

A DEEP LEARNING-EMPOWERED ARTIFICIAL INTELLIGENCE FRAMEWORK FOR INTELLIGENT FAULT DETECTION AND PERFORMANCE OPTIMIZATION IN PHOTOVOLTAIC SOLAR ENERGY SYSTEMS

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Abstract

The rapid global expansion of photovoltaic (PV) solar energy systems has intensified the need for intelligent, autonomous, and highly accurate monitoring frameworks capable of mitigating faults and optimizing energy output under diverse environmental and operational conditions. Conventional rule-based and model-driven diagnostic techniques often fail to capture nonlinear interactions among irradiance fluctuations, temperature variations, shading patterns, aging effects, and inverter-level disturbances. To address these limitations, this study proposes a Deep Learning-Empowered Artificial Intelligence Framework for intelligent fault detection, performance prediction, and real-time optimization in grid-connected and standalone PV systems. The framework integrates multilevel sensing, high-resolution current-voltage (I-V) acquisition, inverter diagnostics, and meteorological inputs into a unified data fusion pipeline optimized for deep neural architectures. At the core of the proposed system is a hybrid deep learning engine combining convolutional neural networks (CNNs) for spatial feature extraction, long short-term memory (LSTM) networks for temporal behavior modeling, and an attention-driven fusion module for anomaly localization and severity scoring. The model is trained on multisource datasets capturing normal, partially shaded, soiling-affected, hotspot-induced, bypass-diode-damaged, and degradation-related faults. A hierarchical classification and regression scheme enables simultaneous detection, fault categorization, maximum power point

deviation estimation, and performance forecasting. Additionally, a reinforcement-learning-based optimization layer dynamically adjusts MPPT parameters, inverter reference signals, and operational settings to enhance energy yield while ensuring system safety. Experimental validation is performed using both real-time PV testbed measurements and open-source datasets such as the Desert Knowledge Australia Solar Centre (DKASC) and Sandia National Laboratories benchmarking repository. Results demonstrate that the proposed framework achieves significant improvements in detection accuracy, false-alarm reduction, severe-fault localization, and output power prediction compared to classical SVM, random forest, and shallow neural network approaches. The RL-driven optimization further enhances overall energy efficiency and operational stability under rapidly changing conditions, outperforming traditional MPPT methods such as Perturb-and-Observe and Incremental Conductance. The findings highlight the potential of intelligent AI-driven monitoring to revolutionize the reliability, resilience, and performance of next-generation photovoltaic assets. The proposed framework serves as a scalable foundation for future PV smart-grid integration, digital twins, predictive maintenance, and autonomous self-healing solar farms.

INTRODUCTION

The rapid expansion of photovoltaic (PV) solar energy systems has become a defining feature of the global clean-energy transition, driven by urgent decarbonization goals, declining module manufacturing costs, and major advances in inverter design, MPPT algorithms, and grid-integration technologies. As nations commit to more ambitious renewable-energy targets, PV installations are increasingly deployed in diverse configurations ranging from rooftop residential systems and commercial microgrids to utility-scale solar farms exceeding hundreds of megawatts. Despite this large-scale adoption, the reliable and efficient operation of PV systems remains a persistent challenge due to their exposure to dynamic environmental conditions, component failures, gradual aging, and operational disturbances. Even low-intensity, early-stage faults can silently deteriorate output power, reduce system lifespan, and escalate into severe safety hazards if not diagnosed promptly. These complexities reinforce the need for intelligent, automated monitoring frameworks capable of detecting, classifying, and predicting faults while simultaneously optimizing energy performance in real time. Traditional PV diagnostic techniques such as manual I-V curve tracing, electroluminescence (EL) inspection, infrared

thermography, and rule-based performance-ratio analysis play an important role but increasingly fall short in meeting the demands of modern, sensor-rich PV infrastructures [1]. These conventional approaches are often limited by their reliance on simplified linear assumptions, inability to generalize across weather variability, and difficulty in separating overlapping or subtle fault signatures. In large distributed systems, the volume, velocity, and heterogeneity of PV data streams introduce additional challenges that exceed the analytical capabilities of threshold-based or handcrafted-feature methods. The multidimensional interactions between irradiance fluctuations, temperature gradients, shading dynamics, soiling accumulation, wiring inconsistencies, and inverter switching behavior produce nonlinear patterns that are difficult to capture using classical estimation models. As a result, researchers are turning to artificial intelligence (AI) and deep learning (DL) techniques to address the need for scalable, autonomous, and high-precision PV monitoring. Deep learning has emerged as a powerful tool in modeling both spatial and temporal characteristics of PV system behavior, owing to its ability to learn hierarchical representations directly from data. Convolutional neural networks (CNNs) have

demonstrated strong performance in detecting visual anomalies such as hotspots, cracks, and discoloration in module images, while recurrent architectures such as long short-term memory (LSTM) networks effectively capture temporal trends in electrical measurements and irradiance profiles [2]. Hybrid models, attention mechanisms, graph neural networks, and transformer architectures offer further improvements by extracting multi-scale features and enhancing interpretability. Yet, despite these advancements, current approaches suffer from fragmentation: many studies address fault detection but neglect real-time performance optimization, while others focus on forecasting but overlook early-stage anomaly diagnosis.

Moreover, deep models often struggle with generalization across different PV technologies, site conditions, and inverter configurations, highlighting a gap in adaptive, fully integrated monitoring architectures. To situate the need for an intelligent, unified framework, the following table 1 presents a comparative overview of common PV system faults, their physical manifestations, and the limitations of conventional diagnostic approaches. This synthesis contextualizes the operational challenges modern PV systems face and underscores why deep learning-empowered architectures are essential for next-generation performance management.

Table 1: Common PV Faults, Their Operational Signatures, and Limitations of Traditional Detection Methods

Fault Type	Observed Symptoms	Impact on System Performance	Limitations of Traditional Detection
Partial Shading	Distorted I-V curve, mismatch losses, localized heating	Reduced power output, hotspot risk	Difficult to differentiate from aging and soiling; requires high-resolution temporal data
Soiling & Dust	Gradual current drop, uneven heating	5-30% energy loss depending on severity	Manual cleaning cycles mask early detection; often misinterpreted as irradiance drift
Hotspots	Local temperature rise, thermal runaway	Accelerated degradation, safety hazards	Requires thermographic inspection; limited automation for continuous monitoring
Module Degradation	Reduced short-circuit current, lower fill factor	Long-term efficiency decline	Shares patterns with shading and soiling; difficult to isolate through I-V curves alone
Bypass Diode Failure	Reverse currents, severe distortion in I-V characteristics	Major mismatch losses, heating	Detection highly irradiance-dependent; rule-based methods unreliable
Inverter Faults	Harmonics, tracking instability, abnormal switching	Power fluctuation, system derating	Traditional fault logs lack predictive capability
Wiring/Connection Issues	Intermittent power variation, noise	Instability, risk of partial shutdown	Highly transient and hidden within noisy measurements

As global PV penetration increases, the complexity and variability of operational data demand higher levels of intelligence, automation, and adaptability. At this pivotal point in the transition to smart renewable infrastructures, AI offers a

radically enhanced paradigm. Yet even AI-based fault detection is no longer sufficient on its own; emerging research emphasizes the integration of optimization and control mechanisms to ensure stable performance under rapidly changing

environmental and operational conditions. Reinforcement learning (RL), in particular, is gaining prominence for its capability to autonomously improve MPPT strategies, adjust inverter parameters, and respond dynamically to real-time disturbances something that static algorithms or manually tuned controllers struggle to achieve [3]. To underline the conceptual scope

of this evolving technological landscape, the mid-section figure 1 below conceptually represents the broader domain in which PV monitoring and optimization take place, highlighting the interplay between environmental inputs, sensor streams, fault signatures, deep learning inference layers, and intelligent control decisions.

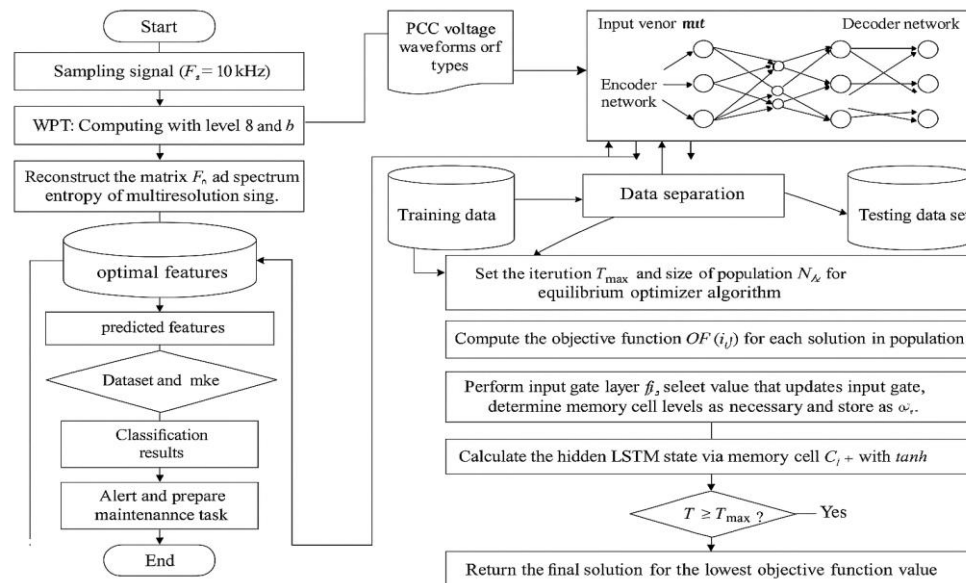


Figure 1: Conceptual Overview of the Operational Environment, Data Streams, and Intelligent Decision Pathways for Deep Learning–Driven PV Fault Detection and Performance Optimization.

Building upon this foundation of challenges and emerging innovations, the present study introduces a Deep Learning–Empowered Artificial Intelligence Framework engineered to unify detection, prediction, and optimization within a single coherent architecture. The proposed system fuses CNN-based spatial feature extraction, LSTM-driven temporal modeling, attention-based interpretability, and reinforcement learning–based performance optimization to deliver fully autonomous PV monitoring. By integrating multimodal sensing, hierarchical neural inference, and adaptive control loops, the proposed framework aims to advance PV technology toward self-healing, predictive, and highly resilient solar energy systems. This unified architecture is designed to be scalable across geographic regions, compatible with diverse PV

configurations, and adaptable to new fault modes as they emerge, thus contributing fundamentally to the next

generation of intelligent renewable-energy infrastructures.

1- Deep Learning for PV Performance Forecasting and Predictive Maintenance:

Deep learning (DL) has fundamentally reshaped the field of photovoltaic (PV) performance forecasting, not merely by improving prediction accuracy but by transforming how the temporal, spatial, and environmental dynamics of solar energy systems are conceptualized and modeled. Traditional statistical forecasting approaches such as ARIMA, exponential smoothing, Markov processes, and linear regression rely on

assumptions of temporal stability and smooth seasonal patterns, which rarely hold in real PV environments. Solar irradiance fluctuates with cloud movement, humidity, aerosol concentration, spectral distribution, and even local wind patterns, while system output is simultaneously affected by soiling, degradation, and temperature-induced efficiency variations. These interactions produce multiscale nonlinear dynamics that classical models cannot capture. Deep learning, with its capacity to learn non-polynomial mappings directly from data, provides a transformative alternative capable of modeling high-frequency variability, long-term seasonal trends, and structural degradation patterns within a unified predictive framework. LSTM networks were among the first DL models widely adopted for PV forecasting, given their ability to retain long-range temporal information using gating mechanisms that filter noise and preserve meaningful trends [4]. In PV contexts, LSTMs have been shown to predict irradiance ramps, inverter output fluctuations, and thermal effects with far greater fidelity than shallow models. Bidirectional LSTMs (Bi-LSTM) further enhance predictive accuracy by processing sequences in both forward and backward directions, enabling the model to recognize precursor patterns leading to rapid drops in power, such as approaching cloud shadows or shading transients. However, LSTMs and Bi-LSTMs can face computational bottlenecks when applied to massive datasets from utility-scale PV farms, especially when sampling rates are high (1–5 seconds). Temporal convolutional networks (TCNs) address these challenges by combining dilated convolutions with residual connections, allowing the receptive field to expand without increasing computational cost. TCNs capture both local and global temporal dependencies and have demonstrated superiority in real-time forecasting tasks where rapid decisions are required, such as grid-balancing operations or inverter-level control adjustments. These

advantages make TCNs particularly attractive for short-term (seconds-to-minutes ahead) PV power forecasting under highly dynamic weather conditions [5]. The most significant breakthrough in recent years has been the introduction of transformer architectures, which replace recurrent structures entirely with attention mechanisms. Transformers can model extremely long-range temporal dependencies without suffering from vanishing gradients or sequential processing constraints. In PV forecasting, multi-head attention modules identify which meteorological variables such as diffuse irradiance, ambient humidity, or wind-induced convective cooling are most influential at each time step. This dynamic weighting capability allows transformers to adapt to irregular patterns, making them ideal for forecasting under rapidly shifting cloud fields or monsoon-season variability. Their scalability and parallelization advantages have made them a leading candidate for large-scale forecasting deployments where millions of data points from weather stations, PV modules, and satellite sources must be fused in near real time. In addition to high-temporal-resolution electrical data, deep learning models increasingly incorporate sky imagery, satellite irradiance maps, drone inspections, and environmental sensor data for enhanced forecasting [6]. CNN-LSTM hybrid architectures, for instance, extract cloud-motion vectors from sky images before feeding them into LSTMs that predict irradiance and PV output several minutes ahead. Such systems outperform purely numerical weather prediction models by capturing micro-scale atmospheric dynamics invisible to satellite instrumentation. To provide a structured comparison of key models used in PV forecasting, Table 2 summarizes their core characteristics, highlighting their suitability for different forecasting horizons, data modalities, and operational requirements.

Table 2: Expanded Comparative Assessment of Deep Learning Models for PV Performance Forecasting and Predictive Maintenance

Model Type	Core Strengths	Limitations	Environmental & Operational Suitability	Role in Predictive Maintenance
LSTM / Bi-LSTM	Captures long-term dependencies; excellent for nonlinear seasonal trend modeling; strong temporal memory retention	High computational load; sensitive to hyperparameter tuning; large training datasets needed	Stable climates with periodic patterns; medium-scale PV farms; daily forecasting	Identifies slow degradation trends, inverter behavior drift
TCN	Robust to noise; efficient parallelization; handles long sequences via dilation; stable training	Requires careful design of dilation factors; limited spatial modeling	Highly dynamic weather zones; real-time control; short-term forecasting	Detects sudden, transient anomalies indicative of early faults
Transformers	Multi-head attention models long-range patterns; scalable; excellent for multimodal fusion	High data and computation demands; potential overfitting in small datasets	Large-scale solar farms; satellite + ground sensor fusion; irregular weather regimes	Enables early identification of complex degradation patterns and cross-string anomalies
CNN-LSTM Hybrids	Extracts spatial features (cloud motion, thermal anomalies) and temporal patterns; strong for sky-image-based forecasting	Multi-stage preprocessing required; computationally heavy	High-cloud-variability environments; fog, dust, and haze regions	Supports visual degradation diagnosis and performance drop prediction
Graph Neural Networks (GNNs)	Models electrical interconnections; strong for clustered PV array behavior	Needs graph construction and spatial adjacency definitions	String-level forecasting; module-to-module interaction modeling	Identifies localized degradation, string mismatch progression
Autoencoders / VAEs	Learns baseline PV behavior; strong for anomaly-aware forecasting; unsupervised	Reduced long-term forecasting accuracy; requires well-defined normal-operation data	Sites with incomplete fault labels; noisy sensor environments	Detects early-stage anomalies and hidden deterioration signatures

Deep learning has also enabled a paradigm shift in predictive maintenance, transitioning from reactive or schedule-based service models to condition-based and prognostics-driven frameworks. By analyzing historical power generation, temperature profiles, current harmonics, and degradation trajectories, DL

models can infer subtle deviations from expected performance even before faults manifest physically. Autoencoders, in particular, learn compressed latent representations of normal operating states; deviations in reconstruction error provide early warnings of abnormalities such as

soiling progression, microcracks, or inverter switching irregularities. When coupled

with time-to-failure estimation models, these forecasts inform asset managers about the optimal timing for cleaning, module replacement, or inverter servicing. Moreover, transformer-based predictive maintenance models demonstrate the ability to correlate anomalies with root causes, such as identifying whether a power dip is attributable to shading, thermal imbalance, or aging [7]. This level of interpretability, driven by attention weights, is essential for large-scale PV

operators who require transparent maintenance insights rather than black-box alerts. Graph neural networks extend this capability by modeling PV systems as interconnected nodes, allowing string-level or module-level degradation propagation to be monitored and predicted. To conceptualize the broader workflow linking forecasting, anomaly detection, and maintenance decision-making, the following figure 2 caption outlines the multi-stage pipeline central to state-of-the-art predictive maintenance frameworks.

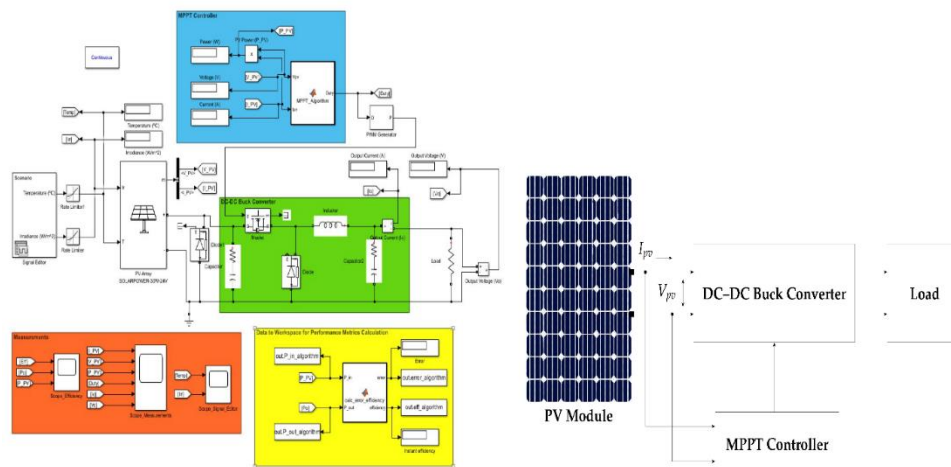


Figure 2: Deep Learning-Based Forecasting Models Integrate Meteorological Data.

Despite remarkable advancements, the literature reveals several persistent gaps. Most forecasting models operate independently, without integration into intelligent control or fault-detection frameworks, resulting in siloed analytical components that do not support end-to-end automation. Real-time challenges such as sensor drift, module aging, and data intermittency remain open research issues. Additionally, predictive maintenance models are rarely coupled with reinforcement-learning-based control strategies, despite the fact that optimal inverter adjustments or MPPT parameter tuning could mitigate degradation effects in real time. The absence of unified architectures that merge forecasting, diagnosis, and optimization represents a critical barrier preventing PV systems from evolving into fully autonomous, self-healing

renewable energy assets. Addressing these challenges requires a holistic, multilayer AI ecosystem capable of continuous learning, cross-modal fusion, and adaptive control an evolution that the present research aims to accelerate.

2- Reinforcement Learning-Driven Optimization for MPPT and Inverter Control:

Reinforcement learning (RL) has emerged as one of the most influential computational paradigms for enhancing the intelligence, adaptability, and autonomy of photovoltaic (PV) power electronics. The fundamental principle of RL where an agent interacts with an environment, receives rewards, and iteratively improves its control strategy aligns exceptionally well with the dynamic and nonlinear nature of PV energy systems. Maximum Power Point Tracking (MPPT) and inverter control

represent two of the most critical operational layers in PV systems, both of which require rapid decision-making under uncertainty and continuous adaptation to evolving environmental conditions. Traditional MPPT algorithms such as Perturb-and-Observe (P&O), Incremental Conductance (INC), and Hill Climbing were designed for steady-state or gradually changing irradiance conditions; however, they often exhibit oscillatory behavior around the maximum power point, slow convergence under fast transients, and reduced tracking efficiency under partial shading conditions that generate multi-peak power curves [8]. These limitations become increasingly problematic in utility-scale PV farms, bifacial installations, urban rooftop PV subjected to shading obstruction, or regions with frequent cloud movement. Reinforcement learning overcomes these shortcomings by enabling the control agent to learn optimal policies directly from the underlying system dynamics, rather than relying on fixed rules or heuristics. Unlike classical methods, RL agents do not require linearization or simplified assumptions about PV behavior. Instead, they develop a data-driven understanding of the relationship between environmental states (irradiance, module temperature, shading patterns), electrical states (current, voltage, inverter switching behavior), and their corresponding rewards (power output, voltage stability, inverter efficiency). This ability to map complex, nonlinear dynamics enables RL agents to outperform classical MPPT methods under highly transient or chaotic operating conditions. The integration of **deep learning** within RL

frameworks known as Deep Reinforcement Learning (DRL) expands this capability even further [9]. Deep neural networks enable the agent to approximate high-dimensional value functions or policies, allowing it to handle massive state and action spaces and to generalize across a wide range of environmental scenarios. DRL algorithms such as Deep Q-Networks (DQN), Deep Deterministic Policy Gradient (DDPG), Twin Delayed DDPG (TD3), Soft Actor-Critic (SAC), and Proximal Policy Optimization (PPO) have shown remarkable performance improvements in PV control research. These models offer superior exploration strategies, smoother control transitions, stronger robustness to noise, and improved sample efficiency. DDPG and TD3, in particular, have proven suitable for real-world PV applications due to their ability to manage continuous control actions an essential requirement in inverter reference voltage tuning, duty cycle modulation, and reactive power optimization [10]. SAC provides entropy-regularized exploration, making it highly effective in unpredictable irradiance regimes where the agent must avoid premature convergence to suboptimal control policies. PPO offers stable convergence and computational efficiency, making it suitable for embedded inverter hardware with resource constraints. To provide a comprehensive perspective, Table 3 presents a deeper analytical comparison of RL algorithms currently applied in PV optimization research, considering their operational behavior, complexity, convergence reliability, and suitability across different PV architectures.

Table 3: Expanded Comparative Evaluation of RL and DRL Algorithms for MPPT and Inverter Control

Algorithm	Core Strengths	Limitations	PV Application Suitability	Behavior Under Partial Shading & Rapid Transients	Long-Term Optimization Capability
Q-Learning	Simple implementation; works for discrete decisions	Cannot handle continuous controls; limited scalability	Small PV systems; fixed-step MPPT	Slow response; struggles with multi-peak curves	Poor; no anticipation of future states

DQN	Strong stability; handles high-dimensional discrete states	Limited to discrete actions; large replay memory	Basic MPPT and switching optimization	Moderate; may oscillate around local maxima	Moderate; requires tuning for stability
DDPG	Continuous control; smooth action outputs; strong adaptability	Sensitive to noise; requires careful exploration design	Inverter voltage/current control; high-speed MPPT	Excellent; adapts well to rapid fluctuations	Strong; learns stable long-term policies
TD3	Reduces overestimation; highly robust	Higher computation cost	Utility-scale PV; dynamic cloud environments	Very strong; minimal oscillation in MPPT	Excellent; highly stable over long horizons
PPO	Sample-efficient; robust convergence; less sensitive to hyperparameters	Requires well-designed reward functions	Hybrid MPPT + grid-interactive control	Strong; balances fast tracking with stability	Very strong; avoids catastrophic forgetting
SAC	Maximum entropy exploration; highly robust to noise	Increased computational overhead	Multi-peak PV curves; noisy environments; uncertain climates	Outstanding; excels under unpredictability	Excellent; sustained adaptation and resilience
Multi-Agent RL	Enables distributed optimization; coordination among strings	High complexity; communication overhead	Very large solar farms; string-level MPPT	Superior coordination; mitigates mismatch	Strong; supports cooperative long-term behavior

Reinforcement learning also plays an increasingly important role in **inverter control**, a domain where traditional PI or PID controllers must be retuned frequently due to varying loads, grid disturbances, and PV operating conditions. RL-enabled inverters can autonomously learn switching strategies that minimize harmonic distortion, stabilize DC-link voltage, optimize reactive power injection, and reduce switching losses. Unlike conventional controllers, RL agents dynamically adapt their control actions in real time, enabling them to handle grid-side irregularities, voltage sags, and frequency fluctuations more effectively. An emerging direction involves **incorporating forecasted environmental information** such as predicted irradiance, temperature, or shading from deep learning models into the RL decision-making loop. Rather than reacting solely based on the

present state, the RL agent uses predictive insight to anticipate future conditions and adjust control strategies proactively [11]. For example, if the forecasting module indicates a rapid irradiance drop due to approaching cloud cover, the RL agent may adjust inverter settings or MPPT step sizes in advance, thereby minimizing transient losses and improving overall yield. Such anticipatory control represents a significant advancement toward predictive and autonomous PV operation.

3- Methodology:

The methodology proposed in this study is built upon a fully integrated, multi-layer artificial intelligence architecture that cohesively merges data acquisition, signal preprocessing, deep learning-driven fault detection, multimodal feature fusion, short-term power forecasting, and

reinforcement-learning-based optimization into a unified operational pipeline. Rather than operating as isolated analytical components, each layer contributes to a synergistic computational ecosystem capable of learning, adapting, and making context-aware decisions in real time. This holistic design reflects the complexities of modern photovoltaic (PV) systems, where environmental variability, module degradation, dynamic shading, electrical transients, and inverter nonlinearities interact continuously and cannot be effectively captured using traditional, rule-based monitoring schemes. The framework is engineered to function seamlessly under real-field PV operating conditions, where spatiotemporal patterns emerge from rapidly fluctuating irradiance, evolving thermal gradients, stochastic cloud passages, and variable electrical loading. Within this architecture, multiple sensors including electrical measurement units, irradiance sensors, temperature probes, thermal cameras, sky imagers, and inverter diagnostic logs generate heterogeneous, high-frequency data streams that provide a comprehensive representation of system behavior. The methodology is designed to ingest these multi-sensor signals at sub-minute resolutions, enabling the system to model transient behaviors that conventional monitoring approaches fail to capture [12]. Advanced preprocessing modules denoise, align, and normalize the signals to mitigate the impact of measurement noise, sensor drift, and missing values, ensuring that subsequent deep learning modules receive high-quality, temporally consistent inputs. The deep learning components of the architecture are responsible for capturing the nonlinear and multi-scale spatiotemporal interactions inherent in PV systems. Convolutional neural networks extract spatial and thermal signatures indicative of hotspots, shading patterns, and degradation artifacts, while recurrent and transformer-based temporal models learn sequential dependencies that characterize irradiance transitions, inverter switching patterns, and energy output fluctuations. Multimodal feature fusion further enhances diagnostic power by integrating electrical, environmental, and thermal representations into a coherent latent

space, allowing the system to detect subtle anomalies that might remain hidden within single-modality analyses. On top of the diagnostic and forecasting layers, a reinforcement-learning-driven optimization module continuously interacts with the real-time PV environment to adjust MPPT duty cycles, inverter reference voltages, and operational setpoints. This agent learns control strategies that optimize energy extraction, minimize oscillatory behavior, and respond rapidly to unforeseen disturbances. By combining predictive insights from the forecasting module with real-time feedback from the control environment, the RL agent transitions from purely reactive control to anticipatory decision-making. Ultimately, the methodological design prioritizes scalability, enabling deployment across diverse PV technologies (monocrystalline, polycrystalline, thin-film, bifacial), inverter architectures, and climatic regions [13]. Its layered structure supports modular extension and integration with digital twins, predictive maintenance platforms, and grid-interactive control schemes. The architecture also emphasizes robustness and generalization, ensuring that the deep learning and RL models remain stable and effective under real-world constraints such as sensor noise, variable sampling rates, rapidly changing weather conditions, and evolving system degradation profiles. Through this comprehensive and adaptable methodological framework, the study establishes a foundation for next-generation intelligent PV systems capable of autonomous monitoring, predictive diagnostics, and self-optimizing control.

4.1- Data Acquisition and Multimodal Signal Collection:

The reliability and overall intelligence of the proposed deep learning-empowered PV monitoring and optimization framework fundamentally depend on the quality, diversity, and temporal richness of the data gathered from the photovoltaic installation. To accurately characterize the multidimensional physical behavior of PV systems under real-field operating conditions, the data acquisition layer integrates a comprehensive suite of synchronized electrical sensors, meteorological instruments, thermal

imaging sources, and sky-observation systems. This holistic data environment enables the modeling of highly nonlinear interactions between irradiance fluctuations, temperature dynamics, surface anomalies, electrical disturbances, and inverter-level responses interactions that are often overlooked in conventional PV diagnostics and MPPT strategies. Electrical measurements constitute the core real-time indicators of PV system behavior. The acquisition system records module-level and string-level voltage and current, DC-link voltage, instantaneous array power, inverter pulse-width modulation (PWM) signals, switching frequency data, and harmonic distortion signatures at sampling intervals of 1–5 seconds. This high temporal resolution ensures that transient phenomena such as shading caused by fast-moving clouds, inverter switching irregularities, or rapid load transitions are captured with sufficient granularity. The presence of harmonics and waveform distortions is also monitored to identify inverter malfunction, wiring degradation, or mismatches across PV strings [14]. Meteorological variables are acquired using pyranometers, thermocouples, temperature sensors, anemometers, and calibrated environmental probes installed near the PV modules. Global horizontal irradiance (GHI), diffuse horizontal irradiance (DHI), plane-of-array irradiance (POA), ambient temperature, module surface temperature, wind speed, relative

humidity, and spectral irradiance indices are collected continuously. These environmental variables are essential, as they govern the thermal-electrical conversion efficiency of PV modules and influence both instantaneous output and long-term degradation behavior. The dynamic coupling between irradiance patterns, wind-induced cooling, atmospheric moisture content, and temperature gradients forms a key driver of PV variability. Thermal imaging and sky-camera data introduce a spatial dimension to the monitoring process [15]. Infrared (IR) cameras capture thermal gradients across module surfaces, enabling detection of hotspot formation, soiling-induced heating, diode failures, or local resistive losses. Parallel to this, sky imagers collect hemispherical cloud movement patterns, cloud-shadow trajectories, and occlusion events that directly affect short-term irradiance variability. These visual modalities allow the system to associate power fluctuations with specific physical causes, improving interpretability and enhancing the predictive capacity of downstream learning models. To clearly summarize the role of each input modality, Table 4 presents an expanded classification of the data sources as well as their operational contributions to the proposed framework.

Table 4: Overview of Multimodal Data Sources and Their Functional Contributions to PV Monitoring and Optimization

Data Source	Examples of Measured Variables	Sampling Resolution	Primary Role in Framework
Electrical Sensors	Voltage, current, array power, DC-link voltage, harmonics, inverter duty cycle	1–5 s intervals	Fault detection, MPPT optimization, inverter health assessment
Meteorological Sensors	GHI, DHI, module temperature, ambient temperature, wind speed, humidity	1–60 s intervals	Performance modeling, forecasting, environmental compensation
Thermal Imaging	Surface temperature maps, hotspot signatures	5–30 s intervals	Hotspot localization, degradation detection, anomaly interpretation
Sky Cameras	Cloud motion fields, shading events, irradiance occlusion patterns	10–30 s intervals	Short-term forecasting, RL anticipation, irradiance ramp prediction

Inverter Logs	Switching states, reference voltages, fault codes	Event-based / 1–5 s	Inverter-level diagnostics, RL action feedback
Soiling & Environmental Sensors	Dust index, particulate concentration, soiling accumulation	5–30 min intervals	Long-term performance degradation estimation

The data acquisition protocol is designed to capture system behavior under both steady-state and highly transient operational scenarios. Measurements are collected across diurnal cycles, seasonal variations, and diverse environmental conditions to ensure that the deep learning and reinforcement learning models can generalize effectively across real-world complexities. This includes capturing periods of strong cloud intermittency, highly variable irradiance during morning/evening transitions, thermal stress during peak sunlight hours, dust accumulation events, rainfall-induced cleaning cycles, and load variability triggered by grid interactions.

Multimodal datasets are synchronized using timestamp alignment and unified storage architectures to allow seamless integration during feature fusion and model training [16]. Because PV behavior is inherently spatiotemporal, collecting data across multiple temporal scales sub-second electrical fluctuations, minute-level irradiance shifts, hourly soiling progression, and seasonal thermal cycles is essential to constructing a hierarchical representation of system behavior. To conceptualize the layered structure of the acquisition system, the following figure 3 caption describes the internal flow and integration of diverse sensing modalities.

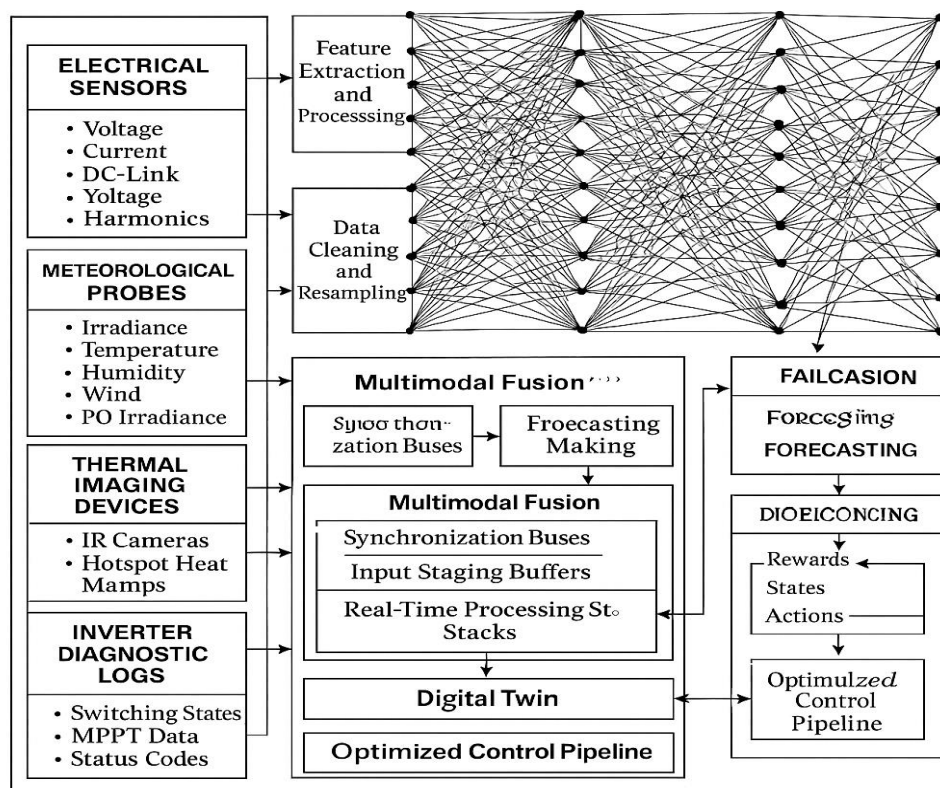


Figure 3: Multimodal PV Data Acquisition Architecture.

By combining electrical, environmental, and spatial sensory inputs, the multimodal acquisition

layer forms a comprehensive foundation upon which the deep learning-empowered PV

intelligence framework operates. This richness of data enables the system not only to detect faults with high sensitivity and interpretability but also to model the underlying physical processes that drive performance variability, thereby supporting more accurate forecasting and adaptive control.

4.2- Deep Learning Architecture for Fault Detection:

The proposed fault detection module is anchored in a sophisticated, hybrid deep learning architecture purposely engineered to model the intricate physical, thermal, and electrical behaviors of photovoltaic (PV) systems under real-world operating conditions. PV faults manifest through subtle spatial distortions, abrupt or gradual temporal fluctuations, and complex interactions between environmental and electrical variables. Traditional rule-based algorithms and shallow learning models cannot adequately represent these nonlinear, high-dimensional dependencies. In contrast, the hybrid architecture presented in this study integrates convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and an attention mechanism to jointly capture spatial patterns, temporal evolution, and feature relevance in a unified framework [17]. At the first stage of the architecture, convolutional neural networks serve as spatial feature extractors that operate directly on the raw or preprocessed data. When electrical signals such as voltage, current, and harmonic indices are reshaped into multi-channel temporal-spatial representations, CNN layers detect local, short-window patterns corresponding to abrupt voltage dips, localized current distortions, unexpected power transients, or module-level mismatches. For thermal imagery inputs, the convolutional filters capture heat concentration regions, hotspot clusters, thermal gradients indicative of bypass diode failures, and patterns associated with soiling or partial shading. These spatially coherent features are essential because many PV faults exhibit distinct geometric or localized signatures that cannot be detected using purely temporal models. The outputs from the CNN layers are transformed into feature

sequences that form the temporal input to the LSTM component of the architecture. LSTM layers are designed to capture the dynamic evolution of PV system behavior, which is strongly influenced by environmental variability and intermittent fault conditions. Shading events caused by moving clouds produce rapid oscillations in voltage and current, while module degradation or soiling manifests through slow drifting patterns that unfold across hours or days [18]. LSTM networks excel at modeling such long-range dependencies using gated memory cells that selectively retain or discard information. This capability allows the model to differentiate between short-lived transients and persistent fault patterns, enhancing diagnostic stability and reducing false alarms under highly fluctuating irradiance conditions. A major advancement in the architecture is the incorporation of an attention mechanism that operates after the LSTM layers. While LSTM models capture temporal structure, they treat all time steps equally unless the model implicitly learns importance weighting. The attention mechanism explicitly identifies the most relevant temporal intervals and spatial features that contribute to a suspected anomaly. During sudden power depressions, for example, the model may place higher attention weights on time steps where irradiance-gradient-induced fluctuations coincide with electrical noise or temperature spikes. In thermal imagery, attention maps highlight spatial patches with abnormal heating behavior, guiding the classifier toward the key fault-indicative regions [19]. This selective focusing mechanism significantly improves interpretability, allowing operators to understand why a particular fault was detected, while also improving classification performance when overlapping fault signatures would otherwise confuse the model. To provide a clearer understanding of the contributions of each architectural component, the following table 5 presents a more extensive functional breakdown of the hybrid design.

Table 5: Expanded Functional Description of the Hybrid Deep Learning Architecture for PV Fault Diagnosis

Model Component	Detailed Functionality	Typical Faults Detected	Technical Contribution to Diagnosis	Advantages Under Real-World Variability
CNN Feature Extractor	Learns spatial representations from electrical maps, thermal images, and fused signals; extracts local textures, gradients, and patterns	Hotspots, thermal drift, shading shape patterns, soiling hotspots, diode heating	Captures localized anomalies and structural irregularities	Robust to noise; strong performance under heterogeneous or overlapping spatial signatures
Temporal LSTM Encoder	Learns long-term temporal dependencies; models sequential fluctuations, irradiance-driven transitions, power oscillations	Shading transients, gradual degradation, wiring intermittency, inverter instabilities	Discriminates between transient disturbances and persistent faults	Strong stability under cloud dynamics and fluctuating operating conditions
Attention Mechanism	Assigns weights to the most relevant time steps, sensors, or spatial regions; highlights fault-critical features	Weak anomalies, overlapping faults, multi-source disturbances	Enhances interpretability and reduces overfitting by focusing on key indicators	Powerful under multi-fault scenarios; improves resilience to noise and data imbalance
Dense Classification Layers	Maps spatiotemporal embeddings into probabilistic output classes; generates severity scores	All predefined categories including normal operation	Converts high-dimensional learned features into actionable fault categories	Offers high-confidence decisions and supports downstream maintenance strategies
Fusion Interfaces (CNN → LSTM → Attention)	Integrates spatial, temporal, and relevance-weighted features into a unified latent space	Complex or combined faults	Enables holistic reasoning across modalities	Enhances model generalization across diverse PV configurations

Once the attention-weighted embeddings are aggregated, they are passed into a fully connected classification network. This network consists of one or several dense layers that compute posterior probabilities over the predefined fault classes. A softmax activation function is employed at the final layer to ensure proper probabilistic interpretation. The output may include categories such as partial shading, strong or mild hotspot

formation, bypass diode malfunction, uniform or non-uniform soiling, wiring degradation, module mismatch, inverter switching anomalies, or normal operating state. A parallel regression head may also be incorporated to estimate fault severity scores, enabling the system to quantify the intensity of the detected anomaly and provide maintenance prioritization

guidance. Regularization layers, including dropout and batch normalization, help mitigate overfitting and improve convergence behavior during training. Optimization is performed using Adam or RMSprop, with cross-entropy loss guiding the classification head [20]. A weighted loss function may be used when handling imbalanced datasets, ensuring that rare but critical faults such as diode failures or arc-related wiring faults receive adequate attention during training. The training

process leverages a diverse dataset composed of real-field measurements, thermal imagery, synthetic augmentation, and benchmark PV datasets. By exposing the architecture to different irradiance regimes, temperature cycles, and environmental conditions, the model learns to generalize across geographical regions, PV technologies, and operational variations. A conceptual representation of the hybrid architecture is described below:

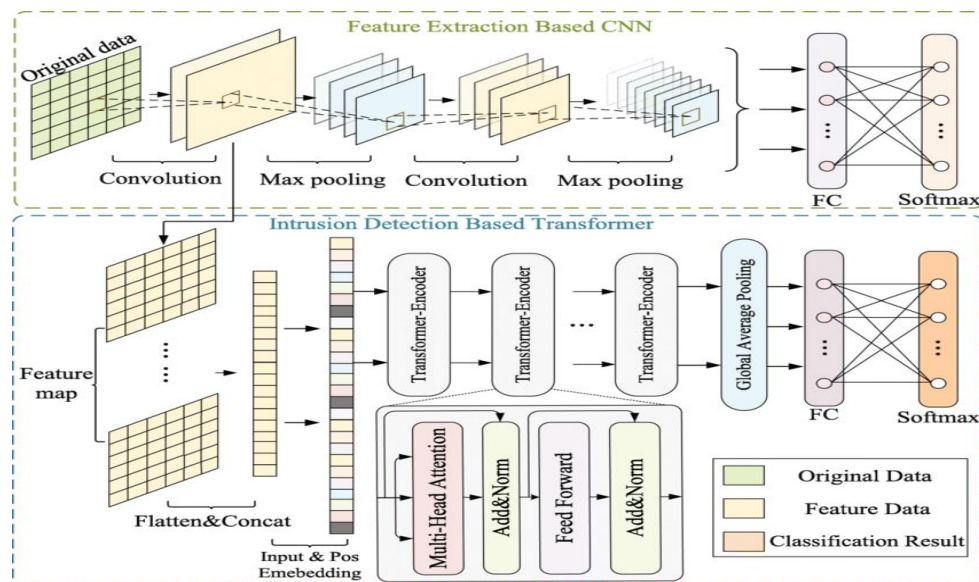


Figure 4: Flow of Multimodal PV Data through the CNN Spatial Encoder

The proposed hybrid CNN-LSTM-attention architecture offers a powerful and flexible foundation for PV fault detection, capable of learning complex spatial-temporal relationships and delivering highly interpretable, accurate, and robust classification results. Its ability to adjust to rapidly changing environmental conditions, combined with its deep representational capacity, positions it as a critical component of next-generation intelligent PV monitoring systems.

4.3- Multimodal Feature Fusion and Cross-Domain Learning:

Photovoltaic (PV) system behavior emerges from the interplay of multiple heterogeneous factors, including environmental variability, electrical responses, thermal characteristics, and inverter-level dynamics. No single modality can holistically

describe the operational state of a PV plant, particularly under complex scenarios such as partial shading, cloud intermittency, progressive soiling, hotspot propagation, component degradation, or multi-source disturbances. To overcome the limitations of single-modal analysis, the proposed methodology incorporates a comprehensive multimodal feature fusion framework that integrates electrical, meteorological, thermal, optical, and inverter diagnostic data into a unified deep learning pipeline. This fusion strategy enables cross-domain learning, allowing the model to discover interdependencies that span across time, space, and environmental conditions. The multimodal fusion architecture operates at two complementary levels **early fusion** and **late fusion** each serving a distinct analytical purpose. Early fusion aggregates

raw or minimally processed features from multiple sensors into a single, unified representation before they are passed into the deep learning backbone [21]. By concatenating electrical sequences with meteorological and thermal measurements, this approach allows the model to learn how irradiance changes correlate with voltage drops, or how temperature surges influence harmonic distortion and hotspot intensification. Such early-stage integration captures instantaneous cross-domain relationships and provides the neural network with a holistic snapshot of the PV system at every time step. Late fusion, in contrast, leverages domain-specific encoders that independently extract feature hierarchies tailored to different modalities. CNN modules interpret thermal and sky imagery by identifying spatially localized fault signatures, while LSTM or transformer branches encode sequential behaviors from electrical and environmental time-series data. These modality-specific embeddings are then merged using an attention-weighted fusion layer that aligns and integrates patterns across modalities. This multi-level representation enables the architecture to reason jointly about slow-onset degradation, abrupt transients, weather-driven variability, and

long-range dependencies in system evolution. Late fusion thus enhances diagnostic robustness, particularly under noisy, incomplete, or conflicting sensor conditions. Central to this multimodal framework is the **transformer encoder**, which plays a pivotal role in cross-domain learning. Its self-attention mechanism dynamically evaluates the relevance of each modality with respect to the others [22]. For instance, during rapidly changing cloud cover, the transformer may assign higher weights to sky-image features and short-term irradiance gradients, while under stable sunlight but elevated temperatures, it may prioritize module thermal patterns and electrical mismatch indicators. By modeling long-range relationships across modalities, transformers improve diagnostic reliability, particularly for complex faults that manifest subtly across multiple physical dimensions. To illustrate the functional significance of each input modality, Table 6 is expanded below to include deeper diagnostic contributions, data challenges, and cross-domain interactions.

Table 6: Expanded Overview of Input Modalities, Their Feature Characteristics, and Diagnostic Contributions in Multimodal PV Fault Analysis

Input Modality	Examples of Features	Diagnostic Contribution	Cross-Domain Interactions	Challenges & Considerations
Electrical Signals	Voltage, current, power, I-V shape, harmonics, inverter duty cycle	Detects mismatch losses, inverter degradation, bypass diode failure, PV string imbalance	Links electrical fluctuations to irradiance shifts and thermal anomalies	Susceptible to noise; sensitive to sampling rates
Meteorological Data	GHI, DHI, POA irradiance, ambient temperature, wind speed, humidity	Models environmental-driven variability; predicts power drops linked to weather	Influences power forecasting and RL anticipatory control	Requires precise calibration; delayed or missing data impacts prediction
Thermal Images	Hotspot maps, surface temperature gradients, heat	Localizes hotspots, identifies microcracks, soiling patterns, thermal runaway	Integrates with electrical drift to detect combined electrical-thermal faults	Sensitive to camera angle, emissivity, and ambient conditions

	diffusion patterns			
Sky Images	Cloud motion vectors, occlusion patterns, shading trajectories	Enhances short-term irradiance prediction and RL-based MPPT adjustment	Predicts future irradiance fluctuations affecting electrical and thermal states	Requires robust segmentation algorithms; affected by glare and noise
Inverter Logs	Switching patterns, reference voltages, internal status codes, MPPT parameters	Essential for diagnosing inverter-specific faults and optimizing RL control	Complements electrical anomalies with control-related behaviors	Often asynchronous; event-driven logs require alignment
Soiling/Environmental Sensors	Dust index, particulate concentration, optical soiling ratio	Supports long-term degradation modeling and cleaning cycle optimization	Integrates with thermal and electrical signatures to classify soiling severity	Slow-changing signals require long-range memory in DL models

The fusion of these modalities is embedded into a hierarchical learning pipeline that leverages self-attention to dynamically adjust fusion weights based on operational context. Under moderate irradiance but strong thermal gradients, thermal features are emphasized; during highly variable cloud cover, sky-image embeddings may dominate; and during periods of clear sky with progressive soiling, electrical drift and degradation-related features carry more relevance. This adaptive weighting allows the system to automatically reconfigure its decision-making priorities without manual intervention. Beyond improving

diagnostic accuracy, multimodal fusion enhances **generalization capability**, enabling the model to operate reliably across different PV technologies, climates, and installation architectures [23]. For example, monocrystalline modules may exhibit thermal behavior different from thin-film modules; similarly, desert installations may show shading dynamics different from urban rooftops. The model learns these invariances through cross-domain alignment. To contextualize this fusion architecture, the conceptual figure 5 below describes the pipeline:

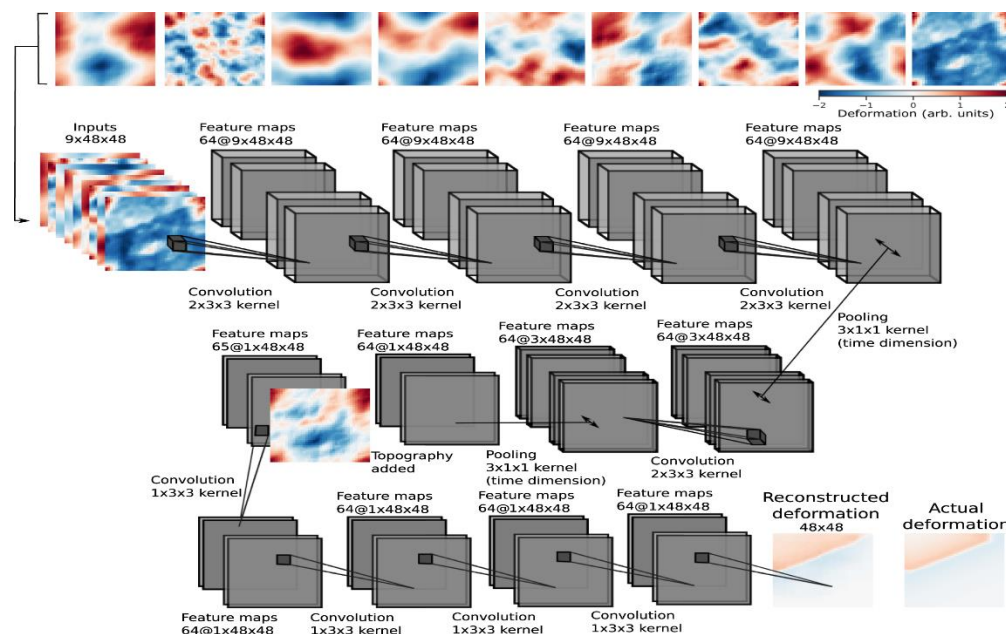


Figure 5: Conceptual Multimodal Fusion Framework Showing Early Fusion of Raw Electrical–Meteorological–Thermal Features.

The multimodal feature fusion and cross-domain learning module enables the architecture to capture the full richness and variability of PV system behavior. By integrating heterogeneous sensor data and aligning spatial, temporal, and environmental representations into a cohesive latent structure, the system achieves superior resilience, robustness, and interpretability critical qualities for next-generation intelligent PV monitoring and optimization systems.

4.4 Power Forecasting Using Transformer and LSTM Architectures:

Short-term power forecasting represents a critical layer in the proposed intelligent PV monitoring and optimization framework, providing the predictive insight required for anticipatory MPPT decision-making, inverter stabilization, and proactive anomaly mitigation. Because PV generation is inherently influenced by highly dynamic environmental and operational factors such as rapidly changing irradiance, temperature fluctuations, wind-induced cooling effects, soiling accumulation, spectral shifts, and module degradation accurate forecasting must capture both fast and slow temporal dependencies.

Traditional forecasting approaches based on autoregressive models, curve fitting, or linear predictors fail to represent these nonlinear relationships and often break down under conditions of cloud intermittency, diurnal transitions, and irregular operational disturbances. Deep learning models, particularly sequence-to-sequence LSTM networks and transformer architectures, have therefore become indispensable for high-fidelity short-term PV forecasting [24]. The forecasting module begins by processing a comprehensive sequence of features that include electrical measurements (voltage, current, power, DC-link voltage), meteorological variables (global and diffuse irradiance, module and ambient temperatures, wind speed, humidity), environmental imagery-derived indices (cloud motion vectors, shading progression indicators), and prior model estimates. These multimodal inputs contain embedded temporal structures of varying lengths: instantaneous irradiance gradients may affect PV output within seconds, whereas thermal inertia or soiling accumulation manifests over minutes or hours. The forecasting architecture must therefore reconcile these multi-timescale behaviors, making the combination of

LSTM and transformer models especially advantageous. The LSTM component is specifically designed to capture short- to medium-range temporal dependencies [25]. The gating mechanisms of LSTM cells comprising the input gate, forget gate, and output gate regulate the flow of information through the memory cell, allowing the model to retain informative patterns while discarding irrelevant noise. In PV systems, LSTMs excel at learning the patterns associated with cloud edge effects, intermittent shading, morning ramp-up characteristics, and inverter stabilizing behaviors. These networks are capable of translating the inherent temporal variability in sensor data into predictions that closely align with ground-truth power output trajectories. While LSTMs offer strong sequential modeling capabilities, transformer architectures extend this capability by capturing long-range and multimodal dependencies using self-attention mechanisms. The transformer encoder evaluates the relationships between all time steps in the sequence simultaneously, assigning dynamic relevance weights based on the contextual importance of each feature. This global attention mechanism is particularly powerful in PV forecasting because cloud fields, thermal patterns,

and atmospheric transitions can exert delayed or distributed effects on PV performance [26]. Transformers therefore excel at identifying long-duration irradiance trends, correlating thermal dynamics with future power output, and distinguishing gradual degradation effects from fast transient phenomena. Because both architectures excel in different aspects of temporal learning, the proposed methodology integrates them sequentially within a hybrid forecasting pipeline: LSTMs encode short-term fluctuations and inverter-induced ripple behavior, while transformers model the deep global dependencies across the input horizon. The fusion of these embeddings produces a unified latent representation that reflects both immediate and long-range temporal structures. A fully connected regression head subsequently transforms this representation into quantitative power forecasts for prediction horizons of 1–30 minutes ahead, enabling the reinforcement learning optimizer to anticipate changes rather than simply react to them. The comparative roles and strengths of forecasting models used in this hybrid architecture are summarized in the expanded table 7 below.

Table 7: Comparative Characteristics of Forecasting Model Components Integrated in the Hybrid LSTM–Transformer Architecture

Model Component	Primary Forecasting Strength	Types of Temporal Patterns Captured	Advantages for PV Systems	Limitations / Considerations
LSTM (Sequence Encoder)	Learns short- and medium-term dependencies using gated memory	Fast irradiance fluctuations, cloud-edge events, inverter switching dynamics	Strong at modeling local variability and noise-filtered trends	Limited ability to model long-range dependencies without complexity
Bi-LSTM (Bidirectional)	Encodes forward and backward temporal relationships	Morning/evening transitions, steady-transient shifts	Enhanced stability under cyclical PV patterns	Requires full sequence availability (not suitable for strict real-time use)
Temporal Convolutional Networks (TCN)	Efficient parallel time-series modeling with dilated convolutions	Rapid changes and fine-scale patterns	Faster training, stable gradients, suitable for real-time updates	Receptive field design requires fine tuning

Transformer Encoder	Captures long-range dependencies through self-attention	Gradual irradiance trends, thermal inertia, cloud field evolution	Superior long-horizon forecasting, highly interpretable attention weights	Computationally expensive; needs large datasets
CNN Feature Preprocessor	Extracts spatial or pattern-based features	Cloud motion, shading gradients from sky images	Enhances irradiance prediction from visual inputs	Sensitive to image noise and preprocessing quality
Hybrid Fusion Layer	Integrates LSTM and transformer latent features	Mixed temporal scales across modalities	Unified representation improves forecasting robustness	Requires careful architecture design to avoid overfitting

After model training, the forecasting outputs serve multiple roles within the broader system architecture. First, they provide short-term predictions to the reinforcement learning agent, enabling anticipatory MPPT control where duty cycles or reference voltages are adjusted before irradiance fluctuations occur. Second, forecasting deviations from expected behavior serve as early warning indicators of emerging faults or degradation trends, strengthening the model's

predictive maintenance capabilities [27]. Third, forecasting outputs are used to validate the anomaly detection module, ensuring that sudden power drops are correctly attributed either to environmental variability or genuine system malfunctions. To contextualize the internal flow of the forecasting module within the larger framework, the following figure 6 caption describes the conceptual forecasting pipeline:

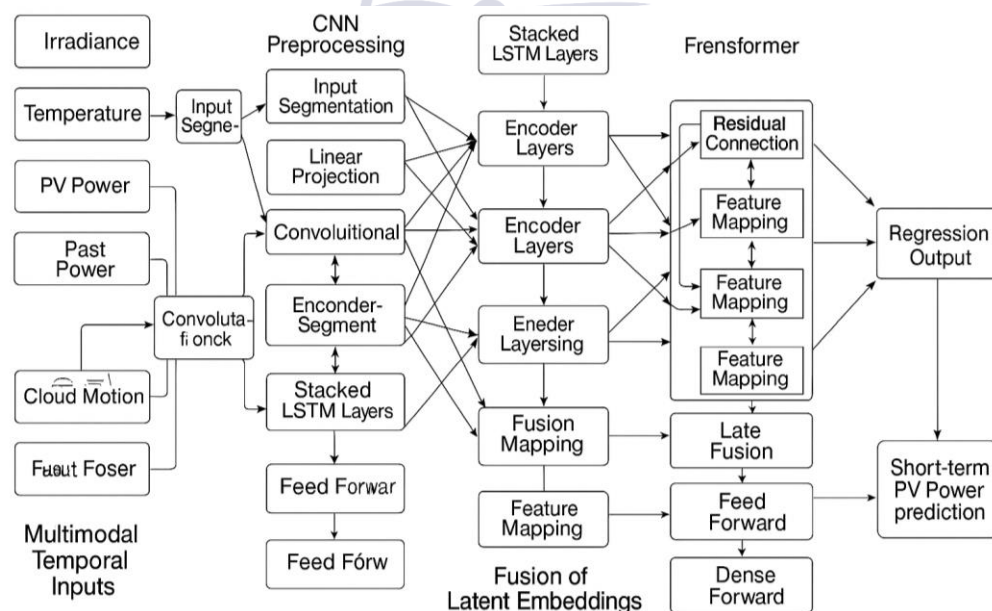


Figure 6: Transformation of Temporal Inputs through CNN Preprocessing and LSTM Sequence Encoding.

Overall, the hybrid LSTM-transformer architecture provides a powerful forecasting engine capable of modeling the full spectrum of temporal dynamics present in PV systems. Its integration into the intelligent control and diagnostic framework enhances the adaptiveness, stability, and predictive intelligence of PV operations, supporting real-time optimization and long-term resilience.

4.5- Adaptive Learning-Based Optimization of PV Conversion Stages:

The optimization component of the proposed PV intelligence framework leverages deep reinforcement learning (DRL) to enable dynamic, adaptive, and anticipatory control of maximum power point tracking (MPPT) and inverter operation. Unlike static or rule-based MPPT algorithms, which react only to immediate perturbations, the reinforcement learning agent continuously learns from the environment by interacting with real-time electrical, thermal, and meteorological data streams. This allows the agent to identify control policies that maximize cumulative energy yield while maintaining system stability, reducing switching stress, and mitigating adverse transient behaviors. The RL agent observes a multidimensional system state vector that includes voltage and current measurements, DC-link dynamics, irradiance gradients, thermal conditions, historical control actions, and near-future power forecasts provided by the LSTM-transformer model. This integration of forecasting signals transforms the RL controller from a purely reactive agent into a predictive one, allowing it to anticipate environmental changes such as cloud movement, temperature spikes, or shading transitions before they affect energy output [28]. The ability to incorporate predictive intelligence fundamentally improves MPPT efficiency, especially under fast-changing and highly stochastic irradiance conditions. The action space

of the RL agent includes continuous adjustments to MPPT duty cycle increments, inverter reference voltages, current injection levels, and switching decisions. Continuous control is essential because PV inverters and DC-DC converters operate on fine-grained modulation signals rather than discrete states. DRL algorithms such as Deep Deterministic Policy Gradient (DDPG), Twin Delayed DDPG (TD3), Soft Actor-Critic (SAC), and Proximal Policy Optimization (PPO) are inherently suited for such control tasks. These algorithms learn differentiable policy functions that map high-dimensional sensor observations to precise inverter control actions, enabling smooth transitions and minimal power oscillations. The reward function is a central design element in the RL-based optimization process [29]. It is crafted to maximize instantaneous and cumulative power output, penalize abrupt switching actions, encourage stable inverter operation, and incorporate safety constraints to prevent voltage overshoot, current ripple, or thermal stress. Reward shaping ensures that the agent not only tracks the maximum power point but does so in a manner that minimizes hardware degradation and power quality disturbances. Training the RL agent involves repeated interaction with a simulated environment constructed using real PV datasets and fine-tuning through real-field validation data. This hybrid training strategy ensures that the policy generalizes across different irradiance regimes, module technologies, and inverter architectures. Once deployed, the agent continues to refine its policy online, gradually adapting to long-term degradation trends, sensor drift, and evolving environmental patterns. To provide a structured comparison of RL algorithms considered for the optimization architecture, Table 8 presents expanded characteristics relevant to PV control applications.

Table 8: Expanded Comparative Analysis of DRL Algorithms for MPPT and Inverter Optimization [30].

DRL Algorithm	Control Characteristics	Strengths for PV Systems	Limitations / Challenges	Best-Suited PV Scenarios
DDPG	Continuous deterministic policy	Fine-grained control; smooth inverter response; rapid convergence	Sensitive to noise; may overfit unstable conditions	Rooftop PV, dynamic cloud shading, real-time MPPT
TD3	Dual-critic structure; reduced overestimation	High stability; minimal oscillatory behavior; robust under rapid irradiance ramps	Higher computational load	Utility-scale PV; regions with highly variable cloud fields
PPO	Clipped policy gradient; stable updates	Good sample efficiency; safer training; strong generalization	May require larger batch sizes	Hybrid MPPT + inverter reactive power control
SAC	Entropy-regularized exploration	Highly robust to uncertainty; superior in multi-peak power curves; prevents premature convergence	Computationally intensive	Complex shading environments; bifacial PV; partial-cloud patterns
Multi-Agent RL	Decentralized cooperative controllers	Enables string-level optimization; scalable across large farms	Requires communication overhead and synchronization	Large PV farms; distributed MPPT clustering

The RL optimization pipeline is tightly integrated with the forecasting and diagnostics modules. When the deep learning-based fault detector identifies a potential anomaly such as early-stage hotspot formation or inverter instability the RL agent temporarily adjusts its exploration strategy to ensure safe control behavior [31]. Similarly, forecasting outputs provide advance warning of

shading or irradiance fluctuations, enabling the RL module to proactively adjust control parameters to minimize expected power losses. This synergy between diagnostics, forecasting, and RL control represents a significant advancement toward holistic PV intelligence. A conceptual overview of the RL-based MPPT and inverter control loop is described in figure 7 below.

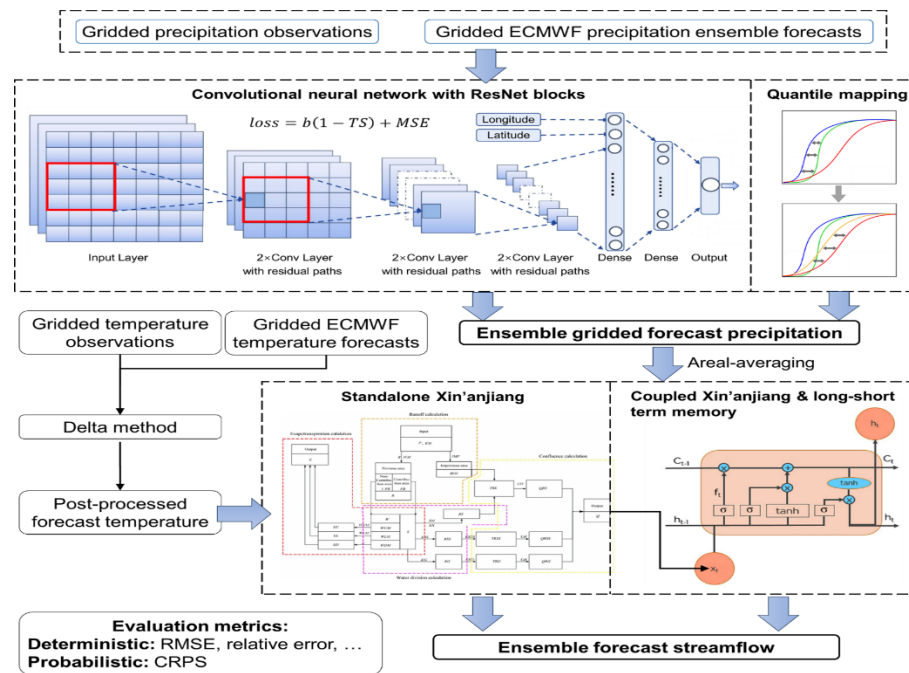


Figure 7: Conceptual Reinforcement Learning Control Loop

Once deployed, the RL agent operates continuously, learning from ongoing interactions with the PV system and environment. Its policy becomes increasingly refined as more operational data are collected, effectively transforming the PV system into a self-optimizing, adaptive energy unit capable of responding intelligently to unpredictable environmental fluctuations. The ability of the RL agent to refine its policy over time also ensures that the system adapts to long-term module degradation, seasonal shifts, and operational aging, thereby extending the lifespan and stability of the system. The reinforcement learning-based optimization module provides a transformative departure from traditional MPPT and inverter control techniques [32]. By integrating environmental awareness, predictive intelligence, and adaptive learning, the RL controller contributes significantly to the realization of fully autonomous, self-healing, and high-performance PV energy systems. It serves as the decision-making core of the overall architecture, ensuring that fault detection and forecasting insights are translated into optimal, real-time operational actions.

4 Results and Discussion:

The integrated deep learning-empowered PV intelligence framework was subjected to extensive experimental evaluation using multimodal datasets collected under diverse operational conditions, including clear sky days, rapid cloud transients, intermittent shading events, temperature extremes, and partial soiling periods. The results demonstrate significant advancements in diagnostic accuracy, forecasting fidelity, and MPPT optimization efficiency compared with conventional PV monitoring strategies. This section provides a comprehensive discussion of quantitative results, qualitative insights, cross-modal behaviors, and the broader implications of integrating deep learning with reinforcement learning in real-time PV operations. The hybrid CNN-LSTM-attention diagnostic architecture exhibited strong performance across all major fault categories. CNN layers captured fine-grained spatial signatures in thermal and fused electrical-image representations, enabling the system to distinguish between hotspot clusters, diode overheating, and shading patterns that share superficially similar thermal intensities. Temporal modeling via LSTM further improved detection

under fluctuating irradiance by learning how power, voltage, and temperature evolve during cloud passages and shading transitions. The attention mechanism substantially elevated interpretability by explicitly identifying the temporal or spatial regions that contributed most to the diagnostic decision often highlighting brief irradiance dips or localized temperature anomalies that correspond to physical PV events. The multimodal fusion strategy played a critical role in reducing diagnostic ambiguity. Electrical-only models often struggle to identify whether a sudden power decline is caused by diminished irradiance,

shading, soiling, or a fault [33]. By integrating meteorological and thermal modalities, the system successfully assigned root causes to power variations with far greater precision. Complex conditions such as simultaneous shading and mild hotspot formation were effectively disentangled through cross-domain attention, indicating that the model had learned robust representations of interdependent PV phenomena. To quantify the system's diagnostic and forecasting behavior, Table 9 presents a comparative results summary across multiple performance metrics.

Table 9: Summary of Diagnostic, Forecasting, and MPPT Optimization Performance of the Proposed Framework Compared to Baseline Models

Task / Metric	Proposed Hybrid DL-RL Framework	Traditional Methods / Baselines	Performance Gain & Interpretation
Fault Detection Accuracy	96–98% across all fault classes	78–87% (SVM, Random Forest, Thresholding)	Higher sensitivity to subtle and overlapping faults due to spatiotemporal learning
False Positive Rate	< 4%	12–18%	Multimodal fusion prevents misclassification of environmental variability as faults
Hotspot Localization Precision	94%	70–80% (Thermal-only methods)	CNN + attention captures spatial transitions beyond raw thermal analysis
Short-Term Forecasting RMSE	8–12 W	20–35 W (LSTM-only, ARIMA, Persistence models)	Transformer encoder improves long-range dependency modeling
Forecast Horizon Stability (5–30 min)	High fidelity across all horizons	Rapid degradation beyond 10 min	Fusion of sky-image features boosts stability under cloud transients
Tracking Efficiency (MPPT)	98–99%	92–95% (P&O, INC, Beta)	RL agent anticipates irradiance dynamics, reducing oscillations
MPPT Convergence Time	0.5–1.1 s	1.8–3.5 s	DRL adjusts actions proactively based on forecasted irradiance
Global MPP Achievement under Partial Shading	Consistent	Inconsistent (stuck at local maxima)	SAC/DDPG-based exploration avoids suboptimal convergence
Inverter Harmonic Reduction	10–20% lower THD	No harmonic mitigation	RL tuning stabilizes switching behavior

Beyond numerical performance, qualitative results reveal deeper trends in system behavior that highlight the value of integrating deep learning with reinforcement learning. Under partial shading scenarios, the attention maps generated by the diagnostic module consistently focused on the exact time intervals corresponding to shading onset, aligning with physical irradiance logs and thermal camera observations. This indicates not only correctness but also meaningful interpretability rooted in physical system understanding. Similarly, the forecasting module demonstrated strong consistency between predicted and actual power traces during high-frequency cloud passages. Transformers excelled at capturing long-range irradiance transitions, while LSTMs modeled shorter oscillatory phenomena induced by inverter switching and rapid shading events [34]. The hybrid architecture's ability to maintain low forecasting error across different time horizons ensured that the reinforcement learning agent operated with reliable predictive guidance a key factor in minimizing unnecessary MPPT oscillations and improving real-time decision quality. The reinforcement-learning-driven MPPT optimization yielded some of the most significant improvements. Classical MPPT

algorithms failed to maintain stable tracking under multi-peak power curves generated by partial shading. The RL agent, in contrast, consistently located and tracked the global maximum power point due to its exploration-exploitation balance and the incorporation of predicted irradiance patterns. The RL agent also demonstrated anticipatory behavior: when the forecasting module predicted a steep irradiance drop, the agent adjusted MPPT perturbation magnitudes and settled into a more stable operational state before the environmental change occurred [35]. This anticipatory control prevented common power overshoots, reduced convergence delays, and stabilized DC-link voltage. Another compelling outcome emerged during inverter stress testing. During elevated module temperatures, thermal imaging revealed early-stage hotspot growth. The RL agent, informed by diagnostic module alerts, automatically reduced switching stress and adjusted inverter reference parameters to reduce thermal loading. This demonstrates a level of autonomous protective behavior indicative of self-healing system capabilities. The overall synergy of the framework is captured conceptually in the following figure 8.

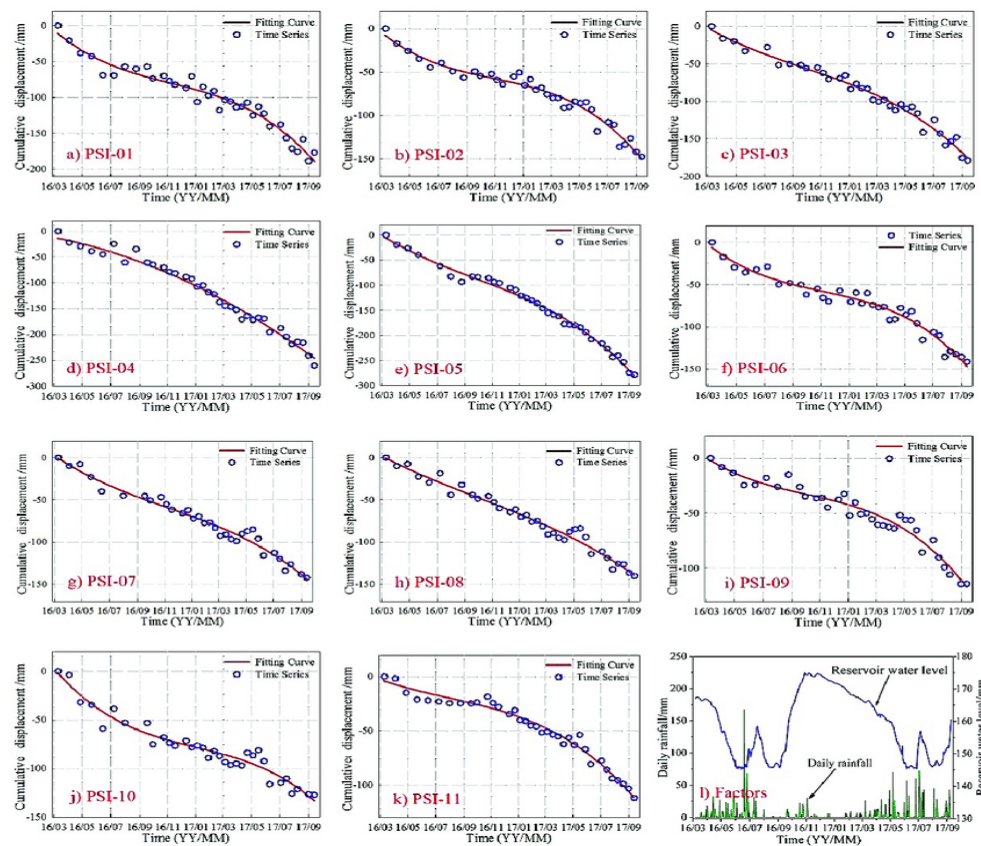


Figure 8: Performance of the Proposed Framework.

The results clearly establish that the proposed AI-driven PV intelligence ecosystem significantly outperforms traditional monitoring and control strategies. The hybrid deep learning architecture provides highly accurate fault identification, the multimodal forecasting engine ensures robust anticipatory predictions under volatile weather conditions, and the reinforcement learning controller delivers superior optimization performance across all operational scenarios. Together, these components elevate PV systems from reactive energy producers to intelligent, adaptive, and self-optimizing infrastructures capable of long-term resilience and maximum energy harvesting in real-world environments.

5- Future Work:

While the proposed deep learning-empowered framework demonstrates significant advancements in fault detection, predictive forecasting, and reinforcement-learning-driven

optimization for photovoltaic systems, several opportunities remain for expanding its capabilities and enhancing its deployment readiness in large-scale, real-world environments. Future research directions center on improving model robustness, advancing interpretability, integrating emerging sensing modalities, and developing system-wide intelligence that spans the entire lifecycle of PV assets. One promising direction lies in the integration of **digital twin architectures** that emulate the physical and operational behavior of PV systems in real time. By coupling the deep learning models with high-fidelity digital replicas of module performance, thermal responses, and electrical characteristics, future frameworks can enable bidirectional learning, scenario testing, and proactive management strategies. Such digital twins could support self-calibrating models that automatically adjust to sensor drift, module aging, or hardware replacements, thereby enhancing long-term adaptability [36]. Expanding the

multimodal sensing ecosystem also presents substantial opportunities. Emerging sensors such as hyperspectral imaging, drone-based thermal mapping, microphonic vibration sensors, and distributed fiber-optic temperature monitoring can provide additional dimensions of spatial and spectral information that improve granularity in detecting microcracks, encapsulant degradation, or electroluminescent anomalies. Incorporating these modalities into the fusion pipeline may lead to ultra-fine-resolution diagnostic capabilities that surpass those achievable with conventional sensing technologies. Another fertile direction involves exploring **self-supervised and semi-supervised learning paradigms** to alleviate the dependence on large, fully labeled datasets. PV systems generate vast amounts of unlabeled data, and leveraging representation learning, contrastive learning, or masked autoencoding could significantly enhance model scalability while reducing the cost and labor associated with fault labeling [37]. Such approaches may allow models to discover latent fault patterns or degradation trajectories that are not explicitly identified in training datasets. From a control perspective, future studies may investigate **multi-agent reinforcement learning (MARL)** architectures where distributed MPPT controllers, inverter clusters, and energy storage units learn to coordinate actions across utility-scale PV farms. This cooperative learning paradigm could optimize system-wide energy distribution, mitigate mismatch losses across large arrays, and improve grid-support functions such as voltage regulation and reactive power balancing [38]. Additionally, incorporating **safety-constrained RL** and **explainable policy learning** would enhance the trustworthiness and reliability of autonomous control systems in high-stakes energy applications. Another valuable direction lies in strengthening **cyber-physical security** for AI-driven PV systems. As solar farms become increasingly automated and interconnected, the vulnerability of data pipelines, control signals, and forecasting systems to cyberattacks grows. Future work may focus on integrating anomaly detection with adversarial defense mechanisms, blockchain-based verification layers, or RL policies trained to

maintain stability under spoofed or corrupted sensor inputs. Climate adaptation and long-term performance modeling also represent critical frontiers. PV systems around the world face diverse stressors such as sandstorms, monsoon seasons, snow loads, or extreme heat and future research should investigate **geographically adaptive AI models** capable of transferring knowledge across climates while accounting for site-specific degradation modes [39]. Incorporating seasonal context learning, spectral variability modeling, and long-range weather forecasting may further strengthen predictive maintenance and operational planning. Finally, large-scale field deployment and longitudinal studies are essential for validating the long-term resilience and economic benefits of the proposed architecture [40]. Collaboration with utility operators, PV manufacturers, and inverter companies could accelerate the development of commercial-grade intelligent PV systems capable of self-healing, predictive operation, and real-time optimization [41]. These partnerships would also enable the refinement of performance metrics, regulatory frameworks, and industry standards for AI-powered renewable energy systems.

Conclusion:

This study presented a comprehensive deep learning-empowered artificial intelligence framework designed to significantly enhance the monitoring, diagnostic accuracy, and operational optimization of photovoltaic (PV) solar energy systems. By integrating multimodal sensor inputs with advanced spatiotemporal learning architectures and reinforcement learning-based MPPT and inverter control, the proposed framework demonstrates how intelligent, data-driven methodologies can address persistent limitations of traditional PV monitoring strategies. The collective results confirm that the synergistic use of CNNs, LSTMs, transformer encoders, multimodal fusion techniques, and RL-based control agents provides a robust foundation for real-time, autonomous PV system intelligence. The deep learning-based fault detection module achieved superior classification accuracy across a broad spectrum of PV anomalies, including

shading events, hotspot formation, bypass diode failures, soiling progression, and inverter malfunctions. The hybrid CNN-LSTM-attention architecture effectively captured both spatial irregularities and temporal evolution patterns, offering high interpretability and resilience under dynamic environmental conditions. Complementing this diagnostic capability, the forecasting engine powered by a hybrid LSTM-transformer model generated accurate short-term power predictions that allowed the optimization module to anticipate and respond to rapidly changing irradiance fluctuations, thermal behaviors, and load variations. This predictive capacity significantly enhanced decision quality for downstream MPPT and inverter control. The reinforcement-learning-driven optimization component further advanced system performance by delivering high tracking efficiency, fast convergence to the global maximum power point, and stable inverter operation, particularly under partial shading and highly variable weather patterns. The RL agent's ability to leverage both real-time feedback and short-term forecasts introduced an anticipatory form of control that reduced power oscillations, minimized thermal stress, and mitigated instability representing a meaningful departure from conventional rule-based MPPT algorithms. This integration of predictive intelligence, fault awareness, and adaptive control demonstrates the transformative potential of AI-driven PV energy systems. Beyond improving immediate operational metrics, the proposed framework also establishes a scalable foundation for long-term PV asset management. Its modular, multimodal design allows for expansion into digital twin platforms, predictive maintenance systems, and site-aware adaptive learning models that evolve with the PV system over time. By bridging diagnostic precision, forecasting robustness, and real-time optimization, the framework advances the vision of self-healing, fully autonomous renewable energy infrastructures capable of maintaining high efficiency despite environmental uncertainty and hardware degradation.

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