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Artificial Intelligence Applications for Fault Prediction and Failure Prevention in Power Transmission Systems

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Abstract- For reliable power transmission it is essential to identify early signs of degradation before such degradation leads to faults that trigger protection systems, to equipment damage, or to a series of outages. Artificial intelligence (AI) has broadened the range of analysis available in the monitoring of transmission systems by enabling the discovery of nonlinear relationships among electrical waveforms, phasor measurements, indicators of asset condition, environmental variables, images from inspections, and records of events. This review critically looks at the use of AI for predicting faults and preventing failures in transmission lines and the associated high-voltage assets, with a focus on research carried out between 2020 and 2025. The analysis makes a distinction between immediate fault detection and classification on the one hand and anticipatory prediction, condition assessment, fault-cause identification, and support for maintenance decisions on the other. It assesses conventional machine learning, artificial neural networks, convolutional and recurrent architectures, transfer learning, ensemble models, autoencoders, and computer-vision methods in relation to operational needs such as speed, generalisation, tolerance to uncertainty, interpretability, and computational cost. It is shown that deep models are able to extract discriminative features directly from raw or only slightly processed signals, while hybrid approaches that combine signal processing and learning still prove valuable when data are scarce or when physics-based constraints are significant. Nevertheless, heavy reliance on simulated data, class imbalance, domain shift, a lack of failure labels, and insufficient validation in real-world settings still hinder implementation. A preventive architecture is therefore suggested which integrates synchronised sensing, multimodal representation learning, uncertainty-aware inference, risk scoring, and human-supervised maintenance actions. The review concludes that future advances will depend less on small improvements in accuracy and more on trusted generalisation, calibrated uncertainty, cross-asset transfer, explainability, cybersecurity, and validation at a utility scale.

I. INTRODUCTION

Power transmission systems function as widely spread infrastructures of high importance, since if protection, maintenance, or system coordination is insufficient a local defect can lead to major outages. Overhead lines are subject to lightning, vegetation, pollution, mechanical damage, conductor deterioration, insulation failure, bad weather, and human interference, whereas substations and the transformers connected to them come under thermal, dielectric, mechanical, and ageing-related stresses. Traditional protection is arranged to quickly detect abnormal electrical conditions once a fault has occurred; predictive maintenance on the other hand looks for signs of degradation early on in order to prevent or reduce the severity of the event. This difference is of operational significance. A protection relay might remove a line-to-ground fault within a few cycles, but a preventive approach aims to detect precursor patterns, vulnerable assets, changes in risk, or recurring causes before a fault reaches the tripping level.

The latest increase in the number of intelligent electronic devices such as phasor measurement units, digital fault recorders, supervisory systems, drones, thermal cameras, and asset sensors has led to a data environment in which artificial intelligence can support deterministic protection logic. Previous reviews have shown that transmission fault diagnosis can be structured in terms of detection, classification, and location, and that voltage and current measurements still serve as the main inputs for these functions [2]. Further research in the area of power electronics has demonstrated that AI makes a contribution through classification, regression, optimization, and exploration of data structures in the areas of design, control, and maintenance [1]. These fundamentals are directly applicable to transmission reliability since failure prevention involves more than just having a classifier; it requires a complete chain running from sensing through to inference, prognosis, risk interpretation, and then to actionable maintenance.

Recent research shows significant progress. Autonomous neural models have incorporated fault detection, type classification, and location estimation into a probabilistic framework [4]. End-to-end recurrent models have learned directly from waveform sequences, without the need for manually engineered features, and have proven to be robust against power swings, fault impedance, noise, and changes in operating conditions [6]. Capsule and convolutional methods have improved the ability to discriminate between transmission-line faults when there are variations in parameters and under high-impedance conditions [7], while hybrid CNN-LSTM structures make use of both the local morphology of the waveforms and the temporal dependence [11]. Transfer-learning methods deal with the ongoing problem that a model developed for one line length, impedance, or topology may not generalize to another [13]. Meanwhile, computer vision has moved failure prevention earlier in the process by detecting insulator and component defects from aerial images before those defects have necessarily caused an electrical fault [10], [17]-[19].

Even though these advances have taken place, the literature tends to show high accuracy when using carefully simulated datasets without at the same time proving that similar reliability can be achieved in the presence of field noise, rare faults, communication losses, unknown topologies, sensor drift, or changing renewable generation. This results in a discrepancy between the performance of the algorithms and the level of trust required for protection or for maintenance purposes. The fundamental issue is therefore not merely whether AI can identify known faults, but whether it can assist in making safe decisions both before and during abnormal conditions while staying robust against uncertainty and changes to the system. This review aims to close that gap by arranging the latest evidence along the entire failure-prevention pathway rather than focusing just on the algorithms. It concentrates on power transmission lines and the other assets closely associated with them, highlights research carried out between 2020 and 2025, and assesses both signal-based and inspection-based intelligence. The goal is to determine in which areas AI currently provides defensible value, in which areas the evidence is still incomplete, and what technical architecture is needed for dependable predictive operation.

II. AIM, OBJECTIVES AND RESEARCH QUESTIONS

This review seeks to critically examine the possibility of advancing transmission-system reliability from a stage of reactive fault recognition to one of anticipatory fault prediction and failure prevention. The analysis is guided by five objectives: (1) to associate transmission failure mechanisms with measurable electrical, environmental, and visual precursors; (2) to compare the various families of AI models with regard to detection, classification, localization, prediction, and condition assessment; (3) to evaluate the role of feature engineering, end-to-end learning, transfer learning, and multimodal fusion; (4) to identify the obstacles to trustworthy field deployment, such as domain shift, uncertainty, data scarcity, interpretability, latency, and cybersecurity; and (5) to develop an AI architecture focused on prevention that links the model's outputs to maintenance and protection decisions.

The review raises four questions: the first is which data and AI techniques are most appropriate for predicting or diagnosing transmission faults before serious failure occurs; the second is how modern deep-learning and transfer-learning methods improve upon traditional feature-based approaches; the third is what stops high accuracy in a laboratory setting from being translated into reliable real-world deployment; and the fourth is what design principles should serve as the basis for an AI-enabled failure-prevention framework for future transmission networks.

III. REVIEW METHODOLOGY

A structured integrative review approach was adopted since the subject area involves protection engineering, condition monitoring, machine learning, computer vision, and asset management. The protocol focused on peer-reviewed articles from journals and conferences published between 2020 and 2025, and

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only a limited number of basic concepts were included when needed in order to explain well-established protection or learning methods. The potential studies were found by searching the publisher's databases, using scholarly indexing services, and carrying out DOI-based cross-checks with combinations of the following terms: "transmission line fault", "fault prediction", "fault diagnosis", "fault classification", "fault location", "predictive maintenance", "machine learning", "deep learning", "CNN", "LSTM", "transfer learning", "PMU", "insulator defect", and "power system protection". The reference papers provided were used as structural and thematic benchmarks, especially in relation to the separation of fault detection, classification, location, AI method families, comparative strengths, and maintenance-oriented analysis [1]-[3].

To be included, a study had to deal directly with transmission-line faults, defects in high-voltage transmission components, power-system protection, or with condition-oriented prediction having transferable relevance to transmission assets. Studies were given priority if they provided information on the model inputs, specified the validation conditions, included comparative baselines, carried out robustness tests, or stated deployment-relevant limitations. Those studies which were purely forecasting in nature and did not have a connection with faults or health management, contained no technical comments, were duplicates, or failed to give adequate methodological details were excluded from the main synthesis. Since the literature varies with respect to test systems, fault scenarios, sampling rates, metrics, and the source of the data, a quantitative meta-analysis was not suitable. Neither any artificial screening totals nor any pooling of effect sizes were introduced.

The quality assessment took into account six different aspects: the relevance to preventing transmission failures; the clarity with which the dataset was generated or acquired; the separation of the training, validation, and testing phases; robustness with respect to noise or varying fault conditions; comparison with appropriate baselines; and the discussion of practical constraints. More emphasis was placed on studies that dealt with generalization across different line parameters, uncertainty, computational efficiency, or the use of real/field measurements rather than simply reporting the peak classification accuracy. The DOI metadata as well as the publisher or journal records were verified for the final set of references. The synthesis was based on a function-oriented approach, consisting of precursor acquisition, feature representation, fault-state inference, localization or identification of the cause, prognosis or risk scoring, and prevention actions. This structure allows the algorithms to be compared according to their operational role rather than merely by the name of their architecture.

IV. FAILURE MECHANISMS, PRECURSORS AND DATA FOUNDATIONS

The performance of AI is limited by the observations made by the sensing layer. Transmission faults can be of an electrical, mechanical, environmental, or mixed nature. Short-circuit and ground faults cause sudden changes in the phase currents, voltages, sequence components, impedance, frequency content, and travelling-wave signatures. High-impedance faults can be rather subtle and may overlap with normal load or switching behaviour, making them hard to detect using fixed thresholds. Component degradation takes place on a longer timescale: cracked or contaminated insulators, damage to the conductor strands, loose fittings, thermal hotspots, corrosion, encroachment by vegetation, and mechanical stress caused by the weather can persist for days or months before an electrical event occurs. Prevention of failure thus demands two complementary kinds of data: fast electrical measurements for detecting the early stages of fault development and slower condition or inspection data for identifying incipient physical deterioration.

Traditionally, signal-based diagnosis involves processing the waveforms using techniques such as wavelets, Fourier methods, S-transform variants, modal transforms, entropy measures, or dimensionality reduction before carrying out classification [2]. Although these transformations incorporate useful engineering structure and are capable of reducing dimensionality, their effectiveness relies on the choice of parameters and on decisions made by experts. Hybrid methods are particularly effective when fault transients are rare or when the datasets are small. For instance, combining wavelet-packet information with neural models can aid in fault localization in hybrid overhead-cable setups [15]. On the other hand, end-to-end models try to learn directly from the raw or only slightly processed sequences. LSTM-based methods are able to capture temporal dependencies without the need to manually create a large feature set [6], while convolutional models pick up on local waveform patterns and can be optimized for efficiency in edge computing [12].

Wide-area measurements give a spatial dimension. By using PMUs and synchronized recorders, time-aligned phasors can be obtained from a number of buses, which enables the models to tell the difference between local abnormalities and disturbances that affect the entire network. Studies employing autoencoder and extreme-learning-machine methods with wide-area data have shown that it is possible to achieve high diagnostic accuracy together with short inference times [27]. However, communication latency, missing channels, errors in time synchronization, and changes in the network topology can undermine the assumptions on which those models were trained. Data quality should therefore be regarded as a variable that can change rather than as a fixed attribute.

Visual inspection also establishes an additional precursor pathway. Using UAV imagery and deep detectors, it is possible to detect broken, cracked, contaminated, or missing insulator components as well as other visible abnormalities in the componentas well as other viThesee abnormaallow AI to move from analysing after a fault has occurred to enabling19]. These methods alsinc to move from anpick up onafter a fault has oatcurred tcausling physical prresponseion since the model can pick uencounter problems such as a defect before that defect causes variations in lighting, weather conditions, camera movementd models encounter problems suchvaluableckground clutter, small tdecids, variations in lighting, weather co insteadnditions, camera mobovent, aninformation on the d class theimbalance. The most vathe loading conditions, the topology, and the age of the assets in orderecide between esingle,nd visual data; instead they will combine both with information on the weather, the maintenance history, the loading conditions, the topology, and the age of the assets in order to estimate a single, time-dependent failure risk.

V. ARTIFICIAL INTELLIGENCE METHODS FOR FAULT PREDICTION AND DIAGNOSIS

Traditional machine-learning techniques are still appealing in situations where the feature vectors are small, the amount of training data is moderate, and it is important to have interpretability or computational simplicity. Support vector machines, decision trees, k-nearest-neighbour methods, ensemble trees, and extreme learning machines are able to effectively distinguish between different fault classes when the input data reflect informative electrical behaviour. The limitation with these methods is not always their accuracy but rather their dependence on stable feature distributions. This is why it matters, as shown by an adaptive ensemble approach applied to transmission lines linked to inverter-based generation: changes in the generation technology lead to changes in fault-current characteristics, and so the model or its settings have to be adjusted to the system configuration [25]. Extreme learning machines provide fast training and classification and can therefore achieve good performance in fault detection in cases where there is a need for low latency [23]. It has also been found that CatBoost and other ensemble methods can classify structured voltage-current datasets without having to use the complex architecture of deep networks [21].

Artificial neural networks offer the ability to carry out nonlinear mapping and have for a long time been applied to the identification of fault type and location. Although recent studies have demonstrated very low-latency detection and location of transmission faults using neural models, those results must be understood in the light of the simulated system, the balance of the dataset, and the operating envelope. Neural networks are able to efficiently interpolate complex relationships once they have been trained, but their reliability decreases when the test data lie outside the range of the training data. This limitation is significant whenever there are changes in the line parameters, the topology, the source impedance, or the level of inverter penetration.

Convolutional neural networks partly solve this problem by learning hierarchical local features directly from one-dimensional waveforms, transformed scalograms, or two-dimensional representations. A 1D-CNN is capable of carrying out detection, classification, and direction discrimination while at the same time reducing the need for handcrafted features [9]. More recent architectures now aim at computational efficiency just as much as they aim at accuracy. A 1D-CNN that has been designed using particle-swarm optimization reduces the resources needed for real-time implementation [12], whereas lightweight attention-enhanced models such as SA-MobileNetV3 aim at achieving both good recognition performance and manageable complexity [24]. Two-dimensional CNN methods convert time-frequency information into scalogram images, enabling feature extraction in an image-like manner from electrical signals [29]. The engineering issue is therefore no longer whether CNNs work, but rather which representation and architecture are able to retain diagnostic sensitivity within the constraints of realistic noise and hardware.

Recurrent networks, particularly LSTM networks and those with gating mechanisms, are well adapted to sequential fault signatures since they account for temporal dependence between samples. End-to-end LSTM models are capable of detecting and classifying faults during power swings and in the case of varying impedance without the need for a separate feature-extraction stage [6]. Hybrid CNN-LSTM models prove to be very effective since the convolutional layers pick up on local patterns and the recurrent layers maintain the temporal context. Frequency-response and sequence information have been combined with CNN-LSTM networks in order to identify the type and location of faults [11], and double-ended CNN-LSTM models can enhance localization at the same time as reducing the reliance on line-specific manual features [14]. The drawback is the high computational demand, particularly when long sequences, multiple terminals, or ensemble architectures are employed.

Transfer learning addresses one of the main problems encountered in deployment: a model that has been trained on one system usually performs badly when it is applied to a different line length, impedance, topology, or operating condition. It has been shown that a generalized transfer-learning framework, which is based on a pre-trained convolutional model, enables knowledge to be adapted among transmission-line datasets that have different physical properties [13]. Transfer learning is also applicable to fault-cause identification since in this case there are few labeled field events and the classes are highly imbalanced. MCNN-LSTM models that use images of transient waveforms have been combined with transfer strategies in order to facilitate recognition on additional lines and to be able to distinguish both the cause and the type of fault [26]. This represents a vital step towards prediction since prevention relies on understanding the recurring causes, not merely on recognizing the electrical symptom.

It is just as important to have uncertainty-aware methods. Traditional classifiers will still give a label even if the input is unlike any of the data they were trained on. Studies into deep transmission-fault analysis under environmental, system, and measurement uncertainty indicate that robustness should be tested directly rather than deduced from average accuracy [16]. Probabilistic neural models offer a more useful decision variable by estimating the probability of different fault locations or states [4]. In the context of maintenance, a calibrated probability or a risk interval is usually more useful than a single class label since it allows for prioritization and enables human review.

The scope for prevention can be extended through the use of computer-vision models. Detectors based at a central location, one-stage object detectors, and deep feature extractors are able to spot defects in transmission components from aerial images [10], [17]-[19]. Studies involving the inspection of high-voltage lines have shown that it is possible to detect important components and defects by using deep networks with imagery acquired remotely [18]. Such models are particularly useful in the case of latent mechanical or insulation defects which have not yet affected the electrical measurements. The problem they face is operational variability: a detector that works well on a carefully selected set of images may fail if changes occur in the size of the target, altitude, lighting conditions, weather, or the background. As a result, the most effective prevention approach is one that is multimodal: electrical models pick up dynamic signatures, vision models detect physical precursors, asset models take into account age and history, and a fusion layer brings together their findings.

Table 1. Comparative suitability of AI method families for transmission fault prediction and diagnosis

Method family	Primary strength	Key limitation	Best-fit use
Ensemble / conventional ML	Fast training and inference; works with compact engineered features	Sensitive to feature and domain shift	Structured relay features, adaptive settings, interpretable screening
ANN / ELM	Strong nonlinear mapping with low inference latency	Training stability and extrapolation limits	Fault type, location and fast classification
CNN / lightweight CNN	Automatic local feature extraction; strong waveform and image recognition	Compute demand; can learn dataset-specific artefacts	Raw waveform classification, scalograms, UAV defect detection
LSTM / GRU	Captures temporal dependencies and sequential evolution	Long-sequence cost and tuning complexity	End-to-end fault sequences, transient evolution, early warning
Hybrid CNN-LSTM	Combines local morphology with temporal context	Higher complexity and deployment burden	Fault type + location + cause identification
Transfer / continual learning	Improves reuse across lines, topologies and small target datasets	Risk of negative transfer and forgetting	Cross-line generalization and changing grid conditions
Probabilistic / uncertainty-aware AI	Supports calibrated risk and abstention	Requires careful calibration and uncertainty validation	Maintenance prioritization and human-supervised decisions

VI. FROM FAULT RECOGNITION TO FAILURE PREVENTION: AN INTEGRATED AI FRAMEWORK

The transmission system should be based on a prevention-focused approach and organised as a closed information loop, not as a separate classifier. The initial stage involves sensing and synchronisation. The high-speed relay waveforms, the PMU data streams, the SCADA values, the readings from transformers and lines, the weather information, the images obtained during inspections, and the maintenance records all need to be time-aligned and equipped with a quality tag. Each observation should include metadata that gives details about the condition of the sensor, any missing data, the communication delay, the calibration status, and the operating topology. This ensures that the model does not regard corrupt measurements as reliable evidence.

The next stage is that of representation. Electrical signals may be directed into multiple parallel branches: one for end-to-end CNN or LSTM learning (the raw-sequence branch) and another dedicated to incorporating physical principles, from which quantities such as impedance trajectories, wavelet energy, harmonics, and travelling-wave features are derived. When it comes to visual data, it is processed by a component-detection branch, and static information about the asset provides details on its age, manufacturer, maintenance record, exposure, and criticality. A multimodal fusion model is then used to create a latent health representation. This kind of combined approach prevents having to make a false dilemma between engineered features and deep learning; rather, it enables the learned representations to be verified against quantities that are understood by engineers.

The fourth stage involves inference accompanied by uncertainty. In this case, the output should go beyond a simple designation of 'healthy' or 'faulty'. The required outputs are an abnormality score, the most probable fault class, an estimated location, the likely cause, model confidence, data-quality confidence, and the short-term risk of deterioration. The models must be calibrated so that a high level of confidence always has a consistent statistical interpretation. The detectors designed to identify out-of-distribution cases should be able to detect situations that lie outside the training range, for example a new topology, an unseen inverter control, unusual weather, or a significant loss of

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sensors. In such instances, the appropriate action by the AI should be to refrain from making a prediction and instead to escalate the issue.

The fourth layer turns the results of inference into risk by combining failure probability with consequence. In the case of an interconnector that is heavily loaded, a line serving vital infrastructure, or a component having limited redundancy, a moderate probability might provide a sufficient reason for earlier action than a higher probability associated with an asset that has low consequences. The risk engine should thus take into account both the likelihood of a condition and the importance of power flow, N-1 security, repair time, accessibility, weather exposure, and replacement availability. As a result, AI becomes a tool for supporting maintenance decisions.

At the fifth level a preventive action is chosen. If there are low-level anomalies then this can lead to more frequent sampling, a specific drone inspection, or to further diagnostic tests. When deterioration continues it may result in a maintenance work order, a reduction in the load, a revised frequency for patrols, or a planned shutdown. In the case of a severe and rapidly increasing risk the situation can be handed over to adaptive protection or to operational security functions, but autonomous tripping should still require evidence that is much stronger than the level of evidence needed for advisory analytics. The current literature provides the strongest support for the use of AI in the areas of diagnosis, supervision, prioritization, and decision support; however, full replacement of deterministic protection needs much broader closed-loop and field validation.

After the decision, learning goes on. Feedback from confirmed field events, inspection results, maintenance outcomes, false alarms, and missed detections has to be fed back into the data layer. This feedback allows for periodic retraining, drift monitoring, and recalibration. The lifecycle is particularly important since transmission systems change over time: there are changes in conductor loading, renewable resources modify the short-circuit behaviour, sensors are replaced, vegetation patterns change, and climate-related stressors become more severe. A static model may therefore become unsafe even if it was originally strongly validated.

Figure 1 illustrates the progression from heterogeneous sensing to preventive action, while Figure 2 highlights the dual timescale involving fast protection intelligence and more slowly developed asset-health intelligence. This approach is in line with recent findings which show that deep learning provides significant capability in the area of protection, but its practical implementation is limited by its dependence on synthetic data, its black-box nature, and the lack of sufficient real-world validation [30]. Likewise, asset-management reviews contend that the value of machine learning lies in its integration with maintenance processes rather than simply in the choice of algorithm [28]. It is therefore clear that a publishable accuracy figure does not mean that the prevention system is operationally trustworthy.

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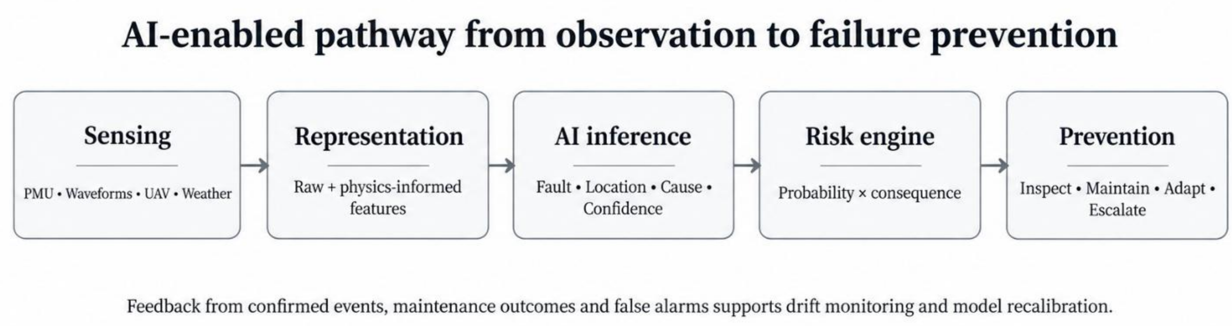

Figure 1. AI-enabled pathway from heterogeneous sensing to actionable failure prevention.

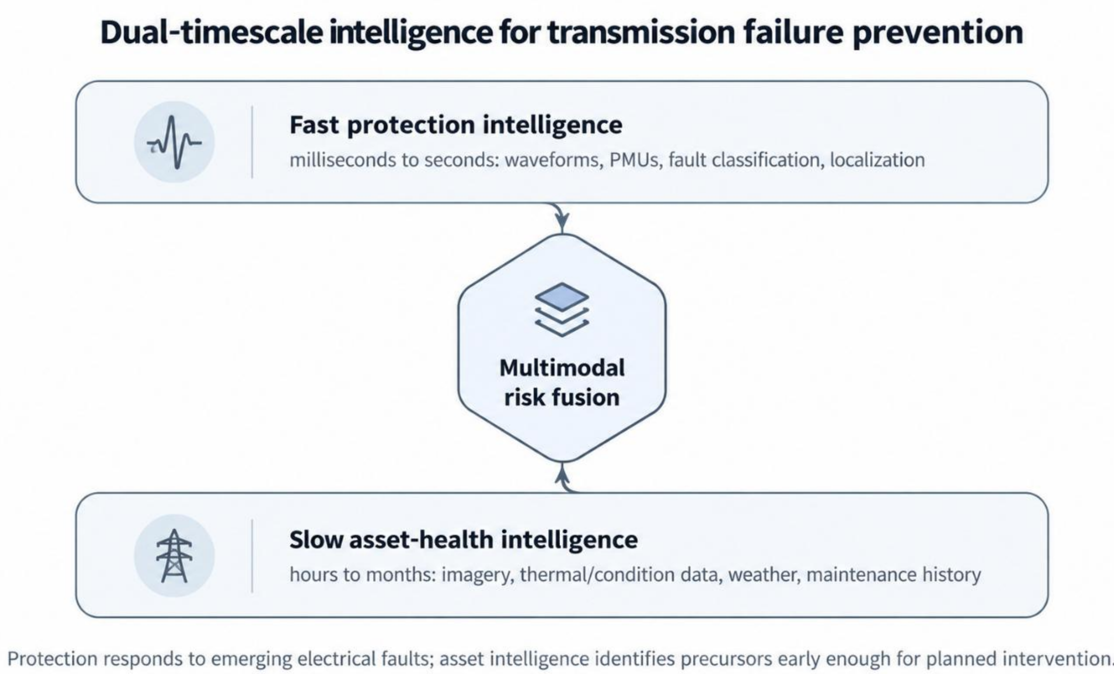

Figure 2. Dual-timescale integration of fast protection intelligence and slower asset-health intelligence.

VII. CRITICAL DISCUSSION

The evidence examined shows that AI brings about three real advances. The first of these is that representation learning decreases the need for features that have been manually selected. This is important in cases where fault signatures are nonstationary, the interactions between phases are complex, or high-impedance events do not meet simple thresholds. The second advance involves transfer and adaptation methods, which recognise that transmission systems are not fixed datasets and thus provide a means of reusing knowledge across different line lengths, source conditions, and topologies [13], [25]. The third is that multimodal AI shifts failure prevention earlier in the causal chain by detecting physical defects from imagery and combining this with electrical evidence.

Yet many of the performance claims that are frequently reported are still less comprehensive than what is actually required. Accuracy figures close to 100% may occur when the simulated fault types are well separated, the distribution of the training data is similar to that of the test data, and all the sensors are available. In practical service, however, the cost of false positives, the failure to detect rare faults, latency, calibration, and the ability to cope with domain shifts are often more important than the average accuracy. It is for this reason that robustness studies, which vary factors such as fault resistance, inception angle, source conditions, noise, or missing data, are more useful than relying on a single benchmark score [6], [13], [16]. The most thorough of these studies also examine computational feasibility, since a protection-related algorithm that demands excessive processing or communication cannot provide any practical benefit [12], [27].

A second point is the distinction between diagnosis and prediction. In much of the transmission AI literature, a fault is identified once its electrical signature has appeared. This is useful for protection and for restoring service, but it does not count as predictive maintenance in the strict sense. Genuine prediction involves having a time-to-event, a degradation trajectory, a hazard score, or a precursor trend that is present before a protection action is taken. Vision-based defect detection, transformer health assessment, thermal monitoring, and repeated condition measurements are therefore important supplements to waveform classification. A well-developed research programme should provide information on lead time as well as on accuracy: namely, how early the system picks up the risk, how stable that warning is, and whether it is realistic to carry out an intervention during that period in order to prevent failure.

Interpretability needs to have a definition that is specific to the domain in question. Engineers do not require a full symbolic explanation of a deep network, but rather want evidence to show that the model is reacting to information that is physically reasonable. Evidence of this kind can be obtained through the use of saliency across waveform intervals, the contribution of phase, time-frequency attribution, references to nearest historical events, uncertainty bounds, and counterfactual sensitivity. The model also ought to indicate when a change in its decision is due to a change in the network's topology or to changes in the quality of the data rather than to an actual condition of the asset. This is especially important in cases where the AI's output affects dispatch, maintenance priorities, or relay settings.

In the end, the use of AI brings with it cyber and regulatory risks; for example, data poisoning, manipulated images, spoofed measurements, model tampering and unauthorized retraining have the effect of turning a reliability tool into a weakness. Model versioning, secure data pipelines, access control, audit trails and rollback procedures should therefore be included as part of the engineering design rather than treated as after-the-fact administrative measures. It is essential that failure prevention also encompasses the prevention of failures caused by AI.

VIII. RESEARCH GAPS AND FUTURE DIRECTIONS

Research in the future ought to shift from comparing models to validating findings on the basis of evidence. The main focus should be on obtaining field-grade datasets which include synchronized waveforms, topology, weather data, the results of inspections, the outcomes of maintenance, and the confirmed causes of faults. Although synthetic data are still useful for covering rare events, the models should be tested using actual disturbances and also on combinations of simulated and measured records. The shared benchmarking procedures should ensure that the systems used for training are separate from those used for testing so that what is measured is generalization rather than simply the memorization of one network.

Second, achieving cross-domain generalization demands more effective transfer, continual learning, and domain adaptation. The aim must be a model

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which maintains its performance even when there are changes to the line parameters, the generation mix, or the sensing hardware without suffering unsafe catastrophic forgetting. Continual learning models require governance mechanisms to prevent uncontrolled online updates. Third, uncertainty calibration and the practice of abstaining should become standard components of the evaluation process. A model that knows when it does not know is more useful than one that always gives a confident label.

Fourth, efforts to apply physics-based learning should be increased. The laws of network behaviour, the sequences of events, the principles governing the operation of relays, and the limitations of equipment can be used to constrain the outputs of the models and thus reduce the number of unrealistic predictions. Hybrid models might also need less data than unconstrained networks. Fifth, multimodal fusion should connect electrical transients with inspection images and the maintenance history so as to model both the physical deterioration and the electrical effects together. Sixth, future studies should include in their reports metrics that are focused on prevention: warning lead time, the number of false alarms per asset month, the number of critical events that were missed, calibration error, inference latency, the number of maintenance actions avoided or initiated, and the decrease in expected outage risk.

In the end, utility-scale validation should proceed by means of staged deployment—starting with offline replay, then moving on to hardware-in-the-loop testing, followed by shadow-mode operation, after that by advisory deployment, and only then by tightly bounded automation. At each stage there should be clearly established acceptance criteria and rollback conditions. Although this approach is slower than simply proposing a new architecture, it directly tackles the main gap between research novelty and the reliable value of a transmission system.

Table 2. Deployment risks and corresponding prevention controls

Deployment risk	Operational consequence	Recommended control
Synthetic-to-field domain shift	Unexpected false alarms or missed events	Field replay, mixed real/synthetic training, shadow-mode validation
Class imbalance and rare faults	Biased model toward common healthy states	Cost-sensitive learning, targeted simulation, event curation, uncertainty reporting
Topology / generation change	Loss of generalization	Topology-aware features, transfer learning, drift detection, retraining gates
Missing or corrupted measurements	Confident inference from invalid inputs	Quality flags, redundant sensing, abstention rules, graceful degradation
Black-box behaviour	Low operator trust and difficult incident review	Attribution, physical plausibility checks, nearest-event evidence, audit logs
Cyber manipulation	Incorrect maintenance or protection action	Secure pipelines, signed models, access control, anomaly monitoring, rollback
Model aging	Performance decay after system evolution	Scheduled recalibration, drift thresholds, versioned lifecycle governance

IX. PRACTICAL, MANAGERIAL AND POLICY IMPLICATIONS

For transmission operators the first chance lies not in replacing the existing relays but in enhancing surveillance, the analysis of events that have taken place, asset inspections, and the prioritisation of maintenance. AI projects must start by making clear decisions as to which inspection to carry out, which line to patrol, which event to examine, or which asset needs more sensing. Since poor records of events will restrict all subsequent models, the data architecture and the quality of the labels should be treated as essential reliability assets and therefore properly funded.

Managers must assess models in terms of lifecycle cost and risk reduction rather than just their overall accuracy. The costs associated with computing hardware, communications, retraining, cybersecurity, human review, and the handling of false alarms should all be included in the business case. When carrying out procurement, documented provenance of the training data, version control, uncertainty reporting, and validation using degraded data should be required. Regulatory bodies and internal assurance teams can help to promote innovation by establishing different levels of evidence for advisory, maintenance, adaptive-setting, and autonomous protection applications. For applications with higher consequences, there should be a gradual increase in the amount of field evidence needed, along with independent testing and change-management controls.

X. LIMITATIONS

The review is hindered by the diversity that exists among datasets, test networks, fault definitions, evaluation metrics, and validation methods, since this makes it impossible to reliably combine the accuracies that have been reported. A large portion of the existing literature is based on simulation, and publication bias might lead to the preferential publication of models that succeed. For this reason, the synthesis places more emphasis on the methodological and deployment aspects of the approaches rather than ranking the various algorithms on the basis of a single metric. The review also concentrates on transmission applications and does not make an attempt to provide a complete treatment of distribution-system protection or generation-asset prognostics. Furthermore, deployment studies ought to record the way in which operators interact with the system, since even a technically accurate model can still fail operationally if the alerts are not properly prioritised, the explanations are vague, or the responsibilities are not clear. A human-factors assessment should look at alarm fatigue, the calibration of trust, escalation procedures, and the amount of time engineers take to check AI suggestions against traditional evidence. Such factors are crucial in situations where maintenance resources are limited and when more than one asset shows a moderate level of risk at the same time. It would also be helpful to have a standard way of reporting information on data provenance, the handling of missing data, class balance, how often the model is updated, and the computational platform used, as this would increase reproducibility and allow for meaningful comparisons between different studies. Future deployment studies should also compare AI recommendations with those of protection engineers and maintenance planners using event records. These studies should measure decision consistency, review time, confidence calibration, and how often human experts override the model. Evaluations carried out over different seasons and operating conditions are important because contamination, temperature, loading, renewable generation, and vegetation patterns can all affect both fault precursors and normal signatures. Utilities should keep independent validation datasets after each retraining cycle and should explain why any changes to the model were accepted. Adopting these practices produces traceable evidence that any performance improvements continue to hold outside the development environment and stay compatible with protection and maintenance procedures. Incident reviews should investigate false positives, false negatives, delayed warnings, and near-miss events so that the model's weaknesses can be turned into controlled updates rather than being concealed by overall performance statistics. This approach enhances accountability, reproducibility, and confidence in the long-term operational use of the system.

XI. CONCLUSION

AI has greatly broadened the range of technical methods available for diagnosing faults in transmission systems and for preventing failures. Traditional machine learning is still useful when it comes to classification tasks that are structured, easy to explain, and computationally efficient; deep convolutional and recurrent models help with automatic feature extraction; transfer learning helps with generalization across different lines; probabilistic and uncertainty-aware models allow for safer decisions; and computer vision can detect physical defects before these defects inevitably cause electrical faults. The main conclusion is that no single architecture can form a prevention system; reliable prevention results from combining trustworthy sensing, multimodal representation, uncertainty-aware inference, consequence-based risk assessment, and controlled maintenance or protection measures.

The research in the next phase should therefore focus on field validation, cross-domain robustness, calibrated confidence, physics-guided learning, secure model governance, and preventative metrics such as warning lead time and avoided risk. AI will be able to make the most credible contribution by speeding up, widening, and making evidence more consistent than ever before when it supports engineering judgment, while still maintaining clear limits in cases that are uncertain or unfamiliar. Having such safeguards in place, transmission intelligence can move on from simply quickly identifying faults to enabling earlier intervention which in turn reduces both the likelihood and the impact of failure.

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