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Efficient 2D DCNN approach for detecting and classifying faults in modular power converters

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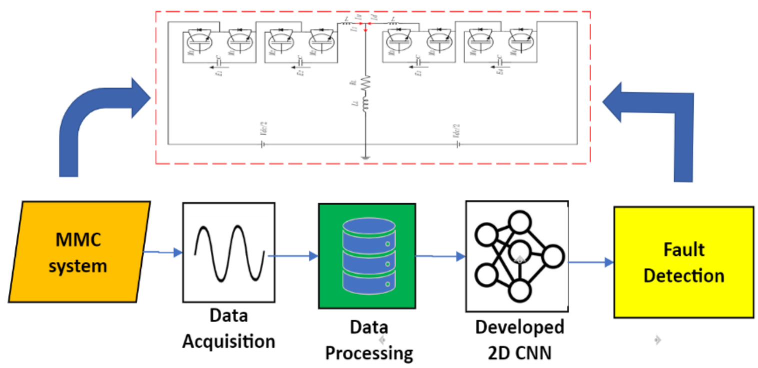
ABSTRACT

This paper introduces a 2D deep convolutional neural network (DCNN) method for automatic fault detection and classification in modular multilevel converters (MMCs). Unlike traditional data-driven approaches that rely on manual signal processing and ignore time dependencies, this method transforms raw sensor data into 2D representations and uses DCNNs to learn fault patterns automatically. This allows for better modeling of temporal relationships between signals and removes the need for hand-crafted ensemble techniques. The model is trained in data covering a range of MMC operating conditions. Simulation and real-time tests in MATLAB Simulink show the approach achieves 100% fault detection accuracy and over 85% classification accuracy. The results demonstrate its effectiveness and potential for improving MMC reliability.



Keywords: Deep Learning, Modular Multilevel Converters, Convolutional Neural Networks, Fault Detection

INTRODUCTION

Electric and electronic circuits are integral to diverse applications, spanning power systems, communication networks, automotive electronics, and consumer devices. Serving as the backbone of modern infrastructure, these circuits facilitate efficient energy generation, transmission, and utilization.[1,2] However, their reliable operation is susceptible to various faults, posing risks to performance, safety, and longevity. Robust fault detection techniques are crucial to mitigate these risks, ensuring uninterrupted operation and safeguarding both equipment and lives. In power systems, where circuits manage energy generation and distribution, faults like short circuits or equipment failures can lead to widespread outages and economic losses.[3,4] Implementing reliable fault detection is vital to promptly identify and isolate faults, minimize disruptions, stabilize the grid, and enhance overall power system reliability.[5–8]

Fault detection in Modular Multilevel Converters (MMCs) is crucial for ensuring the reliability and performance of these power electronic systems, especially in applications like high-voltage direct current (HVDC) transmission and renewable energy systems.[9,10] The complexity of MMCs, with their modular and multilevel structure, poses challenges in identifying faults promptly. Key components, including semiconductor switches, capacitors, and control circuits, are susceptible to various types of faults that can impact the converter's operation.[11,12]

Traditional fault detection methods for MMCs predominantly rely on monitoring various parameters to identify anomalies indicative of faults. These methods, known for their simplicity and effectiveness, employ voltage and current sensors to scrutinize the waveforms of each submodule in the MMC. Anomalies in voltage or current levels are key indicators of potential faults. Additionally, circulating current analysis, which examines currents circulating within the MMC that don't contribute to the output, is a method to identify abnormal current patterns.[13] Harmonic analysis is another widely used technique, involving the scrutiny of harmonic content in voltage and current waveforms. Deviations in harmonic levels can signal faults.[14] Another effective method is model-based fault detection, which compares the actual behavior of the MMC to a predefined model of normal behavior. Discrepancies between actual and predicted behavior serve as indicators of faults.[15] Despite

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their effectiveness, traditional methods have certain limitations. They might not detect all types of faults, could be sensitive to noise and harmonics, and often require a substantial amount of data for comprehensive analysis. These limitations motivate the exploration of advanced fault detection techniques that can overcome these challenges and enhance the reliability of MMCs in various applications.[16]

In the quest for more advanced fault detection techniques for MMCs, the application of Deep Learning, specifically CNNs, has emerged as a promising avenue. Deep learning methods, including CNNs, leverage complex neural networks to automatically learn intricate patterns and representations from data, eliminating the need for explicitly defined rules or models. In the context of MMCs, CNNs can be trained on vast datasets encompassing normal and faulty operation scenarios, allowing them to discern subtle patterns indicative of faults.[17]

The advantage of CNNs lies in their ability to handle complex, high-dimensional data such as voltage and current waveforms. By processing these waveforms through layers of convolutional operations, CNNs can capture hierarchical features and relationships, making them adept at identifying nuanced fault patterns that might escape traditional methods.[18] Moreover, CNNs excel in generalization, meaning they can apply learned patterns to new, unseen data, enhancing their adaptability to diverse fault scenarios in MMCs.[17] The integration of CNNs into fault detection for MMCs represents a paradigm shift towards more automated, data-driven approaches. This methodology has the potential to overcome the limitations of traditional methods by offering improved accuracy, reduced sensitivity to noise, and the capability to detect a broader spectrum of faults. As the field of Deep Learning continues to evolve, the application of CNNs in MMC fault detection holds promise for enhancing the reliability and performance of these critical power electronic systems.

In a report by M. Houchati et.al.[19], researchers explored machine learning techniques for spotting faults in MMCs. They specifically tackled open circuit faults in power switches using Principal Component Analysis (PCA), a data-driven method. Despite MMCs being popular for high-power tasks, their complexity raises the risk of failures, especially in vulnerable parts like power switches. The authors W. Jio et.al.[20] present a fault diagnosis method for open sub-module failures in MMCs using a Firefly Algorithm-optimized Support Vector Machine (FA-SVM). The method incorporates Fast Fourier Transform for fault signal preprocessing and Principal Component Analysis (PCA) for dimension reduction and fault characteristic extraction. While demonstrating efficacy in fault identification and reduced diagnosis time, it's essential to acknowledge potential limitations. In a report by W. Xiang et.al.[21], the authors propose an artificial intelligence (AI)-based protection scheme using an artificial neural network (ANN) for fault detection in MMC-based DC grids. The existing fault detection methods encounter challenges in setting protective thresholds, incomplete function, in-sensitivity to high-resistance faults, and vulnerability to noise. The AI-based approach employs the transient characteristics of DC voltages during faults, utilizing discrete wavelet transform for feature extraction and ANN for fault identification. C. Wang et. al.[22] proposed a fault-diagnosis technique for Modular Multilevel Converter with series and parallel connectivity that utilizes wavelet transform and support vector machines (SVM) for identifying shorted switches. This method is particularly designed for the modular multilevel series/parallel converter (MMSPC), which introduces increased complexity with its series and parallel connectivity, potentially doubling the chances of switch failures. By employing wavelet transform for feature extraction and SVM for classification, the method demonstrates high classification accuracy and robustness. H. Liu et. al.[23] proposed a fault diagnosis technique for short circuit faults in a sub-module of the MMC that employs wavelet transform and Adaptive Neuro Fuzzy Inference System (ANFIS). In the context of MMC, which is widely used in medium- or high-power applications, the large number of sub-modules increases the probability of failures, emphasizing the significance of fault detection and diagnosis. The method utilizes wavelet transform to extract fault features from the output phase voltage and employs ANFIS for fault identification. Notably, this approach does not require additional sensors or capacitor voltages for fault diagnosis. It demonstrates high accuracy, good generalization, and time-saving characteristics, as evidenced by a comparison with the neural network method. However, it's essential to acknowledge that ANFIS, like other intelligent model-based methods, may have some disadvantages. These could include the need for a sufficiently large and diverse dataset for effective training, potential challenges in handling highly complex or nonlinear fault patterns, and the interpretability of the model's decision-making process.

Indeed, most existing data-driven methods rely on complicated signal processing techniques (e.g., signal segmentation) applied to the data collected from MMCs, which degrade the performance of fault detection methods due to the ignorance of the time dependencies among the measured signals. These existing methods also require designing effective ensemble techniques to obtain an adequate fault detection model.

To address the research gap in the literature, this paper proposes a new 2D DCNN approach for automatically detecting faults in modular power converters. Unlike existing data-driven approaches, the proposed method includes a preprocessing stage that converts the measured signals into a 2D signal, like a 2D image. Subsequently, it employs a developed 2DCNN model for automatic fault detection and classification in MMCs. This unique feature enables automated learning of failure patterns from sensor data and detailed modeling of temporal correlations among measured signals. It is important to note that the developed DCNN model is trained on a dataset containing diverse MMC operating conditions. Simulation results on the dataset, as well as real-time evaluation in MATLAB Simulink, validate the efficacy of the proposed approach.

Operation and Control of MMC Converters

The mathematical model of the MMC is essential for designing control algorithms and understanding the system dynamics. The mathematical model should model the relationships between the converter's variables and allow for the prediction of its behavior under different operating conditions. In this study, we employ a single-phase MMC topology that includes 4 cells as shown in

Figure 1. The configuration of the MMC is composed of two identical arms namely upper " u " and lower " l ". Each arm is comprised of " n " identical series submodules which is a half-bridge converter. Each submodule contains two switches of (IGBT) and a capacitor (C) parallel. Moreover, it has an inductor L and a resistance R_f which represents the power losses in each arm. It should be noted that the output voltage of each cell has two states: 0 or capacitor voltage value, depending on the state of the capacitor. The state space model for the MMC can be expressed by Eq. (1) [24–26], in which $E_1 - E_4$ are the voltages across the 4 corresponding capacitors. V_{dc} is the DC Voltage of the source. C is the capacitor of each cell. R and L are resistance and inductor of each arm. I_d is the circulating current, and I_l is the load current. L_L and R_L are the inductor and resistor of the load. $M_1 - M_4$ are the switching states that have a value of either 0 (i.e., off state) or 1 (i.e., on state). It is worth mentioning that further details about this studied MMC system and its control method have been reported by L. Ben-Brahim et. al.[25]

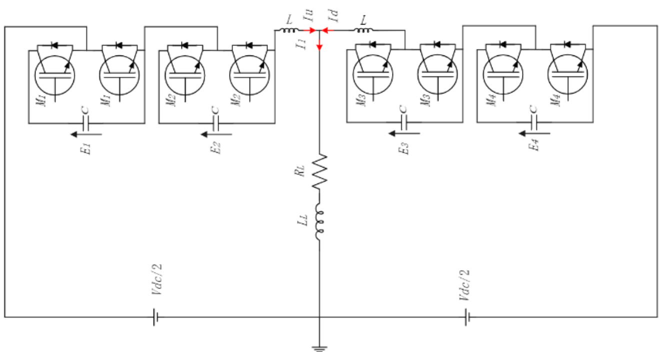


Figure 1: Structure of the modular multilevel converter

Proposed Fault Detection Method for MMCs

The field of fault detection in MMCs has undergone a significant paradigm shift, embracing deep learning techniques in recent times. Crucial for high-power applications such as HVDC transmission and renewable energy systems, MMCs necessitate advanced fault detection mechanisms.

Figure 2 presents the proposed fault detection method based 2D CNN. The main components of the proposed fault detection are data acquisition, data processing, and developing the 2D CNN fault detection model. The proposed method demonstrates the ability to discern intricate spatial patterns within MMC systems and can enhance their adaptability to dynamic operational conditions.

3.1 The Architecture of the 2D-DCNN Fault Detection Model

The 2D CNN architecture used in this study consists of convolutional layer followed by max-pooling layers, with batch normalization and ReLU activation used after convolutional layer (See Figure 3). The input to the network is a 2D matrix of shape (samples, 5, 5000, 1), where "samples" represents the number of data samples, "5" represents the number of channels, "5000" represents the number of time steps, and "1" represents the number of features.

The first layer of the network is a convolutional layer with 64 filters of size 2x2 and a stride of 2. This is followed by a max-pooling layer with a pool size of 1x1. The final layer of the network is a fully connected layer with a SoftMax activation function, which outputs a probability distribution over the different fault classes.

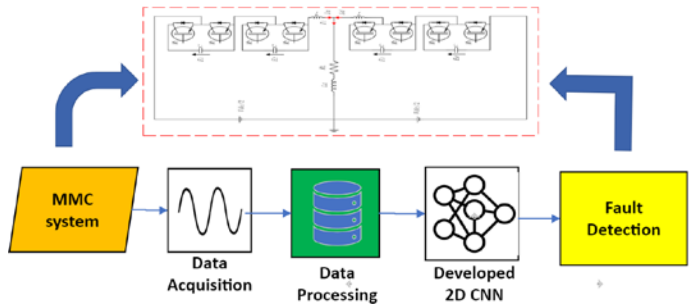


Figure 2: Overview of the proposed fault detection method

3.2 Data Acquisition of the studied MMC system

Five channels of measurement were used to collect data for standard (no-fault) and 8 various fault conditions (faults). The data was recorded for 0.5 seconds afterward the circuit reached a steady-state situation, which was achieved after five seconds of operation. The data were sampled at a frequency of 10 kHz, resulting in a total of 5000 samples for each channel. The data was organized into a 5000x5 matrix, in which each column represents the data for a specific channel. The channels of data that were collected include:

1. Capacitor voltage of Cell1
2. Capacitor voltage of Cell2
3. Capacitor voltage of Cell3
4. Capacitor voltage of Cell4
5. Differential or circulation current

The focus of this research is on detecting and identifying faults in a 4-cell MMC topology with 8 switches. Note that every cell can simulate 2 switch failures, resulting in a number of 8 unique fault cases that can be modeled. Because of this, the classifier is faced with a nine-class classification issue, in which it must identify and detect any defect as soon as it categorizes the raw data as one of the fault scenarios.

The MMC's input voltage frequency was set to 50 Hz, resulting in a 20 ms natural period. The incidence time of each fault instance during a single input voltage cycle might vary. Hence, the data was acquired for 5 separate instant biases (every 5ms from 0 to 20ms) considering the normal as well as 8 fault conditions: $\Delta 1$=0ms, $\Delta 2$=5ms, …, $\Delta 5$=20ms. This means that the normal and every fault type were repeated 5 times starting at (5s + Δi) where i = [1:5].

Additionally, the data was collected for different load currents, to ensure that the classifier could detect and identify any fault occurrence independently of the load current and the time bias. The data acquisition was repeated for 10 different load currents: I_{load}= [1:10]A. The main challenge of this research is to detect and identify faults in the MMC, independent of the load current and the time bias. The parameters of the tested MMC prototype system are provided in Table 1.

$$\begin{bmatrix} \frac{dI_d}{dt} \\ \frac{dE_1}{dt} \\ \frac{dE_2}{dt} \\ \frac{dE_3}{dt} \\ \frac{dE_4}{dt} \\ \frac{dI_l}{dt} \end{bmatrix} = \begin{bmatrix} -\frac{R}{L} & -\frac{M_1}{2L} & -\frac{M_2}{2L} & -\frac{M_3}{2L} & -\frac{M_4}{2L} & 0 \\ \frac{U_1}{C} & 0 & 0 & 0 & 0 & \frac{M_1}{2C} \\ \frac{U_2}{C} & 0 & 0 & 0 & 0 & \frac{M_2}{2C} \\ \frac{U_{31}}{C} & 0 & 0 & 0 & 0 & -\frac{M_3}{2C} \\ \frac{U_4}{C} & 0 & 0 & 0 & 0 & -\frac{M_4}{2C} \\ 0 & -\frac{M_1}{L+2L_L} & -\frac{M_2}{L+2L_L} & \frac{M_3}{L+2L_L} & \frac{M_4}{L+2L_L} & -\frac{R+2R_L}{L+2L_L} \end{bmatrix} \begin{bmatrix} I_d \\ E_1 \\ E_2 \\ E_3 \\ E_4 \\ I_l \end{bmatrix} + \begin{bmatrix} \frac{V_{dc}}{2L} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad (1)$$

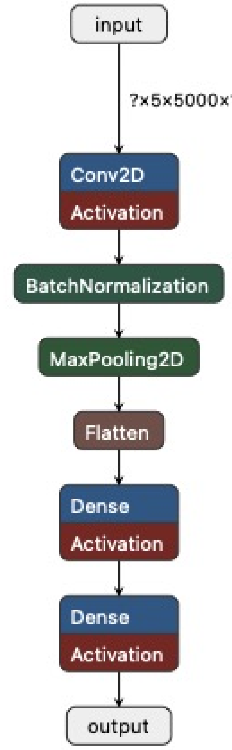


Figure 3: CNN Model Architecture

3.3 Fault Classifications and Classes

In the proposed fault detection and identification (FDI) method, the objective is to accurately classify and identify various faults that can occur in the 4-cell Modular Multilevel Converter (MMC) topology with 8 switches. This problem poses a challenging classification task, as there are 8 different fault cases that can be simulated, resulting in a total of 9 fault classes.

Each cell in the MMC topology has the capability to simulate 2 switch failures, leading to a range of fault cases that can occur. The 8 fault cases encompass different combinations of switch failures, representing various fault scenarios that can potentially impact the performance and reliability of the system. These fault cases include:

1. No Fault: This class represents the normal operation of the MMC without any switch failures. It serves as the baseline for comparison with the fault cases.
2. Switch 1 Failure: This class corresponds to a fault case where switch 1 in the MMC topology has failed.
3. Switch 2 Failure: This class represents a fault case where switch 2 in the MMC topology has failed.
4. Switch 3 Failure: This class corresponds to a fault case where switch 3 in the MMC topology has failed.
5. Switch 4 Failure: This class represents a fault case where switch 4 in the MMC topology has failed.
6. Switch 5 Failure: This class corresponds to a fault case where switch 5 in the MMC topology has failed.
7. Switch 6 Failure: This class represents a fault case where switch 6 in the MMC topology has failed.
8. Switch 7 Failure: This class corresponds to a fault case where switch 7 in the MMC topology has failed.
9. Switch 8 Failure: This class represents a fault case where switch 8 in the MMC topology has failed.

As an example, Figure 4 shows the Cell 1 Capacitor Voltage plots of the fault classes 1 and 8 for I = 1A, where we can notice significant waveform variations. The accurate detection and identification of these fault classes are of utmost importance in ensuring the reliable operation and performance of the MMC system. Detecting faults at an early stage allows for timely intervention and preventive measures to mitigate the potential consequences of faults, such as equipment damage, system malfunctions, safety hazards, and financial losses.

By accurately classifying and identifying the specific fault cases, the FDI method can provide valuable information for maintenance and troubleshooting. It enables maintenance personnel to identify the exact location and type of fault, facilitating targeted repairs and minimizing downtime. Additionally, accurate fault identification

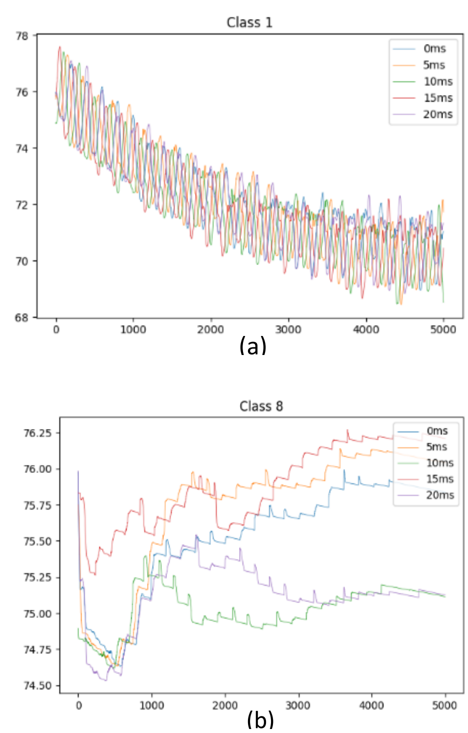


Figure 4: The Cell Capacitor Voltage plots of the fault classes 1 and 8 for I = 1A

aids in enhancing system resilience and fault-tolerant operation, as appropriate actions can be taken to isolate faulty components or activate backup systems. Furthermore, reliable fault detection and identification contribute to the overall system optimization and performance improvement. By proactively addressing faults, the FDI method enables the system to operate at its full capacity, minimizing energy losses and optimizing system efficiency. This has significant implications for various applications of the MMC topology, including renewable energy systems, electric vehicle charging stations, and high-power electrical grids.

In summary, the classification and identification of the 8 different fault cases in the MMC topology represent a critical aspect of the proposed FDI method. Accurate fault detection and identification enable timely interventions, improve system reliability, and contribute to the efficient and optimal operation of the MMC system.

Table 1: Parameters of the studied MMC system

Parameters	Values
Inductor load L_l	50mH
Resistor load R_l	19Ω
Inductor arm L	1mH
Resistor arm R	0 Ω
Capacitor C	1000 µF
Fundamental frequency f	50 Hz
Sampling frequency F_s	10 KHz
Input Voltage V_{dc}	150 V
Reference Current $I_{Loadref}$ (peak)	3A
Number of cells per arm	2

3.4 Data Preparation

In this study, the data preparation process began with normalizing the dataset, which consisted of time series measurements of 5 channels. These channels include the capacitor voltage of each of the four cells in the MMC and the differential current. The time series data had 5000 samples in ms. Normalization was performed to ensure that all input features were on the same scale, which helped to improve the performance and convergence of the model. In this study, Min-Max Scaling was chosen as the normalization technique.

Min-Max scaling is a simple and widely used normalization method that scales the values of the input features between a range of 0 and 1. This is done by subtracting the minimum value of the feature from each data point and then dividing it by the range of the feature. Mathematically, it can be represented as :

$$Z = \frac{(\mathcal{X} - \mathcal{X}_{min})}{(\mathcal{X}_{max} - \mathcal{X}_{min})} \tag{2}$$

Where Z is the normalized value, $\mathcal{X}$ is the original value, $\mathcal{X}_{min}$is the minimum value and $\mathcal{X}_{\max}$is the maximum value of the feature. This method is particularly useful when the data is distributed unevenly and has extreme values, such as outliers.

Simulation and Experimental Results

4.1 Results of the Fault Detection Model

In this subsection, we provide the results of the proposed fault detection model trained of the training dataset mentioned in the previous section. To assess the model's ability to generalize and detect faults accurately in practical scenarios, we employ a diverse set of data samples from the validation dataset. These samples have been carefully withheld during the training and validation phases, allowing us to test the model's performance on unseen data. The validation data encompasses a wide range of fault cases, offering a comprehensive evaluation of the model's real-world applicability.

Experiments were conducted with varying testing data proportions, ranging from 0.1 to 0.9. The testing data proportion denotes the ratio of test samples to the total number. Table 2 provides an overview of the detection accuracy of the proposed model. The network's output for fault detection is categorized into two types: normal and abnormal (i.e., one of the 8 faults occurs). As one can see in Table 2, the detection accuracy of the proposed method is 100% at each testing data portion.

Table 2: Faulty detection accuracy

Testing Data portion	Fault detection (%)
0.1	100
0.2	100
0.3	100
0.4	100
0.5	100
0.6	100
0.7	100
0.8	100
0.9	100
1	100

Actual Class \ Prediction	0	1	2	3	4	5	6	7	8
0	1.00	0	0	0	0	0	0	0	0
1	0	0.84	0	0.16	0	0	0	0	0
2	0	0	1.00	0	0	0	0	0	0
3	0	0.02	0	0.98	0	0	0	0	0
4	0	0	0	0	1.00	0	0	0	0
5	0	0	0	0	0	0.87	0	0.13	0
6	0	0	0	0	0	0	1.00	0	0
7	0	0	0	0	0	0.09	0	0.91	0
8	0	0	0	0	0	0	0	0	1.00

Figure 5: Confusion matrix of the proposed fault detection model with 10% of testing data. The classification accuracy of the model on the unseen data is 95.56%.

Actual Class \ Prediction	0	1	2	3	4	5	6	7	8
0	1	0	0	0	0	0	0	0	0
1	0	0.64	0	0.36	0	0	0	0	0
2	0	0	0.95	0	0.01	0	0.04	0	0
3	0	0.28	0	0.71	0.01	0	0	0	0
4	0	0	0	0	0.99	0	0.01	0	0
5	0	0	0	0	0	0.55	0	0.45	0
6	0	0	0	0	0	0	0.96	0	0.04
7	0	0	0	0	0	0.16	0	0.84	0
8	0	0	0	0	0	0	0	0.01	0.99

Figure 6: Confusion matrix of the proposed fault detection model with 50% of testing data. The classification accuracy of the model on the unseen data is 84.60%.

Figure 5 presents the confusion matrix that shows the classification results of the proposed fault detection model with the nine fault classes of the MMC system explained in Section 4. Each row in the confusion matrix represents the actual fault class, while each column represents the predicted fault class. The values in the cells represent the percentage of cases that were classified as a particular fault class. Overall, the confusion matrix indicates that the model performs well in detecting and identifying faults in the MMC system. Specifically, it achieves high accuracy for most of the fault classes, with some classes having a slightly lower accuracy. For instance, the classification accuracy rates of class 0 (no fault), 2, 4, and 8 are 100%, while the classification accuracy of class 5 (fault in capacitor voltage measurement) is 87%. The confusion matrix also shows some misclassifications, where some fault classes were incorrectly classified as another class. For instance, some cases of class 1 were misclassified as class 3 (misclassification rate of 16%), and some cases of class 3 were misclassified as class 1 (misclassification rate of 2%), a similar observations are noted with class 5 and class 7. These misclassifications suggest that there may be some similarities or overlap between these fault classes, and further investigation is needed to improve the model's performance in distinguishing between them. Overall, the classification accuracy of the model on the unseen data is 95.56%.

Actual Class \ Prediction	0	1	2	3	4	5	6	7	8
0	1	0	0	0	0	0	0	0	0
1	0	0.71	0	0.29	0	0	0	0	0
2	0	0.01	0.95	0	0.01	0	0.03	0	0
3	0	0.27	0	0.72	0.01	0	0	0	0
4	0	0	0	0	0.99	0	0	0	0
5	0	0	0	0	0	0.59	0	0.41	0
6	0	0	0	0	0	0	0.94	0	0.05
7	0	0	0	0	0	0.13	0	0.87	0
8	0	0	0	0	0	0	0	0.02	0.98

Figure 7: Confusion matrix of the proposed fault detection model with 100% of testing data. The classification accuracy of the model on the unseen data is 85.91%.

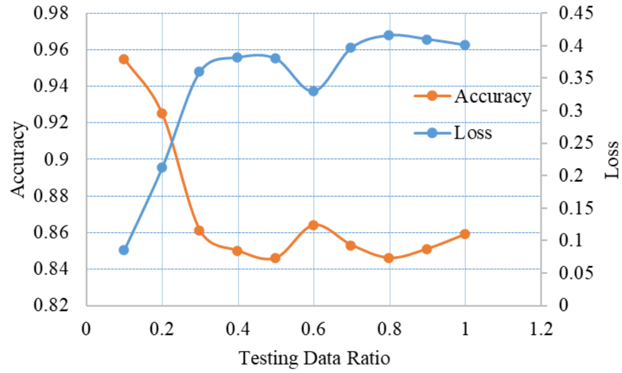


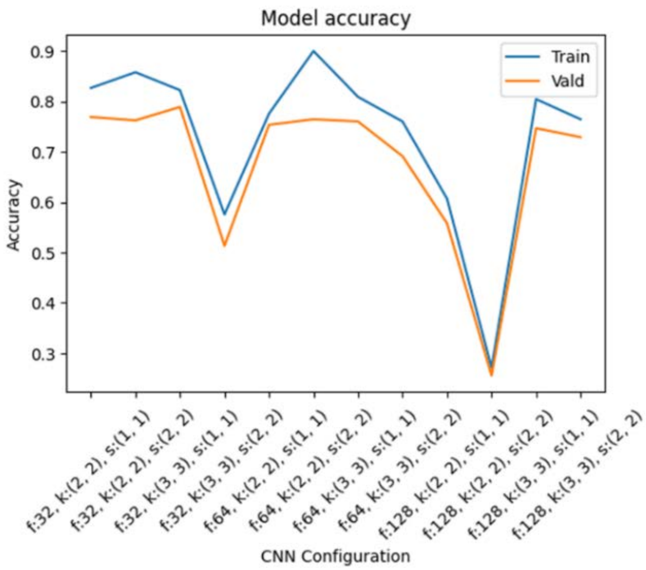
Figure 8: The fault detection results of the proposed model at different testing data ratios.

Figure 8 shows the performance metrics of the proposed fault detection model across varying testing data ratios (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1). The open circuit fault detection accuracy ranges from 0.846 to 0.955. This provides valuable information about the model's ability to correctly identify open circuit faults at different testing data ratios. The loss values indicate a potential challenge in the model's ability to generalize to unseen data, as the loss increases with higher testing data ratios. The highest accuracy at a testing data ratio of 0.1 indicates that the model performs exceptionally well when a smaller portion of the data is used for testing. However, as the testing data ratio increases, the accuracy shows a gradual decline, reaching 0.846 at a testing data ratio of 0.8. This decline in accuracy may stem from challenges in generalization, where the model faces difficulty in adapting to new fault patterns not encountered during training.

4.2 Analyzing the effect of different configurations of the proposed model

This study aims to identify the optimal parameters that result in the best fault detection accuracy. By analyzing the results with the training and validation datasets, we can draw conclusions about the impact of pooling operations on the model's performance and make informed decisions regarding the final architecture of the 2D-DCNN FDI model.

First, we present the results of the ablation study conducted on the 2D-DCNN FDI model by varying the filter size, kernel size, and stride. The purpose of this study is to identify the optimal configuration of these architectural parameters to achieve the highest fault detection accuracy. We performed experiments with different combinations of filter size (f), kernel size (k), and stride (s) and evaluated their impact on the model's performance using both training and validation datasets. To analyze the performance of each configuration, we trained the 2D-DCNN FDI model with the corresponding parameters and recorded the accuracy and loss values for both the training and validation datasets during the training process. Figure 9 shows the results of the different parameter combinations with training and validation dataset. As shown in Figure 9(a) the best accuracy (90%) is achieved with a filter size of 64, kernel size of (2, 2), and stride of (1, 1). The highest loss (worst combination) is obtained with a filter size of 128, kernel size of (2, 2), and stride of (1, 1). Table 3 presents the results of each combination with the validation dataset. As shown, the best accuracy (78.89%) is achieved with a filter size of 32, kernel size of (3, 3), and stride of (1, 1).



(a)

(b)

Figure 9: Results of different combinations of filter size, kernel size, and stride with the training and validation dataset (a) Accuracy, and (b) Loss.

Second, we study the impact of different pooling methods on the performance the proposed model. Table 4 shows that the proposed model achieves the highest accuracies with the “Average” pooling method with both training and validation datasets. The corresponding training and validation accuracies are 92.44 and 78.44%, respectively, which are much higher than those of Max, GlobalMax, and GlobalAverage pooling methods.

Table 3: Analyzing the effect of different combinations of filter size, kernel size, and stride on the performance of the proposed model with the training and validation datasets

Filter size, Kernel, Stride	Training Accuracy (%)	Validation Accuracy (%)
f:32, k:(2, 2), s:(1, 1)	81.55	76.89
f:32, k:(2, 2), s:(2, 2)	82.67	76.23
f:32, k:(3, 3), s:(1, 1)	85.78	78.89
f:32, k:(3, 3), s:(2, 2)	82.22	51.33
f:64, k:(2, 2), s:(1, 1)	57.56	75.33
f:64, k:(2, 2), s:(2, 2)	77.56	76.44
f:64, k:(3, 3), s:(1, 1)	90.00	76.00
f:128, k:(3, 3), s:(2, 2)	80.89	69.11
f:128, k:(2, 2), s:(1, 1)	76.00	55.77
f:128, k:(2, 2), s:(2, 2)	60.67	25.56
f:128, k:(3, 3), s:(1, 1)	27.11	74.67
f:128, k:(3, 3), s:(2, 2)	80.44	72.89

Table 4: Effect of different pooling methods on the performance of the proposed model.

Pooling Strategies	Max	Average	GlobalMax	GlobalAverage
Training Accuracy (%)	88.22	92.44	18.44	44.22
Validation Accuracy (%)	77.78	78.44	16.22	40.00

Third, we analyze the performance of the 2D-DCNN FDI model when varying the activation function type. We experimented with five different activation functions: rectified linear unit (ReLU), Sigmoid, Tanh, SoftMax, and exponential linear unit (ELU). The model's performance was evaluated using both training and validation datasets. Table 5 demonstrates that SoftMax and ELU obtain the highest accuracy rates of 89.56% with the training dataset, while Tanh yields the best accuracy (79.56%) with validation dataset. In turn, Sigmoid activation function obtains the lowest accuracies with both training and validation datasets, and thus it is not recommended for the 2D-DCNN FDI model.

Fourth, we study the effect of the selection of the optimization technique of the performance of the 2D-DCNN FDI. Specifically, we experimented with five different optimizers: Adam, SGD (Stochastic Gradient Descent), RMSprop, Adagrad, and Adadelta. It is found that Adagrad leads to the best performance with the training and validation datasets with corresponding accuracies of 79.11 and 75.33%, respectively. We also experimented with four different batch sizes: 2, 4, 8, 16, 32, 64, 128, and 256. It is found that the best performance of the proposed model is attained by a batch size of 16, which leads to accuracies of 93.11 and 82.67%

with the training and validation datasets, respectively. Additionally, we experimented with three different learning rates: 0.001, 0.01, and 0.1, finding that the best one is 0.01. We experimented with five different numbers of epochs: 20, 50, 100, 150, concluding that training the model up to 100 epochs leads to the highest accuracy when compared to the other epoch numbers.

Table 5: Impact of different activation functions on the performance of the proposed model.

Activation Functions	ReLU	Sigmoid	Tanh	Softmax	ELU
Training Accuracy (%)	69.78	55.33	88.00	89.56	89.56
Validation Accuracy (%)	66.67	48.00	79.56	78.22	76.44

Fifth, we present the results of the ablation study conducted on the 2D-DCNN FDI model by varying the depth of the CNN model. It should be noted that the depth of CNN layers refers to the number of layers used in the model architecture, and in this study, we experimented with four different configurations: 1, 2, 3, and 4 CNN layers. To evaluate the impact of each depth configuration on the model's performance, we trained the 2D-DCNN FDI model with each setting and recorded the accuracy and loss values for both the training and validation datasets during the training process. As shown in Table 6, the highest accuracy of the CNN model is achieved with 2 layers in the case training dataset, while 3 layers leads to the best accuracy with the validation dataset.

Table 6: Impact of different activation functions on the performance of the proposed model.

No. of Layers	1 layer	2 layers	3 layers	4 layers
Training Accuracy (%)	92.89	95.78	94.89	93.78
Validation Accuracy (%)	80.22	80.44	81.33	79.11

It was observed that when the model was trained with only 1 CNN layer, it demonstrated promising performance during the training phase. The accuracy and loss values for the training dataset indicated that the model was learning well and achieving high accuracy on the training data. However, a noticeable difference was observed during the validation phase. The model's performance on the validation dataset, as reflected by the accuracy and loss values, did not match the results seen during training. This discrepancy suggests that the model may have overfit the training data when using only one layer. Overfitting occurs when a model becomes too specialized in learning the training data, leading to poor generalization on unseen data.

In turn, when the model's depth was increased to four CNN layers, a distinct improvement was observed in the validation performance. The accuracy and loss values for the validation dataset showed significant enhancements compared to the one-layer model. This indicates that the model with four CNN layers was better at generalizing and capturing relevant patterns from the validation data, resulting in improved fault detection accuracy. The discrepancy in performance between the one-layer and four-layer models highlights the importance of model complexity and capacity. A deeper model with more layers can capture more complex patterns and features in the data, making it more adaptable to a variety of fault scenarios. However, it is essential to strike a balance between model complexity and overfitting. A model with too many layers or parameters may become overly complex and risk overfitting the training data, which can negatively impact its performance on unseen data.

Table 7: Data augmentation options

	'width_shift_range'	'height_shift_range'	'rotation_range'	'zoom_range'	'horizontal_flip'	'vertical_flip
Option 1	0.1	0.1	10	0.1	Activated	Deactivated
Option 2	0.2	0.2	20	0.2	Activated	Deactivated
Option 3	0.3	0.3	30	0.3	Activated	Deactivated
Option 4	0.4	0.4	40	0.4	Activated	Deactivated
Option 5	0.5	0.5	50	0.5	Activated	Deactivated

4.3 Analyzing the impact of data augmentation of the performance of the proposed model

Data augmentation is a common approach used to artificially increase the size of the training dataset by applying various transformations to the original data. Table 7 presents the five options of the data augmentation with Gaussian noise used in this study.

Here, we present the results of the ablation study conducted on the 2D-DCNN FDI model by applying different data augmentation techniques during the training phase. The ablation study results show that data augmentation has a positive impact on the model's performance, but the improvement is relatively modest. The highest accuracy achieved with data augmentation (option 4) was approximately 94%, compared to around 93% without data augmentation (See Table 8). While data augmentation helps the model generalize better to unseen data, it does not lead to a significant increase in accuracy. The reason for this observation might be that the original dataset was already sufficiently diverse to capture the variations in the fault patterns. It is essential to carefully select data augmentation techniques based on the specific dataset and problem at hand. In this case, Gaussian noise augmentation with option 4 provided the best balance between improving generalization and preventing overfitting. However, it is crucial to consider the potential trade-off between augmentation complexity and computational cost, as extensive augmentation may increase training time and resource requirements.

Table 8: Impact of data augmentation option on the performance of the proposed model

Data Aug.	option 1	option 2	option 3	option 4	option 5
Training Accuracy (%)	96.22	91.55	92.67	94.00	95.33
Validation Accuracy (%)	79.55	85.33	81.56	80.67	78.22

4.4 Comparisons

Table 9 presents a comparison between the proposed fault classification model and a 1D-CNN-based model presented in [17]. The 1D-CNN-based fault detection model is designed to incorporate both 1D-CNN architecture and a data segmentation process. Following [17], we implemented the 1D-CNN model with a segment length of 1000 and overlap of 500. Additionally, majority voting is applied to combine the predictions of all data segments to obtain a final prediction. As one can see in Table 9, the proposed 2D-CNN model achieves detection and classification accuracies 6 and 4% higher than the 1D-CNN model. Figure 10 shows the classification rates of the proposed method and the 1D-CNN method with the normal class (1) and the eight fault types (2-9). As shown, the proposed method achieves the highest classification rates with the normal class (no fault) and with most of fault classes.

Table 9: Comparison between the proposed and the 1D-CNN methods.

Method	Detection Accuracy (%)	Classification Accuracy (%)
Proposed	100	85.91
1D-CNN [17]	94	82.44

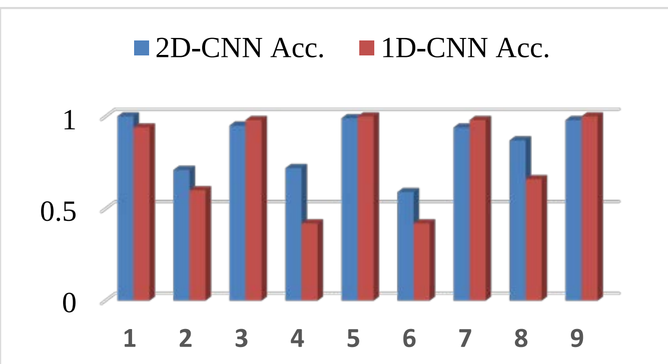


Figure 10: Classification rate of the proposed method and the 1D-CNN method with the normal class (1) and the eight fault types (2-9).

Discussion

The proposed method detected every fault (100 % detection) and classified most faults correctly (> 85 %), clearly outperforming the baseline approach. Converting raw converter signals into compact 2-D maps allowed the network to capture fault patterns without extra signal processing.

Next, we will deploy the model on a real-time controller (FPGA or microcontroller) and test it on a laboratory MMC. We also plan to extend the dataset to include ageing-related faults and other converter topologies, and to add confidence scores to each prediction to aid maintenance scheduling.

Conclusion

This paper designed a novel fault detection and classification method for modular power converters by employing a 2D deep CNN approach. Traditional methods relied on complex signal processing, such as signal segmentation, which degraded the accuracy of the classification model due to the ignorance of temporal dependencies among various signals. Additionally, these approaches required fine-tuning for a sufficient ensemble technique. In turn, the CNN-based approach handles these defects by providing a data-driven solution. This unique feature enables the automatic learning of fault patterns from sensor data and precise modeling of the temporal dependencies among the measured signals. Furthermore, a specialized CNN-based fault detection system for MMCs was presented by utilizing a dataset containing diverse MMC operating conditions. Simulation results on the dataset and real-time evaluation in MATLAB Simulink demonstrated the efficiency of the proposed approach in distinguishing normal and faulty operations. The findings emphasized the potential of the proposed approach as a valuable tool for enhancing the reliability and performance of MMCs.

Conflict of Interest Statement

Authors declare that there are no known associated academic or financial interests that would have influenced this work.

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