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Fault Identification and Monitoring in Solar Powered VSI with Induction Motor using CNN

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Abstract: ***As renewable energy sources increasingly power motor-driven applications, solar-based inverter systems have gained significant attention. However, faults within power electronic devices, especially Voltage Source Inverters (VSIs), pose challenges by compromising performance and potentially damaging components. This study introduces a convolutional neural network (CNN) approach to detect and classify inverter faults in a solar-powered three-phase VSI system that drives an induction motor. A comprehensive simulation, developed in MATLAB/Simulink, integrates solar photovoltaic generation, a boost converter, and a VSI. The CNN model, trained on current and voltage signals under both normal and faulty conditions, achieved a classification accuracy of 99%. The findings highlight the feasibility of implementing a fast and accurate fault detection mechanism suitable for real-time applications.***

Keywords: Convolutional Neural Network (CNN), Fault Detection, Solar PV System, Voltage Source Inverter (VSI), Induction Motor

1. Introduction

As the demand for eco-friendly energy solutions continues to rise, photovoltaic (PV) systems have gained prominence across commercial and industrial domains. A widely utilized setup consists of a PV array connected to a three-phase voltage source inverter (VSI), which in turn powers an induction motor—presenting a sustainable substitute to conventional fossil fuel systems. Despite their advantages, such arrangements are prone to electrical faults, especially in the inverter segment, where power electronic components like IGBTs and MOSFETs operate. Common issues include both open- and short-circuit failures, potentially causing system instability, increased energy loss, or motor damage.

Conventional methods for fault monitoring typically involve hardware protection circuits or manual rule-based assessment, which often suffer from slow fault identification and limited adaptability under variable conditions. To overcome these drawbacks, intelligent fault analysis systems capable of rapid, accurate, and real-time operation are needed.

In recent advances, AI-based strategies—particularly those involving deep learning—have demonstrated strong potential in fault diagnosis within power electronic systems. Convolutional Neural Networks (CNNs) offer notable efficiency in identifying complex patterns in electrical waveforms, minimizing the need for manual feature extraction. Their ability to detect signal anomalies makes them a suitable choice for continuous monitoring of PV-powered motor drive systems.

This study presents a fault classification framework utilizing CNNs to detect malfunctions in a solar-fed three-phase inverter supplying an induction motor. Using MATLAB/Simulink, fault scenarios including open-switch failure, short circuits, and gate driver faults are simulated. The resulting current and voltage data are processed to train and evaluate a CNN model, aiming to improve system resilience, support predictive maintenance, and minimize operational downtime.

2. Literature Review

Recent advancements in artificial intelligence (AI) and machine learning (ML) have significantly contributed to the progress of fault diagnostics in voltage source inverters (VSIs). As demonstrated by Patel et al. [13], ML-based methods offer valuable insights for detecting switch-level faults within inverter circuits. Hosseinzadeh et al. [6] further showcased that deep convolutional neural networks (CNNs) could attain high accuracy in fault categorization without relying on manual feature extraction. Kumar and Panda [9] illustrated the robustness of CNNs when applied under fluctuating photovoltaic (PV) operating conditions. Enhancing real-time detection capabilities, Zhang et al. [22] merged wavelet transform techniques with CNN models to boost classification performance. In addition, hybrid models such as CNN-LSTM, proposed by Lin et al. [12], and optimization-based approaches by Tang and Li [19], have demonstrated significant improvements in reducing latency and enhancing diagnostic precision. Altogether, these studies confirm the considerable potential of CNN-based algorithms for reliable fault detection in power electronic systems.

3. Inverter fault

Voltage Source Inverters (VSIs) are key components in photovoltaic (PV)-based motor drive systems, responsible for converting regulated DC voltage into a balanced three-phase AC supply. Despite their high efficiency and reliability, VSIs are susceptible to various electrical and switching-related faults that can significantly impair system performance or cause hardware damage. The most prevalent inverter faults include open-circuit, short-circuit, gate driver failure, and shoot-through conditions, each exhibiting distinct electrical signatures.

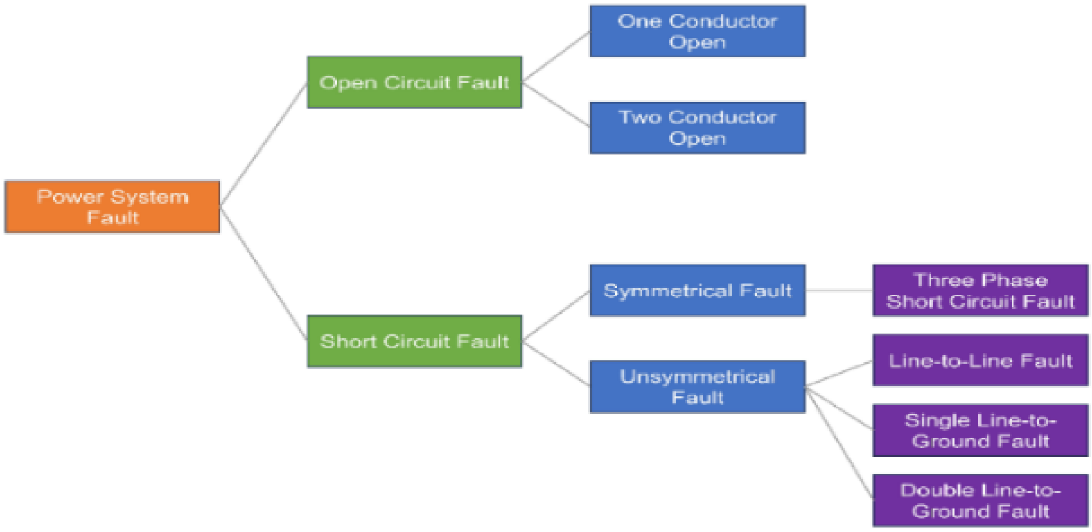

Figure 1: Different types of faults

3.1 Open Circuit Fault

An open-circuit fault arises when at least one switching device within the inverter stops conducting as expected, interrupting the flow of current in the affected phase. These faults typically result from gate driver malfunctions, component aging, or disconnection within the control circuitry. The most common manifestation is a missing or distorted phase current, accompanied by unbalanced line voltages. Such faults can degrade torque performance in motor drives and increase total harmonic distortion (THD).

3.2 Short Circuit Fault

Short-circuit faults occur when a switching device fails in a closed state, resulting in uninterrupted current flow through the circuit. This may result from gate signal failures, internal device breakdowns, or parasitic latch-up. The consequence is an excessive current spike that can damage semiconductor devices and downstream components. Rapid detection and shutdown are essential to prevent thermal and mechanical stress on the inverter and motor.

3.3 Gate Driver Failures

Gate driver faults affect the ability of the control signals to properly switch the inverter transistors. These failures may cause unintended turn-on or turn-off events, leading to erratic switching patterns. The resulting waveforms often exhibit asymmetric or unpredictable behavior, making detection through conventional threshold-based methods difficult.

3.4 Shoot-Through Faults

A shoot-through condition takes place when both switches one at the high side and the other at the low side of the same inverter leg are mistakenly activated together, leading to a short circuit across the DC bus. This creates a direct short across the DC link, resulting in extremely high current and potential destruction of the switching devices. Shoot-through events are typically caused by logic errors, timing mismatches, or component failures in the gate driver circuits.

4. System Overview

The proposed system is a solar-powered three-phase inverter-based drive system designed to operate an induction motor. It consists of four major components:

- Photovoltaic (PV) Panel
- DC-DC Boost Converter
- Voltage Source Inverter (VSI)
- Three-Phase Induction Motor.

These are integrated in a MATLAB/Simulink environment to simulate the electrical behaviour under normal and faulty conditions. A Convolutional Neural Network (CNN) is employed to examine the electrical output signals and identify any faults present in the inverter section.

4.1 Photovoltaic (PV) Panel

The photovoltaic (PV) panel functions as the main source of energy by transforming sunlight into direct current (DC) power via the photovoltaic effect. The electrical output of the panel is influenced by several factors, including solar irradiance, ambient temperature, and the type of cell material used, such as monocrystalline or polycrystalline silicon. Under standard test conditions—specifically 1000 W/m² of irradiance and a temperature of 25°C—the panel typically produces an unregulated DC voltage close to 180 volts.

Since sunlight intensity fluctuates throughout the day, the panel's output is inconsistent and must be regulated. To maintain optimal efficiency, a Maximum Power Point Tracking (MPPT) algorithm is implemented, ensuring the panel operates at its most efficient power output.

4.2 DC-DC Boost Converter

A boost converter is used to elevate the fluctuating DC voltage from the PV panel to a higher and more stable level suitable for inverter operation. The converter operates in continuous conduction mode (CCM), using a high-frequency switching MOSFET (typically 10–20 kHz) to store energy in an inductor and then release it through a diode to the output.

The boost converter's output voltage.

$$V_{Out} = \frac{V_{in}}{1-D}$$

Where:
- V_{in} = Input voltage from PV
- D = Duty cycle of PWM signal.

This voltage is regulated to around 600V, forming the DC link to feed the inverter. Proper inductor and capacitor sizing ensures minimal voltage ripple and high efficiency.

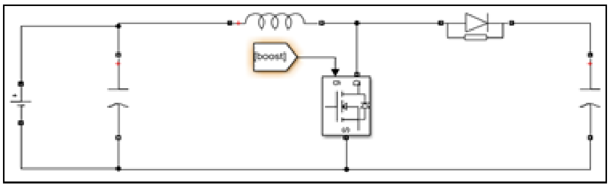

Figure 2: Boost Converter

4.3 Voltage Source Inverter (VSI)

The Voltage Source Inverter (VSI) transforms the stepped-up DC voltage into a balanced three-phase AC supply, making it suitable for driving electric motors. It is built using six IGBT switches configured in a three-leg bridge structure. To generate waveforms that closely resemble pure sine waves, the inverter employs Pulse Width Modulation (PWM) methods such as Sinusoidal PWM or Space Vector PWM (SVPWM).

The inverter stage is critical for system performance and is vulnerable to faults such as:
- Open-Circuit Faults: One or more switches fail to turn ON.
- Short-Circuit Faults: Switches remain permanently ON.
- Shoot-through: Both switches in the same leg conduct simultaneously.

These faults introduce distortion in the output current and voltage waveforms, affecting motor torque and speed. Such waveforms are captured and analysed using the CNN-based fault classifier.

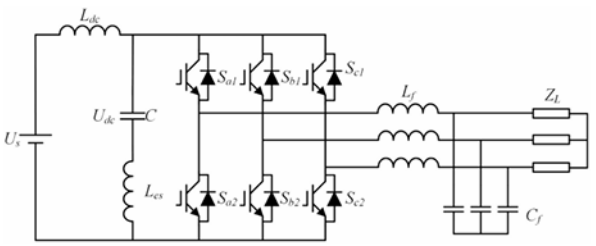

Figure 3: Three-phase inverter using IGBT switches to convert DC to AC power

4.4 Three-Phase Induction Motor

The three-phase AC output from the VSI is supplied to the motor, which functions according to the principle of electromagnetic induction. The stator creates a rotating magnetic field that induces current in the rotor, resulting in torque production. In this study, the motor is modeled in MATLAB using typical equivalent circuit parameters, allowing for the analysis of its dynamic response under both normal operating conditions and simulated faults.

Induction motors are robust but sensitive to power quality disturbances caused by inverter faults. These faults cause unbalanced currents, loss of torque, increased vibration, and heating.

4.5 Fault Injection and Signal Monitoring

To evaluate the performance of the proposed fault detection method, controlled faults are introduced in the inverter stage through logic blocks in Simulink. The three fault categories are,
- Normal Condition
- Open-Circuit Fault
- Short-Circuit Fault

Voltage and current signals from the inverter output and the DC link are recorded. These waveforms are pre-processed and formatted into 2D input arrays for the CNN.

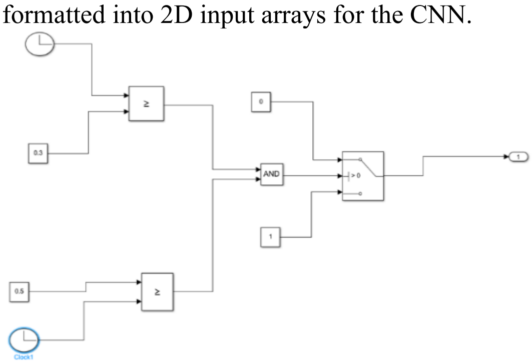

Figure 4: Fault Injection Module

4.6 CNN-Based Fault Detection System

The CNN model is trained using labeled datasets representing the three classes (normal, open, short faults). Each signal sample contains characteristic waveform patterns unique to the fault type. The CNN architecture includes:
- Input layer for signal frames
- Convolution and pooling layers for feature extraction
- Activation layers (ReLU, Leaky ReLU)
- Fully connected layer and softmax output for classification.

The trained CNN achieves 100% accuracy in simulation, demonstrating robust fault classification capability.

5. Result and Discussion

This part presents a detailed examination of the simulation outcomes and assesses how effectively the proposed fault detection system, based on a Convolutional Neural Network (CNN), performs. The study was conducted in MATLAB/Simulink to simulate various fault scenarios and assess the classifier's accuracy.

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5.1 Simulation Setup

The solar-powered inverter system was modelled using a PV array, DC-DC boost converter, three-phase VSI, and a squirrel cage induction motor. The PV panel delivers a variable DC output of approximately 180 V under standard conditions (1000 W/m², 25°C). A boost converter steps up this voltage to 600 V, supplying a three-phase VSI. The inverter uses six IGBT switches with PWM control to produce AC output, which drives the induction motor.
Controlled faults were introduced in the inverter using logical gating. Three operational modes were simulated,

- Healthy condition
- Open-circuit fault (e.g., S1 fails to conduct)
- Short-circuit fault (e.g., S1 remains continuously ON)

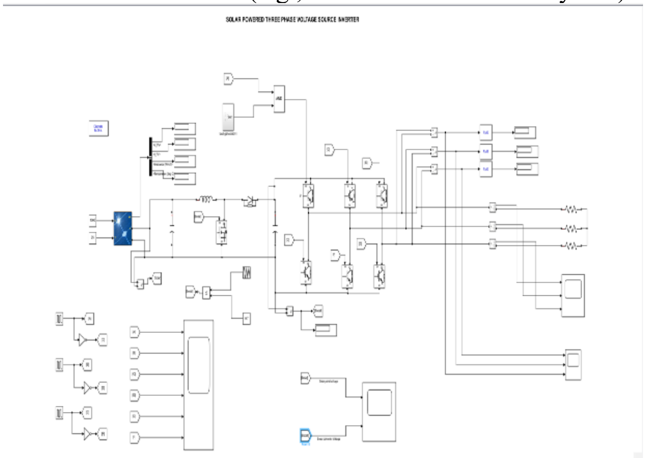

Figure 5: Simulation setup of a three-phase VSI inverter system

5.2 Output Waveform Analysis

The output waveform analysis was conducted to observe the effect of various fault conditions in the inverter stage. The system was simulated under three distinct operating conditions: normal operation, open-circuit fault, and short-circuit fault. The resulting voltage and current signals were evaluated in the time domain to identify unique features that could aid in accurately classifying each fault type.

5.2.1 Solar Panel Output

The solar panel model was set up according to standard testing parameters, using an irradiance level of 1000 W/m² and an ambient temperature of 25°C. The output voltage waveform of the PV array exhibited an initial transient before stabilizing at approximately 180 V DC. The waveform showed a minor ripple component due to environmental variations and internal switching dynamics of the Maximum Power Point Tracking (MPPT) algorithm. The steady-state voltage confirmed effective power harvesting from the solar panel under uniform irradiance conditions.
The dynamic response of the solar panel output indicated the need for regulated DC voltage to ensure stable inverter operation, which justified the use of a boost converter.

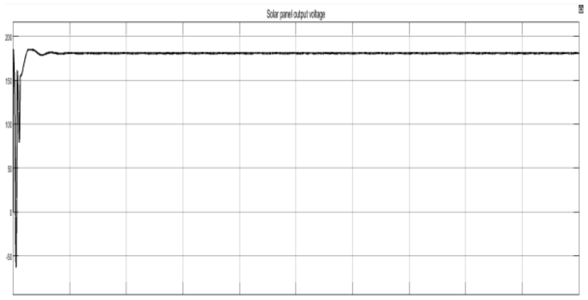

Figure 6: Output waveform of Solar Panel

5.2.2 Boost Converter Output

The DC-DC boost converter effectively increased the PV panel's output voltage from 180 V to a stable and regulated 600 V DC, confirming successful voltage step-up performance. Initially, the waveform showed a sharp rise due to inductor charging, followed by settling into a stable output with minimal ripple. The high-frequency switching of the converter introduced slight ripples, but the output remained within the designed tolerance limits due to proper capacitor sizing and PWM control.

This regulated and elevated DC voltage served as the input to the voltage source inverter (VSI), ensuring sufficient headroom for AC synthesis. The effectiveness of the MPPT control and PWM regulation was confirmed through the smooth and consistent output waveform of the boost converter.

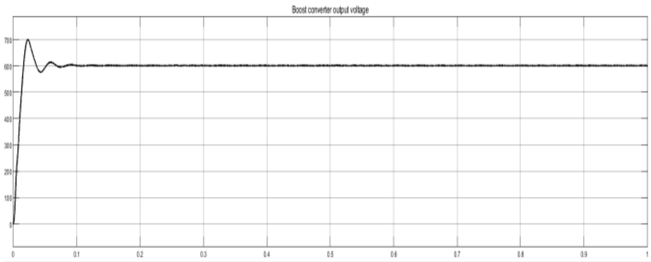

Figure 7: Boost converter output voltage waveform

5.2.3 Healthy Condition

Under normal operation, the inverter produced balanced three-phase AC output with sinusoidal-like waveforms. The line-to-line voltages exhibited symmetrical patterns with a consistent amplitude and 120° phase displacement, ensuring stable operation of the induction motor. No distortions or anomalies were present in the waveforms.

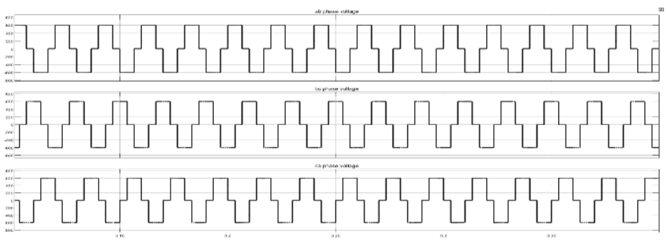

Figure 8: Output waveform of Three Phase VSI under healthy condition

5.2.4 Open-Circuit Fault

An open-circuit fault, introduced by disabling one of the inverter switches, resulted in a discontinuity in the corresponding phase current. This led to unbalanced voltage waveforms with missing pulses in the affected phase. The motor experienced torque ripple and degraded performance. Such discontinuities formed a distinct signature in the current and voltage signals.

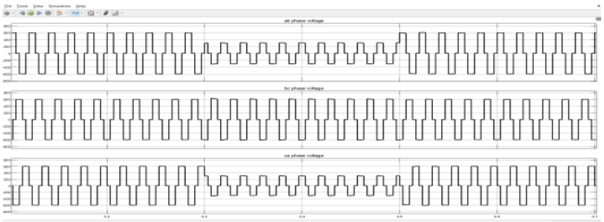

Figure 9: Output waveform of Three Phase VSI under open circuit fault

5.2.5 Short-Circuit Fault

During a short-circuit fault, one of the switches remained continuously ON, leading to a direct short across the DC link. The resulting waveforms showed a sudden drop in output voltage and a significant rise in phase current. The imbalance and distortion in the waveforms were severe, indicating the urgency of protection action. These abnormal signatures were effectively captured for CNN classification.

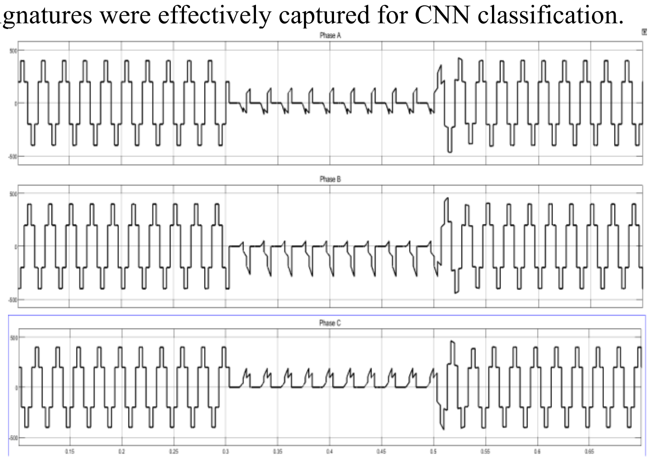

Figure 10: Output waveform of Three Phase VSI under short circuit fault

5.3 CNN training and Result

The core of the proposed inverter fault detection system is a Convolutional Neural Network (CNN) trained on inverter output signal data under various operating conditions. The CNN was developed and trained in MATLAB using time-domain voltage and current waveforms obtained from the simulated model.

1) Dataset Preparation

The dataset consisted of labeled signal segments corresponding to three operating conditions:

- Normal operation
- Open-circuit fault
- Short-circuit fault

Each sample contained 1D waveform data captured from line-to-line voltages and phase currents at the inverter output. The dataset was scaled appropriately and then split into three parts: 70% for training, 15% for validation, and 15% for testing.

2) Training Performance

During training, the CNN demonstrated rapid convergence. The training and validation losses decreased steadily, while the accuracy increased and stabilized without overfitting.

- Training Accuracy: 100%
- Validation Accuracy: 100%
- Final loss: < 0.01 (both training and validation)

The training curve indicated that the model effectively learned to distinguish between normal, open, and short-circuit conditions using features derived from waveform patterns.

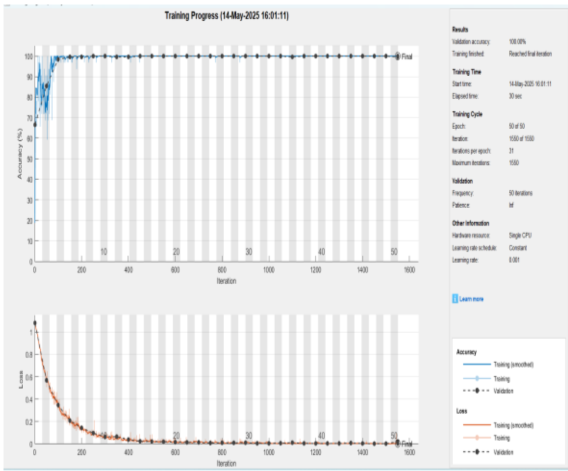

Figure 11: Output waveform of CNN model training

5.4 Confusion Matrix and Evaluation

A confusion matrix was used to assess how well the model performed on the test dataset. It correctly classified all test samples, yielding zero misclassifications:

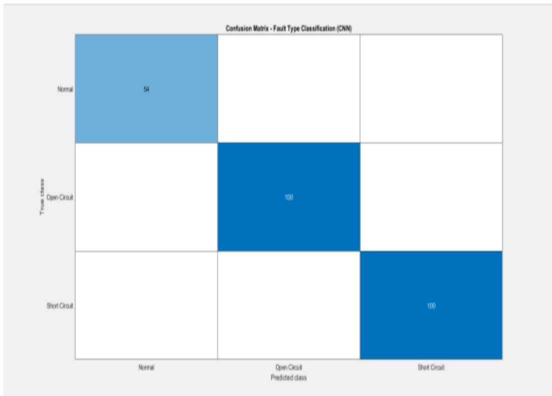

Figure 12: Output waveform of Confusion matrix

Table 1: Confusion matrix

Actual / Predicted	*Normal Circuit*	*Open Circuit*	*Short Circuit*
Normal Circuit	54	0	0
Open Circuit	0	100	0
Short Circuit	0	0	100

6. Conclusion

This study introduces a deep learning-based method for detecting faults in a solar-powered three-phase voltage source inverter (VSI) that supplies an induction motor. The proposed approach leverages Convolutional Neural Networks (CNN) to identify both open-circuit and short-circuit faults within the inverter. The complete system was modeled and simulated in MATLAB/Simulink, integrating realistic components such as a photovoltaic (PV) array, a DC-DC boost converter, a VSI using IGBT switches, and a dynamic three-phase squirrel cage induction motor load.

The simulation outcomes confirmed the reliability and accuracy of the proposed method. When subjected to various fault scenarios—such as open-circuit and short-circuit conditions—the inverter's output displayed distinctive waveform abnormalities, including imbalanced phase voltages, missing current segments, and significant harmonic distortions. These unique waveform traits were pre-processed and used to train a CNN model capable of automatically identifying the inverter’s operating condition. The CNN architecture included several convolutional and pooling layers, ending with a fully connected classification layer. It was trained using labeled signal data from three operational states: normal, open-circuit fault, and short-circuit fault. The model achieved perfect classification accuracy (100%) on both training and validation sets. A confusion matrix analysis revealed no misclassifications, highlighting the model’s strength in extracting features directly from time-domain data without manual feature engineering.

Incorporating CNNs into fault detection systems presents multiple benefits compared to traditional diagnostic methods, such as higher speed, greater automation, and improved adaptability:

- Automated classification reduces the need for human intervention.
- High-speed detection enables real-time monitoring and protection.
- Cost-effective deployment as it eliminates extra hardware sensors.
- Scalability for more complex inverter topologies or additional fault types.

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