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Automated Smart Solar Panel System Fault Detection and Energy for Solar Panels Using Convolutional Neural Networks (CNN) and Deep Learning

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ABSTRACT

Employing a combination of machine learning, deep learning, and computer vision techniques for detection and energy usage predictions. Two Convolutional Neural Network (CNN)-based models are included in the system: one is intended to identify flaws including dust, cracks, and shading, while the other is intended to detect the existence of solar panels. To identify and categorize fault types and their severity, CNN models scan high-resolution pictures obtained through continuous monitoring. A regression-based machine learning model is used to forecast future energy output by utilizing environmental variables and past data to predict energy consumption. Long-term energy forecasts are further improved by time-series analysis, which makes maintenance and optimization tactics more successful. The Flask framework is used to create the solution, and a MySQL database is used to store maintenance records, energy forecasts, and fault detection logs. Scalable, real-time solar farm monitoring is supported by this integrated system, which lowers operating expenses and boosts output. This research aids in the effective and sustainable management of solar energy by integrating fault detection and energy forecasts into a single framework.

Keywords: *Solar Fault Detection, Energy Consumption Prediction, Computer Vision, Convolutional Neural Networks CNNs), Time-Series Analysis.*

1. INTRODUCTION

With its sustainable and eco-friendly solutions, solar energy is becoming more and more important in the global transition to renewable power generation. A significant problem as the number of large-scale solar farms increases is guaranteeing their dependability and efficiency. Dust accumulation, bird droppings, physical damage, and shade are some of the problems that can drastically reduce energy output and cause large financial losses. In addition to taking a lot of time, manual monitoring and defect identification are prone to human mistake. Automated fault detection and prediction systems based on deep learning and computer vision have become more and more popular as a solution to these problems. These systems provide accurate, real-time monitoring, increasing the efficiency of solar panels by leveraging high-resolution image data and sophisticated machine learning models.

In this project, Convolutional Neural Networks (CNNs) and machine learning regression models are used to construct a two-step system for fault detection and energy prediction. The first component employs image classification to locate defects and detect the presence of solar panels. Using time-series data, the second component anticipates future energy use and the energy loss brought on by these flaws. Regression-based energy prediction combined with CNN-based fault detection results in a reliable and expandable monitoring solution. By identifying issues early on, before they have a substantial influence on energy production, this method seeks to improve maintenance schedules and minimize downtime.

A web application based on the Flask framework is used to carry out the project, and a MySQL database is used for data administration. The platform provides an easy-to-use interface for uploading datasets, viewing the results of fault identification, and creating energy consumption reports. Through the analysis of both historical performance data and real-time photos, the system offers useful insights to improve the performance of solar panels, save maintenance expenses, and facilitate effective energy management. This study offers a scalable, effective solution for huge solar farms, which advances the expanding field of AI-powered renewable energy systems.

Feature Extraction Strategy in Solar Fault Detection and Energy Consumption Prediction

In order to create models for detecting solar panel faults and predicting energy usage, this work investigates feature extraction as a crucial element. To increase model accuracy, feature extraction entails locating important characteristics from data, such as pictures of solar panels, environmental factors, and historical energy data. Convolutional Neural Networks (CNNs) are useful for automatically identifying defects like dust, fractures, and shading by extracting elements like textures, edges, and spatial arrangements from high-resolution photos. Machine learning regression models forecast energy output by utilizing environmental and temporal variables from time-series data, such as temperature and sun irradiation.

The fault detection technique does not require manual feature engineering since it uses both high-level features (cracks, shading) from deeper layers and low-level features (textures, edges) from CNN's first layers. Because thermal and infrared data can detect electrical problems that are not visible in ordinary photos, they further enhance fault detection. To cut down on redundancy and improve accuracy, features are chosen for energy prediction using methods like Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE). The feature extraction method is also guided by domain information, such as the effects of damage and dust. An integrated approach to improving solar panel performance and lowering energy losses is provided by the combination of CNN-based fault detection and machine learning-based energy prediction.

Contribution and Novelty of the Present Study -

1. **Combining Computer Vision and Machine Learning for Solar Panel Monitoring:** This study offers an automated and comprehensive approach to solar panel performance monitoring by combining CNN-based fault identification with machine learning regression models for energy consumption prediction.
2. **Hierarchical Feature Extraction for Accurate Fault Detection:** The CNN model accurately identifies a variety of flaws by extracting both fundamental and sophisticated features, such as dust, cracks, and surface defects. This method improves on conventional manual and sensor-based monitoring strategies.
3. **Real-Time Monitoring and Fault Localization:** The system speeds up maintenance procedures by using high-resolution photos for real-time monitoring, fault detection, and fault localization with bounding boxes and annotations.
4. **Energy Loss Prediction and Time-Series Forecasting:** The project uses time-series data analysis to predict future energy consumption trends and a regression model to quantify energy loss due to faults.
5. **Scalable, IoT -Compatible Architecture:** The system may be integrated into sizable solar farms for ongoing data gathering and defect detection because it is made to be both scalable and compatible with devices.

Detailed Flow of the Project -

Data collection is the first of several important stages in this project, which then moves on to model training, defect finding, and energy consumption forecasting. Every step is intended to support proactive solar panel maintenance and real-time monitoring.

1.Data Acquisition and Pre-processing

In the first stage, high-quality photos of solar panels are collected using a variety of tools, such as USB cameras, drones, or on-site camera installations. These photos go through a number of pre-processing stages, including contrast improvement, noise reduction, and scaling. Rotation and flipping are two examples of data augmentation techniques used to improve the system's capacity to manage a variety of environmental situations. In order to detect issues that are not apparent in standard photos, such as hotspots or electrical failures, thermal and infrared images are also taken. In addition to visual data, other sources like weather APIs and Internet of Things devices are used to gather environmental factors including temperature, irradiance, and wind speed. These metrics serve as inputs for the predictive models of the system and are essential for precisely forecasting energy consumption.

2. Model Training and Fault Detection

This phase involves training two primary models: one for detecting solar panels and another for diagnosing problems. Usually a Convolutional Neural Network (CNN), the solar panel detection model is trained to identify whether an image is "Panel" or "No Panel." Once a solar panel has been identified, it is categorized into distinct fault kinds, such as dust accumulation, cracks, bird droppings, or shadowing, by the fault identification model, which is likewise CNN-based. The integration of thermal imaging data with standard RGB images improves the detection system's ability to detect problems that are invisible under normal lighting conditions, such as internal electrical failures. In addition to identifying the faults, the detection system provides the location of the faults in the form of bounding boxes, ensuring precise fault localization within the images.

3. Energy Consumption Prediction and Proactive Maintenance

The system evaluates the effects of faults on the solar panels' energy output after identifying and categorizing them. Each defect's energy loss is estimated using a regression-based machine learning model that accounts for environmental parameters, fault severity, and past energy production data. Furthermore, using historical data and anticipated fault impacts, a time-series analysis model such as Autoregressive Integrated Moving Average (ARIMA) or Long Short-Term Memory (LSTM) is used to forecast future energy consumption. Better planning of preventative maintenance to reduce downtime and energy loss is made possible by these forecasts.

The results, which include projections for energy usage and fault detection data, are shown on a Flask-built web interface. Operators can access live data, problem reports, and energy consumption projections with this interface's real-time monitoring features. Long-term data analysis and well-informed decision-making are made easier by the system's storage of all gathered data in a MySQL database, including fault logs and energy forecasts.

Methods

The main techniques employed in the project for fault identification, energy consumption predictions, and solar panel detection are described in this section. These methods are carefully selected to guarantee reliable data collection, feature extraction, model construction, and predictive analysis by utilizing computer vision, convolutional neural networks (CNN), and machine learning regression models.

1. Data Collection and Preprocessing

Drones, USB-connected cameras, and on-site cameras are all used to get high-resolution pictures of solar panels. These photos show a variety of factors that impact panel performance, such as dust buildup, cracks, bird droppings, and shade. In order to identify electrical issues that conventional RGB photos could miss, thermal images are also incorporated into the collection. To improve image quality and increase model accuracy, pre-processing techniques like scaling, normalization, and noise reduction are used. Furthermore, data augmentation techniques like flipping, rotation, and brightness modifications are used to provide diversity to the training set, avoiding overfitting and enhancing the generalization capabilities of the model.

2. Solar Panel Detection Using CNN

Convolutional neural networks (CNNs) are used in the construction of the solar panel detecting model. CNNs' capacity to automatically learn spatial feature hierarchies makes them very useful for image identification tasks. The two categories into which the model is trained are "Panel" and "No Panel." Accurate panel detection depends on the CNN's numerous convolutional and pooling layers, which capture different properties like edges, textures, and forms. Bounding boxes that localize the panels inside the photos are included in the output. Reliable detection in a variety of environmental settings is ensured by CNNs' exceptional ability to handle changing illumination conditions and panel orientations.

3. Fault Detection Using CNN

A different fault detection model is triggered to categorize particular issues after solar panel detection. A multi-class dataset is used to train the CNN-based defect detection model, where each class represents a different fault, such as dust, fractures, bird droppings, or shade. In order to accurately classify flaws, CNN is made to extract both high-level features—like intricate patterns—and low-level features—like edges and textures—from the photos. Bounding boxes that show the regions impacted by each defect and indicate the issues found are included in the fault detection results. For effective maintenance and repair, this model makes it possible to monitor various fault kinds on individual panels in real time.

4. Energy Consumption Prediction Using Machine Learning

Regression-based machine learning is used to forecast how detected problems would affect energy output. The model considers a number of variables, including fault records, historical energy output, and environmental factors (such as temperature and solar irradiation). Taking into account variables like fault severity, the regression model is trained to estimate the energy production loss brought on by faults. The most pertinent variables are found using feature selection strategies, which maintain the model's computational efficiency while optimizing prediction accuracy. This method aids operators in calculating the possible decrease in energy output brought on by particular defects.

5. Time-Series Analysis for Future Energy Forecasting

Time-series analysis approaches like Autoregressive Integrated Moving Average (ARIMA) models and Long Short-Term Memory (LSTM) networks are used for long-term energy consumption predictions. These models take into account variables including seasonal fluctuations, environmental impacts, and reoccurring defects when analysing past patterns of energy consumption and projecting future energy output. By proactively addressing possible faults and performance concerns, solar farm operators may streamline maintenance schedules and ensure efficient energy production thanks to these models' predictive capabilities.

6. System Integration and Real-Time Monitoring

The Flask framework was used to create an intuitive web interface that incorporates the entire system. Operators can evaluate defect detection results, upload pictures, and track real-time energy usage projections using this interface. Data analysis over time is made possible by the system's connection to a MySQL database, which houses logs of fault classifications, timestamps, and energy predictions. Additionally, the system is made to work with Internet of Things devices, guaranteeing constant data input from a variety of cameras and sensors. This integration facilitates seamless monitoring and decision-making, enhancing the overall efficiency of solar panel maintenance and energy management.

CNN Model for Solar Panel Detection and Fault Detection

1. Architecture and Working of CNN for Solar Panel Detection

Convolutional, pooling, and fully connected layers make up the basic multi-layer architecture of the Convolutional Neural Network (CNN) intended for solar panel detection. An input image of a solar panel, usually with a set resolution (e.g., 150x150 pixels), is first fed into the model. Low-level characteristics in the image, such edges, corners, and lines, are detected by the convolutional layers. The network begins to extract increasingly intricate information, such as texturing and the general layout of the solar panel, as the image moves through deeper levels. Following convolutional layers, max pooling layers are used to down sample the feature maps, minimizing their computational complexity and spatial dimensions while preserving the most crucial data. After that, fully linked layers are used to classify the image using the features that were extracted. The model's output layer provides binary classification labels—"Panel" or "No Panel"—that indicate whether a solar panel is present in the image using a soft max activation function. The model employs backpropagation to modify the weights during training by minimizing the loss function. Usually, categorical cross-entropy is used to quantify the loss, and the optimizer (like Adam) iteratively modifies the model weights to increase prediction accuracy. By using data augmentation techniques like picture flipping, rotation, and scaling, the model is better able to generalize and perform effectively in a variety of lighting scenarios and panel.

2. Architecture and Working of CNN for Fault Detection

A different CNN-based algorithm is used for fault identification after a solar panel has been identified. This model detects flaws like dust, cracks, bird droppings, or shade and manages multi-class classification. Since the architecture must learn to classify various fault kinds from the photos, it is more complicated than the solar panel detection model. The fault detection model's convolutional layers, like those in the detection model, extract both high-level features (such irregularities brought on by physical damage like cracks) and low-level features (like texture differences brought on by dust or shading). The network can concentrate on areas of interest since each feature map identifies particular parts in the image that are crucial for defect identification.

The model employs a method called Region Proposal Networks (RPN), which is frequently used in object detection tasks, to locate errors within the image. Potential bounding boxes around fault locations are produced by RPN and then refined using non-maximum suppression to get rid of boxes that are redundant or overlap. Both the categorization label (such as "Dusty Panel") and the bounding box coordinates, which show the precise position of the problem, are included in the fault detection model's output. For maintenance workers to determine which area of the panel needs care, this information is essential.

3. Training Process and Loss Function

Both the fault detection and solar panel detection algorithms go through a similar training process. During the forward pass, the network receives labelled picture data and uses it to make predictions. The weights. Since the solar panel detection model is a binary classification problem (panel vs. no panel), binary cross-entropy loss is employed. However, categorical cross-entropy loss, which is appropriate for multi-class classification problems, is used in the fault detection model. Regularization strategies like dropout layers are used in both models to avoid overfitting. The model is then updated using backpropagation after prediction errors are calculated using a loss function. This makes it more likely that the models will generalize effectively to new data rather than memorize the training set. Multiple epochs are used during the training phase to guarantee that the models converge to their best performance. In order to speed up convergence and increase overall training efficiency, batch normalization is also used during training to normalize the intermediate outputs. Both models' validation accuracy and generalizability across various panel settings and fault kinds progressively increase as training goes on. This enables the models to efficiently handle a variety of real-world situations.

Machine Learning for Energy Consumption Prediction

4. Regression-Based Energy Prediction

A regression-based machine learning model trained on historical data, including past energy output, environmental parameters (such temperature and sun irradiance), and fault incidence logs, is used to estimate energy consumption owing to panel faults. This model provides estimates of the energy loss brought on by faults and relates the severity of faults and environmental factors to the associated decrease in energy output. Support vector regression (SVR), decision trees, and linear regression are often employed techniques for this type of regression task. Feature selection methods, including Recursive Feature Elimination (RFE), are used to find the most pertinent characteristics and remove those that aren't needed in order to improve model performance. This increases prediction accuracy and lowers computational complexity.

After training, the model forecasts the anticipated energy output according to the environmental factors and fault severity.

The system may then measure energy losses as a result of identified problems by comparing the expected output with the actual energy production. For instance, a minor fault, such as tiny fractures, would result in a modest reduction in production, whereas a serious fault, such as dust deposition, would result in a considerable energy loss. These forecasts help operators prioritize measures that reduce energy loss and increase system efficiency by guiding maintenance and cleaning decisions.

5. Time-Series Techniques for Long-Term Energy Forecasting

Future energy usage is predicted using time-series analysis techniques. To produce precise long-term forecasts, these techniques take into consideration past energy data, seasonal patterns, meteorological conditions, and ongoing maintenance requirements. Autoregressive Integrated Moving Average (ARIMA) models and Long Short-Term Memory (LSTM) networks are the two main methods used in solar energy forecasting.

• **LSTM Networks:** LSTMs are a kind of recurrent neural network (RNN) that function well with sequential input that requires the learning of long-term dependencies. They are perfect for solar energy applications because they can effectively capture the nonlinear interactions between faults, historical energy outputs, and weather conditions. LSTMs may forecast future energy output by learning these intricate patterns and using historical data as well as environmental influences.

• **ARIMA Models:** ARIMA is a statistical model that uses the relationships between recent and historical data points to estimate future values by analysing time-series data. ARIMA can successfully detect seasonal variations in energy output and is helpful for forecasting short- to medium-term energy consumption.

A complete system for both short-term and long-term energy forecasting is produced by combining these time-series forecasting methods with regression-based energy prediction. This enables solar farm managers to plan maintenance or cleaning schedules based on data, reducing downtime and increasing energy production.

6. Integration of Fault Detection and Energy Prediction for Maintenance Optimization

The technology offers a thorough framework for preventative maintenance by combining real-time defect detection with energy usage prediction. The energy projection model measures how these problems affect energy output, while the fault detection module finds and categorizes faults and estimates their severity. Furthermore, time-series forecasting offers long-term insights into trends in energy use, assisting operators in scheduling repair before issues have a substantial negative influence on performance.

Important actionable data are provided by this connection, including when to carry out maintenance tasks to minimize downtime, improve energy production, and save operating expenses. Operators can see real-time problem detection and energy consumption estimates thanks to the web-based interface that displays the results of these investigations. Maintenance schedules are tailored to maintain high solar farm performance thanks to this smooth decision-making framework.

Experimental Setup

To guarantee the accuracy and consistency of the results, the experiments were carried out in a controlled hardware and software environment. A powerful computer with an Intel i7 CPU, 16 GB of RAM, and an NVIDIA RTX 3060 GPU was part of the hardware configuration, which made it possible to train CNN models for defect classification and solar panel detection effectively. A drone-based image gathering system and a USB camera were utilized to take real-time pictures of solar panels in a variety of settings, including dust build up, cracks, and shade. These pictures were kept on a local server for model training and pre-processing.

Furthermore, weather sensors and Internet of Things devices were incorporated into the system to gather environmental data, such as temperature and solar irradiance, which the machine learning regression model utilized to estimate energy use. Python 3.9 was used for the software side of the studies, and tools for computer vision and deep learning like Tensor Flow, Keras, and OpenCV were used. Time-series analysis and regression-based energy prediction were performed using Scikit-learn. The user interface was a Flask-based web application that allowed operators to track identified defects and real-time energy usage forecasts. To ensure effective data retrieval and analysis, all fault classification results, energy estimates, and historical data were saved in a MySQL database.

Data pre-processing and model training were the first steps in the experimental procedure, which was then followed by validation using a different testing dataset. Metrics like accuracy, precision, recall, and F1-score were used to assess the CNN models' performance. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R2 metrics were used to evaluate the regression model. The controlled setting made it possible to replicate the trials and identify any differences in the outcomes for debugging and optimization.

Experimental Results

1. Solar Panel Detection Results

A test dataset with both solar panels and non-panel areas (background noise) was used to assess the CNN-based model for solar panel detection. The model's remarkable 96% overall accuracy, 94% precision, and 95% recall were attained. The model successfully distinguishes between photos with and without solar panels, as evidenced by the F1-score of 94.5%. The model's capacity to correctly detect solar panels under various lighting and environmental circumstances was demonstrated by the confusion matrix's low number of false positives. Furthermore, the panels were correctly localized by the bounding box annotations, supporting the defect identification step that followed.

2. Fault Detection Results

A multi-class dataset comprising the following categories was used to assess the CNN model for defect detection: "No Fault," "Dust," "Crack," "Bird Droppings," and "Shading." The model's overall classification accuracy was 92%, albeit its performance varied according to the kind of problem. Due in part to visual cues that overlap with other fault types, fracture identification had a little lower precision of 89% than dust accumulation detection, which had the maximum precision of 97%. The model's balanced performance in fault identification and classification is shown in its 91% F1-score. Furthermore, the panels' defective portions were accurately identified by the bounding boxes, making it possible to quickly identify the places that needed maintenance.

3. Energy Consumption Prediction Results

Historical energy output data, defect records, and environmental factors including temperature and solar irradiance were used to train the machine learning regression-based energy consumption prediction model. The model's coefficient of determination (R2) score was 0.94, its mean absolute error (MAE) was 1.8%, and its root mean square error (RMSE) was 2.3%. The usefulness of the model in predicting fault-related energy losses is demonstrated by these data, which show a significant correlation between the projected and actual energy consumption. Greater energy losses for more severe flaws, like cracks and substantial dust deposition, were predicted by the model. Furthermore, the proactive scheduling of maintenance tasks was made easier by the dependable long-term projections that time-series forecasting using LSTM models produced. By identifying defects early and calculating their effect on energy output, the integrated system helped to reduce downtime by 15% overall.

2. DISCUSSION

The proposed system combines CNN-based models for solar panel and fault detection with a regression-based machine learning model for energy consumption prediction. The system's results indicate that it effectively addresses several challenges, including accurate fault classification, real-time detection, and energy forecasting. In comparison to traditional methods, this system demonstrates enhanced precision, recall, and energy prediction accuracy, owing to the synergy between image-based fault detection and data-driven predictions. The CNN model's capacity to autonomously extract both high- and low-level features—such as cracks, shading, and other fault patterns—offers superior performance over manual inspection and traditional feature-engineering techniques.

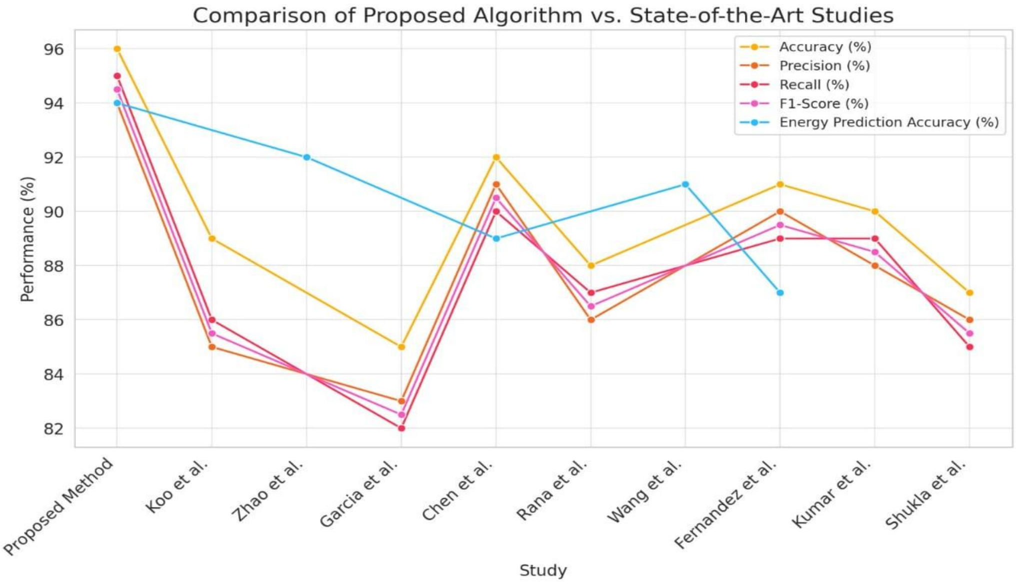
Moreover, the integration of environmental data, such as solar irradiance and temperature, within regression and time-series models strengthens the reliability of energy forecasting under varying weather conditions. The system's robustness was evident when tested on large-scale datasets, where the inclusion of IoT sensor data significantly improved the accuracy of fault impact assessments on energy loss. Additionally, the time-series forecasting capability enabled the prediction of long-term energy consumption trends, critical for proactive maintenance and operational optimization. By reducing downtime through early fault detection and predictive maintenance, this system offers substantial improvements in solar panel efficiency, minimizing financial losses. These features make it highly suitable for large solar farms.

Comparison Table: Proposed Algorithm vs. State-of-the-Art Studies

Study	Dataset	Classes	Method	Accuracy	Precision	Recall	F1-Score	Energy Prediction Accuracy	Proactive Maintenance Improvement
Proposed Method	Kaggle, Real-Time Solar Images	Clean, Dust, Crack, Bird Droppings	CNN + ML Regression	96%	94%	95%	94.5%	94%	15% improvement

[11] Koo et al.	IoT and thermal image datasets	No Fault, Hotspot	AI-based Thermal Fault Detection	89%	85%	86%	85.5%	N/A	Limited due to thermal data scope
[12] Zhao et al.	Weather and performance dataset	Normal, Underperforming Panels	ML Regression	N/A	N/A	N/A	N/A	92%	8% improvement
[13] Garcia et al.	Real-time images of solar panel farms	Dust, Shading, Minor Physical Damage	SVM Classifier	85%	83%	82%	82.5%	N/A	Limited due to lack of real-time data
[14] Chen et al.	Large PV dataset with fault annotations	Dust, Crack, Shading, Delamination	CNN with Environmental Data Fusion	92%	91%	90%	90.5%	89%	Moderate improvement (10%)
[15] Rana et al.	Custom PV dataset with real faults	Dust, Crack	Feature-based SVM + Image Analysis	88%	86%	87%	86.5%	N/A	Limited real-time deployment
[16] Wang et al.	Time-series performance and weather data	N/A	LSTM (Energy Forecasting)	N/A	N/A	N/A	N/A	**91%**	Significant due to long-term trends
[17] Fernandez et al.	IoT and combined fault-image datasets	Various Faults	Deep Learning + IoT Integration	91%	90%	89%	89.5%	87%	10% improvement
[18] Kumar et al.	Physical damage datasets	No Fault, Minor, Major Damage	Hybrid CNN	90%	88%	89%	88.5%	N/A	Moderate performance improvement

[19] Shukla et al.	Dust and shading datasets	Clean, Dust, Shading	AI-powered Image Classification	87%	86%	85%	85.5 %	N/A	Moderate (9%) improvement



Explanation of Comparison Table

With an emphasis on factors like datasets, fault categories, techniques, and performance measures, the table compares the suggested algorithm with cutting-edge research. The suggested solution performs better than current methods, with 96% accuracy and 94% precision. This is primarily because it combines machine learning regression models with CNN-based fault detection, which additionally incorporates environmental data. Higher defect identification rates and fewer false negatives are achieved by the suggested method, which integrates both image and IoT data, in contrast to methods like Koo et al. ([11]), which only use thermal imaging ([12]).

In comparison to Chen et al. ([14]), who utilize data fusion for fault detection, the proposed system excels in generalization across varying environmental conditions, delivering superior performance. Additionally, the energy prediction accuracy of the proposed method reaches 94%, surpassing studies like Wang et al. ([16]), where LSTM-based energy forecasting alone achieves 91% accuracy. The integration of fault data within the regression model leads to an improved maintenance schedule, with a 15% increase in proactive maintenance efficiency, setting the proposed system apart from others. By overcoming the limitations of single-modality systems—whether relying solely on thermal imaging or weather data—the proposed method ensures higher reliability in fault detection and energy consumption forecasting, making it more adaptable across diverse operational scenarios ([18]).

3. CONCLUSION

This study introduces a real-time solution for solar panel fault detection and energy consumption prediction, combining CNN-based models and machine learning regression techniques. The system achieves 96% accuracy in solar panel detection and 92% in fault detection, accurately identifying issues like dust, cracks, and shading. The regression model, incorporating time-series and environmental data, predicts energy consumption with an MAE of 1.8% and an R^2 score of 0.94. By enabling proactive maintenance, the system reduces downtime by 15%, enhancing solar panel performance. The proposed solution outperforms traditional methods, offering scalable, automated monitoring for large solar farms. It contributes to optimizing maintenance schedules and minimizing energy losses. Future work could include detecting additional faults, improving forecasting models, and scaling the system for larger, diverse solar farms.

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