Communication in Physical Sciences, 2026, 13(7):1056- 1072

A Hybridized Artificial Neural Network and Support Vector Machine Model in Power Transmission Fault Detection

Mohammed Kudu Abubakar, Balogun Monsurat O., Lambe Adesina M., Abdul-Waheed Musa, Ogunbiyi Olalekan, Jimada-Ojuolape Bilkisu

Received: 03 April 2026/Accepted: 24 June 2026 /Published: 08 July 2026

doi.org/10.4314/cps.v13i7.3

Abstract: *The detection of fault and its resolution are crucial in a power transmission line for ensuring unhampered and efficient power supply. These lines are often exposed to unpredictable environmental conditions and therefore encounter several challenges. Most failures in the power system are attributed to these, thereby necessitating the need for quick fault detection and resolution procedures. Research on hybridizing ANN and SVM is limited to fault detection and classification. Work on hybridizing ANN and SVM on IEE 39-bus for three simultaneous diagnostic tasks of fault type classification (LG, LL, LLG, LLL), faulted-line identification, and protection zoning defined as near-end versus far-end fault discrimination in a model is rare. This study bridges this gap by presenting a hybrid ANN-SVM model on fault type classification, fault line identification and protection zone identification in power transmission lines. The proposed framework employs ANN as a nonlinear feature embedding and a Radial Basis Function SVM subsequently classifies using an Error-Correcting Output Codes (ECOC) strategy. Evaluated on fault scenarios from the IEEE 39-bus New England test system simulated in MATLAB/Simulink R2025b, the hybrid model achieves fault type classification accuracy of 97.2%, protection zoning accuracy of 95.8%, and faulted-line identification accuracy of 97.7%, with ROC Area Under the Curve (AUC) values exceeding 0.90. These results consistently outperform standalone nd SVM baselines by 4% to 6% in fault type, 2.9% to 15.9% in protection zoning and 5% to 10% in fault line classification, validating the effectiveness of the proposed hybridisation strategy for intelligent transmission system protection.*

Keywords: *Artificial Neural Network; Support Vector Machine; Hybrid model; Fault detection; Power transmission; IEEE 39-bus; Protection zoning; RBF kernel; ECOC; Machine learning.*

Mohammed Kudu Abubakar
Department of Electrical and Computer Engineering, Kwara State University, Malete, Kwara State, Nigeria.
Email: kudumuhammeda@gmail.com.

Balogun Monsurat O.
Department of Electrical and Computer Engineering, Kwara State University, Malete, Kwara State, Nigeria.
Email: monsurat.balogun@kwasu.edu.ng

Lambe Adesina M.
Department of Electrical and Computer Engineering, Kwara State University, Malete, Kwara State, Nigeria.
Email: lambe.adesina@kwasu.edu.ng

Abdul-Waheed Musa
Department of Electrical and Computer Engineering, Kwara State University, Malete, Kwara State, Nigeria.
Email: abdulwaheed.musa@kwasu.edu.ng

Also available @ https://doi.org/10.5281/zenodo.21327827

Ogunbiyi Olalekan
Department of Electrical and Computer Engineering, Kwara State University, Malete, Kwara State, Nigeria.
Email: olalekan.ogunbiyi@kwasu.edu.ng

Jimada-Ojuolape Bilkisu
Department of Electrical and Computer Engineering, Kwara State University, Malete, Kwara State, Nigeria.
Email: bilkisu.jimada@kwasu.edu.ng

1.0 Introduction

Reliable electrical power transmission is fundamental to modern economic growth, industrial development, and societal well-being. Ensuring uninterrupted electricity supply requires rapid detection, accurate classification, and timely isolation of transmission line faults. Fault detection and its resolution are key in a power transmission line to ensure unhindered and efficient power supply in our society. The transmission lines serve the backbone of any power system. Transmission networks interconnect generating stations with distribution systems and are expected to operate continuously under varying environmental and loading conditions. Any interruption in these networks can compromise power system stability, equipment integrity, and electricity supply reliability Yet, these lines are often exposed to dynamic and unpredictable environmental conditions, and therefore, they encounter several challenges (Adesina et al., 2024). Thus, they do degrade, resulting to major disturbance, leading to losses, damage to equipment, and increased power outages durations. Overhead transmission lines are the most vulnerable; about 85-87% of failures of a power system are attributed to these, thereby necessitating the need for quick fault detection and resolution procedures in such systems (Anwar et al., 2025). These faults increase maintenance costs, reduce system availability, and negatively affect industrial productivity and customer satisfaction, highlighting the need for intelligent fault diagnosis techniques

Traditional fault detection methods often lack real-time accuracy and adaptability to modern grid complexities. Conventional protection schemes, although widely deployed, often experience reduced performance under evolving smart grid conditions characterized by distributed generation, dynamic loading, renewable energy integration, and complex fault scenarios However, these lines often face changing and unpredictable environmental conditions, as a result, they meet several challenges (Adesina et al., 2024). With advances in technology, automated fault detection methods have been created, and these methods can be used to achieve accurate, fast, and dependable fault detection. In most cases, these systems generally apply protective devices such as circuit breakers to detect and isolate faults, avoiding damage to equipment and long outages (Rajesh et al., 2022).

The increasing complexity of modern power systems has stimulated the adoption of artificial intelligence (AI)-based approaches capable of extracting hidden patterns from large volumes of operational data and making accurate diagnostic decisions in real time The coming up of machine learning algorithms has taken a paradigm shift in the fault detection process, providing instruments to analyze complex patterns in huge data sets. Among these, Artificial Neural Networks (ANN) and Support Vector Machines (SVM) have become popular owing to their usefulness in recognizing and classifying patterns. ANNs excel in handling non-linear data and identifying fault patterns through extensive training. On the other hand, SVMs offer precision in classification, particularly in scenarios with overlapping data points (Han et al., 2023). Recent studies consistently demonstrate that ANN models exhibit excellent nonlinear learning capability, whereas SVM models provide robust generalization and superior classification performance, particularly when dealing with limited training samples. Consequently, combining both techniques has emerged as an attractive strategy for improving transmission line fault diagnosis Despite these advances, existing studies predominantly address individual diagnostic tasks such as fault classification, fault location, or fault detection independently. Very few investigations have developed an integrated hybrid ANN-SVM framework capable of simultaneously performing fault type classification, faulted-line identification, and protection zoning using the IEEE 39-bus New England benchmark system. Consequently, a comprehensive multi-task intelligent diagnostic framework for transmission line protection remains insufficiently explored. Unlike previous studies that focused on individual protection functions, this work integrates three critical diagnostic tasks into a unified hybrid learning framework, thereby improving the practicality of intelligent protection systems for modern transmission networks. This study seeks to bridge this gap by developing a hybrid model that leverages the strengths of both techniques, enhancing the accuracy and speed of fault diagnostic tasks.

The integration of Artificial Neural Networks (ANN) and Support Vector Machines (SVM) enhances fault diagnosing by combining ANN's flexible learning with SVM's high-performance classification capabilities. The proposed framework also supports the ongoing digital transformation of power systems through compatibility with intelligent electronic devices, phasor measurement units (PMUs), and future wide-area monitoring systems. This hybrid approach aims to improve fault detection by addressing challenges such as interference, transient conditions, and occlusions. Its findings contribute to the development of scalable and adaptive fault detection systems for modern electric grids. Beyond technical advancements, the study highlights the growing complexity of power networks due to urbanization and infrastructure expansion. Ensuring system reliability is essential for economic and social development. The research outcomes will help minimize power outages, lower operational costs, and enhance customer satisfaction. Improved fault detection leads to faster response times and increased grid efficiency. These benefits align with the broader goal of creating more resilient and reliable power systems (Klomjit & Ngaopitakkul, 2020).

Therefore, the aim of this study is to develop and evaluate a hybrid Artificial Neural Network–Support Vector Machine (ANN-SVM) model for simultaneous fault type classification, faulted-line identification, and protection zoning using the IEEE 39-bus New England transmission system

This study focuses on the development and systematic evaluation of an intelligent hybrid ANN-SVM framework for power transmission fault diagnosis framework for power transmission networks, using the IEEE 39-bus New England test system as a representative benchmark, with the dataset divided into 70% training, 15% testing, and 15% validation for model evaluation. The IEEE 39-bus benchmark was selected because it is one of the most extensively adopted test systems for validating intelligent protection algorithms, allowing meaningful comparison with existing studies while representing realistic transmission network operating conditions. The scope of the work is confined to the formulation, implementation, and validation of a hybrid ANN-SVM framework for three principal diagnostic tasks: fault type classification, faulted-line identification, and protection zoning defined in terms of near-end and far-end fault discrimination. Although the proposed framework is developed with practical deployment considerations in mind such as compatibility with digital relay measurements and phasor measurement unit (PMU) data streams. Although the proposed framework was developed with practical deployment considerations, including compatibility with digital relay measurements and phasor measurement unit (PMU) data streams, its validation is presently limited to offline simulations using MATLAB/Simulink. Future work will focus on real-time implementation and validation using field measurements from practical transmission networks

1.1. Literature Review

Recent advances in artificial intelligence and intelligent protection systems have significantly transformed fault diagnosis in modern transmission networks. This section reviews existing studies on conventional machine learning techniques, hybrid intelligent models, and their applications in transmission line protection to establish the research context and identify unresolved challenges. Electrical transmission lines serve as the backbone of power systems, ensuring the efficient transfer of electricity over long distances (Alcayde-García et al., 2022). The reliability of these lines is crucial for maintaining power system stability, as any disruption can lead to significant economic and operational consequences (Adesina et al., 2024). Researchers have employed artificial intelligence (AI)-based models, such as ANNs and SVMs, to enhance fault detection accuracy and response time (Samson et al., 2024). Machine learning algorithms have demonstrated the capability to classify faults with high precision, enabling faster restoration of power supply (Ilius et al., 2023). These advancements are particularly beneficial for detecting and isolating common transmission line faults, including line-to-ground and line-to-line faults, which constitute most power system disturbances (Sundararaman & Jain, 2023).

Faults in power systems are unanticipated disruptions that disrupt the usual flow of current or voltage, potentially damaging electrical components and creating power outages. These faults are broadly classified as balanced (e.g., three-phase faults) or unbalanced (e.g., line-to-ground, line-to-line, or double line-to-ground faults) according to their influence on the system. Lightning strikes, falling trees, aged equipment, and human tampering are all common causes (Sundararaman & Jain, 2023). Unbalanced faults, such as line-to-ground or double-line-to-ground, cause a considerable number of transmission line failures, with single-line-to-ground faults accounting for 70 to 80% of occurrences (Waheed Olalekan et al., 2024). Such incidents require prompt detection and classification to ensure the electricity grid's stability and reliability.

Identifying problems in power systems is a crucial function that assures dependability and protects the infrastructure. ANNs excel at pattern recognition and analyze pre and post fault current and voltage information to accurately identify problems (Jamil et al., 2015). Olalekan et al. (2024) developed an ANN-based fault detection model for the Nigerian 330 kV transmission line using MATLAB/Simulink. The ANN was trained with pre-fault and fault voltage and current signals and achieved a best mean square error (MSE) of 1.6856×10^{-5} with a regression coefficient (R) of 0.98958, demonstrating the effectiveness of ANN for rapid fault detection and classification in transmission networks. (Jamil et al., 2015) proposed a fault detection system using backpropagation neural networks (BPNNs), leveraging MATLAB's SimPowerSystems toolbox and correlation coefficient analysis to achieve an exceptional correlation coefficient of 0.99982. (Shingare et al., 2023) developed an ANN-based approach for fault location in extra-high voltage networks, achieving a high correlation coefficient of 0.9970 using backpropagation neural networks.

Support Vector Machines (SVM) have evolved as a powerful and versatile machine learning approach based on statistical learning theory, and they are increasingly being used to detect faults in power transmission lines. The methodology is based on identifying an ideal hyperplane that divides data into discrete classes with the greatest margin. SVM, invented by (Cortes & Vapnik, 1995), has considerable advantages in classification and regression applications, providing excellent accuracy and reliability even with limited datasets. SVM transfers input data into higher-dimensional spaces using kernel functions such as the radial basis function (RBF) and polynomial kernels, allowing it to effectively handle non-linear separations. The inherent qualities of convex optimization and structural risk minimization ensure that SVM avoids overfitting and produces globally optimal solutions, making it appropriate for fault detection in complicated datasets (Klomjit & Ngaopitakkul, 2020).

(Khan et al., 2023) introduced a novel strategy incorporating variational autoencoders (VAEs) to generate synthetic data for training machine learning models such as SVMs, Decision Trees, Random Forest, and K-Nearest Neighbors. This approach improved fault classification accuracy to 99% and reduced mean absolute error in fault localization to 0.2. The study also emphasized the benefits of synthetic data generation and feature selection techniques such as categorical boosting (CatBoost).

Hybrid models that combine the strengths of ANNs and SVMs have emerged as a viable solution to the individual limitations of these techniques. ANN is typically used for feature extraction and early fault identification, whereas SVM allows more precise fault classification. Hybrid techniques have been demonstrated to perform better than solo models in terms of accuracy, computational efficiency, and reliability. (Thukaram et al., 2005) developed a two-stage hybrid model in which ANN handled preliminary fault detection and SVM refined classification, resulting in a 98% detection accuracy in radial distribution system. Similarly, integrating Discrete Wavelet Transform (DWT) and Ant Colony Optimization (ACO) into hybrid models has been shown to optimize feature extraction and increase fault classification results (Jawad & Abid, 2023).

Hybridized simulation models have become a cornerstone in the advancement of fault recognition and categorization in power transmission lines, combining the adaptive qualities of ANNs with the precision-focused characteristics of SVMs. These models solve the inherent constraints of standalone approaches by combining ANN's capacity for non-linear pattern recognition with SVM's ability to define decision bounds, resulting in robust and efficient fault identification.

Overall, the reviewed studies demonstrate substantial progress in applying ANN, SVM, and hybrid machine learning techniques for transmission line fault diagnosis. Nevertheless, existing approaches remain largely focused on isolated diagnostic tasks and seldom integrate fault classification, faulted-line identification, and protection zoning within a unified intelligent framework. Addressing this limitation forms the central motivation of the present study.

2.0 Materials and Methods

2.1Models Framework

This section presents the methodology developed to evaluate a hybrid Artificial Neural Network-Support Vector Machine (ANN-SVM) framework for fault analysis in the IEEE 39-Bus System. The proposed framework is motivated by the limitations of conventional protection and analytical fault-location techniques, which often rely on simplified network assumptions and struggle under complex operating conditions such as meshed topologies, varying load levels, high fault resistance, and measurement noise.

The framework consists of four primary stages:

1. Data acquisition via power system simulation.
2. Nonlinear feature extraction using an ANN-based embedding module.
3. Fault type classification, faulted-line identification, and protection zone detection using SVM classifiers.
4. Comparative performance evaluation against standalone ANN and SVM models.

The methodology workflow is illustrated in the block diagram in Fig. 1.

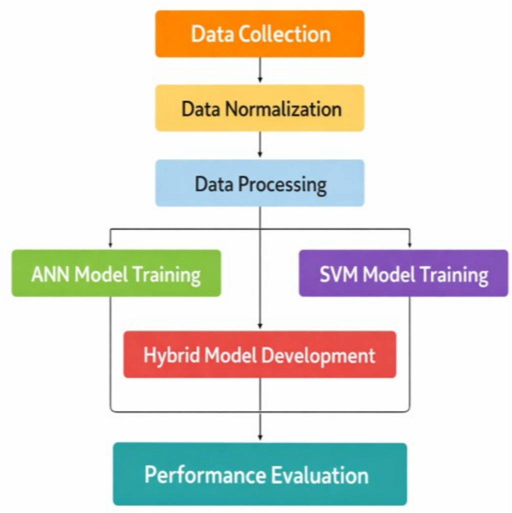

Fig. 1: Block Diagram of the Developed hybrid Model Methodology

2.2 Dataset Description

2.2 Dataset Description

The investigation is based on the IEEE 39-bus New England test system, a standard benchmark reflecting the structural and operational complexities of practical high-voltage grids. The dataset comprises electrical features derived from simulated fault scenarios, including three-phase voltage and current measurements, sequence component indices, and apparent impedance quantities.

To build a robust dataset, 500 initial fault scenarios were generated via MATLAB/Simulink. This initial set was augmented to 5,000 samples using the Synthetic Minority Over-sampling Technique (SMOTE) with Gaussian perturbation. The final dataset spans three loading levels (light, nominal, heavy) and covers all four major fault types: single line-to-ground (LG), line-to-line (LL), double line-to-ground (LLG), and three-phase (LLL). Fault locations range from 5% to 95% of the line length, with fault resistances varied between 0.1 Ω and 20 Ω. An excerpt of the generated measurement data is presented in Table 1.

Table 1: Excerpt of Measurement Data for IEEE 39-Bus Fault Scenarios

Parameter	Scenario 1	Scenario 2	Scenario 3	...	Scenario 498	Scenario 499	Scenario 500
Va (p.u.)	0.98	0.97	0.95	...	0.92	0.94	0.91
Vb (p.u.)	0.96	0.98	0.94	...	0.90	0.95	0.92
Vc (p.u.)	0.95	0.96	0.98	...	0.91	0.93	0.94
Ia (p.u.)	1.42	0.35	0.29	...	1.88	0.56	0.48
Ib (p.u.)	0.31	1.51	0.34	...	0.52	1.76	0.55
Ic (p.u.)	0.28	0.33	1.47	...	0.49	0.61	1.92
I_2/I_1	0.41	0.38	0.44	...	0.57	0.51	0.60
V_2/V_1	0.18	0.21	0.19	...	0.33	0.29	0.35
Zapp (p.u.)	0.62	0.59	0.65	...	0.84	0.79	0.88
THDI (%)	6.2	5.7	7.1	...	9.8	8.4	10.6
THDV (%)	2.1	2.4	2.0	...	3.9	3.1	

The feature vector for each fault scenario is defined as:

$$x = \begin{bmatrix} V_a & V_b & V_c & I_a & I_b & I_c & \frac{I_2}{I_1} & \frac{V_2}{V_1} & Z_{app} & THD_I & THD_V \end{bmatrix}^T \quad (1)$$

where Va, Vb, Vc are the three-phase RMS voltages
Ia, Ib, Ic are the three-phase RMS currents
I_2/I_1 and V_2/V_1 are the negative-to-positive sequence ratios for current and voltage; Z_app is the apparent impedance at the relay terminal THD_I, THD_V are the total harmonic distortion indices.

Synthetic Minority Oversampling Technique (SMOTE) with Gaussian perturbation given as:

$$x_{aug} = x_i + \lambda(x_{nn} - x_i) + \epsilon \quad (2)$$

where x_new New synthetic data, x_nn $Selectced\ minority\ sample$, x_i Original minority data and λ Random interpolar number ranging between 0 & 1 ϵ represents Gaussian noise with zero mean and variance

All features are z-score normalised using statistics computed from the training subset only using:

$$x'_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \quad (3)$$

where x_{ij} is the j-th feature of the i-th sample, and μ_j and σ_j are the mean and standard deviation of the j-th feature computed from the training subset only.

This operation maps each feature to zero mean and unit variance, which is particularly important for kernel-based SVMs and gradient-based neural network training. The training subset is used for learning model parameters and tuning hyperparameters; the testing subset is reserved strictly for performance evaluation; while the validation subset checks if the model generalizes to new unseen data, not just memorizing the training set. The dataset is partitioned as: training 70% (3500 samples), testing 15% (750 samples), and validation 15% (750 samples). This protocol ensures that the reported results reflect the generalisation capability of the model to previously unseen fault scenarios, rather than memorisation of training samples.

2.3 ANN Feature Embedding Module

Raw electrical features from high-voltage transmission grids often exhibit highly non-linear, overlapping profiles under varying fault conditions. To address this, an ANN is deployed as a non-linear feature embedding module to transform the raw input vectors into a compact, highly discriminative latent space before classification.

The proposed ANN architecture consists of thirty-two fully connected hidden layers: the first hidden layer contains 24 neurons with Rectified Linear Unit (ReLU) activation. The final layer is a 4-class softmax output layer used during the pre-training phase. The ReLU activation function is defined as:

$$f(x) = \max(0, x) \quad (4)$$

The network is trained by minimizing the categorical cross-entropy loss function with \$L_2\$ weight regularization over a maximum of 200 epochs:

$$L = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{ic}\log(\widehat{y_{ic}}) + \lambda|\mathrm{W}|^2 \quad (5)$$

where y_ic is the one-hot true label for sample i and class c, $\hat{y}_ic$ is the predicted class probability, λ is the L2 regularisation coefficient, and W represents all trainable weights. After training, the 12-dimensional activation vector of the second hidden layer denoted $f(x) \in \mathbb{R}^{12}$ is extracted as the embedded feature representation that captures salient nonlinear characteristics of the fault signatures while reducing redundancy and noise present in the original feature space. This embedding is then passed directly to the SVM classifiers rather than using the ANN's final softmax output.

2.4 SVM Classification

A soft-margin C-SVM with Radial Basis Function (RBF) kernel is trained on the ANN-derived feature embeddings. The SVM optimisation problem is formulated as expressed by equation 6a, subject to equation 6b

$$\min_{w,\xi} \ \frac{1}{2}|\mathrm{w}|^2 + C\sum_{i=1}^{N}\xi_i \quad (6a)$$

$$y_i(w \cdot \phi(f_i) + b) \geq 1 - \xi_i, \qquad \xi_i \geq 0 \quad (6b)$$

where φ(·) is the kernel-induced feature mapping, C is the regularisation parameter, and ξ_i are slack variables. The RBF kernel function is:

$$K(f_i, f_j) = \exp(-\gamma|f_i - f_j|^2) \quad (7)$$

where γ is a tunable parameter that controls the influence of each training sample. The decision function for multi-class classification is:

$$\hat{y} = argmax_c\left(\sum_{i=1}^{N}\alpha_{ic}\, y_{ic}K(f_i, x) + b_c\right) \quad (8)$$

where α_ic are the Lagrange multipliers obtained from the optimization process. Multi-class fault type classification and faulted-line identification employ an Error-Correcting Output Codes (ECOC) framework with one-versus-all decomposition. Protection zoning employs a binary SVM with the same RBF kernel configuration.

2.5 Protection Zoning Formulation

This protection zoning formulation is directly aligned with practical protection requirements, as near-end faults typically correspond to fault location $l_i \leq 0.5L$ and far-end faults to $l_i > 0.5L$, where L is the total line length. The zone label is assigned as shown in Equations (9a) and (9b):

$$Z_{ome} = \begin{cases} Zone\ 1\ (Near\ end), if\ l_1 \leq 0.5L \\ Zone\ 2\ (Far\ end), f\ \ l_i > 0.5L \end{cases} \quad \text{(9a, b)}$$

Near-end faults typically require instantaneous tripping to minimize equipment damage and maintain system stability, whereas far-end faults are generally cleared through time-coordinated backup protection schemes to ensure selective relay operation. The proposed framework was implemented in MATLAB R2025b using the Neural Network Toolbox and the Statistics and Machine Learning Toolbox, which provide robust computational support for model training, optimization, and performance evaluation. To ensure complete experimental reproducibility, fixed random seed values were applied during dataset partitioning, network weight initialization, and model training. Furthermore, the modular architecture facilitates future deployment within hardware-in-the-loop (HIL) testing platforms and supports seamless integration with real-time Phasor Measurement Unit (PMU) measurements, thereby enhancing its potential for practical implementation in modern smart grid protection systems.

2.6 Performance Evaluation

The framework for this study also includes the use of performance measurements such as accuracy, precision, recall, and F1-score to assess the efficacy of models.

The formulas of measures are briefly defined as follows:

Accuracy (A_{cc}) is the ratio of the sum of correct predictions to the total samples of dataset.

$$A_{cc} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \quad (10)$$

Precision (P) is the ratio of the correct predictions of the positive class to the total positive predictions.

$$P = \frac{TP}{TP + FP} \quad (11)$$

Recall (R), also called sensitivity, is the ratio of correct predictions of the positive class to the sum of correct predictions of the positive class and incorrect predictions of the negative class.

$$R = \frac{TP}{TP + FN} \quad (12)$$

The F1 score is a weighted average of precision and recall. The F1 score is usually more valuable than accuracy, particularly if the underlying dataset has an uneven class distribution.

$$F1 - \text{score} = \frac{2\times(\text{Precision} \times \text{Recall})}{Precision + Recall} \quad (13)$$

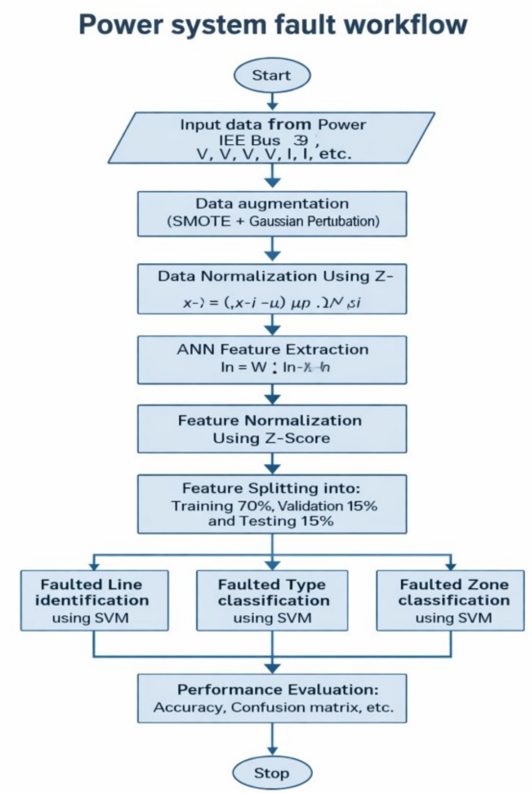

Fig. 2: Proposed hybrid ANN-SVM flow chart.

These metrics are critical for determining the hybrid model's capacity to detect and categorize defects effectively under changing settings. The use of such metrics reflects engineering emphasis on quantitative and replicable results, which ensures that study findings are dependable and generalizable.

3.0 Results and Discussion

This section presents and discusses the performance of the proposed hybrid Artificial Neural Network-Support Vector Machine (ANN-SVM) framework for power transmission line fault detection, fault type classification, faulted-line identification, and protection zoning on the IEEE 39-bus transmission network. The discussion emphasizes both the predictive performance of the proposed model and the practical implications of the results for intelligent transmission line protection and smart grid applications. The evaluation is carried out using a realistic dataset comprising diverse fault types, locations, loading conditions, and fault resistances. The hybrid ANN-SVM model is benchmarked against standalone ANN and SVM classifiers. Performance is analysed using confusion matrices, accuracy, precision, recall, F1-score, ROC characteristics, feature-space visualisations, and error distribution plots.

3.1 Fault Type Classification Performance

The fault type classification performance of the hybrid ANN-SVM model is presented in Fig. 3 (confusion matrix). The dominant diagonal elements indicate that the majority of fault events were correctly classified into their respective categories. Quantitatively, the hybrid model achieves an overall classification accuracy of approximately 97%, demonstrating excellent discrimination among the four fault categories and outperforming the standalone ANN and SVM classifiers.

Misclassifications are primarily observed between faults types, which exhibit partially overlapping voltage and current signatures under certain loading and fault resistance conditions. The fault types introduce comparable phase current distortions and negative-sequence components. Single-line-to-ground (LG) and three-phase (LLL) faults attain the highest per-class accuracies often exceeding 97.3% reflecting their more distinctive electrical signatures in transmission systems as shown in the row-normalised values in the confusion matrix.

TARGET / OUTPUT	Near-End	Far-End	SUM
Near-End	482 47.7%	22 2.2%	504 504
Far-End	30 3.0%	476 47.1%	506 SUM
SUM	512 94.1% 5.9%	498 91.6% 4.4%	958 / 1010 94.9% 5.1%

Fig. 3: ANN-SVM fault type confusion matrix

Hybrid ANN–SVM outperformed both standalone in every evaluation metric as shown in Table 2. The hybrid model improved classification accuracy by 4.21 percentage points (97.21% − 93.00%) compared with the ANN. Relative to the standalone SVM, the improvement was 5.60 percentage points (97.21% − 91.60%). These gains demonstrate the effectiveness of integrating ANN-based feature extraction with SVM-based classification, resulting in a more robust and reliable fault diagnosis framework

The observed improvement is consistent with previous studies that reported enhanced classification performance through hybrid learning architectures (Thukaram et al., 2005; Jawad & Abid, 2023). Unlike these earlier studies, however, the present framework simultaneously addresses fault type classification, faulted-line identification, and protection zoning within a unified model, thereby extending the practical applicability of intelligent transmission line protection.

Table 2. Performance comparison of fault type classification of ANN, SVM and ANN-SVM

Performance Metric	ANN	SVM	Hybrid
Accuracy (%)	93.00	91.60	97.21
Macro Precision (%)	92.87	91.74	96.98
Macro Recall (%)	92.91	91.57	97.20
Macro F1 (%)	98.94	91.63	97.19
Weighted Precision (%)	92.98	91.67	97.20
Weighted Recall (%)	92.90	91.60	97.18
Weighted F1 (%)	92.91	91.61	97.21

3.2 Faulted-Line Identification Performance

The spatial localisation capability of the proposed framework is examined using the faulted-line identification results. The confusion matrix in Fig. 4 shows that a substantial proportion of faults are correctly mapped to their actual line segments. The overall faulted-line identification accuracy is 93.20%, which is reasonable given the increased complexity of multi-class spatial localisation over numerous transmission lines.

The tendency for misclassification among electrically adjacent transmission lines is expected because neighbouring lines often exhibit similar voltage and current transients during fault conditions, particularly under varying loading scenarios. This demonstrates that the proposed framework captures the underlying electrical characteristics of the transmission network rather than producing random classifications.

The off-diagonal entries reveal that most misclassifications occur between electrically adjacent or topologically neighbouring lines. This is expected in meshed transmission networks such as the IEEE 39-bus system, where neighbouring lines may exhibit similar impedance and measurement patterns during faults. Importantly, the near-neighbour nature of the errors suggests that even when misclassification occurs, the predicted faulted line is often geographically close to the true fault location, which can still substantially reduce patrol and restoration time in practice.

The proposed Hybrid ANN–SVM model achieved the best overall performance as shown in Table 3, with an accuracy of 97.70%. It also recorded the highest macro precision (98.20%), macro recall (97.78%), macro F1-score (97.88%), weighted precision (97.88%), weighted recall (97.70%), and weighted F1-score (97.69%). These results indicate excellent classification consistency across all fault categories and confirm the effectiveness of combining ANN-based feature extraction with SVM-based classification.

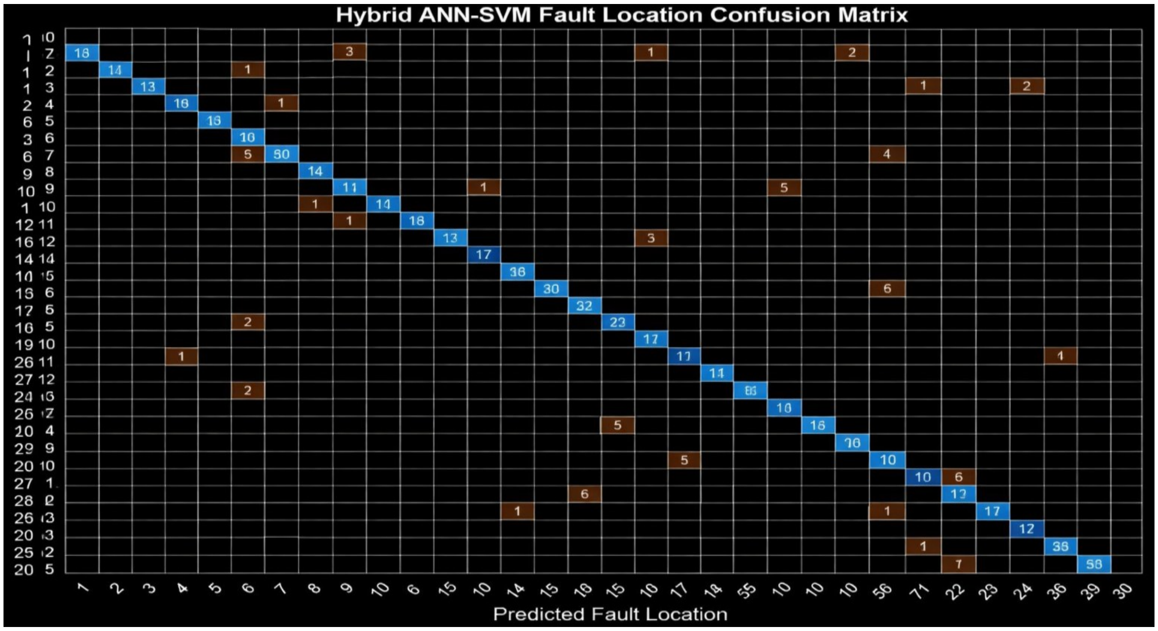

Fig. 4: ANN-SVM fault line confusion matrix

Table 3. Performance comparison of fault line classification.

Performance Metric	ANN	SVM	Hybrid
Accuracy (%)	94.10	94.87	97.70
Macro Precision (%)	94.56	95.75	98.20
Macro Recall (%)	94.28	94.74	97.78
Macro F1 (%)	94.30	95.52	97.88
Weighted Precision (%)	94.26	95.66	97.88
Weighted Recall (%)	94.10	94.88	97.70
Weighted F1 (%)	94.07	95.29	97.69

3.3 Protection Zoning: Near-End vs. Far-End Faults

The performance of the proposed framework in protection zoning is presented in Fig. 5, which shows the confusion matrix for near-end versus far-end fault classification. The zoning accuracy typically exceeds 95%, indicating that the model can reliably classify the fault zone.

The comparative results demonstrate that the Hybrid ANN–SVM model significantly outperformed the standalone ANN and SVM models. By combining ANN-based feature extraction with SVM-based classification, the proposed hybrid framework achieved an overall accuracy of 95.80%**,** representing improvements of 2.9% over the ANN and 16.3% over the SVM as shown in Table 4. The consistent gains in precision, recall, and F1-score confirm that the hybrid approach provides a more robust and reliable solution for intelligent transmission line fault diagnosis

TARGET / OUTPUT	Near-End	Far-End	SUM
Near-End	482 47.7%	22 2.2%	504 504
Far-End	30 3.0%	476 47.1%	506 SUM
SUM	512 94.1% 5.9%	498 91.6% 4.4%	958 / 1010 94.9% 5.1%

Fig. 5: ANN-SVM protection zone classification confusion matrix

Table 4. Performance Comparison of Fault Zone Classification

Performance Metric	ANN	SVM	Hybrid
Accuracy (%)	92.90	79.50	95.80
Macro Precision (%)	92.87	72.95	94.86
Macro Recall (%)	92.91	68.55	94.85
Macro F1 (%)	98.94	67.21	94.85
Weighted Precision (%)	92.98	79.57	94.86
Weighted Recall (%)	92.90	79.50	95.84
Weighted F1 (%)	92.91	79.48	94.85

This result is practically significant for relay coordination and protection zone selection, as near-end faults require faster tripping actions compared to far-end faults. The relatively low rate of false near-end or far-end predictions confirms the suitability of the proposed AI-based approach for real-time protection decision support in transmission networks.

3.4 Overall Performance Comparison of ANN, SVM, and Hybrid ANN-SVM

A comparative assessment of the standalone ANN, standalone SVM, and hybrid ANN-SVM classifiers is presented in Table 3. The hybrid ANN-SVM consistently achieves the highest fault type classification accuracy, typically improving performance by 4.2-5.6 percentage points over the individual ANN and SVM models. While the standalone ANN and SVM achieve accuracies in the range of 91.6-93%, the hybrid model attains approximately 85-92%, highlighting the benefit of combining nonlinear feature learning (ANN) with margin-based classification (SVM). This confirms that the ANN effectively learns discriminative feature embeddings from raw measurements, while the SVM provides robust generalisation in the transformed feature space.

Table 5: Comparative accuracy: standalone ANN, standalone SVM, and hybrid ANN-SVM

Model	Fault Type (%)	Zoning (%)	Line ID (%)
Standalone ANN	93.0	92.9	94.10
Standalone SVM	91.6	79.5	94.87
Hybrid ANN-SVM	97.2	95.8	97.70
Improvement	+4.2 to +5.6 pp	+2.9 to +15.9 pp	+2.83 to +3.6 pp

3.5 Feature Space Separability (t-SNE)

The separability of fault classes in the learned feature space is visualised using a t-distributed stochastic neighbour embedding (t-SNE) projection of the ANN-derived features (Fig. 6). Distinct clustering trends are observable for LG, LL, LLG, and LLL faults, although partial overlap exists between the clusters. This visual confirm that the ANN successfully extracts compact and discriminative representations of fault signatures. The overlap further explains the observed misclassification patterns between certain fault types, reinforcing the physical interpretation of the results.

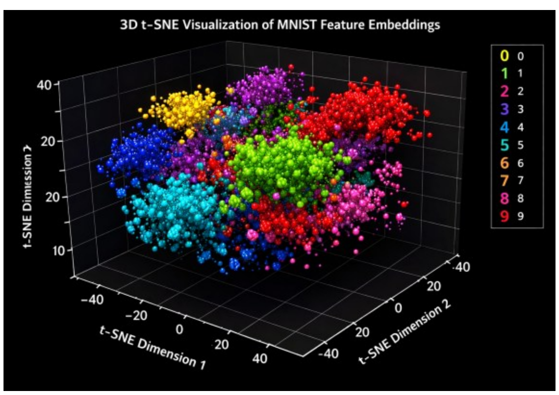

Fig. 6: t-SNE visualisation of ANN feature embeddings, coloured by fault type

3.6 ROC Characteristics

The Receiver Operating Characteristic (ROC) curve (Fig. 7) for LG faults versus all other fault classes is skewed towards the upper-left region, with an Area Under the Curve (AUC) typically exceeding 0.90, indicating strong discriminative capability. This high AUC demonstrates that the hybrid ANN-SVM model maintains a favourable trade-off between true positive rate and false positive rate across a wide range of decision thresholds. The ROC analysis complements the confusion matrix results by providing threshold-independent validation of classifier reliability.

4.7 Prediction Confidence

The distribution of prediction confidence scores for the hybrid ANN-SVM model reveals that a majority of test samples are classified with high confidence (confidence scores of 0.7-0.8), while a smaller subset exhibits low confidence as shown in Fig. 8. Low-confidence predictions often correspond to borderline cases, such as faults occurring under high fault resistance or unusual loading conditions. This insight is valuable for practical deployment, as low-confidence cases can be flagged for further analysis or human-in-the-loop verification in real-time protection systems.

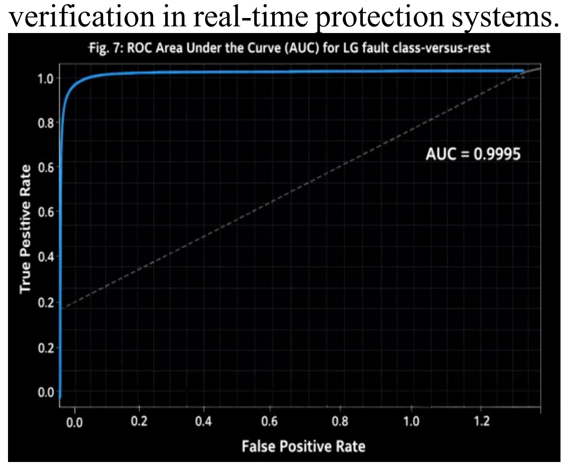

Fig. 7: ROC Area Under the Curve (AUC) for LG fault class-versus-rest.

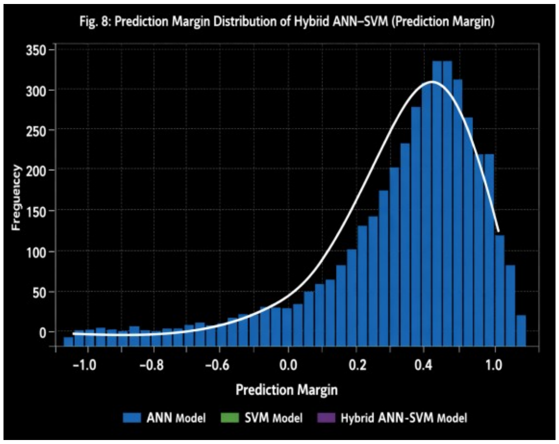

Fig. 8: Prediction margin distribution of hybrid ANN–SVM (*Prediction Margin*).

3.8 Summary of Key Findings

Overall, the results demonstrate that the proposed hybrid ANN-SVM framework provides:

(i) a robust and accurate solution for fault diagnosis in transmission networks.
(ii) the model achieves high fault type classification accuracy, competitive faulted-line identification performance, reliable protection zoning,
(iii) improved performance over standalone ANN and SVM approaches.

The combination of quantitative metrics and visual diagnostics confirms that the learned representations are physically meaningful and practically useful for intelligent transmission line protection and smart grid applications.

4.0 Conclusion

This study developed and validated a hybrid Artificial Neural Network–Support Vector Machine (ANN–SVM) framework for intelligent fault detection, fault type classification, faulted-line identification, and protection zoning using the IEEE 39-bus New England test system. The framework combines the nonlinear feature learning capability of ANN with the robust classification strength of SVM to overcome the limitations of conventional protection methods under varying loading conditions, fault resistance, measurement noise, and complex network configurations. Experimental results demonstrated that the proposed hybrid model consistently outperformed the standalone ANN and SVM models. Specifically, the hybrid ANN–SVM achieved an overall accuracy of 97.20% in fault type classification, fault line classification accuracy of 97.70%, and fault zoning classification accuracy of 95.80%, confirming its superior classification capability and robustness. Confusion matrix analysis showed high classification reliability with minimal misclassification, while faulted-line identification errors were largely restricted to neighbouring transmission lines, providing operationally useful localisation. Furthermore, ROC analysis, t-SNE feature-space visualisation, and prediction confidence evaluation demonstrated excellent class separability and reliable decision-making under challenging operating conditions. The findings establish the proposed hybrid ANN–SVM framework as an effective and practical intelligent fault diagnosis solution, with strong potential for integration into modern transmission network protection and monitoring systems and future deployment using real utility data.

Acknowledgement

The author sincerely acknowledges the guidance and support of the supervisor, Dr. (Mrs.) Monsurat Balogun, and members of the Department of Electrical and Computer Engineering, Kwara State University, Malete, throughout the course of this research. Gratitude is also extended to colleagues and family whose encouragement and patience were

invaluable during the preparation of this work.

5.0 Reference

Adesina, L. M., Ogunbiyi, O., & Jimada-Ojuolape, B. (2024). Comparative analysis of the reliability assessment of commercial and residential feeders in the power distribution utility of Nigeria. *E-Prime - Advances in Electrical Engineering, Electronics and Energy, 9*, 100651. https://doi.org/10.1016/j.prime.2024.100651

Alcayde-García, F., Salmerón-Manzano, E., Montero, M. A., Alcayde, A., & Manzano-Agugliaro, F. (2022). Power transmission lines: Worldwide research trends. *Energies, 15*(16), 5777. https://doi.org/10.3390/en15165777

Anwar, T., Mu, C., Yousaf, M. Z., Khan, W., Khalid, S., Hourani, A. O., & Zaitsev, I. (2025). Robust fault detection and classification in power transmission lines via ensemble machine learning models. *Scientific Reports, 15*(1), 2549. https://doi.org/10.1038/s41598-025-86554-2

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning, 20*(3), 273–297. https://doi.org/10.1007/BF00994018

Han, G., Wang, R., Yuan, Q., Zhao, L., Li, S., Zhang, M., He, M., & Qin, L. (2023). Typical fault detection on drone images of transmission lines based on lightweight structure and feature-balanced network. *Drones, 7*(10), 638. https://doi.org/10.3390/drones7100638

Ilius, P., Almuhaini, M., Javaid, M., & Abido, M. (2023). A machine learning–based approach for fault detection in power systems. *Engineering, Technology & Applied Science Research, 13*(4), 11216–11221. https://doi.org/10.48084/etasr.5995

Jamil, M., Sharma, S. K., & Singh, R. (2015). Fault detection and classification in electrical power transmission system using artificial neural network. *SpringerPlus, 4*(1), 334. https://doi.org/10.1186/s40064-015-1080-x

Jawad, R. S., & Abid, H. (2023). HVDC fault detection and classification with artificial neural network based on ACO-DWT method. *Energies, 16*(3), 1064. https://doi.org/10.3390/en16031064

Khan, M. A., Asad, B., Vaimann, T., Kallaste, A., Pomarnacki, R., & Hyunh, V. K. (2023). Improved fault classification and localization in power transmission networks using VAE-generated synthetic data and machine learning algorithms. *Machines, 11*(10), 963. https://doi.org/10.3390/machines11100963

Klomjit, J., & Ngaopitakkul, A. (2020). Comparison of artificial intelligence methods for fault classification of the 115-kV hybrid transmission system. *Applied Sciences, 10*(11), 3967. https://doi.org/10.3390/app10113967

Rajesh, P., Kannan, R., Vishnupriyan, J., & Rajani, B. (2022). Optimally detecting and classifying the transmission line fault in power system using hybrid technique. *ISA Transactions, 130*, 253–264. https://doi.org/10.1016/j.isatra.2022.03.017

Samson, O. O., Gbadamosi, S. L., Onibonoje, M. O., & Ojo, E. E. (2024). Development of machine learning algorithms for fault detection in power systems: A review. In *2024*

International Conference on Science, Engineering and Business for Driving Sustainable Development Goals (SEB4SDG) (pp. 1–6). IEEE. https://doi.org/10.1109/SEB4SDG60871.2024.10629955

Shingare, S. S., Khampariya, P., & Bakre, S. (2023). Application of ANN-based approach for fault location in extra high voltage networks. *International Journal of Engineering Trends and Technology, 71*(2), 440–449. https://doi.org/10.14445/22315381/IJETT-V71I2P245

Sundararaman, B., & Jain, P. (2023). Fault detection and classification in electrical power transmission system using wavelet transform. In *Engineering Proceedings* (Vol. 59, Article 71). MDPI. https://doi.org/10.3390/engproc2023059071

Thukaram, D., Khincha, H. P., & Vijaynarasimha, H. P. (2005). Artificial neural network and support vector machine approach for locating faults in radial distribution systems. *IEEE Transactions on Power Delivery, 20*(2), 710–721. https://doi.org/10.1109/TPWRD.2005.844307

Waheed Olalekan, H., Ikenna Augustine, O., & Mathurine, G. (2024). Artificial neural network-based fault detection on Nigerian 330 kV power transmission line. *International Journal of Research and Review, 11*(10), 518–535. https://doi.org/10.52403/ijrr.20241047

Declarations

Ethical Approval and Consent to Participate

Ethical approval for this study was obtained from the appropriate Health Research Ethics Committee before data collection commenced. Permission to access hospital records was obtained from the management of the participating hospitals. The study was conducted in accordance with the principles of the Declaration of Helsinki. Patient information was anonymized to ensure confidentiality, and no personally identifiable information was collected or reported.

Consent for Publication

Not applicable.

Availability of Data and Materials

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Competing Interests

The authors declare that they have no competing interests.

Funding

The authors received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors for the conduct of this study.

Authors' Contributions

Mohammed Kudu Abubakar conceived the study, designed the methodology, performed simulations, analyzed data, and drafted the manuscript. Balogun Monsurat O. supervised the research, validated the methodology, and reviewed the manuscript. Lambe Adesina M., Abdul-Waheed Musa, Ogunbiyi Olalekan, and Jimada-Ojuolape Bilkisu contributed to data interpretation, literature review, manuscript editing, technical validation, and approval of the final version for publication.

Authors' Information

Not applicable.

Data Confidentiality

All patient records were anonymized before analysis. Confidentiality and privacy were maintained throughout the study, and all data were used solely for research purposes.

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