].

Stanek et al. (2022) investigated the impact of solar tracking errors on the optical and thermodynamic efficiency of parabolic-trough solar concentrating systems. Their findings showed that even small errors in tracking could cause significant decreases in efficiency, with a 2° tracking error resulting in a reduction of up to 42.5 percentage points in efficiency. The study highlights the importance of precise tracking, especially for systems with low concentration ratios, and emphasizes the need for highly accurate solar tracking systems to optimize performance [26].

Amjad et al. (2023) presented an autonomous dual-axis solar tracking system that operates without requiring location or seasonal data. Using solar sensors and DC motors, the system adjusts the incidence and declination angles to maintain optimal alignment with the sun. The experimental results in Jordan showed a significant improvement in energy efficiency, with the system enhancing performance by 76% in summer and 41% in winter compared to fixed PV panels [27].

Al-Othman et al. (2023) developed a hybrid solar tracking system for PV panels in Jordan, designed to adapt to fluctuating weather conditions. Their system integrates an open-loop monitoring system with a dynamic feedback controller that uses an active search algorithm to adjust in real-time based on solar irradiance readings. Experimental results indicated a 35% increase in power generation, demonstrating the system's effectiveness, particularly under overcast conditions [28].

Hicham et al. (2022) proposed a solar tracking system that improves PV panel efficiency by regulating power output using Maximum Power Point Tracking (MPPT). This system activates the tracking motor when the power output increases and stops when the optimal solar radiation is reached, thus ensuring accurate alignment with the sun. Their approach, validated through simulations and experiments, showed a significant improvement in energy yield compared to traditional tracking methods [29].

Venkata et al. (2022) explored a solar tracking system that uses machine learning algorithms—both linear and nonlinear regression—to predict the maximum available power based on irradiation and temperature data. This system was shown to achieve efficiencies above 95%, outperforming traditional MPPT methods such as Beta MPPT and Artificial Neural Networks (ANN) in terms of accuracy and adaptability to changing weather conditions [30].

Sushmi et al. (2022) developed a forecasting technique for irradiation levels using Artificial Neural Networks (ANN) and Support Vector Regression (SVR). Their research showed that ANN outperforms SVR, especially for non-linear and noisy data, making it more suitable for predicting irradiation levels. This technique enhances the performance of MPPT systems, enabling more effective decision-making under varying environmental conditions [31]. Traditional solar tracking systems (STS) typically rely on fixed astronomical data such as time, date, and elevation. While simple and cost-effective, these systems have limited adaptability to dynamic environmental conditions, which can compromise alignment accuracy. Sensor-based systems improve responsiveness and accuracy but face challenges related to environmental sensitivity, increased complexity, and maintenance demands. These limitations have driven recent research toward more advanced solutions that leverage computer vision, machine learning (ML), and artificial intelligence (AI) to create adaptive, efficient, and robust solar tracking approaches.

2.4 Advances in Solar Tracking System

Recent advancements in solar tracking focus on integrating intelligent algorithms and vision-based technologies to overcome the constraints of traditional and sensor-based systems. By combining cameras with ML and AI, these innovative approaches can dynamically adjust to changing environmental conditions, optimize panel orientation, and enhance energy yield. The following studies illustrate how modern AI-driven tracking techniques are transforming system performance and reliability.

Abdollahpour et al. (2018) developed a dual-axis solar tracking system that uses image processing for panel orientation adjustment based on shadow analysis. This method led to significant improvements in energy absorption. The system achieved an accuracy of about ±2°, ensuring optimal alignment with solar irradiance and maximizing power output. This solution is cost-effective and location-independent, though challenges remain in overcast conditions where shadow clarity is reduced. One potential solution to this is incorporating higher-resolution cameras to improve performance under diverse weather conditions [32].

Rahmawati et al. (2020) focused on the importance of precise solar panel positioning for optimal energy production. They employed image processing techniques to track the sun's position, calculating its angle by analyzing the shadow of a small object. Their system achieved tracking accuracies of 95% in azimuth and 96% in altitude, ensuring the panels were aligned to maximize energy capture. This approach holds promise for enhancing energy efficiency through precise solar tracking and shows potential for adaptability under different weather conditions [33].

AL-Rousan et al. (2020) explored the application of AI techniques, specifically the Adaptive Neural Fuzzy Inference System (ANFIS), to manage solar tracking systems. ANFIS models proved effective in predicting the optimal tilt and orientation angles for solar panels, enhancing energy efficiency. Research suggests that solar trackers using ANFIS outperform traditional control methods, including fuzzy logic and neural networks, offering superior performance with fewer errors and higher prediction accuracy [34].

Traditional solar tracking systems (STS), which depend on time, date, and elevation data, have significant limitations in adapting to environmental changes, leading to reduced alignment accuracy. In contrast, sensor-based systems face challenges due to their sensitivity to environmental conditions, complexity, and ongoing maintenance needs. These systems also tend to consume a considerable amount of energy, suffer from reliability issues, and require frequent upkeep. As a result, there is a growing interest in exploring innovative solutions that integrate cameras with machine learning (ML) and artificial intelligence (AI) technologies to create more adaptable and efficient solar tracking systems. This approach seeks to enhance the overall performance and adaptability of these systems to varying environmental conditions.

Abdollahpour et al. (2018) developed a dual-axis solar tracking system that uses image processing for panel orientation adjustment based on shadow analysis. This method led to significant improvements in energy absorption. The system achieved an accuracy of about ±2°, ensuring optimal alignment with solar irradiance and maximizing power output. This solution is cost-effective and location-independent, though challenges remain in overcast conditions where shadow clarity is reduced. One potential solution to this is incorporating higher-resolution cameras to improve performance under diverse weather conditions [32].

Rahmawati et al. (2020) focused on the importance of precise solar panel positioning for optimal energy production. They employed image processing techniques to track the sun's position, calculating its angle by analyzing the shadow of a small object. Their system achieved tracking accuracies of 95% in azimuth and 96% in altitude, ensuring the panels were aligned to maximize energy capture. This approach holds promise for enhancing energy efficiency through precise solar tracking and shows potential for adaptability under different weather conditions [33].

AL-Rousan et al. (2020) explored the application of AI techniques, specifically the Adaptive Neural Fuzzy Inference System (ANFIS), to manage solar tracking systems. ANFIS models proved effective in predicting the optimal tilt and orientation angles for solar panels, enhancing energy efficiency. Research suggests that solar trackers using ANFIS outperform traditional control methods, including fuzzy logic and neural networks, offering superior performance with fewer errors and higher prediction accuracy [34].

Phiri et al. (2023) conducted a systematic review on the use of Deep Learning (DL) in solar tracking systems, underlining its potential to improve solar energy applications. The review highlighted that traditional Machine Learning (ML) models struggle with large datasets and data representation, while DL models show great promise in forecasting temperature and predicting solar irradiance. The review covers 37 academic papers published between 2012 and 2022, examining various topics such as dataset usage, preprocessing methods, feature engineering, DL algorithms, and performance metrics. Despite the rise of deep hybrid learning models, the review identifies ongoing challenges, including dataset availability, the use of image-based data, and the need for optimized preprocessing. Addressing these issues is essential for advancing DL in solar tracking systems [35].

Paletta et al. (2023) investigated methods to improve solar energy forecasting accuracy using physics-informed transfer learning. The study utilized deep learning techniques, specifically convolutional neural networks (CNNs), to analyze cloud images from ground-level sky cameras to predict solar irradiance. Transfer learning techniques such as zero-shot learning (ZSL) and few-shot learning (FSL) were used, enabling pre-trained models to adapt to new environments without requiring extensive local data. The results indicated a significant improvement in forecasting accuracy in both cloudy and clear-sky conditions, facilitating the rapid deployment of reliable forecasting models in industrial settings. The study addressed traditional deep learning limitations, which often rely on large local datasets, making them unsuitable for immediate use in situations requiring timely solar forecasts. By using multi-location datasets, these models showed improved generalization, making them more scalable for solar energy forecasting solutions [36].

Mohammad et al. (2023) discussed the transformative role of AI in the solar energy sector, emphasizing its ability to revolutionize the generation, management, and grid integration of solar power. AI innovations in solar panel technology have significantly enhanced both efficiency and scalability. Moreover, machine learning techniques contribute to improved grid stability and energy forecasting accuracy. AI-powered management systems also convert data into actionable insights, optimizing system performance and enabling predictive maintenance. These advancements are critical for creating a more efficient, reliable, and sustainable future for solar energy, which is vital for meeting global energy needs and combating climate change [37].

Lorilla et al. (2022) designed a system that dynamically tracks the sun's centroid with remarkable flexibility, even under low irradiation conditions, such as cloud cover. The system uses a high-resolution camera with a 180-degree field of view, facilitating precise image processing and employing adaptive control techniques to adjust the pan and tilt of servo motors. The system achieved azimuth and altitude tracking accuracies of 0.23° and 0.66%, respectively, using the Solar Position Algorithm (SPA), comparable to commercial solar trackers. This prototype shows strong performance for dynamic solar tracking, making it suitable for Parabolic Dish Solar Concentrators. It also integrates AI-based computing for remote applications, using low-cost hardware to ensure commercial viability. Future plans include incorporating AI for direct normal irradiance estimation and implementing wireless motor control at Concentrating Solar Power (CSP) sites, as well as data collection during various solar events [38].

Oğuz et al. (2020) explored the use of embedded systems with wide-angle cameras to accurately track the sun's trajectory. Their system captures images of the sun and processes them to determine its position in the sky. The system, which uses a Raspberry Pi 2 B and a 5MP wide-angle camera, demonstrated the potential for improved accuracy in solar tracking, presenting the mechanical and electronic setups, image acquisition procedure, and initial processing results [39].

Carballo et al. (2019) introduced an innovative solar tracking system that combines computer vision, low-cost hardware, and deep learning techniques to address the cost and operational challenges faced by traditional systems. Deployed at the Plataforma Solar de Almería, the system uses convolutional neural networks (CNNs) to detect objects and track the sun's position. By forecasting cloud movements, detecting shadows, and measuring concentrated solar radiation, the system enhances solar panel efficiency. This method minimizes reliance on expensive and complex mechanical tracking systems. Moreover, its ability to predict cloud coverage and shadow effects enables proactive adjustments to the panels, leading to more efficient energy production. The system reduces costs and enhances the reliability and efficiency of solar power generation, positioning it as a promising alternative for sustainable energy systems [40].

Adel et al. (2019) introduced a new methodology for improving solar flux analysis in solar central receiver (SCR) systems. Traditional single-CCD cameras often struggle to capture solar flux accurately due to their limited dynamic range. To overcome this, the authors proposed using a double-CCD camera that captures two images at different exposure levels, which are then combined into a high dynamic range (HDR) image using a newly developed weighting function. This method improves the resolution of solar flux details, providing more accurate analysis of beam accuracy and optical quality in SCR systems. The paper presents experimental results that demonstrate the new weighting function's superiority over existing methods, marking a significant advancement in solar flux analysis and aiding in the design and operation of solar power plants [41].

Garcia-Gil et al. (2019) presented a solar tracker design that uses panoramic images captured by a fisheye camera. The images are processed digitally to estimate the sun's azimuth and elevation angles, which are then used to position the solar tracker accurately. The system operates effectively under various weather conditions without the need for GPS or complex calculations and does not require latitude or longitude data. However, the fisheye camera needs to be oriented north and leveled with the ground. The proposed method demonstrates impressive precision compared to established algorithms, with future research focused on developing maximum power point tracking systems [42].

Gozhyj et al. (2020) discussed the use of neural networks to optimize the control mechanisms of solar power plants and electricity distribution. They described a system based on a neural network designed to track the maximum power point (MPP) of photovoltaic systems, adjusting battery charging to maximize energy output. The system uses a multilayer neural network trained with a backpropagation algorithm, which improves system efficiency by optimizing voltage and current distribution based on real-time solar panel and battery conditions [43].

Rahate et al. (2021) introduced a two-axis solar tracking system that combines computer vision with photosensor technologies to enhance solar energy collection. The system employs a Raspberry Pi 4 for real-time image processing, while an ATmega128 microcontroller controls stepper motors based on the processed data. The system integrates image-based feedback to address disturbances like cloud cover and uses photosensor-based control to make accurate adjustments. This approach enhances both solar tracking precision and energy efficiency, making it adaptable to changing weather conditions [44].

Jose et al. (2019) explored a new solar tracking method that uses deep learning techniques via TensorFlow, an open-source machine learning framework. This framework enhances flexibility and allows the implementation of neural networks across various devices, including embedded systems and mobile platforms. The networks accurately recognize the Sun and its trajectory, enabling precise tracking without additional data. The advanced machine learning framework outperforms the original system in terms of speed and accuracy. Future research will focus on training networks with larger datasets, optimizing implementations, and achieving autonomous control of heliostats to improve tracking accuracy and minimize errors [45].

Sections 2.3 and 2.4 reviewed various solar tracking system designs, optimization strategies, and AI-based enhancements. Table 2 provides a consolidated summary of the key studies, outlining the system type, techniques used, and the main performance results reported.

Table 2 Summary of Key Studies in Sections 2.3 and 2.4

Authors	System Type	Technique Used	Key Results
Ben Taher et al. (2023)	PTC	MCRT	Optical efficiency: 83.01%, heat flux uniformity: 92.24%
GARIP et al. (2023)	Dual-axis	Stirling engine	1 kW electricity + 3 kW heat generation
Balaji et al. (2022)	PV	SPPT + SSPO	>98% tracking efficiency, <1 s response time
Abdel-hamed et al. (2022)	Single-axis	HHO + WGAF	Significant performance improvement
Hariri et al. (2022)	SAST / STS	Light sensors	STS outperformed SAST in energy output and accuracy
Tchao et al. (2023)	Dual-axis CSP	Computer vision + Arduino	High accuracy, low operational cost

Venkata et al. (2022)	PV	ML regression	>95% efficiency, outperformed traditional MPPT
Phiri et al. (2023)	Various	Deep Learning	Improved solar irradiance forecasting
Paletta et al. (2023)	PV	Transfer Learning + CNN	Enhanced cloud and irradiance prediction
Lorilla et al. (2022)	Parabolic Dish	180° camera + AI	Azimuth accuracy: 0.23°, altitude accuracy: 0.66°

In summary, the reviewed literature demonstrates the significant advancements in solar tracking technologies, particularly through the integration of AI and deep learning, which have shown substantial potential to enhance system efficiency, adaptability, and reliability under diverse environmental conditions. These findings lay the groundwork for future innovations.

3. Conclusion

This review has examined the evolution of solar tracking systems, highlighting the transition from traditional time-based and sensor-driven mechanisms to advanced solutions powered by artificial intelligence (AI) and deep learning (DL). The literature indicates that AI- and DL-enhanced tracking systems offer substantial improvements in accuracy, adaptability, and energy yield, particularly under dynamic and challenging environmental conditions. Furthermore, integration of computer vision, optimization algorithms, and hybrid control strategies has shown promising results in reducing tracking errors, improving system efficiency, and lowering operational costs.

Despite these advancements, several research gaps remain. Scalability and real-time implementation of AI-based tracking systems require further exploration, especially for large-scale solar power plants. Challenges such as high initial costs, maintenance complexity, and performance variability under extreme weather still hinder widespread adoption. Moreover, the lack of standardized datasets and benchmarking methods limits the ability to compare solutions objectively across different studies.

Future research should focus on developing cost-effective, energy-efficient, and self-calibrating tracking systems capable of operating autonomously in diverse environmental contexts.

Integrating AI with emerging technologies such as Internet of Things (IoT) networks, edge computing, and predictive maintenance frameworks can further enhance system resilience and efficiency. By addressing these challenges, the next generation of solar tracking systems can significantly contribute to the global transition toward sustainable and reliable renewable energy solutions.

4. References

[1] S. I. Salah, M. Eltaweel, and C. Abeykoon, “Towards a sustainable energy future for Egypt: A systematic review of renewable energy sources, technologies, challenges, and recommendations,” Clean. Eng. Technol., vol. 8, no. April, p. 100497, 2022, doi: 10.1016/j.clet.2022.100497.

[2] N. A. Moharram, A. Tarek, M. Gaber, and S. Bayoumi, “Brief review on Egypt’s renewable energy current status and future vision,” Energy Reports, vol. 8, no. May, pp. 165–172, 2022, doi: 10.1016/j.egyr.2022.06.103.

[3]M. Mostafa, F. El-Shahat, M. Riede, and G. Bassioni, Solar Energy in Africa - An Overview, with a Focus on Egypt, vol. 541 LNICST. Springer Nature Switzerland, 2024. doi: 10.1007/978-3-031-51849-2_12.

[4]K. Zhao, X. Wang, Z. Gai, Y. Qin, Y. Li, and H. Jin, “Enhancing the efficiency of solar parabolic trough collector systems via cascaded multiple concentration ratios,” J. Clean. Prod., vol. 437, no. January, p. 140665, 2024, doi: 10.1016/j.jclepro.2024.140665.

[5]S. Shaaban, “A Novel Optimized Solar Trough Profile for Better Solar Energy Collection, Storage, and Levelized Cost,” Energy Technol., vol. 11, no. 1, p. 2200535, Jan. 2023, doi: 10.1002/ENTE.202200535.

[6]A. S. S. Khamees, U. A. Rahoma, A. H. Hassan, T. Sayad, and M. Morsy, “Investigating of Solar Energy Potential for Highest Intensity Radiation Over Egypt,” SSRN Electron. J., no. January, 2022, doi: 10.2139/ssrn.4093744.

[7]S. Elshafey et al., “Solar thermal power in Egypt,” 2018 IEEE Ind. Appl. Soc. Annu. Meet. IAS 2018, no. September, 2018, doi: 10.1109/IAS.2018.8544513.

[8]H. R. Patel, V. B. Patel, and A. R. Chaudhari, “A Comprehensive Review on Design aspects and Performance Characteristics of Solar Parabolic Trough Collector,” Int. J. Renew. Energy Res., vol. 12, no. 3, pp. 1566–1588, 2022, doi: 10.20508/ijrer.v12i3.12999.g8541.

[9]W. Ajbar, A. Parrales, A. Huicochea, and J. A. Hernández, “Different ways to improve parabolic trough solar collectors’ performance over the last four decades and their applications: A comprehensive review,” Renew. Sustain. Energy Rev., vol. 156, no. December 2021, 2022, doi: 10.1016/j.rser.2021.111947.

[10]M. A. Ben Taher, U. Pelay, S. Russeil, and D. Bougeard, “A novel design to optimize the optical performances of parabolic trough collector using Taguchi, ANOVA and grey relational analysis methods,” Renew. Energy, vol. 216, no. July, p. 119105, 2023, doi: 10.1016/j.renene.2023.119105.

[11]A. Oufadel et al., “In-situ heat losses measurements of parabolic trough receiver tubes based on infrared camera and artificial intelligence,” Environ. Challenges, vol. 10, no. November 2022, p. 100679, 2023, doi: 10.1016/j.envc.2023.100679.

[12]I. Bouarfa, M. El Ydrissi, H. El Hafdaoui, M. Boujoudar, A. Jamil, and E. G. Bennouna, “Developing optical and thermal models with experimental validation of parabolic trough collector for moroccan industrial heat applications,” Sol. Energy Mater. Sol. Cells, vol. 266, no. November 2023, p. 112676, 2024, doi: 10.1016/j.solmat.2023.112676.
[13]H. H. Khalaf, A. R. Al-tameemi, B. Abdulrazzaq, A. A. Ali, M. S. Hamza, and S. H. Hlail, “Solar Micro-Cogeneration using Small Energy,” vol. 13, no. 4, 2023.
[14]V. Balaji and A. P. Fathima, “A Selective Power Point Tracking Algorithm for Reduced Power Tracking in PV System,” vol. 12, no. 1, 2022.
[15]A. M. Abdel-hamed, “An Optimized Control Scheme for Solar Energy Tracking Systems,” vol. 12, no. 3, 2022.
[16]H. B. Nguyen and T. A. Bui, “Developing the solar tracking system for trough solar concentrator,” Int. J. Adv. Sci. Eng. Inf. Technol., vol. 6, no. 1, pp. 58–60, 2016, doi: 10.18517/ijaseit.6.1.651.
[17]N. G. Hariri, M. A. Almutawa, I. S. Osman, I. K. Almadani, A. M. Almahdi, and S. Ali, “Experimental Investigation of Azimuth- and Sensor-Based Control Strategies for a PV Solar Tracking Application,” Appl. Sci., vol. 12, no. 9, 2022, doi: 10.3390/app12094758.
[18]A. Ruelas, N. Velázquez, C. Villa-Angulo, A. Acuña, P. Rosales, and J. Suastegui, “A solar position sensor based on image vision,” Sensors (Switzerland), vol. 17, no. 8, pp. 1–13, 2017, doi: 10.3390/s17081742.
[19]M. G. Satué, F. Castaño, M. G. Ortega, and F. R. Rubio, “Auto-calibration method for high concentration sun trackers,” Sol. Energy, vol. 198, no. September 2019, pp. 311–323, 2020, doi: 10.1016/j.solener.2019.12.073.
[20]U. Mamodiya and N. Tiwari, “Dual-axis solar tracking system with different control strategies for improved energy efficiency,” Comput. Electr. Eng., vol. 111, no. PA, p. 108920, 2023, doi: 10.1016/j.compeleceng.2023.108920.
[21]A. Pirayawaraporn, S. Sappaniran, S. Nooraksa, C. Prommai, N. Chindakham, and C. Jamroen, “Innovative sensorless dual-axis solar tracking system using particle filter,” Appl. Energy, vol. 338, no. February 2022, p. 120946, 2023, doi: 10.1016/j.apenergy.2023.120946.
[22]T. Q. Saldivar-Aguilera, L. M. Valentín-Coronado, M. I. Peña-Cruz, A. Diaz-Ponce, and J. A. Dena-Aguilar, “Novel closed-loop dual control algorithm for solar trackers of parabolic trough collector systems,” Sol. Energy, vol. 259, no. December 2022, pp. 381–390, 2023, doi: 10.1016/j.solener.2023.05.024.
[23]E. T. Tchao et al., “An Implementation of an optimized dual-axis solar tracking algorithm for concentrating solar power plants deployment,” Sci. African, vol. 16, p. e01228, 2022, doi: 10.1016/j.sciaf.2022.e01228.
[24]M. Saeedi and R. Effatnejad, “A new design of dual-axis solar tracking system with ldr sensors by using the wheatstone bridge circuit,” IEEE Sens. J., vol. 21, no. 13, pp. 14915–14922, 2021, doi: 10.1109/JSEN.2021.3072876.
[25]M. L. Bharathi et al., “Developing a dual axis photoelectric tracking module using a multi quadrant photoelectric device,” Energy Reports, vol. 8, no. May, pp. 1426–1439, 2022, doi: 10.1016/j.egyr.2022.07.095.
[26]B. Stanek, D. Węcel, Ł. Bartela, and S. Rulik, “Solar tracker error impact on linear absorbers efficiency in parabolic trough collector – Optical and thermodynamic study,” Renew. Energy, vol. 196, pp. 598–609, 2022, doi: 10.1016/j.renene.2022.07.021.

[27]A. Alsakarneh, T. Tabaza, D. Jyothishmathi, and A. Afghani, “Design , Development and Control of Dual-Axis Solar Tracking System,” vol. 13, no. 3, 2023.

[28]A. Al-Othman et al., “An experimental study on hybrid control of a solar tracking system to maximize energy harvesting in Jordan,” Sol. Energy, vol. 263, no. May, p. 111931, 2023, doi: 10.1016/j.solener.2023.111931.

[29]A. Abbou, Z. Abousserhane, and R. El Idrissi, “Equatorial Solar Tracker Control Using MPPT Technique,” vol. 12, no. 2, 2022.

[30]S. Meyyappan and R. Alla, “Maximum Power Point Tracking with Regression Machine Learning Algorithms for Solar PV systems,” vol. 12, no. 3, 2022.

[31]N. B. Sushmi, “Robust Solar Irradiation Forecasting Mechanism for Maximum Power Point Trackers : A Comparative Review,” vol. 12, no. 4, 2022.

[32]M. Abdollahpour, M. R. Golzarian, A. Rohani, and H. Abootorabi Zarchi, “Development of a machine vision dual-axis solar tracking system,” Sol. Energy, vol. 169, no. February, pp. 136–143, 2018, doi: 10.1016/j.solener.2018.03.059.

[33]D. Rahmawati, W. Priharti, and M. I. Y. Mardiana, “A prototype of solar panel position control system based on image processing,” IOP Conf. Ser. Mater. Sci. Eng., vol. 830, no. 3, 2020, doi: 10.1088/1757-899X/830/3/032045.

[34]N. AL-Rousan, N. A. Mat Isa, and M. K. Mat Desa, “Efficient single and dual axis solar tracking system controllers based on adaptive neural fuzzy inference system,” J. King Saud Univ. - Eng. Sci., vol. 32, no. 7, pp. 459–469, 2020, doi: 10.1016/j.jksues.2020.04.004.

[35]M. Phiri, A. Zimba, C. I. Eke, and M. Mulenga, “Deep Learning Techniques for Photovoltaic Solar Tracking Systems: A Systematic Literature Review,” 2023, [Online]. Available: https://doi.org/10.21203/rs.3.rs-2539961/v1

[36]Q. Paletta, Y. Nie, Y. M. Saint-Drenan, and B. Le Saux, “Improving cross-site generalisability of vision-based solar forecasting models with physics-informed transfer learning,” Energy Convers. Manag., vol. 309, no. December 2023, p. 118398, 2024, doi: 10.1016/j.enconman.2024.118398.

[37] A. Mohammad and F. Mahjabeen, “International Journal of Multidisciplinary Sciences and Arts Revolutionizing Solar Energy: The Impact of Artificial Intelligence on Photovoltaic Systems,” vol. 2, no. 1, pp. 117–127, 2023, [Online]. Available: https://doi.org/10.47709/ijmdsa.vxix.xxxx

[38] F. M. A. Lorilla and R. B. Barroca, “Flexible Dynamic Sun Tracking System (STS) Employing Machine Vision Control Approach,” Int. J. Renew. Energy Res., vol. 12, no. 2, pp. 685–691, 2022, doi: 10.20508/ijrer.v12i2.12949.g8456.

[39] O. Gora and T. Akkan, “Image Acquisition with Wide-angle Camera for Sun Location Tracking,” HORA 2020 - 2nd Int. Congr. Human-Computer Interact. Optim. Robot. Appl. Proc., pp. 6–9, 2020, doi: 10.1109/HORA49412.2020.9152933.

[40] J. A. Carballo, J. Bonilla, M. Berenguel, J. Fernández-Reche, and G. García, “New approach for solar tracking systems based on computer vision, low cost hardware and deep learning,” Renew. Energy, vol. 133, pp. 1158–1166, 2019, doi: 10.1016/j.renene.2018.08.101.

[41] M. Adel, A. Peña-Lapuente, M. Rady, and A. Hamdy, “Development of a new high dynamic range technique for solar flux analysis using double- CCD optical camera,” Int. J. Renew. Energy Res., vol. 9, no. 2, pp. 783–794, 2019, doi: 10.20508/ijrer.v9i2.9183.g7646.

[42] G. Garcia-Gil and J. M. Ramirez, “Fish-eye camera and image processing for commanding a solar tracker,” Heliyon, vol. 5, no. 3, p. e01398, 2019, doi: 10.1016/j.heliyon.2019.e01398.
[43] A. Gozhyj, V. Nechakhin, and I. Kalinina, “Solar Power Control System based on Machine Learning Methods,” Int. Sci. Tech. Conf. Comput. Sci. Inf. Technol., vol. 1, pp. 24–27, 2020, doi: 10.1109/CSIT49958.2020.9321953.
[44] R. Ahmed et al., “Computer vision and photosensor based hybrid control strategy for a two-axis solar tracker - Daylighting application,” Sol. Energy, vol. 224, no. May, pp. 175–183, 2021, doi: 10.1016/j.solener.2021.05.077.
[45] J. A. Carballo, J. Bonilla, M. Berenguel, J. Fernández-Reche, and G. García, “Machine learning for solar trackers,” AIP Conf. Proc., vol. 2126, no. July, 2019, doi: 10.1063/1.5117524.