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Enhancing Solar Power Reliability: AI-Driven Anomaly Detection for Fault Diagnosis and Performance Optimization

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Abstract: Reliable solar power generation is essential for industries relying on renewable energy to sustain operations efficiently. However, fluctuations in solar energy output due to environmental conditions, equipment wear, and system inefficiencies create challenges in maintaining a consistent power supply. An alloy manufacturing company facing unstable energy production has encountered difficulties in meeting production demands, emphasizing the need for an advanced anomaly detection and performance optimization system. Unidentified faults in solar infrastructure can lead to energy losses, decreased efficiency, and operational disruptions, negatively impacting overall industrial productivity.

This study introduces an AI-powered anomaly detection framework designed to improve solar power reliability and performance. By leveraging machine learning models alongside real-time sensor data, historical power trends, and environmental metrics, the proposed system detects irregularities in energy output, identifies faults, and predicts potential failures before they cause significant disruptions. Utilizing time-series analysis and pattern recognition techniques, the model enables early fault detection, supports predictive maintenance, and minimizes operational risks. Additionally, the system provides data-driven insights to enhance energy distribution, ensuring maximum utilization of available solar resources.

The experimental results confirm that AI-based anomaly detection significantly improves solar energy efficiency by reducing downtime, optimizing energy consumption, and ensuring stable industrial operations. The proposed intelligent monitoring system enhances renewable energy utilization while strengthening industries against power fluctuations. Implementing AI-driven solutions can facilitate the transition toward more efficient and sustainable energy management strategies. This research highlights the transformative impact of AI and data-driven methodologies in advancing solar energy infrastructure, contributing to long-term sustainability and energy security in industrial applications.

Keywords: *Solar Power Reliability, AI-Driven Anomaly Detection, Machine Learning, Renewable Energy Optimization, Industrial Energy Management, Predictive Maintenance, Smart Monitoring Systems, Fault Diagnosis, Energy Sustainability, Manufacturing Process Optimization, Solar Infrastructure Resilience, Data-Driven Energy Management.*

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I. INTRODUCTION

The integration of solar power into industrial operations has emerged as a key strategy for achieving sustainable energy utilization and reducing reliance on fossil fuels. However, the inherent variability and unpredictability of solar energy pose challenges in ensuring a stable and consistent power supply. Anomalies such as equipment malfunctions, environmental fluctuations, and suboptimal system performance can lead to power inefficiencies, directly affecting energy-intensive industries[1].

In alloy manufacturing, where production processes are heavily dependent on an uninterrupted energy supply, solar power fluctuations have become a major bottleneck. The company under study has been experiencing power

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inconsistencies from its solar infrastructure, leading to missed production targets and operational inefficiencies[2]. Investigating these anomalies is essential for ensuring energy reliability and minimizing the impact on manufacturing throughput[3]. Traditional monitoring approaches, which rely on manual inspections and threshold-based alerts, often fail to capture early signs of system degradation. This necessitates the implementation of AI-driven anomaly detection systems for proactive fault diagnosis[4].

Recent advancements in artificial intelligence (AI) and machine learning (ML) have introduced sophisticated techniques for solar power anomaly detection and predictive maintenance. In particular, unsupervised learning models such as K-Means, DBSCAN, One-Class SVM, Isolation Forest, and KNN have shown great potential in classifying normal vs. anomalous energy patterns[5]. These clustering techniques enable the detection of irregularities in solar power output, allowing industries to take timely corrective actions and improve overall system performance[6]. The ability to analyze large-scale time-series data from SCADA systems further enhances fault detection accuracy, ensuring optimal energy management[7].

This study follows the CRISP-ML(Q) methodology [Fig.1], a structured framework for deploying machine learning models in industrial applications. Data was collected from SCADA systems, including inverter readings (DC Current, DC Power, DC Voltage, Temperature) and weather data (GII, GHI, Humidity, Wind Speed, Module Temperature, Ambient Temperature)[8]. Advanced Exploratory Data Analysis (EDA) was conducted to identify key influencing factors, with DC Power and Global Irradiance (GII) being the most significant features. The dataset was preprocessed by removing zero-variance features and ensuring high-quality inputs for anomaly detection models[9].

The research builds upon previous literature in AI-based solar anomaly detection, integrating a voting-based decision system where a data point is classified as anomalous if at least three models flag it[10]. The deployed Streamlit-based

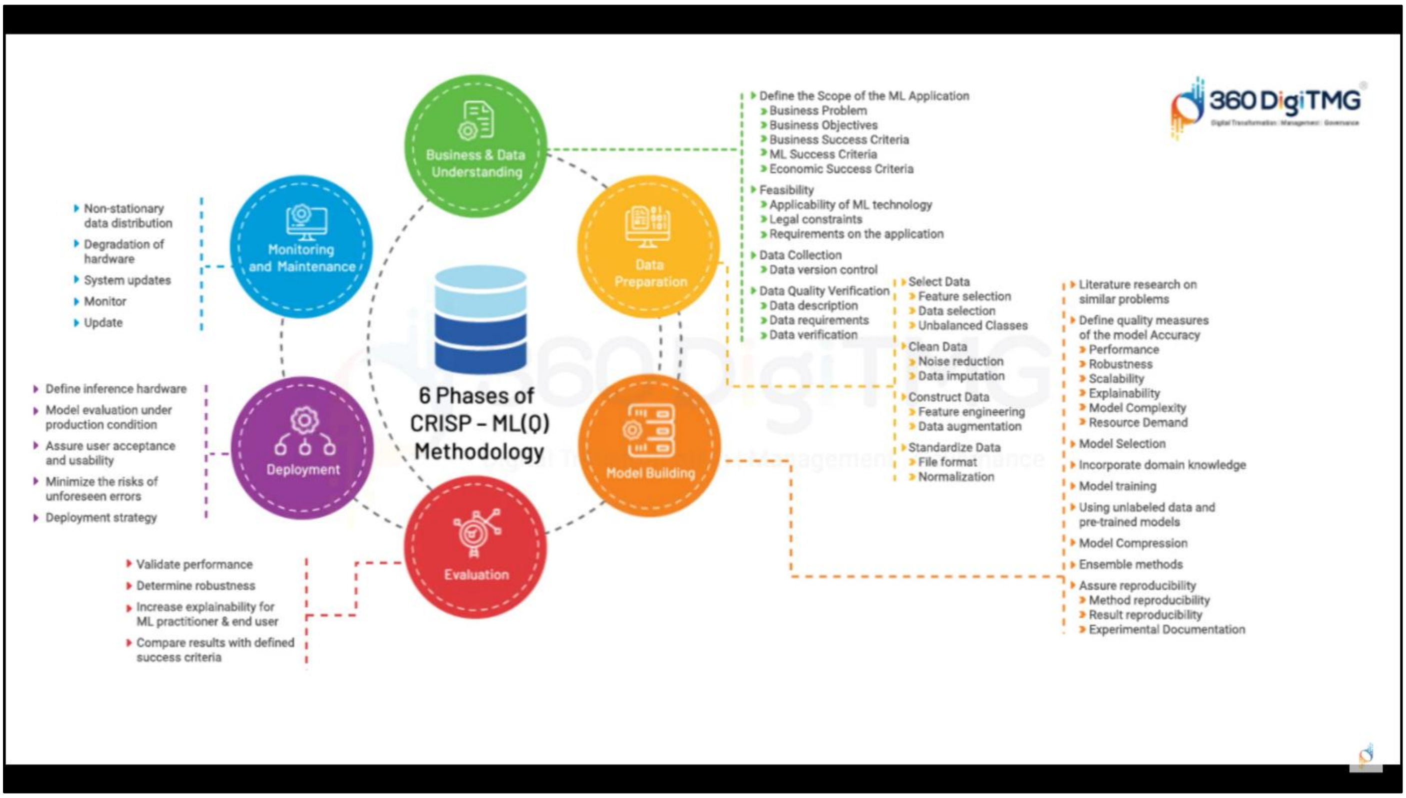

Fig 1: CRISP-ML (Q) Methodological Framework, Outlining its Key Components and Steps Visually.
(Source: -Mind Map - 360DigiTMG)

A monitoring system provides real-time insights into power inconsistencies, helping industries mitigate energy losses and optimize solar power utilization[11].

II. METHODOLOGY AND TECHNIQUES

To develop an effective anomaly detection system for solar power generation, real-time data was collected from SCADA (Supervisory Control and Data Acquisition) systems. The dataset consists of inverter readings and weather conditions, which play a crucial role in detecting anomalies in solar energy production. Before feeding the data into the machine learning models, it was carefully pre-processed and augmented to enhance model performance.

A. Data Collection:

The dataset includes minute-level inverter and data collected over four months.

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- Inverter Data: Contains 175,641 records with parameters such as Date & Time, DC Current, DC Power, DC Voltage, and Temperature.
- Weather Data: Consists of 89,785 records, including features like Global Horizontal Irradiance (GHI), Global Inclined Irradiance (GII), Humidity, Wind Speed, Wind Direction, Rain, Module Temperature, and Ambient Temperature.

B. Model Architecture & AI Workflow

To develop a highly accurate and efficient anomaly detection system, an AI-driven workflow was designed. This multi-stage pipeline integrates machine learning models, statistical techniques, and rule-based anomaly classification to improve fault detection accuracy.

C. Machine Learning Workflow

The proposed workflow consists of the following steps:

- Data Pre-processing: Cleaning and transforming SCADA data for analysis.
- Feature Selection: Choosing the most significant features affecting solar power variations.

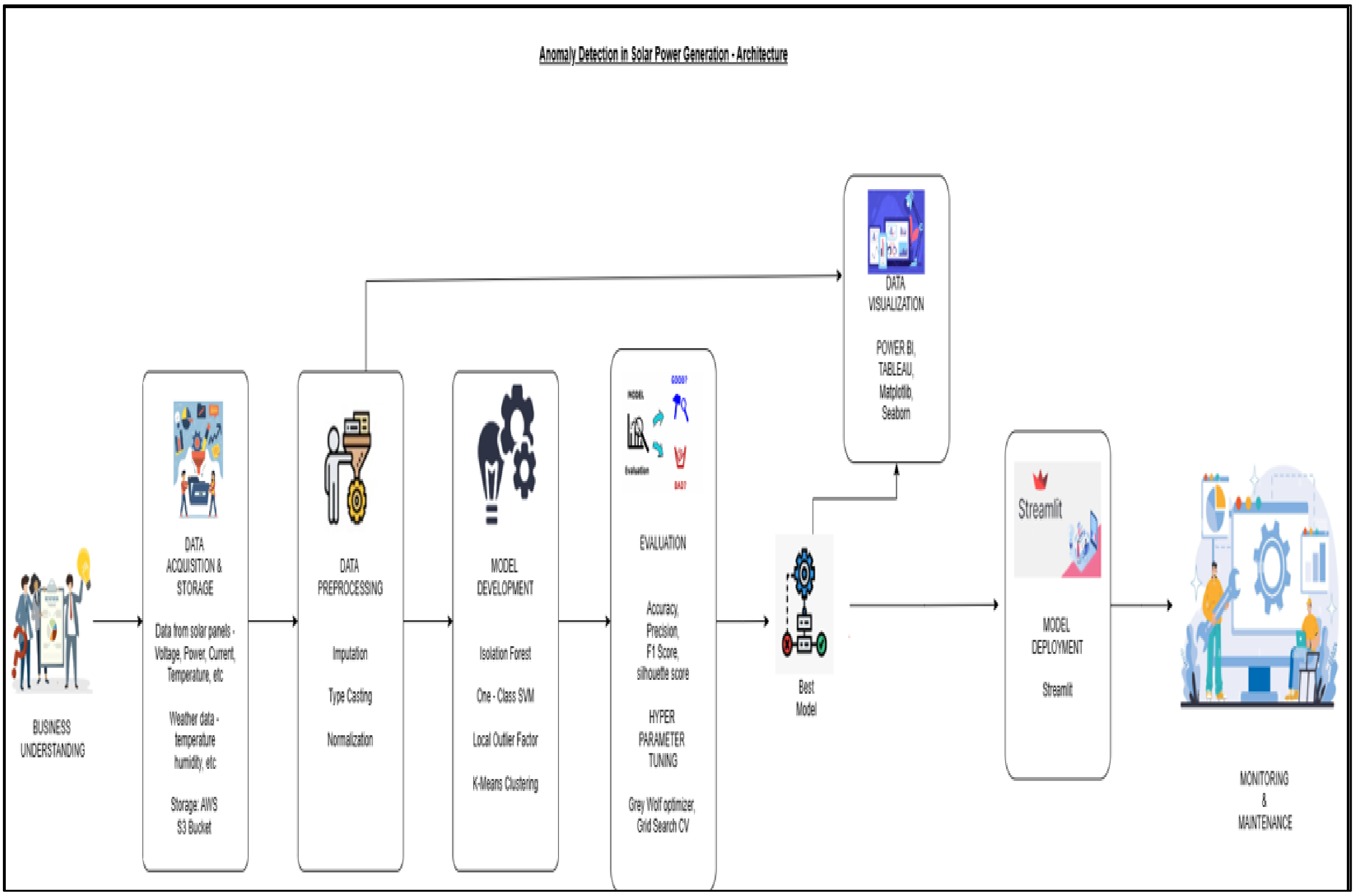

Fig 2: Architecture Diagram

- Model Training: Developing multiple machine learning models for anomaly detection.
- Anomaly Detection & Post-Processing: Using clustering-based and statistical approaches to flag abnormal power patterns.
- Deployment & Monitoring: Visualizing real-time anomalies and sending alerts to operators.[Fig.2]

D. Exploratory Data Analysis (EDA) and Data Visualization

Understanding patterns, trends, and relationships within a dataset is crucial for effective analysis. In this study, Exploratory Data Analysis (EDA) was performed on SCADA data from solar power generation systems, which includes inverter readings and weather parameters. This process helps detect anomalies, correlations, and distribution patterns, ensuring data quality and reliability before applying machine learning models for further analysis.

E. Statistical Summary of Data

➢ *The Dataset Consists of Two Primary Components:*

- Inverter Data – Records electrical parameters, including Current, Voltage, Power, and Temperature, which are essential for monitoring solar energy generation.
- Weather Data – Encompasses meteorological factors such as Global Horizontal Irradiance (GHI), Global Inclined Irradiance (GII), Wind Speed, Humidity, and Temperature, which influence solar power output.
- A descriptive statistical analysis was conducted to gain insights into the dataset's characteristics. This analysis

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examined key statistical measures such as mean, median, mode, variance, standard deviation, skewness, and kurtosis, providing a comprehensive understanding of data distribution and variability.

➢ *Key Observations:*

Exploratory Data Analysis [EDA]

Inverter 3				
	Current	Voltage	Power	Temp
Mean	643.8947074	1087.017292	705.7200875	33.52531188
Median	12.5	1100	13.8	32.5
Mode	0	1100	0	31.200001
Var	790264.0389	15425.51677	934148.6738	34.28149407
Std	888.9679628	124.1995039	966.5136697	5.855040057
Range	999.900024	999.900024	999.900024	8.6
Skewness	1.0785691	-6.894500185	1.052217355	-0.104729598
Kurtosis	-0.410453138	55.15599942	-0.467991866	2.977401355

Weather								
	GHI	GII	Rain	Wind direction	Wind speed	Humidity	Ambient temp	Avg_mod_tem p
Mean	462.5106	456.9664	0.000327453	0	0	51.64266924	33.29247973	42.793653
Median	441	432	0	0	0	48	33.400002	43.6
Mode	3	2	0	0	0	99.900002	39	0
Var	98043.12755	98443.12993	7.87487E-05	0	0	429.8982511	34.15224347	158.5960056
Std	313.1183922	313.7564819	0.008874046	0	0	20.73398782	5.843992083	12.5934906
Range	1279	1234	0.6	0	0	99.900002	47.599998	67.85
Skewness	0.106995843	0.110140642	0	0	0	0.46930589	-0.248565751	-0.395642928
Kurtosis	-1.384371266	-1.41837051	1121.868134	0	0	-0.597621538	-0.532641412	-0.343949082

Fig 3: Summary Statistics of Inverter and Weather Data

The average temperature of the inverter system is 33.52°C, with a standard deviation of 5.85, signifying moderate fluctuations in operating conditions.

The high variance in DC Power (934,148.67) suggests significant inconsistencies in power generation, potentially due to environmental factors or system inefficiencies.

A strong correlation between GHI and GII confirms their expected relationship, as both parameters represent solar irradiance from different orientations.

Meanwhile, Wind Speed, Wind Direction, and Rain exhibit minimal variations, indicating that these factors had a negligible influence on power generation during the observation period. [Fig.3]

F. Data Correlation Analysis:

To examine the relationships between different parameters, scatter plots were created to visualize the interaction between inverter readings and weather data.

➢ *Key Observations:*

- GHI vs. GII: A strong positive correlation exists between Global Horizontal Irradiance (GHI) and Global Inclined Irradiance (GII), confirming their mutual influence on solar energy estimation.
- Temperature vs. Humidity: Higher module temperatures tend to align with increased humidity levels, suggesting environmental effects on solar panel efficiency.
- DC Power vs. GHI: Power generation directly corresponds to solar irradiance, reinforcing the expected relationship.
- DC Current vs. DC Power: A near-linear relationship is observed, emphasizing the critical role of current regulation in optimizing power output. [Fig.4]

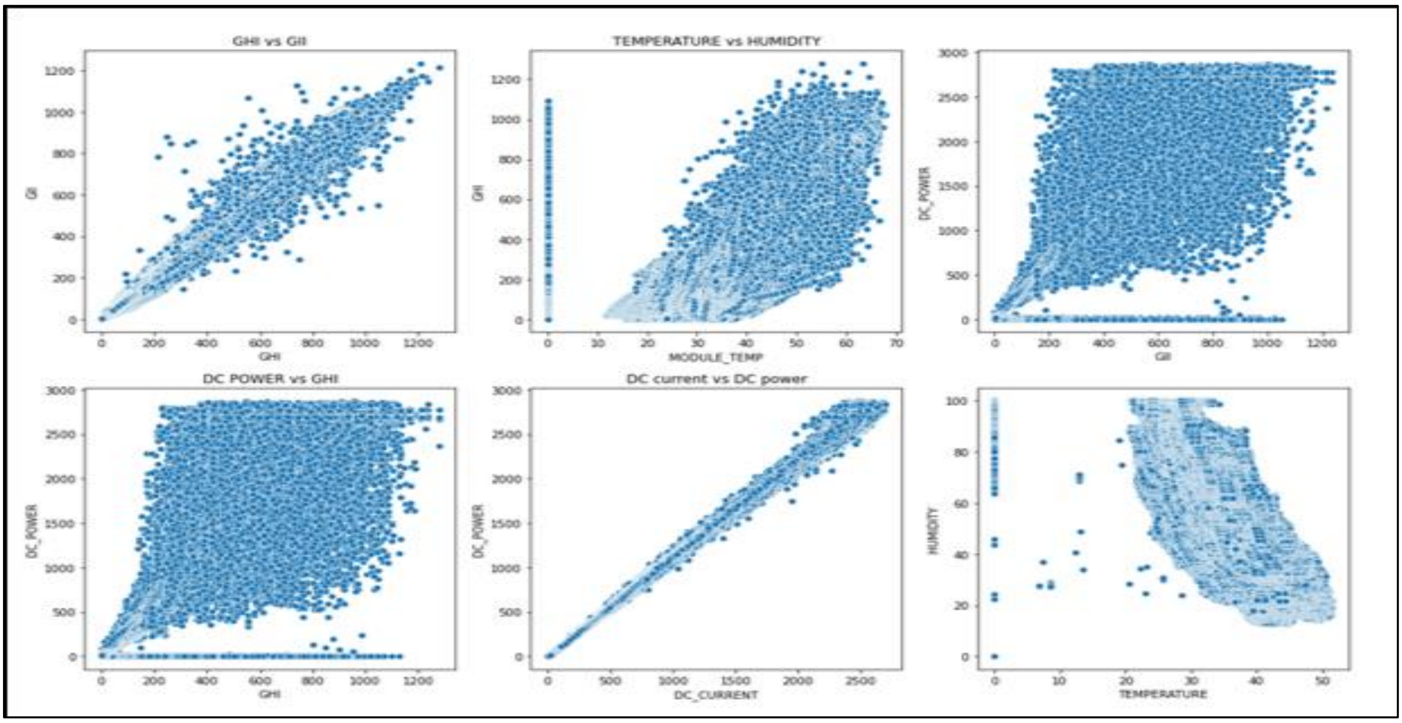

Fig 4: Scatter Plots Showing Correlation Between Key Parameters

G. Distribution Analysis:

Analyzing the distribution of key parameters is essential for detecting potential anomalies and data skewness. To achieve this, histograms, box plots, and quantile-quantile (Q-Q) plots were utilized.

➢ *Key Observations:*

- Histogram of GHI: The data exhibits a right-skewed distribution, indicating that most values are concentrated at lower irradiance levels.
- Boxplot of GHI: No extreme outliers were detected, suggesting a consistent solar exposure pattern throughout the data collection period.
- Histogram of Humidity: A bimodal distribution was observed, implying varying humidity conditions at different times of the day.
- Boxplot of Humidity: Displays some variability, though no significant outliers were present.
- Q-Q Plot for GHI and Humidity: Both parameters show minor deviations from normality but largely adhere to a log-normal distribution pattern. [Fig.5]

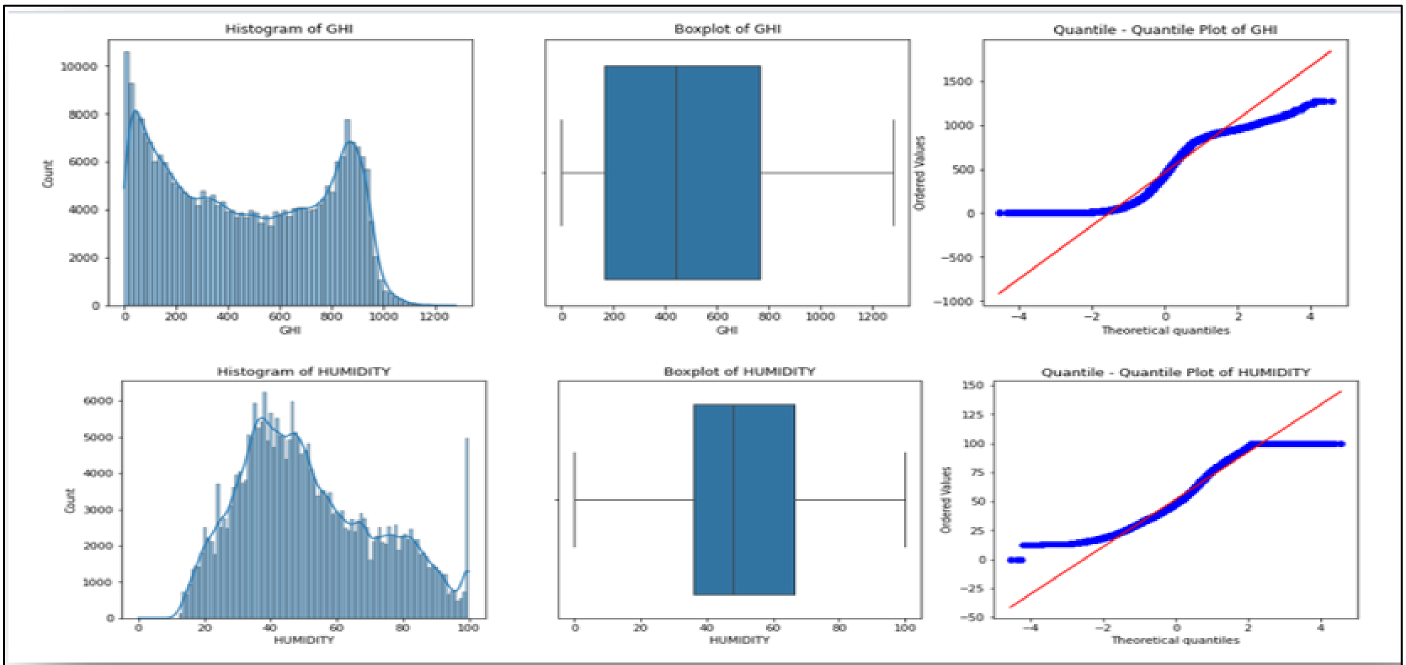

Fig 5: Histograms, Box Plots and Q-Q Plots of Solar Irradiance and Humidity

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H. Outlier Detection and Anomaly Identification

To detect anomalies in solar power generation, a combination of statistical methods and visualization techniques was applied.

I. Techniques Used for Anomaly Detection:

Box Plots were utilized to identify extreme values in DC Power, Temperature, and GII, highlighting potential deviations from normal operating conditions.

Z-Score and Interquartile Range (IQR) Methods were employed to flag outliers, ensuring that unusual patterns in the dataset were effectively detected.

Anomalous Power Output Trends were observed, particularly during low irradiance periods when DC Power remained unexpectedly high, suggesting possible sensor errors or inverter malfunctions.

J. Key Insights:

- Outliers in DC Power may be indicative of inverter faults or temporary cloud cover effects impacting energy conversion.
- Humidity levels showed occasional spikes, which could reduce solar panel efficiency due to condensation build-up.
- Night-time data was excluded as solar panels do not generate power in the absence of sunlight, ensuring that the analysis focused solely on active energy production periods. [Fig.5]

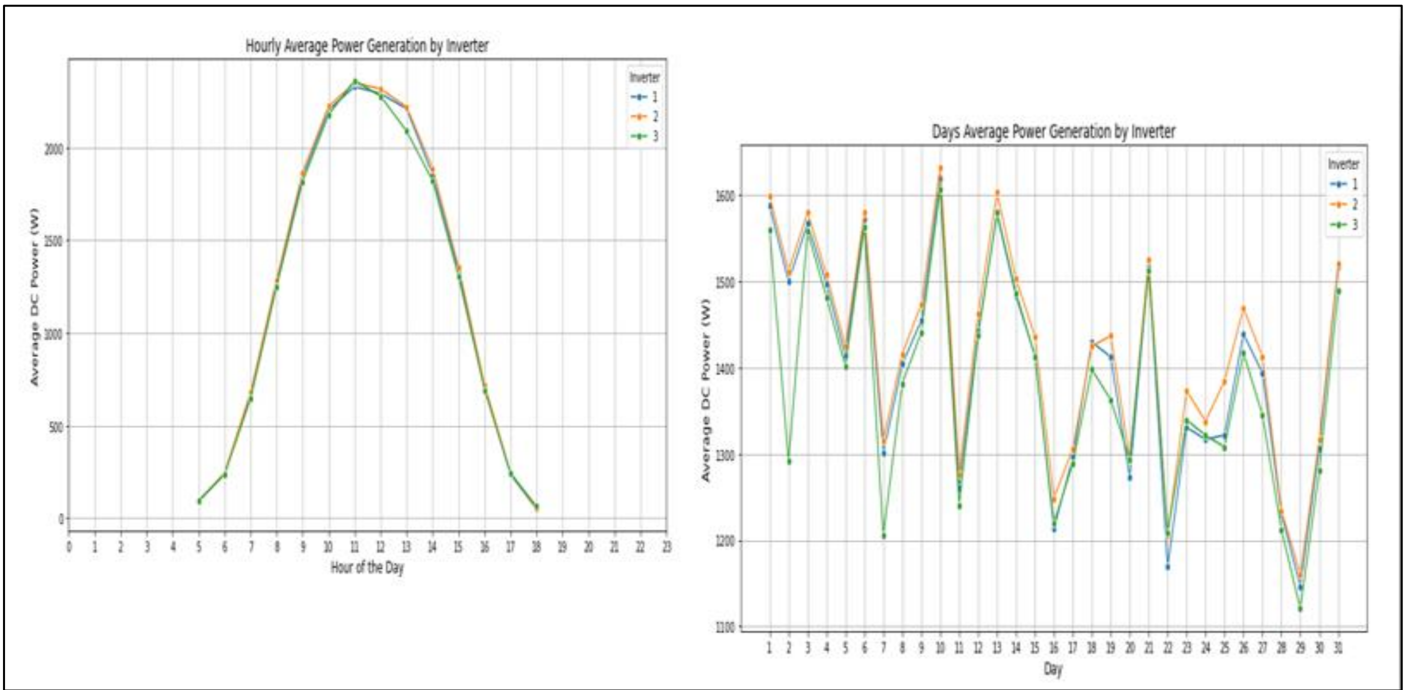

Fig 6: Hourly and Daily Power Generation Trends of Inverters

K. Power Generation Analysis: Hourly and Daily Trends:

The analysis of solar power generation trends plays a crucial role in understanding energy production patterns and identifying potential inefficiencies. The provided graphs illustrate hourly and daily variations in power generation across three different inverters, offering insights into system performance and potential anomalies.

L. Hourly Power Generation Trends;

The hourly average power generation curve follows a predictable solar energy pattern, starting at dawn, reaching peak production around midday, and gradually declining towards the evening. The power output begins increasing between 6 AM and 7 AM, peaks between 11 AM and 1 PM, and steadily decreases after 2 PM, with minimal production post 5 PM. This trend aligns with solar irradiance patterns, confirming that power generation is dependent on sunlight availability.

The power output across three different inverters (1, 2, and 3) shows a high degree of consistency, suggesting balanced energy distribution within the system. However, minor deviations among inverters at peak hours may indicate variations in panel efficiency, shading effects, or slight operational inefficiencies. If a particular inverter shows an unexpected drop during peak hours, it could be due to temporary shading, dirt accumulation on panels, or hardware-related inefficiencies.

M. Daily Power Generation Trends:

The daily average power generation analysis reveals significant fluctuations in solar energy production over a month. While power generation remains relatively stable on most days, certain days exhibit notable peaks and dips, which could be attributed to various external and operational factors.

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The highest power output is observed on days 9, 10, and 30, indicating optimal sunlight conditions. Conversely, sharp declines in power generation on days 6, 15, and 27 suggest potential weather disturbances (e.g., cloudy or rainy days), maintenance shutdowns, or temporary system inefficiencies. The synchronized behavior of all three inverters across multiple days further indicates that these fluctuations are likely influenced by external factors rather than isolated equipment failures.

N. Potential Causes of Variability:

➢ *Several Factors could Contribute to the Observed Daily and Hourly Fluctuations in Power Output:*

- Weather Conditions: Cloud cover, rainfall, or high humidity levels could reduce solar irradiance, directly impacting power generation.
- Panel Efficiency and Maintenance Issues: Dust accumulation, shading, or hardware degradation may cause lower-than-expected output.
- System-wide vs. Localized Anomalies: If all inverters show a drop in power output, the cause is likely external (e.g., weather), whereas if only one inverter underperforms, it may indicate a localized issue such as equipment failure.
- Operational Interruptions: Scheduled maintenance or temporary inverter shutdowns could explain certain dips in daily power production.

III. DATA PREPROCESSING AND DATA AUGMENTATION

A. Data Preprocessing:

- Handling Missing Values: No missing values were found in the dataset.
- Feature Selection: The most relevant features for anomaly detection were identified. DC Power & GII were selected as the primary indicators.
- Normalization & Scaling: Min-Max normalization was applied to ensure consistent feature ranges.
- Removal of Low-Impact Features: Variables such as Wind Direction, Wind Speed, and Rain were removed due to low correlation with anomalies.

B. Data Augmentation Techniques:

- To improve the robustness of the anomaly detection models, data augmentation techniques were applied. This helped generate additional training samples and enhance the model’s ability to detect irregularities in power fluctuations. The following transformations were used:
- Scaling and Normalization to maintain consistency in feature values.
- Time-series augmentation using rolling window techniques to smoothen power output variations.
- Noise Injection to simulate sensor inaccuracies and real-world variability.
- Outlier Handling using machine learning-based anomaly detection models like Isolation Forest and One-Class SVM.
- Augmenting data in this manner improves model generalization and reduces bias, ensuring better detection of real-world anomalies in solar power generation.

IV. RESULTS AND DISCUSSION

The implementation of unsupervised anomaly detection models for solar power generation provided meaningful insights into identifying irregularities in power output. This section discusses the model predictions, comparative analysis, anomaly distribution, and implications of the findings.

A. Model Performance and Anomaly Detection:

The dataset was processed using three unsupervised machine learning models: Isolation Forest, One-Class SVM, and Local Outlier Factor (LOF). After fitting the models to the dataset, anomalies were identified based on deviations from expected power output trends.

Each model classified data points into normal (1) or anomalous (-1), with anomalies representing irregular fluctuations in power generation. The detected anomalies were further analyzed based on environmental and operational factors.

➢ *Key Findings from Anomaly Detection Models Include:*

Anomalies were consistently detected during peak temperature and irradiance periods, suggesting potential inverter overheating or energy conversion inefficiencies.

Sudden drops in power output despite stable irradiance indicate possible inverter malfunctions or shading effects.

Anomalies in humidity and temperature correlations suggest environmental conditions may be affecting panel performance or sensor accuracy.

B. Visualization and Interpretation of Anomalies:

To assess the reliability of detected anomalies, data points were visualized by plotting anomalies against key operational parameters, such as:

➢ *DC Power vs. Ambient Temperature*

Power fluctuations at high temperatures could indicate thermal stress on inverters. If power output is lower than expected at optimal temperature, it suggests efficiency degradation.

➢ *DC Power vs. Humidity*

Higher humidity levels may impact panel performance, potentially causing anomalies in power generation. Unusually high power readings during humid conditions could suggest sensor calibration issues.

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➢ *GHI vs. Power Output*

- A strong correlation between GHI and power generation is expected.
- If anomalies appear in high irradiance but low power conditions, panel inefficiencies or wiring issues could be present.
- By analyzing these plots, it was observed that many detected anomalies align with expected operational inconsistencies, validating the model outputs.

C. Comparative Model Analysis and Rule-Based Classification:

- To refine anomaly detection, a comparative analysis of the three models was conducted. Each model flagged a varying number of anomalies, prompting the development of a rule-based classification system to enhance accuracy.
- A data point was classified as an anomaly if at least two models detected it.
- A bar plot was generated to visualize the anomaly count per model, highlighting the differences in sensitivity among models.

D. Anomaly Detection Comparison:

Table 1: Anomaly Detection Comparison

Models	Anomalies Detected
Isolation Forest	2694
One-Class SVM	2698
Local Outlier Factor (LOF)	2223
Common Anomalies (Detected by Any Two Models)	1527

E. Observations:

- Isolation Forest identified the highest number of anomalies, possibly due to its sensitivity to local deviations.
- One-class SVM detected a moderate number of anomalies, performing well in high-dimensional environments.
- LOF flagged fewer anomalies, indicating its effectiveness in reducing false positives.
- The rule-based classification significantly improved anomaly detection precision, ensuring that only consistent anomalies across models were flagged for investigation[Table 1].

F. Model Deployment and Real-Time Monitoring:

To facilitate real-time anomaly detection, the trained machine learning models were saved using joblib in pickle format for seamless integration into a monitoring system. This approach enables:

Live anomaly detection on incoming SCADA data, allowing for immediate identification of irregularities.

Effortless integration with a visualization dashboard, providing operators with real-time insights into system performance.

Automated anomaly alerts ensure proactive maintenance and minimize response time for potential faults.

The deployment of these models supports continuous monitoring and rapid fault detection, reducing operational downtime and improving energy efficiency in solar power systems.

G. Discussion and Implications

The results confirm that unsupervised machine learning models can effectively detect inconsistencies in solar power generation, contributing to improved fault identification and system reliability. The analysis highlights the impact of environmental conditions, equipment performance, and operational inefficiencies on power fluctuations.

By leveraging AI-driven anomaly detection, industries can optimize solar energy utilization, enhance predictive maintenance strategies, and ensure long-term sustainability in power management. The integration of real-time monitoring solutions further strengthens system resilience, allowing for proactive interventions before faults escalate into major disruptions.

H. Key Takeaways:

- Hybrid Model Approach Enhances Accuracy
- A combination of Isolation Forest, One-Class SVM, and LOF significantly improves anomaly detection accuracy.
- The rule-based classification method effectively reduces false positives and ensures robust detection of irregularities.
- Environmental Factors Affect Anomalies
- High temperatures and humidity fluctuations can impact panel efficiency, leading to unexpected power deviations.
- Shading effects and panel soiling can cause anomalies, emphasizing the need for frequent maintenance and cleaning schedules.
- Real-Time Monitoring Supports Predictive Maintenance
- Deploying models for live monitoring enables early fault detection and reduces system failures.
- Anomaly-based alerts ensure proactive interventions, improving operational stability.[Fig.7]

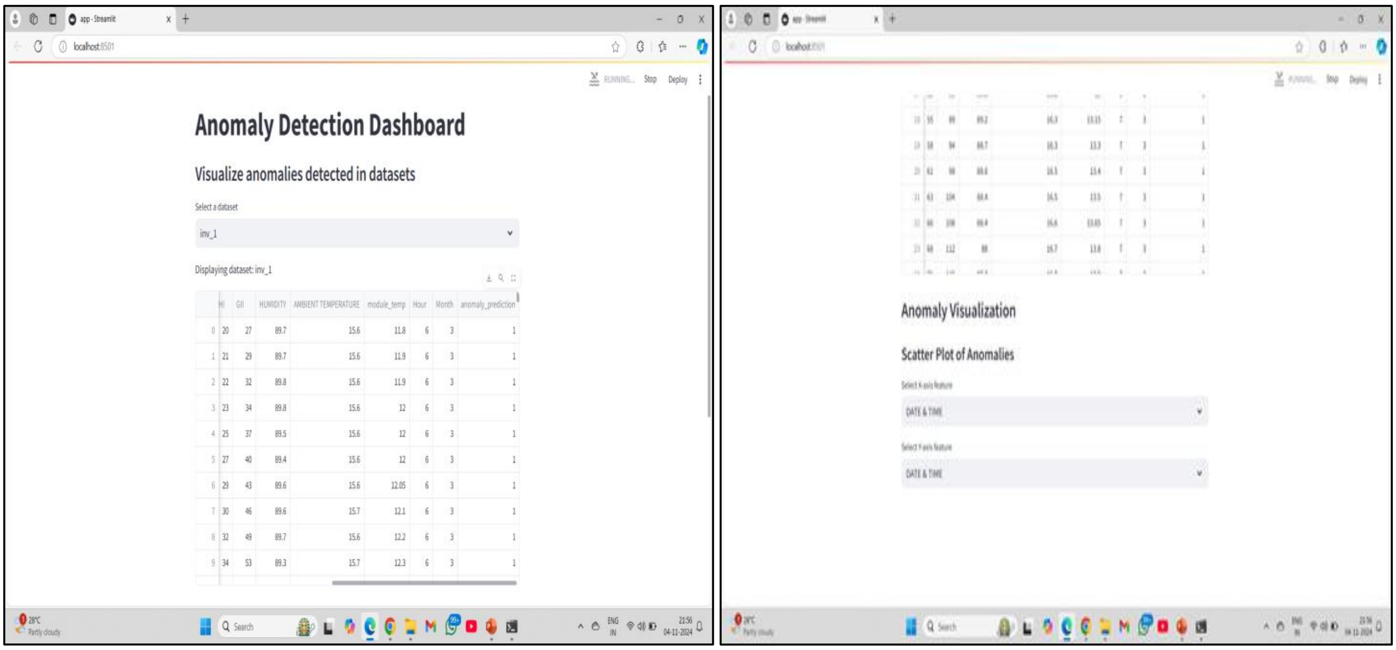

Fig 7: Anomaly Visualization Interface: An Interactive Scatter Plot Tool for Visualizing Anomalies in Solar Power Data. Users can Select Specific Features for Analysis, Enabling a Deeper Understanding of Power Fluctuations and Operational Inconsistencies

V. CONCLUSION

This study highlights the potential of machine learning models in identifying anomalies in solar power generation and improving system efficiency. By employing multiple unsupervised learning approaches within a structured classification framework, the system enhances real-time monitoring and proactive maintenance. This reduces operational inefficiencies, minimizes downtime, and ensures optimal solar energy utilization.

Future developments, including expanded data collection for seasonal analysis, advanced deep learning integration for improved pattern recognition, and automated alert mechanisms, will enhance anomaly detection accuracy. These improvements will improve system reliability, efficiency, and long-term sustainability in solar energy management, ensuring stable power generation and uninterrupted performance.

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- The authors affirm that no financial support, grants, or funding were obtained during the research or the manuscript preparation.
- The authors confirm that they have no financial or non-financial conflicts of interest to disclose.

➢ *Data Availability Statement:*

The datasets utilized, generated, and/or analyzed during the current study are not publicly accessible due to internal data privacy policies. However, they can be obtained from the corresponding author upon reasonable request.

FUTURE SCOPE

The future potential of this AI-powered anomaly detection system in solar power management lies in its ability to integrate with advanced predictive analytics. By incorporating weather data and seasonal trends, the system could more accurately forecast energy production, allowing industries to better anticipate energy needs and reduce reliance on external power sources. This would enhance planning and optimize the use of available solar resources, ensuring more efficient energy management.

Additionally, the integration of IoT sensors and edge computing could further improve the system's performance. Real-time monitoring of solar panels through localized data processing would enable faster fault detection and response, minimizing downtime and maximizing energy output. The system could also evolve into an autonomous energy management solution, dynamically adjusting solar power production to meet grid demands, contributing to a more resilient, efficient, and sustainable energy infrastructure.

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