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Deep Learning Based High Impedance Fault Detection in Electrical Distribution System Using CNN–BiLSTM with Noise Robustness Analysis

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High impedance faults (HIFs) in electrical distribution systems are difficult to detect due to their low fault current magnitude and irregular behaviour. The growing integration of distributed energy resources further increases system complexity, requiring more reliable and adaptive fault detection methods. Traditional methods of protection typically do not find HIFs because the currents that flow through the fault are similar to the normal load current and do not activate the conventional relays (that use fault current levels). In addition, the existing approaches for signal processing and machine learning techniques, which are commonly used to detect HIFs, are very sensitive to noise and require threshold-value settings to be successful, leaving them with limited capabilities to capture non-linear characteristics of the fault, resulting in decreased effectiveness as system operating conditions change. This research presents a hybrid deep-learning architecture that combines the strengths of both Convolutional Neural Networks (CNNs) to extract spatial features and Bidirectional Long Short-Term Memory (BiLSTM) networks to learn the temporal relationships in fault behaviours. The CNN is designed to extract spatial features from voltage and current signals. The BiLSTM is designed to learn temporal dependencies between faults for detecting faults in real use cases. A comprehensive preprocessing pipeline is developed that includes feature construction, normalisation, class balancing and noise augmentation to improve the generalisation of the model. With an overall accuracy of 94.92 %, the model is reliable in accurately detecting faults as well as robust against noisy data, making it ideal for use in real-time smart grid protection applications.

Keywords: High impedance fault (HIF), CNN-BiLSTM, Deep learning, Power system protection, Noise robustness, Smart grid

1 Introduction

High impedance faults (HIFs) in electrical distribution networks create significant challenges to traditional means of protecting systems because of low amounts of fault current and their nonlinear characteristics. In contrast to short circuit or other fault currents, HIF currents are frequently similar to normal load currents, which makes it difficult to differentiate between the two when using a conventional over current relay[1-3]. In addition, as distributed energy resources have continued to be integrated into the grid, the operational complexity of power systems has also increased as a result of utilization of smart grid technology, and thus finding and coordinating fault protection methods continue to be more difficult than before[4-5]. A number of methods have been developed to find HIFs by using different ways to study temporary and frequency properties of failure signals. Some techniques used to try to find the unusual characteristics that are common with arcing faults include statistical pattern recognition, inter-harmonic analysis, and wavelet transforms. These methods are typically affected by noise, they require a set threshold defined prior to analysis, and they need careful parameter tuning which limits how dependable they will be in practical use because of the variations of conditions in the systems[6-7].

Machine learning-based systems are widely used in automated fault classification solutions where faster and more efficient detection can be achieved than conventional systems. Better accuracy has been improved through the automation of errors by using different machine learning algorithms for automatic fault classification including decision trees, artificial neural networks, graph learning techniques, and more [8-9], but currently, so far only based on hand-crafted feature extraction and domain knowledge and not on the knowledge of the person is most efficient and able to respond to many conditions such as different types of working conditions/settings and the context[10-11].

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Deep learning has changed the way to detect faults by allowing automatic extraction of features from raw signal data to make systems smarter. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are two examples of deep learning models that have been able to capture difficult-to-detect spatial and temporal patterns within power system data throughout the power grid[12-14]. CNN-based models are great for extracting unique features from signal representations whereas LSTM-based architectures can accurately model time-based fault characteristics[15-17]. Additionally, researchers have implemented recurrent deep learning frameworks for the classification of faults in microgrids with much greater results compared to traditional techniques[18]. Recently hybrid deep learning architectures have become increasingly popular due to their capability to blend together advantages of several model types. An example is combining CNN and Bidirectional Long Short-Term Memory (BiLSTM) techniques, which synergistically extract spatial features and apply bidirectional temporal learning to better represent faults[19-21]. Many different applications have reported success where these models were used for detecting faults and processing signals by capturing previous as well as future dependencies from sequential data[20-22]. Nonetheless, challenges such as robustness in noisy environments, managing skewed datasets, as well as computing efficiently enough for real time use are all still key issues.

In response to these obstacles, an integrated CNN-BiLSTM architecture for recognizing and identifying high impedance faults with a high degree of automation and dependability have been developed. To support good generalization of the model, a comprehensive preprocessing framework that incorporates feature creation, normalization, data balancing and noise augmentation is created. Due to combined effect of the spatial and temporal aspects of this model, it has the ability to correctly detect various types of high impedance faults regardless of operational conditions allowing for timely use in protecting smart grid systems in near real time. Detecting HIFs is difficult in contemporary power distribution systems because the magnitude of fault current is small, the load characteristics are not linear and the fault currents can closely resemble normal load currents. Traditional protection schemes do not generally detect HIFs in modern distribution systems with inherent characteristics that result from increased embedded/ distributed energy resource penetration and the evolution of smart grid technology. It, therefore, is necessary to develop an intelligent, flexible and adaptive fault detection framework to detect HIFs in various operating and noise conditions.

2 Literature Review

High Impedance Fault (HIF) detection has received much attention in research over the years because of its importance in the safety and reliability of power distribution systems. Previous research mostly investigated fault induced (current and voltage waveform) distortions using signal processing techniques. For example, reconstruction algorithms have been proposed that use transient characteristics to improve the accuracy of HIF detection in a microgrid[1]. Inter-harmonic analysis can also use the frequency variation caused by the arcing of fault currents to identify conditions that would indicate an HIF[2] (although this may not always be reliable). Finally, decision trees have been developed for HIF classification and determination of zones due to their greater interpretability compared with other HIF analysis techniques[3].

Traditional methods for analysing signals include wavelets and statistical pattern matching to obtain signals from wavelets and statistical patterns to find the temporal and frequency-based features of a fault signal. Such methods are useful in detecting some of the features of a fault but there are limitations to these methods like poor noise immunity, reliance on thresholding and the difficulty in adapting to the changing scenario of the system. The smart grid is constantly changing which leads to the need for new methods to detect faults that rely on adaptive and resilient approaches to detect and control the faults[4-5]. To overcome these limitations, machine learning techniques have been developed for automated fault detection and classification. Artificial neural networks, as well as graph search and statistical methods have all demonstrated superior levels of detection accuracy compared to traditional techniques. Most importantly, all of these methods rely on manually extracted features from the data, requiring specialized domain knowledge, and are likely not able to generalize across the many possible configurations and operational environments[6-8].

Deep Learning has become an attractive option for fault identification in recent times because it can learn complex relationships from unprocessed data and

Table 1 — Summary of existing studies

Reference	Approach Used	Application	Contribution	Research Gap
[1]	Reconstruction-based method	Microgrid fault detection	Adaptive fault detection using signal reconstruction	Sensitive to noise and computational complexity
[2]	Interharmonic analysis	Distribution systems	Detects HIF using arc characteristics	Requires precise filtering and affected by noise
[3]	Decision tree	Transmission lines	Fault classification and zone identification	Depends on handcrafted features
[5,11]	Wavelet + statistical methods	Distribution systems	Extract transient fault features	Threshold dependency and noise sensitivity
[8-10]	Machine learning (ANN, graph-based)	Fault detection	Improved classification accuracy	Requires feature engineering and large data
[12-14]	Deep learning (CNN, Autoencoder)	HIF detection	Automatic feature extraction	Limited temporal modelling
[16-18]	LSTM / BiLSTM	Time-series fault detection	Captures temporal dependencies	Miscue spatial features
[20-22]	Hybrid CNN–BiLSTM	Fault detection & signal processing	Combines spatial + temporal learning	Limited noise robustness analysis
Proposed Work	CNN–BiLSTM + noise augmentation	HIF detection	High accuracy with noise robustness	-

identify those relationships automatically. The development of deep learning models has made it possible to effectively identify and extract hierarchical features using automated systems without any manual work[9-12]. CNNs are commonly used to identify spatial and frequency domain characteristics of electrical signals. In addition, using deep networks such as Convolutional Auto Encoders allows for an improvement in feature representation of HIF detection. Furthermore, CNNs that are based on transfer learning and combined with time-frequency analysis, have shown to produce better performance in identifying faults within the power distribution system[13-15].

The use of hybrid deep learning architectures has become very popular over the past couple of years, mainly because they allow researchers to combine both spatially and temporally extractive properties of features. Similarly, CNN/BiLSTM hybrid models have performed exceptionally well by combining convolutional extrication of features with Bi-directional temporal learning[19-21]. With these two methods, researchers have been able to extract both instantaneous characteristics of signals as well as time-related signs, which ultimately leads to an improved overall accuracy in fault identification. In addition, researchers have explored the use of models built with enhanced attention mechanisms and hybrid architectures in order to further improve performance within complex systems[22]. While this field has made many advances in HIF identification over the past few years, there are still many challenges that exist with current methods such as reliability under noisy conditions, class imbalance and real-time execution limitations. Current weak-shoulder models typically have difficulties in generalizing, while many strong-shoulder models will require excessive computation to build and operate.

To provide a brief comparison of existing high impedance fault detection methods, some of the representative studies are summarized in Table 1. The table summarizes the methodologies, application areas, key contributions, and research gaps.

3 Proposed Method

The development of an innovative method is proposed for detecting high impedance faults (HIF) in electrical power distribution networks using a hybrid deep learning architecture. The hybrid model includes CNN's for extracting spatial features, and BiLSTMs networks to model temporal dependencies. The complete workflow consists of four major activities: Acquiring data, preprocessing data, Learning Features and Assessing Model Performance. The hybrid architecture allows for the effective extraction of currently available data into highly discriminative signals from voltage and current data while maintaining sequential relationships.

3.1 Overview

An overview of the HIF detection framework is shown in Fig. 1. The HIF detection framework will

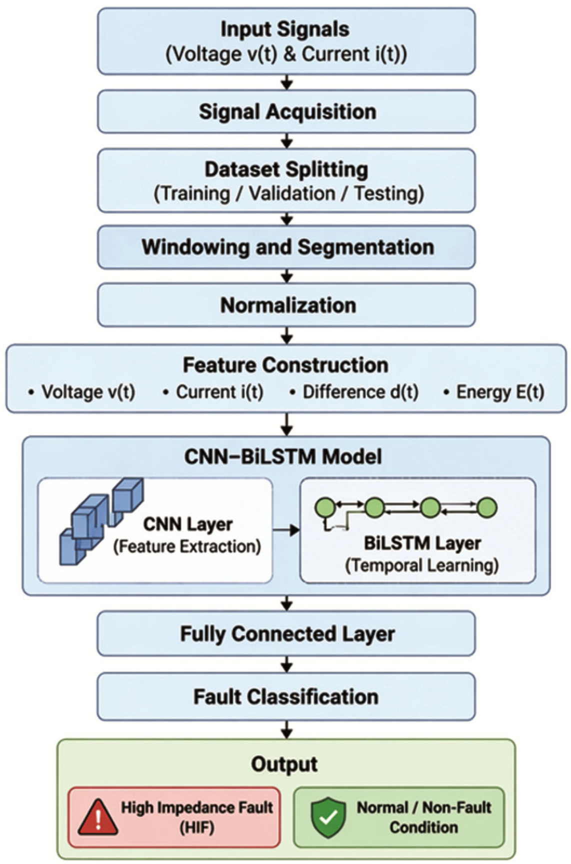

Fig. 1 — Flowchart of proposed CNN-BiLSTM framework

acquire voltage/current data from a three-phase distribution system. Then the voltage/current data will be segmented into three separate datasets (training, validation, testing) for proper development and evaluation of the model.

Next, all the signals were broken into fixed-length windows to find localized temporal patterns. Additionally, once the windows were constructed, the data was normalized to a uniformly consistent scale to assist with stabilizing optimal training. Following the preprocessing step of the data, the signals are then utilized in the feature construction stage via several representations of each signal, i.e., voltage, current, voltage and current deviations, and energy components.

After constructing the features, all features will then be passed through a hybrid CNN-BiLSTM architecture. The CNN will extract relevant spatial features from the data while the BiLSTM will capture temporal dependencies in both the forward and backward directions. The resulting features are then passed through fully connected layers for classification. Lastly, the output from the model is the fault type (high impedance or normal operation).

3.2 Test System Description

To confirm that the HIF detection framework is successful; a representative medium voltage distribution test system was used for the assessment. The test system was set up to simulate realistic operational conditions experienced in actual power distribution systems[2]. The test system operates at a nominal voltage level of 13.8 kV and was designed as a typical radial distribution feeder which is usually employed in utility systems. Additionally, a 500 kVA distributed load was added to the feeder in order to properly represent the normal operating customer demand on the feeder. In doing so, it will enable the assessment of fault behaviour under typical load conditions.

The test network consists of multiple surface conditions, each having different electrical properties such as sand, grass, clay, gravel, asphalt, and cement. Because of these different resistivity levels, the ground resistivity and contact conditions influence on the behaviour of HIFs can be determined[2]. For the purpose of measuring HIF currents, the system used to obtain the current is a current transformer (CT). With the CTs properly rated for low currents, HIF event-related transient current waveform signals can be recorded on a high-resolution data acquisition system. Transient current waveforms are transmitted to both substation monitoring units and field monitoring units for accurate temporal alignment of measurements.

In this research, High impedance faults (HIFs) are classified into two types: the first occurs when a conductor contacts external objects like vegetation without breaking, while the second occurs when a conductor breaks and intermittently arcs to the ground. Voltage and current signals from the test system are fed into a CNN-BiLSTM model, enabling detection of both spatial and temporal fault features, with a realistic setup ensuring the model's applicability to real power system conditions.

Different types of feeding plants have been created to extend feeder services further into additional lateral branches that are all ascribed to a different environmental state such as sand, gravel, clay, asphalt, cement, grass. Each branch has been created, with varying degrees of earth resistivity represented by it therefore demonstrating many different types of

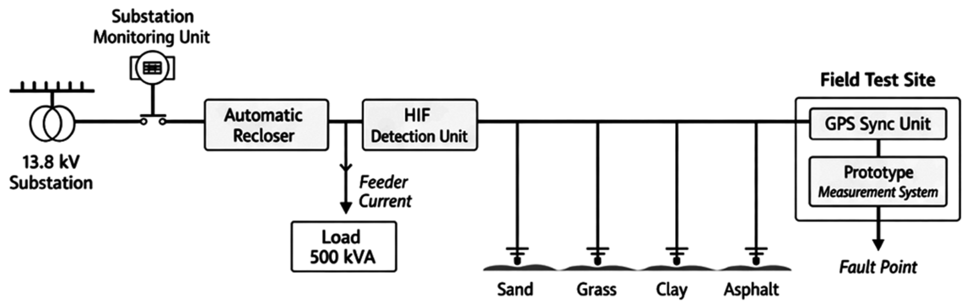

Fig. 2 — Single-line diagram of the 13.8 kV radial distribution system[2]

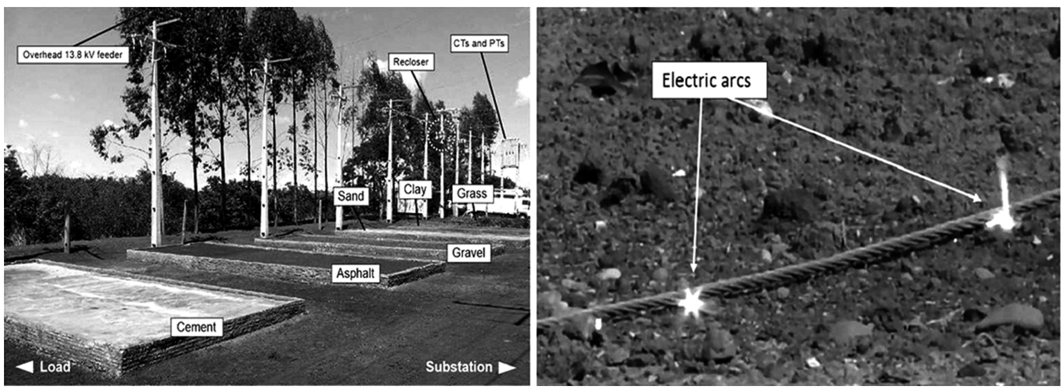

Fig. 3 — Views of conducted field tests[2]

ground resistance and also the effect that surface materials can have on the performance and the detectability of modelled transient events. Each of these locations has controlled faults installed at them to assess performance based on terrain conditions.

Approximately two measurement units have been set up to carry out comprehensive monitoring of these site locations. At the substation monitoring unit, information is captured about both the currents of the feeder and the performance of the system as a whole. A second measurement unit at the field test site captures detailed information relating to current signals during the occurrence of a fault. By time-synchronising data captured from each measurement site it is assured that objective evaluations may be completed against the captured data for an assessment into overall performance of the system.

3.3 Single Line Diagram Description

Figure 2, illustrates the overall arrangement of the test system with components including the substation, protective devices, electrical feeder architecture, branching feeder segments, and measurement points.

Besides this schematic representation of the test system, Fig. 3 shows real-world views of the experimental setup used to create high impedance faults and analyse high impedance faults at various surface conditions[2]. Among other things, these photographs illustrate physical arrangements of the tests conducted and also demonstrate actual arcing events that show the irregularity and complexity of HIF characteristics in actual environments.

After obtaining data from the test system, the data were processed through the proposed deep-learning model, which included the extraction of both spatial and temporal characteristics to separate normal from fault conditions.

3.4 Signal Acquisition and Segmentation

Instantaneous three phase voltage signals of power system are represented by $v_a(t)$, $v_b(t)$ and $v_c(t)$ of phases a, b, c respectively. Similarly, instantaneous three phase current signals of power system are represented by $I_a(t)$, $I_b(t)$ and $I_c(t)$ of phases a, b, c respectively. Voltage and current signals from a variety of high impedance fault conditions constitute the dataset. Each data file contains consecutive data where the first half contains voltage signals and the second half contains current signals.

Let input signal expressed as;

$$x(t) = [v_a\,(t), v_b\,(t), v_c\,(t), i_a\,(t), i_b\,(t), i_c\,(t)]^T \quad \ldots (1)$$

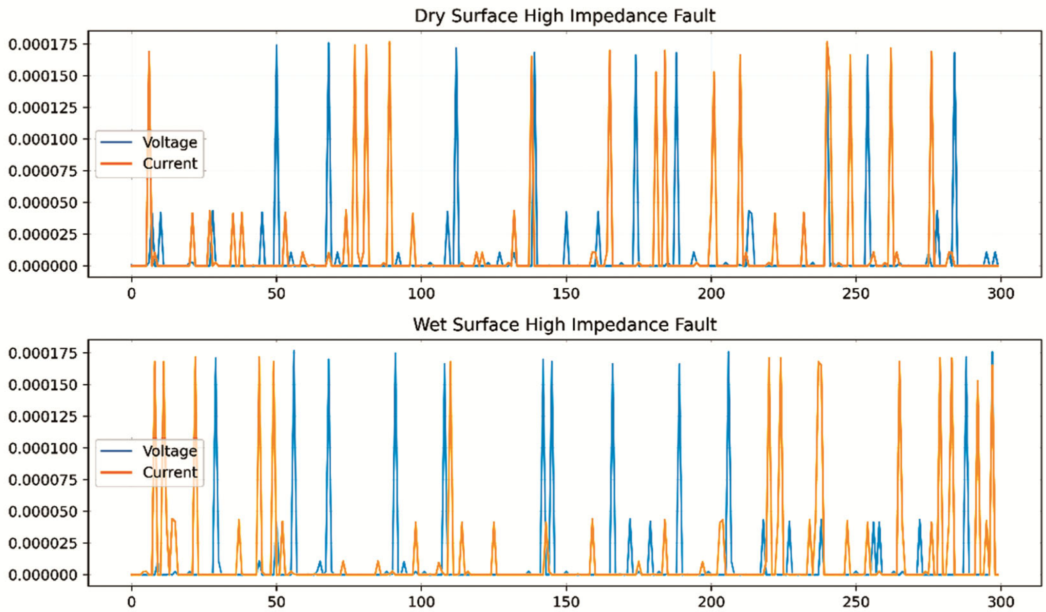

Fig. 4 — Sample signals of voltage and current under HIF

Training samples are determined using a sliding window method;

$$X(k) = \{x(k), x(k+1), \ldots, x(k+N-1)\} \qquad \ldots (2)$$

where "N" represents the length of the sliding window and "k" indicates the segment number, allowing the model to learn localized temporal behaviour in the signal.

Figure 4 illustrates the sample voltage and current waveforms measured during HIF conditions. The shapes of the signals were consistent with the presence of large irregular or non-linear deviations compared to typical steady-state behaviour. Such distortions are created from the arcing-type behaviour of high impedance faults and give rise to variations in the degree of asymmetry and fluctuations in the waveform shape. As a result, it is difficult to detect high impedance faults using conventional protection methods because the fault signatures are usually relatively subtle and closely resemble normal operating conditions. The complexity and variability of HIF's voltage and current signal characteristics demonstrate a need for more sophisticated data-driven methods to collect both spatial and temporal feature sets in order to accurately determine HIF locations.

3.5 Data Pre-processing

The input features were normalized to enhance training efficiency and maintain numerical uniformity by utilizing means and standard deviations. This process involves focusing the data (by subtracting the mean from all values) and scaling it (by dividing each value by its corresponding standard deviation).

$$\tilde{x} = \frac{x-\mu}{\sigma} \qquad \ldots (3)$$

In this equation, μ represents the mean, while σ denotes the standard deviation of the dataset.

Due to the fact that fault datasets generally have an undesirably imbalanced class distribution, oversampling techniques are regularly utilized in order to create a balanced dataset before proceeding with application of a model - thereby enhancing the generalization of the final model.

For greater robustness in "real world" scenarios, Gaussian noise has been added to the data inputs;

$$x_{noisy} = x + \varepsilon, \qquad \varepsilon \sim \mathcal{N}(0, \sigma^2) \qquad \ldots (4)$$

Here "x" is original signal and "x_{noisy}" is new noisy signal and "ε" is the noisy component. This action aids in the ability of the model to learn invariant characteristics when working with noisy environments.

3.6 Feature Representation

To construct the multi-dimensional feature representation of the fault signals for each of the segmented windows, the following features included;

- Measured voltage waveform $v(t)$
- Measured current waveform $i(t)$
- Difference signal is expressed as;

$$\Delta v[k] = \frac{(v[k]-v[k-1])}{\Delta t} \quad \dots (5)$$

$$\Delta i[k] = \frac{(i[k]-i[k-1])}{\Delta t} \quad \dots (6)$$

$\Delta t = \frac{1}{f_s}$ is the sampling interval and f_s is the sampling frequency.

- Composite signal magnitude feature is represented by;

$$E[k] = v^2[k] + i^2[k] \quad \dots (7)$$

Thus, feature vector is at each time instant represented by;

$$F[k] = [v[k], i[k], \Delta v[k], \Delta i[k], E[k]]^T \quad \dots (8)$$

This multi-dimensional feature representation gives the model a way to capture the non-linear and subtle characteristics of high impedance fault conditions.

3.7 Using CNNs for Feature Extraction

The feature extraction of the input feature maps is performed using the CNN layers, which use convolution operations to extract spatially and locally related features from the input data.

$$h^{(l)} = f\left(w^{(l)} * h^{(l-1)} + b^{(l)}\right) \quad \dots (9)$$

where: $w^{(l)}$ and $b^{(l)}$ are the l^{th} weights and biases respectively, and the activation function is denoted by f (·).

In addition, pooling layers are used to decrease the dimensionality and keep the most significant features found in each layer after applying the pooling operation;

$$P = MaxPool\left(h^{(l)}\right) \quad \dots (10)$$

3.8 Temporal analysis using BiLSTM

A Bi-directional Long Short-Term Memory (BiLSTM) network is selected because it can learn temporal dependencies in sequential voltage and current signals. Bi-LSTMs are different from regular LSTMs in that the data sequence is not transmitted only in one direction, but in two directions. BiLSTM is able to combine temporal information from past and future data and it can also detect complex temporal behaviour associated with high impedance faults.

Let x_t be the input feature vector at time t. The Bi-LSTM's temporal output is the concatenation of the hidden states produced by the forward pass and those produced by the backward pass expressed as;

$$h_t = BILSTM(x_t) = \left[\overrightarrow{h_t}\,;\,\overleftarrow{h_t}\right] \quad \dots (11)$$

where, $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ are the hidden states for both the forward and backward sequences (i.e., "forward" means from beginning to end) and [;] denotes concatenation.

Through combining information from both temporal directions, the BiLSTM Layer improves a model's ability to learn dynamic variations and subtle temporal characteristics that exist within a fault signal. Improved discrimination between operating conditions will occur as a result of this method of model design because the model can also identify faulty behaviours as they change over time.

3.9 Classification Layer

After obtaining high-level features from the CNN-BiLSTM network, all the extracted high-level features are fed into fully connected dense layers performing the final classification stage. The final classification stage converts the learned representations of the features into the classes of given faults and provides a probability distribution over those classes.

The output of the classification layer is produced by using an activation function, which operates on a linear transformation of the input features, as described by;

$$\hat{y} = sigmoid(W_h + b) \quad \dots (12)$$

where, $\hat{y}$ is the probability that the fault will occur.

The classification layer's output is computed using a nonlinear activation function applied to a linear transformation of function h, the input feature vector from previous layers, where W is the weight matrix and b is the bias vector, and sigmoid (·) is the activation function. The predicted occurrence of a fault is the output $\hat{y}$, which represents the probability of a fault occurring.

3.10 Loss Function

To enhance the performance of an imbalanced data set, during the training process, a new loss function called focal loss is utilized. In fault detection problems, classes that have fewer samples compared to other classes can cause biased learning if standard loss functions are used for example cross-entropy loss.

The focal loss (FL) is defined;

$$FL = -\alpha(1 - p_t)^{\gamma} \log(p_t) \quad \dots (13)$$

where, P_t is the predicted probability of the true class, α is a weighting factor to balance the importance of different classes, and γ is a focusing parameter that reduces the contribution of easily classified samples.

3.11 Performance Metrics

The CNN-BiLSTM architecture will be evaluated against traditional classification performance methods to assess its performance to detect High Impedance Faults. Reviewing these classification accuracy metrics will provide a better perspective of this model's predictive ability under various operating conditions.

True Positives (α), True Negatives (β), False Positives (δ), and False Negatives (λ) will be measured using conventional terms.

The overall classification accuracy will then be calculated using:

$$Accuracy\ (A) = \frac{\alpha+\beta}{\alpha+\beta+\delta+\lambda} \quad \dots (14)$$

The definition of accuracy relates to the amount of accurately classified cases compared to the total number of observations. Additional performance metrics should be developed when evaluating model performance on a detection problem due to class imbalance.

Precision is defined as the ratio of correct positive predictions made by the model and can be calculated as;

$$Precision\ (P) = \frac{\alpha}{\alpha+\delta} \quad \dots (15)$$

Recall (also called Sensitivity) is defined as the ability of the model to correctly identify fault examples.

$$Recall\ (R) = \frac{\alpha}{\alpha+\lambda} \quad \dots (16)$$

The F1 score (generally viewed as measuring the balance between precision and recall) can be defined by the following expression;

$$F1\ Score = \frac{2 \times P \times R}{P+R} \quad \dots (17)$$

Receiver Operating Characteristic curve and Area Under the Curve are other evaluation metrics that can be used to measure the ability of a model to discriminate between different thresholds. Collectively, these evaluation metrics allow for a thorough evaluation of overall performance of the model, both for imbalanced datasets and for changing fault conditions.

Algorithm (Pseudocode): CNN–BiLSTM Based HIF Detection

Input: Voltage and current signals $x(t)$

Output: Fault classification label $\hat{y} \epsilon \{HIF, Normal\}$

Acquire three-phase signals $v_a\ (t), v_b\ (t), v_c\ (t), i_a\ (t), i_b\ (t), i_c\ (t)$

Form input vector $x(t) = [v_a\ (t), v_b\ (t), v_c\ (t), i_a\ (t), i_b\ (t), i_c\ (t)]^T$

for each time window k do

Extract segment X(k) $= \{x(k), x(k+1), \dots, x(k+N-1)\}$

Compute derivatives:

$\Delta v[k] = \frac{(v[k]-v[k-1])}{\Delta t}$

$\Delta i[k] = \frac{(i[k]-i[k-1])}{\Delta t}$

Composite signal magnitude:

$E[k] = v^2[k] + i^2[k]$

Construct feature vector:

$F[k] = [v[k], i[k], \Delta v[k], \Delta i[k], E[k]]^T$

Normalize:

$F_{norm} = \frac{F[k]-\mu}{\sigma}$

Add Gaussian noise:

$F_{noisy} = F_{norm} + \varepsilon$

CNN feature extraction using convolution and pooling layers:

$h^{(l)} = f\left(w^{(l)} * h^{(l-1)} + b^{(l)}\right)$

Temporal modeling:

$h_t = BILSTM(x_t) = \left[\overrightarrow{h_t}\ ;\ \overleftarrow{h_t}\right]$

Classification:

$\hat{y} = sigmoid(W_h + b)$

end for

Compute focal loss:

$FL = -\alpha(1 - p_t)^{\gamma} \log(p_t)$

Update model parameters using back propagation

return $\hat{y}$ (Output predicted class label)

4 Results & Discussion

4.1 Experimental Setup

The experimental setup for the proposed CNN-BiLSTM model comprises data of voltage and current signals measured under different conditions generated by different types of HIFs. It uses a sliding window for the different sections of time for processing (i.e., normalizing) so that they are scaled to the same scale. Both training and testing data were then selected to test how well the trained model can generalise to testing data. The training of the CNN-BiLSTM model with the Adam optimizer and a loss function based on categorical cross-entropy was done. The trained model provides evaluation metrics on classification algorithm accuracy, precision, recall, and F1 score.

The implemented CNN-BiLSTM prototype model was created using Python 3.11 with the Tensor flow / Keras deep learning framework. The data used in the experiments were preprocessed and evaluated for performance using the NumPy, Pandas, and Scikit-Learn libraries. Experiments were conducted on a workstation with an Intel Core i5 processor, 16 GB of RAM, and uses an NVIDIA GPU to accelerate model training. Through the utilization of fixed simulation time step of 50 µs (correspondent with 20 kHz sampling frequency), the voltage and current signals that were collected from the simulation were processed with fixed length windows and utilized as inputs into the proposed CNN-BiLSTM model. The choice of both the timestep and sampling frequency allows sufficient capture of transients associated with high impedances faults while still allowing for computational efficiency.

The dataset of this study consists of 37,533 segmented samples originating from voltages and currents collected during both HIF & normal operating conditions. Each sample has a time window of 100-time intervals, two inputs corresponding to selected voltage & current feature channels, yielding a total input size of (100, 2). To minimize bias during the development/evaluation of models, the dataset was randomly split into training (70 %), validation (15 %), test (15 %) sets. The training set was used to determine optimal parameters for CNN-BiLSTM models; the validation set was used to tune hyperparameters & to prevent overfitting; and the independent test sets provided evidence on how well the proposed model can generalize.

4.2 Quantitative Performance Evaluation

The quantitative performance of the proposed CNN-BiLSTM model using standard metrics to classify the test dataset are evaluated. Standard classification metrics were used to assess performance, showing that the model produced accurate results that consistently achieved a high level of performance. The accuracy of 94.92 % means that the model has an extremely high ability to classify whether a fault or not is present for each case. The high precision value of 97.08 % indicates that the model has done an excellent job of avoiding false positives during classification. The recall metric of 92.63 % indicates that the model has a very high percentage of true faults (i.e., it is performing well by successfully identifying fault instances). Finally, the F1-score reflects the balanced performance with respect to precision and recall, yielding a value of 94.80 %, providing substantial evidence that the approach will be strong and consistent.

The recall value shows that the majority of each of the faults was correctly identified so that the detection of faults would be reliable. The F1 score also indicates that the model produced balanced results with regards to the precision and recall measures confirming its overall effectiveness of the classification compared to other modelling techniques. These results suggest that the proposed method has demonstrated capability of extracting the complexity of fault characteristics from the input signals, which improves reliability of fault detection with the model over a range of operating conditions.

4.3 Training Behaviour

Both training accuracy and validation accuracy curves in Fig. 5, demonstrate an overall upward trend indicating good learning of a model. The close match between training and validation shows that the model is well-generalized to previously unseen data. Likewise, both training loss and validation loss curves demonstrate a gradual decrease over epochs indicating stable convergence throughout the optimization process.

4.4 Performance Evaluation Through Confusion Matrix

The confusion matrix in Fig. 6 and Table 2 shows a comprehensive view of how well our new model is performing when it comes to classifying data points that contain faults or do not contain faults (normal). The confusion matrix clearly illustrates that our model is able to accurately classify the majority of the

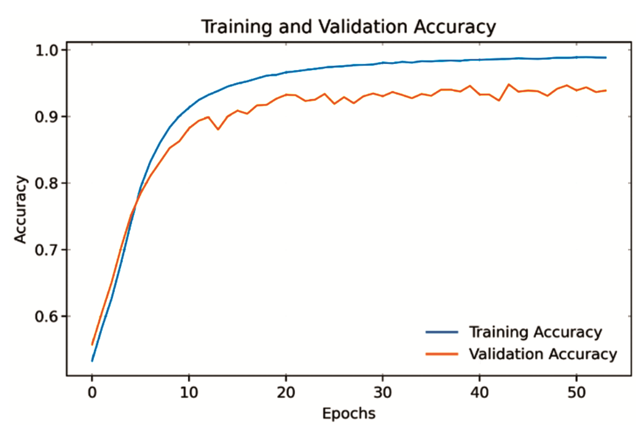

Fig. 5 — Training and validation accuracy of proposed CNN-BiLSTM model

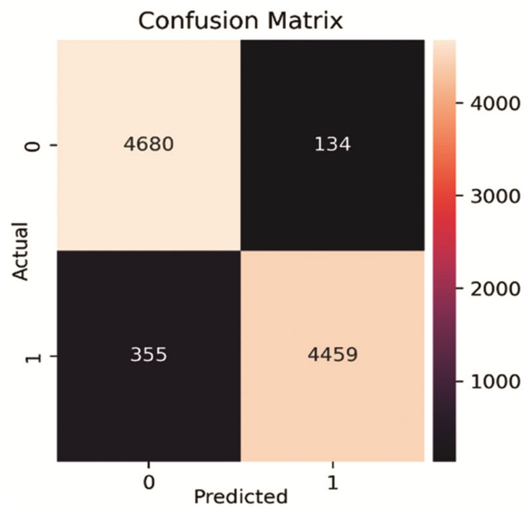

Fig. 6 — Confusion matrix of proposed CNN-BiLSTM model

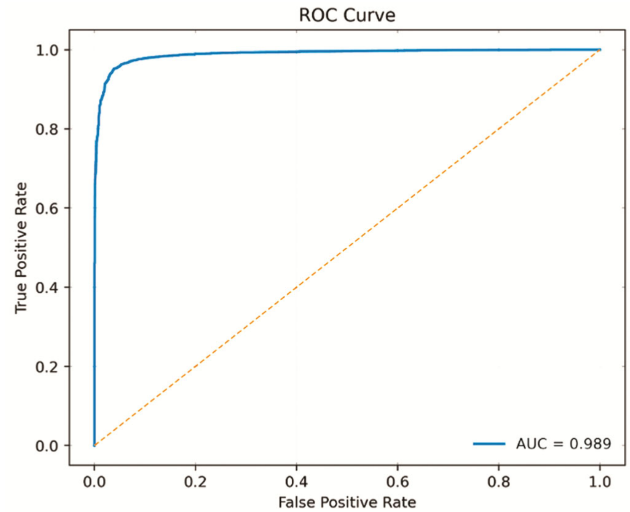

Fig. 7 — ROC Curve of proposed CNN-BiLSTM model

Table 2 — Confusion matrix statistics

Parameter	Value
True Positive (TP)	4459
True Negative (TN)	4680
False Positive (FP)	134
False Negative (FN)	355

samples in the dataset with 4680 true negatives and 4459 true positives, which demonstrates the significant predictive ability of the model.

In terms of misclassification, there were only 134 false positives and 355 false negatives identified in the confusion matrix. Given the low number of false positives, the model does not generate many false alarms, which is crucial for any protection system to be reliable. Additionally, since the false negative rate is also very low, the vast majority of faults in the system will be detected. Overall, as shown by the confusion matrix, the CNN-BiLSTM model has successfully separated the normal condition from the fault condition. The results show that by utilizing the developed framework, an ability exists to identify even the most minor changes in the behaviour of the signal, thus allowing for correct classification of signals in even the most complex situations.

4.5 ROC and Precision-Recall Analysis

The Receiver Operating Characteristic (ROC) curve of the CNN-BiLSTM model is shown in Fig. 7. The ROC curve shows how the true positive rate and the false positive rate differ for each classification level. It is clear that the curve is very close to the top-left corner of the plot, which indicates good classification performance.

The Area Under the Curve (AUC) is 0.989. That is a high level of separation between fault and non-fault conditions. That shows that the developed framework can distinguish different classes with little misclassification. The steep rise of the curve at low false positive rates is further evidence for the strong detection ability of the model.

In addition to the ROC analysis, Precision–Recall (PR) characteristics are also considered to analyse the model performance under the imbalanced conditions. The high precision of the model for different recall levels indicates that the model is not able to keep a low false positive rate while accurately identifying fault instances. This is crucial for power system protection since false alarms can result in unnecessary system interruptions. In general, the ROC and Precision–Recall analysis suggest that the proposed CNN-BiLSTM model provides reliable and consistent classification performance and is suitable for use in high impedance fault detection challenges.

4.6 Noise Robustness Analysis

The robustness of the proposed CNN-BiLSTM model is tested by varying the noise in the input signal. The model performance in terms of accuracy and recall under different noise conditions is shown in Fig. 8 and the values are summarized in Table 3.

The model is still very good at low noise levels, with accuracy of around 94. 9 % and recall of 92.6 % under noise-free conditions. As the noise level increases, a gradual decline in performance is observed, but it is relatively moderate up to a noise level of 0.10 and it indicates that the model can handle a moderate noise level without any significant degradation. As noise is increased (0.15 and 0.20) the accuracy drops more sharply, but recall remains relatively stable. This implies that the classification model is not losing overall accuracy and still finding fault instances. The ability to retain high recall in noisy conditions is especially important in fault detection where finding a fault can be very serious. The developed framework is robust against noise in general, due to its presence of noise-aware training and the combined spatial-temporal learning capability of the CNN and BiLSTM architecture.

4.7 Computational Efficiency

The evaluation of the computational capability of the CNN-BiLSTM architecture has provided measures associated with the model complexity and the time required to use the model. Based on the architecture created, the total number of parameters is 399,557 with 133,057 of these being trainable. The base model will require approximately 1.52MB of memory in order to run. The average time taken to produce a valid prediction from the trained model on 100 input samples was approximately 0.2282 seconds resulting in approximately 2.28 ms/sample in inference time. This indicates the proposed architecture is efficient from a computational perspective and should be suitable for use in modern-day power distribution systems in near real-time for the detection of HIFs.

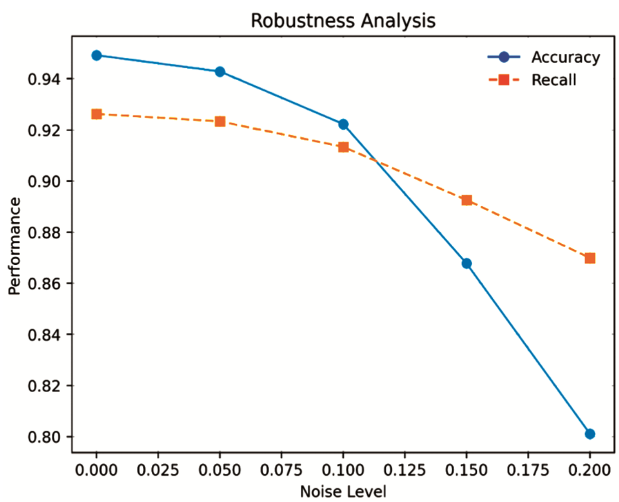

Fig. 8 — Performance of proposed CNN-BiLSTM model under different noise levels

Table 3 — Performance under noise

Noise Level	SNR (dB)	Accuracy (%)	Recall (%)
0.00	Noise free	94.92	92.63
0.05	25	94.30	92.40
0.10	20	92.20	91.30
0.15	16	86.80	89.20
0.20	14	80.10	87.00

4.8 Discussion and Comparison

The outcome shows that the CNN-BiLSTM model developed for this study can better perform than traditional signal processing and machine learning methods in terms of performance (accuracy), robustness and adaptability. Unlike the traditional techniques, which have historically depended upon manually developed features from raw data, the new technique learns appropriate features directly from the raw data itself.

The benefit of combining the spatial and time-series components of the CNN and BiLSTM, respectively, has shown to allow for a more efficient way to model the relationships between the faults being modelled and how they impact one another. In addition, the robustness of the CNN-BiLSTM model under noisy conditions makes it applicable for use in today's smart grid environments.

Table 4 summarizes the comparison between the proposed method and existing approaches. It can be seen that conventional and machine learning-based techniques suffer from limitations such as noise sensitivity and reliance on handcrafted features. Deep learning methods improve performance but lack spatial or temporal representation. The proposed CNN–BiLSTM model is able to combine both aspects

Table 4 — Comparison of existing methods with proposed approach

Method	Accuracy	Noise Robustness	Limitation
Reconstruction based[1]	Moderate	Poor	Noise sensitive
Interharmonic analysis[2]	Moderate	Moderate	Filtering required
Decision Tree[3]	Moderate	Poor	Feature dependent
Machine Learning[8,10]	High	Poor	Manual features
CNN[12,14]	High	Moderate	No temporal learning
LSTM/BiLSTM[16-18]	High	Moderate	No spatial features
Hybrid DL[19-22]	High	Moderate	Limited Robustness Proposed
CNN-BiLSTM (Proposed)	94.92 %	Strong	-

Table 5 — Performance comparison of CNN, BILSTM and Proposed CNN-BILSTM

Model	Accuracy (%)
CNN	56.30
BILSTM	85.23
CNN-BILSTM	94.92

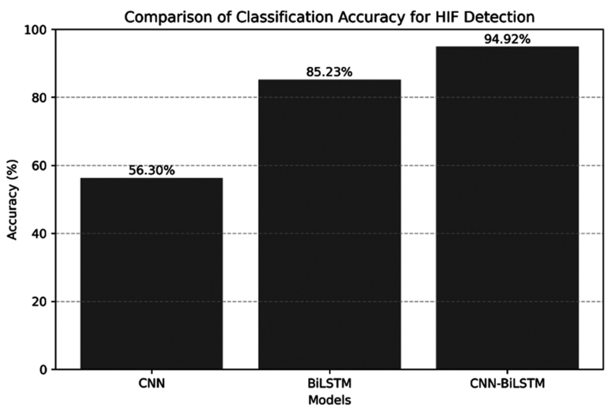

Fig. 9 — Bar chart comparison of classification accuracy for different models

in a very effective way and exhibits robustness under noisy conditions.

To test the effectiveness of the hybrid deep learning Framework being tested, the performance of stand-alone CNN and BiLSTM models were compared to that of the proposed framework CNN-BiLSTM using the HIF dataset as an input. The findings from this study revealed that the Hybrid framework had a much higher classification accuracy than the individual models that were tested. The Accuracy of the Standalone CNN model was 56.30 %, which is a measure of classification success but does not accurately represent the capabilities of the model itself. While CNNs are very effective in extracting local spatial features from fault signals, they do not have the capability to capture much of the long-term temporal dependencies that are inherent in sequentially ordered electrical signals. For that reason, the performance of the model's classification accuracy is lower when compared to that of the hybrid framework. The BiLSTM network independently provided significantly improved accuracy at 85.23 %. The BiLSTM learned temporal relationships bidirectionally in the HIF (High-Voltage Insulation Failure) signals, improving fault discrimination compared to the CNN (Convolutional Neural Network). However, without strong spatial feature extraction, the overall results were limited.

Hybrid CNN–BiLSTM provided the best overall classification accuracy at 94.92 %. The superior performance of this model is due to the combined strengths of the individual CNN and BiLSTM architectures. The CNN layers extracted local feature characteristics effectively from the input signal data, while the BiLSTM layers captured temporal dependencies for both forward and backward movements. This hybrid learning ability allowed the hybrid model to identify complex fault patterns better than using the standalone models only.

According to Table 5, the standalone CNN model had lower accuracy ratings due to its inability to fully acquire the temporal relationship between sequential fault signals. In contrast, while the BiLSTM model outperformed the standalone model because it captured generalities about the HIF data using bidirectional temporal features, the proposed hybrid CNN-BiLSTM architecture significantly outperformed all other models tested on this dataset with an accuracy of 94.92 % by combining convolutional features with bidirectional learning on a temporal basis. The hybrid CNN-BiLSTM architecture excels in detecting high-impedance faults using accurate classification methods. Figure 9 shows a bar graph illustrating the classification accuracies between CNNs, BiLSTM and proposed CNN-BiLSTM model for HIF detection. The CNN-BiLSTM model performed better than either the CNN or BiLSTM by achieving a classification accuracy of 94.92 %. This indicates that combining both spatial feature extraction with temporal learning can produce more accurate results for fault classification.

5 Conclusion

High impedance fault detection remains a challenging task in power distribution systems due to the low magnitude and irregular nature of fault currents, which often resemble normal operating conditions. Conventional protection methods are therefore insufficient for reliable detection under such scenarios. In this work, the hybrid CNN-BiLSTM-based framework is proposed to address these difficulties. The framework combines convolutional layers to learn spatial features from voltage and current signals and bidirectional LSTM layers to capture time dependencies. A comprehensive preprocessing pipeline including segmentation, normalization and feature construction is implemented to promote model learning and generalization.

Compared to conventional signal processing and machine learning approaches, the method reduces the need to manually extract features and is more effective for different situations. Unlike standalone CNN or LSTM models, the proposed hybrid architecture is able to capture the spatial and temporal characteristics of fault signals. Also, noise-aware learning is incorporated to make the model more effective in real situations for signal disturbances. The proposed approach achieves 94.92% accuracy, high precision, recall and F1-score which means that the classification performance is reliable. The model also retains stable detection under noisy situations and shows that it is a good solution for real-time high impedance fault detection in modern power systems.

While the Proposed CNN-BiLSTM framework exhibited a high level of accuracy on the dataset available to us, it is important to note that these datasets were derived from laboratory settings. Therefore, we will use data normalization, class imbalances, and augmented by the addition of Gaussian noise during training purposes only in order for the proposed model achieve a better ability within real world applications. However, prior to being able to make any conclusive findings regarding the overall effectiveness of the proposed method an additional validation process (utilizing separate datasets created from distinct working conditions, network topologies, fault resistance levels, and actual field measurement results) will need to take place during future works. Cross-condition validations are a critical piece of future research endeavours to enhance the reliability and implementability of our proposed method.

Subsequent investigations will examine the application of this CNN–BiLSTM structure as developed to the existing commercial devices of real-time embedded hardware and to the evaluation of its capabilities based on actual smart grid operating conditions. Additionally, application in intelligent protection systems, integration into the IoT-based monitoring environments, and performance assessment using field data further broaden the scope of the proposed structure's utility for attaining accurate, timely, and dependable high-impedance fault identification capabilities for any modern distribution system.

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