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Machine learning for energy conversion prediction and photovoltaic-on grid protection system using IoT

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ABSTRACT

The advancement of photovoltaic (PV) systems in tropical regions faces significant efficiency challenges due to fluctuating panel surface temperatures. This study addresses these issues by implementing machine learning (ML) models, specifically k-nearest neighbors (KNN) and extreme gradient boosting (XGBoost), to classify and monitor panel temperatures. To enhance system resilience, an internet of things (IoT) based on-grid protection system was developed, featuring a dual-relay redundancy mechanism that triggers an automated trip when the current exceeds 1.30 A. This integration ensures the protection of both the PV infrastructure and household electrical loads. Experimental results demonstrate that the KNN model exhibits superior reliability with a testing accuracy of 93% and a baseline performance of 96.67%, successfully identifying both normal (25 °C to 35 °C) and high-temperature (36 °C to 48 °C) states. In contrast, while the XGBoost model reached a maximum validation accuracy of 94.44% during training, it only achieved a testing accuracy of 84% and showed significant limitations in detecting normal temperature patterns. Beyond classification, the IoT framework proved highly precise in real-time energy monitoring, with sensor error rates below 2%. This research offers a strategic solution for optimizing energy conversion and system reliability, providing a robust framework for sustainable clean energy management in tropical climates.

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1. INTRODUCTION

The global transition toward renewable energy has positioned solar power as a cornerstone of sustainable development, particularly in tropical regions like Indonesia [1]. With its strategic location along the equator, Indonesia possesses immense solar irradiation potential, which offers a viable solution for reducing dependency on fossil fuels and achieving environmentally friendly energy independence. Photovoltaic (PV) technology has become increasingly accessible for community-scale use, primarily due to its ease of operation and declining installation costs [2]–[4]. However, the practical application of PV systems in tropical climates is not without significant technical hurdles. The most critical factor affecting energy conversion efficiency is the thermal sensitivity of the silicon cells. High ambient temperatures and excessive heat accumulation on the panel surface create a non-linear degradation of power output, where temperatures exceeding the optimal threshold lead to a drastic drop in voltage and overall system performance [5]–[8].

Maintaining the stability of the panel surface temperature within the range of 25 °C to 35 °C is essential for maximizing the fill factor and energy yield. Fluctuations caused by weather unpredictability and dust accumulation often lead to suboptimal energy distribution to household loads [5]–[10]. To mitigate these issues, advanced computational approaches are required to recognize and classify thermal patterns in real-time. Machine learning (ML) methods, such as k-nearest neighbors (KNN) and extreme gradient boosting (XGBoost), have demonstrated exceptional capabilities in handling complex environmental datasets [11], [12]. By utilizing data captured through thermographic sensors or thermal imaging, these algorithms can effectively categorize temperature states, allowing for rapid interventions when the system detects overheating. The implementation of such intelligent classification ensures that the energy conversion process remains within safe and efficient parameters [13]–[15].

In addition to thermal management, the reliability of PV-on grid installations remains a major concern for both users and grid operators [16]–[18]. Integrating PV systems with the existing residential electricity network requires a robust protection framework to prevent system failures. Many existing installations do not strictly adhere to the International Electrotechnical Commission (IEC) standards, increasing the vulnerability to overloading, short circuits, and fire hazards [19]–[21]. This lack of standardized protection not only threatens the longevity of the PV infrastructure but also poses a direct risk to household safety. Therefore, a proactive protection system is necessary to monitor electrical parameters continuously and respond to anomalies before they escalate into catastrophic failures. This research proposes an integrated solution by combining ML-based thermal classification with an internet of things (IoT) powered protection system [22]–[24]. By employing the PZEM-004T module for high-precision measurement of voltage, current, and active power, coupled with the ESP8266 microcontroller, the system enables real-time data transmission to mobile and web platforms [25]. The core of this protection system is an automated safety protocol designed to trip or disconnect the circuit when the current exceeds a critical threshold of 1.30 A. This integration not only optimizes energy conversion through intelligent monitoring but also ensures a high level of operational security. The evaluation of this system focusing on accuracy and real-time response provides a comprehensive framework for the next generation of smart, safe, and efficient solar energy systems in tropical environments.

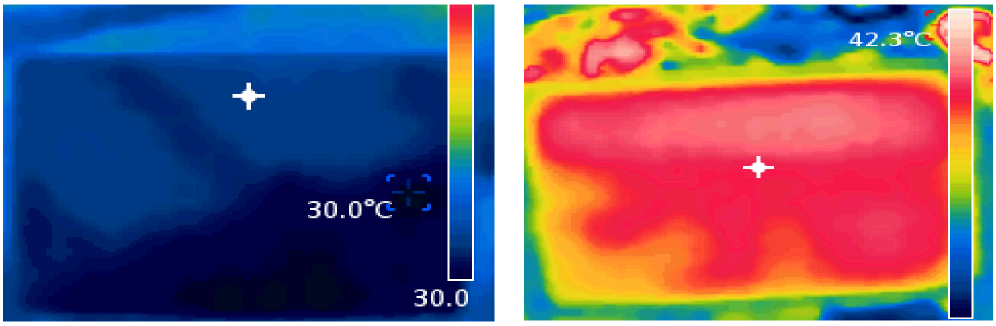
2. METHOD

The efficiency of a PV system is fundamentally dependent on the geographical focal point of solar radiation. This research begins with a comprehensive analysis of the natural resources in North Sumatra, Indonesia. Located in close proximity to the equator, this region possesses a high-potential climate for solar energy exploitation. The study specifically focuses on the Medan city area and surrounding coastal regions. Medan's geographical advantage provides a solar irradiation window of approximately 12 to 13 hours per day, with peak optimal generation occurring over a 7 to 8-hour period. These environmental parameters serve as the baseline for evaluating the performance of the proposed energy conversion and protection system. The strategic location of the on-grid PV installation in the North Sumatra region in the development of energy conversion optimization is shown in Figure 1.

Figure 1. Strategic location of on grid PV installation in North Sumatra region

The research implements KNN and XGBoost algorithms to classify the temperature patterns on the PV surface. Data acquisition is performed using thermography (thermal imaging) technology, providing high-resolution image data of the panel's heat distribution. The raw temperature data is pre-processed and fed into the models to categorize the thermal state into two primary classes: normal operating temperatures and high-temperature conditions 25 ºC to 35 ºC. The performance of these models is evaluated based on accuracy, ensuring that the system can provide rapid information for energy conversion optimization.

To achieve precise energy conversion optimization, the research utilizes thermovision technology to capture direct thermal images of the PV surface. This non-invasive imaging technique allows for the synchronization of the installation's physical state with digital pattern recognition models. The primary objective is to identify specific thermal signatures that directly impact the energy conversion efficiency of the solar cells. Thermal images of the PV modules were collected using a thermovision camera under normal and high-temperature operating conditions. The overall workflow of the data collection process for solar cell pattern recognition is presented in Figure 2. This dataset distinguishes between two critical states, Figure 2(a) illustrates the solar cell conditions under normal surface temperatures, while Figure 2(b) captures the thermal profile during high-temperature (hot) conditions. These captured patterns serve as the fundamental input for the KNN and XGBoost classification models, enabling the system to detect and respond to thermal anomalies that could hinder electrical energy production.



(a) (b)

Figure 2. Introduction of solar cell patterns to convert PV energy into electrical energy; (a) solar cell temperature conditions when the surface temperature is normal and (b) solar cell temperature conditions when the surface temperature is hot

The thermal dataset served as the primary input for ML analysis to evaluate energy conversion prediction using accuracy, precision, recall, and F1-score metrics. Simultaneously, an IoT-based protection system was developed for PV-on-grid installations to mitigate the risks of short circuits and overloads by utilizing a relay-controlled mechanism that responds to abnormal electrical parameters. The hardware architecture consists of a NodeMCU ESP8266 interfaced with a PZEM-004T module and a relay powered by a step-down module, enabling real-time transmission of sensor readings through RX and TX communication. For a 900 VA household-scale system, the protection mechanism automatically trips the relay and miniature circuit breaker (MCB) when the current exceeds the 1.30 A threshold. This integrated framework enhances the reliability of the grid-connected PV network through real-time monitoring of voltage, current, and active power via a WiFi-enabled IoT dashboard.

3. RESULTS AND DISCUSSION

PV systems serve as a primary energy source for reducing household electricity consumption and minimizing utility costs. The development of an on-grid PV system integrated with IoT technology offers an innovative and eco-friendly solution for modern energy management. This system utilizes the PZEM-004T module for precise power acquisition, with data transmitted to a NodeMCU ESP8266 as the central controller for real-time measurement and analysis. Leveraging Wi-Fi connectivity, the system enables remote monitoring of electrical loads via smartphones and personal computers. To optimize energy conversion, thermal imaging is employed to recognize and classify normal versus excessive heat patterns on the solar panels, allowing for proactive thermal control. The integrated sensors are further developed into a robust protection system that utilizes a relay for automated circuit breaking and connection, while the MCB serves as a secondary backup for abnormal electrical conditions. To ensure system reliability, the NodeMCU ESP8266 performance was evaluated based on data transmission rates (kb) and received data (bytes), while the PZEM-004T readings for voltage, current, and power were validated against multimeter benchmarks. Once accuracy was confirmed, the protection system's reliability was tested to determine the optimal response and efficiency of the relay in safeguarding the grid-connected installation.

3.1. Performance analysis of the internet of things-based protection system and sensor accuracy

The NodeMCU ESP8266 microcontroller serves as the primary gateway for web-based data transmission, facilitating real-time monitoring of both standalone and integrated PV configurations. To ensure the reliability and integrity of the data stream, the communication system underwent a rigorous calibration process. This evaluation focuses on verifying the consistency between the transmitted data (kb) and received data (bytes), which is fundamental for maintaining the validity of measurements across the IoT network. The empirical results of these connectivity tests, highlighting the throughput performance of the NodeMCU ESP8266, are detailed in Table 1.

Table 1. Data throughput and communication performance of NodeMCU ESP8266

No	NodeMCU ESP8266	Transmitted data (kb)	Received data (bytes)
1	Experiment 1	1.0	21
2	Experiment 2	1.3	26
3	Experiment 3	1.5	34
4	Experiment 4	2.3	54
5	Experiment 5	2.6	58

Analysis of the experimental data in Table 1 reveals a significant and consistent upward trend in data transmission efficiency. The transmitted data (kb) increased from an initial 1.0 kb in the first trial to 2.6 kb in subsequent tests, demonstrating a stable positive trajectory. Similarly, the received data exhibited a consistent expansion from 21 bytes to 58 bytes. This steady growth indicates that the NodeMCU ESP8266 operates with high scalability, effectively handling increased data throughput without latency, which is essential for complex communication in IoT-based monitoring. Furthermore, to validate the measurement accuracy of the PZEM-004T module in monitoring PV energy conversion, a comparative analysis was conducted against high-precision multimeter benchmarks. This calibration step is crucial to ensure that the electrical parameters recorded from the on-grid PV system are accurate and reliable. The comparative results, encompassing voltage (V), current (A), and power (W) measurements between the multimeter and the PZEM-004T module, are systematically presented in Table 2.

Table 2. Accuracy evaluation of PZEM-004T sensor through multimeter comparative testing

No	Measurement experiment	Multimeter (voltage) (V)	PZEM 004T (voltage) (V)	Multimeter (current) (A)	PZEM 004T (current) (A)	Multimeter (power) (W)	PZEM 004T (power) (W)
1.	Experiment 1	220.8	221.2	1.21	1.23	267.17	272.08
2.	Experiment 2	220.9	221.5	1.24	1.26	273.92	279.09
3.	Experiment 3	221.5	221.6	1.23	1.24	272.45	274.78
4.	Experiment 4	221.9	222.7	1.25	1.27	277.38	282.83
5.	Experiment 5	221.7	222.3	1.22	1.26	270.47	280.10

The calibration results between the multimeter benchmarks and the PZEM-004T module, as documented in Table 2, demonstrate high precision under a 900 VA residential electrical load. The analysis reveals an average voltage error of only 0.23% and an average current error of 1.75%. These values indicate that the energy conversion data from the on-grid PV installation aligns closely with actual parameters, significantly exceeding the standards set by the International Electrotechnical Commission (IEC). According to IEC regulations, the acceptable tolerance for measurement instruments is ±3.2% for ammeters and ±2.5% for voltmeters [14]; thus, the proposed system's performance falls well within these professional safety and accuracy margins. To further evaluate the system's resilience, an experimental assessment of the relay-based protection mechanism was conducted to verify its operational response during critical conditions. The performance metrics of this protection framework are systematically presented in Table 3.

The protection system performance evaluation, detailed in Table 3, focuses primarily on the dynamic control of electric current through the relay mechanism. The system is engineered with a critical threshold of 1.30 A to ensure the reliability of the on-grid PV installation. Under normal operational scenarios where the current remains below this threshold, the relay remains active, facilitating a continuous energy supply to the electrical loads. However, upon detecting an overcurrent surge or electrical disturbance exceeding the 1.30 A limit, the system triggers an automated trip response, causing the relay to disconnect the circuit instantaneously.

This operational transition is captured in real-time via the IoT monitoring dashboard, where a significant drop in current signifies the successful activation of the protection layer. Beyond its role as a safety breaker, the relay serves as an essential regulator for current flow and an intelligent distributor for energy supply within the managed electrical load.

Table 3. Functional testing results of the automated circuit breaker and relay mechanism

No	Protection	Voltage (V)	Current (A)
1	Experiment 1	220.9	1.25
2	Experiment 2	221	1.26
3	Experiment 3	221.7	1.31
4	Experiment 4	221.9	1.29
5	Experiment 5	221.8	1.32

3.2. Evaluation of KNNs and XGBoost algorithms for photovoltaic thermal diagnostic prediction

The implementation of ML is essential for identifying thermal patterns and predicting energy conversion efficiency based on high-resolution imaging. In this study, thermal image data acquired via thermovision technology is stored and processed to analyze the correlation between solar cell temperature distribution and energy output. This approach is critical for understanding how temperature fluctuations and weather instability impact the overall efficiency of PV systems. The predictive modeling focuses on the application of KNN and XGBoost algorithms, utilizing a structured dataset of training and testing images to classify thermal states into normal and high-temperature categories. By comparing predicted data against actual ground-truth measurements, the system evaluates the robustness of each algorithm in detecting thermal anomalies during the energy conversion process. The resulting performance metrics, showcasing the visualization of prediction accuracy and model reliability for both KNN and XGBoost, are presented in Figure 3.

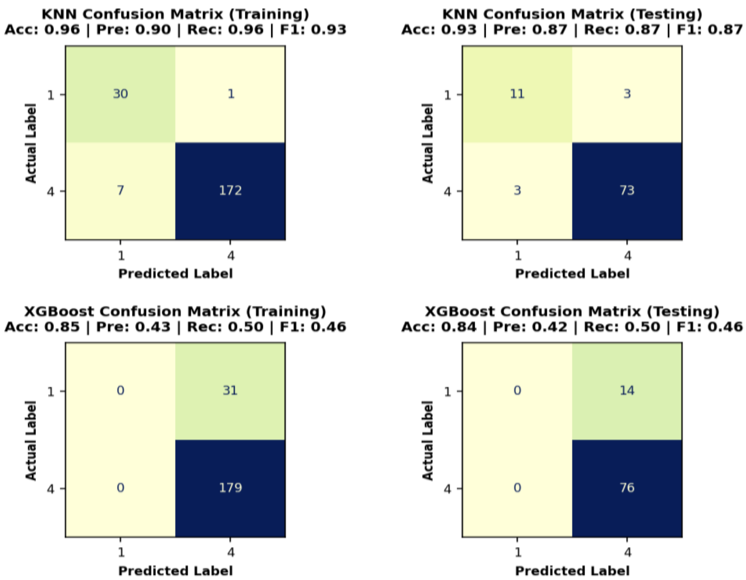
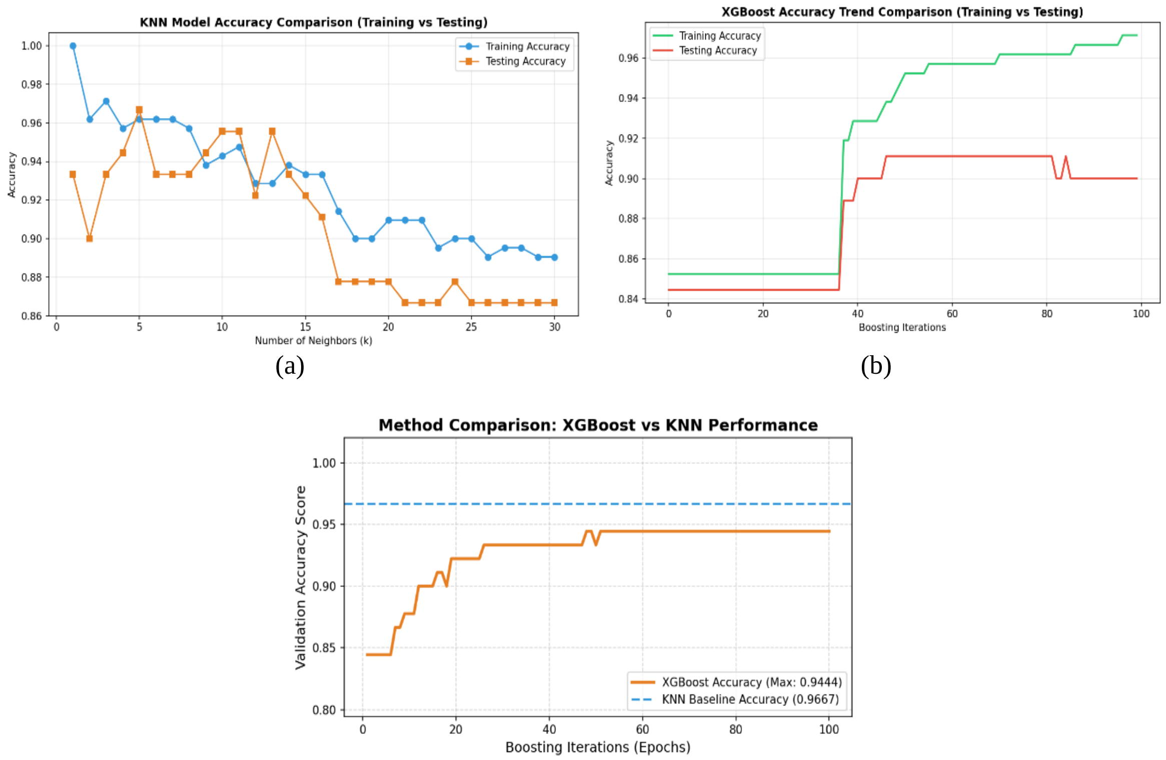


Figure 3. Comparative performance analysis: confusion matrices of KNN and XGBoost models for thermal state classification

The performance of the ML models was evaluated using confusion matrices for both the KNN and XGBoost algorithms, as illustrated in Figure 3. Based on the experimental results, the KNN model demonstrated superior performance in classifying the thermal patterns of the PV panels. In the training phase, KNN achieved an accuracy (acc) of 0.96, with a precision (pre) of 0.90 and an F1-score of 0.93. During testing, while there was a slight decrease, KNN maintained a robust accuracy of 0.93, with balanced precision and recall (rec) values of 0.87. The matrix reveals that KNN effectively distinguished between classes, with 11 correct predictions for normal states (Label 1) and 73 for high-temperature states (Label 4) in the testing set, showing minimal misclassification. In contrast, the XGBoost algorithm exhibited significantly lower predictive reliability for this specific dataset. Although it reached a testing accuracy of 0.84, a closer inspection of the confusion matrix shows a critical failure in class detection; the model failed to correctly identify any instances of the normal temperature state (Label 1), resulting in a precision of only 0.42 and an F1-score of 0.46. This indicates that while KNN is highly effective for energy conversion prediction through thermal imaging, XGBoost struggled with class imbalance or feature differentiation in this study. Consequently, the KNN algorithm is identified as the more reliable model for integration into the real-time PV monitoring and protection system. To complement the findings obtained from the confusion matrix analysis, Figure 4 illustrates the evaluation trends and validation performance of both classifiers.

To further analyze the performance characteristics of both classifiers, Figure 4 presents the evaluation trends obtained during model development and validation. Figure 4(a) shows the variation in KNN accuracy with different numbers of neighbors (k), indicating that the optimal k value achieved the highest validation accuracy of 0.9667. Figure 4(b) depicts the accuracy trend of the XGBoost model over boosting iterations, where the validation accuracy gradually improved and reached a maximum value of 0.9444. Furthermore, Figure 4(c) provides a direct comparison of the validation accuracies of KNN and XGBoost, confirming the more stable and superior performance of KNN for PV thermal pattern classification.



(c)

Figure 4. Performance evaluation metrics; (a) KNN accuracy vs. number of neighbors (k), (b) XGBoost accuracy trend over boosting iterations, and (c) validation accuracy comparison between XGBoost and KNN baseline

3.3. Development of integrated dashboard for on-grid photovoltaic power surveillance

The graphical user interface (GUI) is engineered to facilitate seamless, real-time monitoring of the on-grid PV system's performance via a web-based Thinger.io dashboard. This IoT-integrated platform is specifically designed to visualize critical electrical parameters, including voltage, current, and power, enabling users to manage energy consumption and system status effectively. As illustrated in Figure 5, the dashboard serves as a centralized surveillance hub, ensuring that all PV activities and protection triggers can be monitored directly through any internet-connected device.

The architecture presented in Figure 5 illustrates an integrated protection system that has undergone rigorous standardized testing to ensure its readiness for electrical installations. To enhance system reliability, a dual-relay redundancy configuration is employed: Relay 1 serves as the primary breaker, while Relay 2 acts as a fail-safe backup to guarantee isolation if the primary unit underperforms. The system is programmed to trigger a trip response once the current exceeds the 1.30 A threshold, with all electrical parameters-voltage, current, and power-monitored in real-time via the IoT dashboard. Beyond simple monitoring, the IoT integration facilitates the analysis of historical consumption patterns and enables early detection of overcurrent surges. This proactive diagnostic capability significantly mitigates the risk of component degradation, ensuring the long-term durability of on-grid PV assets.

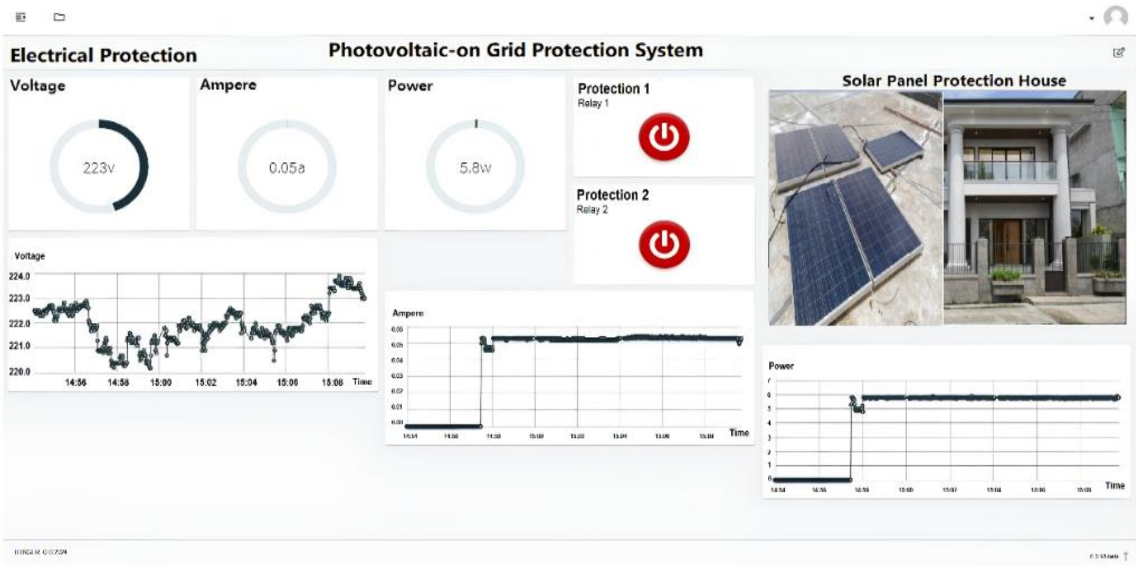


Figure 5. Monitoring display of protection system on grid-connected PV

4. CONCLUSION

This research successfully integrated an IoT monitoring and protection system into an on-grid PV installation. Based on ML analysis, the KNN algorithm proved far superior and more stable than XGBoost in classifying solar panel thermal conditions. Although XGBoost achieved a maximum accuracy of 94.44% in the iteration graph, the model failed to detect normal temperature classes in the confusion matrix test. In contrast, KNN delivered consistent performance with a test accuracy of 93% and a baseline accuracy of 96.67%, making it more reliable for detecting temperature anomalies between 25 °C to 48 °C. In terms of hardware, the PZEM-004T module demonstrated a very high level of precision with an average voltage error of only 0.23% and a current error of 1.75%. The developed dual-relay redundancy protection system also functioned optimally, cutting off the power supply when the current exceeded the 1.30 A threshold. All these parameters were integrated in real time through the Thinger.io dashboard, which not only facilitated monitoring but also minimized the risk of component damage in the PV power grid.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research presented in this paper focuses on the development and validation of ML for energy conversion prediction and PV-on grid protection system using IoT. This study involves the collection of technical sensor data and algorithmic processing for system protection and energy forecasting. It does not involve human subjects, animal testing, or the use of sensitive personal data. Therefore, formal approval from an institutional review board (IRB) or an Ethics Committee was not required for this study.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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