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Using CNNs for Photovoltaic Panel Defect Detection via Infrared Thermography to Support Industry 4.0

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Abstract

Background: This study demonstrates how convolutional neural networks (CNNs), supported by open-source software and guided by corporate social responsibility (CSR), can enhance photovoltaic (PV) panel maintenance. Connecting industrial informatics with sustainable practices underscores the potential for more efficient and responsible energy systems within Industry 4.0. The rapid expansion of solar power necessitates effective maintenance and inspection of PV panels to ensure optimal performance and longevity. CNNs have emerged as potent tools for detecting defects in PV panels through infrared thermography (IRT). **Objectives:** The review aims to evaluate CNNs' effectiveness in detecting PV panel defects, align their capabilities with the IEC TS 62446-3:2017 standard, and assess their economic benefits. **Methods/Approach:** A systematic review of literature focused on studies using CNNs and IRT for PV panel defect detection. The analysis compared performance metrics, economic benefits, and alignment with industry standards. **Results:** CNN models demonstrated high accuracy in defect detection, with most achieving above 90%. Integrating UAVs for image acquisition significantly reduced inspection times and costs. **Conclusions:** CNNs are highly effective in detecting PV panel defects, offering substantial economic benefits and potential for industry-wide standardisation. Further research is needed to enhance model robustness across diverse conditions and PV technologies.

Keywords: Convolutional Neural Networks; Photovoltaic Panels; Defect Detection; Infrared Thermography; Solar Energy

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Introduction

Industry 4.0 has introduced transformative technologies such as artificial neural networks, which play a critical role in predictive maintenance across various sectors (Pejić Bach et al., 2023a). By aligning these technologies with corporate social responsibility (CSR) principles, businesses can enhance both efficiency and sustainability (Barić, 2022). The growing field of industrial informatics, as highlighted by Pejić Bach et al. (2023b), underscores the increasing importance of data-driven technologies in modern industry. Specifically, the role of open-source software in predictive maintenance is emphasised as a cost-effective solution that enhances the accessibility and implementation of advanced technologies like neural networks (Pejić Bach et al., 2023a, 2023b). These insights have motivated the authors to conduct a systematic review to assess the effectiveness of convolutional neural networks (CNNs) in PV panel defect detection, along with evaluating their economic benefits and alignment with industry standards.

In the photovoltaic (PV) industry, CNNs are becoming increasingly important for the defect detection process, thanks to their superior capabilities over traditional techniques. CNNs are a type of deep learning algorithm designed to process structured grid data like images. They learn spatial hierarchies of features through layers of convolutional filters, making them particularly effective for image classification and pattern recognition tasks. A significant advantage of CNNs is their ability to autonomously learn and identify patterns in images, enabling them to accurately detect and categorise defects in images of PV panels (Hassan & Dhimish, 2023). Recent advancements in CNN architectures, such as ResNet, Inception, and EfficientNet, have significantly enhanced their performance and efficiency, making them essential tools for many high-tech applications. These advanced models can learn intricate features and patterns in large datasets, leading to breakthroughs in object detection, segmentation, and image classification (Taye, 2023). Input data for these CNN models in the PV industry are usually images of PV panels, which can be obtained using various imaging techniques such as electroluminescence (EL) images, infrared (IR) thermography of PV panels, fluorescence images, photoluminescence images, etc. (Ahmed et al., 2021). This review will focus on IR thermography images as input for CNN models. Infrared thermography (IRT) measures the infrared radiation emitted from a surface. Thermal imaging cameras capture this radiation and generate images or videos that depict temperature variations. These images, known as thermograms, use colours to illustrate thermal patterns, making them easy to interpret. IRT is a highly effective method because defective PV modules typically show irregularities in their temperature distribution (Lofstad-Lie et al., 2022). IRT of photovoltaic (PV) panels is extensively utilised in the literature due to its rapid execution, cost-effectiveness, suitability for large-scale outdoor applications, ease of use, and high accuracy (Ahmed et al., 2021). These characteristics are particularly beneficial in the PV industry, where numerous panels require frequent and thorough inspection (Hassan & Dhimish, 2023; Jia et al., 2024).

The economic benefits of using convolutional neural networks (CNNs) for automatic defect detection in IR images of PV panels in their operational phase are significant. Reviewing images manually by the human eye is labour-intensive and time-consuming, causing high inspection costs and longer times for generating final reports. Fast detection of abnormalities is crucial for the preservation of the longevity of PV panels and maximising energy production. By employing CNNs, the PV industry can reduce these opportunity costs, increase inspection accuracy and eliminate human bias in the defect identification process. CNNs enhance the inspection process by quickly and accurately identifying defects, ensuring that PV panels operate efficiently and reliably for their expected lifespan, thus supporting the industry's growth and sustainability (Hussain et al., 2023; Wang et al., 2022). Inspection times for PV panels can be further reduced by utilising unmanned aerial vehicles (UAVs) equipped with IR cameras. UAVs can quickly scan large solar installations, capturing high-resolution IR images that are essential for identifying defects. Research indicates that UAVs can speed up the inspection process by approximately 85%, significantly reducing the time required to conduct thorough inspections of extensive PV arrays (Zefri et al., 2018). Another research done by Huerta Herraiz, Pliego Marugán, and García Márquez (2020) claims a 97% average increase in inspection efficiency using UAVs as opposed to manual inspection and also pinpoints the ease of locating the defects utilising GPS metadata from the UAV. As seen in the work of Nooralishahi et al. (2021), the utilisation of UAVs can enable simultaneous acquisition of IR and standard Red, Green, and Blue (RGB) images. This can enhance the detection rate of defects and enable better determination of root-cause problems.

By enabling sophisticated defect detection, CNNs help maintain the reliability and efficiency of PV systems, thereby supporting the sustainable growth of solar energy worldwide. As solar installations continue to rise, especially in leading markets like China and Europe (SolarPower Europe [SPE], 2024), the implementation of effective inspection methods becomes increasingly vital to uphold the integrity and performance of these renewable energy assets. Connecting this advanced defect detection and classification technology with industry standards is crucial for consistent and reliable PV panel maintenance. The International Electrotechnical Commission (IEC) standard IEC TS 62446-3:2017 outlines guidelines for the use of IR thermography in inspecting PV panels, detailing specific abnormalities (defects) and their corresponding patterns (IEC, 2020). The abnormalities listed by IEC (2020) are Modules in an open circuit, Modules in a short circuit, Substring in a short circuit, Substrings in an open circuit, Single cells with differences in temperature, Module with cells shaded by dirt, Broken glass – crack, Transfer resistance, and Heated module junction box. The effectiveness of CNNs in identifying these patterns, as described in the IEC standard, will be a key focus of this review. They layout 12 classes, but some of them were merged in this list as they are the same defects, just on different PV panel technology.

The purpose of this paper is to evaluate the effectiveness of different CNNs for defect detection in PV panels using IRT images, align their capabilities with the IEC TS 62446-3:2017 standard (International Electrotechnical Commission [IEC], 2020) and assess their economic benefits. This review synthesises existing research on the application of CNNs for PV panel defect detection, providing insights into their performance metrics, economic advantages pinpointed in the papers analysed, and potential for industry-wide standardisation. A systematic review of the literature focusing on studies utilising CNNs and IRT for PV panel defect detection was conducted, and the data were analysed to compare performance metrics and list economic benefits. Current state-of-the-art CNN models have demonstrated significant potential in accurately detecting various abnormalities listed in the IEC standards, as seen in the works of Fonseca Alves, Deus Júnior, Marra, and Lemos (2021) and Bommes et al. (2021) as most of their model output classes are the same as in IEC standard. This leads to the central research questions of this review:

1. RQ1. Can CNNs identify all defect patterns proposed in the IEC standard?
2. RQ2. Can they achieve an acceptable detection rate, effectively replacing human inspection and speeding up the process, thereby providing economic benefits?

To address these questions, we propose the following research hypotheses:

1. H1: Convolutional neural networks (CNNs) can accurately identify all defect patterns listed in the IEC TS 62446-3:2017 standard for PV panel inspection.
2. H2: CNNs can achieve a detection rate that meets or exceeds the accuracy of human inspectors, thus validating their effectiveness in identifying PV panel defects.
3. H3: The implementation of CNNs in defect detection will significantly reduce inspection time and costs, providing substantial economic benefits compared to traditional manual inspection methods.

This review paper aims to make several theoretical contributions to the field of solar energy and photovoltaic system maintenance through the application of convolutional neural networks (CNNs). Firstly, the review will provide a comprehensive analysis of CNN's effectiveness. Synthesising existing research on the application of CNNs for defect detection in PV panels will offer a thorough understanding of how well these networks perform in identifying various defects as per the IEC standards because many of the recent works detect only 2-3 defect classes (Bakır et al., 2023; Cipriani et al., 2020; Hwang et al., 2021; Manno et al., 2021). This critical evaluation of different CNN models' performance metrics will highlight their strengths and limitations, contributing valuable insights into their practical applications. Secondly, the paper will evaluate the economic and operational benefits of adopting CNN-based defect detection in the PV industry. It will discuss cost savings, reduced inspection times, and the elimination of human error, providing a theoretical framework for understanding the broader impact of CNN technology on the sustainability and scalability of solar energy systems. This analysis will offer a new perspective on the economic implications of technological advancements in the PV sector.

Additionally, by aligning the defect detection capabilities of CNNs with the IEC TS 62446-3:2017 standard (IEC, 2020), the review will bridge the gap between advanced technological solutions and industry requirements. This alignment will offer a theoretical basis for standardising the use of CNNs in PV panel maintenance, promoting consistency and reliability across the industry. Such a connection between technology and industry standards is critical for the practical implementation of new inspection methods. These theoretical contributions aim to advance the understanding of how CNNs can revolutionise the inspection and maintenance of photovoltaic systems, supporting the sustainable growth of solar energy on a global scale. By providing a thorough and critical examination of the existing research, this review will serve as a valuable resource for researchers, industry professionals, and policymakers in the field of renewable energy.

The structure of the paper is designed to provide a comprehensive review of the use of convolutional neural networks (CNNs) for defect detection in photovoltaic (PV) panels using infrared thermography (IRT). Following the introduction, the paper is divided into several sections that each address critical aspects of the research. The Background section outlines the rapid growth of solar power and highlights the importance of maintaining PV panel efficiency and longevity through advanced inspection techniques. Next, the Methodology section details the systematic approach taken to gather, analyse, and synthesise relevant literature, including the criteria for selecting studies and the methods for data analysis and synthesis. The Results section presents a comparative analysis of key studies, highlighting their findings on the effectiveness of various CNN models in detecting PV panel defects. The Discussion section delves into the implications of these findings, addressing the research questions regarding CNN's capabilities and their economic benefits. It also identifies limitations in current research and suggests directions for future studies. Finally, the Conclusion summarises the key insights from the review and underscores the potential of CNN-based defect detection methods to enhance the reliability and efficiency of PV systems, supporting the sustainable growth of solar energy.

The remainder of this paper is structured as follows: The Background section discusses the significance and growth of the photovoltaic (PV) industry and the need for effective maintenance and inspection of PV panels. The Methodology section outlines the systematic approach used for the literature review, including the literature search strategy, inclusion and exclusion criteria, and data analysis techniques. In the Literature Review section, we summarise and compare key studies on the application of CNNs for defect detection in PV panels using infrared thermography. The Results section presents a comparative analysis of the performance metrics, economic benefits, and alignment with industry standards from the reviewed studies. The Discussion section addresses the central research questions, evaluates the strengths and limitations of the reviewed studies, and suggests future research directions. Finally, the Conclusion provides a summary of the key findings and theoretical contributions of this review, emphasising the practical implications for the PV industry.

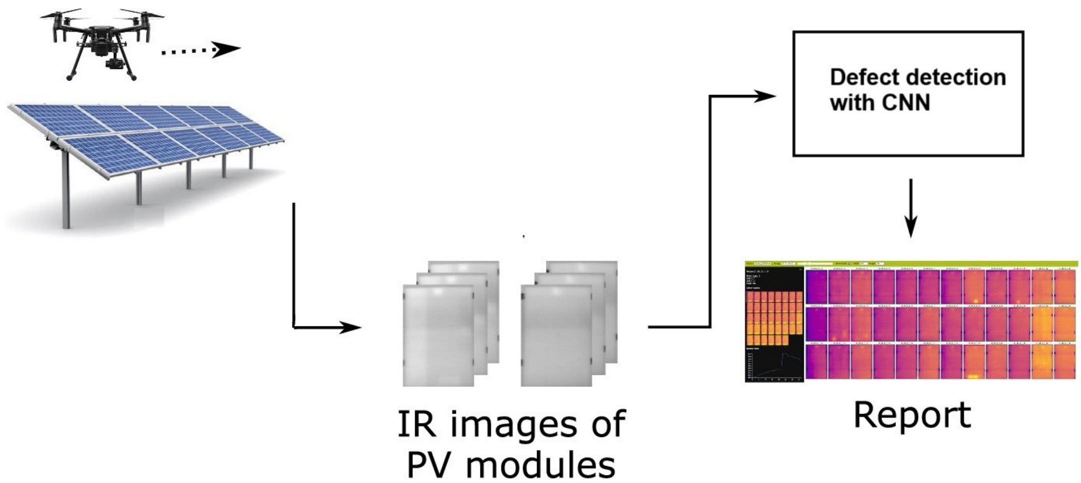
Background

The rapid growth of solar power on a global scale has been nothing short of remarkable. In 2023, the world saw an unprecedented addition of 447 gigawatts (GW) of new photovoltaic (PV) capacity, a staggering 87% increase from the previous year (SolarPower Europe, 2024). This surge underscores solar energy's critical role in the global energy transition, highlighting its potential to meet increasing energy demands while mitigating climate change and aligning with the goals of the Paris Agreement (United Nations Framework Convention on Climate Change [UNFCCC], 2023) and the latest commitments outlined at COP28 (UNFCCC, 2023). COP28, held in Dubai, United Arab Emirates, marked several significant milestones in global climate action. One of the key outcomes was the agreement to triple renewable energy capacity and double the global rate of energy efficiency by 2030, according to UNFCCC (2023). This commitment is crucial for limiting global warming to 1.5 °C above pre-industrial levels, a core objective of the Paris Agreement (UNFCCC, 2015). PV accounted for a dominant 78% of the 576 GW of new renewable capacity added globally, reaffirming its leadership in the renewable energy sector. Europe, in particular, has been a significant contributor to this growth of renewable energy capacity, installing a record 70.1 GW of new solar capacity in 2023, marking a substantial 51% year-on-year increase (SolarPower Europe, 2024). This growth trajectory is set to continue, driven by robust policy frameworks, technological advancements, and strong market demand (SolarPower Europe, 2023).

Recent years have witnessed substantial progress in the photovoltaic sector, characterised by significant reductions in the cost of solar panels and notable improvements in their efficiency. The cost of polycrystalline silicon modules, for instance, has decreased by approximately 68% from $0.67 per watt in the first quarter of 2014 to $0.214 per watt in the second quarter of 2019, according to Abou Jieb and Hossain (2022). Concurrently, the efficiency of PV modules has also seen remarkable enhancement. At present, the efficiency of single-junction solar PV cells ranges from 15% to 28%, with a maximum theoretical efficiency of 33.16% (National Renewable Energy Laboratory, 2019, as cited in Abou Jieb and Hossain, 2022). Continuous research and development efforts have led to the creation of high-efficiency modules, such as those produced by Hanwha Q Cells, which have set records with module efficiencies of up to 20.4%, as stated by Abou Jieb and Hossain (2022). This trend of increasing efficiency and decreasing costs is pivotal for making solar energy more accessible and competitive with conventional energy sources.

However, the expansion of solar power also brings to light the importance of maintaining the efficiency and longevity of PV systems. As noted by Sharma and Chandel (2013), electrical energy generated using PV technology can only be economical if the PV modules operate reliably for 25–30 years under field conditions. Proper inspection and maintenance are essential to ensure that PV panels operate at their peak performance, minimising downtime and maximising energy output. This is where advanced technologies, particularly convolutional neural networks (CNNs), come into play. Convolutional neural networks (CNNs) are a class of deep learning algorithms that have revolutionised image and video recognition tasks. These networks are designed to automatically and adaptively learn spatial hierarchies of features from input images through layers of convolutions, pooling, and fully connected layers. The convolutional layers apply filters to the input to create feature maps, which are then down-sampled by pooling layers to reduce spatial dimensions. Finally, fully connected layers perform classification based on the extracted features. This architecture allows CNNs to excel in tasks requiring a high-level understanding of image content, making them indispensable in a field such as computer vision (Alzubaidi et al., 2021; Taye, 2023). CNNs are not limited to photovoltaic inspections; their applications span across various domains, including medical imaging, autonomous driving, and facial recognition. For instance, in medical imaging, CNNs assist in diagnosing diseases by analysing X-rays, MRIs, and CT scans with remarkable accuracy (Taye, 2023).

Figure 1
Inspection phases with UAV / IR / CNN technology in PV systems



Source: Authors' adaption of Bommes et al. (2021) figure

Figure 1 illustrates the inspection phases of photovoltaic (PV) systems utilising UAV (Unmanned Aerial Vehicle), infrared (IR) imaging, and convolutional neural network (CNN) technology. This comprehensive approach involves multiple stages where UAVs capture aerial images, IR sensors detect thermal anomalies, and CNN algorithms analyse the data to identify potential issues in the PV systems.

Literature Review

The intersection of CSR and industrial strategy has been increasingly recognised as vital for achieving long-term sustainability in Industry 4.0. Barić (2022) argues that integrating CSR into core business operations not only fulfils ethical obligations but also provides a strategic advantage, particularly in industries closely tied to environmental impacts, such as solar energy. This perspective underlines the importance of responsible practices in the deployment of technologies like CNNs for PV panel maintenance.

Pejić Bach et al. (2023a) highlight the rapid growth of industrial informatics as a crucial area of research, emphasising how data-driven approaches are transforming industrial processes. The integration of predictive analytics, especially in maintenance operations, allows companies to pre-emptively address issues, thereby reducing downtime and costs. This research supports the need for advanced technologies like CNNs to be incorporated into routine maintenance strategies to enhance their effectiveness.

The use of open-source software in predictive maintenance is highlighted by Pejić Bach et al. (2023b), who emphasise its benefits across various industries. By leveraging tools like R, companies can implement sophisticated maintenance systems without the financial burden of proprietary software. This accessibility is particularly crucial in the context of Industry 4.0, where cost-effective solutions are needed to democratise the use of advanced technologies like CNNs.

Developing a computer vision tool that integrates CNNs and IRT, Bommes et al. (2021) focused on detecting, mapping, and classifying faults in PV modules. The tool, combined with unmanned aerial vehicles (UAVs), enables rapid data acquisition and high accuracy in identifying various fault types, significantly reducing maintenance costs and improving the reliability of PV systems. This study concentrated on ten classes of defects: Module open-circuit, module short-circuit, substring open-circuit, substring short-circuit, module potential-induced degradation (PID), multiple hot cells, single hot cell, warm cell(s), diode overheated and hot spot. This research is closest to the IEC classification mentioned before. They have used the ResNet-50 CNN model and achieved test accuracy of more than 90%.

Research conducted under Algerian climatic conditions by Kellil, Aissat and Mellit (2023) focused on fault diagnosis of PV modules using a fine-tuned VGG-16 model and deep neural networks. The study achieved remarkable accuracy rates of 99.91% for fault detection and 99.80% for diagnosing five defect types, including bypass diode failure, shading effect, short-circuit, dust deposit, and partially covered PV module. The use of infrared thermographic images underlines the effectiveness of the VGG-16 model in diverse environmental conditions.

In 2021, Hwang et al. proposed a hybrid detection scheme utilising custom CNN architecture and the XGBoost algorithm to enhance the detection of malfunctioning PV modules. By using infrared images captured by UAVs, the study demonstrated high detection accuracy and efficiency, particularly in large-scale or remote solar power plants. The hybrid scheme's integration of multiple machine learning methods provided robust fault detection capabilities, predicting three classes of defects: hot spots, PID (Potential Induced Degradation), and open circuits (Hwang et al., 2021). Their best classification model based solely on image detection had 99% accuracy, while the hybrid model upped it to 99.2%. Hybrid models combine CNNs with other machine learning algorithms, such as XGBoost or support vector machines (SVMs), to enhance performance. These models leverage the strengths of each component, improving accuracy and reducing false positives in defect detection tasks.

Implementing UAV-based infrared thermography to detect faults in PV systems, Manno et al. (2021) highlighted significant efficiency gains and cost reductions in maintenance processes. The integration of UAVs allowed for rapid and precise inspection of extensive solar installations, emphasising the practicality of combining UAV technology with advanced image processing techniques for PV system monitoring. This study focused on only 1 class of defect: hotspot. The main reason it was chosen for review is because it compares ground-based and UAV acquisition methods. The conclusion was that the UAV acquisition method allows a considerable reduction in inspection time. The architecture they used was VGG-16, and they achieved 98% classification accuracy.

Moreover, Benghanem et al. (2023) introduced a method using CNNs to analyse and classify defects in PV modules under various environmental conditions. Their approach highlighted the importance of adapting inspection techniques to different climatic settings to maintain high detection accuracy and efficiency. This study identified seven defect types: covered PV module, cracked PV module, degradation, diode overheating, dirty PV module, sand accumulated on PV module, and short-circuited PV module. Their best model, which they call CNN-ML, achieved 94% accuracy over these 7 defects. That model is a hybrid model consisting of a custom CNN and support vector machines (SVM) model.

Mellit (2022) introduced an embedded system for fault detection and diagnosis in PV modules using thermographic images and deep convolutional neural networks. The study developed a binary classifier for fault detection and a multiclass classifier for diagnosing four types of defects: partial shading effect, dust deposit on PV modules surface, short-circuited PV module, and bypass diode failure. The system was embedded in a low-cost microprocessor for real-time application, demonstrating high feasibility and accuracy. Final accuracy for defect classification was 95.55%.

In their study, Fonseca Alves et al. (2021) explore the development of an automatic fault classification system for photovoltaic (PV) modules using convolutional neural networks (CNNs) and infrared thermography. The researchers aimed to classify up to eleven different defect types in PV modules, including cell, cell-multi, cracking, hotspot, hot-spot-multi, shadowing, diode, diode-multi, vegetation, soiling, and offline module. They utilised data augmentation techniques to improve the performance of their CNN model on an unbalanced dataset, achieving a testing accuracy of 92.5% for anomaly detection and 78.85% for classifying eight selected defect classes. Data augmentation involves techniques used to increase the diversity of a training dataset without collecting new data. This can include transformations like rotations, translations, and flips, which help improve the robustness and performance of CNN models by simulating various real-world scenarios.

Methodology

In this review article, the methodology section outlines the systematic approach taken to gather, analyse, and synthesise information regarding the use of convolutional neural networks (CNNs) for defect detection in infrared (IR) images of photovoltaic (PV) panels. The methodology ensures a comprehensive and unbiased review of the existing literature and identifies gaps and trends in the research landscape. The methodology section provides a structured approach to reviewing the use of CNNs for defect detection in PV panels, ensuring a comprehensive understanding of current capabilities, challenges, and prospects. This systematic review aims to contribute valuable insights for researchers, industry professionals, and policymakers in advancing the sustainable growth of solar energy through innovative inspection technologies. The steps undertaken are laid out in the subheadings of this section.

Literature search strategy

A thorough literature search was conducted across multiple academic databases, including ScienceDirect, Google Scholar, Wiley Online Library, and SpringerLink. The search focused on articles published between 2010 and 2024 to ensure the inclusion of both foundational studies and the latest advancements in the field. Key search terms included combinations of the following keywords: "Convolutional Neural Networks," "CNN," "PV panel defect detection," "infrared thermography," "solar energy," "photovoltaic inspection," and "deep learning."

Inclusion and Exclusion Criteria

Specific inclusion and exclusion criteria were established for the inclusion and exclusion of the papers. The inclusion criteria were:

- Peer-reviewed journal articles and conference papers
- Studies focusing on CNN applications for defect detection in PV panels
- Research utilising infrared thermography for PV panel inspection
- Articles published in English.

The exclusion criteria were:

- Non-peer-reviewed articles, such as preprints, thesis papers, and technical reports
- Studies not involving CNNs or IR imaging in the context of PV panels
- Articles with insufficient methodological details or experimental data.

Data analysis and synthesis

Relevant data were gathered from the selected articles, focusing on the following aspects:

- Study Objectives and Scope: The primary goals and coverage of each study
- CNN Architectures Used: Specific CNN models (e.g., ResNet, EfficientNet) employed in the defect detection process
- Performance Metrics: The main metric for comparison will be the accuracy of classification.
- Applications and Results: Key findings, applications in the PV industry, and practical outcomes of each study.

The gathered data were organised into tables to facilitate a clear comparison of different studies and highlight the performance and applicability of various CNN models.

Analysis of CNN Effectiveness

The review critically analysed the effectiveness of CNNs in identifying the defect patterns specified by the International Electrotechnical Commission (IEC) standard IEC TS 62446-3:2017 (IEC, 2020). This involved:

1. Mapping Defect Types: Comparing the identified defect types in the reviewed studies with the IEC standards
2. Detection Rates: Evaluating the detection rates achieved by CNN models and their potential to replace human inspection
3. Economic Benefits: Assessing the economic implications of using CNNs, including inspection speed, cost savings, and reduction in human error.

Technological Integration and Future Directions

The review also explored the integration of UAVs equipped with IR cameras in the inspection process, considering their impact on efficiency and accuracy as several reviewed studies have employed UAVs as their channel of acquisition of IR images (Grimaccia, Leva, Dolara, & Aghaei, 2017; Huerta Herraiz et al., 2020; Hwang et al., 2021; Kirsten Vidal de Oliveira, Aghaei, & Rüther, 2020; Masita, Hasan, & Shongwe, 2022; Zefri, Sebari, Hajji, & Aniba, 2022). Additionally, future research directions were identified based on current gaps and limitations in the literature.

Quality Assessment and Bias Mitigation

To ensure the reliability of the review, a quality assessment of the selected studies was conducted using standardised tools like the Critical Appraisal Skills Programme (CASP) checklist (Critical Appraisal Skills Programme, 2018). Efforts were made to mitigate bias by including studies from diverse geographical regions and research groups and by considering both positive and negative findings.

Seven research studies were chosen for results synthesis as they have passed the inclusion and exclusion criteria out of 23 research found in the literature search. These studies were selected based on their relevance to the application of convolutional neural networks (CNNs) and infrared thermography (IRT) for the detection and classification of defects in photovoltaic (PV) modules. The selected research collectively demonstrates the significant advancements in automated PV system inspection and maintenance technologies. These advancements are critical for enhancing the efficiency, accuracy, and economic viability of solar energy systems, contributing to their sustainable growth and reliability. Each of the studies will be briefly described in a paragraph, and the final results of all studies will be presented in a tabular form afterwards.

In this study, we conducted a review of seven key research articles that focus on the application of convolutional neural networks (CNNs) and Infrared Thermography (IRT) for detecting and classifying defects in photovoltaic (PV) modules. The results from these studies are compared in the form of a table in the Results section to highlight defect classes recognised, compatibility with IEC classification, and respective accuracies.

Compatibility with the IEC standard (IEC, 2020) was evaluated based on the defect class names and examples provided in the respective articles, as well as the reviewer's domain knowledge. Although the accuracies are not directly comparable due to the differing number of classes each study predicted, they present a clear picture of the performance of individual models. This comparative analysis demonstrates the effectiveness of CNNs in identifying various defect types in PV modules, thereby enhancing their maintenance and operational efficiency.

Results

The integration of convolutional neural networks (CNNs) with infrared thermography (IRT) has shown significant advancements in the inspection and maintenance of photovoltaic (PV) panels.

These advancements, detailed in the reviewed studies summarised in Table 1, are crucial for the PV industry as they not only enhance the efficiency and accuracy of defect detection but also reduce the associated costs and time required for maintenance. The use of CNNs allows for the automated identification of defects, which is essential for the rapid and accurate inspection of large-scale PV installations, as reflected in the objectives and scopes of the analysed research.

Table 1
Analysed Papers

Authors, year	Paper title	Objectives and scopes
Bommes et al. (2021)	Computer vision tool for detection mapping and fault classification of photovoltaics modules in aerial IR videos	Develop a semi-automatic tool for extracting PV modules from thermographic UAV videos and classifying anomalies with ResNet-50 CNN, achieving over 90% accuracy for automated PV plant inspection.

Kellil et al. (2023)	Fault diagnosis of PV modules using deep neural networks and infrared images under Algerian climatic conditions	Address fault diagnosis in PV modules using VGG-16 CNN with thermographic images, achieving high accuracy in diverse conditions with binary and multiclass classification.
Hwang et al. (2021)	Detection of Malfunctioning Photovoltaic Modules Based on Machine Learning Algorithms	Propose a hybrid detection scheme combining CNN and XGBoost to enhance the detection of malfunctioning PV modules, achieving high detection accuracy with infrared thermography.
Manno et al. (2021)	Deep learning strategies for automatic fault diagnosis in photovoltaic systems by thermographic images	Develop a system for automatic classification of thermographic images using CNNs, achieving high accuracy for remote and ground-based inspections to maintain PV system efficiency.
Benghanem et al. (2023)	Embedded Hybrid Model (CNN-ML) for Fault Diagnosis of Photovoltaic Modules Using Thermographic Images	Develop a hybrid CNN-ML model for real-time fault diagnosis of PV modules, optimising and implementing it in a microprocessor with a user-friendly interface for diverse climatic conditions.
Mellit (2022)	An embedded solution for fault detection and diagnosis of photovoltaic modules using thermographic images and deep convolutional neural networks	Introduce an embedded system for real-time fault detection and diagnosis of PV modules using DCNN, focusing on common defects and optimised for low-cost microprocessor deployment.
Fonseca Alves et al. (2021)	Automatic fault classification in photovoltaic modules using Convolutional Neural Networks	Investigate the use of CNNs with data augmentation for classifying up to eleven defect types in PV modules through thermographic images.

Source: Authors' work

Overall, the reviewed studies, as summarised in Table 2, demonstrate the potential of CNNs to improve the inspection and maintenance of PV panels significantly. The high accuracy rates achieved by various CNN models indicate that these technologies can effectively identify a wide range of defects, ensuring that PV systems operate at their optimal efficiency. As the demand for solar energy continues to rise, the adoption of advanced inspection techniques like CNNs and IRT will be essential for maintaining the performance and reliability of PV installations worldwide.

Table 2
Findings in analysed papers

Authors, year	Findings of own research	Relation to existing findings in the literature
Bommes et al. (2021)	High accuracy (>90%) in classifying PV module anomalies using ResNet-50 CNN.	Confirms the effectiveness of CNNs for defect detection, extending it to large-scale PV plants with UAV integration.
Kellil et al. (2023)	Achieved 99.91% accuracy in fault detection and 99.80% in fault diagnosis using VGG-16 CNN.	Supports prior work on the high accuracy of CNNs in diverse environmental conditions, enhancing fault diagnosis precision.

Hwang et al. (2021)	High detection accuracy with a hybrid CNN and XGBoost scheme.	Aligns with previous studies on hybrid models, improving detection accuracy, particularly in large-scale settings.
Manno et al. (2021)	99% accuracy in fault classification using CNNs for UAV-acquired images.	Validates the use of UAV and CNN combinations for efficient PV module inspection, consistent with other research.
Benghanem et al. (2023)	Effective real-time fault diagnosis using a hybrid CNN-ML model.	Builds on existing literature by demonstrating practical embedded solutions for real-time applications in varied climates.
Mellit (2022)	Feasibility of real-time fault detection using DCNN, optimised for low-cost microprocessors.	Reinforces the potential for cost-effective, real-time PV module inspection using embedded DCNN systems.
Fonseca Alves et al. (2021)	92.5% accuracy for anomaly detection and 78.85% for defect classification with data augmentation in CNNs.	Extends current knowledge by addressing classification challenges in unbalanced datasets with data augmentation.

Source: Authors' work

Infrared thermography (IRT) is a widely used technique in PV panel inspection due to its ability to detect thermal anomalies that indicate potential defects. By capturing temperature variations on the surface of PV panels, IRT provides a visual representation of the panel's thermal profile, making it easier to identify areas that may require further inspection or maintenance. The CNN architectures used and their respective classification accuracies, as listed in Table 3, demonstrate the effectiveness of these models in quickly and accurately classifying different types of defects based on the thermal patterns observed. Classification accuracy is a metric used to evaluate the performance of a classification model by measuring the proportion of correct predictions out of the total predictions made. In PV panel inspection using infrared thermography (IRT) and convolutional neural networks (CNNs), "detection" and "classification" are often synonymous. This is because the main goal is to identify and categorise defects, as knowing the type of defect informs the necessary remedial action. GPS tracks the panel's location, making the exact location of the defect on the panel less critical. IRT highlights temperature variations, and CNNs classify these thermal patterns to determine defect types. Therefore, detection inherently includes classification, ensuring efficient maintenance and repair of the panels.

Table 3
CNN Architectures and classification accuracy in analysed papers

Authors, year	CNN Architecture Used	Classification accuracy score of the best model
Bommes et al. (2021)	ResNet-50	90.91%
Kellil et al. (2023)	VGG-16	99.80%
Hwang et al. (2021)	Custom CNN + XGBoost	99.00%
Manno et al. (2021)	VGG-16	98.00%
Benghanem et al. (2023)	Custom CNN + SVM	94.00%
Mellit (2022)	Custom CNN	95.55%
Fonseca Alves et al. (2021)	Custom CNN	78.85% (for 8 classes)

Source: Authors' work

Table 4
Key Findings, Applications, and Outcomes in Analysed Paper

Study	Key findings	Applications in the PV industry	Practical outcomes of each study
Bommes et al. (2021)	High accuracy in classifying PV module anomalies using ResNet-50 CNN, achieving over 90% test accuracy.	UAV-based thermographic inspection for large-scale PV plants.	Significant reduction in inspection time and costs, improved scalability for multi-gigawatt plants.
Kellil et al. (2023)	High fault detection and diagnosis accuracy using VGG-16 CNN, achieving 99.91% and 99.80%, respectively.	Fault detection and diagnosis in PV modules under diverse environmental conditions.	Enhanced accuracy and reliability in PV module performance, minimised energy production losses.
Hwang et al. (2021)	High detection accuracy with a hybrid scheme combining CNN and XGBoost, achieving better accuracy and low time consumption.	Maintenance of large-scale or remote solar power plants.	Reduced maintenance time and costs, timely replacement of malfunctioning PV cells.
Manno et al. (2021)	High accuracy in fault classification using CNN with various pre-processing techniques, achieving 99% accuracy for UAV-acquired images.	Automatic classification of thermographic images for remote failure detection.	Improved fault detection efficiency, a practical tool for both UAV and ground-based inspections.
Benghanem et al. (2023)	Effective hybrid CNN-ML model for real-time fault diagnosis, optimised and implemented in a microprocessor.	Real-time fault diagnosis of PV modules with a user-friendly interface.	Feasibility of embedded solutions for diverse climatic conditions enhanced PV module analysis and maintenance.
Mellit (2022)	Feasibility of real-time fault detection and diagnosis using DCNN, optimised for low-cost microprocessor deployment.	Embedded systems for real-time fault detection and diagnosis in PV modules.	Cost-effective maintenance solution with acceptable accuracy real-time notifications for PV module state.
Fonseca Alves et al. (2021)	Effective use of CNNs with data augmentation for classifying multiple defect types, achieving 92.5% accuracy for anomaly detection.	Automated fault classification in large-scale PV plants.	Improved inspection efficiency and reduced labour costs, a practical tool for diverse defect classification.

Source: Authors' work

Manual inspection methods are not only time-consuming and labour-intensive but also prone to human error. As highlighted in Table 4, CNNs offer a high degree of accuracy and consistency in defect detection, thereby reducing the likelihood of missed defects and subsequent panel failures. Additionally, the use of unmanned aerial vehicles (UAVs) equipped with infrared cameras can further expedite the inspection process, allowing for the rapid assessment of large PV installations with minimal human intervention. This combination of UAVs and CNNs represents a significant leap forward in the field of PV panel maintenance, as reflected in the practical outcomes of the reviewed studies.

Moreover, aligning the defect detection capabilities of CNNs with the IEC TS 62446-3:2017 standard is crucial for ensuring consistent and reliable PV panel maintenance across the industry. Table 5 presents the defect types recognised by each study and compares them to the IEC standard, providing a benchmark for evaluating the performance of CNN models. By adhering to these standards, the PV industry can ensure that the inspection methods used are not only effective but also compliant with established guidelines, thereby enhancing the overall reliability and longevity of PV systems.

Table 5
Defect types and comparison to IEC

Study	Defect types classes names	Number of defect classes recognised	Defect classes comparable to IEC standard (IEC, 2020)
Bommes et al. (2021)	Module open-circuit, module short-circuit, substring open-circuit, substring short-circuit, module PID, multiple hot cells, single hot cell, warm cell(s), diode overheated, hot spot	10	6/9
Kellil et al. (2023)	Bypass diode failure, shading effect, short-circuit, dust deposit, partially covered PV module	5	3/9
Hwang et al. (2021)	Hot spots, PID, open circuits	3	1/9
Manno et al. (2021)	Hotspot	1	0/9
Benghanem et al. (2023)	Covered PV module, cracked PV module, degradation, diode overheating, dirty PV module, sand accumulation, short-circuited PV module	7	4/9
Mellit (2022)	Partial shading effect, dust deposit on PV module surface, short-circuited PV module, bypass diode failure	4	3/9
Fonseca Alves et al. (2021)	Cell, cell-Multi, cracking, hotspot, hot-spot-multi, shadowing, diode, diode-multi, vegetation, soiling, offline module	11	6/9

Source: Authors' work

The results from the reviewed studies indicate that no single research comprehensively covered all the IEC classes for PV panel defects. However, by combining the defect classes identified in different studies, it is possible to cover all IEC-determined classes, suggesting a potential for developing a model in line with the IEC standard. Most of the reviewed models, except the one by Fonseca Alves et al. (2021), achieved accuracies above 90%, showcasing the efficacy of CNNs in PV panel defect detection. This high accuracy rate suggests that CNNs can potentially surpass human capabilities in detecting PV panel defects, aligning well with the research questions on the feasibility of CNNs in maintaining PV system reliability and efficiency by identifying defect patterns as per IEC standards and surpassing the human eye in detection rate.

The reviewed studies highlight several economic benefits. The economic benefits of using CNN-based defect detection methods in PV panels are substantial. The key advantages include significant reductions in maintenance and inspection costs, increased accuracy in defect detection, and consequentially minimised energy production losses. The use of UAVs combined with CNNs allows for rapid and precise inspections, particularly in large-scale installations, further reducing costs associated with manual labour. The adoption of low-cost microprocessors for real-time fault detection and diagnosis also contributes to overall cost savings, making these advanced technological solutions both efficient and economical for the PV industry. Table 6 summarises these benefits in the 7 papers reviewed.

Table 6
Summary of economic benefits pinpointed in articles

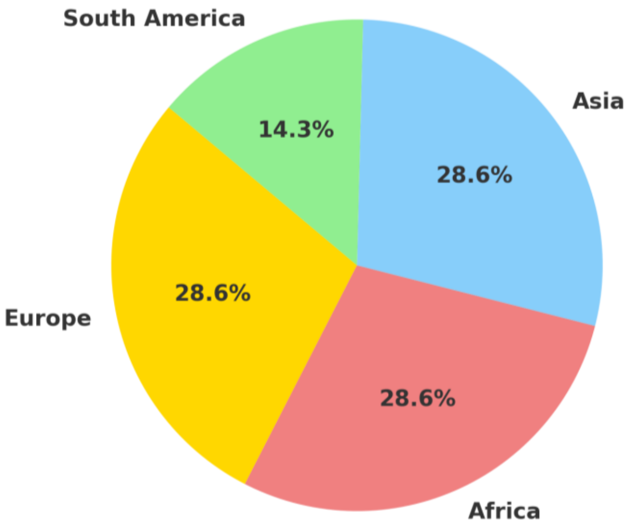
Study	Economic Benefits
Bommes et al. (2021)	Significant reduction in maintenance costs and improvement in PV system reliability through rapid data acquisition and accurate fault detection using UAVs.
Kellil et al. (2023)	Enhanced accuracy of fault detection leads to minimised energy production losses and reduced costs associated with manual inspections and maintenance.
Hwang et al. (2021)	High detection accuracy and efficiency, especially in large-scale or remote solar power plants, resulting in reduced maintenance time and costs.
Manno et al. (2021)	Significant efficiency gains and cost reductions in maintenance processes through rapid and precise inspection using UAVs.
Benghanem et al. (2023)	Reduced operational costs through effective fault diagnosis under various environmental conditions, ensuring optimal performance of PV modules.
Mellit (2022)	Cost savings through the use of a low-cost microprocessor for real-time fault detection and diagnosis, reducing the need for extensive human intervention.
Fonseca Alves et al. (2021)	Economic benefits from automated classification of defects, though less accurate than other models, still provide substantial improvements over manual inspection methods, reducing labour costs and increasing inspection efficiency.

Source: Authors' work

The global nature of the reviewed studies is evident from the wide range of authors' home countries, which include Germany, Algeria, Taiwan, Italy, Saudi Arabia, and Brazil. This geographical diversity is crucial for ensuring that the findings and methodologies are robust and applicable across different climatic and environmental conditions. Research conducted across various continents helps mitigate biases that may arise from studying PV panel defect detection in a single environmental context. Different regions present unique climatic and operational challenges that can affect the performance and reliability of CNN models. For example, studies from Algeria and Saudi Arabia provide insights into PV panel defect detection under harsh desert climates, while research from Germany and Italy offers perspectives from more temperate climates.

Additionally, incorporating data from multiple continents strengthens the generalizability and applicability of the research findings. The varied climatic conditions and operational settings represented in the studies contribute to developing universally applicable CNN models for PV panel defect detection, enhancing their reliability and effectiveness worldwide. The distribution of reviewed studies across different continents is illustrated in Figure 2. By presenting these visualisations and analyses, we emphasise the global scope and relevance of the reviewed research, providing a strong foundation for the broader applicability of the findings. This comprehensive approach ensures that the inspection methods developed are not only technically sound but also environmentally resilient, catering to the diverse needs of the global solar energy industry.

Figure 2
Distribution of Studies by Continent



Source: Authors' work

The importance of this geographical diversity cannot be overstated. Research conducted across various continents helps mitigate biases that may arise from studying PV panel defect detection in a single environmental context. Different regions present unique climatic and operational challenges that can affect the performance and reliability of CNN models. For example, studies from Algeria and Saudi Arabia provide insights into PV panel defect detection under harsh desert climates, while research from Germany and Italy offers perspectives from more temperate climates. This diversity ensures that the findings and methodologies are robust and applicable across a wide range of environmental conditions.

Additionally, incorporating data from multiple continents strengthens the generalizability and applicability of the research findings. It highlights the widespread interest and relevance of CNN-based defect detection methods in the global push for more efficient and reliable solar energy systems. The varied climatic conditions and operational settings represented in the studies contribute to developing universally applicable CNN models for PV panel defect detection, enhancing their reliability and effectiveness worldwide.

Conclusion and discussion

Summary of research

This research has successfully addressed the primary research questions, providing substantial insights into the application of convolutional neural networks (CNNs) for defect detection in photovoltaic (PV) panels using infrared (IR) thermography. The analysis of seven key studies reveals significant advancements in automated PV system inspection and maintenance technologies, demonstrating that CNNs can effectively identify various defect types in PV modules, thus enhancing maintenance and operational efficiency.

Can CNNs identify all defect patterns proposed in the IEC standard? The first hypothesis suggested that CNNs could accurately identify all defect patterns listed in the IEC TS 62446-3:2017 standard. Reviewed studies demonstrated high accuracy rates above 90% for several defect classes, supporting this claim partially. However, no single study covered all the IEC-defined defect types comprehensively. This indicates that while CNNs are effective, further refinement is needed to align with the IEC standard fully. Combining the defect classes identified across different studies suggests the potential for developing a comprehensive model in line with the IEC standard.

Can CNNs achieve an acceptable detection rate, effectively replacing human inspection and speeding up the process, thereby providing economic benefits? It was proposed that CNNs could achieve a detection rate that meets or exceeds the accuracy of human inspectors. The high accuracy rates achieved by most reviewed models (above 90%) showcase the efficacy of CNNs in defect detection, suggesting that CNNs can surpass human capabilities in detecting PV panel defects. Combining that with the high inference times of humans answers our question. Models can classify hundreds of pictures in a matter of seconds, while humans need hours for manual inspection of a hundred images. The economic benefits of using CNN-based defect detection methods in PV panels are substantial. The key advantages include significant reductions in maintenance and inspection costs, increased accuracy in defect detection, and minimised energy production losses. The use of UAVs combined with CNNs allows for rapid and precise inspections, particularly in large-scale installations, further reducing costs associated with manual labour. Studies reviewed highlighted substantial reductions in inspection times, especially when UAVs were used, and significant cost savings compared to manual inspections. This efficiency gain confirms the predicted economic benefits. However, further research is needed to quantify these benefits across different scales of PV installations.

Theoretical Contributions

This review paper makes several theoretical contributions to the field of solar energy and photovoltaic (PV) system maintenance through the application of convolutional neural networks (CNNs).

Firstly, it offers a comprehensive analysis of CNN effectiveness by synthesising existing research on the application of CNNs for defect detection in PV panels. The review provides a thorough understanding of how well these networks perform in identifying various defects according to IEC standards. By critically evaluating different CNN models' performance metrics, the paper highlights their strengths and limitations, offering valuable insights into their practical applications. For instance, models like ResNet-50 and VGG-16 have demonstrated high accuracy rates in defect detection, showcasing the potential of CNNs in this domain.

Secondly, the paper evaluates the economic and operational benefits of adopting CNN-based defect detection in the PV industry. It discusses cost savings, reduced inspection times, and the elimination of human error, providing a theoretical framework for understanding the broader impact of CNN technology on the sustainability and scalability of solar energy systems. This analysis offers a new perspective on the economic implications of technological advancements in the PV sector, highlighting how CNNs can reduce maintenance costs and enhance the reliability of PV systems.

Thirdly, by aligning the defect detection capabilities of CNNs with the IEC TS 62446-3:2017 standard, the review bridges the gap between advanced technological solutions and industry requirements. This alignment offers a theoretical basis for standardising the use of CNNs in PV panel maintenance, promoting consistency and reliability across the industry. Such a connection between technology and industry standards is critical for the practical implementation of new inspection methods, ensuring that CNN-based solutions are widely adopted and trusted within the PV industry.

Lastly, these theoretical contributions aim to advance the understanding of how CNNs can revolutionise the inspection and maintenance of photovoltaic systems, supporting the sustainable growth of solar energy on a global scale. By providing a thorough and critical examination of the existing research, this review serves as a valuable resource for researchers, industry professionals, and policymakers in the field of renewable energy. It underscores the potential of CNNs to enhance the efficiency, accuracy, and economic viability of solar energy systems, thereby contributing to their sustainable expansion and reliability.

The application of convolutional neural networks in photovoltaic panel defect detection represents a significant technological advancement with substantial theoretical and practical implications. This review highlights the effectiveness, economic benefits, and alignment with industry standards of CNN-based defect detection methods, offering valuable insights for future research and practical implementation in the PV industry.

Concluding remarks

This review paper makes several contributions to the field of photovoltaic (PV) system maintenance and solar energy sustainability through the application of convolutional neural networks (CNNs). By synthesising existing research, this study provides a comprehensive understanding of the efficacy, economic benefits, and practical applications of CNNs in detecting defects in PV panels.

The review partially supports the first hypothesis, indicating that CNNs are highly accurate in identifying many IEC-defined defect patterns, though not all. Future work should aim to develop more comprehensive models that cover all defect types specified by the IEC standard to ensure complete alignment.

The paper concludes that CNNs are highly effective in identifying various defect types in PV panels, often surpassing traditional inspection methods in accuracy and efficiency and strongly supporting our second hypothesis. Models such as ResNet-50 and VGG-16 have demonstrated significant potential in real-world applications, achieving high accuracy rates in defect detection. This finding underscores the viability of CNN-based approaches in enhancing the reliability and longevity of PV systems.

Secondly, the review highlights the substantial economic benefits associated with adopting CNN-based defect detection methods. The integration of UAVs and CNNs not only reduces inspection times and costs but also minimises human error, leading to more reliable maintenance processes. All of this validates our third hypothesis. These economic advantages are crucial for the sustainable growth of the solar energy sector, making advanced inspection technologies more accessible and cost-effective.

This study has demonstrated the significant potential of CNNs in enhancing PV panel maintenance, particularly when integrated with open-source software solutions and guided by CSR principles. The broader trend of data-driven technologies transforming industry processes aligns with the findings of this review, highlighting the growing importance of industrial informatics. The accessibility and economic viability of adopting advanced technologies like CNNs, especially within the framework of Industry 4.0, are underscored by the emphasis on predictive maintenance and the use of open-source tools. All the CNN architectures discussed in this review, along with other algorithms like XGBoost, are open source, making them readily accessible for implementation without the high costs associated with proprietary software. This availability allows for widespread adoption of these advanced techniques, even by smaller enterprises, contributing to the democratisation of technology in industrial applications.

Furthermore, the strategic integration of CSR into technological innovations reinforces the importance of responsible practices in achieving sustainable business operations. By aligning CNN applications with CSR, businesses can enhance their operational efficiency while also contributing to broader sustainability goals. This review suggests that the convergence of artificial neural networks, open-source software, and CSR can lead to more resilient and sustainable energy systems, paving the way for future advancements in the industry.

In reflecting on these contributions, this study emphasises the need for continued research and development in CNN technologies to further improve their performance and integration with industry standards. Future research should focus on optimising CNN architectures and exploring new applications to ensure that PV systems can operate at their peak efficiency, supporting the global transition to renewable energy.

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