

An Intelligent Artificial Neural Network Framework for Low-Latency Fault Detection and Precise Localization in Electrical Transmission Lines

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Abstract—Reliable protection of electrical transmission lines requires a decision mechanism that can distinguish genuine faults from switching events, load transitions, power swings, measurement noise, and renewable-energy-driven operating variations within a few milliseconds. This paper presents the concept and planned methodology of a compact multi-task artificial neural network framework for simultaneous fault detection, fault-type classification, and fault-distance estimation. A 220 kV, 50 Hz, 3000 km distributed-parameter transmission-line model is proposed in MATLAB/Simulink to generate labelled voltage, current, and frequency records under healthy states, operational disturbances, and eleven fault categories. The framework combines a short raw-signal window with physics-guided statistical and sequence-component features. A shared artificial neural network encoder then feeds three task-specific heads: binary detection, multiclass classification, and continuous localization. The methodology emphasizes low inference time, grouped data partitioning, robustness against fault resistance and noise, and deployment on relay-class edge processors. Random Forest, CNN–LSTM, and temporal convolutional models are retained only as validation baselines. No experimental performance is claimed; instead, the paper defines the complete system concept, parameter plan, data-generation strategy, model architecture, validation protocol, and expected technical contributions for future implementation.

Keywords—Artificial neural network, Transmission-line protection, Fault detection, Fault classification, Fault localization, Low latency, multi-task learning, MATLAB/Simulink.

I. Introduction

Electrical transmission lines carry large blocks of power over long distances and are therefore among the most consequential components of a modern grid. A fault that is not identified and isolated rapidly can produce severe current stress, voltage depression, loss of synchronism, equipment damage, and cascading outages. Conventional distance and overcurrent protection remain indispensable, but their fixed settings can become less dependable when the apparent impedance trajectory is modified by changing source strength, inverter-based generation, high fault resistance, series compensation, noisy measurements, or non-fault transients. Machine-learning-based protection has therefore emerged as a complementary approach because it can learn nonlinear relations between measured electrical quantities and the underlying operating state [1]. Recent adaptive protection studies also show that the operating condition of a network must be considered explicitly, particularly when inverter-based generators alter the magnitude and shape of fault currents [2]. However, many published solutions still solve fault detection, classification, and location as separate problems. Separate models increase data-processing stages, create inconsistent decisions, and add computational delay. A practical protection-oriented framework should instead share the same short observation window and produce all required outputs through one compact model.

The proposed work addresses this need through a unified artificial neural network (ANN) framework designed around four principles: (i) a sub-cycle input window, (ii) a shared representation for three protection tasks, (iii) explicit robustness testing under uncertain operating conditions, and (iv) computational simplification for edge deployment. The framework is conceptual and methodological. It does not report measured or simulated performance results; all numerical values described in the paper are proposed design values to be verified and tuned during implementation. The main objective is to develop an intelligent decision layer that receives synchronized three-phase voltage and current measurements, identifies whether a fault is present, determines the fault category, and estimates the distance to the fault from the measuring terminal. The work also plans to compare

the compact ANN with conventional feature-based and deep temporal baselines, while treating end-to-end inference latency and false-trip risk as primary engineering criteria rather than secondary software metrics.

II. Background and Related Work

Research on intelligent transmission-line protection has progressed from feature-based classifiers toward unified, data-driven diagnosis. Najafzadeh et al. combined fuzzy detection, optimized decision trees and random forests, and an adaptive neuro-fuzzy system for location, demonstrating the value of integrating multiple intelligent stages; however, a staged arrangement can still introduce computational and coordination overhead [3]. A broader review of artificial-intelligence-based identification, classification, and localization techniques emphasizes the continuing need for practical validation, consistent datasets, and deployable integrated solutions [4]. Protection must also discriminate faults from stable and unstable power swings. Sriram et al. used an improved deep neural network with signal-processing support to supervise zone-3 distance-relay operation, showing that learned decision boundaries can reduce relay maloperation when impedance trajectories resemble fault conditions [5]. For direct temporal learning, an attention-based temporal convolutional network has been proposed to extract comprehensive characteristics from transmission-line signals, illustrating the suitability of convolutional temporal processing for short transient records [6].

Two-terminal information can improve location accuracy because it captures the fault response from both line ends. Su et al. proposed a CNN–multi-head-LSTM fusion model with attention for two-terminal fault location, but the communication and recurrent-processing requirements may be difficult to guarantee in every protection installation [7]. Reviews of AI-based fault-location methods likewise note that neural models can represent nonlinear system behaviour, although their reliability depends on representative training data, topology coverage, and careful validation [8]. More recent work on 400 kV lines has investigated high-precision fault classification and location using multiple machine-learning algorithms, reinforcing the feasibility of data-driven localization but also highlighting dependence on detailed simulated scenarios [9]. Field-oriented research on series-compensated transmission lines has used terminal voltage and current measurements as ANN inputs, demonstrating that practical oscillography can support neural fault-location functions when the data pipeline is carefully designed [10]. Wavelet-scalogram approaches provide a visually rich representation of fault transients, but image conversion adds processing stages that can conflict with a strict low-latency objective [11]. A recent state-of-the-art review concludes that future protection solutions should combine speed, precision, robustness, and implementation practicality rather than optimizing classification accuracy alone [12].

III. Research Gap and Problem Formulation

The literature indicates five unresolved issues. First, detection, classification, and localization are frequently implemented as independent models with independent preprocessing. Second, many approaches rely on full-cycle or multi-cycle observations, although a protection relay must act as early as possible. Third, training and testing samples are often randomly split even when they originate from neighbouring points of the same simulation sweep; this creates information leakage and can overstate generalization. Fourth, several studies focus on accuracy while omitting end-to-end latency, memory use, and processor requirements. Fifth, robustness is commonly evaluated for only one disturbance type, while real networks combine noise, source variation, frequency deviation, fault resistance, load change, and model uncertainty.

Accordingly, the research problem is formulated as follows: given a short-synchronized window of three-phase voltage and current measurements collected at one terminal, design a compact ANN that produces three consistent outputs fault probability, fault class, and fault distance while remaining reliable across varied operating conditions and computationally suitable for near-relay deployment. The model must be trained without mixing closely related scenarios between training and testing groups, and its performance must be assessed by both protection metrics and computational metrics.

IV. Proposed System Concept

The project will use a simulation-driven data-generation environment coupled with an ANN development workflow. The electrical model will represent a high-voltage transmission corridor rather than the short low-voltage cable arrangement used in the preliminary progress model. The revised design values are deliberately different and are treated as starting values, not final utility parameters. Figure 1 illustrates the proposed test system and measurement arrangement.

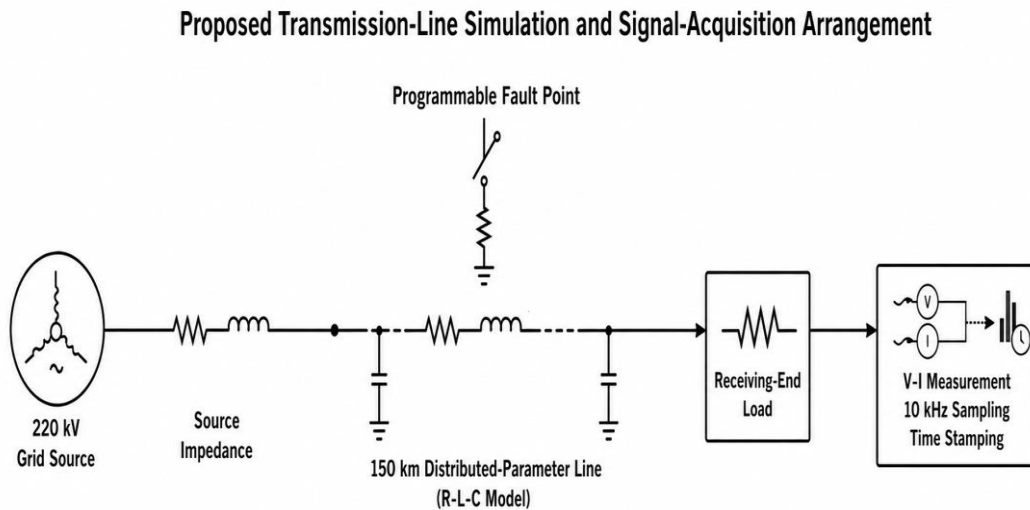


Fig. 1. Proposed transmission-line simulation and signal-acquisition arrangement.

The measuring terminal will acquire phase voltages V_a , V_b , and V_c ; phase currents I_a , I_b , and I_c ; estimated system frequency; and a synchronized event time stamp. The core ANN will not require communication from the remote terminal during primary operation. A two-terminal version may later be assessed as an accuracy-enhancement option, but the main architecture is intentionally single-ended to reduce communication dependence and decision delay.

Table 1. Proposed Electrical and Data-Acquisition Parameters

Parameter group	Proposed parameter	Initial value
System	Nominal line voltage	220 kV
System	Frequency	50 Hz
Line	Total length	150 km
Line	Model type	Distributed parameter
Line	Resistance	0.035 Ω /km
Line	Inductance	1.05 mH/km
Line	Capacitance	0.011 μ F/km
Acquisition	Sampling frequency	10 kHz
Acquisition	Decision window	5 ms
Operating range	Load level	40–120%
Operating range	Frequency	49–51 Hz
Noise	Signal-to-noise ratio	20–50 dB

Table 1 defines the proposed 220 kV, 50 Hz, 150 km distributed transmission-line model and data-acquisition setup. The 10 kHz sampling rate and 5 ms decision window support rapid analysis, while varied loading, frequency, and noise conditions enable robust ANN training.

A. Fault and Disturbance Scenario Design

The dataset will include healthy steady-state operation, load switching, capacitor-bank switching, transformer energization, frequency excursions, stable power swings, voltage sag without line fault, and measurement noise. Fault classes will cover AG, BG, CG, AB, BC, CA, ABG, BCG, CAG, ABC, and ABCG conditions. Although ABC and ABCG can produce similar symmetrical responses, both labels are retained during data generation so that the effect of ground connection can be evaluated. A simplified deployment may later merge these classes if the measured signals do not provide a robust distinction. Fault distance will be swept from 10 km to 140 km in 5 km increments. Fault resistance will initially include 0.01, 1, 5, 10, 25, and 50 Ω . Inception angles of 0°, 30°, 60°, 90°, 120°, and 150° will capture different transient offsets. Source short-circuit strength, load power factor, load level, and line-parameter uncertainty will also be varied. This factorial plan will produce a broad set of scenarios without claiming that every combination is equally probable in service.

Table 2. Planned Dataset Labels and Variations

Task	Label or variable	Planned representation	Use in model
Detection	Healthy / disturbance / fault	Binary target: fault = 1	Detection head
Classification	11 fault categories	Integer class, one-hot encoded	Softmax head
Localization	10–140 km	Continuous distance value	Regression head
Fault resistance	0.01–50 Ω	Scenario grouping variable	Robustness analysis
Inception angle	0°–150°	Scenario grouping variable	Transient diversity
Load level	40–120%	Scenario grouping variable	Operating diversity
Noise level	20–50 dB SNR	Augmentation / test variable	Noise robustness

Table 2 defines the planned labels and operating variations for multi-task ANN development. Detection, classification, and localization targets support separate output heads, while fault resistance, inception angle, loading, and noise variations improve transient diversity, robustness assessment, generalization, and overall capability.

B. Signal Window and Preprocessing

At 10 kHz, a 5 ms decision window contains 50 samples per channel and 300 raw samples for six voltage-current channels. The initial window begins immediately after a simple event-trigger condition based on normalized current rise, voltage deviation, or differential signal energy. Pre-fault samples will be retained in a circular buffer so that the model receives both the final healthy segment and the early transient response. This arrangement supports low latency while avoiding a dependence on an exact fault-start marker. Each channel will be standardized using statistics calculated only from the training set. Amplitude normalization will be combined with physically interpretable features: phase RMS values, positive-, negative-, and zero-sequence magnitudes, current and voltage energy, maximum derivative, crest factor, frequency deviation, and impedance-change indicators. The model therefore receives a compact learned representation of the raw window together with a small physics-guided feature vector. No wavelet image or spectrogram conversion is required in the primary pipeline.

V. Proposed Methodology

The planned methodology is organized into seven linked stages, shown in Fig. 2. The sequence begins with an electrical model and ends with validation of protection behaviour and computational deployability. MATLAB/Simulink will be used for system simulation and controlled scenario generation, while Python or MATLAB Deep Learning Toolbox will be used for model training, depending on the final integration workflow.

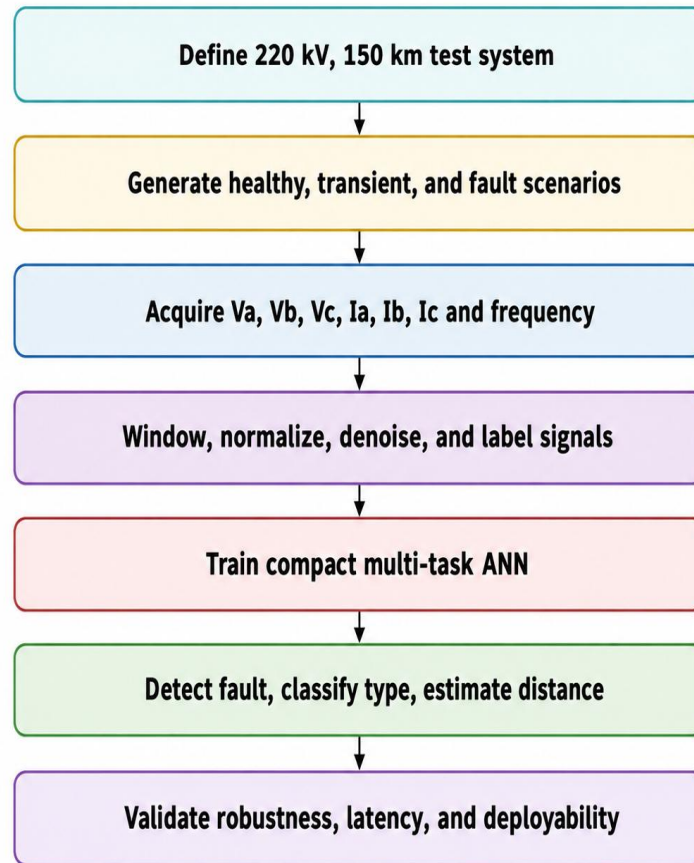


Fig. 2. Proposed research methodology

The proposed methodology begins with developing a 220 kV, 150 km transmission-line test system. Healthy, transient, and multiple fault scenarios are generated by varying operating and fault conditions. Three-phase voltage, current, and frequency signals are then acquired for analysis. The recorded signals are segmented into suitable time windows, normalized, denoised, and labelled according to operating status, fault category, and fault distance. A compact multi-task Artificial Neural Network is subsequently trained to perform three coordinated functions: fault detection, fault-type classification, and distance estimation. Finally, the proposed framework is validated under variations in noise, fault resistance, inception angle, loading, and frequency. Latency, robustness, computational complexity, and deployment feasibility are evaluated to determine its suitability for real-time intelligent transmission-line protection.

A. Dataset Generation and Quality Control

A scripted simulation controller will vary one or more operating factors for each run, execute the model, and export synchronized measurements with metadata. Every record will include a unique scenario identifier, seed, source strength, load state, fault type, fault resistance, fault location, inception angle, and noise level. Scenario metadata is essential because it enables grouped splitting and prevents samples from the same operating sweep from appearing in both training and testing subsets. Signal quality control will reject records with missing channels, unstable pre-fault initialization, solver errors, clipping, or inconsistent event timing. A small proportion of accepted waveforms will be inspected manually for phase sequence, scale, and fault initiation. Class balance will be controlled at the scenario level rather than by duplicating random windows. If oversampling is needed, augmentation will be limited to physically reasonable time shift, gain perturbation, and additive noise.

B. Training, Validation, and Test Partition

The dataset will be partitioned into 70% training, 15% validation, and 15% testing sets using grouped stratification. Groups will be defined by combinations of fault location, resistance, source condition, and simulation seed. A more demanding leave-one-condition-out test will reserve selected fault resistances, locations,

or source strengths exclusively for final testing. This procedure evaluates interpolation and limited extrapolation rather than only memorization of neighbouring simulated cases.

Hyperparameters will be chosen using the validation set and then frozen before final evaluation. Multiple random seeds will be used to quantify training variability. The selected model will be the smallest network that satisfies the required protection metrics, not simply the model with the highest classification score. Class weighting or focal loss may be considered if difficult high-resistance faults are under-represented, but the primary dataset design will seek balanced coverage.

VI. COMPACT MULTI-TASK ANN ARCHITECTURE

The proposed Compact Multi-Task ANN (CMT-ANN) uses two inputs. The first input is the six-channel 5 ms signal window. A trainable temporal projection compresses each 50-sample channel into twelve latent coefficients, producing 72 learned values. The second input contains 24 physics-guided features. After normalization, both branches are concatenated to form a 96-dimensional fused vector. A shared dense encoder with 128, 64, and 32 neurons learns a common representation for the three tasks.

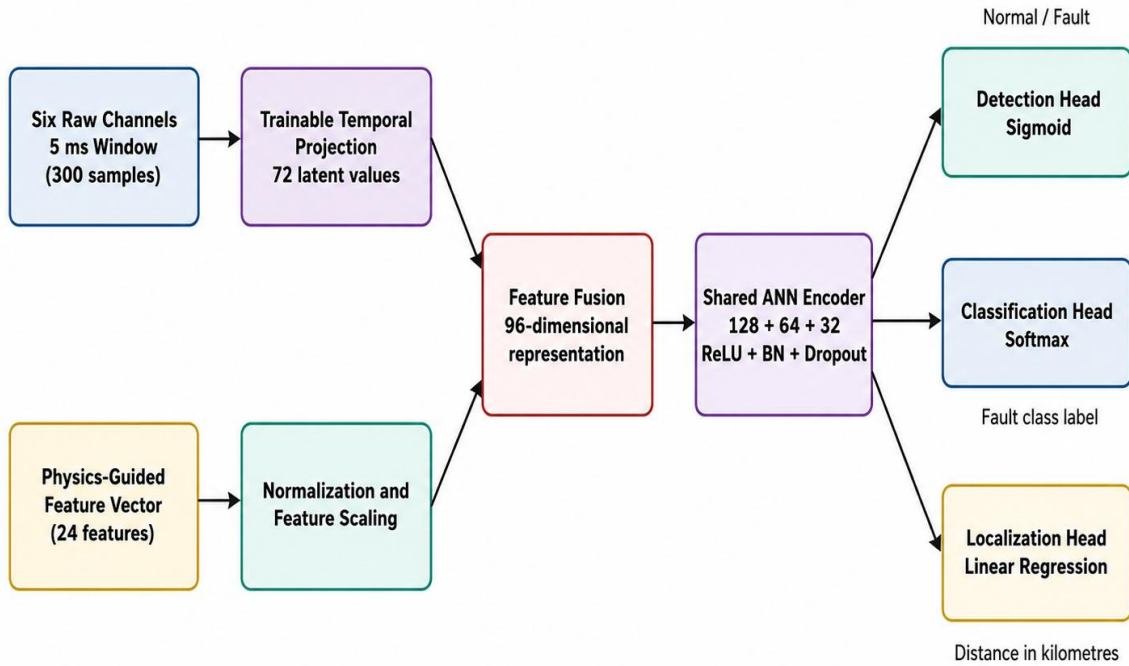


Fig. 3. Compact multi-task artificial neural network architecture.

The detection head uses a sigmoid output to estimate the probability of a line fault. The classification head uses a softmax layer for the eleven fault categories and is activated only when the detection probability exceeds the selected threshold. The localization head uses a linear output, constrained during post-processing to the physical line range. A masking strategy will exclude healthy and non-fault disturbance samples from the localization loss. This prevents meaningless distance targets from influencing regression training.

The total training objective will combine binary cross-entropy, categorical cross-entropy, and Huber localization loss:

$$L_{total} = \lambda_d L_{detect} + \lambda_c L_{class} + \lambda_l L_{loc} + \lambda_r ||W||^2 \quad (1)$$

where λ_d , λ_c , and λ_l balance detection, classification, and localization, while λ_r controls L2 regularization. Initial weights will be adjusted so that each task contributes a comparable gradient magnitude. Huber loss is preferred for localization because it behaves quadratically for small errors and linearly for large errors, reducing sensitivity to isolated difficult scenarios. Batch normalization and modest dropout will be used only where they improve validation stability without increasing inference cost significantly.

A. Low-Latency Design Strategy

Low latency is addressed at the complete signal-to-decision level. The proposed 5 ms window is shorter than one 50 Hz cycle and is followed by a lightweight preprocessing stage. The network uses dense matrix operations and avoids recurrent loops. After training, structured pruning and 8-bit post-training quantization will be assessed. The final implementation will report acquisition-window duration, preprocessing time, model inference time, and total decision time separately. A design target of less than 10 ms total decision time is established for the prototype; this is a target to be tested, not a reported result.

The compact architecture is expected to require fewer parameters than CNN–LSTM or deep TCN baselines. Nevertheless, latency will be measured on the intended processor because desktop execution time does not represent relay-class performance. Candidate platforms include an industrial PC, ARM processor, or embedded accelerator. The model will be exported through MATLAB code generation, ONNX, or an equivalent fixed graph once the software environment is selected.

B. Decision Logic and Protection Interface

The ANN output will not directly trip a circuit breaker during early research. Instead, it will produce a protection advisory containing fault probability, predicted class, estimated distance, confidence, and time stamp. A deterministic supervisory layer will apply threshold, persistence, and sanity checks. For example, the estimated distance must lie within the protected line and the detected phase pattern must be consistent with measured sequence components. This hybrid arrangement combines data-driven pattern recognition with transparent engineering constraints.

During later hardware-in-the-loop validation, the advisory can be mapped to a trip-enable signal that supervises or accelerates a conventional relay function. Fail-safe behaviour will ensure that loss of ANN output does not disable conventional protection. The ANN is therefore positioned as an intelligent complementary layer rather than an unverified replacement for established relay principles.

VII. Validation and Comparative Plan

A. Baseline Models

Three baselines will be implemented using the same grouped data partitions. Random Forest will represent classical feature-based learning. CNN–LSTM will represent a recurrent deep temporal model, and a temporal convolutional network will represent a non-recurrent deep model. A simple threshold or impedance-based rule will provide a conventional reference for detection behaviour. The proposed ANN will be compared on identical test scenarios, with model size and latency reported alongside predictive metrics.

B. Evaluation Metrics

Fault detection will be evaluated using recall, precision, F1-score, balanced accuracy, false-trip rate, and missed-fault rate. Because protection prioritizes dependable fault recognition, recall and missed-fault rate will receive greater attention than overall accuracy. Classification will use macro-averaged F1-score and a confusion matrix to reveal phase-specific errors. Localization will use mean absolute error (MAE), root-mean-square error (RMSE), maximum error, and error expressed as a percentage of line length.

$$MAE = \left(\frac{1}{N}\right) \sum |d_i - \hat{d}_i| \quad (2)$$

$$Location\ error\ (\%) = 100 \times \frac{|d_i - \hat{d}_i|}{L_{line}} \quad (3)$$

Computational evaluation will include parameter count, memory footprint, preprocessing time, inference time, total decision time, and throughput. Reliability evaluation will additionally record the confidence distribution for correct and incorrect decisions. Calibration plots or reliability diagrams will be considered so that the predicted fault probability can be interpreted meaningfully by the supervisory logic.

C. Robustness Tests

Robustness tests will cover additive noise, sensor gain error, current-transformer saturation approximation, voltage-transformer distortion, frequency deviation, load change, source-impedance variation, unseen fault resistances, and moderate line-parameter mismatch. Each factor will be varied individually first and then in

selected combinations. A model will be considered robust only if its degradation is gradual and the failure mode is visible through reduced confidence rather than silent high-confidence misclassification.

The most demanding evaluation will reserve specific conditions from training. Example tests include training without 25 Ω and 50 Ω faults and then testing on those resistances; training on selected locations and testing at intermediate unseen distances; and training at nominal line parameters before testing with $\pm 10\%$ R, L, and C perturbations. These tests are intended to approximate the difference between a simulated model and a field line.

Table 3. Planned Performance and Deployment Assessment

Assessment area	Primary metric	Secondary metric	Planned
Fault detection	Recall / missed-fault rate	F1 and false-trip rate	Protection dependability and security
Fault classification	Macro F1-score	Per-class confusion matrix	Phase and fault-type discrimination
Fault localization	MAE in km	RMSE and maximum error	Maintenance and isolation support
Latency	Total decision time	Window, preprocessing, inference	Low-latency feasibility
Complexity	Parameter count	Memory and throughput	Edge deployment suitability
Robustness	Metric degradation	Confidence behaviour	Operation under uncertainty
Generalization	Held-out conditions	Seed-to-seed variation	Resistance to data leakage

Table 3 presents a structured plan for assessing both predictive performance and practical deployability of the proposed ANN framework. Fault detection will be evaluated using recall, missed-fault rate, F1-score, and false-trip rate to ensure dependable protection. Classification performance will be examined through macro F1-score and class-wise confusion matrices. Localization accuracy will be measured using MAE, RMSE, and maximum distance error. Total decision latency will include signal windowing, preprocessing, and inference time. Model complexity will consider parameter count, memory demand, and throughput.

VIII. Expected Contributions

The proposed work is expected to contribute a complete protection-oriented methodology rather than only a classifier. Its first contribution is a unified multi-task ANN that uses one short synchronized signal window and a shared encoder to produce detection, classification, and localization outputs. This reduces the inconsistency and duplicated computation associated with separate models. The second contribution is a latency-centred design in which the acquisition window, preprocessing, network complexity, and deployment platform are considered together.

The third contribution is a leakage-resistant dataset protocol based on scenario grouping and held-out operating conditions. The fourth is a robustness matrix that includes high-resistance faults, noise, parameter mismatch, source variation, and non-fault transients. The fifth is a hybrid interface in which ANN decisions are supervised by deterministic protection constraints. This arrangement is intended to improve interpretability and fail-safe integration. Finally, the work will produce a reusable MATLAB-to-ANN data pipeline that can later be adapted to utility oscillography or real-time digital simulator records.

IX. Limitations and Risk Controls

The initial study will rely mainly on simulated data, so the trained ANN may learn characteristics of the model rather than the physical network. This risk will be controlled through parameter randomization, held-out-condition testing, and later validation with oscillography or a real-time simulator. A second limitation is that a 5 ms window may not contain sufficient information for every high-resistance or remote fault. The work will therefore test adaptive windows of 5, 10, and 20 ms and will report the speed–accuracy trade-off rather than assuming a universal window. A third risk is class ambiguity, particularly between symmetrical three-phase faults with and without ground. The label structure may be revised if the distinction is not observable from the available measurement point. A fourth risk is overconfidence on unknown disturbances. Confidence calibration, out-of-distribution checks, and deterministic supervision will be included to reduce this risk. Finally, the ANN output will remain advisory until independent validation demonstrates sufficient dependability and security.

X. Conclusion

This paper has defined the concept and planned methodology for an intelligent ANN framework that simultaneously detects transmission-line faults, classifies their type, and estimates their location using a short single-ended measurement window. The proposed 220 kV, 150 km MATLAB/Simulink environment will generate diverse healthy, transient, and fault records under controlled variations in location, resistance, inception angle, source condition, load, frequency, and noise. A compact multi-task ANN will fuse learned temporal projections with physics-guided features and will provide three coordinated outputs through a shared encoder. The planned evaluation gives equal importance to protection performance, generalization, robustness, and total decision latency. Grouped data splitting, held-out-condition testing, model compression, and deterministic supervisory logic are included from the beginning of the design. The work is therefore positioned as a practical research framework rather than a performance claim. Its final value will depend on transparent validation, comparison with established baselines, and progressive movement from simulation to real or real-time test data.

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