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SOLAR PANEL FAULT DETECTION SYSTEM

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ABSTRACT

Solar energy surpasses all other sources of energy generation and is the cleanest, most sustainable source of energy. Generally speaking, solar panels don't require constant maintenance and require little care. But because a malfunctioning panel might impact the generation of the entire array, a number of problems could result in a production loss of up to 20 percent. If the power plant is properly maintained on schedule, it will live longer and produce more electricity overall, which will reduce the cost of repairs. Remote solar plantations are more difficult for humans to access, and large solar farms necessitate costly and time-consuming manual panel monitoring. In this article, thermal images from an unmanned aerial vehicle (UAV) fitted with infrared sensors are used to demonstrate deep learning-based techniques for identifying issues in solar systems. With the help of previously observed voltage and current values, the software that will be created as a result of this research and work will be able to precisely identify internal solar panel faults and forecast how much solar energy will be generated as a result of these defects. In the future, this software might also be able to recognize flaws in solar panel photos.

Keywords: Maximum Power Output, Artificial Neural Network, Deep Learning, Solar Panel Fault Detection, Preprocessing, and Photovoltaic-Cells.

I. INTRODUCTION

The best performance in any power production system, including photovoltaic (PV) systems, depends on fault detection and prompt troubleshooting. Specifically, the objective of any commercial power-generating house is to maximize power generation, minimize energy loss and maintenance expenses, and ensure the facility operates safely. Given the variety of problems and failures that PV systems can experience, early detection of these issues is essential to reaching the objective. The installation of ground fault detection interrupters (GFDI) and overcurrent protection devices (OCPD) in photovoltaic installations is mandated by the US National Electric Code in order to protect against specific problems. Nevertheless, the Bakersfield Fire case from 2009 and Mount Holly from 2011 demonstrate how these instruments are unable to identify the blame in those specific situations. Faults in a PV system can arise from either physical, environmental electrical conditions. In order to identify malfunctioning modules and further categorize the problem type that applies to all environmental situations, we suggest an intelligent fault diagnosis model.

The model utilizes the machine learning and follows the supervised learning approach. Using historical data of various faulty and normal states under various environmental conditions, it has been rigorously trained.

II. METHODOLOGY

1. Data Collection: Data collection is a process of systematically collecting and calculating information from multiple sources to get an absolute and precise picture of an area of interest. For the proposed system, we are using varied number of dataset for training the machine learning model.
2. Data Preparation: Data preparation is a process of getting data ready to By cleaning and modifying raw data. This step is performed before processing and analysis and involves reformatting of data, rectification of data and the merging of data sets to improve the data.
3. Data Exploration: Data exploration is a process of understanding the data by visually representing it in the form of charts, histograms, graphs, etc.
4. Data Mining: Data mining is a procedure used to convert raw data into helpful information. It discovers patterns in large set of data using software.
5. Information Retrieval: Information retrieval (IR) is a software program that works with the retrieval, evaluation, organization and storage of information and fulfills the information need from within the collection of resources.

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6. Evaluation: Evaluation is a procedure that includes analyzing and collecting information about programs tasks, characteristics and result.

Deep Learning

Deep learning is a type of machine learning that uses artificial neural networks to learn from data. Artificial neural networks are inspired by the structure and function of the human brain,and they are able to learn complex patterns from data. Deep learning has been used to achieve state-of-the-art results in a variety of tasks, including image recognition, natural language processing, and machine translation.

Deep learning is also being used to develop new and innovative applications in a variety of fields, including healthcare, finance, and transportation.

In the context of panel fault detection, deep learning can be used to develop algorithms that can automatically detect faults in the data uploaded. Deep learning algorithms can be trained on large datasets of current vs voltage readings of solar panels. These algorithms can be used to automatically identify solar panel problems once they have been trained.

Deep learning-based Solar Panel fault detection algorithms have the potential to revolutionize the way that faults are detected and managed. These algorithms can automate the clerical fault detection process, improve the accuracy of early detection, and enable technicians to make more informed decisions about grid management.

Here are some of the benefits of using deep learning for Solar Panel Fault detection:

- ➢ Accuracy: Deep learning algorithms can be trained to achieve high levels of accuracy in detecting Major faults, even in challenging conditions.
- ➢ Speed: Deep learning algorithms can automatically detect faults in solar panel grid, which can save technicians a significant amount of time.
- ➢ Early detection: Deep learning algorithms can detect faults in their early stages, which can help to reduce power loss.
- ➢ Scalability: Deep learning algorithms can be scaled to detect faults in large areas of Ground connected Grid system.

Deep learning-based solar panel fault detection system are still under development, but they have the potential to have a major impact on Power generation. These systems can help technician to reduce power losses, improve output, and make more sustainable energy resource generation.

The deep learning model is trained by iteratively adjusting the weights of the artificial neurons. The goal is to minimize the error between the model's predictions and the correct answers. Once the model is trained, it can be used to make predictions on new data.

In a number of tasks, such as machine translation, picture identification, and natural language processing, deep learning has produced state-of-the-art outcomes. Deep learning is also being used to develop new and innovative applications in a variety of fields, including healthcare, finance, and transportation.

- ➢ Accuracy: Deep learning models can be trained to achieve high levels of accuracy in a variety of tasks.
- ➢ Scalability: Deep learning models can be scaled to handle large datasets and complex problems.
- ➢ Flexibility: Deep learning models can be adapted to a wide range of tasks and data types.

- **Deep learning in Solar Panel Fault Detection.**

1. Artificial Neural Networks:-

ANNs are designed to automatically and adaptively learn patterns directly from data. Artificial layers apply a set of learnable filters (kernels) to input datasets. The features are covered by these filters, and variables, performing element-wise multiplications and accumulating the results to create a feature map. These maps capture various features at different levels of abstraction.

1. Pooling Layers:-

Pooling layers preserve crucial information while reducing the feature maps' spatial dimensions.Common pooling operations include max pooling (selecting the maximum value in a certain region) and average pooling (calculating the average value).

2. Activation Functions:-

Non-linear activation functions (e.g., ReLU - Rectified Linear Unit) are applied after each pooling layer to introduce non-linearity into the model. This allows ANNs to learn complex patterns and relationships in the data.

3. Fully Connected Layers:-

Fully connected layers follow a number of pooling layers. These layers perform classification based on the features learned in the previous layers. They are typical dense layers where all neurons are connected.

4. Dropout:-

Dropout layers are employed to mitigate overfitting. During training, random neurons are "dropped out," meaning they are temporarily ignored, reducing co-dependencies and encouraging the network to learn more robust features.

5. Batch Normalization:-

Batch normalization layers help in stabilizing and accelerating the training process. They normalize the activations of each layer in a mini-batch, reducing internal covariate shifts and aiding in faster convergence.

6. Loss Function:-

In the context of solar panel fault detection, a categorical cross-entropy loss function is commonly used. This measures the difference between the predicted probabilities and the true labels. Optimization Algorithm:-

Stochastic Gradient Descent (SGD) or advanced variants like Adam are popular optimization algorithms used to update the weights of the network during training. The loss function is minimized by these algorithms.

7. Output Layer:-

The output layer consists of neurons equal to the number of disease classes. It uses a softmax activation function to provide a probability distribution over the different disease classes.

III. MODELING AND ANALYSIS

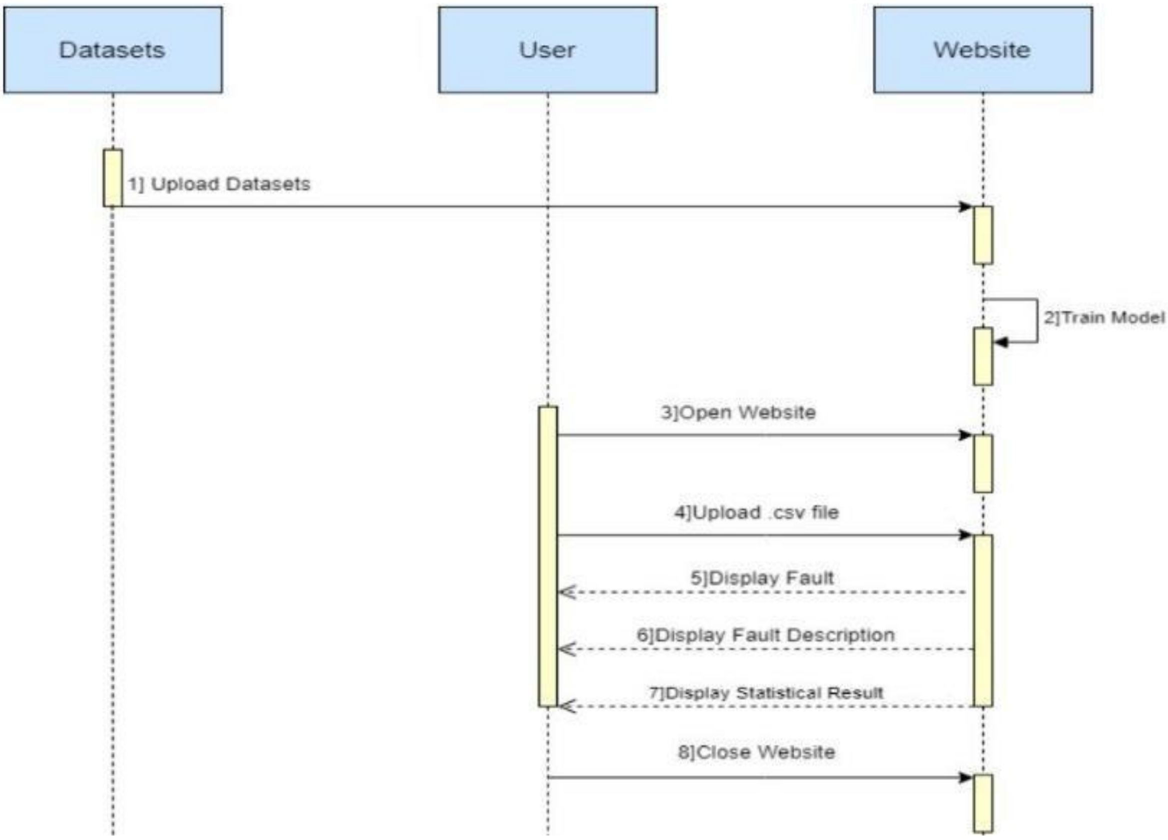

Figure 1: Sequence Diagram of Solar Panel Fault Detection System.

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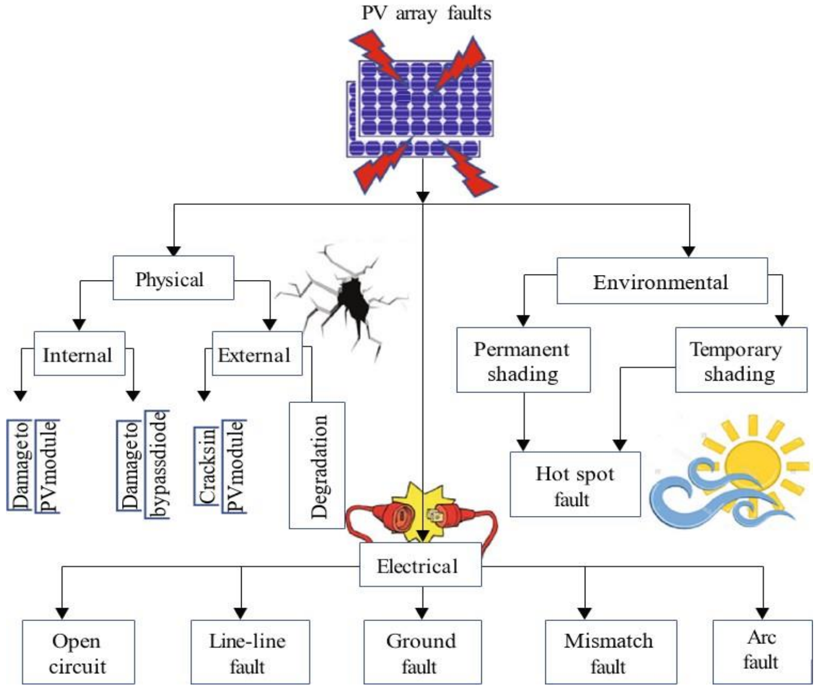

Figure 2: PV Array Faults

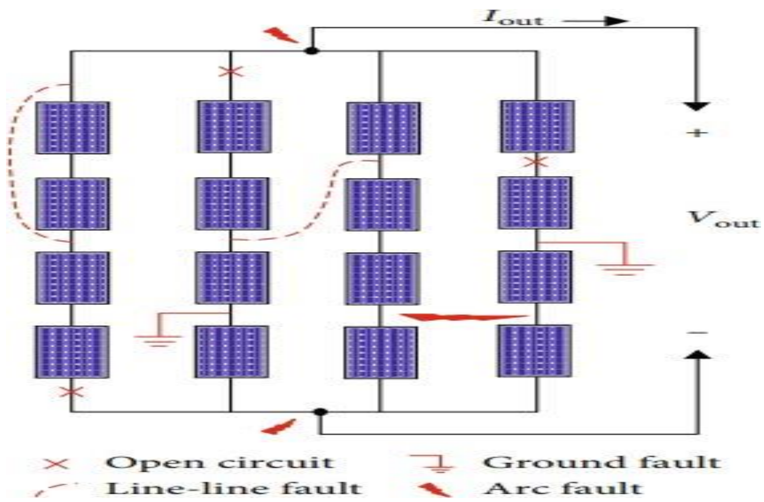

Figure 3: Main types of Electrical Faults.

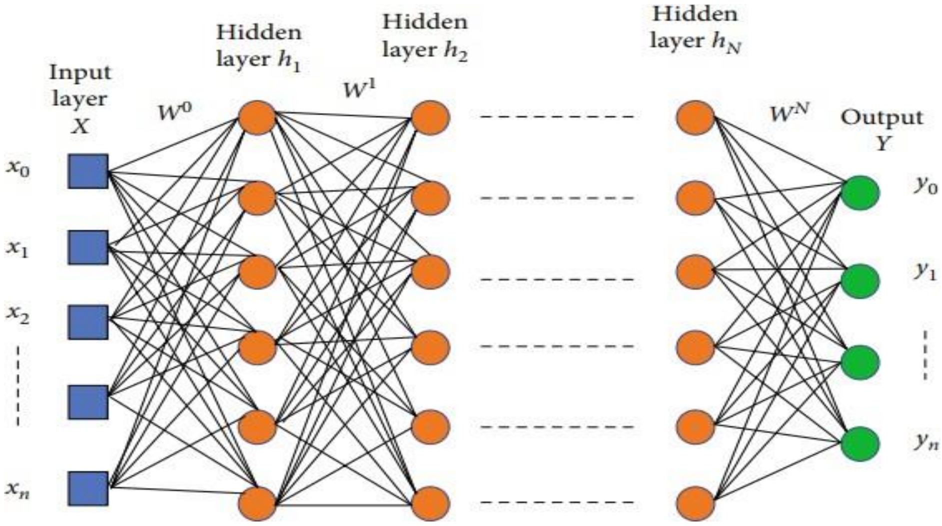

Figure 4: Multi-Layer Perceptron used for Model.

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IV. RESULT AND DISCUSSION

1. Experimental Results. Data without any hardware or circuit modifications in the PV system were classified as "normal" for the purposes of gathering experimental data. Several deliberate faults in the PV array's circuit were made in order to gather fault data. the variance, minimum range, and maximum range of the data gathered under various environmental circumstances in order to train the suggested model. We set up a PV system that is used in the actual power generation business with the standards for the experimental verification. The winter dataset has significantly more variation than the summer dataset, necessitating extra care during model training to provide accurate predictions. The input variable x1 and x2 have normal and line-line fault dataset features over the summer and winter seasons on sunny and cloudy days, respectively. In absolute terms, the irradiation intensity appears to have the highest variance level among the input dataset. However, visualizing the current sensor (SI1/SI2) data would make much sense since its relative variance (σ2 x/x) was the highest among other input variables. During the winter, it is difficult to differentiate between "normal cloudy" and "line-line" fault data since they frequently overlap.
2. Discussions. Recently, ML-based methods for defect diagnosis and detection have been used, and this trend is anticipated to continue in the years to come. The training data has a significant impact on the ML-based model's quality. Research indicates that models trained using PV data typically have extremely high forecast accuracy rates, sometimes reaching 100%. We tested our dataset with other machine learning models and got quite high accuracies in each case. Finding the key characteristics in the input dataset is crucial when building a machine learning model.

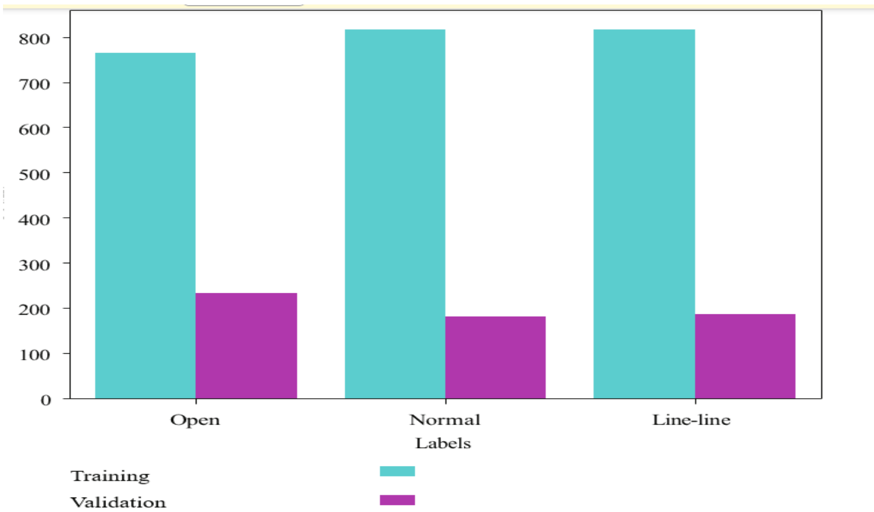

Figure 5: Training-test validation dataset of the collected data

V. CONCLUSION

PV systems are susceptible to a variety of defects and failures, and the effectiveness and safety of the systems depend heavily on the early detection of these defects and failures. DL-based fault detection models are trained with data and provide prediction results with very high accuracy. However, data based fault detection models for PV systems can sometimes give false predictions, especially when the environmental parameters are not taken intoconsideration. This paper developed an intelligent fault detection model for PV arrays based on ANN for accurately classifying the fault types. The model was trained on a sizable dataset that included a range of data values from summer and winter months under various environmental circumstances. For the experimental verification, various fault state and normal state datasets are collected from 1.8 kW (six 300W panels, 2 parallelly connected lines, each with 3 serially connected panels) into the grid-connected PV system. The model was trained on a sizable dataset that included a range of data values from summer and winter months under various environmental circumstances.

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