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SIGNAL TO IMAGE TRANSFORMATION FOR PV FAULT DIAGNOSIS :ML PREP

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Abstract

This study explores various techniques for transforming 1-dimensional time-series data into 2-dimensional images, preparing for the application of machine learning models designed for 2D data. Eight distinct methods are introduced, including recurrence plots, Markov transition, Gramian angular field, spectrogram, heatmap, direct plot, phase space transformation, and Poincaré plots. These methods are tested using data from a Modeled photovoltaic (PV) Grid connected system, specifically simulating a shorted string fault and a no-fault condition. The fault and no-fault responses are captured with a fixed window size of 256 sample points, consistently applied across all methods. All transformation method is tested through python 3 programming using a laptop with minimal computing capability. The generated image of each transformation may contain 1-channel image in grayscale or 3-channel **RGB i**mage. Dimension of the generated image can be increase or decrease during saving process. Each method produces a unique visual representation of the shorted string fault and a no-fault, demonstrating diverse perspectives in transforming 1D time-series data into 2D images for subsequent machine learning applications.

Keywords: Deep learning, Convolutional Neural Network, Image processing, Machine Learning, Support Vector Machine, K nearest Neighbour , Sensors to Detect the signals .

1.INTRODUCTION

Various applications of artificial intelligence (AI) in machine learning (ML) and deep learning (DL) across different disciplines are steadily increasing. One significant area where AI is applied is within the various disciplines and sub-disciplines of the power system, specifically addressing microgrids, renewable energy sources (RES), and the power utility grid . AI applications in these areas include optimization techniques to enhance power quality generation, control strategies, and the diagnosis of faults and failures. Due to the commitment of both developed and developing countries to the Kyoto Protocol, efforts to reduce CO2 emissions in power generation have been actively pursued. Consequently, the incorporation of RES into power generation systems, as an alternative to traditional energy sources like coal and fossil fuels, is being implemented. Some of these RES include geothermal, wind, biofuel, and solar . Among them, solar energy production through photovoltaic (PV) generation systems is growing faster than others due to its advantages including ease of installation, noiselessness, cost effectiveness, easy integration, low maintenance, absence of pollution, reliability, and an essentially unlimited source. Similar to other systems, PVS will eventually malfunction. The primary cause of these failures is a variety of defects that arise in various PV parts or components, including converters, inverters, interconnections, protective devices, and PV modules External operating conditions, including dirt or dust in the modules failures of the converter and/or inverter, shading conditions, manufacturing mismatches, and module aging, are the main causes of these issues .Lineto-line faults, arc faults, ground faults, and mismatch faults are the four main types of catastrophic defects in a PVS .These faults when not attended immediately may cause fire, reduce revenues, and sometimes may cause loss of lives .Therefore, it is necessary to detect and classify these faults to know appropriate steps to do when fault occurs. PV fault diagnosis also helps in understanding the nature of fault to implement preventive measures in preventing to happen again. In addition, strategies to counteract these faults can also be developed. Furthermore, it helps in improving the efficiency and longevity of the PV system. In the review presented in ,various methods of photovoltaic (PV) fault diagnosis through machine learning (ML) and deep learning (DL) have been discussed. Some of the methods utilized for PV fault diagnosis involve DL models such as VGG16, VGG19, 3DCNN, ResNet, AlexNet, GoogleNet , and vision transformers . These DL architectures typically accept 2D or 3D images, often obtained through aerial or on-site photography using standard cameras or thermal imaging equipment (infrared cameras). Apart from using images from standard or infrared cameras, different electrical parameters of the PV system acquired by sensors, such as DC voltage (V), current (I), and power (P), can also be employed. However, these parameters are presented as time-series signals, meaning responses are in the form of voltage, current, or power versus time measurements. In other words, the Additionally, when transforming a 1D signal to a 2D image with the same length in terms of sample points (1D signal) to dimensions (2D image) the resulting 2D image contains much more information Consider, for instance, the transformation of a 1D power signal with 512 sample points into a 2D image.

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In this case, the resulting image dimensions expand to a size of 512 by 512 pixels. This augmentation in dimensions proves beneficial as it allows for a more detailed representation, enhancing the features that can be learned from the data. Moreover, the utilization of unmanned aerial vehicles to collect RGB or infrared (IR) image data is contingent on weather conditions and may not effectively identify hidden faults, which are often only discernible through electrical-based methods. To address this limitation, the presented work introduces several methods for transforming 1D signals into 2D images, offering potential applications in photovoltaic (PV) fault diagnosis.

2. LITERATURE SURVEY

1.Ying-Yi Hong Rolando

Photovoltaic (PV) fault detection and classification are essential in maintaining the reliability of the PV system (PVS). Various faults may occur in either DC or AC side of the PVS.

The detection, classification, and localization of such faults are essential for mitigation, accident prevention, reduction of the loss of generated energy, and revenue. In recent years, the number of works of PV fault detection and classification has significantly increased.

These works have been reviewed by considering the categorization of detection and classification techniques. This paper improves of the categorization of methods to study the faulty PVS by considering visual and thermal method and electrical based method.

Moreover, an effort is made to list all potential faults in a PVS in both the DC and AC sides. Specific PV fault detection and classification techniques are also enumerated.

A possible direction for research on the PV fault detection and classification, such as quantum machine learning, internet of things, and cloud/edge computing technologies, is suggested as a guide for future emerging technologies.

2 .Zhao et al. – Wavelet Transform-Based Fault Diagnosis

Method: Zhao et al. proposed using Continuous Wavelet Transform (CWT) to transform voltage and current signals into time-frequency images. The images were then fed into a Convolutional Neural Network (CNN) for fault classification.

Contributions: Their work demonstrated that this transformation improves fault detection accuracy, enabling the identification of faults such as shading, inverter malfunction, and panel degradation.

Key Result: The method showed a significant improvement in fault classification performance compared to traditional time-domain analysis.

3. Nguyen et al. – Spectrograms for Fault Diagnosis

Method: Nguyen et al. applied Short-Time Fourier Transform STFT to current and voltage signals to produce spectrograms. These spectrograms were then used as images for fault detection.

Contributions: They explored how spectrograms, which capture both frequency and time information, could be used to detect anomalies such as inverter failures or short-circuits in PV systems.

Key Result: Their study confirmed that spectrogram-based images, when analyzed with CNNs, significantly enhanced the detection of transient faults, yielding faster and more accurate diagnosis.

4. Kumar et al. – Time-Frequency Representations for Anomaly Detection

Method: Kumar et al. utilized Wavelet Packet Transform (WPT) to convert time-domain signals (voltage and current) into 2D images. These images were then classified using machine learning techniques, including CNNs.

Contributions: Their work focused on detecting anomalies in PV systems by analyzing both steady-state and transient fault conditions. The authors emphasized that converting signal data into images allowed better feature extraction for fault diagnosis.

Key Result: Their method showed a notable improvement in fault diagnosis over conventional time-domain analysis by providing richer feature representations.

5. Sengupta et al.– I-V Curve Analysis with Image Representations

Method: Sengupta et al. explored using I-V characteristic curves (current-voltage curves) for fault detection. The I-V curves were transformed into image representations, capturing the performance of the PV system under various fault conditions.

Contributions: The authors applied deep learning algorithms, including CNNs, to these transformed images to identify faults such as module degradation or shading effects.

Key Result: Their approach demonstrated that the image representation of I-V curves provided enhanced diagnostic capabilities and could detect faults related to partial shading and module degradation.

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6. Li et al. – Image Mapping of Signal Data

Method: Li et al. proposed a technique for mapping time-series signals (voltage and current) directly into 2D matrix images. The method employed Principal Component Analysis (PCA) to reduce the dimensionality of the signal data before mapping it to an image.

Contributions: Their work highlighted that this signal-to-image transformation method preserved key features in the data, which were later processed by deep learning models (such as CNNs) for fault classification.

Key Result: The method was shown to provide accurate fault diagnosis, particularly in detecting inverter malfunctions and performance degradation.

3. PROPOSED METHODOLOGY

The Proposed system for photovoltaic fault diagnosis leverages advanced technologies such as machine learning and Internet of Things (IoT) devices to enhance accuracy and efficiency. By utilizing real-time data collection and analysis, the system can quickly detect and diagnose faults, minimizing downtime and maintenance costs. Automated processes reduce the risk of human error and improve consistency in fault detection. Additionally, the integration of predictive analytics allows for proactive maintenance, ensuring optimal performance and longevity of the photovoltaic system. The proposed system for photovoltaic fault diagnosis leverages advanced technologies such as machine learning and Internet of Things (IoT) devices to enhance accuracy and efficiency. By utilizing real-time data collection and analysis, the system can quickly detect and diagnose faults, minimizing downtime and maintenance costs. Automated processes reduce the risk of human error and improve consistency in fault detection. Additionally, the integration of predictive analytics allows for proactive maintenance, ensuring optimal performance and longevity of the photovoltaic system.

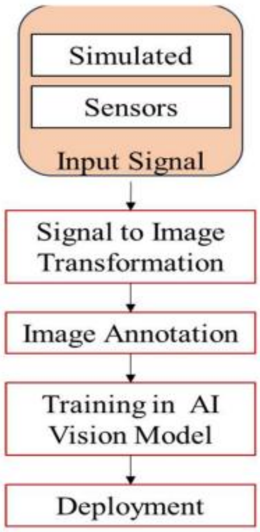

Figure 1: Proposed LIME system.

The **Convolutional Neural Network (CNN)** algorithm is a powerful deep learning architecture primarily used for tasks like image recognition, classification, and object detection. It mimics the human visual system's way of processing images, breaking them down into simpler patterns and gradually abstracting complex features. Let's elaborate on each step of the CNN process:

Step 1. Input Layer

Purpose: The input layer receives the image that the CNN will process. **Process:** An image is represented as a 3D matrix (or tensor), where:

Depth (or channels) represents the

Example: A colored image of size 224x224 pixels will be represented as a tensor of shape 224×224×3224 \times 224 \times 3224×224×3.
Importance: The input layer ensures the image data is properly formatted to pass through the CNN architecture.
number of color channels (typically 3 for RGB images—Red, Green, and Blue).
Width and Height represent the spatial dimensions (number of pixels along the horizontal and vertical axes).

Step 2. Convolution Layer

Purpose: This is the core component of the CNN, responsible for extracting features like edges, textures, and patterns from the input image.
Process: A set of filters (or kernels) are applied to the input image. These filters are small matrices (e.g., 3x3 or 5x5) that slide over the input image, performing elementwise multiplication with portions of the image to produce feature maps. o Filters are designed to detect various features, such as vertical and horizontal edges, textures, corners, etc.
Each filter focuses on a specific aspect of the image, and several feature maps are generated, capturing different image characteristics.

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Example: A 3x3 filter detects edge patterns in a small 3x3 region of the image.
Importance: The convolution operation helps the model detect low-level features in the early layers, which become more abstract and complex in deeper layers (e.g., shapes, objects).
Benefits of the Proposed System
Enhanced Fault Detection: Using signal-to-image transformation allows the system to detect faults that may not be visible in the raw signal data.
Higher Accuracy: Machine learning models (especially CNNs) excel at identifying complex patterns in image data, leading to more accurate fault classification and diagnosis.
Real-Time Monitoring: Continuous monitoring of PV system performance allows for early detection of faults and timely corrective actions, improving overall system efficiency.
Automated Fault Reporting: Automated reports and notifications reduce the need for manual inspection and improve response times.
Scalability: The system can be easily scaled to larger PV installations or adapted to monitor multiple PV systems concurrently.

4. EXPERIMENTAL ANALYSIS

Figure 1: Admin Login Form

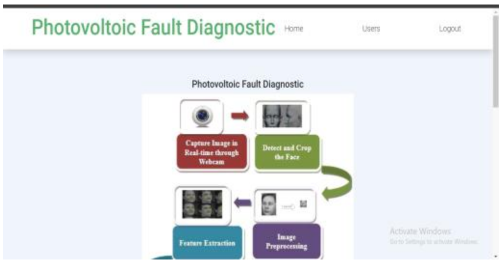

Figure 2: Admin Home Page

Figure3: User Home Page

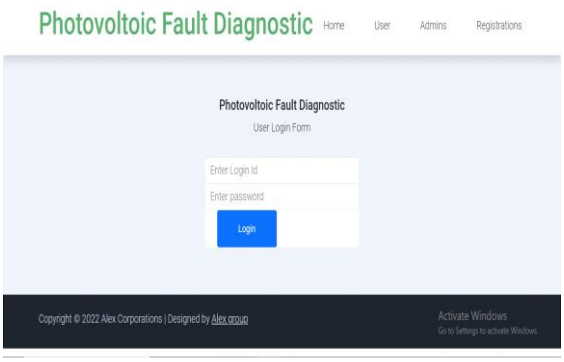

Figure 4: User Login

Figure 5: User register page

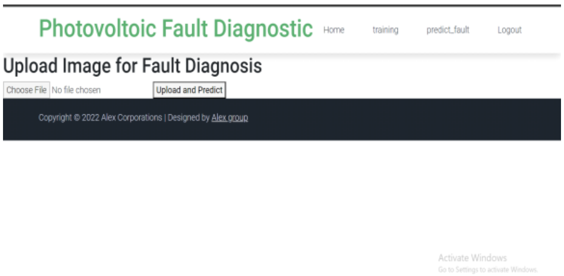

Figure 6: Predication Page

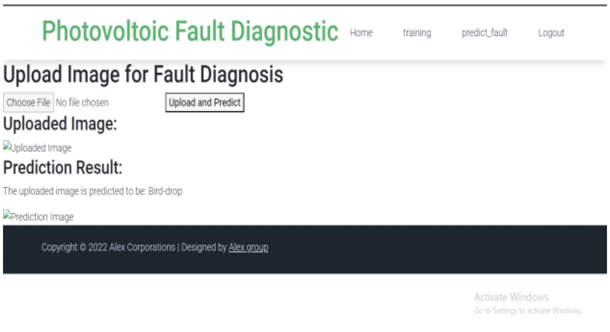

Figure 7: Final Output

The final output of the proposed Signal to Image Transformation for PV Fault Diagnosis system provides comprehensive fault detection and diagnosis for photovoltaic (PV) systems. It classifies faults based on signal data transformed into images (using methods like wavelet transforms or spectrograms), then identifies the type, location, and severity of the fault (e.g., shading, inverter malfunction, or short circuits). A real-time monitoring dashboard presents this information visually, helping operators track the health of individual panels, prioritize issues, and make informed decisions for maintenance.

Additionally, the system generates automated diagnostic reports summarizing fault details and provides actionable recommendations. Real-time alerts and notifications are sent to operators, enabling quick responses to critical issues. Over time, the system also tracks fault trends and predicts potential future issues, supporting proactive maintenance to optimize the PV system's performance and reduce downtime.

5. CONCLUSION

In this study, various methods for transforming 1D signals into 2D images have been introduced. The resulting images from each transformation were collected, experimented with, and subsequently presented. Each transformation underwent testing using actual data from both PV fault and no-fault conditions, specifically focusing on the shorted string fault within a modeled grid-connected PV system derived from an existing PV installation. The outcome of each transformation can be either a 1-channel grayscale image or a 3-channel RGB color image. Additionally, the resulting image size is flexible and can be set to a desired dimension based on preferences and the computing capability of the computer, especially when applied to chosen machine learning (ML) or deep learning (DL) architectures. The generated images of both no-fault conditions and shorted string faults serve as input data for demonstrated.

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