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A Deep Hybrid 1D-CNN-LSTM Framework for Mechanical Fault Detection in Switchgear Using Time–Frequency Domain Analysis

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ABSTRACT

Medium voltage (MV) switchgear systems provide network stability and dependability in electric distribution networks. Operational disturbances and safety considerations make mechanical failure detection in these systems difficult. The study proposes a hybrid 1D Convolutional Neural Network and Long Short-Term Memory (1D-CNN-LSTM) model for time-frequency analysis to identify MV switchgear faults efficiently. This model captures mechanical and non-mechanical fault characteristics using LSTM's temporal pattern recognition and 1D-CNN's spatial feature extraction. Combining temporal and frequency domain research improves defect identification in real-world situations. Experimental findings show that hybrid 1D-CNN-LSTM can identify a variety of switchgear faults with 100% accuracy. This research improves MV switchgear reliability and operational efficiency by reducing interruption times, enhancing maintenance, and stabilizing and securing power networks. Firms combining time-frequency analysis and deep learning (DL) propose a unique MV switchgear failure detection method.

1. INTRODUCTION

Modern power systems rely on medium voltage (MV) switchgear, which controls and protects a wide variety of electrical equipment [1, 2]. Nevertheless, MV switchgear reliability is at risk from electrical and mechanical issues, which may lead to insulation deterioration and, eventually, switchgear failure [3, 4]. These issues emphasize the critical necessity of advanced fault-registration schemes that would allow these faults to be detected early and fixed afterward [5].

Electrical failure modes that may occur in switchgear include arcing, corona discharge, and surface tracking [6-10]. Insulation damage may occur when electrical energy causes arcing between energized contacts separated by air, thus producing high temperatures [7, 11]. When ionization materializes around high-voltage conductors, corona discharge occurs, generating electromagnetic noise and limiting the efficient transfer of power [12-14]. Surface tracking, the formation of conducting pathways on non-conductive surfaces, may lead to electrical malfunction and poor performance of the device [9, 15, 16].

Mechanical failures, on the other hand, can cause a range of physical damage to the physical components of switchgear [6]. Busbars, disconnect switches, and circuit breakers may have damage, misalignment, and normal wear, which trigger corrosion [10, 17]. These mechanical complications result in low efficiency of the operations and reduce the level of safety, thus increasing the risk of a disastrous failure of the switchgear that might carry far-reaching consequences [18, 19]. Modern studies have also focused more on the improvement of the identification of mechanical failures in MV switchgear by incorporating new practices. In the past, expert systems based on rules and traditional signal-processing methods were the main detection mechanisms [20-22]. However, these conventional methods were not sufficient to address the complex environmental factors that are typical of switchgear.

Moreover, the researchers have been able to illustrate significant improvements in the mechanical fault detection of switchgear through the development of the existing approaches. The study of Liu et al. [23] marked a landmark.

The authors developed a specific monitoring system that has the capacity to pick up vibration signals during circuit breaker openings and closings. Thereafter, the authors automatically extracted informative features of the incoming data sequences using an autoencoder neural network, which they finally classified with a Support Vector Machine (SVM).

The consequent approach achieved a strong level of precision to categorise mechanical faults and, as a result, demonstrated an ability to mine salient signal patterns. Despite such outcomes, the effectiveness of the method used will depend upon the accuracy of the vibration data sensed, which is in many cases, impaired by the high background noise that dominates industrial scenes. In addition, an explicit comparison with the rest of the contemporary diagnostic methods was not given by the authors, limiting the judgment to the consideration of its generality and advantageousness.

However, Wang et al. [24] offered an elaborate survey of the methods of image-based fault detection with the help of deep learning (DL) in the last five-year period. Their conversation traces a typical processing pipeline—data acquisition, signal-image conversion, model development, and decision-making—the shared pre-processing approaches and imaging methods, a continuum of DL frameworks, and the main problems and further research directions in the field. The review, though providing valuable information about the state of the art, has a rather descriptive character and a relatively small number of empirical assessments and comparisons, which restricts its opportunities to aid the practitioner in searching for the most feasible methodological decisions.

Furthermore, Sun et al. [25] proposed an inexpensive mechanical diagnosis procedure for induction motors based on stator current indications as compared to conventional vibration measuring devices. The researchers derive a noise reconstruction model that makes the signal clear by adaptively compensating for the relatively poor fault representation achieved by the existing signals. The method is above 96% accurate in diagnosing bearing and eccentricity faults and above 90% accurate in differentiating between the six different types and levels of bearing faults. The researchers achieve this accuracy by automatically extracting features from the residual current envelope spectrum. Despite its effectiveness, the given solution is sensitive to signal noise and highly reliant on controlled experiment practices, aspects that might restrict its stability and utility in industry in cases where signal quality is subject to variability.

On the other side, An et al. [26] introduced NISTA-Net, a neural-network design able to diagnose mechanical faults in an interpretable approach, which is leveraged based on the unrolling of the Nested Iterative Soft Thresholding Algorithm (NISTA). However, unlike most black-box deep-learning frameworks, NISTA-Net is theoretically sound, providing insights and clarity into architectural design decisions and the feature-learning process. There is also a complementary method of visualization so that users can see how the network can build and utilize representation in fault classification. Empirical evaluations show that NISTA-Net is the most successful at identifying defects in bearings and gears compared to a number of state-of-the-art neural architectures.

However, the model performance and credibility depend on the assumption of sparse coding, which might be biased during the modelling of signals or the fault configurations that do not lead to these assumptions. In addition, its noise resistance, multi-source signal, and generalization ability will need more thorough confirmation. Nevertheless, Chen and Li [27] suggested a hybrid model in centrifugal pump fault detection that is reliant on multi-sensor vibrations. They combine the Continuous Wavelet Transform (CWT), Parallel Factor Analysis (PARAFAC), and SVM into their pattern because they make it possible to complete time-frequency decomposition, feature extraction, and classification. Moreover, the Improved Particle Swarm Optimization (IPSO) is used to tune the parameters.

The CWT-PARAFAC-IPSO-SVM model that was achieved demonstrated the best results in terms of diagnostics in comparison with other variants and high potential concerning the repetitive processing of multi-source vibration data in an ongoing state of monitoring. However, this method is characterized by its relatively high computational costs and the necessity to carefully optimize the parameters, which can limit its application in real-time contexts or low-resource industrial environments.

Chen and Wan [28] proposed a new condition monitoring scheme of the High-Voltage Circuit Breakers (HVCBs) based on the Density-Weighted One-Class Extreme Learning Machine (DW-OCELM). This way of dynamically adjusting the boundary of the classification based on the local concentration of data demonstrates greater responsiveness to outlier samples and hence increases responsiveness to detecting faults in anomalous behavior. The authors suggest a multi-class approach to deal with several known fault conditions (by combining several DW-OCELMs into one ensemble). The predictions are achieved based on the multi-segment permutation entropy feature of the vibration signals and have excellent results on a 35 kV HVCB system.

However, the given approach is prone to the shortcomings of effective density estimation regarding highly skewed or noisy data, which is a frequent issue on the industrial level. Furthermore, the complexity of the algorithms can also increase with the increase in the size of the dataset. In addition, Li et al. [29] developed a fault-diagnosis approach to gas-insulated switchgear (GIS) with a combination of multi-source signal fusion and DL networks. The preprocessing of fault-induced simulated tests is performed through wavelet transform, which would provide feature maps that would be further fused and augmented in a Wasserstein Generative Adversarial Network (WGAN).

The obtained samples are categorized with the help of the VGG16 deep convolutional neural network. This framework scores 95% accuracy of the classification, which is better than the traditional diagnostic procedures. However, its operation depends on the quality of signal fusion and data augmentation; spatial and temporal noise, variability of the signal, and environmental effects may all affect results in practical environments.

Not to mention how challenging it is to execute in real time and how expensive computing resources are required for training. There is a growing need for reliable methods for detecting mechanical failures in contemporary power distribution networks due to the complicated and parameterized nature of MV switchgear systems [18, 30]. In noisy settings or with variable load circumstances, traditional diagnostic methods sometimes fall short when confronted with complicated problem patterns [31]. Consequently, there has been a dramatic increase in the necessity of developing intelligent, data-driven diagnostic tools in the last few years.

DL is a promising new paradigm that might help with these problems as it provides powerful resources for automatically finding and learning hierarchical representations of raw signal data [32, 33]. Some of these networks have shown great promise in defect detection applications, such as Long Short-Term Memory (LSTM) networks and 1D Convolutional Neural Networks (1D-CNNs) [34, 35]. There are distinct benefits to each method: While LSTMs are adept at learning relationships across sequences generally, 1D-CNNs excel in targeted temporal feature extraction [36, 37]. The one-dimensional convolutional neural network (1D-CNN) is a CNN variant used to analyze one-dimensional sequential data, particularly time series [38]. Traditional CNNs infer spatial properties from 2D pictures, whereas 1D-CNNs infer local temporal circumstances from sequential sequences [39, 40].

Because the features are derived in layers, they are very innovative when dealing with time-series data, due to their versatility. Considering the case of fault detection in the mechanical MV switchgear, a 1D-CNN could automatically detect and classify the essential temporal patterns and characteristics embedded within fault-related signals, thus supporting the classification of specific fault types based on the unique features that belong to them [10, 41]. On the other hand, Long-short-term memory (LSTM) networks are a category of the family of recurrent neural networks (RNNs) that are explicitly designed to allow long-range data to be processed [42].

LSTMs have a higher learning and information-storing capability in the long run compared with traditional RNNs, which makes the latter highly beneficial in the context of tasks where one needs to have a long-term memory about things that happened before. LSTMs have the ability to adequately learn complicated temporal dependencies within time-series data in the context of fault detection [43, 44].

Speaking of an example, within the realm of MV switchgear, LSTMs will enable the identification of the manner in which a certain pattern of electrical or mechanical behavior evolves, which will, in turn, allow the detection of the fault in question. This shall be the main aim of the current research: the refinement of mechanical fault detection in MV switchgear by adopting a method that combines both Time and frequency-domain analysis, i.e., a hybrid 1D-CNN-LSTM model.

Two things together. Taking into account the well-documented shortcomings of conventional approaches in characterizing intricate fault patterns in electrical power systems, this approach seeks to address existing problems and advance the area of fault detection. Combining the local feature representation of a 1D-CNN with the long-term memory capacity of an LSTM, the hybrid 1D-CNNLSTM model achieves [45]. 1D-CNN introduces the short-term time variances, and the next layer of the LSTM successively records the bigger temporal fluctuations. Furthermore, in this method, it is easy to study both temporal and frequency-domain features simultaneously [34].

The synthesis provides a detailed opinion of fault signatures, thus facilitating the literature model to understand and interpret the complex spectral properties and time patterns of mechanical failure indicators [46]. The hybrid 1D -CNN-LSTM model provides a wide-ranging representation of mechanical fault data by combining time- and frequency-domain features arranged. Having been provided the frequency-band domain information, the model has been seen to discriminate fine-grained local dynamics and faults of larger scale, applying both to better predictive performance and resilience to a wide range of faults and operating conditions. In this type of architecture, the danger of overfitting is reduced.

Moreover, to realize a systematic observation of mechanical failures, the Hybrid 1D - CNN - LSTM model supplements the opportunity to detect the temporal with a strict knowledge of their longitudinal course and spectral dynamics. The design, therefore, creates a more profound understanding of fault behavior in an MV switchgear setting, thus improving the operational decision-making and maintenance consciousness.

This paper proposes a hybrid 1D-CNN-LSTM framework to identify mechanical faults associated with switchgear and hence combines time and frequency analysis. The following outcomes and advancements will be produced by the study:

1. One of the main aims of this study is to derive a new hybrid 1D-CNN-LSTM model that exploits the synergies of 1D-CNNs and LSTMs and overcomes the weaknesses of both. Combining the local feature-extraction ability of 1D-CNNs with the memory-enhanced properties of LSTMs, the suggested approach has the potential to improve the accuracy of fault detection. This is a substantial improvement, because the model has the benefit of integrating the ideal qualities of the two classes of neural networks in a manner that enhances their respective interdependency.

2. The structure uses two modalities, time-domain segmentation and frequency-domain feature extraction techniques, to describe the variability of mechanical fault data, allowing for multimodal synthesis of data variability. This technique has two main goals: reducing data variability and improving fault detection.

3. This paper will employ a hybrid research method, which combines time-domain and frequency-domain analysis to improve the level of fault detection. This method allows simultaneous extraction of spectral components of fault signals and extraction of patterns of instantaneous data points. Through the adjuvant expertise of the two aspects of analysis, it is expected that the model will provide a more detailed representation of fault patterns, which is why it will be more sensitive and proactive. Building on previous research, this study advances by creating a new synthesis that integrates several analytical models to enhance fault diagnostics.

4. By developing a hybrid model, we aim to achieve a more effective solution for detecting mechanical defects in switchgear systems. Power distribution system operations are expected to become more reliable as a result of less downtime and less danger of catastrophic loss. This contribution's real-world applicability is where its value is added; the model has the capacity to greatly improve mechanical property dependability.

5. Lastly, the research aims at advancing methodological advancements in fault detection by harmonizing deep-learning procedures with domain-relevant examination. The paper makes steps towards the wider effort in designing fault-detection techniques, demonstrating the effectiveness of artificial-intelligence solutions in solving complicated engineering problems. This example shows the potential role of alternative forms of computation in changing the current diagnostic practice. The current article suggests a combined approach to the improvement of the mechanical fault detection through the introduction of a hybrid 1D-CNN-LSTM structure that combines the time- and frequency-domain approaches. In this way, it is planned to increase the level of quality of diagnoses and to support the stability of work in the field of power distribution.

The intended contributions occupy the field of model development as well as the following model application that is able to be used as a basis for substantiating current fault-detecting techniques.

This paper is divided into the following. Section 2 provides an in-depth presentation of the hybrid approach, and it discusses the architectural framework of the Hybrid 1D-CNN-LSTM model and the reasoning for integrating time and frequency. Section 3 presents the performance of the suggested architecture, empirical results illustrating the detection of mechanical faults using this architecture, and a comparative evaluation with other fault detection methods. Section 4 will finish off by summing up the concepts of this study in relation to the future development of mechanical fault detection upon MV switchgear.

2. MATERIAL AND METHODS

The suggested research will follow a series of phases, each aimed at the determination of the mechanical defects within MV switchgear by virtue of both time-like and frequency-like analysis. The first need is to develop an extensive dataset that is measured in situ: the dataset would include mechanical and non-mechanical arcing, corona, and tracking in addition to samples of relatively normal operating conditions.

A hybrid 1D-CNN-LSTM model is employed to derive patterned insights, which is a DL model specially trained to handle ultrasonic recordings made during fault occurrences and improvisation in audio format. Figure 1 presents a schematic representation of the consequent classification system of a mechanical fault.

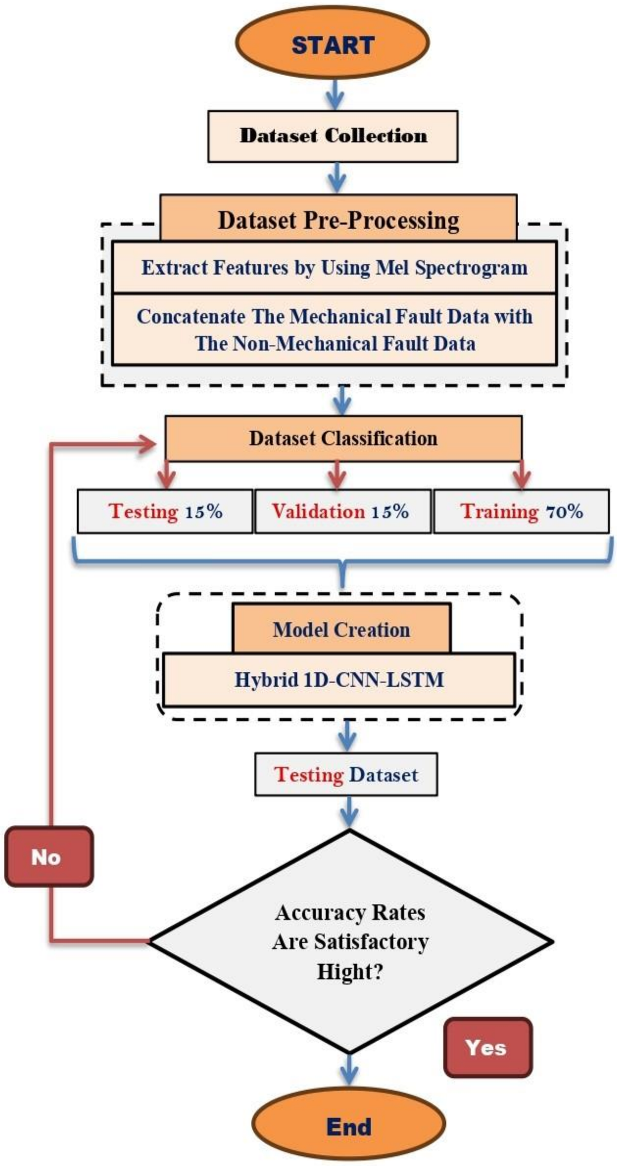


Figure 1. Diagram illustrating the overall research approach

The data-collection part of the work involved the collection of raw distribution data from the seven states of Peninsular Malaysia, namely Kedah, Kuala Lumpur, Melaka, Selangor, Perak, Negeri Sembilan, and Johor, through the power utility company (PUC). MATLAB was used to achieve the subsequent processing. The choice of the hybrid model was driven by the fact that it is one of the DL techniques that is highly applicable to the problem.

The data preprocessing and processing via MATLAB were performed to initiate the workflow that continued with the development process of a neural network using Google Colab. Airborne Ultrasonic Testing (AUT) equipment is utilized as an essential tool to detect surface Partial Discharges (PD) and as such is useful as a diagnostic indicator of ineffective insulation of the electric circuit. As such, the source data that was studied was in the form of audio files, usually in the format of MP3, MPEG, or WAV. The following paragraphs explain how each step of the methodology described in Figure 2 took place.

Figure 2. Airborne ultrasonic test equipment visualization [47]

2.1 Data collection

The conducted research uses a combined data set, which combines switchgear recordings acquired earlier with a new ultrasonic recording set. The previous papers [11, 12, 41], provided comprehensive accounts of the data collection process, preprocessing procedure, and instrument strategy. This generated corpus is the complete set of ultrasonic signal traces of various operating states that include arcing, corona discharge, tracking events, mechanical failures, and normal operation, recorded in both the time and frequency domains.

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

Fault	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)

It is built so that real-life operating conditions are reflected, and thus there is a balance in the dataset in terms of faulty and normal switchgear operating modes. Because of this variety, diagnostic models are more able to be trained and evaluated, and they are also better able to discriminate between various sorts of errors. A large-scale data set that is both believable and practical was prioritized so that it may be utilized to validate trustworthy and computationally efficient fault-detecting strategies in MV switchgear configurations. Investigating the use of DL approaches, particularly hybrid tools like the 1D-CNN-LSTM model, is especially crucial.

The goal of this design is to improve performance in the face of different types of faults. There was a significant manifestation of this into the real world since the dataset was configured in a way that was near to the actual task. The dataset has been summarized in Table 1, representing both cases of mechanical and non-mechanical faults in the time domain as well as in the frequency domain.

2.2 Data pre-processing

At this stage, a highly structured algorithm of data processing was developed to make the data accessible to further studies. The selection of features took place through the usage of the Mel spectrogram technique. Along with the inclusion of new classes—including arcing, corona, and tracking—and the synthesis of mechanical faults, regular events have also been introduced. Training, validation, and testing were the three stages that the dataset went through once this data synthesis was finished. In order to provide a seamless dataset integration into the suggested hybrid 1D-CNN-LSTM model, this data processing step was necessary.

The aspect of data preprocessing is an essential part of DL projects and includes a step of procedures that should be carried out to ensure the input data are of high quality and provides a relevant interpretation of the data. This involves the elimination of noise, variable normalization and treatment of anomalies and missing values. The sequencing technique is a network of steps, that are interdependent:

1. Data Cleaning: The data were thoroughly audited, and this involved correcting any data that was missing or erroneous in order to maintain data integrity.
2. Data Normalization: Using standardization of variables, biases caused by scale were reduced and balance was achieved during model training.
3. Feature Engineering: Extraction of meaningful characteristics out of the raw data was considered necessary and held significance when it comes to intelligible operational representations of switchgear and to improve the performance of the model.
4. Sequence Development: Data sequences with successive and equal length data sequences allowed the LSTM network to discover repetitive trends across days. The stages will give a strong basis to the training of the proposed hybrid 1D-CNN-LSTM DL model that exhibits a fine predictive power to detect mechanical failures in MV switchgear. The offered methodology, therefore, contributes greatly to the establishment of efficient fault-detection systems, and the direct way of application could be related to regular switchgear maintenance and general efficiency.

Moreover, the experimental data used in the research was obtained through ultrasonic sensing procedures that were aimed at measuring acoustic emissions caused by mechanical faults in MV switchgear [41]. The ultrasonic sensors were chosen by the research team because it is more sensitive to partial discharges, arcing phenomena and mechanical defects, which produce high-frequency acoustic signals. These were mounted on the switchgear enclosure in fixed, repeatable positions to ensure that they received a consistent, reliable signal under all operating conditions.

The records of ultrasonic signals were taken at a fixed sampling frequency in the ultrasonic frequency that was selected to ensure that the high-frequency components associated with mechanical faults were well represented, as well as to allow easy time-frequency domain analysis. Data collection was conducted in controlled operating conditions that modeled realistic operating conditions of switchgear, including constant voltage levels and reproducible mechanical conditions. Noise and external disturbances were reduced when recording so that the quality of the signal was not affected.

Different recordings were taken under each operating condition, including normal and faulty conditions, to increase the robustness of data and minimize randomness. Before model training the obtained ultrasonic signals were divided into constant-length samples and were normalized. These preprocessed signals were further converted into time-frequency representations and utilized as inputs into the proposed hybrid 1D - CNN -LSTM framework.

2.3 Extract features by using "Mel spectrogram"

The Mel spectrogram is an easy-to-understand evaluation tool for practitioners working in the field of time domain analysis; it may be used to ultrasonic recordings of switchgear components captured under different fault states in order to identify useful characteristics. Transposing a discrete time-domain signal to a two-dimensional matrix, the Mel spectrogram shows the visual representation where the spectrum content is vertically shown and the time progression is horizontally represented [48].

To achieve this transformation, a series of Mel filters is used, which in fact reproduces the human ear's nonuniform frequency sensitivity. This enables precise timing of mechanical failure patterns to be determined by using Mel filters to boost certain frequency components in the signal. Ultrasound waveforms that change over time may be represented using the Mel Spectrogram in a way that incorporates both the frequency content and a temporal variation. Such an approach allows a successful capture of the frequency components in the process of changing over the signal duration. With this resulting Mel spectrogram, thus, complex fault-related patterns would not have otherwise been identified in the original time-domain alone [49, 50].

Due to these reasons, it is best to transform the Mel spectrogram into enriched data providing input to the proposed hybrid 1D-CNN-LSTM model, which, in its turn, will increase its ability to differentiate between the various types of faults by relying on their distinctive frequency patterns. Besides, the fact that the Mel spectrogram is implemented in the architecture used in the proposed fault detection system makes the frequency-domain analysis component a serious addition to the time-domain analysis core, which cannot be omitted and would serve as the addition to the recent defects recognized [51, 52].

Through translating ultrasound signals in the time domain into spectral display in the frequency domain with the Mel Spectrogram, we are able to see the characteristic patterns of the frequencies of a fault. Such transformation allows extracting spectral features that assist in a model discerning between the different kinds of faults. Under the frequency space, the Mel spectrogram could be used as input to a convolutional neural network with LSTM to drive prediction and classification of mechanical faults into their characteristic spectral signatures.

Figure 3 shows the Mel spectrogram aspect of the mechanical faults. The current mechanism couples time and frequency directions and is therefore accurate and robust. As a method of extracting features, the Mel spectrogram has been proven to enhance the functioning of the hybrid model and enhance production of the mechanical faults in switchgear systems.

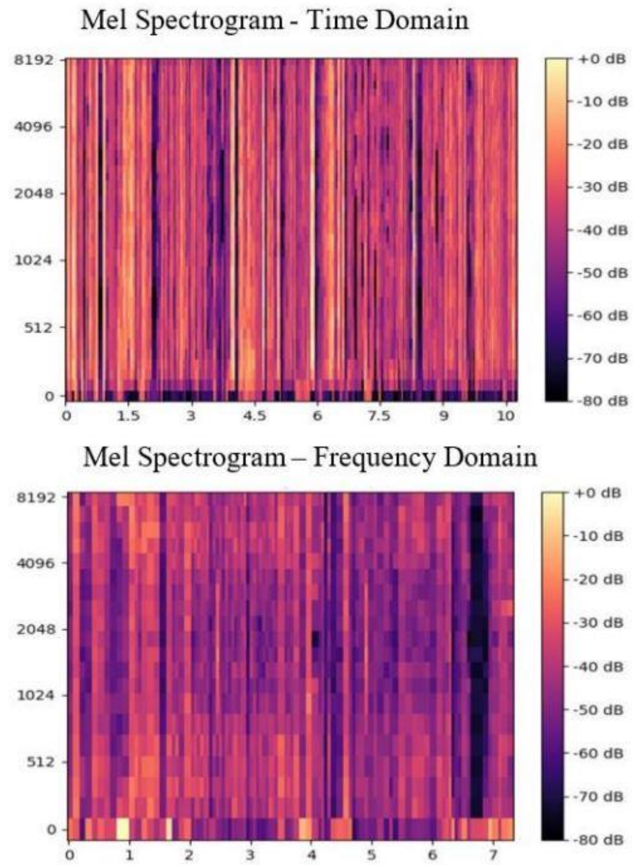


Figure 3. The Mel spectrogram for mechanical faults in both time and frequency domains

The Mel spectrogram is more discriminating on the type of faults by highlighting frequency bands that are more perceptually relevant and which fault-induced variation of energy is most apparent. This code gives inter-class separability by modeling specific time-frequency images of different mechanical faults and, at the same time, reducing high-frequency noise sensitivity. Therefore, the model proposed will have stronger and more discriminatory feature learning.

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

The subsequent step involved the integration of data sources, merging mechanical fault data with instances with occurrences of non-mechanical faults such as arcing, corona, and tracking, as well as normal cases. This all-inclusive integration enabled wholehearted examination of a broad sector of the possible operating conditions and fault manifestations.

The need for a full and balanced training set drove this integration. We subjected the model to many real-world patterns and variations by including mechanical and non-mechanical faults. Through this experience, the model learned to distinguish between normal and unhealthy behavior, improving its diagnostic accuracy. Even with new parameters, the model's versatility in handling arcing, corona, tracking, and normal instances enabled it to identify even the tiniest departure from normal behavior. Thus, the Hybrid 1D-CNN-LSTM model has mastered the complexity of mechanical and non-mechanical fault patterns, advancing analysis.

2.5 Dataset classification

Normalization and scaling of the input variables are carried out as part and parcel of the data consolidation process to guarantee uniformity of the data and are done to improve the quality of the samples. Such a preprocessing step increases the generalization ability of the proposed hybrid model, allows making the learning process more efficient, and adds to the prediction accuracy. After preprocessing, the data is divided into three subsets, namely training, validation, and testing. Randomized stratified data splitting is used to ensure that all fault classes are proportionately represented in the subsets. Particularly, 70% of the data is used to train, and 15% to validate and test data, respectively.

The same partitioning protocol is used in all the experiments to eliminate the possibility of data leakage as well as have a fair and replicable performance evaluation. At the training stage, the model learns discriminative time-frequency characteristics of ultrasonic MV switchgear signals, and thus it can effectively detect the signature of mechanical faults. The exposure of the model to different operating conditions during training further enhances the ability of the model to distinguish mechanical and non-mechanical events during switchgear operation.

2.6 Hybrid 1D-CNN-LSTM model

In this paper, we suggest the introduction of a new framework to be applied to fault detection and differentiation in switchgear: the Hybrid 1D-CNN-LSTM new model, which will be able to handle features that are the result of such a method as the Mel Spectrogram. Improved fault type and identification accuracy and resilience are achieved by the use of convolutional and neural networks, which enhance the system's capacity to detect intricate spatial and temporal patterns of electrical signals.

Both mechanical and non-mechanical faults constitute the dataset, which was processed through several important stages of data processing that were aimed at isolating the two classes of faults. These steps were carried out at the preprocessing stage and allowed proper preparation of the datasets before feeding them to the fault detection model.

– **Input Layer**

The architecture will start with an input layer where the time-domain features of the electrical signal in the form of a Mel spectrogram representation have already been computed. Through the Short-Time Fourier Transform (STFT) of the raw time-domain data, each Mel Spectrogram provides a succinct overview of its original signal spectrum along time-axis boundaries and therefore imparts a representation to the model that condenses both the time and the spectrum dimensions.

– **1D-CNN Module**

A 1D-CNN block plays a key role in the process of spatial feature extraction by the model [35]. Applied in the form of a cascade of 1D convolutional, each convolutional filter is an optimized set of filters designed to recognize local patterns of Mel Spectrogram inputs. Following each convolution, there is a max pooling layer that shrinks feature maps by selecting the highest value in small local regions so that the computational cost is reduced and the risk of overfitting is combated. The mathematical background of such an operation is expressed in the following equations:

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

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:

$$A_i = ReLU(X_i) \quad (2)$$

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

$$Y_i = Maxpool(A_i) \quad (3)$$

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

$$H_i = ReLU(Y_i) \quad (4)$$

All convolutional layers in the proposed 1D-CNN model have an iterative process that is initiated by transforming the Mel spectrograms to a series of feature vectors. The 2D convolution of these vectors takes place with the spatial extent of the kernel being mostly determined by the layer it is contained in: a kernel size of 1 × 1 is used in the first layer, with a later, wider kernel size of 2 × 2 used in all the other layers. After every convolution, max-pooling is done, and the downsampling burst pressure is done across the time as well as spectral axes.

The result of this layer, which is known as *H*, is the input of the next convolutional layer. The same is done to all the convolutional layers, giving rise to the production of *H-final*, which is the final output of the network that carries codes of the significant spatial characteristics of the original Mel spectrograms. The downsampled spatial features are routed to the next LSTM module, where they form the basis of capturing the complexity of temporal dependencies that are inherent in the electrical signals. Figure 4 provides a full visual description of the architecture of the 1D-CNN, given the time and frequency domains.

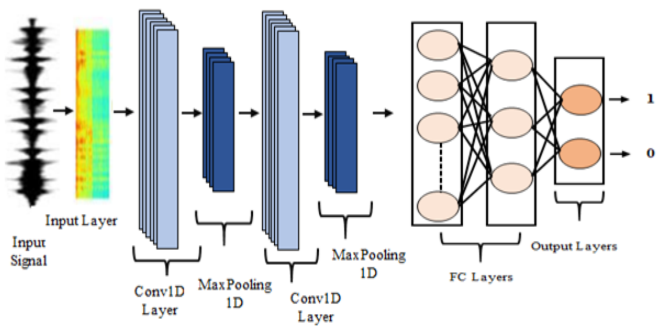


Figure 4. The representation of the 1D-CNN model in both the time and frequency domains

– **LSTM Module**

In the proposed neural architecture, 1D-CNN outputs whose features have been downsampled will be fed to an LSTM module whose purpose is to train the model to learn temporal dependencies within the Mel spectrogram sequence. This is because each of the LSTM cells in the module is used to model the time-series nature of the data in order to recognize patterns that are associated with non-mechanical and mechanical faults over time [53]. As follows, the equations that describe the work of LSTM cells (5)-(9) are performed:

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \quad (5)$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (6)$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (7)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c.[h_{t-1}, x_t] + b_c \quad (8)$$

$$h_t = o_t \odot \tanh(c_t) \quad (9)$$

where, x_t is the input at time step t, h_t is the hidden state at time step t, c_t is the cell state at time step t, W_f, W_i, W_o, W_c are the weight matrices, b_f, b_i, b_o, b_c are the bias vectors, and σ is the sigmoid function. Figure 5 depicts the LSTM model representation in the time and frequency domains.

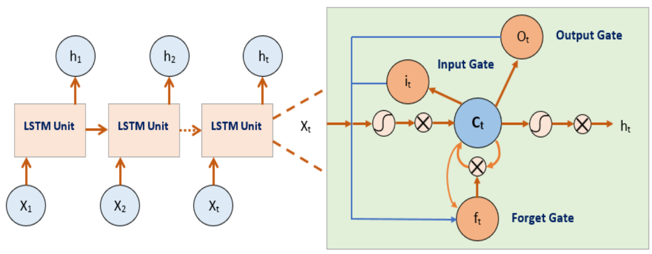


Figure 5. The representation of the LSTM model in both the time and frequency domains

– **Fully Connected Layer**

Upon capturing the temporal dependencies within the LSTM, the final hidden representation is obtained, which is termed *H-final* and passed through a fully connected layer. This layer carries out a weighted combination of the hidden state, which is instantaneously activated through the SoftMax operation. In so doing, the probabilities expected to be encountered with respect to the different fault types in each of the samples to be considered are derived.

The SoftMax function lowers the outcome to make the possibilities adjusted to the sum of unity and hence make an inclusive probability distribution encompassing the expanse of fault classes.

– **Training and Optimization**

The current study explores how well the hybrid 1D-CNN-LSTM model performs after training using an aggregate data set that contains both non- and mechanical fault cases. The categorical cross-entropy loss is the key training metric that will be computed during the training phase by taking the difference between predicted probability distributions and known fault labels. The process of parameter refinement is performed by means of backpropagation, where the computed gradients are treated as feedback to gradient-based optimization.

To optimize the process, the Adam stochastic optimization algorithm is employed, and a well-furnished learning rate of 0.0001 is used. Also, epochs of 60 are run on each pair of faults and normal cases, i.e., a batch size of 16 samples is performed per epoch. The choice of Adam is beneficial due to its dynamical scaling of each of the learning rates based on historical gradients. This kind of adversative behavior leads to increased efficiency and quicker convergence in comparison with classical stochastic gradient descent (SGD).

The model can be very appealing to a diverse rich set of mechanical and non-mechanical fault scenarios since the unified dataset was used along with the powerful optimization strategy, which boosts the ability of the Hybrid 1D-CNN-LSTM model. This enhanced capability further increases the model's ability to generalize, and consequently, this model assists in the classification of a wide range of switchgear-related faults in an effective and correct manner across the whole system. The use of coding was completed on Google Colab.

– **Evaluation and Performance Metrics**

A range of performance measures was utilized to perform an arduous comparison of the performance of the suggested model, specifically the accuracy, precision, recall, and F1-score. It was tested in a systematic manner to determine its suitability to detect and discriminate different fault types in switchgear systems. In particular, the addition of the Mel Spectrogram features to the Hybrid 1D-CNN-LSTM architecture granted the compound approach the ability to make use of the temporal and spectral advantages present within electrical signals.

This synergetic merger gave rise to a method capable of providing true and repeatable diagnostics in the switchgear space. The Hybrid 1D-CNN-LSTM model was the only one that perfectly combined the spatial capability feature extraction of the 1D-CNN with the temporal consideration of the LSTM to provide an overall better result and stability in classifying the mechanical faults and non-mechanical faults. These findings are demonstrated in Figure 6, which shows the representation of the Hybrid 1D-CNN-LSTM model in both time and frequency universes.

A flawless testing data set that fully covers a wide array of fault categories was also developed and meticulously curated to include arcing, corona, tracking, mechanical faults, and normal cases. The model was tested in full. Quantitative evaluation of its performance showed that it could discriminate among these various diagnostic classes at a rate higher than 90%. These findings prove the feasibility of the hybrid 1D-CNN-LSTM model in practice concerning switchgear fault detection and promote the use of the model in preference to the alternative approaches in this field, classifying it as an innovative one.

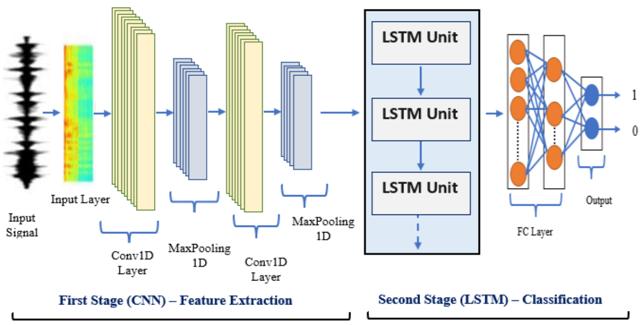


Figure 6. Illustrates the representation of the hybrid 1D-CNN-LSTM model in both the time and frequency domains

While the general accuracy is rather good, there are instances when the performance falls short of 90%. This indicates that the model is not yet fully developed and needs further work. In reality, thorough examination of the testing dataset leads to the conclusion that the proposed model is useful and adaptable, while simultaneously producing the essential insights for enhancing switchgear performance and stabilizing power systems. Consequently, the model's future as a crucial decision-making tool in the switchgear fault detection and management sector will be highlighted by the accomplishment of a high accuracy rate that is unusual.

3. RESULTS AND DISCUSSION

Creating a hybrid system capable of effectively detecting mechanical and non-mechanical defects on power-system switchgear is the overall goal of our work. The primary goal is to provide a faithful performance in both the temporal and frequency domains by using the complementary characteristics of 1D-CNN and LSTM. The goal of this hybrid framework is to improve classification performance and achieve practical efficacy by integrating the feature-extraction capabilities of 1D-CNN with the origin of the LSTM's temporal-dependence model.

The outcome is an all-encompassing knowledge of the inner workings of switch gears and the common defects that affect them, achieved by merging the spatial extraction capabilities of the 1D-CNN with the temporal dependency extraction capabilities of the LSTM. To create a complementary system that can benefit both locally specified patterns and long-term reliance in time, we may use this technique to extract situation-sensitive, local features from 1D-CNN and establish general, occasion-free connections with the assistance of LSTM.

This integration type shows promise for improved fault detection and resilience, particularly in systems with complicated switchgear. Improved dependability and operational efficiency in monitoring switchgear assets may be within reach with the help of the suggested architecture, which improves upon current state-of-the-art methodologies by combining the strengths of 1D-CNN and LSTM into a single system.

Table 2. Detailed architecture of the proposed 1D-CNN-LSTM model for time–frequency domain mechanical fault detection

Time Domain	Frequency Domain
1D-CNN-LSTM	1D-CNN-LSTM
1DConv (64-RELU)	1DConv (64-RELU)
1DMaxPooling	1DMaxPooling
Drop-out	Drop-out
1DConv (128-RELU)	1DConv (128-RELU)
1DMaxPooling	1DMaxPooling
1DConv (128-RELU)	Drop-out
1DMaxPooling	LSTM (128)
Drop-out	Drop-out
LSTM (1024)	LSTM (32)
Drop-out	Dense (2) (SoftMax)
LSTM (128)	-
Dense (2) (SoftMax)	-

To ensure reproducibility and provide a clear understanding of the proposed hybrid 1D-CNN-LSTM framework, Table 2 summarizes the detailed architecture of the model. The table includes the configuration of both the convolutional and recurrent layers, specifying the number of filters, kernel sizes, activation functions, and other hyperparameters.

The framework can be used to detect faults in a variety of mechanical faults by leveraging both the time and frequency domains of switchgear vibration signals, which are represented as time-frequency domain representations, to detect mechanical fault types.

3.1 Time domain analysis

To predict mechanical damage to the switchgear, including a variety of electrical and mechanical defects, a hybrid 1D-CNN-LSTM network was used in this study. Depending on the areas of study, the measurement was carried out in time (time-domain) and frequency (frequency-domain) to provide a complete analysis of mechanical flaws. The experiment that trains, validates, and tests the 1D-CNN-LSTM classifier on the dataset described in Table 3 uses a total of 438 samples overall, 146 of which were subjected to the training phase, 146 samples were subjected to the validation phase, and 146 samples were subjected to the test phase.

Table 3. The classification outcomes obtained from the hybrid 1D-CNN-LSTM model within the time domain

	Training	Validation	Testing
Sample phases total	306	66	66
Accuracy	100%	100%	100%
Error	0%	0%	0%
Number of Features		20001	
Number of Output		2	

One of the tools that was used in the process of time-domain analysis during the training, validation, and testing processes was the confusion matrix of the 1D-CNN-LSTM classification model, which is depicted in Table 4. The accuracy in the mechanical faults in switchgear is high, accompanied by the matrix. The data supplies evidence of the ability to detect and classify the classes of mechanical and non-mechanical faults in the time domain offered by the architecture.

Table 4. Time domain classification output matrix: Mechanical and non-mechanical faults

	Hybrid 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

3.2 Frequency domain analysis

How well they did Table 5 displays the characteristics of a 1D-CNN-LSTM hybrid model that classifies mechanical failures in switchgear based on frequency-based data. The model performs well, with a perfect score of 100% in classification and 0% errors out of 160 samples evaluated on a big dataset. This discovery validates the model's capability to detect and accurately categorize mechanical problems in the frequency domain.

Frequency-reading analysis maps data onto the frequency spectrum, enabling the model to identify trends and features related to mechanical defects in the switchgear. The upper accuracy indices in Table 5 assure the existence of extraordinary patterns and features with different frequencies. These features can provide insights that enable the model to classify mechanical faults with high specificity. The results of this paper suggest that deep-learning-based models, and in this case, one of the deep-neural-network-and-LSTM-based applications (1D-CNN-LSTM), are an optimal solution to detect and predict mechanical faults in switchgear.

The precision achieved in the frequency-domain analysis emphasizes the possibility of the model becoming an invaluable instrument to identify the mechanical flaws of MV equipment, thus minimizing operational downtime, improving the overall system stability, and improving the switchgear location of fault studies.

Table 5. The classification outcomes obtained from the hybrid 1D-CNN-LSTM model within the frequency domain

	Training	Validation	Testing
Sample Phases Total	112	24	24
Accuracy	100%	100%	100%
Error	0%	0%	0%
Number of Features		10001	
Number of Output		2	

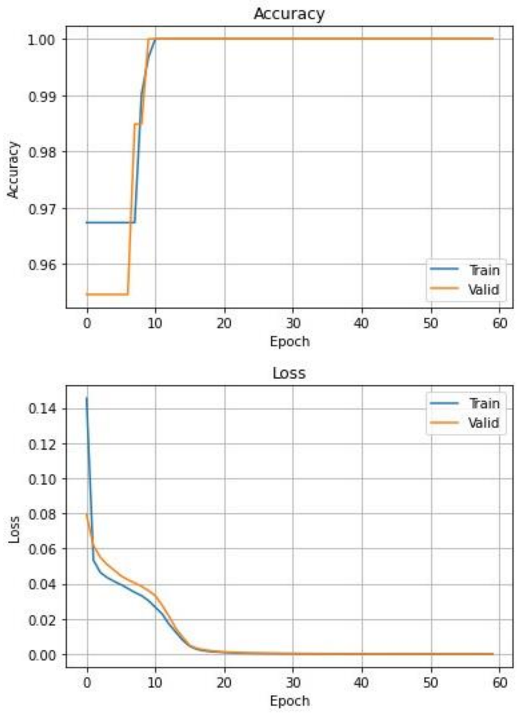
The confusion matrix is shown in Table 6. It shows the results that were seen during the training, validation, and testing stages of the model's deployment, when data from the frequency domain was used. This matrix provides a comprehensive snapshot of the model's performance in correctly classifying various fault categories within the context of switchgear analysis.

Table 6. Frequency domain classification output matrix: Mechanical and non-mechanical faults

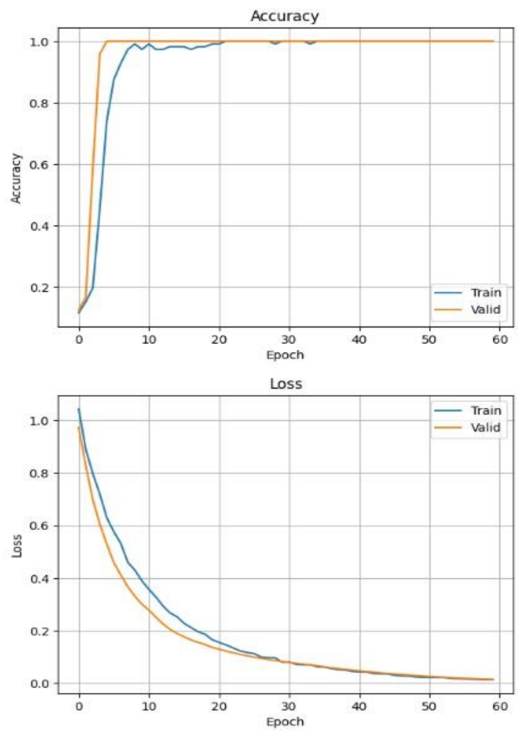
	Hybrid Model Training Phase	
	Mechanical	Non-Mechanical
Actual Mechanical	10	0
Actual Non-Mechanical	0	102
Validation Phase		
	Mechanical	Non-Mechanical
Actual Mechanical	3	0
Actual Non-Mechanical	0	21
Testing Phase		
	Mechanical	Non-Mechanical
Actual Mechanical	3	0
Actual Non-Mechanical	0	21

Table 7 will provide more details of the performance indicators generated in the 1D-CNN-LSTM classification model when testing mechanical and non-mechanical data. The results achieved with each scenario in terms of accuracy, precision, recall, and the F1 score are included and collectively indicate the performance of the model in detecting the faults in heterogeneous domains overall.

Notably, there is a similar level of accuracy in the two categories, confirming the stability and robustness of the model for recognizing and categorizing errors regardless of their inherent characteristics.



(a) Time domain



(b) Frequency domain

Figure 7. Curves of accuracy and loss for the hybrid 1D-CNN-LSTM model of mechanical and non-mechanical defects

Figure 7 is a pictorial display of the accuracy and the loss profile of the two cases of mechanical faults and non-mechanical faults during the training, validation, and testing phases. The accuracy curve follows the gradual amelioration and consistent performance of the model, so it gives a clear account of the entire process in terms of diagnosis. At the same time, the loss curve has a one-sided learning pathway depicting congruence with the training set. A comprehensive view of how performance varies during different types of failure is provided by these constantly shifting graphics.

Table 7. The evaluation of metrics and performance for the hybrid model's testing outcomes

		Time Domain Case Mechanical Findings (0)		
Technique	Accuracy	Precision	Recall	F1-Measure
1D-CNN-LSTM	100	100	100	100
		Case Non-Mechanical Findings (1)		
Technique	Accuracy	Precision	Recall	F1-Measure
1D-CNN-LSTM	100	100	100	100
		Frequency Domain Case Mechanical Findings (0)		
Technique	Technique	Technique	Technique	Technique
1D-CNN-LSTM	1D-CNN-LSTM	1D-CNN-LSTM	1D-CNN-LSTM	1D-CNN-LSTM

3.3 Cross-validation analysis

A five-fold cross-validation (5-fold CV) plan evaluated the generalization ability of the hybrid 1D-CNN-LSTM framework. The data were separated into five mutually exclusive folds; in each round, four of the folds would be used as the training data and the rest as the test data. Each round was repeated five times to ensure every fold acts as a test set only once. The results of the cross-validation showed satisfactory performance in all folds with an average accuracy of 100 percent.

This similarity over a clear set of data partitions hints at the fact that the reported high accuracy rate is independent of a particular training-testing split but is indicative of the strength of the suggested model in identifying discriminative time-frequency features linked to mechanical failures in switchgear. In addition, regularization methods, including dropout and early stopping, are applied, which helps to reduce the possible overfitting and provides the model with better generalizability. The results of the five-fold cross-validation of the proposed hybrid 1D-CNN-LSTM model are provided in Table 8, and they show that the model performs consistently in all five folds.

Table 8. Five-fold cross-validation performance of the proposed model

Fold	Accuracy	Precision	Recall	F1-Measure
Fold 1	100	100	100	100
Fold 2	100	100	100	100
Fold 3	100	100	100	100
Fold 4	100	100	100	100
Fold 5	100	100	100	100
Average	100	100	100	100

The fact that all of the cross-validation folds are performing relatively similarly shows that the given architecture is successfully learning fault-related patterns, thus proving that there is no bias towards a certain subset of the data.

3.4 Comparison with state-of-the-art approaches

The use of machine learning in fault diagnosis in power systems and switchgear has been studied several times.

LSTM-based defect detection method has been shown to achieve a precision of 95.8%. However, it relies solely on handcrafted features and a single LSTM network, potentially limiting generalization and robustness in broad operating environments.

Dubaish and Jaber [54] used vibration signals from gearboxes, applying Wavelet Packet Transform (WPT) to extract features, which were then selected using the gain ratio. Further SVM and artificial neural network (ANN) classifiers showed 96% and 98% classification accuracy, respectively, and improved precision and recall. Nevertheless, widespread use of the manual preprocessing and handcrafted methods of feature extraction limits flexibility, and the lack of end-to-end learning of raw signals can reduce performance in complicated or noisy conditions.

Furthermore, El Mrabet et al. [55] created a model to localize faults and determine the fault duration in power distribution networks using a Random Forest regression; a synthetic data set was created using the GridPACK. The model achieved 84%localization of the faults and 72% classification accuracy on duration. The model has demonstrated the ability to handle streaming inputs and missing values; however, its testing was confined to a narrow range of fault conditions, which may limit its performance in estimating duration and hinder its scalability to larger, more complex systems.

On the other hand, Zhang et al. [17] gave an example of a feature-fused acoustic approach to gas-insulated switchgear mechanical fault diagnosis, which combines wave-plus-reduction, a feature extractor (an auto-encoder-based spectrogram feature extractor), and a subsequent multimodal fusion step to generate classification results. The result of the experimental assessment was 98.5 of detection accuracy. However, the extraction and fusion pipeline is multi-stage, which means that it has a heavy computational burden, and validation has only been conducted over a limited range of operating conditions, which makes it questionable how it is going to generalize.

Song et al. [56] suggested a lightweight convolutional neural network-based auditory fault-diagnosis system specifically designed to work with gas-insulated switchgear with an accuracy of 99.1% on a real-world 110 kV GIS data set. However, the method is based on a multi-stage auditory feature-extraction pipeline, and it is only proved to be effective in a narrow range of operating conditions, which may limit its generalizability.

Table 9. Performance comparison against recent models

Model	Accuracy	Precision	Recall	F1-Measure
LSTM	95	89	100	94
SVM	96	94	95	96
ANN	98	97	98	97
RF	84	83	82	83
Auto-Encoder	98	98	99	99
CNN	99	99	98	99
Our Method	100	100	100	100

In comparison, the current study presents a deep hybrid 1D-CNN-LSTM Model to detect mechanical faults in switchgear through a time-frequency domain analysis applied to implement automatic feature extraction and learn a time sequence of labels end-to-end. The model demonstrates perfect accuracy (100%) in cross-validation folds and performs ideally in terms of precision, recall, and F1-score measures, as indicated in Table 9, indicating that its efficacy surpasses that of the studies mentioned above.

4. CONCLUSIONS

Mechanical faults in MV switchgear are important to detect to ensure dependability of operation and safety of the system. This paper hypothesizes an improved hybrid 1D-CNN-LSTM model that utilizes both time- and frequency-domain features to precisely identify mechanical and non-mechanical faults based on the measurement of ultrasonic signals. The model is able to capture discriminative spatial and temporal faults by combining convolutional and recurrent learning capabilities. The presented methodology has proven to be highly efficient and steady in a wide range of fault cases, with a 100 percent classification rate, and thus, it has proven to be effective in real-world use.

A significant improvement in fault classification accuracy and informed maintenance decisions through the integration of time-frequency representations is thus a contribution to increasing reliability and minimizing downtime in power distribution systems. Though these are encouraging findings, they have several limitations that should be considered. The test was conducted on a small set of data in controlled conditions, and it might not be generalizable to the wide real world.

Moreover, the hybrid deep-learning system makes the computational complexities more complicated than the conventional techniques, which can challenge the availability of resource-constrained systems. It will be possible to further work in the field in the future with the expansion of the dataset, the introduction of a wider set of fault conditions, and the streamlining of the complexity of the models to make them useful for real-time and large-scale work in the industry.

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