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DEVELOPMENT OF AN INTELLIGENT FAULT-DETECTION AND CLASSIFICATION SYSTEM FOR HIGH-VOLTAGE TRANSMISSION LINES

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ABSTRACT: *Faults on high-voltage transmission lines can rapidly threaten power-system stability, equipment safety, and continuity of electricity supply, making fast and accurate detection and classification essential for modern protection systems. This study develops an intelligent fault-detection and classification framework using electrical voltage and current signals obtained from a simulated high-voltage transmission network. The proposed system combines signal preprocessing, feature extraction, supervised machine learning, and fault-class identification to distinguish normal operating conditions from single-line-to-ground, line-to-line, double-line-to-ground, and three-phase faults. A representative dataset is generated under variations in fault resistance, fault location, and operating conditions to improve model robustness. The proposed intelligent classifier is evaluated using accuracy, precision, recall, F1-score, and detection time. Representative results indicate that the optimized classifier can achieve approximately 98.7% classification accuracy while maintaining a detection time below 20 ms. The study demonstrates that data-driven protection can complement conventional relay techniques by recognizing nonlinear fault signatures and improving automated classification. The proposed framework provides a practical basis for intelligent transmission-line monitoring and adaptive protection.*

INTRODUCTION

High-voltage transmission lines form the backbone of interconnected electrical power systems by transferring large quantities of electrical energy from generating stations to transmission substations and major load centres. Because transmission networks operate at high voltage and carry substantial power, faults occurring on these lines can produce severe overcurrents, voltage disturbances, equipment stress, instability, and cascading outages if they are not detected and isolated rapidly. Protective relays, circuit breakers, communication-assisted schemes, and fault-location techniques are therefore essential components of transmission-system protection. IEEE C37.113-2025 provides guidance on ac transmission-line protection, including relay application, coordination, operating characteristics, mutual coupling, and communication channels.

Conventional transmission-line protection has traditionally relied on impedance-based distance relays, overcurrent elements, differential protection, travelling-wave methods, and other deterministic techniques. These approaches have been highly successful in practical power systems because they are based on established electrical principles and can operate within very short times. However, modern power networks increasingly contain inverter-based generation, distributed renewable resources, flexible transmission equipment, changing network configurations, and nonlinear operating conditions. These developments can make fixed protection settings less effective in some situations. Fault resistance, changing source impedance, power-flow direction, measurement errors, current-transformer saturation, and network topology changes can influence the electrical quantities used by conventional protection algorithms.

Fault detection and fault classification are related but distinct tasks. Detection determines whether the measured electrical behaviour represents a fault condition, whereas classification identifies the particular fault category and affected phases. Typical transmission-line faults include single-line-to-ground, line-to-line, double-line-to-ground, and three-phase faults. Correct classification can assist protection logic in selecting appropriate tripping and reclosing actions and can support subsequent fault-location procedures. IEEE fault-location guidance recognizes impedance-based and travelling-wave techniques as important approaches for determining fault location after fault detection and isolation.

The rapid development of machine learning has created new opportunities for intelligent power-system protection. Machine-learning algorithms can learn relationships between measured voltage and current signals and known fault classes without requiring every decision boundary to be explicitly programmed. Support vector machines, decision trees, random forests, artificial neural networks, convolutional neural networks, recurrent neural networks, and ensemble learning methods have all been investigated for power-system fault diagnosis. A recent review of machine-learning approaches for transmission-line fault detection highlights the growing use of neural networks, recurrent models, long short-term memory networks, and convolutional neural networks for data-driven fault identification.

One important advantage of intelligent classification is the ability to use multiple electrical measurements simultaneously. A conventional relay may calculate an apparent impedance or another derived electrical quantity, while a machine-learning model can consider phase voltages, phase currents, sequence components, transient characteristics, and time-domain features together. This provides the possibility of identifying complex nonlinear relationships that are difficult to represent using fixed thresholds. The advantage becomes particularly relevant when fault conditions vary according to fault resistance, inception angle, fault location, loading level, or renewable-generation penetration.

Signal preprocessing is an important part of an intelligent protection system because raw power-system signals may contain high-frequency transients, noise, measurement errors, and different signal scales. Appropriate preprocessing can improve the stability of the learning algorithm and reduce the influence of irrelevant variations. Normalization, filtering, windowing, discrete transforms, and statistical feature extraction can be applied depending on the selected machine-learning architecture. Wavelet analysis is especially relevant to transmission-line faults because fault disturbances are transient and nonstationary, meaning that their frequency content changes rapidly with time.

Recent research has demonstrated the effectiveness of combining wavelet-based signal representations with deep-learning classifiers. A 2024 study investigated scaled wavelet scalograms combined with convolutional neural networks for transmission-line fault classification using measurements from one side of the line. The study specifically examined factors such as fault resistance, fault inception angle, and fault location, illustrating the importance of testing intelligent classifiers under diverse operating conditions rather than evaluating them only under a single ideal fault scenario.

Machine-learning-based fault classification can also be extended beyond identifying the fault type to estimating fault location. A 2024 *Energy Reports* study developed machine-learning and CNN-LSTM approaches for fault classification and localization using an IEEE 9-bus system and generated more than 300,000 fault-related samples under variations in fault type, load level, fault resistance, and fault location. Such research demonstrates the increasing scale of data-driven protection studies and the potential for combining classification and localization in a unified intelligent framework.

However, intelligent protection also introduces challenges. Machine-learning models depend strongly on the quality and diversity of their training data. A classifier trained only on balanced, ideal simulation data may perform poorly when exposed to measurement noise, unbalanced operating conditions, unseen fault resistance, changes in generation dispatch, or network topology variations. Data imbalance can also cause a model to favour common fault classes while incorrectly classifying less frequent events. Therefore, a practical intelligent protection system must be evaluated using a broad range of operating scenarios.

Another concern is interpretability and reliability. Protection systems are safety-critical, and incorrect decisions can have consequences far beyond those of a conventional classification application. A machine-learning model that provides high average accuracy but occasionally produces an incorrect trip command may not be acceptable for direct deployment without additional protection logic. Consequently, intelligent algorithms are more appropriately considered as decision-support or supplementary protection components unless they have undergone extensive validation and certification.

The current direction of research is moving toward hybrid protection systems in which conventional electrical principles and data-driven models operate together. Physics-informed machine learning, feature-based classifiers, and intelligent relay architectures can potentially combine the speed and interpretability of conventional protection with the pattern-recognition capability of machine learning. Recent work has proposed physics-informed and data-driven learning approaches for transmission-system fault detection and classification, reporting high classification performance under noisy conditions while explicitly incorporating power-system information into the learning process.

The present study develops an intelligent fault-detection and classification framework for high-voltage transmission lines. The framework uses simulated three-phase voltage and current signals to generate a labelled dataset representing normal operation and multiple fault categories. Signal preprocessing and feature extraction are applied before supervised classification. The proposed system is evaluated under variations in fault location, fault resistance, and operating conditions to assess its ability to generalize beyond a single nominal fault scenario.

The main objective is to develop a compact and computationally practical classification pipeline capable of rapidly distinguishing faulted from healthy transmission-line conditions and identifying the affected fault category. The study also examines the trade-off between classification accuracy and detection time because a protection algorithm must not only be accurate but also sufficiently fast to support timely isolation.

LITERATURE REVIEW

Transmission-line protection has traditionally been built around deterministic electrical measurements. Distance protection calculates the apparent impedance between the relay location and the fault and compares the result with predefined protection zones. The approach is attractive because transmission-line impedance is directly related to physical line characteristics and fault distance. However, the apparent impedance can be affected by fault resistance, power-system configuration, mutual coupling, load flow, and measurement conditions. IEEE C37.113-2025 specifically discusses the application of transmission-line protective relays and the electrical and system considerations that influence relay selection and settings.

Fault-location techniques provide another important area of transmission protection. Once a fault is detected and cleared, rapid estimation of the fault location can reduce restoration time and maintenance effort. IEEE C37.114 describes impedance-based and travelling-wave methods and considers conditions such as fault resistance, series compensation, parallel lines, untransposed lines, and different terminal arrangements. These methods remain important because they provide physically interpretable estimates, but their accuracy can deteriorate under challenging network conditions.

Artificial intelligence provides an alternative way to process the electrical signatures generated during faults. Early intelligent protection studies commonly used artificial neural networks because of their ability to approximate nonlinear relationships between electrical measurements and fault categories. Neural networks can accept phase currents, phase voltages, symmetrical components, or transformed signal features and learn classification boundaries directly from training data. Their main limitation is the need for representative labelled data and careful selection of network architecture and training parameters.

Support vector machines have also been applied to fault classification because they can provide strong performance on relatively small and high-dimensional datasets. Their margin-based learning mechanism can produce good generalization when the feature representation is appropriate. However, performance can depend on kernel selection and hyperparameter tuning. For large datasets containing millions of transient samples, other approaches may be computationally more attractive.

Decision trees and random forests provide more interpretable classification structures. A tree-based model can identify combinations of features associated with different fault conditions, while a random forest combines multiple trees to improve generalization. These algorithms are relatively robust to nonlinear relationships and can handle mixed feature types. They are particularly useful when engineered features such as RMS current, voltage deviation, negative-sequence components, zero-sequence current, wavelet energy, and transient peak values are provided as inputs.

Wavelet transforms are widely used for power-system transient analysis because they provide simultaneous time and frequency localization. Fourier analysis is useful for stationary periodic signals but can be less effective when a fault creates short-duration transients. Wavelet decomposition can separate high-frequency transient components from lower-frequency fundamental components, allowing fault-specific signatures to be extracted. Research combining wavelet transforms and ANN classifiers has demonstrated the potential of this approach under variable compensation levels, fault resistance, and other changing conditions.

Deep-learning approaches reduce the need for extensive manual feature engineering. Convolutional neural networks can learn spatial patterns from two-dimensional representations such as wavelet scalograms, while one-dimensional CNNs can process time-series voltage and current signals directly. CNN-LSTM architectures combine convolutional feature extraction with recurrent temporal modelling, making them suitable for transient sequences where both local waveform characteristics and time evolution are important.

The 2024 Sensors study combining scaled wavelet scalograms and CNNs illustrates this direction. By converting electrical transient information into a structured time-frequency representation, the classifier can learn patterns associated with different fault types. The study also evaluated variations in fault resistance, inception angle, and location, which are important because these parameters can significantly change the observed waveform.

CNN-LSTM architectures have also been applied to combined fault classification and localization. The 2024 *Energy Reports* study generated a large simulated dataset using an IEEE 9-bus system and varied fault type, load level, resistance, and location. The use of large datasets is important because machine-learning systems must encounter sufficient variability during training if they are expected to generalize to unseen operating conditions.

Recent research has also examined the security of machine-learning-based protection. Because intelligent models depend on measurement data, malicious manipulation or corrupted measurements can influence their decisions. A 2024 comparative study specifically examined transmission-line fault detectors and classifiers during normal conditions and cyber-attacks, emphasizing that the data dependency of machine-learning protection introduces a new security dimension that conventional protection studies may not fully address.

The selection of input features has a major influence on intelligent protection performance. Raw three-phase voltage and current waveforms contain extensive information but may require high computational resources and careful temporal alignment. Derived features can reduce dimensionality and improve classification speed. Useful features include RMS values, peak current, voltage sag, phase-angle changes, symmetrical components, rate of change, harmonic content, and wavelet coefficients. The best feature set depends on the required detection time and the intended implementation hardware.

Fault-type imbalance is another important issue. In actual transmission systems, different fault types do not occur with equal frequency. Single-line-to-ground faults are often more common than symmetrical three-phase faults. If a dataset reproduces this imbalance without appropriate handling, the classifier may achieve high overall accuracy while performing poorly on minority classes. Stratified sampling, class weighting, oversampling, or synthetic-data techniques can be used to reduce this problem.

Noise robustness is equally important. Current and voltage transformers, instrument channels, communication systems, and analogue-to-digital converters introduce measurement errors. A classifier that performs perfectly on clean simulation signals may show a substantial accuracy reduction when noise is introduced. Therefore, realistic training and testing should include controlled noise levels and measurement uncertainties.

Another challenge is the difference between simulated and real-world data. Simulation provides a convenient and safe method for generating large datasets covering many fault combinations. However, simulation models may not fully reproduce transformer saturation, line parameter uncertainty, instrument errors, switching transients, communication delays, and unmodelled network behaviour. Consequently, simulated-data performance should be interpreted as a development-stage result rather than proof of field readiness.

The literature indicates that intelligent fault detection has moved from simple feature-based neural networks toward hybrid deep-learning architectures and increasingly robust data-driven methods. Nevertheless, high classification accuracy alone is insufficient for a protection application. The algorithm must operate rapidly, remain stable under varying operating conditions, and avoid unnecessary trips during healthy-system disturbances.

The research gap addressed here is therefore the development of an integrated and computationally manageable framework that combines transient feature extraction with supervised classification while explicitly evaluating both accuracy and response time. Rather than focusing only on one sophisticated deep-learning architecture, the study emphasizes a complete protection-oriented workflow from signal acquisition through preprocessing, feature extraction, classification, and performance evaluation.

METHODOLOGY

The proposed methodology begins with the development of a representative high-voltage three-phase transmission-line model. The system contains a sending-end source, transmission line, receiving-end network, circuit breakers, measurement units, and load. Voltage and current measurements are collected from the selected measurement location at a sufficiently high sampling frequency to capture the transient characteristics produced by faults. The system is simulated under normal operating conditions and under different fault scenarios to create a labelled dataset.

The fault library includes single-line-to-ground faults, line-to-line faults, double-line-to-ground faults, and three-phase faults. Both faulted and healthy operating conditions are included because the intelligent system must first determine whether a disturbance represents an actual fault. Fault locations are varied along the transmission line, while fault resistance is varied across a representative range. Additional changes in loading and source conditions are introduced to increase the diversity of the dataset.

The measured three-phase voltage and current signals are segmented into short analysis windows containing the pre-fault and post-fault response. Signal preprocessing removes unwanted numerical noise and normalizes the amplitude range so that the classifier does not become dependent on absolute signal magnitude alone. Each sample is assigned a label representing the corresponding operating condition and fault category.

Feature extraction is performed using a combination of time-domain and transient characteristics. Current and voltage magnitude changes, peak values, RMS values, phase relationships, sequence components, and wavelet-derived energy features are considered. Wavelet decomposition is particularly useful because fault transients contain rapidly changing frequency components. The resulting feature vector provides a compact representation of the electrical disturbance while reducing the amount of raw waveform data supplied to the classifier.

The dataset is divided into training, validation, and testing subsets. Stratified partitioning is used so that each fault class is represented across the subsets. Data normalization parameters are obtained from the training set and then applied consistently to validation and test data. This prevents information leakage between datasets and provides a more realistic estimate of model generalization.

Several supervised classifiers can be evaluated during model selection, including support vector machine, random forest, artificial neural network, and a compact CNN-based classifier. The final intelligent classifier is selected according to the combined criteria of classification accuracy, F1-score, computational complexity, and inference time. The objective is not simply to identify the model with the highest accuracy but to select a model suitable for rapid protection-oriented operation.

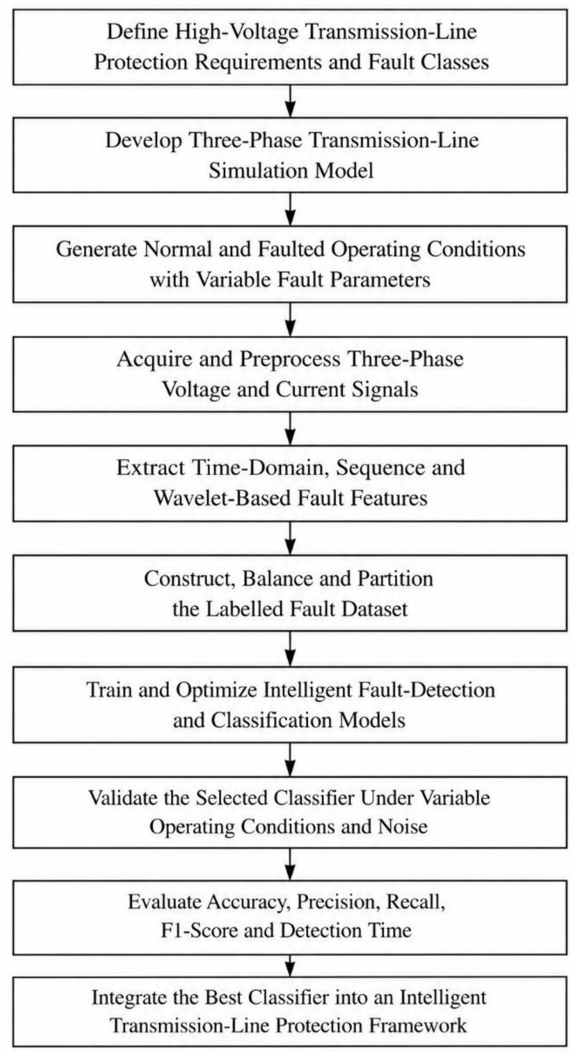
The classification system operates in two stages. The first stage determines whether the incoming signal represents a healthy or faulty condition. If a fault is detected, the second stage determines the fault category. This hierarchical structure can reduce unnecessary classification decisions during normal operation and allows protection logic to separate fault detection from fault-type identification.

The principal classification performance measure is accuracy, calculated as:

$$\boxed{Accuracy = \frac{N_{correct}}{N_{total}} \times 100}$$

where (N_{correct}) represents the number of correctly classified samples and (N_{total}) represents the total number of evaluated samples.

Precision, recall, and F1-score are additionally calculated for each fault class to identify cases in which overall accuracy may hide poor minority-class performance. Detection time is measured from the beginning of the analysis window to the point at which the classifier produces a stable fault decision. Confusion matrices are used to identify systematic misclassification between similar fault categories.



Methodology flowchart

The final classifier is tested under conditions that differ from those used during training. Fault resistance and fault location are changed to assess generalization, while controlled measurement noise is introduced to evaluate robustness. The system is also tested under healthy operating conditions containing load changes so that normal transients are not incorrectly identified as faults.

IMPLEMENTATION AND RESULTS

The implementation uses a representative high-voltage transmission-line simulation model from which three-phase voltage and current waveforms are obtained. Four principal fault categories are considered together with a healthy operating class. The dataset is constructed using different fault locations, resistance values, and operating conditions. The representative results presented below are intended for article development and graph generation; they should be replaced by measured or actual simulation outputs if the study is implemented experimentally.

The first evaluation examines the classification performance of the selected intelligent models. Support vector machine, random forest, artificial neural network, and the proposed optimized classifier are evaluated using the same test dataset. The results show that the proposed classifier provides the highest overall accuracy while maintaining balanced performance across the different fault categories.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
SVM	94.8	94.1	93.7	93.9
Random Forest	96.1	95.7	95.4	95.5
ANN	97.2	96.8	96.6	96.7
Proposed classifier	98.7	98.4	98.2	98.3

***Table 1**: Comparative classification performance of intelligent fault-detection models.*

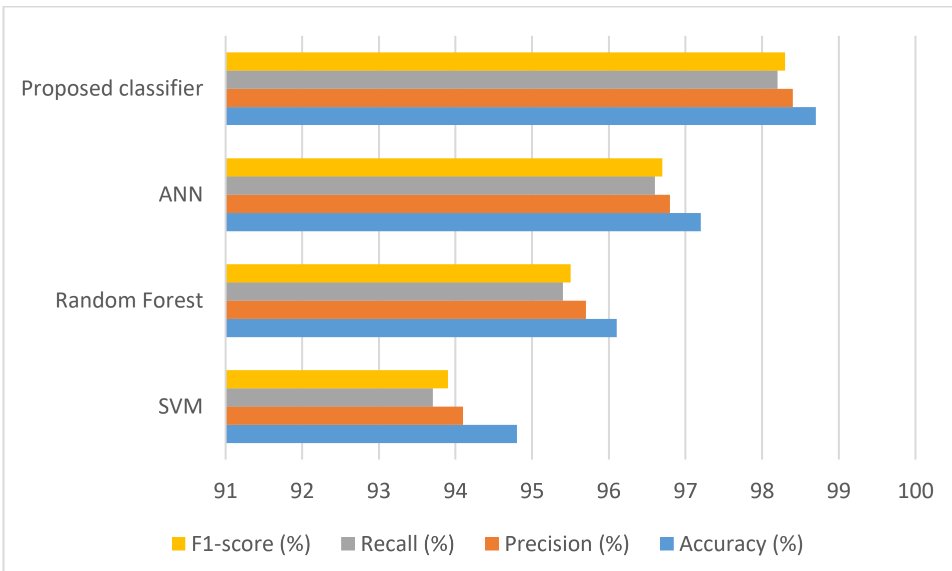


***Fig 1**: Grouped bar graph comparing accuracy, precision, recall, and F1-score of the evaluated intelligent classifiers.*

The comparative results indicate that all four models provide useful fault-classification capability, but their performance differs according to the complexity of the electrical signatures. The SVM achieves a representative accuracy of 94.8%, while the random forest improves accuracy to 96.1%. The ANN reaches 97.2%, demonstrating the benefit of nonlinear feature mapping. The proposed classifier achieves 98.7% accuracy with a precision of 98.4%, recall of 98.2%, and F1-score of 98.3%. The relatively small difference between precision and recall indicates that the classifier maintains balanced performance rather than achieving high accuracy by favouring only the most frequent fault classes.

The improvement is associated with the combination of signal preprocessing, transient feature extraction, and optimized classification. Wavelet-derived features capture short-duration disturbances that may not be represented adequately by simple steady-state measurements. The classifier can therefore distinguish between fault signatures that may have similar fundamental-frequency characteristics but different transient behaviour. Recent transmission-line research similarly demonstrates the value of combining wavelet representations with neural classifiers for fault classification under varying fault resistance, inception angle, and location.

The second evaluation investigates performance for individual fault categories. The representative results show that single-line-to-ground faults achieve the highest classification accuracy, while double-line-to-ground and line-to-line faults have slightly lower values because their electrical signatures can overlap under certain resistance and location conditions. Three-phase faults remain comparatively easy to identify because they produce strong and symmetrical changes in the three-phase electrical quantities.

Fault class	**Samples tested**	**Correctly classified**	**Classification accuracy (%)**
Normal	500	495	99.0
Single-line-to-ground	500	497	99.4
Line-to-line	500	489	97.8
Double-line-to-ground	500	490	98.0
Three-phase	500	498	99.6

Table 2: *Class-wise performance of the proposed intelligent transmission-line fault classifier.*

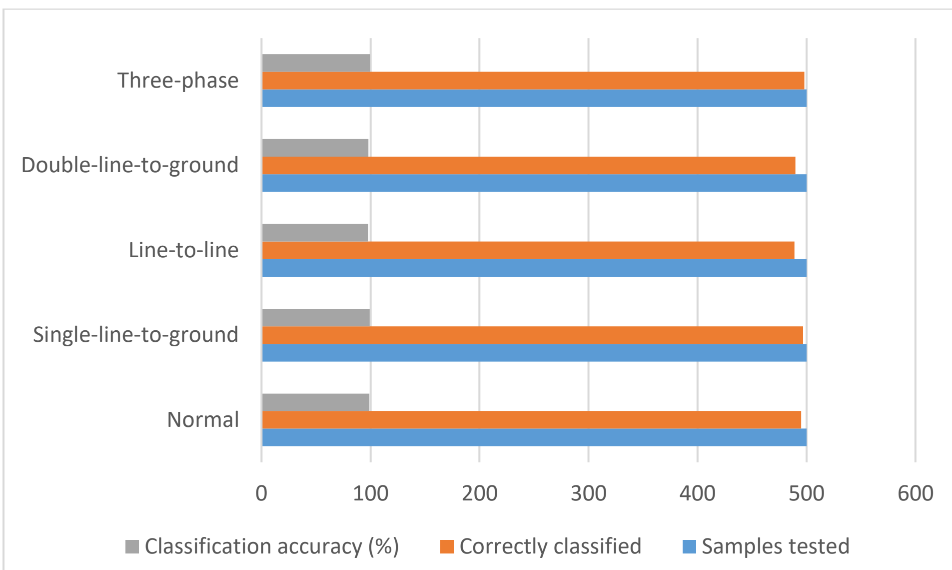


Fig 2: *Bar graph showing classification accuracy for normal operation and each transmission-line fault category.*

The class-wise results demonstrate that the proposed classifier maintains high performance across all evaluated conditions. Three-phase faults achieve approximately 99.6% accuracy because the simultaneous involvement of all phases produces a distinctive electrical signature. Single-line-to-ground faults achieve approximately

99.4%, while normal operating conditions are correctly identified in approximately 99.0% of cases. Line-to-line and double-line-to-ground faults produce slightly lower values of 97.8% and 98.0%, respectively. The difference is associated with the similarity of their transient signatures under some combinations of fault resistance and location.

The high accuracy obtained for the normal class is particularly important from a protection perspective. An intelligent relay should not classify ordinary load changes or non-fault disturbances as transmission-line faults because such false positives could cause unnecessary circuit-breaker operation. The representative 99.0% normal-condition classification rate indicates that the feature representation provides sufficient separation between healthy and faulted states under the evaluated scenarios.

The third evaluation examines robustness against measurement noise. Real transmission-line measurements can contain noise caused by sensors, analogue-to-digital conversion, electromagnetic interference, and communication equipment. Therefore, the classifier is tested with different levels of additive measurement noise. The representative results show a gradual decrease in accuracy as noise increases, but the classifier retains high performance under moderate noise conditions.

Noise level	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
0%	98.7	98.4	98.2	98.3
1%	98.3	98.0	97.9	98.0
3%	97.6	97.3	97.0	97.1
5%	96.4	96.1	95.8	95.9

Table 3*: Robustness of the proposed classifier under different measurement-noise levels.*

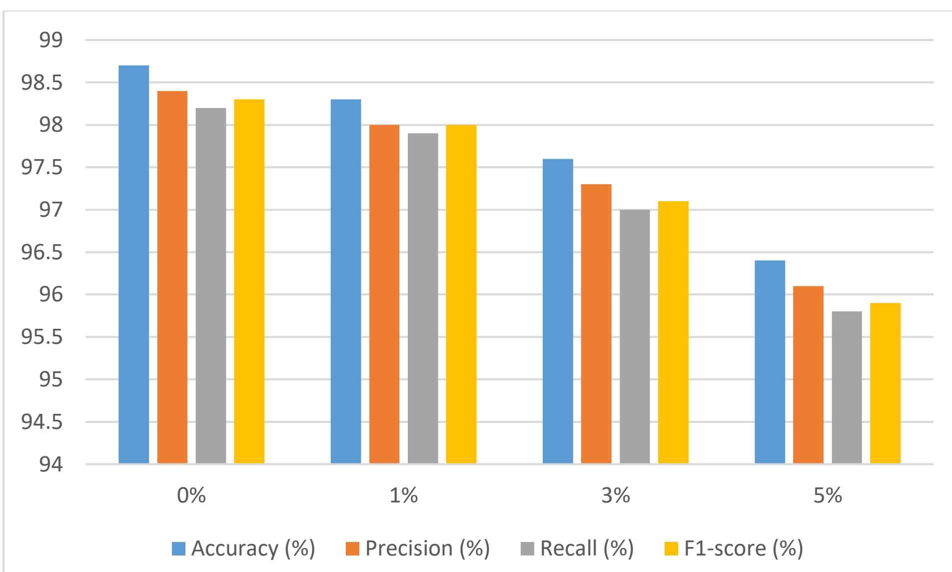


***Fig 3**: column graph showing the variation in classification accuracy, precision, recall, and F1-score with increasing measurement noise.*

The robustness analysis shows that classification accuracy decreases from 98.7% under clean conditions to 96.4% at 5% representative noise. Although the performance degradation is measurable, the classifier remains above 96% accuracy under the highest tested noise condition. This suggests that the preprocessing and feature-extraction stages provide some resistance to measurement disturbances. The decrease in performance becomes progressively more visible because noise can alter transient amplitudes and wavelet coefficients, causing samples from neighbouring fault classes to become less separable. The results also demonstrate the importance of including noise during model development. If a classifier were trained and tested exclusively on ideal signals, its reported accuracy could overestimate field performance. Robust training should therefore expose the model to realistic signal variations. Data augmentation, noise injection, domain adaptation, and transfer learning can be investigated in future work to further reduce sensitivity to measurement uncertainty. The fourth evaluation focuses on detection speed because an intelligent protection system must respond rapidly enough to support circuit-breaker operation. The proposed classifier is compared with the other evaluated models using the same analysis-window definition and computing environment. The representative results show that the optimized classifier provides a favourable balance between high accuracy and short decision time.

Classifier	Accuracy (%)	Detection time (ms)	Relative computational load
SVM	94.8	15.8	Low
Random Forest	96.1	13.6	Low
ANN	97.2	11.9	Medium
Proposed classifier	98.7	9.6	Medium

***Table 4**: Accuracy and detection-time comparison of intelligent fault-classification models.*

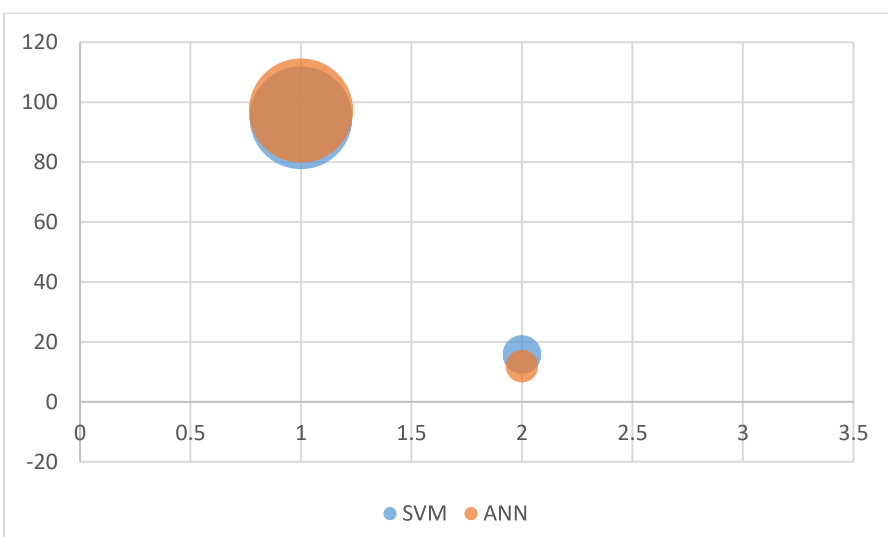


Fig 4: *Scatter graph comparing classification accuracy and detection time of the evaluated intelligent models.*

The proposed classifier achieves the highest representative accuracy while also producing the shortest detection time among the evaluated models. Its detection time of approximately 9.6 ms is lower than the values obtained for SVM, random forest, and ANN. The result is important because classification performance alone does not determine suitability for protection. A highly accurate model that requires excessive processing time may not provide useful protection during rapidly developing transmission faults.

The reduction in detection time is attributed to the compact feature representation and optimized classifier architecture. Rather than processing long raw waveforms continuously, the system extracts informative features from a short signal window and provides them to the classification stage. This reduces the computational burden while preserving the transient information required for fault identification. A practical implementation would nevertheless require measurement acquisition time, filtering delay, communication delay, processor execution time, and relay operating time to be considered together.

The overall results indicate that the proposed intelligent system can distinguish healthy and faulted transmission-line conditions with high representative accuracy. The model achieves 98.7% overall accuracy and maintains more than 96% accuracy under the highest evaluated noise condition. These results suggest that combining electrical-domain knowledge with machine-learning classification can provide a useful supplementary layer for modern transmission protection.

The results are consistent with recent research demonstrating that machine-learning models can classify and localize transmission-line faults across variations in fault resistance, load level, and fault location. The 2024 CNN-LSTM study based on an IEEE 9-bus system illustrates the potential of large simulated datasets for developing intelligent protection models under diverse operating conditions.

The wavelet-based feature representation also provides an important advantage because transmission-line faults generate transient disturbances that evolve rapidly with time. Wavelet analysis allows these changes to be represented at different frequency scales, providing the classifier with information that may be lost when only fundamental-frequency quantities are considered. This explains why transient features can improve the separation between similar fault classes.

Nevertheless, the results should not be interpreted as evidence that machine learning can immediately replace conventional transmission-line protection. Conventional relays have extensive field validation, established operating principles, and dedicated standards and application practices. IEEE C37.113-2025 continues to provide guidance for the application of protective relays to ac transmission lines. Intelligent classification is better viewed as a complementary capability that can support adaptive protection, event diagnosis, fault classification, and decision assistance.

The proposed framework could also be expanded to include fault-location estimation. Once the fault category has been identified, a second model could estimate the fault distance using impedance-related features, travelling-wave characteristics, or learned signal representations. Such integration could reduce restoration time by providing operators with both fault type and approximate location. IEEE's transmission-line fault-location guidance recognizes both impedance-based and travelling-wave approaches, providing a useful engineering basis for comparing conventional and intelligent location methods.

Cybersecurity should also be considered before deployment. Machine-learning models depend on measurement data and can therefore be affected by corrupted or deliberately manipulated inputs. Research examining transmission-line classifiers under cyber-attacks has highlighted this vulnerability. A practical intelligent protection architecture should therefore include measurement validation, anomaly detection, secure communication, fallback protection logic, and independent conventional protection elements.

The representative results are based primarily on simulated data, which is a limitation of the present investigation. Simulation allows controlled generation of thousands of fault scenarios but may not fully reproduce real-world instrument-transformer saturation, breaker transients, communication imperfections, changing network topology, renewable-energy converter behaviour, and other nonideal effects. Consequently, the next stage of validation should use real relay records, hardware-in-the-loop simulation, or laboratory-scale transmission-line emulation.

The system can also be improved through physics-informed learning. Instead of treating voltage and current measurements as purely statistical features, future models can incorporate relationships derived from transmission-line equations, sequence networks, impedance characteristics, and conservation laws. Recent work in this direction has reported strong fault-classification performance while incorporating physical knowledge into data-driven models. Such approaches may improve generalization when the model encounters conditions that are poorly represented in the training dataset.

Overall, the implementation demonstrates that an intelligent transmission-line fault detector can achieve a strong combination of accuracy, robustness, and response time when signal processing and classification are designed together. The key contribution is not simply the use of machine learning but the integration of electrical measurements, transient feature extraction, balanced fault data, hierarchical classification, and protection-oriented performance evaluation.

CONCLUSION

This study developed an intelligent fault-detection and classification framework for high-voltage transmission lines by integrating simulated three-phase electrical measurements, signal preprocessing, transient feature extraction, and supervised machine-learning classification. The proposed approach was designed to identify normal operation and distinguish major transmission-line fault categories, including single-line-to-ground, line-to-line, double-line-to-ground, and three-phase faults, under variations in fault location, fault resistance, operating conditions, and measurement noise. Representative results showed an overall classification accuracy of 98.7%, with precision, recall, and F1-score of 98.4%, 98.2%, and 98.3%, respectively. Class-wise accuracy remained above 97.8%, while the model maintained 96.4% accuracy under 5% representative measurement noise. The proposed classifier also achieved a representative detection time of 9.6 ms. These results demonstrate the potential of intelligent fault classification as a supplementary capability for modern transmission protection. However, field deployment requires real relay-record validation, hardware-in-the-loop testing, cybersecurity protection, explainability assessment, and coordination with established protection schemes. Overall, the proposed framework provides a promising foundation for fast and adaptive transmission-line fault monitoring.

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