UNIABUJA Journal of Engineering and Technology

https://ujet.uniabuja.edu.ng/

ISSN: 2714-3236 (Online); 2714-3228 (Print)

Volume 2, Issue 2, 2025; 224-232

# Fault Diagnosis System Using CNN-LSTM Networks

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***Abstract***
*Prompt classification and detection of faults along transmission lines is critical to the smooth operation of energy companies, the maintenance of their power systems, and efficient transmission. Traditional methods are characteristically limited in their ability to handle large volumes of data thus, the need for intelligent networks such as neural networks. This research proposes the use of a hybrid of two of such networks - the Convolutional Neural Network (CNN), and the Long Short-Term Memory (LSTM), to improve the fault diagnostics capabilities for a three-phase transmission line. Fault data for twelve possible scenarios are obtained from a SIMULINK model. The CNN-LSTM model is trained and tested using this dataset in 80-20 training-testing split. The features are four current values - three phases' currents and ground current with targets labeled as 0 (no fault) and 1 (faulty). The targets enable the model to classify faults into the twelve already defined labels. The CNN-LSTM model was trained using normalized values to prevent overfitting. The CNN-LSTM model which is robust and good for time-series prediction and adapting to changing load patterns. The model's performance was evaluated using confusion matrix, accuracy, precision, recall, and F1-score. The test accuracy was 94.56%, precision 95.89%, recall 95.40%, F1 score 94.88%, and the confusion matrix showing 13 faults were misclassified out of 239, representing approximately 5%. The CNN-LSTM model is saved for real-time fault diagnosis.*

***Keywords:*** *Convolutional neural networks, long short-term memory, neural networks, transmission lines.*

## 1.0 Introduction

The role of transmission lines in the functioning of power systems is critical considering that they are responsible for conveying electrical energy from the generating stations to the distribution stations. The efficiency and reliability of power systems structure rely heavily on the seamless operation of transmission lines. That said, these critical components are vulnerable to faults which might lead to even catastrophic system failures. These faults could be due to environmental factors, equipment malfunctions, external interference and disturbances (Khoshbouy et al., 2022; Tong and Wen, 2020). These types of faults are shown in figure 1.

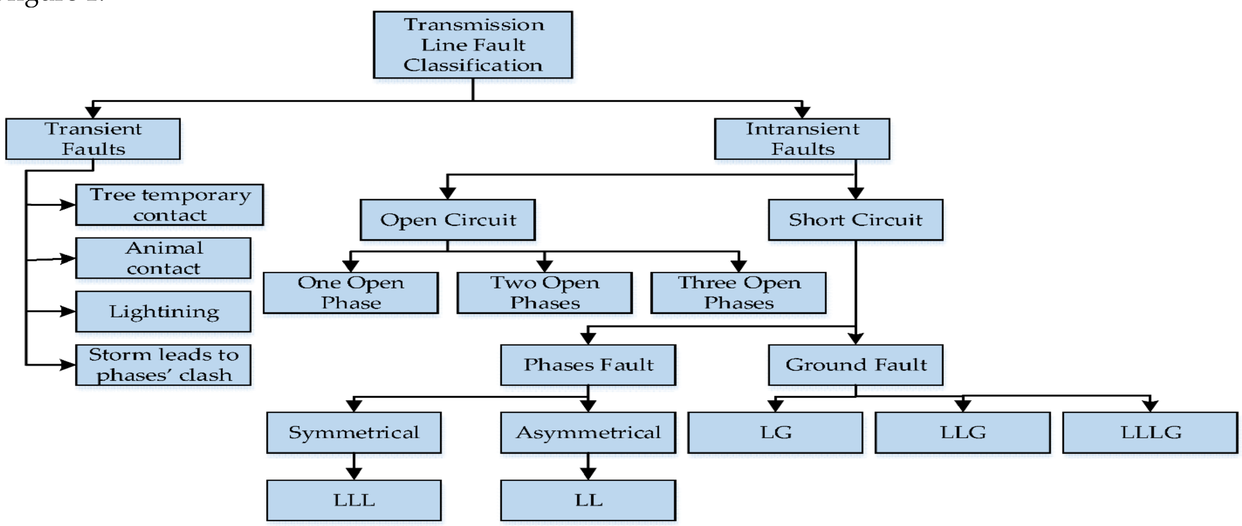


Figure 1: Transmission line fault classification (Al-Mtawa et al., 2022)

Short circuits are the most common of faults in power-lines. It simply involves any of the conductors (ground inclusive) coming into contact with other conductors. This scenario creates an unintended current path which may disrupt operations and damage system components. Line outages refer to complete disruptions in the transmission line, resulting in the cessation of power flow and substantial disruptions in electricity supply. Additionally, insulation degradation can gradually occur over time, leading to reduced transmission efficiency and increased risk of more severe fault (Das et al., 2022; Al-Mohammed et al., 2022).

When it comes to fault clearing, time and accuracy are essential. Thus, timely diagnosis of the fault and implementation of accurate counter-measures is imperative to ensure the overall reliability and stability of power systems. Swift identification of faults is essential for implementing appropriate countermeasures promptly, minimizing downtime, and prevention of cascading failures. Traditional fault diagnosis methods often rely on rule-based approaches, to detect and classify faults. While these methods have been effective to some extent, they are quite limited when dealing with the complexities and intricacies of transmission line data (Tong and Wen, 2020; Das et al., 2022; Al-Mohammed et al., 2022). Modern power systems generate large volumes of data. Transmission lines generate substantial amounts of data from various sensors, monitoring devices, and supervisory control systems. Processing this data poses a significant challenge for traditional methods. Manually analyzing this vast data is laborious and time-consuming, making it difficult to achieve real-time fault detection (Park et al., 2019; van Houdt et al., 2020; Shafiullah et al., 2022). Moreover, handcrafted features may not fully capture the intricate patterns and relationships present in transmission line data. The fault signatures can be subtle and may evolve over time, making it challenging for rule-based methods to adapt and provide accurate diagnoses consistently.

Modern fault diagnosis techniques such as machine learning and deep learning, offer a promising solution to these challenges. One of these approaches, Long Short-Term Memory (LSTM) network, which is a type of Recurrent Neural Network (RNN), is capable of learning automatically, and extract relevant features from large volumes of data. They are specifically designed to handle sequential data, making them suitable for time-series data like that generated by transmission lines. Another neural network is the convolutional neural network (CNN) which is a type of deep learning technique used to process images and time-series data. They are quite capable of extracting spatial and temporal information automatically from a given data-set. CNNs are effective in classification and detection tasks, such as in fault classification for transmission lines such as in this study. CNN can be combined with LSTM for improved learning for sequential data and also to improve time-dependent pattern recognition. Features extracted using the CNN are fed into the LSTM layers, for sequential processing.

By leveraging these networks, researchers and engineers can develop fault diagnosis models that learn from historical data and recognize subtle patterns indicative of potential faults. The models can adapt and improve their accuracy over time as they receive more data, enabling better fault detection and classification (Yan and Ma, 2021). The utilization of CNN-LSTM networks, with their ability to process sequential data and capture long-term dependencies, holds great promise for revolutionizing fault diagnosis in transmission lines, ensuring grid reliability, and addressing safety concerns in power systems (Yan et al., 2023).

This study combines CNN's strength in pattern identification and feature engineering with LSTM's capability to handle sequential or time-series data thus creating a robust model with improved accuracy. Figure 2 shows the structure an intelligent fault diagnostic system.

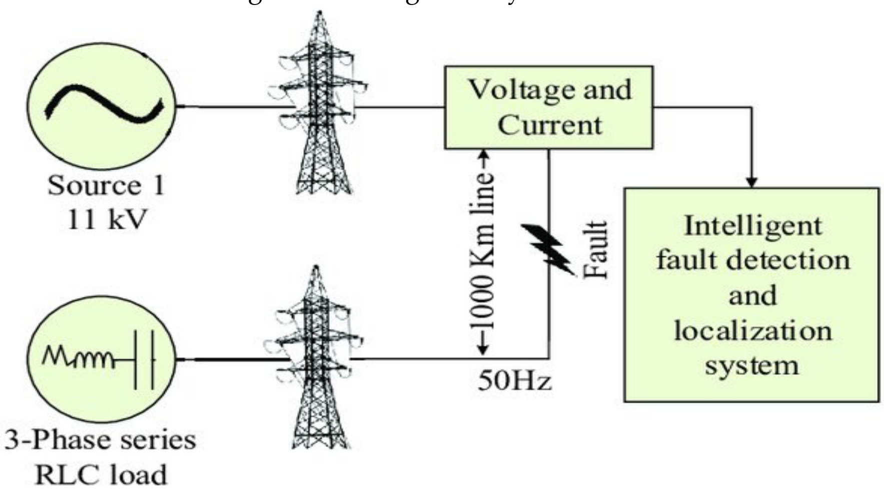

Figure 2: Power line fault diagnostic system (Ogar et al., 2022)

Several studies have demonstrated the effectiveness of LSTM-based models, in fault diagnosis across different domains. For instance, Park et al. (2019) proposed a hybrid auto-encoder-LSTM model for rare events detection in time-series data, while Yan et al. (2023) applied a CNN-LSTM approach to aircraft hydraulic systems. Similar LSTM-based techniques were employed by Qin et al. (2018) for autonomous underwater vehicles and Yang et al. (2020) for bearing vibration signal fault analysis using a CatBoost classifier. Liu et al. (2019) developed a low-delay lightweight recurrent neural network (LLRNN) based on LSTM for rotating

Received: 05-06-2025 / Accepted: 22-06-2025 / Published: 18-07-2025 
https://doi.org/10.70118/ujet.2025.0202.21

machinery fault diagnosis. Liu et al. (2022) developed an LSTM neural network for a nuclear power plant fault diagnosis. The test findings indicate over 99% accuracy by the model. An LSTM-based fusion module was implemented by Li et al. (2025), to aggregate continuous signals from multiple dimensions, and found effective with faults in distribution systems. In Kaplan et al. (2021), LSTM is proposed as an approach in detection of faults within the electro-chemical conversion chain for conventional electric vehicles (EV). Zheng et al. (2022) proposed a fault diagnosis and data recovery algorithm based on PCA and LSTM to mitigate failure during dry-type transformer temperature monitoring sensor working. Su et al. (2023) proposed two fusion models – CNN with attention module (AM) and multi-head LSTM to overcome limitations of traditional artificial intelligence based fault location methods.

Wang et al. (2021) proposed a deep hybrid CNN-LSTM network model for single-terminal fault location on an HVDC system containing mixed cables and overhead line segments while Alsumaidee (2023) explored the effectiveness of deep learning techniques, specifically 1D-CNN model, LSTM model, and 1D-CNN-LSTM model, in detecting arcing problems in switch-gear. A CNN-LSTM-based approach was used by Qi et al. (2024) for wind motor fault detection, achieving up to 97% accuracy. Lim et al. (2024) proposed a bidirectional LSTM approach for fault diagnosis in medium-voltage direct current (MVDC) systems, while Wang et al. (2021) applied LSTM neural network in the classification of raw sensor data for a simulated MMC-HVDC (Modular Multilevel Converter in High Voltage Direct Current Systems) transmission system. Wang et al. (2020) proposed a fault diagnosis method based on wavelet packet to improve the LSTM network in solving the issue of accuracy in vibration motor fault. Feng et al. (2023) addressed class imbalance using a stacked de-noising autoencoder-generative adversarial network-long short-term memory (SDAE-GAN-LSTM) for a three-phase permanent-magnet synchronous motor (PMSM) drive system. Elhalwagy and Kalganova (2022), presented a novel neural network (NN) utilizing a LSTM encoder and capsule decoder in a multi-channel input autoencoder architecture for use on multivariate time series data. BiLSTM and residual network (ResNet) were implemented by Xie et al. (2022) in fault classification for electric drives used in a marine electric propulsion system. This approach when compared to conventional deep learning algorithms, according to results, is faster and the accuracy can reach over 95% under 25 – 19 dB. Bai et al. (2025) also employed BiLSTM with improved temporal convolution network (TCN), to predict temporal fault patterns in industrial equipment. To overcome the inefficiency of traditional transmission line fault diagnosis in handling faults, Lu et al. (2023) proposed an extraction based convolutional LSTM (ECLSTM) approach which tackles dynamic coupling of process variables. In de Abreu et al. (2023) spiking neural networks (SNN) was shown to be better than LSTM in anticipating faults in syntactical time. In Attouri et al. (2023), a novel fault detection and diagnosis (FDD) method, trained using a BiLSTM model for a wind energy converter (WEC) was presented. Hasan et al. (2024) proposed a sensor fault detection method using LSTM autoencoder (LSTM-AE) using a multistep-based approach while Alhamd et al. (2024) in order to train an LSTM model, introduced a method of feature extraction through advanced wavelet transform analysis of differential current for detection of faults within power transformers. Zhou et al. (2023) applied CNN, back propagation (BP) and LSTM to battery fault diagnosis. Lee et al. (2020) implemented a CNN-LSTM algorithm and Fast Fourier Transform (FFT) in deriving the threshold setting of the abnormal pattern in data collected from manufacturing sites. Cha et al. (2023) proposed a CNN-LSTM model that was trained on the signal sequences of Hall sensors and can effectively distinguish between normal and faulty signals, achieving an accuracy of the fault-diagnosis system of around 99.3% for identifying the type of fault.

The versatility of LSTM-integrated models is further explored in Khan et al. (2024) who evaluated the performance of FedLSTM (Federated LSTM) against the centralized approach based on performance statistics like F1 score, precision, accuracy, and sensitivity. Also, Sabireen and Venkataraman (2023) used a Recurrent Neural Network (RNN)-based method, based on LSTM-CRP (Computation Memory and Power) to predict proactive faults in the event of insufficient resources in fog devices. In Al-Hardanee and Demiral (2024), artificial neural network algorithms (RNN and LSTM) are used to predict the condition of the hydropower station, identify the fault before it occurs, and avoid it. Jafari and Lopes (2023) integrated the kernel principal component analysis (KPCA) and LSTM to detect fault, and compared the performance to support vector machine (SVM), K-nearest neighbors (KNN) algorithm, and decision trees, in determining the type of fault. In Sanchez et al. (2022), LSTM, BiLSTM, multilayer perceptron and CNN networks are used for fault-isolation and detection in induction motors. Ahsan and Salah (2023) proposed a highly accurate Deep Convolution Neural Network (DCNN)–Long Short-Term Memory (LSTM) model with a SoftMax classifier. Zhang et al. (2023) proposed a 1D-CNN (one-dimension CNN) and interpretable BiLSTM for intelligent fault diagnosis in LREs (liquid rocket engines) while Agarwal et al. (2022), presented a Deep LSTM supervised autoencoder neural network (Deep LSTM-SAE NN) for the detection and classification and detection of faults in industrial plants.

Using Long Short-Term Memory (LSTM) Networks in combination with other algorithms or neural networks holds great promise for enhancing fault diagnosis accuracy and reliability in power transmission

Received: 05-06-2025 / Accepted: 22-06-2025 / Published: 18-07-2025

https://doi.org/10.70118/ujet.2025.0202.21

systems. By leveraging the capabilities of CNN and LSTM networks, the research aims to address the limitations of traditional fault diagnosis methods in handling time-series data and capturing complex fault patterns. The systematic approach outlined seeks to develop a robust CNN-LSTM-based fault diagnosis model and validate its effectiveness with real-world transmission line data. These studies highlight the potential of LSTM-based networks in fault diagnosis and provide valuable insights for the proposed study.

**2.0 Materials and Methods**

MATLAB is used to train the CNN-LSTM model. The fault data used to train the CNN-LSTM model was obtained using the SIMULINK model in Figure 3.

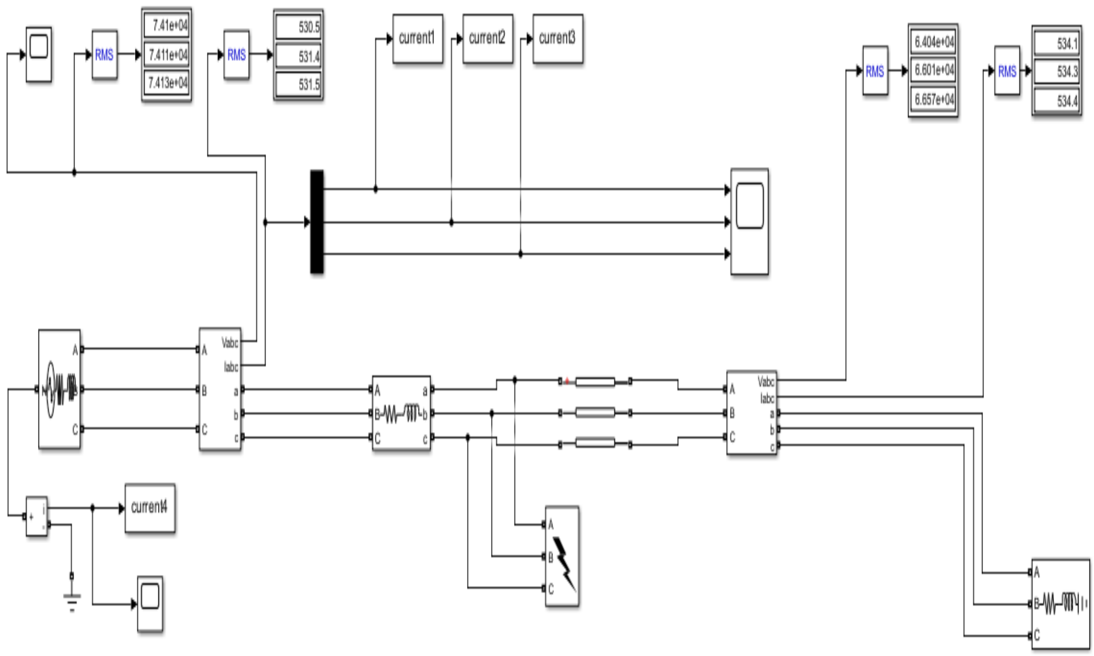


Figure 3: Transmission line model in Simulink

The fault block was used to simulate several types of fault. The fault scenario simulated are tabulated in table 1 below. A, B and C represent the three phases, while G represents ground. For model training, 100 samples for each fault type was used, totaling 1200 samples. The training-validation data split used was 80-20%. A clean dataset was used, meaning no irrelevant data was included to the pattern to be learnt was used in the training and testing.

Table 1: Fault categorization

| S/N | Fault Label | General Category |
|---|---|---|
| 1 | No Fault | |
| 2 | A - B | Line-to-line fault (LL) |
| 3 | A – C | |
| 4 | B – C | |
| 5 | A – G | Single-Line-to-Ground Fault (SLG) |
| 6 | B – G | |
| 7 | C – G | |
| 8 | AB – G | Double-Line-to-Ground Fault (LLG) |
| 9 | AC – G | |
| 10 | BC – G | |
| 11 | ABC | Three-Phase Fault (LLL and LLLG) |
| 12 | ABC – G | |

**2.1 Network flowchart**

The flowchart for the CNN-LSTM model development and training is shown in figure 4. Table 2 shows the network simulation parameters.

Received: 05-06-2025 / Accepted: 22-06-2025 / Published: 18-07-2025 
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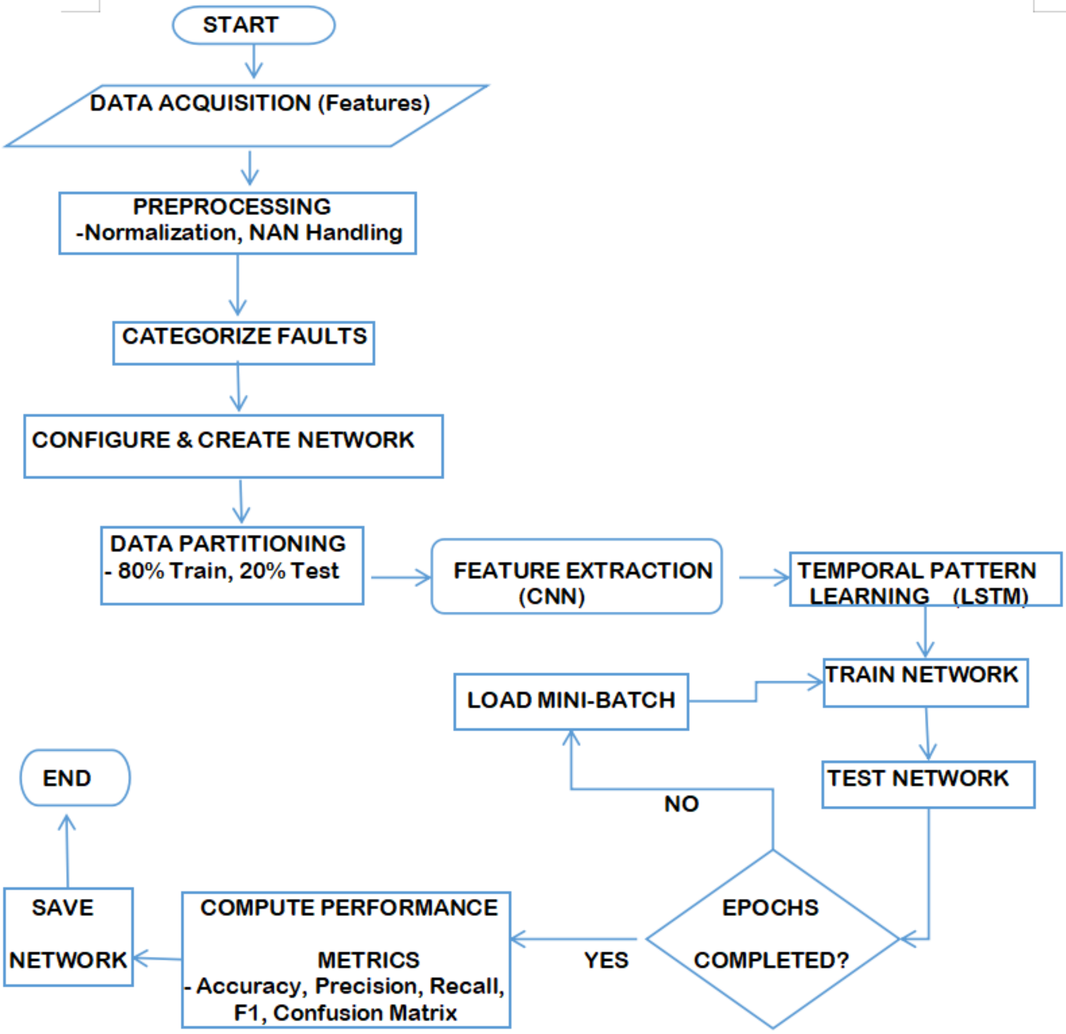


Figure 4: Flowchart for the model

The flowchart in figure 4 captures the process of creating, training and eventual implementation of the model for fault diagnosis.

Table 2: Model training and testing parameters

| Parameter | Value |
|---|---|
| LSTM Layers | 100 |
| Epoch | 200 |
| Iterations per Epoch | 120 |
| Maximum Iterations | 24000 |
| Learning Rate | 0.001 |
| Dropout Rate | 0.2 |
| Mini-batch Size | 8 |
| Optimizer | Adam |

### 2.2 Network architecture

The CNN-LSTM model combines the spatial features extraction capabilities of the CNN with the temporal sequence learning ability of the LSTM networks. This makes it possible for adapting the network to time-series sensor data used in this study. In this study, the CNN layers learn local spatial features from time-series data, while the LSTM layer captures the temporal properties for accurate fault classification. The architecture of the CNN-LSTM includes the following:

1. Input
2. CNN layers: Here, convolutional filters are added to extract spatial features
3. Flatten or Reshape: This converts the CNN output to a shape the LSTM can handle: (samples, time steps, features)
4. LSTM Layers: These layers capture sequential dependencies in the features extracted by CNN.

Received: 05-06-2025 / Accepted: 22-06-2025 / Published: 18-07-2025

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5. Dense layer and output: Final dense layers for prediction.

The model was trained using a fixed dataset split. The limitation was that k-fold cross-validation was not implemented. Model performance was observed using the batch-level training loss and accuracy.

**3.0 Results and Discussion**

Due to the available computational resources (Lenovo ThinkPad T460s with a 2.4 GHz processing speed, 8 GB RAM, intel core i5), and the need for high values of training and testing accuracy, the training process lasted for 23 minutes. Figure 5 presents the model's training accuracy and loss over time.

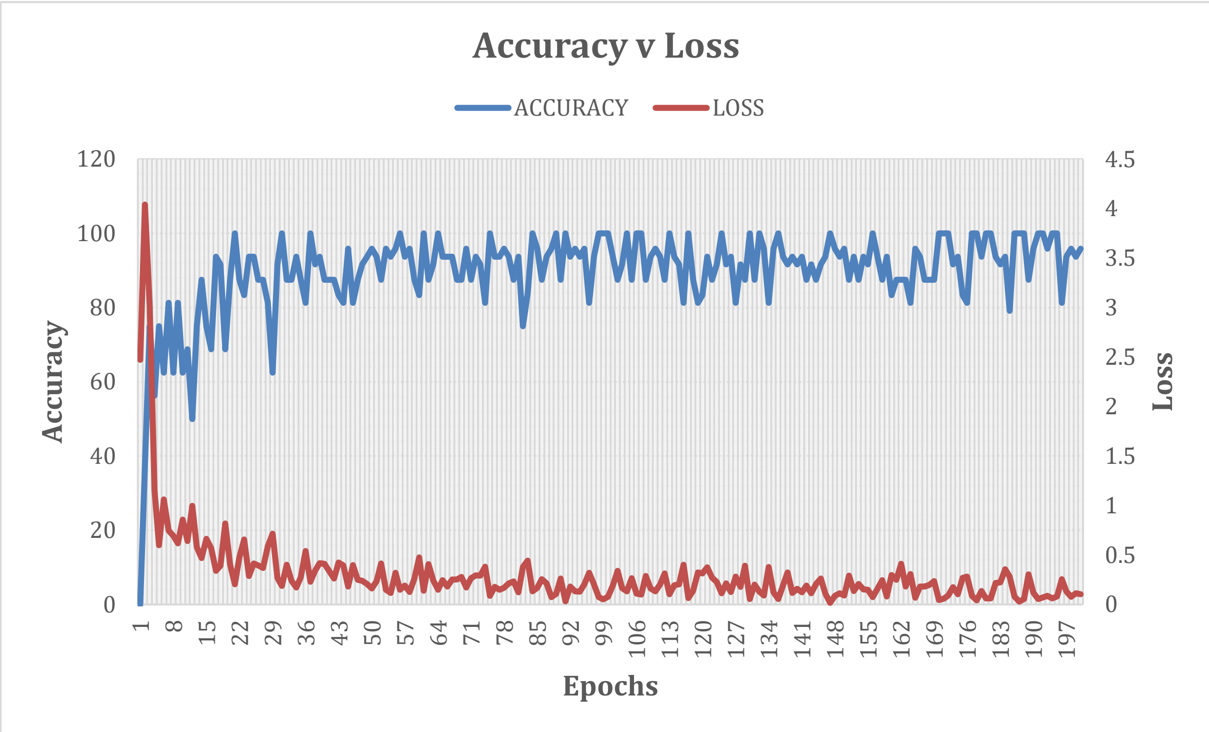


Figure 5: Model training accuracy and training loss

For each epoch, recorded mini-batch accuracies and losses were aggregated to obtain epoch-level metrics. This was done to ensure consistent tracking of the model's performance over time. The chart shows that as the number of epochs increased, the loss decreased with progression in epoch.

The performance metrics as obtained from the training of the CNN-LSTM model are in Table 3.

Table 3: Performance metrics

| Performance Metric | Value (%) |
|---|---|
| Test Accuracy | 94.5607 |
| Precision | 95.8889 |
| Recall | 95.4049 |
| F1 Score | 94.88 |

The performance metrics in Table 3 confirm the model's reliability for fault detection in energy carrying lines. The computed metrics each serves a purpose. The accuracy provides an overall measure of the process, recall is critical to ensuring that no fault goes undetected while precision reduces the possibility of false alarms. The F1-score provides a balance between precision and recall scores. The F1-score provides a comprehensive measure that reflects both the ability to detect actual faults and the correctness of such predictions.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (1)$$

The key metrics presented in Table 3 achieve approximately 95% which indicates that the model predicts events correctly and consistently across considered fault types. Table 4 compares the accuracy achieved from this study with some from the literature reviewed.

Table 4: Performance comparison

| Reference | Approach | Accuracy (%) |
|---|---|---|

Received: 05-06-2025 / Accepted: 22-06-2025 / Published: 18-07-2025 
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| | | |
|---|---|---|
| Qi et al (2024) | CNN-LSTM | 97 |
| Cha et al (2023) | CNN-LSTM | 99.3 |
| Zhang et al (2023) | CNN-BiLSTM | 97.39 |
| Sabireen and Venkataram (2023) | LSTM-CRP | 98.69 |

The confusion matrix provides insight into which fault types are frequently misclassified, and thus helps guide improvements in the model architecture and data preparation. The confusion matrix presented in figure 6 provides insight into the class-wise performance. Figure 6 shows the confusion matrix as obtained from the training. The accuracy of the trained CNN-LSTM model is approximately 95%.

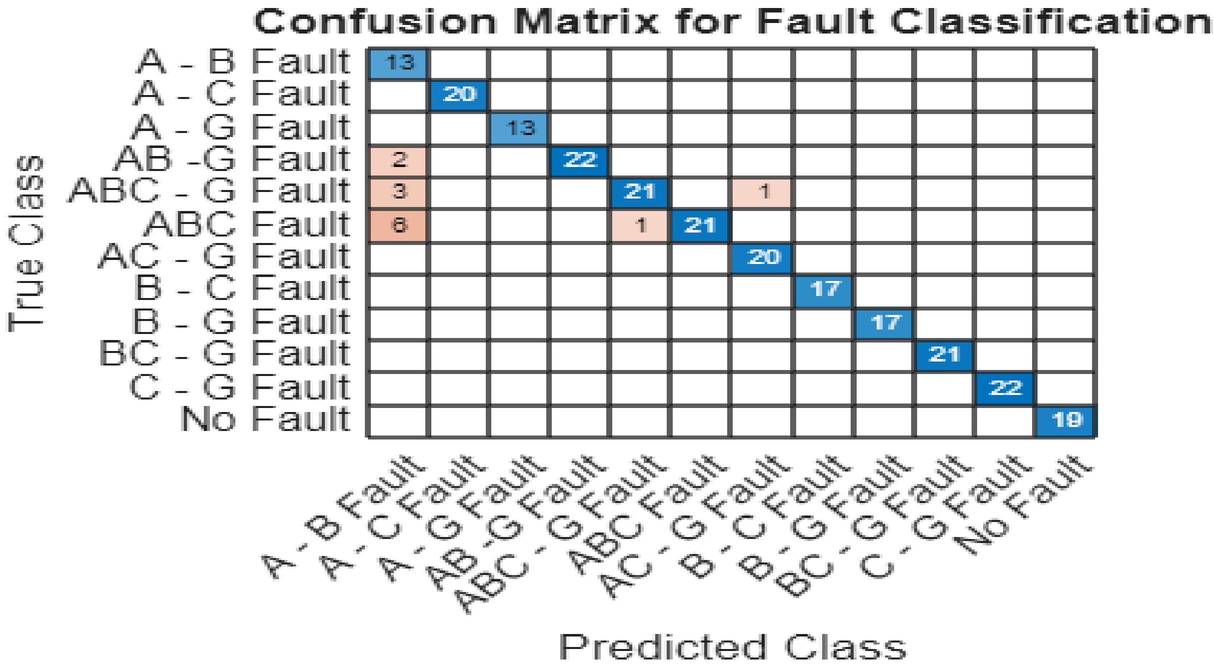


Figure 6: Confusion matrix for fault classification

The confusion matrix shows that out of 239 fault scenarios, 226 were properly classified (diagonal in blue). The remaining thirteen which represents approximately 5% of the data, was misclassified. Eleven (11) out of the misclassified data were A-B fault. The chart shows that most misclassifications occur between LLL and LL, six.

**4.0 Conclusion**

LSTM has been employed in several research for fault classification and identification due to its ability to handle time-series data. Integrating CNN with LSTM for a hybrid CNN-LSTM model suggests a robust model capable of extracting spatial and temporal features or patterns (due to the CNN) and the handling of sequential detail or features extracted from the CNN by using LSTM. The results show a test accuracy of 95.5607%, precision of 95.8889%, recall of 95.4049%, F1 value of 94.88% and the confusion matrix. The CNN-LSTM model has been adopted to improve fault diagnostics of a 132kV transmission line, and achieving an accuracy of 95.56%. This result suggests that the trained CNN-LSTM model is suitable for real-time identification and classification of faults in transmission systems.

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