
DESIGN AND SIMULATION OF ARTIFICIAL INTELLIGENCE-BASED ADAPTIVE PROTECTION SCHEME FOR NIGERIA'S POWER GRIDS USING BIG DATA ANALYTICS

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ABSTRACT

Conventional distance relay schemes often fail to detect high-impedance faults on Nigeria's 330 kV transmission network, contributing to grid instability and unreliable supply. This study proposes an adaptive deep neural network protection system for the Shiroro–Jebba–Oshogbo corridor, leveraging Big Data Analytics and convolutional neural networks (CNN) to overcome impedance-based limitations. Using MATLAB/Simulink, the corridor was modeled with validated parameters, and 1,000 scenarios across seven classification classes (Normal operation plus six fault types: single line-to-ground AG/BG/CG, line-to-line AB, double line-to-ground ABG, and three-phase ABC) and six fault locations were simulated, varying resistance from 0.01Ω to 500Ω . This produced 5.6 million measurement points. A CNN with four convolutional blocks and 1.39 million trainable parameters was implemented in TensorFlow/Keras, trained on 700 scenarios, validated on 150, and tested on 150. The model achieved 98.67% accuracy on unseen data, with an inference time of 100.56 ms. Performance was perfect (100%) for resistances up to 100Ω and remained strong (92%) at 500Ω , where conventional relays fail. Comparative analysis showed CNN sensitivity of 100% versus 21.48% for distance relays, a 78.52-point improvement, as confirmed by McNemar's test ($p < 0.0001$). Results demonstrate that deep learning-based protection provides robust detection of high-impedance faults, offering transformative reliability for Nigerian transmission networks beyond conventional methods.

Keywords: Adaptive protection; Big Data Analytics; Convolutional Neural Networks; distance relay; high impedance faults; Nigerian power grid; transmission line protection

1. INTRODUCTION

Electric power is an indispensable cornerstone of modern society, underpinning industrial, commercial, and residential activities. In Nigeria, the energy sector assumes a pivotal role in the country's economic growth and sustainable development. However, the Nigerian power grid has been grappling with persistent challenges rooted in insufficient infrastructure, operational inefficiencies, and vulnerabilities within its protection and stability mechanisms. These issues manifest as frequent power outages, voltage fluctuations, and grid instability. Statistics reveal a concerning trend: In 2018, there were thirteen (13) instances of national grid collapses (Oluwagbemi, 2018), followed by eleven (11) in 2019 (TheCable, 2019), four (4) in 2020, four (4) in 2021, eight (8) in 2022 (Nnodim, 2022; CuteNaija, 2022), and eight (8) between January and September 2023 (Onoja, 2023), totalling approximately forty-eight (48) collapses in a span of five years and eight months. These persistent issues not only disrupt the lives of millions of Nigerians but also have severe repercussions on the nation's economy (Adegioriola & Agbanuji, 2020).

The Nigerian 330kV transmission network, particularly the critical Shiroro-Jebba-Oshogbo corridor, experiences frequent grid collapses, with 46 recorded incidents in 2023 alone (Adejo, 2024). This corridor-level figure is considerably higher than the eight (8) national grid collapses reported for the same January-September 2023 period (Onoja, 2023) cited earlier; the two statistics differ in scope rather than being contradictory, as Adejo's count of 46 encompasses localised fault and instability events specific to the Shiroro-Jebba-Oshogbo corridor (including partial disturbances that trigger protective relay operations without a full national collapse), whereas Onoja's count of eight reflects only incidents

severe enough to cause a total national grid collapse. This distinction underscores why corridor-specific adaptive protection, rather than national-level statistics alone, is the appropriate frame for this study. These systemic failures stem from conventional protection relays' inability to adapt to real-time grid dynamics characterised by significant frequency deviations (± 1.25 Hz) and high-impedance faults with resistances up to $500\ \Omega$ in rural areas (Adeniji, 2025; Araga et al., 2024). Traditional distance relays, which rely on apparent impedance calculations ($Z = V/I$), exhibit poor selectivity under varying system conditions and struggle to distinguish legitimate fault transients from operational disturbances such as power swings or load switching, leading to nuisance tripping that can precipitate cascading failures across the Northern backbone. The legacy "bolted fault" logic fails to detect High-Impedance Faults (HIFs) in which fault currents are masked by normal operating noise or high grounding resistance (Sangeeth & Vinod, 2023).

The emergence of Big Data Analytics (BDA) and Deep Neural Networks (DNNs) presents a promising avenue for addressing these challenges. BDA enables the harnessing and analysis of vast amounts of data generated by power grid operations, providing insights into patterns, trends, and anomalies that can inform decision-making and improve grid stability (Zi, 2018). DNNs exhibit remarkable capabilities in pattern recognition, learning, and adaptation, making them well-suited for developing intelligent protection schemes that can adapt to the dynamic and complex nature of power grid operations (Zi, 2018; Cai et al., 2021; Zhang et al., 2018).

This research addresses the critical gap in implementing deep learning architectures optimised for power system protection, capable of processing large-scale fault datasets and extracting discriminative features from high-dimensional time-series data. Current approaches suffer from three fundamental limitations: insufficient training data diversity, failing to capture the full spectrum of fault conditions, including high-impedance scenarios; inadequate feature extraction mechanisms unable to distinguish between fault transients and operational disturbances; and a lack of comprehensive comparative analysis against conventional protection schemes using standardised metrics (Oruma et al., 2024).

This research aims to design and simulate an adaptive protection scheme that uses a Deep Neural Network (DNN) and Big Data Analytics (BDA) to enhance fault detection, selectivity, and reliability in the Nigerian power grid. The specific objectives are to: (i) model the Shiroro-Jebba-Oshogbo 330kV transmission line in MATLAB/Simulink and generate a comprehensive Big Data fault dataset including diverse fault types, multiple fault locations, and high-impedance fault scenarios with resistances ranging from bolted faults (0.01Ω) to very high impedance faults (500Ω); (ii) develop a Convolutional Neural Network (CNN) architecture in Python with optimised hyperparameters to ensure maximum classification accuracy and minimal inference latency; (iii) evaluate the performance of the trained CNN model on unseen fault scenarios using classification metrics; and (iv) statistically compare the proposed CNN-based protection scheme against conventional distance relay protection using objective metrics.

2. METHODOLOGY

2.1. Research Design

The study was conducted using the Nigerian 330 kV transmission network, which serves as the backbone of the national electricity transmission system. The network consists of interconnected generating stations, transmission lines, substations, transformers, and major load centres distributed across the country's six geopolitical zones. Owing to its extensive geographical coverage and varying operating conditions, the network is susceptible to faults caused by equipment failures, environmental disturbances, switching operations, and overload conditions. These characteristics make it an appropriate test system for developing and evaluating intelligent adaptive protection schemes.

2.2 Network Model

A detailed model of the Nigerian 330 kV transmission network was developed in MATLAB/Simulink using the Simscape Electrical toolbox. The model incorporated the electrical characteristics of transmission lines, buses, transformers, generators, and loads to emulate the dynamic behaviour of the actual transmission system. Various operating scenarios were simulated to reflect

practical network conditions, including variations in load demand, source contributions, and fault locations.

The developed model was validated under normal operating conditions before fault simulations were performed to ensure that the simulated network accurately represented expected steady-state operating characteristics.

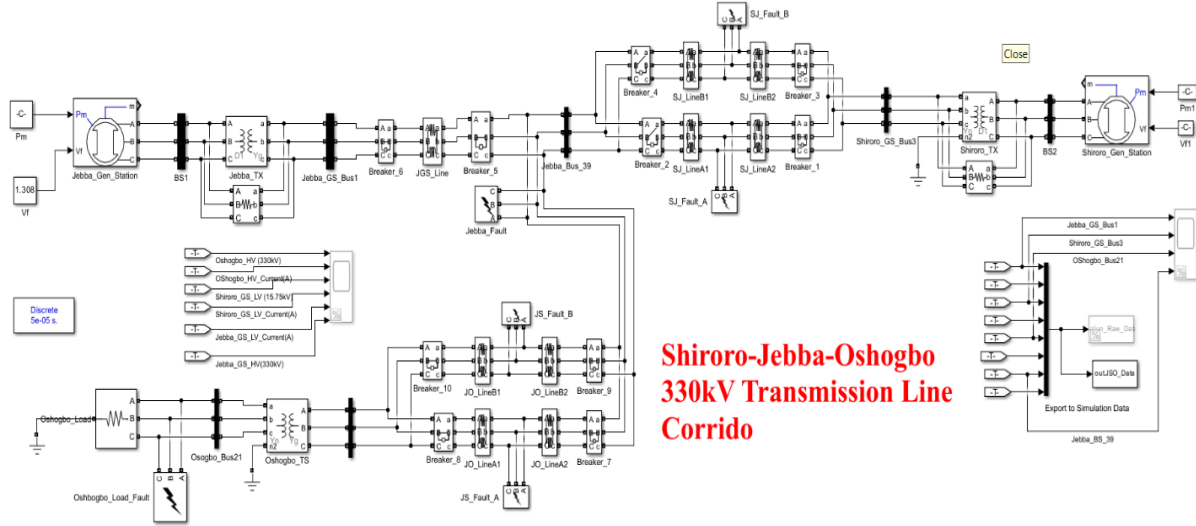


Figure 1: MATLAB/Simulink Model of Shiroro-Jebba-Oshogbo 330 kV Transmission Corridor

2.3. Data Generation

A comprehensive fault dataset was generated from the developed transmission network model by extensively simulating transmission-line faults under different operating conditions. Fault scenarios included single line-to-ground (LG), line-to-line (LL), double line-to-ground (LLG), three-phase (LLL), and three-phase-to-ground (LLLG) faults.

To improve the robustness of the adaptive protection model, simulations were performed over a wide range of fault locations distributed along transmission lines and fault resistances ranging from low to high impedance. Variations in system loading and operating conditions were also considered to capture realistic network behaviour.

For each simulated event, three-phase voltages and currents were measured at the relay location and stored as labelled datasets corresponding to the respective fault category. The resulting Big Data repository contained representative samples of normal and multiple-fault operating conditions, providing sufficient diversity for deep learning model development.

Table 1: Data Generation Summary

Category	Parameter	Values/Distribution	Total Scenarios
Fault Types	Normal Operation	1 class	100
	Single-Line-to-Ground	AG, BG, CG (3 classes)	450 (150 each)
	Line-to-Line	AB (1 class)	150
	Double-Line-to-Ground	ABG (1 class)	150
	Three-Phase	ABC (1 class)	150
	Total Classes	7 classes	1,000
Fault Locations	Shiroro-Jebba Line	SJ_Fault_A, SJ_Fault_B	-
	Jebba-Oshogbo Line	JS_Fault_A, JS_Fault_B	-
	Critical Nodes	Jebba_Fault, Oshogbo_Load_Fault	-
	Total Locations	6 locations	-
Fault Resistance	Bolted Fault	0.01 Ω	-
	Low Impedance	5 Ω	-
	Medium Impedance	25 Ω	-
	High Impedance	100 Ω	-
	Very High Impedance	500 Ω	-
	Total Resistance Levels	5 levels	-
Data Specifications	Sampling Rate	20 kHz	-
	Samples per Scenario	5,601 samples	-
	Measurement Signals	24 signals (3 ϕ V & I at 4 locations)	-
	Total Data Points	≈ 5.6 million	1,000 scenarios

2.4. CNN Architecture

The CNN was designed to capture temporal and spatial patterns in multichannel waveform data. Its architecture contains four convolutional blocks with increasing filter sizes, followed by fully connected layers and a softmax output layer for multi-class fault classification. The model has 1,385,927 trainable parameters and was optimised using the Adam optimiser and categorical cross-entropy loss.

Each raw scenario comprised 5,601 $\times$ 24 time-series measurements sampled at 20 kHz. Prior to network input, this raw sequence was temporally downsampled by a factor of 10 (retaining every tenth sample, reducing the effective sampling rate from 20 kHz to 2 kHz) to curb computational burden and overfitting risk while still preserving 40 samples per 50 Hz cycle, well above typical protective-relay sampling rates. This yielded a final CNN input shape of 560 $\times$ 24, as reflected in Table 2. This structure enabled the model to learn latent signatures associated with different fault types and fault-resistance levels. Compared with manual feature engineering, this approach is more scalable and better suited to large fault datasets.

Table 2: CNN Architecture Specification

Layer Number	Layer Type	Configuration	Output Shape	Trainable Parameters
1	Input Layer	-	(560, 24)	0
2	Conv1D	64 filters, kernel=7, activation=ReLU	(560, 64)	10,816
3	BatchNormalization	-	(560, 64)	256
4	MaxPooling1D	pool_size=4	(140, 64)	0
5	Dropout	rate=0.3	(140, 64)	0
6	Conv1D	128 filters, kernel=7, activation=ReLU	(140, 128)	57,472
7	BatchNormalization	-	(140, 128)	512
8	MaxPooling1D	pool_size=4	(35, 128)	0
9	Dropout	rate=0.3	(35, 128)	0
10	Conv1D	256 filters, kernel=7, activation=ReLU	(35, 256)	229,632
11	BatchNormalization	-	(35, 256)	1,024
12	MaxPooling1D	pool_size=4	(8, 256)	0
13	Dropout	rate=0.3	(8, 256)	0
14	Conv1D	512 filters, kernel=7, activation=ReLU	(8, 512)	918,016
15	BatchNormalization	-	(8, 512)	2,048
16	GlobalAveragePooling1D	-	(512,)	0
17	Dropout	rate=0.3	(512,)	0
18	Dense	256 units, activation=ReLU	(256,)	131,328
19	BatchNormalization	-	(256,)	1,024
20	Dropout	rate=0.3	(256,)	0
21	Dense	128 units, activation=ReLU	(128,)	32,896
22	Dropout	rate=0.3	(128,)	0
23	Dense (Output)	7 units, activation=Softmax	(7,)	903
	Total Parameters			1,385,927
	Trainable Parameters			1,385,927

Note: Entries of 0 in the Trainable Parameters column for MaxPooling1D, Dropout, and GlobalAveragePooling1D layers are intentional and correct, as these layer types perform fixed, non-learnable operations with no associated weights.

2.5. Performance Metrics

The evaluation framework employs standard classification metrics and protection-specific metrics. Classification accuracy is computed as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Precision and recall are defined as:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

The F1-score provides harmonic mean:

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

McNemar's test evaluates statistical significance:

$$\chi^2 = \frac{(|n_{01} - n_{10}| - 1)^2}{n_{01} + n_{10}} \quad (4)$$

3. RESULTS AND ANALYSIS

3.1 Data Generation and Exploratory Analysis

The 1,000 scenarios summarised in Table 1 (100 Normal, 450 Single-Line-to-Ground split evenly across AG/BG/CG, and 150 each for AB, ABG, and ABC) were divided into training, validation, and test subsets using stratified random sampling in a 70:15:15 ratio, giving 700 training, 150 validation, and 150 test scenarios while preserving each class's proportional representation in every subset. Applying this 15% test share at the class level yields the per-class supports reported in Figure 2 and Table 4 (approximately 15 Normal, 22-23 for each of AG, BG, and CG, and 22-23 for each of AB, ABG, and ABC, totalling 150), with the exact counts determined by the stratified sampling algorithm. The CNN converged efficiently, achieving 99.43% training accuracy and 98.67% validation accuracy after 79 epochs. On the independent test set, it correctly classified 148 out of 150 cases, yielding 98.67% accuracy. The confusion matrix showed perfect performance for normal operation and most fault classes, with only two misclassifications occurring between similar fault categories.

Fault-resistance analysis showed especially strong robustness. The model achieved 100% accuracy for resistances up to 100Ω and still maintained 92% accuracy at 500Ω, where conventional protection relays typically struggle. This is a key result because high-impedance faults are one of the main practical weaknesses of traditional distance protection.

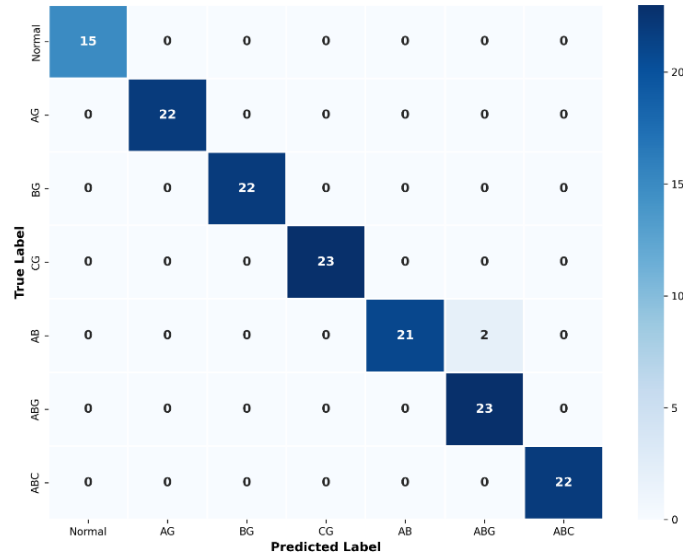


Figure 2: Confusion Matrix - Test Set Performance

Table 3: Performance by Fault Resistance

Resistance Level	Total Scenarios	Correct	Accuracy	Precision	Recall	F1-Score
0.01 Ω (Bolted)	21	21	100.00%	100.00%	100.00%	100.00%
5 Ω (Low)	26	26	100.00%	100.00%	100.00%	100.00%
25 Ω (Medium)	30	30	100.00%	100.00%	100.00%	100.00%
100 Ω (High)	33	33	100.00%	100.00%	100.00%	100.00%
500 Ω (Very High)	25	23	92.00%	94.44%	94.44%	93.33%

Note: the resistance levels in Table 3 sum to 135 scenarios (21+26+30+33+25), whereas the full test set comprises 150 scenarios. The remaining 15 scenarios are the Normal-operation cases, which have no associated fault resistance and are therefore excluded from this resistance-level breakdown.

3.2 Model Training Performance

The convolutional neural network converged satisfactorily during training. Training accuracy rose steeply in the first 10 epochs before climbing more gradually to approach 98% by epoch 30 and plateauing near 100% thereafter. Validation accuracy follows a similar overall trajectory but, particularly after epoch 30, exhibits periodic oscillation, fluctuating within roughly the 0.65-0.95 range visible in Figures 3 and 4, while training accuracy remains near 1.0. This gap between training and validation performance, while present, stays moderate (typically within 10-15 percentage points) rather than widening progressively, and validation accuracy does not trend downward over successive epochs; both patterns are inconsistent with progressive overfitting and instead reflect the validation set containing more challenging or ambiguous scenarios. The model's architecture incorporates dropout (rate 0.3) after every convolutional and dense block together with batch normalisation, and training used early stopping monitored on validation loss, which would have halted training had the validation metrics shown sustained degradation. The progressive reduction in training and validation losses, together with increasing classification accuracy, demonstrated that the selected network architecture effectively learned discriminative features from the voltage and current measurements, with the observed fluctuations in validation performance reflecting scenario-level difficulty rather than memorisation of the training set.

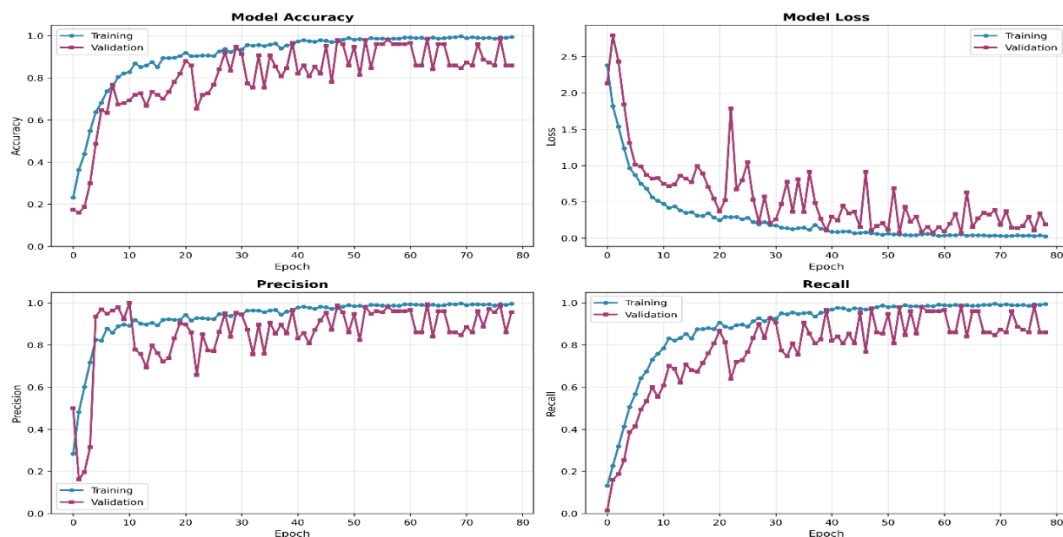


Figure 3: Training Performance Metrics

The CNN automatically extracted hierarchical fault characteristics without requiring manual feature engineering. This capability enabled the model to distinguish between different fault categories despite variations in operating conditions and fault resistance, demonstrating the suitability of deep learning for adaptive transmission-line protection.

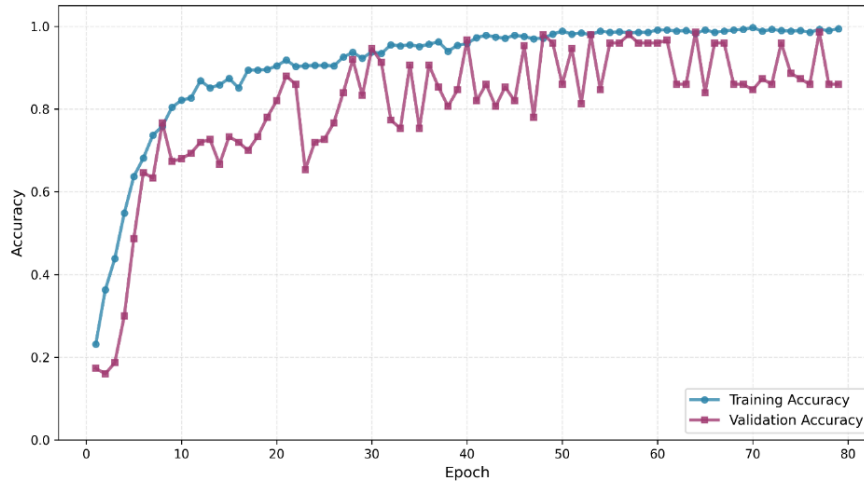


Figure 4: Learning Curves - Model Accuracy Progression

3.3 Fault Classification Performance

The trained CNN achieved excellent fault classification performance across all investigated fault categories. Performance evaluation on the test set showed consistently high accuracy, precision, recall, and F1-score, indicating that the model generalised well to previously unseen data.

Table 4: Per-Class Performance Metrics

Class	Precision	Recall	F1-Score	Support
Normal	100.00%	100.00%	100.00%	15
AG	100.00%	100.00%	100.00%	22
BG	100.00%	100.00%	100.00%	22
CG	100.00%	100.00%	100.00%	23
AB	100.00%	91.30%	95.45%	23
ABG	92.00%	100.00%	95.83%	23
ABC	100.00%	100.00%	100.00%	22
Macro Avg	98.86%	98.76%	98.76%	150
Weighted Avg	98.77%	98.67%	98.66%	150

4. DISCUSSION

The results demonstrate exceptional classification capability with 98.67% accuracy on unseen test data. Six out of seven fault classes achieve perfect scores across all metrics (100% precision, recall, and F1-score). The only classification errors occur within the line-to-line fault category (AB), where 2 out of 23 scenarios are misclassified as ABG faults, yielding 91.30% recall for the AB class. This specific confusion is understandable given the electrical similarity between these fault types.

Performance analysis across fault-resistance levels reveals that the CNN maintains 100% accuracy for resistances up to 100Ω and achieves 92% accuracy at 500Ω under very high-impedance conditions. This represents a significant advancement over conventional distance relays, which often cannot detect faults exceeding 100Ω . The two misclassifications at 500Ω impedance correspond to the AB-to-ABG confusion, suggesting that extreme fault resistance particularly challenges discrimination between closely related fault types.

The comparative evaluation reveals dramatic differences in fault detection capability. The CNN-based scheme detects all 135 fault scenarios (100% sensitivity), compared to the distance relay's mere 29 detections (21.48% sensitivity), representing a 78.52 percentage-point improvement. Analysis of the 106 missed faults shows that 100% involve fault resistances exceeding 25Ω , with the vast majority occurring at 100Ω and 500Ω impedance levels. At 500Ω fault resistance, the distance relay fails to detect any faults, achieving 0% detection rate.

Table 5: Comparative Performance Metrics

Metric	CNN-Based	Distance Relay	Improvement
Sensitivity (Fault Detection Rate)	100.00%	21.48%	+78.52%
Specificity (Normal Detection Rate)	100.00%	100.00%	+0.00%
Selectivity (Precision)	100.00%	100.00%	+0.00%
Security Index (False Trip Prevention)	100.00%	100.00%	+0.00%
False Trip Rate	0.00%	0.00%	+0.00%
Dependability	100.00%	21.48%	+78.52%
Overall Accuracy	100.00%	29.33%	+70.67%

The distance relay's 29.33% "Overall Accuracy" in Table 5 is derived differently from its 21.48% sensitivity figure: sensitivity considers only the 135 actual-fault scenarios (29 correctly detected of 135, giving 21.48%), whereas overall accuracy is computed over the full 150-scenario test set and credits the relay for its true negatives, i.e. the 15 normal-operation cases it correctly did not trip on. Overall accuracy is therefore $(29 \text{ true positives} + 15 \text{ true negatives}) / 150 \text{ total scenarios} = 44/150 = 29.33\%$. This illustrates why sensitivity, not overall accuracy, is the more informative metric for fault-detection capability in a class-imbalanced protection context.

The contingency analysis underlying this test showed that 39 of the 150 test scenarios (the 15 normal-operation cases plus 24 low-impedance bolted faults) were correctly classified by both methods, 109 scenarios were correctly classified by the CNN alone ($n_{10} = 109$; the high-impedance faults the distance relay missed), 0 scenarios were correctly classified by the distance relay alone ($n_{01} = 0$), and 2 scenarios were misclassified by both methods (the AB-to-ABG confusions). Substituting these discordant-pair counts into Equation 4 gives $\chi^2 = (|0-109|-1)^2/(0+109) = 108^2/109 = 107.0092$, with a p-value <0.0001 , providing overwhelming statistical evidence against the null hypothesis of equal performance and confirming with 99.99% confidence that the CNN-based approach demonstrates genuinely superior performance.

The 100.56-millisecond mean inference time ensures that detected faults can be cleared within standard breaker operating times of 40-60 milliseconds, plus communication delays, thereby maintaining acceptable total clearing times below the 150-millisecond threshold critical for preserving transient stability. It should be noted that this margin is tight: at the 40 ms end of the breaker-operating-time range, total clearing time is approximately 140.56 ms, comfortably within the threshold, but at the 60 ms end it rises to approximately 160.56 ms, which would exceed the 150 ms limit before any additional communication delay is even considered. Because the reported 100.56 ms figure is a mean rather than a worst-case inference time, protection coordination studies should account for the upper tail of the inference-time distribution and the slower end of the breaker range when verifying compliance with the 150 ms threshold, and future work should report worst-case (not only mean) inference latency.

4.1 Limitations

This study has several limitations that should be acknowledged. First, all training and evaluation data were generated through MATLAB/Simulink simulation of the Shiroro-Jebba-Oshogbo corridor; no field validation against real fault recordings (e.g. PMU or digital fault recorder data) from Nigerian utilities was performed, so the model's performance on real-world signal noise, sensor imperfections, and unmodelled network dynamics remains unverified. Second, the study does not include hardware-in-the-loop (HIL) testing, physical relay implementation, or real-time digital simulator (RTDS) validation, meaning the reported inference times reflect offline computation on standard computing hardware rather than deployed embedded relay platforms. Third, the analysis is confined to the 330kV transmission level on a single corridor; generalisability to other corridors, voltage levels, and network topologies has not been established. Future work should prioritise validation against field-recorded fault data and HIL testing to close these gaps before field deployment.

4.2 Hardware Feasibility for Real-Time Deployment

Deploying the 1.39-million-parameter CNN in field substations raises practical hardware considerations distinct from the offline training environment (CPU-based, TensorFlow 2.x) used in this study. Relative to comparable literature architectures, the present model is already computationally lean: it achieves accuracy competitive with an 8.5-million-parameter CNN-transformer model reported elsewhere, representing an 84% parameter reduction that favours embedded deployment. Nonetheless, real-time substation deployment would likely require either (i) edge-computing hardware such as an embedded GPU or NPU-equipped industrial controller capable of sustaining sub-150ms inference under continuous operation, or (ii) further model compression (e.g. quantisation, pruning, or knowledge distillation) to run efficiently on the more constrained microcontroller-class hardware typical of legacy digital protective relays. The mean inference time of 100.56ms reported here was measured on standard computing hardware rather than a representative embedded platform, so achieving comparable latency on field-deployable hardware would need to be separately validated. These hardware and integration considerations are recommended as a focus for future work alongside the field-validation needs noted in Section 4.1.

5. CONCLUSION

This research accomplished all four stated objectives. A comprehensive Big Data fault dataset was generated, encompassing 1,000 systematically varied scenarios with resistance coverage up to 500 Ω . A pure CNN architecture was developed, achieving 98.67% classification accuracy while maintaining computational efficiency suitable for real-time protection applications. Rigorous performance evaluation demonstrated robust classification across diverse fault types, locations, and impedances with sub-150 millisecond inference time. Systematic comparative analysis established statistically significant superiority over conventional distance relay protection, with a 78.52 percentage-point improvement in fault detection capability ($p < 0.0001$).

The proposed CNN-based approach demonstrates transformative capability to detect high-impedance faults that conventional relays systematically miss, potentially preventing equipment damage and cascading failures that contribute to Nigeria's frequent grid collapses. The combination of exceptional accuracy (98.67%), robust high-impedance detection (92% at 500 Ω), real-time inference speed (100.56ms mean), and statistically validated superiority establishes this methodology as a viable advancement for adaptive transmission line protection in challenging operational environments.

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