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Reliable Mechanical Fault Diagnosis in Medium Voltage Electrical Switchgear Using a 1D-Convolutional Neural Network

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ABSTRACT

Medium-Voltage (MV) electrical switchgear is some of the essential equipment for ensuring the stability of electrical networks. However, detecting mechanical faults in these systems, especially in light of current operations and safety concerns, is a complex task. This paper presents a useful method that uses a one-dimensional convolution neural network (1D-CNN) to find both mechanical and non-mechanical faults in MV electrical switchgear with a high level of accuracy. The identification of mechanical faults in MV electrical switchgear requires accuracy and speed to avoid aggravation of the faults and the occurrence of risks. The proposed 1D-CNN model proved to work very well in identifying spatial features. Thus, by combining time domain and frequency domain analysis, it not only refines the classifier but also increases the fault detection probability in real-world situations. Even during real-time signal pre-processing and model validation, our model was able to predict the incurred faults for the scenarios in the time and frequency domains with 100% accuracy. The study provides an original approach that increases the efficiency of fault identification and the reliability of MV electrical switchgear at the same time. Introducing our 1D-CNN model, we advance the field of fault detection by minimizing downtime and maximizing maintenance effectiveness, in both time and frequency domain analyses.

1. INTRODUCTION

Since it is essential for the protection and control of various types of electrical equipment, MV electrical switchgear can be considered one of the key elements in power systems [1, 2]. However, when electrical and mechanical problems occur, it becomes difficult for MV electrical switchgear to function normally. This can lead to insulation damage and, eventually, electrical switchgear failure [3-5]. All of these factors highlight the importance of sophisticated approaches to fault detection and handling, which would help address the problems quickly [6]. Faults prevalent in electrical switchgear necessitate the consideration of electrical faults that involve arcing, corona discharge, and surface tracking [7-10]. Arcing is when an electric current passes through air, separating the contacts and forming an electric arc that is very hot and capable of causing damage to the insulation [11]. Corona discharge can be defined as the ionization of air surrounding high-voltage conductors, which causes power waste and electromagnetic emissions [12].

Surface tracking, on the other hand, occurs when conduction paths form on insulating surfaces, paving the way for electrical discharges that compromise the functionality of the affected equipment [13]. Furthermore, mechanical faults within electrical switchgear encompass a broad range of issues related to the mechanical components of the electrical switchgear system [14]. It is clear that these faults may originate due to wear and tear, misalignment, and physical damage to vital electrical parts, including circuit breakers, disconnect switches, and bus bars [15].

Such mechanical faults not only cause a decrease in overall efficiency but also become sources of dangerous risks that can turn into catastrophic consequences, including the abrupt failure of electrical switchgear [16]. Moreover, within the deep learning (DL) framework, the 1D-CNN is a unique type of neural network that handles sequential data with only one dimension, such as time series signals [17, 18]. Conventional 2D CNNs excel at extracting spatial features from images, while 1D CNNs specialize in identifying local temporal modes within sequences. Their ability to extract features in a hierarchical manner across different layers makes them highly suitable for tasks involving time series. When it comes to finding mechanical faults in MV electrical switchgear, a 1D-CNN can tell the difference between the fault-related signals and their temporal patterns and features [19, 20]. This, in turn, helps to categorize various types of faults based on their features.

2. LITERATURE REVIEW

Modern methods have improved the identification of mechanical faults in MV electrical switchgear over the past few years. Earlier approaches used for fault detection incorporated rule-based expert systems along with the basic signal processing methodologies [16, 21]. However, these methods appeared to be impractical for the complex fault patterns that occur in electrical switchgear systems, particularly when considering the variations in working conditions. The researchers have put a lot of effort into identifying mechanical faults in electrical switchgear. A hugely effective research study by Liu et al. [22] have proposed a new approach to integrating an autoencoder neural network (AENN) with a support vector machine (SVM) for the identification of mechanical faults in circuit breakers. Reflection analysis applications focus on enhancing fault detection and addressing important maintenance concerns. These results show that the suggested AENN-SVM method improves the classification outcome. AENN is good at pulling out useful features from sensor data, and SVM improves the classification outcome. This integration yields excellent results in identifying a number of mechanical fault types for all the cases.

Another relevant study by Chen and Wan [23] described an enhanced method for fault diagnosis in a high-voltage circuit breaker. They use Multi-Segment Permutation Entropy (MSPE) and a density-weighted one-class extreme learning machine (DW-OCELM) to improve the speed and performance of finding faults. The MSPE-DW-OCELM approach is valuable in diagnosing mechanical faults because it is able to extract complicated patterns from sensor data and improve classification results for normal and faulty situations. As a result, comparative analysis proves the effectiveness of MSPE-DW-OCELM compared to other approaches, making it indispensable for high-voltage circuit breaker maintenance. The benefits of this technique are obvious in terms of fault perspectives, which help to improve the system's functioning and stability.

Furthermore, Ma and Wang [24] developed a new idea for precise mechanical malfunction detection for gas-insulated switchgear (GIS) disconnectors. They combined the Synchrosqueezing Wavelet Transform (SWT) with a stacked autoencoder (SAE) to enhance fault detection performance, resolving issues with signal decomposition and data feature representation. The results clearly demonstrate the high effectiveness of the proposed SWT-SAE method in fault diagnosis of rotating machinery, as it accurately dissects vibration signals through the synchronous wavelet transform and enhances fault pattern learning through the stacked SAE model. Another study by Li et al. [25] proposed an intelligent method for evaluating the GIS mechanical performance with the help of the VGG16 network. Building upon the DL methods, their research increases the level of precision and efficiency of the GIS mechanical ailment diagnosis. Consequently, the proposed VGG16-based method well processes the mechanical performance information and enables the evaluation of the GIS equipment. Due to its strong capability to learn, VGG16 helps increase the maintenance and equipment reliability. Nevertheless, the VGG16 model tends to have high computational requirements and the problem of overfitting that may affect real time operations and proper generalization of the model in actual industrial applications.

Liu et al. [26] designed a new mechanical fault diagnosis model that incorporated 1D-CNN, Gated Recurrent Unit (GRU) layer and knowledge graph and an attention mechanism. By extracting features and having attention mechanisms, this has been found to have almost perfect accuracy of up to 99% improving the fault diagnosis accuracy. However, the paper raises questions about adaptability and practicality since it requires large amounts of labeled data and has a highly layered and intricate structure, which inhibits the model's ability to run efficiently in the real world, in terms of computational complexity, training time, and hardware demands.

On the other hand, Long et al. [27] proposed an exceptional fault diagnosis method that enriched one-dimensional data using CNNs. This research utilizes DL to enhance the facets of the diagnosis of mechanical failures, especially when the faults are complicated and there are few samples for training. Thus, they employed a stacked AE, which the Backpropagation Neural Network (BPNN) had improved, and achieved excellent results, with training accuracy at 98.89% and test accuracy at 97.25%. Nevertheless, similar to most DL algorithms, it greatly relies on the availability of sufficient labeled data, which may turn into a problem in a real-world industrial environment.

Hong and Suh [28] looked at how to use the SCRLSTM model to find problems in industrial machinery. This model combines stacked two-dimensional and one-dimensional CNNs with residual long-short-term memory (LSTM) and supervised LSTM. It works well at finding abnormal points and extracting spatial features from time-series vibration data in a variety of settings. However, one of its flaws is that it relies on supervised learning and needs a lot of training labeled data. This means that it might not work well in situations where labeled data is hard to come by. Certifying its performance in different spheres of industry with varied interactions and types of equipment remains effective. Furthermore, the incorporation of several DL components suggests that the scale of large-scale installations will impact the performance of the proposed systems.

In contrast, this research work is concerned with the use of a 1D-CNN model for diagnosing as well as detecting mechanical faults in electrical switchgear. Particularly, the 1D-CNN architecture handles one-dimensional sequential data and vibration signals from the switchgear components. Taking full advantage of the fact that 1D-CNN can extract features in the hierarchical layers, this work successfully applies 1D-CNN to identify patterns relating to mechanical faults with high accuracy and efficiency. This reduces the time spent on feature extraction compared with the traditional approach, whose time-consuming aspect mostly involves feature engineering.

This approach addresses the inherent problems in traditional fault diagnosis because it uses DL to self-learn and automatically classify fault patterns from raw vibration data. 1D-CNN's ability to learn features and differentiate signals related to various types of faults can be advantageous in real-time monitoring of electrical switchgear and other preventive maintenance policies. Furthermore, our proposed method enhances the reliability and safety of electrical distribution networks by incorporating less labeled dataset input and enhancing the computational aspect.

Such integration is also beneficial in working on the identification of mechanical faults and studying the dynamics of these faults and their frequency characteristics. Therefore, the model expands the understanding of fault behaviors into additional dimensions, enabling more informed decisions in maintenance and operational plans. As a result, the suggested 1D-CNN model is a big step forward in finding mechanical faults in MV electrical switchgear. It is made better by combining the two useful techniques of time domain analysis and frequency domain analysis. Based on this, the paper aims to diagnose and identify mechanical faults in electrical switchgear using a one-dimensional convolutional neural network with time and frequency domain techniques. The research endeavors to achieve the following objectives and contributions:

1. Development of an Enhanced Model: The main idea of this paper is to design and train a new 1D-CNN model that uses the advantages of convolutional neural networks. Therefore, the proposed model, which targets enhancing the fault detection accuracy, concentrates on the feature extraction aspect of 1D-CNNs at a local level. This contribution can be narrowed down to the creation of a distinct model that proves to be efficient in fault detection with the help of neural network architectures.
2. Integration of Time and Frequency Domain Analyses: Another important aim is to incorporate the time and frequency domain features into the 1D-CNN. This integration allows for the parsing of temporal patterns existing in signals collected in a particular period of time while at the same time detecting faults of certain frequency. Through the integration of the two knowledge domains, it is believed that the proposed model will obtain a more accurate and robust perception towards the fault signatures, and thus improve the fault detection performance. To this contribution, it also expands in the area of integrating various analytical domains as a way of enhancing fault diagnosis
3. Advancement of Fault Detection: The general goal of the research is considered to be the improvement of the prospects for detecting mechanical faults in switchgear systems with the use of the introduced 1D-CNN model. As a result of decreasing the time when the machinery is not available for work, and avoiding various crucial breakdowns, the application of the model is expected to increase operational reliability. The main input is made in terms of the actual implementation of the established model where actual real-world situations have the potentiality of enhancing the serving reliability of the power distribution networks.

However, it is crucial that our study presents a robust approach to mechanical fault diagnosis of switchgear systems using the proposed 1D-CNN model, while also highlighting some of its limitations. First, such a model's intuition is highly dependent on the volume and type of training data. Inefficiency is identified as occurring when inadequate or low-quality data is utilized in the application of the current set.

Furthermore, even though the test dataset exhibits highaccuracy, the issue of overfitting and consequent generalization to other datasets or different operational environments persists. The complexity of the DL model may also be another drawback when it comes to real-time applications, especially in factories where holding time is very important. Based on these limitations, the following points could be considered as ways for future research in this field to be directed: For more efficient model training and less sensitivity to data scarcity, new methods of data augmentation should be created. Exploring transfer learning could help boost generalization in a variety of tasks and datasets.

We would implement a number of explainable Artificial intelligence (AI) techniques to get an idea of what kind of decision-making is going on, thus increasing the interpretability of the model.To improve the real time operation of the model, it might be beneficial to reduce the complexity of the network or use hybrid models. Moreover, the paper suggests integrating multi-domain information based on the fault mode for diagnosis, despite the current array of fault types being quite diverse. This approach could potentially expand further. To overcome these limitations and follow these research directions, we will endeavor to expand the field of mechanical fault diagnosis and improve the dependability of switchgear systems.

In summary, this paper outlines an integrated approach to enhancing the identification of mechanical faults with a focus on a 1D-CNN model in both time and frequency domains. As a result, the overall goal is to improve the fault detection rate while simultaneously increasing the operational reliability of power distribution systems. The contributions extend to the model's formulation, utilization, and implications for improving fault identification techniques.

3. METHODOLOGY

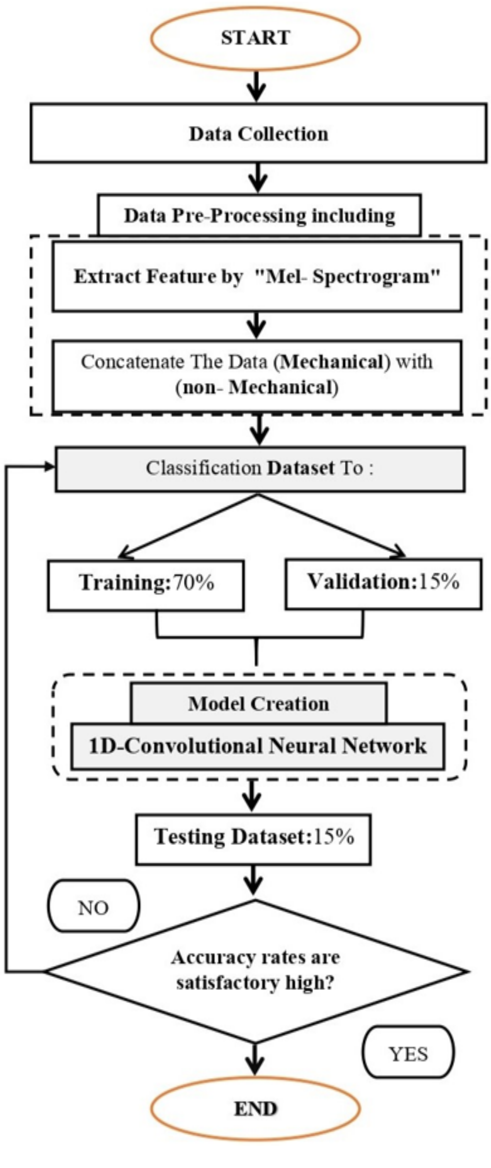


Figure 1. Diagram illustrating the overall research approach

The research proposed in the present work can be divided into the following sequential steps, which mainly deal with the detection of mechanical faults in MV electrical switchgear. The research encompasses both time-domain and frequency-domain analysis. The first component involves creating a comprehensive database that includes data such as mechanical faults, arcing, corona, and tracking, in addition to normal operation data. To solve it, a 1D-CNN model is employed to work on the ultrasonic data acquired during faults and presented in audio form. The mechanical fault classification system described until now and enabled by using the 1D-CNN model is summarized in the schematic representation of Figure 1. The process of undertaking the research means that distribution data in its raw form was collected from the power utility company (PUC) concerning seven states in the Peninsular Malaysia namely Kedah, Kuala Lumpur, Melaka, Selangor, Perak, Negeri Sembilan, and Johor. The subsequent data processing activities were performed in MATLAB. The selection of the 1D-CNN model stemmed from its suitability as a DL technique.

We used MATLAB for the entire data import and preprocessing process, and Google Colab for the model creation. The Airborne Ultrasonic Testing (AUT) equipment uniquely records raw data in sound formats such as mp3, MPEG, or wav. It is clear from the AUT equipment, as shown in Figure 2, that the equipment is central to detecting Partial Discharge (PD) which is a diagnostic of inadequate electrical insulation between conductors. The following sections explicate the procedures described in the section titled Figure 1, which explains the extensive approach used in this study.

Figure 2. Airborne ultrasonic test equipment visualization [29]

3.1 Dataset

The dataset employed in the current study is a compilation of electrical switchgear data by data obtained from prior studies [8, 9, 30]. It contains detailed records of the ultrasonic signals of arcing, corona, tracking, mechanical faults, and normal cases in terms of time and frequency. This way, this dataset can contribute to fault identification and rectification because it includes various types of faults and different operation conditions. As a result, the primary emphasis was on data collection and pre-processing to develop a reliable fault detection system for MV electrical switchgear using a 1D-CNN model. The goal of this paper was to employ the 1D-CNN model methodology to accurately identify faults within electrical switchgear systems.

Actual operating data were harvested that included normal conditions and different classes of faults, including arcing, corona, tracking, and mechanical faults. It also makes the data diverse and allows the model to easily tell one type of fault from another, thus improving the model's detection ability. Table 1 displays an extensive assortment of datasets that includes both mechanical and non-mechanical scenarios, covering both the time and frequency domains.

Table 1. Provides an overview of the datasets, encompassing both mechanical and non-mechanical faults

Faults	Samples in Time Domain	Samples in Frequency Domain
Arcing	54 × 20,001	53 × 10,001
Corona	41 × 20,001	39 × 10,001
Tracking	313 × 20,001	40 × 10,001
Mechanical	17 × 20,001	16 × 10,001
Normal	13 × 20,001	12 × 10,001
Size of Dataset	17.5 Mega-Byte (MB)	11.3 Mega-Byte (MB)

3.2 Data pre-processing

This step involved cleaning the data to set the stage for subsequent processes. Initially, feature extraction was performed using the "Mel Spectrogram" technique. We combined mechanical fault data with non-mechanical cases such as arcing, corona, tracking, and normal circumstances, and subsequently divided the dataset into three sections. We use this process to refine the data integrity before interacting with the 1D-CNN model. This preprocessing procedure provided a suitable platform for training the proposed 1D-CNN model. The developed model demonstrated exceptional classification accuracy in forecasting mechanical faults in MV electrical switchgear.

3.3. Extract features by using "Mel Spectrogram"

In this stage, we employ the Mel Spectrogram to extract features from the ultrasound signals of the switchgear systems under different fault conditions [31, 32]. This technique converts the raw time-domain signals into a 2D matrix where one axis is the timeline, and the other is the frequency line. Like how humans hear, we use filters in the Mel Spectrogram to focus on certain frequencies. This lets us find different temporal features that are often linked to machine failures. In the time and frequency domains, Figure 3 depicts the Mel Spectrogram view of the mechanical faults. This transformation process tracks changes over time in the frequency band and thus extracts fault related features that might be hidden in raw signals. The work generates the Mel Spectrogram, a rich input to the 1D-CNN model, which enhances fault type differentiation based on their frequency characteristics. The spectrogram explains various fault scenarios by transforming the time-domain ultrasound signals into frequency-domain representations. This transformation shows the fault-specific spectral features for each fault that help our model in the differentiation of various fault types. Adding the Mel spectra to both time domain analysis and frequency domain analysis improves our fault-finding method by providing a complete picture of the temporal and spectral features. The merging of Mel Spectrogram as a feature extraction technique improves the stability and efficiency of the 1D-CNN model, thus improving the detection of mechanical faults in switchgear system.

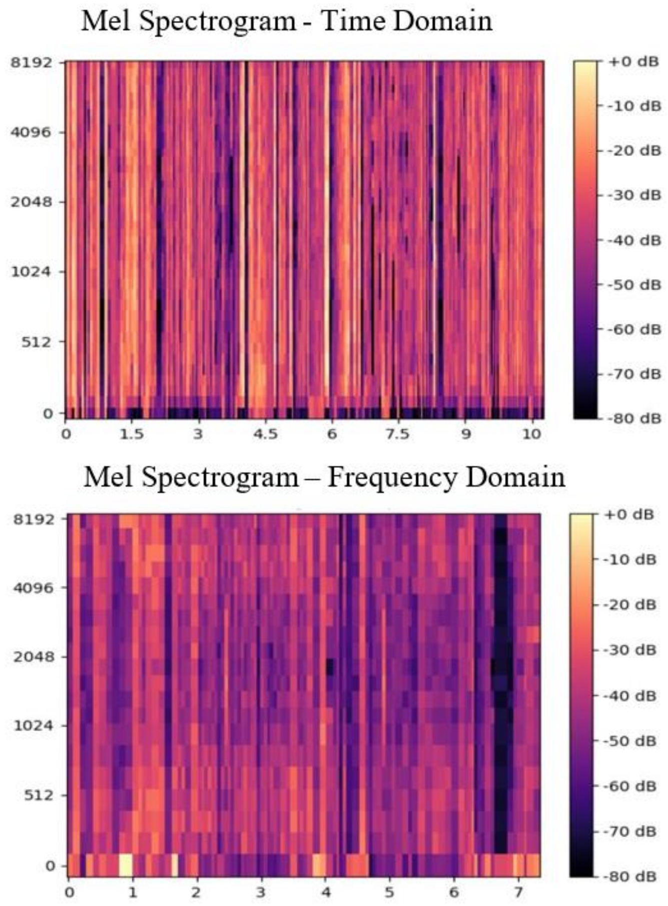


Figure 3. Represent the Mel Spectrogram for mechanical faults in both time and frequency domains

3.4 Concatenate the mechanical fault data with the non-mechanical fault data

We then proceeded to integrate the mechanical fault data with the non-mechanical fault data, which encompassed arcing, corona, tracking, and normal cases. It was easier to evaluate a lot of different operational conditions and faults because of this integration, which led to the creation of a lot of training data. By taking into account non-mechanical faults, the model acquires a diverse range of behaviours that aid in distinguishing between mechanical and non-mechanical faults. This step is critical because it enables the 1D-CNN model to accurately capture the details of both mechanical and non-mechanical fault features.

The process of concatenation involved the following steps:

- Data Preparation: Switchgear fault data comprising mechanical faults was obtained from diverse subcomponents, mainly vibrations and operational signals of mechanical faults such as misalignment, wear, or physical damage. Therefore, the mechanical data included signals that characterized faults, such as mechanical shocks and vibrations, as well as some non-mechanical fault data of an electrical nature, such as arcing, corona discharge, surface tracking, and normal operation signals.
- Combining Data: In order to do this, we merged the two datasets of fault type mechanical and non-mechanical after they had been preprepared. Still, the data points were retained with their labels (mechanical fault, arcing, corona, normal, etc.). This step increased the range of faults that are modeled in the training data by at least an order of magnitude, giving a tool a better chance at learning from new conditions.
- Significance in Model Performance: One benefit of such integration is the model's ability to distinguish between mechanical and non-mechanical faults. Since non-mechanical fault data are incorporated into the model, the mechanical faults can be detected as well as distinguished from the other types of faults. This diversity in the training data is beneficial because it allows the 1D-CNN model to study temporal and spatial relationships that define mechanical faults from non-mechanical ones. As a result, the model is less likely to learn to identify one type of fault and more likely to generalize to different operational scenarios.
- Enhancement in Fault Detection: Including non-mechanical faults enhances the model's comprehension of the overall fault environment, enabling the recognition and implementation of both mechanical and non-mechanical fault features. Applying this in the real field, where both types of faults are likely to occur, enhances the model's performance. In addition, by giving normal operating data out to the model, the model learns to distinguish particular norms or a faulty condition, thus minimizing false alarms.

Overall, the integration of mechanical and non-mechanical fault data is beneficial for improving fault diagnosis because the 1D-CNN model has the ability to identify various types of faults.

3.5 Dataset classification

After merging the dataset, the next step involves normalizing the data and scaling the input data to standard formats. Min-max scaling was applied to rescale all input features to a [0, 1] range ensuring consistency in data representation and preventing features with larger scales from skewing model predictions. This standardization also enables the 1D-CNN model to learn and recognize data patterns better, as well as generalize from these patterns to give a very accurate forecast. This is necessary to arrive at a training, validation, and test split of 70:15:15%, respectively. For this research, we considered 70% for training data, 15% for validation data, and 15% for testing data. This distribution is widely recognized in machine learning (ML) as well as DL platforms, as it furnishes an equitable treatment in model building, optimization, and assessment.

- Training Set (70%): The training group consists of data, which accounts for 70%, which allows the 1D-Convolutional Neural Network (1D-CNN) to learn from a wide range of mechanical fault data. This larger training dataset increases the model’s capacity to detect other finer details and relationships to spur better performance and future generalization.
- Validation Set (15%): The percent of the validation set is 15%, and it is applied during training as a subset for adjusting the model’s parameters and decision-making in architecture. Using another validation set, we are able to estimate the error on unseen data while tuning the hyperparameters and avoid overfitting. This set plays a very important role in the model by acting as a checkpoint of generalization.
- Testing Set (15%): Last but not least, the 15 % data is reserved for the testing set, which is employed only at the end phase of the construction of the model. This way, the assessment takes place on an entirely separate and

independent data set so as to give the model a true indicator of what to expect when implemented in real-life scenarios.

Altogether, the 70:15:15 ratio is justified for our investigation for the reason that it offers ample information for the training processes while at the same time offering strong validation and the test set sizes. This configuration enables learning and model tuning and performance evaluation, thereby enhancing the reliability and accuracy of the fault diagnosis model.

Furthermore, to address class imbalance, we used oversampling techniques to equalize the ratio of frequent and rare faults during training data collection. This enhanced the capability of the model to diagnose several fault categories efficiently.

3.6 Training and optimization

The 1D-CNN model is trained on a new training set that is made up of both mechanical and non- mechanical fault data. During training, the said model seeks to reduce the categorical cross-entropy loss in relation to the probability predictions and real fault labels. Optimization uses the Adam algorithm and set the learning rate of 0. 0001. The training is carried out using 60 epochs with a batch size of 16; then, the parameters are updated by backpropagation. Adam's adaptive learning rate mechanism is better in the convergence than the traditional forms of stochastic gradient descent (SGD). This approach utilizes the feature that the given dataset is large enough which enables the model to learn about the faults in the switchgear systems depending on the various scenarios.

3.7 One dimensional convolutional neural network model

In our quest for accurate fault detection and differentiation between mechanical and non-mechanical faults within switchgear, we propose a novel approach: the 1D-CNN model to distinguish between mechanical and non-mechanical faults in switchgear. This model utilizes Mel Spectrograms, averaging spectrum diagrams that effectively capture the time and frequency domain characteristics of electrical signals. Therefore, by utilizing these spectrograms, the proposed model should make fault classification and differentiation tasks more precise and reliable.

During this research, we paid special attention to the preparation of the dataset, which included both mechanical and non-mechanical faults. This process entailed a sequence of careful and elaborate processes aimed at achieving a proper separation of these two main types of faults. Some of the preparatory procedures led to the creation of a dataset for the fault detection model's training.

The first layer in the proposed model is the Input Layer that takes in preprocessed Mel Spectrograms which have been generated from electrical signals. These spectrograms are computed using the short-time Fourier transform (STFT) on raw time domain signals and they detect and display the frequency spectrum of different signals. This transformation allows the model to give a compact representation of the signal and its spectrum content over different time periods which are inherent in the signals due to their frequency content. The core of our approach lies in the 1D-CNN module, which serves as a critical component for spatial feature extraction from the Mel Spectrograms. This module is made up of a sequence of one-dimensional convolutional layers each containing learnable filters. These filters are specifically tailored to help the module in capturing local patterns in the Mel Spectrograms and to let the module study the spatial components of the signal.

Mathematically Eqs. (1)-(4), the operations within the 1D-CNN module can be represented as follows:

$$X_i = Conv1D(H_{i-1}, W_i) + b_i \tag{1}$$

where, H_{i-1} is the input feature map of the $(i-1)-th$ layer, W_i is the weight tensor of the $i-th$ and b_i is the bias vector. The output of the $(i-1)-th$ convolutional layer after applying ReLU activation is given as:

$$A_i = ReLU(X_i) \tag{2}$$

Subsequently, the Maxpooling layer downsamples the feature maps to obtain Y_i:

$$Y_i = Maxpool(A_i) \tag{3}$$

Finally, the downsampled spatial features Y_i are passed through the activation function to obtain H_i:

$$H_i = ReLU(Y_i) \tag{4}$$

For time and frequency dominance, a 1D-CNN model is made with Google Colab. The first layer is of the Conv1D type, has 32 filters, a size of 3, "same" padding, and a ReLU activation function. This is based on the proposed architecture. This is followed by a dropout layer that operates at a rate of 0.2. The benefits that we are going to get from the proposed model include a dropout rate of 0.2 to keep the model from overfitting and the 1DMaxPooling necessary for the effective extraction of features. Consequently, more layers, Conv1D with 64 filters and the same configurations as earlier layers, are added in sequence, among which Dropout and MaxPooling1D are included again. The flattening layer then flattens the output before it is passed to a dense layer with 32 neurons and ReLU activation. We use the SoftMax activation function with 2 nodes for binary classification in the output layer, along with a categorical cross-entropy loss function and an 'Adam' optimizer for high accuracy.

The frequency domain model changes the structure with the time domain but similarly begins with a Conv1D layer containing 16 filters for the frequency analysis. To deal with overfitting, Dropout and the MaxPooling1D layers are used to extract more relevant features from the model. A stack of other layers is added: the next Conv1D with 32 filters, Dropout, and one more MaxPooling1D. To form the bill, the flattening layer is used to produce the feature map into a 1D vector, which is fed to the dense layer with 32 neurons and activated with ReLU. The output layer in the CNN uses a SoftMax activation function with 2 neurons for binary classification; the loss function, optimizer, and evaluation metric are the same as in the time domain model.A representation of the architecture of the 1D-CNN model in both the time and frequency domains is shown in Figure 4. This figure graphically presents how information is processed in the method and the components that are crucial for accurate fault detection using the proposed technique.

3.8 Evaluation and performance metrics

Metrics of performance includes accuracy, precision, recall and F1-Score in evaluating the discovered 1D-CNN effective on distinguishing fault type within switchgear. Since the Mel Spectrogram features are incorporated in the architecture, temporal and spectral properties of electrical signals are well harnessed, leading to accurate fault diagnosis. 1D-CNN helps the model in the spatial feature extraction which facilitates the classification of mechanical and non-mechanical faults. Thus, this methodology checked against a wide range of testing data including arcing, corona, tracking, mechanical faults and normal case proves the usefulness of the created model in practice.

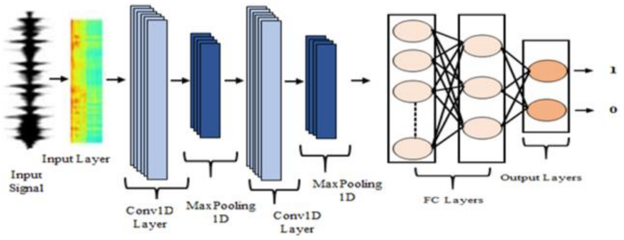


Figure 4. The representation of the 1D-CNN model in both the time and frequency domains

More importantly, the accuracy above the 90% reveals its applicability in the diagnosis of switchgear faulty conditions in real power systems, thereby improving the dependability and safety of the power systems. This stage is concerned with the training, optimization, and assessment of the 1D-CNN model together with their accuracies in the detection and classification of faults in switchgear systems.

4. RESULTS AND DISCUSSION

We conducted several tests to evaluate the efficiency of the formulated algorithm in diagnosing potential mechanical faults in MV electrical switchgear using sound signals generated during the equipment's operation. All these experiments were conducted in the time and frequency domains. The outcomes of the proposed algorithm in the training, validation, and test phases are shown and analyzed. For the time domain analysis and experiments in the 1D-CNN model, we used a total of 438 samples for training, validation, and testing in the case time domain and 160 samples in the frequency domain, respectively.

The feature number is 20.001 in the time domain and 10.001 in the case frequency domain. The mechanical classifier assigns a positive or negative classification to each case in the test data set. This classification leads to four possible outcomes: It therefore defines four parameters, namely the true positive, the true negative, the false positive, and the false negative. We calculate fault detection or classification accuracy by dividing the total number of correct classifications (TP + TN) by the total number of instances in the dataset (P + N), using the following equation:

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \times 100\% = \frac{TP+TN}{P+N} \times 100\% \tag{5}$$

The error rate (ERR) is calculated as the number of all incorrect classifications divided by the total number of the dataset by using the equation as follows:

$$Error\ Rate = \frac{FP+FN}{TP+TN+FN+FP} \times 100\% = \frac{FP+FN}{P+N} \times 100\% \tag{6}$$

Table 2 shows the output matrix for the training, validation, and testing phases in time domain analysis. The training phase utilized a total of 306 data sets. Among these, the system correctly detected 10 instances of mechanical defects and 296 instances of non-mechanical defects. determine the overall correctness of the calculation to be 100% accuracy, with an error rate of 0%. For the validation phase, we used a total of 66 data sets. We have successfully discovered 63 non-mechanical defects and 3 mechanical defects. Overall, the accuracy was 100%, and the error rate was 0%.

For the testing phase, we also used a total of 66 data sets. The program accurately detected 4 instances of mechanical defects and correctly classified all 62 cases as non-mechanical. The testing demonstrates a perfect accuracy of 100% with no errors, resulting in a 0% error rate.

Table 2. Time domain classification confusion matrix: mechanical and non-mechanical faults

1D-CNN Model		
Training Phase		
	Mechanical	Non- Mechanical
Actual Mechanical	10	0
Actual Non-Mechanical	0	296
Validation Phase		
	Mechanical	Non- Mechanical
Actual Mechanical	3	0
Actual Non-Mechanical	0	63
Testing Phase		
	Mechanical	Non- Mechanical
Actual Mechanical	4	0
Actual Non-Mechanical	0	62

Table 3. Frequency domain classification confusion matrix: mechanical and non-mechanical faults

1D-CNN Model		
Training Phase		
	Mechanical	Non- Mechanical
Actual Mechanical	10	0
Actual Non-Mechanical	0	102
Validation Phase		
	Mechanical	Non- Mechanical
Actual Mechanical	3	0
Actual Non-Mechanical	0	21
Testing Phase		
	Mechanical	Non- Mechanical
Actual Mechanical	3	0
Actual Non-Mechanical	0	21

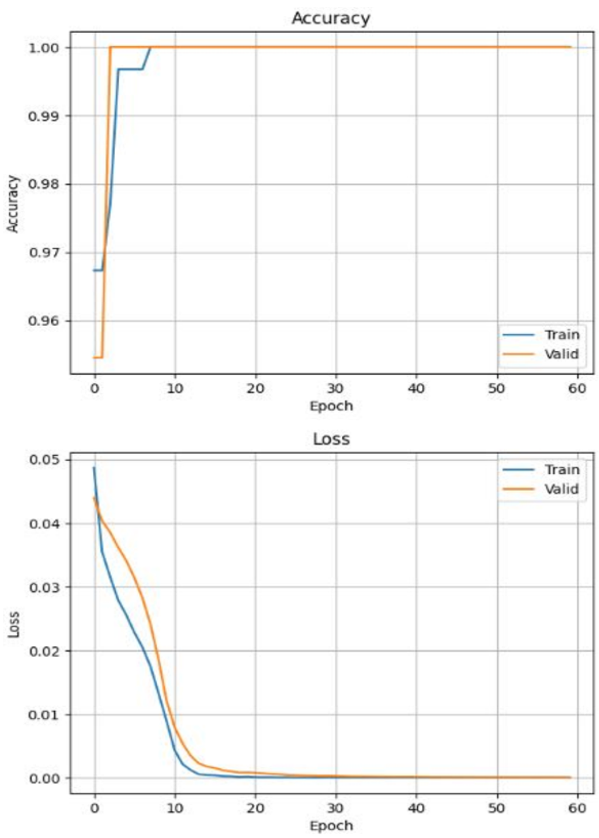
In case the frequency domain analysis. Table 3 shows the output matrix for the training, validation, and testing phases in the time domain. The training phase utilized a total of 112 datasets. Among these, the system accurately detected 10 instances of mechanical defects and 102 instances of non-mechanical defects. We determined the overall correctness of the calculation to be 100% accuracy, with an error rate of 0%. For the validation phase, we used a total of 24 datasets. We have successfully discovered 21 non-mechanical defects and 3 mechanical defects. Overall, the accuracy was 100%, and the error rate was 0%. For the testing phase, we also used a total of 24 datasets. The program accurately detected 3 instances of mechanical defects and correctly classified all 21 cases as non-mechanical. The testing demonstrates a perfect accuracy of 100% with no errors, resulting in a 0% error rate.

In addition, the evaluation results, including accuracy, precision, recall, and F1 score of the 1D-CNN classification model, are listed in Table 4 for mechanical and non-mechanical cases. The above assessments measure the effectiveness of a model in diagnosing faults in switchgear. However, the figure demonstrates that the performance constants indicate that this model is capable of accurately categorizing errors.

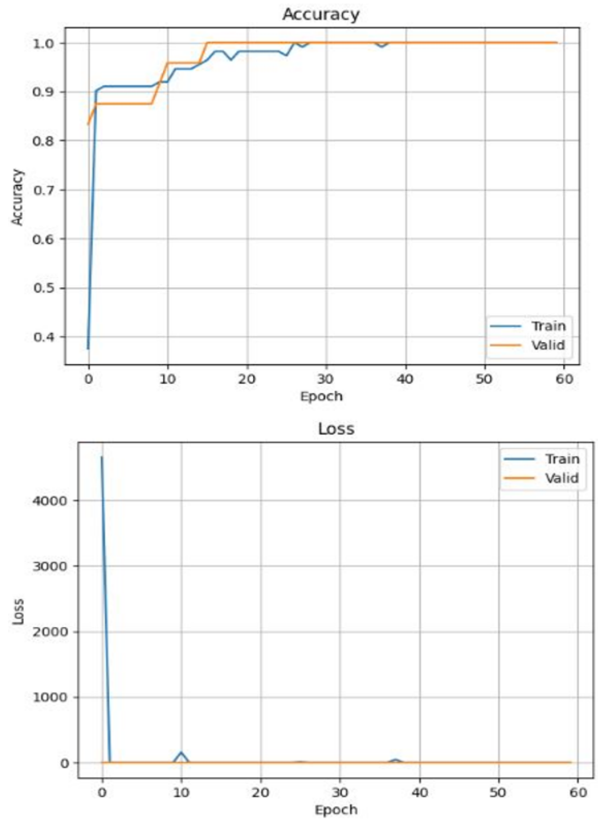
Table 4. The evaluation of metrics and performance for the 1D-CNN model testing outcomes

Time Domain			
Case Mechanical Findings (0)			
Accuracy	Sensitivity	Dependability	F1-Measure
100	100	100	100
Case Non-Mechanical Findings (1)			
Accuracy	Sensitivity	Dependability	F1-Masure
100	100	100	100
Frequency Domain			
Case Mechanical Findings (0)			
Accuracy	Sensitivity	Dependability	F1-Measure
100	100	100	100
Case Non-Mechanical Findings (1)			
Accuracy	Sensitivity	Dependability	F1-Measure
100	100	100	100

Furthermore, Figure 5 illustrates the accuracy and loss curve of the 1D-CNN model during the training and validation phases. The loss curve shows the learning and understanding phases that occur, whereas the accuracy curve shows the model's ability to detect errors. Plotting both curves provides a comprehensive view of the model's evolution.



(a) Time domain



(b) Frequency domain

Figure 5. Curves of accuracy and loss for the 1D-CNN model of mechanical and non-mechanical defects

The implications of our findings for real-world applications are substantial. Improved diagnostic accuracy can aid in the early detection of mechanical failures, leading to a reduction in repair time and maintenance expenses in traditional industrial settings. Our proposed model can be incorporated into current maintenance structures to allow operators to perform effective predictive maintenance instead of traditional break-fix activities.

Furthermore, by distinguishing different types of faults, management teams can order their interventions based on the type and severity of the identified fault. This has the benefit of effectiveness in resource use but also an increase in the reliability and safety of switchgear operations. Last but not least, our model's ability to provide enhanced and real-time constant monitoring assurances of the equipment's health provides crucial guidance for the design of subsequent models. The work also shows areas for future investigation, including noise resilience tests and the incorporation of IoT devices to continuously monitor and test the proposed model.

4.1 Comparison with state-of-the-art methods

In order to assess the performance of our proposed 1D-CNN model, we compared its results with several state-of-the-art techniques previously used for mechanical fault diagnosis in switchgear systems. These include methods such as the AENN combined with SVM [22], the MSPE and DW-OCELM [23], the SWT with a SAE [24], the VGG16 network for mechanical performance evaluation [25], the 1D-CNN with GRU and attention mechanism [26], the stacked autoencoder improved by BPNN [27], and the SCRLSTM model combining CNNs with Residual LSTM [28].

While these models have demonstrated notable performance in detecting mechanical faults, our approach offers several improvements:

- Simplified Architecture: Compared with other models, our proposed 1D-CNN has a simpler architecture, less computational cost, and fewer training times, which is indeed realistic for industrial applications.
- Data Efficiency: Most of the existing approaches, including those based on combining autoencoders or SVM, are trained on large, labeled databases. On the other hand, our model performs well with high accuracy at a limited number of iterations, solving an issue that is very rampant in real-life applications.
- Fault Diversity Recognition: Combining mechanical and non-mechanical fault data also improves the identification ability of the model to differentiate between diverse types of faults, providing more reliability across different functioning scenarios.
- Generalization and Accuracy: The implementations of data normalization, scaling, and splitting the datasets provide good results with less overfitting in a controlled environment and with real-world data.

Such improvements make our 1D-CNN model as promising and useful for practical diagnosis of mechanical faults in switchgear systems as compared with conventional approaches in terms of diagnosing efficiency and distinguishing the diverse faults.

5. CONCLUSION

Diagnosis of mechanical faults is critical for serviceability of MV electrical switchgear in handling electric power. This paper proposes a 1D-CNN for the detection and diagnosis of both mechanical and non-mechanical faults in the time and frequency domains. By examining such faults carefully, the model herein demonstrated 100% accuracy in terms of revealing all the tested fault conditions. This advancement greatly increases the ability to identify faults in MV electrical switchgear and improves the ability to represent problems, giving the electrical industry a proven technique to protect infrastructure and guarantee steady power delivery. Furthermore, the proposed approach improves operational productivity by reducing procedural time and making more informed maintenance decisions.

To enhance the performance of the proposed model, we should gather more datasets. Additionally, to expand the use of DL for component analysis in power distribution networks, future studies should explore the potential of utilizing a variety of datasets and DL models, as well as investigating the effectiveness of various forms of ensemble learning. Furthermore, the real-time integration of fault detection and maintenance techniques will be useful for the system's long-term, effective operation. Engaging the members of the relevant industry in field testing of the proposed model will confirm real-world applications. In conclusion, this research provides a starting point for the evolution of mechanical fault diagnosis in MV electrical switchgear systems with the goal of improving electrical assets.

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